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Artificial Intelligence in Energy Systems: A Critical Review of Conceptual Evolution, Theoretical Gaps, and Future Research Pathways

Antonis Diamantis[1*], Katerina Pappa[1], Nikolaos Christou[2]

Abstract

Artificial intelligence has become a central force in energy systems research, enabling advances in forecasting, control, optimization, demand response, grid management, and renewable energy integration. Yet despite the rapid expansion of technical applications, the field's conceptual foundations remain fragmented and its theoretical maturity has received limited critical examination. This article presents a targeted critical review of 34 peer-reviewed studies published between 2017 and 2025 to synthesize the conceptual evolution of AI in energy systems, identify major theoretical, methodological, and practical gaps, and develop a structured agenda for future interdisciplinary research. The review is thematic and critical rather than quantitative or bibliometric, focusing on how the field has evolved from rule-based automation toward data-driven learning, autonomous optimization, and emerging visions of cognitive energy systems. The analysis shows that current research is often technology-driven rather than problem-oriented, with insufficient attention to the social, institutional, and normative dimensions of AI-enabled energy transitions. Key gaps include underdeveloped theories of agency, governance, accountability, justice, and human participation; methodological weaknesses related to validation, reproducibility, benchmarking, and real-world generalizability; and practical barriers that limit adoption by utilities, regulators, and energy communities. The review argues that the next generation of energy AI scholarship must move beyond isolated technical performance gains toward theoretically grounded, methodologically rigorous, and socially responsive research. By offering a conceptual map of the field and a research roadmap for future inquiry, this article contributes to a more coherent understanding of AI in energy systems and supports the development of intelligent energy technologies that are not only efficient and adaptive, but also trustworthy, governable, and aligned with the needs of sustainable energy transitions.

Keywords Critical review, Artificial intelligence, Energy systems, Conceptual evolution, Theoretical gaps, Future research pathways

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Introduction

Artificial intelligence has moved from a specialist computational tool to a pervasive organising logic in contemporary energy systems research. Studies now position AI as relevant to renewable energy integration, smart grid analytics, demand response, building energy management, predictive maintenance, and system optimisation, indicating that the field has broadened beyond narrow engineering applications [1]. This expansion is intellectually significant because AI no

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longer merely supports isolated energy decisions; it increasingly shapes how energy systems are sensed, interpreted, governed, and automated. The literature therefore reveals a need for critical reflection on whether the conceptual foundations of energy AI have matured at the same pace as its technical applications.

The rapid growth of surveys and application reviews has helped consolidate knowledge about methods, domains, and opportunities in energy AI. Reviews of machine learning in energy systems [2], smart meter data analytics [3], renewable energy AI [4], and sustainable energy applications [5] have mapped important technical developments, but they often emphasise capabilities more than conceptual coherence. Bibliographic and trend-oriented studies have also shown the increasing visibility of AI in energy scholarship, yet such work tends to describe the field rather than interrogate its underlying assumptions [6, 7]. As a result, a critical review of the field's intellectual development remains necessary.

This article addresses that gap by reviewing the conceptual evolution, current research state, and unresolved gaps in AI for energy systems. Rather than treating AI as a neutral set of tools, it examines how the field constructs problems, defines intelligence, validates knowledge, and imagines future energy systems [8, 9]. The contribution is therefore synthetic and critical: it evaluates the maturity of energy AI as a research domain while identifying pathways for more theoretically informed, methodologically rigorous, and socio-technically grounded scholarship. In doing so, the review connects technical energy informatics with debates in energy transitions, governance, and public value [10, 11].

Motivation for Critical Review

A critical review is timely because AI in energy systems has reached a point of conceptual saturation without equivalent theoretical consolidation. The literature now spans sustainable energy industry transformation [1], reinforcement learning for demand response [12], machine learning-assisted energy optimisation [13], and physics-informed learning for power systems [14], suggesting that AI has become embedded across multiple layers of energy research. Yet this breadth has also produced fragmentation, with studies often advancing method-specific contributions without clarifying how those methods reshape energy system theory. The growing policy relevance of digitalisation and automation further increases the need to examine the assumptions behind AI-enabled energy transitions [8].

