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An AI-Enabled Energy Resilience Framework for Climate-Uncertain Power Systems

Thomas Dupont[1*], Marie Leclerc[1]

Abstract

Climate change is introducing deep uncertainty into power system planning and operation by intensifying extreme weather events, shifting electricity demand patterns, and altering resource availability. As a result, resilience has become a central paradigm for securing energy systems, emphasizing the capacity to anticipate, absorb, adapt to, and recover from disruptions. However, many existing resilience frameworks continue to rely on historical data and stationary assumptions that are increasingly unsuitable under non-stationary climate conditions. At the same time, the role of artificial intelligence in supporting resilience decisions remains conceptually underdeveloped and insufficiently integrated with resilience engineering principles. This article develops an AI-enabled energy resilience framework for climate-uncertain power systems by synthesizing insights from resilience engineering, climate change adaptation, uncertainty quantification, and AI applications in power systems. The study is entirely conceptual and does not involve experimental validation. The proposed framework organizes AI-enabled resilience into four interconnected capability areas: climate-informed anticipation and risk assessment, real-time disruption absorption and situational awareness, adaptive recovery and reconfiguration, and long-term transformational adaptation. These capabilities are supported by an uncertainty governance layer that links AI-generated insights to institutional decision-making, risk prioritization, and operational accountability. The framework shows how AI can move beyond prediction alone to support actionable, adaptive, and institutionally embedded resilience intelligence. By connecting technical AI capabilities with resilience lifecycle management, the article provides a conceptual foundation for future research, policy development, and practical deployment in climate-uncertain power systems.

Keywords Artificial intelligence, Power systems, Energy resilience, Climate uncertainty, Climate adaptation, Extreme weather

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Introduction

Power systems are increasingly exposed to climate-driven hazards that disrupt generation, transmission, distribution, and demand. Heatwaves can intensify cooling loads and stress thermal generation, while storms, floods, and wildfires can damage network assets, interrupt fuel supply chains, and create spatially extensive outages. Climate-energy research shows that climate change affects both renewable energy supply and system demand, creating interacting operational pressures rather than isolated technical challenges [1]. These pressures require resilience strategies that are sensitive to changing hazard patterns, infrastructure exposure, and evolving system dependencies.

Traditional reliability planning assumes that future operating conditions can be meaningfully inferred from historical patterns, but climate change weakens this assumption by altering the frequency, intensity, and spatial distribution of

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hazards. Reviews of power system resilience emphasize that resilience differs from reliability because it addresses high-impact disruptions, adaptive response, and recovery under abnormal conditions rather than routine adequacy alone [2]. Existing resilience assessment approaches provide valuable metrics and engineering concepts, yet they often struggle to represent non-stationary climate risk and evolving vulnerability [3]. A resilience paradigm is therefore needed that treats learning, adaptation, and uncertainty management as central design requirements.

Artificial intelligence could support this paradigm by processing heterogeneous data streams, detecting weak signals of emerging disruptions, and assisting operators before, during, and after extreme events. Machine learning has already been used to support weather-related outage prediction and event severity characterization, showing how data-driven models can translate meteorological information into grid-relevant warnings [4]. AI-enabled restoration and control methods, including reinforcement learning, also suggest that adaptive decision-support tools may help coordinate response when grid conditions change rapidly [5]. However, these tools remain conceptually fragmented when they are not embedded within a broader resilience framework that links analytic outputs to anticipation, absorption, adaptation, and recovery.

The objective of this article is to develop an AI-enabled energy resilience framework for climate-uncertain power systems. The proposed framework builds on resilience literature that defines power system resilience through preparation, absorption, recovery, and adaptation, while extending this logic to climate uncertainty and AI-supported decision-making [6]. It treats AI not as a replacement for engineering judgment or institutional governance but as a resilience intelligence layer that could enhance sensing, forecasting, control, learning, and policy support. In doing so, the article contributes a conceptual architecture for aligning AI capabilities with the full lifecycle of climate-driven disruption.

Background

Climate uncertainty and power system vulnerabilities

Climate uncertainty affects power systems through epistemic uncertainty in climate projections, stochastic uncertainty in event occurrence, and deep uncertainty about future socio-technical pathways. Climate-energy modeling studies show that changing temperature, hydrology, wind, solar resources, and demand patterns can influence both energy supply and infrastructure performance [7]. These uncertainties create vulnerabilities across generation assets, transmission corridors, distribution feeders, and demand-side flexibility, particularly where assets were designed for historical climate envelopes. Extreme heat, storms, and other hazards also expose the limits of planning approaches that assume stable relationships between weather, demand, and infrastructure stress [8].

Energy resilience: concepts, metrics, and engineering approaches

Energy resilience can be conceptualized as the capacity of a power system to prepare for, absorb, recover from, and adapt to disruptive events. This makes resilience distinct from reliability, which mainly concerns service continuity under expected operating conditions, and from security, which often focuses on protection against specific threats [9]. Reviews of resilience metrics show that power system resilience assessment remains methodologically diverse, with different studies emphasizing degradation curves, recovery speed, robustness, resourcefulness, or adaptability [10]. These concepts are valuable, but climate-driven disruptions require frameworks that can accommodate compounding hazards, uncertain baselines, and adaptive decision cycles rather than static performance indicators alone.