This review differs from prior descriptive surveys by asking not only what AI methods are used, but also what kinds of energy futures they make thinkable. Earlier reviews have usefully catalogued applications and challenges in sustainable energy [1], renewable energy [4], machine learning models [2], and smart meter analytics [3]. However, a recurring limitation is that these surveys generally organise the field around technical categories rather than conceptual tensions, such as autonomy versus accountability, optimisation versus public value, or predictive accuracy versus operational legitimacy. A critical review is therefore needed to move from inventory-building toward interpretive synthesis.

The critical stance adopted here is distinct from systematic mapping because the aim is not to count publications, rank methods, or quantify research clusters. Energy social science has shown that transitions are socio-technical processes shaped by institutions, infrastructures, users, and power relations, rather than purely technical substitutions [10, 15]. Applying that insight to energy AI means asking how algorithmic systems participate in wider transformations of energy governance, organisational practice, and knowledge production. This review therefore evaluates the field's conceptual trajectory while remaining attentive to methodological and practical limits.

Review Scope and Method

The review focuses on peer-reviewed journal articles published between 2017 and 2025 that address artificial intelligence, machine learning, digitalisation, energy systems, smart grids, and socio-technical energy transitions. The selected literature includes technical reviews of AI in energy [1, 2], domain-specific analyses of smart meter data and demand response [3, 12], and broader transition scholarship that helps interpret the social and institutional significance of energy AI [10, 16]. Books, policy reports, standards, theses, and non-peer-reviewed sources are excluded to maintain a

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journal-based academic scope. The review is therefore targeted rather than exhaustive, with emphasis on conceptual relevance and critical contribution.

The analytical method is thematic and interpretive, organised around conceptual evolution, current research state, theoretical gaps, methodological gaps, practical barriers, and future pathways. This approach draws on the recognition that energy AI cannot be understood only through model performance, because digitalisation changes how energy systems are organised, governed, and experienced [8, 9]. The review reads technical studies alongside socio-technical scholarship to identify recurring assumptions, silences, and tensions. In this sense, the method is critical synthesis rather than meta-analysis or bibliometric mapping.

A targeted review has limitations because it cannot claim full coverage of every AI application in energy systems. However, depth is justified because the purpose is to examine intellectual structure rather than publication volume, and critical reviews are especially useful when a field has expanded rapidly but remains conceptually fragmented [16, 17]. The review therefore prioritises influential surveys, agenda-setting papers, and representative studies that reveal how AI in energy has been framed. This scope allows the analysis to evaluate patterns across technical, institutional, and socio-technical literatures without reducing the field to a purely descriptive taxonomy.

Conceptual Evolution of AI in Energy Systems

Phase 1: expert systems and rule-based automation

The earliest conceptualisation of AI in energy systems was closely aligned with expert systems, rule-based automation, and decision support for predefined operational problems. Although many articles in the current review focus on later machine learning methods, the historical narrative in renewable energy and sustainable energy reviews recognises that AI first entered the field through structured reasoning, fault diagnosis, and optimisation routines rather than adaptive intelligence [1, 4]. In this phase, intelligence was largely understood as the codification of expert knowledge into computational procedures. The conceptual limitation of this phase was that energy systems were treated as controllable technical objects rather than dynamic socio-technical systems.

Phase 2: statistical learning and data-driven intelligence

The second phase shifted attention from explicit rules to statistical learning from increasingly abundant energy data. Smart meter analytics exemplifies this transition because it reframed consumers, buildings, and grids as data-generating environments suitable for classification, forecasting, segmentation, and anomaly detection [3]. Machine learning reviews further show that energy research began to define intelligence through pattern recognition, predictive modelling, and data-driven optimisation rather than formalised expert rules [2, 18]. This shift expanded analytical capacity, but it also encouraged a tendency to equate empirical fit with system understanding.

Phase 3: deep learning and end-to-end optimisation

The deep learning phase intensified the data-driven orientation by enabling more complex representations of temporal, spatial, and high-dimensional energy phenomena. Reviews of machine learning and deep learning in energy systems describe the increasing use of neural architectures for forecasting, control, and optimisation tasks [18], while broader sustainable energy scholarship frames AI as a tool for coordinating efficiency, reliability, and renewable integration [5]. Physics-informed machine learning added a further conceptual development by attempting to combine data-driven models with physical constraints, thereby responding to concerns that purely statistical approaches may lack interpretability and domain coherence [19]. Yet the deep learning turn also sharpened concerns about opacity, reproducibility, and the distance between algorithmic performance and operational trust.

Phase 4: autonomous and multi-agent energy systems

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The autonomy turn emerged as AI research moved from prediction toward active decision-making, adaptive control, and distributed coordination. Reinforcement learning for demand response illustrates this shift because it positions energy agents as learners interacting with uncertain environments rather than passive forecasting tools [12]. Energy optimisation studies also show how AI can support operational decision-making across generation, storage, buildings, and demand-side flexibility [13]. However, autonomy raises unresolved questions about accountability, human oversight, and the governance of systems that adapt in ways not fully specified at design time.

Emerging phase: cognitive and foundation model-based systems

The emerging phase is characterised by growing interest in cognitive, explainable, federated, and foundation model-based energy systems. Reviews of federated learning in renewable energy point toward privacy-preserving distributed intelligence [20], while explainable AI for energy systems maintenance reflects a broader demand for interpretable and accountable algorithmic reasoning [21]. Recent discussions of AI prospects in sustainable energy systems and power systems suggest that future energy AI may involve more general-purpose learning systems capable of reasoning across heterogeneous data, operational contexts, and policy objectives [22, 23]. This phase remains nascent, and its conceptual promise depends on whether the field can avoid repeating earlier patterns of technological enthusiasm without sufficient theoretical grounding.

The conceptual trajectory of AI in energy systems can therefore be understood as a staged movement from rule-based automation toward data-driven, autonomous, and potentially cognitive forms of energy intelligence, as summarised in **Table 1.**

Table 1. Conceptual Evolution of AI in Energy Systems: From Automation to Cognitive Energy Intelligence

Evolutionary phase	Dominant AI logic	Typical energy-system applications	Main contribution to the field	Key conceptual limitation
Phase 1: Expert systems and rule-based automation	Codified expert knowledge and predefined rules	Fault diagnosis, decision support, operational automation	Introduced computational reasoning into energy operations	Treated energy systems mainly as controllable technical objects
Phase 2: Statistical learning and data-driven intelligence	Pattern recognition from historical energy data	Load forecasting, smart meter analytics, anomaly detection, customer segmentation	Expanded predictive capability through data-driven modelling	Often equated empirical accuracy with system understanding
Phase 3: Deep learning and end-to-end optimisation	High-dimensional representation learning	Renewable forecasting, building control, grid optimisation, predictive maintenance	Improved modelling of complex temporal and spatial energy patterns	Increased opacity, reproducibility concerns, and trust barriers
Phase 4: Autonomous and multi-agent energy systems	Adaptive decision-making and distributed control	Demand response, microgrids, storage coordination, reinforcement learning control	Shifted AI from prediction toward active operational agency	Raised unresolved questions of accountability, oversight, and governance
Emerging phase: Cognitive and foundation model-based systems	Generalisable, explainable, federated, and	Cross-domain reasoning, privacy-preserving coordination, explainable	Points toward more flexible and integrated energy intelligence	Risks technological enthusiasm without sufficient theoretical grounding

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	context-aware intelligence	maintenance, energy decision support		

Current State of Research

Dominant application domains

The current literature is dominated by applications in forecasting, grid operation, demand response, renewable energy integration, building energy management, and maintenance. Smart meter analytics has become a major domain because granular consumption data enables new forms of load profiling, demand forecasting, and customer-side intervention [3]. Demand response and residential microgrid studies show how AI is used to coordinate flexible consumption, distributed energy resources, and uncertainty-aware operation [12, 24]. Maintenance, energy sustainability, and renewable energy applications further demonstrate that AI research is distributed across both infrastructure-side and consumer-side domains [20, 21].

Prevalent AI techniques and their evolution

The technique landscape has evolved from conventional machine learning toward deep learning, reinforcement learning, physics-informed learning, and distributed learning approaches. Systematic reviews of machine learning in energy systems show the continued importance of supervised models, ensemble methods, and optimisation techniques [2], while newer work highlights deep learning as a dominant approach for complex prediction and representation tasks [18]. Reinforcement learning has become influential where sequential decision-making and adaptive control are central [12], and physics-informed machine learning has gained attention as a response to the need for models that respect energy system constraints [14, 19]. The literature reveals technical diversification, but also a recurring lack of integration between method selection and theory of energy system behaviour.