AI in power systems: from operations to resilience

AI applications in power systems have expanded from forecasting and optimization toward fault detection, outage prediction, adaptive control, and decision support. Weather-related outage studies illustrate how machine learning can connect vegetation, meteorological, and infrastructure variables to outage risk, thereby supporting resilience-oriented situational awareness [11]. Nevertheless, many AI applications remain oriented toward normal operations, market

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efficiency, or asset management rather than climate-uncertain resilience. A framework perspective is needed because AI tools that perform well in narrow operational tasks may not automatically produce resilient outcomes under extreme, cascading, or data-scarce conditions.

Climate adaptation and infrastructure planning under deep uncertainty

Climate adaptation literature emphasizes that infrastructure planning must account for futures that cannot be reduced to a single forecast. Studies extending energy system modeling to extreme weather risk show that planning can become more resilience-relevant when it incorporates hazard scenarios, disruption pathways, and recovery considerations [12]. Under deep uncertainty, power system planners may require robust strategies, adaptive pathways, and staged investment decisions rather than one-time optimization against a presumed future. AI could support such planning, but only if its outputs are interpreted as decision-support evidence within adaptive governance processes rather than deterministic predictions.

Integrating AI, resilience, and climate adaptation: the missing link

The literatures on AI for power systems, resilience engineering, and climate adaptation remain partly siloed. Resilience reviews identify conceptual and methodological challenges in defining, measuring, and improving power system resilience, while AI-oriented studies often focus on specific prediction or control tasks [13]. At the same time, climate impact studies highlight shifting risks to energy systems but do not always specify how AI-enabled operational intelligence should be integrated into resilience governance [14]. The missing link is a conceptual framework that connects AI capabilities to climate-informed resilience phases, institutional decision-making, and long-term adaptation.

Recent research also emphasizes that resilient energy transitions increasingly require integration between AI-driven operational intelligence and socio-technical adaptation governance. Studies examining climate-resilient electricity systems suggest that resilience planning becomes more effective when predictive analytics, infrastructure adaptation, and institutional coordination are treated as interconnected rather than isolated domains [15]. This reinforces the need for AI-enabled resilience architectures that support both real-time operational response and long-term adaptive transformation under climate uncertainty.

Conceptual Foundation of the Framework

Resilience as a dynamic, multi-phase process

The framework conceptualizes resilience as a dynamic process rather than a fixed infrastructure attribute. Contemporary resilience scholarship increasingly treats resilience as a sequence of capabilities involving anticipation, absorption, recovery, and adaptation, with each phase requiring different forms of information and decision support [16]. Anticipation requires climate-informed risk intelligence, absorption requires real-time situational awareness, recovery requires restoration sequencing, and adaptation requires long-term learning. This lifecycle view is essential because AI tools that support one phase, such as outage prediction, may be insufficient unless connected to response, restoration, and transformation decisions.

Climate uncertainty as a design condition

Climate uncertainty should be treated as a design condition of resilient power systems rather than as a residual error term in planning models. Research on climate impacts on renewable energy supply demonstrates that changing climatic conditions can alter the resource base on which future power systems depend [1]. Similarly, climate-sensitive power system studies indicate that energy scenarios and climate projections interact, meaning that future resilience depends on both physical climate hazards and evolving energy system configurations [14]. The proposed framework therefore requires AI tools that can represent uncertainty, update assumptions, and support decisions that remain useful across multiple plausible futures.

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Table 1 summarizes the major categories of climate uncertainty affecting power system resilience and the corresponding AI-enabled analytical responses.

Table 1. Climate-Uncertainty Categories and AI-Enabled Resilience Responses

Climate uncertainty category	Example manifestation in power systems	AI-enabled resilience function	Operational resilience implication
Extreme weather uncertainty	Unpredictable storms, floods, and wildfires	Hazard forecasting and outage prediction	Supports preparedness and emergency resource allocation
Demand variability uncertainty	Heatwave-driven electricity demand surges	Load forecasting and adaptive demand management	Reduces overload risk and improves service continuity
Renewable resource uncertainty	Variable wind and solar generation patterns	Renewable generation forecasting	Enhances balancing and operational flexibility
Infrastructure vulnerability uncertainty	Unknown asset exposure to climate stress	Asset risk screening and vulnerability mapping	Improves infrastructure hardening prioritization
Cascading system uncertainty	Multi-sector infrastructure interdependencies	Cross-system anomaly detection and dependency analysis	Helps identify cascading failure pathways
Long-term climate pathway uncertainty	Uncertain future climate trajectories and adaptation needs	Scenario analysis and adaptive planning support	Enables flexible long-term resilience planning

AI as a resilience intelligence layer

AI can be conceptualized as a resilience intelligence layer that links sensing, prediction, learning, and decision support across the disruption lifecycle. Rather than functioning as a standalone technical module, this layer would draw from climate projections, grid telemetry, outage histories, asset data, and operational constraints to support context-specific resilience decisions. Distribution resilience research shows that active distribution systems require integrated approaches to monitoring, control, and restoration as distributed energy resources and flexible loads become more important [17]. In this framework, AI provides adaptive intelligence, while engineering constraints and governance processes determine how that intelligence is translated into action.