Institutional and geographic concentration

The production of energy AI research appears concentrated in technologically advanced research systems, engineering-oriented institutions, and regions with strong smart grid, renewable energy, and digital infrastructure agendas. Bibliographic perspectives on AI and machine learning in energy systems show that the field is strongly shaped by publication networks, disciplinary clusters, and application-driven research communities [6, 7]. Studies on digitalisation and smart energy transitions suggest that such concentration matters because AI capabilities are not evenly distributed across societies, utilities, or users [9, 25]. The current state of research therefore reflects not only technical progress but also institutional asymmetries in who defines research problems, controls data, and benefits from algorithmic innovation.

Critical Evaluation of Existing Studies

Over-reliance on benchmark performance metrics

A recurring weakness in the literature is the tendency to evaluate AI systems primarily through benchmark performance rather than through their contribution to reliable, accountable, and usable energy decision-making. Reviews of machine learning in energy systems show that predictive accuracy, error reduction, and optimisation performance often dominate the assessment of model value [2, 18]. Although such measures are important, they can obscure whether a model remains useful under changing grid conditions, heterogeneous user behaviour, or institutional constraints. Demand response research similarly illustrates how algorithmic success may be framed around control performance while questions of user acceptance, fairness, and governance receive less sustained attention [12, 26].

Insufficient engagement with real-world constraints

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Many AI studies remain closer to controlled computational settings than to the operational realities of utilities, buildings, and energy markets. Work on residential microgrids and HVAC load coordination shows that AI can support complex operational decisions, but these studies also indicate the importance of forecast uncertainty, system constraints, and coordination requirements that are difficult to capture in simplified research settings [24, 27]. Building energy research further demonstrates that energy performance depends on physical infrastructure, occupancy patterns, and long-term retrofitting conditions, not only on algorithmic optimisation [28]. This review identifies a recurring gap between technically promising prototypes and the messy conditions under which energy organisations must actually deploy AI.

The neglect of socio-technical and governance dimensions

The literature frequently treats AI as a technical solution to optimisation problems, while giving less attention to how algorithmic systems interact with institutions, users, governance structures, and social priorities. Socio-technical transition scholarship shows that energy change is shaped by regimes, infrastructures, practices, and political contestation rather than by technology alone [10, 15]. Studies of smart meter transitions and digitalisation further indicate that digital energy systems can reproduce institutional power asymmetries if governance, inclusion, and public accountability are weakly addressed [25, 29]. Existing AI-in-energy research therefore risks under-theorising the social conditions that determine whether algorithmic systems become legitimate, trusted, and beneficial.

Replication and reproducibility deficits

Replication and reproducibility remain underdeveloped in energy AI because studies often rely on context-specific datasets, inconsistent preprocessing choices, and evaluation settings that are difficult to compare. Reviews of machine learning and deep learning in energy systems note substantial diversity in methods and application domains, but this diversity is not always matched by transparent reporting practices or reusable evaluation protocols [2, 18]. The reproducibility problem is intensified when models are trained on proprietary smart meter, utility, or building datasets that cannot be openly shared [3, 30]. As a result, the field may overstate generalisability when results are actually dependent on local data conditions, modelling assumptions, and unreported implementation details.

Theoretical Gaps

Absence of a unified theory of AI in energy systems

The most important theoretical gap is the absence of an integrative account of what AI means for energy systems as socio-technical systems. Existing reviews document applications across renewable energy, smart grids, and sustainable energy industry transformation, but they rarely develop a coherent theory linking algorithmic intelligence to energy system structure, governance, and transition dynamics [1, 4, 5]. Energy transition theory provides resources for understanding systemic change, but it has not been fully integrated with AI research in energy informatics [11, 16]. The result is a field rich in methods but comparatively thin in theoretical explanation.

Under-developed concepts of agency, trust, and control

The literature has not sufficiently theorised agency, trust, and control in AI-enabled energy systems. Reinforcement learning, autonomous optimisation, and distributed intelligence imply that decision-making authority may shift from human operators toward adaptive computational agents [12, 13]. Yet explainable AI research shows that interpretability is still treated mainly as a technical property rather than as part of a broader relationship of trust between users, institutions, and automated systems [21]. Future scholarship should therefore examine how human judgment, algorithmic recommendation, organisational responsibility, and regulatory oversight are redistributed when AI becomes embedded in energy operations.

The missing justice and equity dimension

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A further theoretical gap concerns justice and equity in AI-enabled energy transitions. Research on digitalisation and social inclusion shows that smart energy systems may generate uneven benefits when access, literacy, infrastructure, and institutional representation are unequally distributed [8, 9]. Smart meter transition scholarship also demonstrates that digital energy technologies are embedded in national governance arrangements and public acceptance dynamics, not simply technical deployment pathways [29]. Few AI-in-energy studies systematically connect model design, data access, and algorithmic decision-making to energy justice, which leaves questions of exclusion, bias, and unequal benefit distribution insufficiently theorised.

Methodological Gaps

Lack of standardized benchmarks and evaluation protocols

Methodological fragmentation is visible in the lack of standardised benchmarks, shared datasets, and comparable evaluation protocols across energy AI studies. Smart meter analytics research highlights the diversity of applications, data resolutions, and methodological choices that make cross-study comparison difficult [3]. Machine learning reviews similarly reveal that models are often evaluated within narrow task settings, limiting the ability to judge robustness across different energy contexts [2]. Without stronger methodological conventions, the field may continue to accumulate isolated performance claims rather than transferable knowledge.

Overfitting to historical data and neglect of uncertainty

Many energy AI studies depend heavily on historical data, which creates risks when systems face non-stationary demand, extreme weather, infrastructure change, market disruption, or policy shifts. Model predictive control and microgrid operation research explicitly recognise forecast uncertainty as central to energy decision-making [24], but much of the broader AI literature still treats historical patterns as sufficiently representative of future conditions. Physics-informed learning offers one response by embedding domain constraints into learning processes, but it does not eliminate the need to evaluate models under uncertainty and distributional shift [14, 19]. A recurring methodological gap is therefore the limited treatment of robustness, failure modes, and uncertainty-aware validation.

Underutilisation of qualitative and mixed-methods approaches

The methodological culture of energy AI remains heavily computational, with limited use of qualitative or mixed-methods approaches to understand implementation, organisational adoption, and user experience. Energy social science has argued for methodological rigor and pluralism when studying socio-technical change, particularly because transitions involve institutions, practices, and contested meanings that cannot be captured by metrics alone [17]. Co-creation research further suggests that participatory and qualitative methods can reveal barriers, expectations, and legitimacy concerns in energy transitions [31]. Future energy AI research should therefore combine modelling studies with interviews, case studies, ethnography, participatory design, and institutional analysis where appropriate. **Figure 1** illustrates how qualitative and mixed-methods approaches complement computational energy AI research by revealing organisational, institutional, participatory, and user-experience dimensions that cannot be captured through modelling metrics alone.

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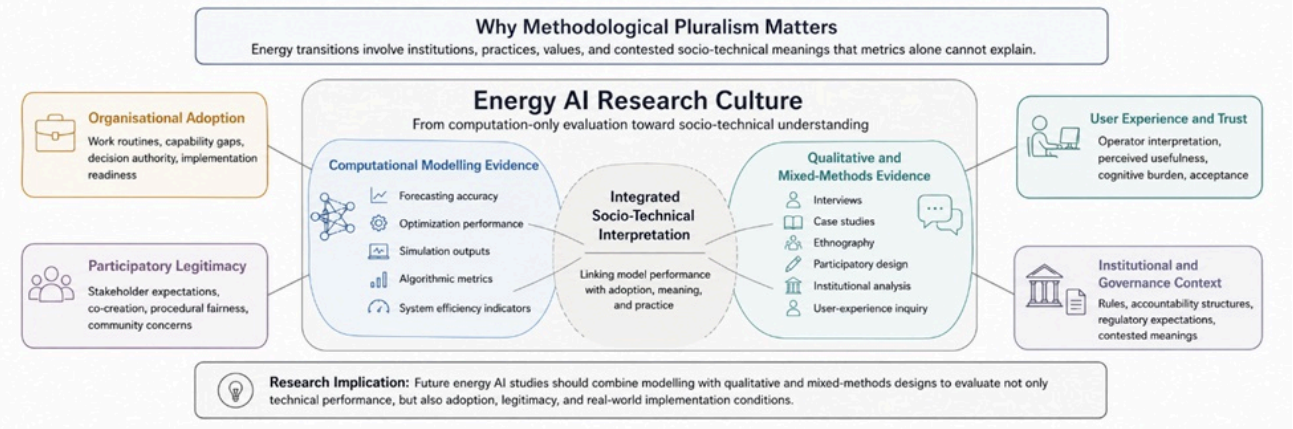

Figure 1. Methodological Pluralism for Understanding Energy AI Implementation

Practical and Industrial Gaps

The research-to-practice translation deficit

The literature reveals a persistent translation deficit between AI research and operational energy practice. Although AI is frequently presented as transformative for sustainable energy systems, many studies remain focused on proof-of-concept modelling rather than deployment pathways, maintenance requirements, and organisational integration [1, 22]. Energy Internet research illustrates that business models, market arrangements, and platform governance are central to digital energy transformation, not peripheral implementation details [32]. The gap is therefore not only technical; it concerns whether AI systems can be embedded into viable operational, regulatory, and economic contexts.

Organisational and institutional barriers in utilities

Utility adoption of AI is shaped by organisational routines, risk cultures, regulatory obligations, and legacy decision processes. Digitalisation research shows that energy systems do not automatically become more sustainable through ICT adoption, because digital tools can add complexity, energy demand, and organisational dependence [8]. Smart electricity meter transitions further demonstrate that national institutions, governance styles, and public legitimacy shape whether digital energy technologies are accepted and stabilised [29]. AI research that ignores these institutional barriers may underestimate the difficulty of moving from academic models to trusted utility practice.

Data access, interoperability, and legacy system constraints

Data access and interoperability remain major practical obstacles for AI in energy systems. IoT and smart home analytics research shows that energy data are increasingly distributed across devices, platforms, cloud infrastructures, and user environments, creating integration and governance challenges [30]. Federated learning has emerged partly because energy data are sensitive, fragmented, and institutionally difficult to centralise [20]. These conditions mean that future AI systems must contend with privacy restrictions, legacy infrastructures, incompatible data standards, and uneven digital capacity across organisations.

Taken together, the theoretical, methodological, and practical weaknesses identified in the review reveal a layered gap structure that constrains the maturity of AI in energy systems research, as shown in **Table 2.**

Table 2. Critical Gap Matrix for AI in Energy Systems Research

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Gap category	Specific gap	How it appears in the literature	Why it matters	Research implication
Theoretical	Absence of a unified theory of AI in energy systems	AI is often treated as a set of tools rather than as part of socio-technical energy transformation	Limits conceptual coherence and cumulative knowledge-building	Develop middle-range theories linking AI functions to energy governance, transition dynamics, and public value
Theoretical	Underdeveloped concepts of agency, trust, and control	Autonomous optimisation and reinforcement learning are discussed without sufficient attention to responsibility and oversight	Creates uncertainty over who is accountable for AI-enabled decisions	Study how decision authority is redistributed among algorithms, operators, regulators, and users
Theoretical	Missing justice and equity dimension	Few studies connect AI design, data access, and algorithmic outcomes to energy justice	Risks reproducing unequal access, bias, and uneven benefit distribution	Integrate energy justice, fairness, inclusion, and community impact into AI energy research
Methodological	Lack of standardised benchmarks and protocols	Studies use different datasets, preprocessing methods, and evaluation metrics	Makes results difficult to compare or reproduce	Build shared datasets, reporting standards, and evaluation protocols
Methodological	Overfitting to historical data	Models are trained on past patterns that may not hold under climate, market, or policy disruption	Weakens robustness in real-world deployment	Evaluate models under uncertainty, non-stationarity, and distributional shift
Methodological	Limited qualitative and mixed-methods research	Computational performance dominates over implementation, user, and institutional analysis	Leaves adoption barriers and legitimacy issues underexplored	Combine modelling with interviews, case studies, participatory design, and institutional analysis
Practical	Research-to-practice translation deficit	Many studies remain proof-of-concept rather than deployment-oriented	Prevents academic models from becoming operationally useful	Study deployment pathways, maintenance needs, business models, and regulatory fit
Practical	Utility organisational barriers	Legacy systems, risk cultures, regulation, and routines are often overlooked	Slows adoption and reduces trust in AI systems	Examine organisational readiness, operator trust, procurement, and regulatory compliance
Practical	Data access and interoperability constraints	Energy data are fragmented, sensitive, proprietary, and platform-dependent	Limits scalability, reproducibility, and cross-context learning	Advance privacy-preserving, interoperable, and federated data infrastructures

Future Research Pathways

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Building middle-range theories for energy AI

Future research should develop middle-range theories that connect AI techniques to specific energy system functions, institutional settings, and transition dynamics. Rather than proposing universal claims about AI transformation, scholars should explain how particular forms of algorithmic intelligence affect forecasting, coordination, control, accountability, and public value in defined contexts [11, 16]. Such theory-building can draw from socio-technical transitions, information processing, institutional analysis, and energy informatics without collapsing them into a single grand theory. The aim should be conceptual clarity that supports cumulative knowledge and critical evaluation.

Advancing interdisciplinary and mixed-methods research

A more mature field will require interdisciplinary and mixed-methods research that links computational performance with organisational, social, and governance outcomes. Technical studies should be complemented by qualitative inquiry into how operators, regulators, communities, and consumers interpret and contest AI-enabled energy decisions [17, 31]. This does not diminish the value of machine learning research; rather, it situates algorithmic methods within the systems where they are expected to operate. Future research should therefore treat modelling, implementation, governance, and social legitimacy as connected dimensions of energy AI scholarship.

Co-designing AI with utilities, regulators, and communities

Future research should place greater emphasis on co-design with utilities, regulators, communities, and affected users. Digital energy transitions show that technological systems gain legitimacy through institutional alignment, social inclusion, and transparent governance, not only through technical efficiency [9, 25]. AI for energy systems should therefore be developed through collaborative research models that address practical constraints, regulatory responsibilities, data governance, and community impacts from the beginning. Such co-design would help shift the field from technology-driven experimentation toward problem-oriented and socially accountable innovation.

Figure 2 translates the review's critical synthesis into a conceptual framework showing how future energy AI research can move from technology-driven model development toward socio-technical energy intelligence.

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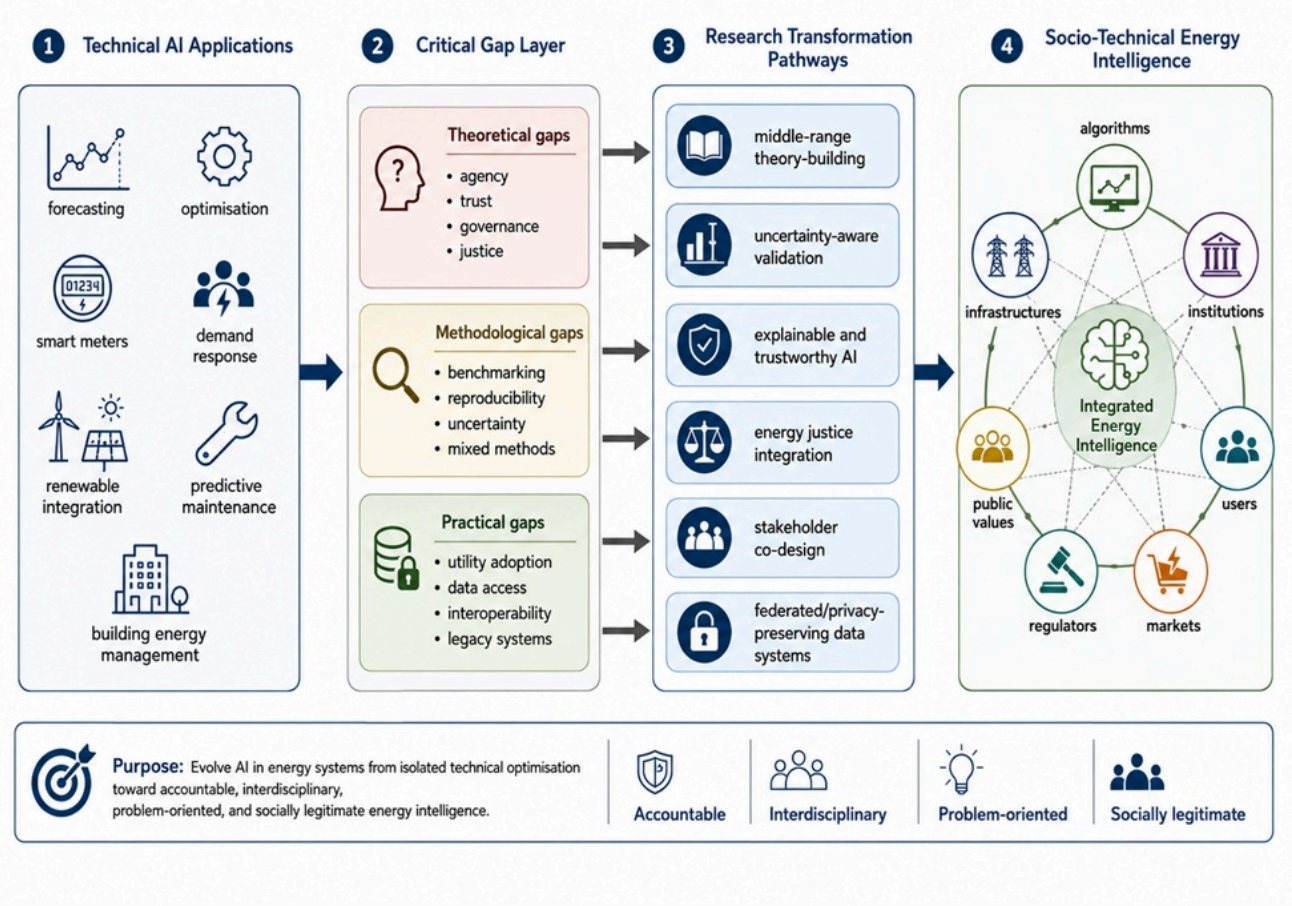

Figure 2. From Technical AI Applications to Socio-Technical Energy Intelligence: A Conceptual Framework

A problem-oriented future research agenda should therefore connect technical AI development with theory-building, methodological rigour, institutional adoption, and public accountability, as outlined in **Table 3.**

Table 3. Future Research Agenda for Problem-Oriented Energy AI Scholarship

Future research pathway	Core research question	Suggested methods	Expected contribution
Build middle-range theories of energy AI	How do specific AI techniques reshape forecasting, coordination, control, governance, and public value in particular energy contexts?	Conceptual synthesis, comparative case analysis, theory-building reviews	Moves the field beyond descriptive application surveys toward cumulative theoretical development
Develop uncertainty-aware validation frameworks	How robust are AI models under non-stationary demand, extreme weather, policy change, infrastructure disruption, and market volatility?	Stress testing, scenario analysis, out-of-distribution testing, uncertainty quantification	Improves reliability and operational trustworthiness
Integrate explainability with institutional trust	What kinds of explanations are meaningful to operators, regulators, consumers, and affected communities?	Explainable AI evaluation, user studies, operator interviews, human-in-the-loop experiments	Links technical interpretability to real-world accountability and trust

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Advance energy justice in AI design	Who benefits from AI-enabled energy systems, who is excluded, and how are risks distributed?	Equity audits, participatory design, community-based research, fairness analysis	Embeds justice, inclusion, and public value into AI energy scholarship
Strengthen reproducibility and benchmarking	How can energy AI studies become more comparable, transparent, and reusable?	Open datasets, model cards, benchmark tasks, shared reporting protocols	Reduces fragmented performance claims and improves scientific credibility
Study utility adoption and organisational readiness	What organisational, regulatory, and infrastructural conditions enable or constrain AI deployment?	Case studies, interviews, organisational analysis, regulatory analysis	Bridges the gap between academic models and operational practice
Co-design AI with stakeholders	How can utilities, regulators, communities, and users shape AI systems from the beginning?	Co-design workshops, living labs, participatory modelling, policy labs	Shifts the field from technology-driven experimentation to socially accountable innovation
Explore federated and privacy-preserving energy AI	How can AI learn from distributed energy data without compromising privacy or control?	Federated learning, privacy-preserving analytics, interoperability studies	Supports scalable AI under real-world data governance constraints

Conclusion

This critical review has shown that AI in energy systems has evolved from rule-based automation toward statistical learning, deep learning, autonomous optimisation, and emerging cognitive approaches. The field has generated substantial technical knowledge, but its conceptual development remains uneven. Its dominant research culture still privileges algorithmic capability more than theoretical explanation, methodological transparency, or socio-technical accountability.

The review identifies theoretical gaps around agency, governance, control, trust, and justice. It also identifies methodological weaknesses related to benchmarking, reproducibility, uncertainty, and the limited use of qualitative and mixed-methods research. These gaps matter because AI systems increasingly shape real energy decisions, infrastructures, and institutional responsibilities.

Future research should move beyond descriptive application surveys and narrow performance comparisons. It should build stronger middle-range theories, develop more robust evaluation practices, and integrate computational research with energy social science, policy analysis, and organisational studies. The next stage of the field should be less technology-driven and more problem-oriented, interdisciplinary, and accountable.

Artificial intelligence can contribute meaningfully to sustainable, reliable, and inclusive energy systems only if the research community treats it as more than a technical instrument. It must be studied as part of a wider socio-technical transformation involving infrastructures, institutions, users, markets, and public values. Building such a field will require collective effort across engineering, computer science, policy, social science, and practice communities.

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