Figure 1 presents the proposed AI-enabled resilience architecture, showing how climate uncertainty, AI-supported intelligence, resilience lifecycle phases, and governance mechanisms interact across power system disruption and adaptation processes.

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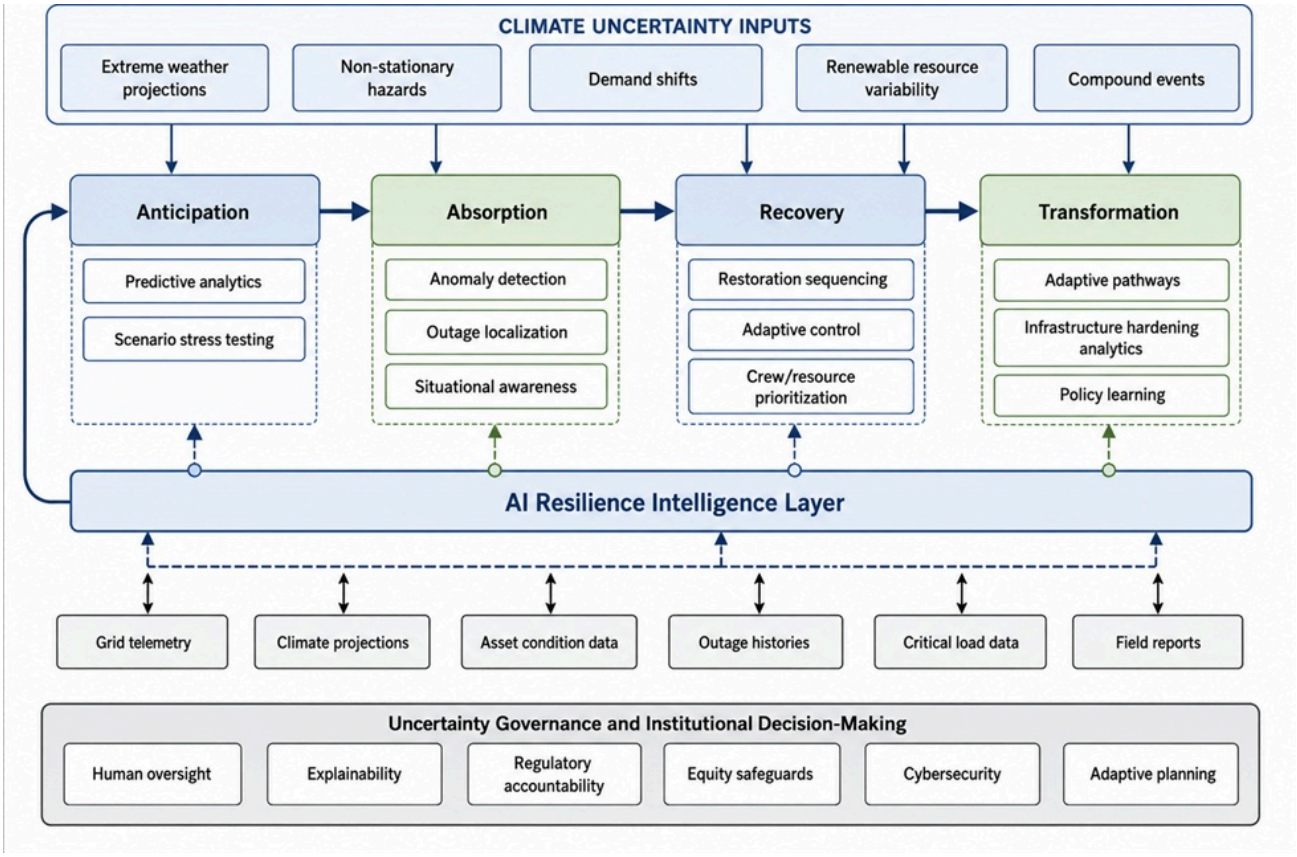


Figure 1. AI-Enabled Energy Resilience Architecture for Climate-Uncertain Power Systems

Framework Components

Anticipation and risk assessment layer

The anticipation and risk assessment layer is designed to support climate-informed preparedness before disruption occurs. AI could enable extreme event forecasting, outage likelihood estimation, vulnerability mapping, and early warning by combining meteorological, environmental, asset, and historical outage information. Studies on weather-related outage modeling show how event severity classification and expanding spatial domains may improve the generalizability of outage prediction under varied weather conditions [4, 18]. Within the framework, such predictive functions would be linked to resilience planning decisions, including pre-positioning crews, hardening vulnerable assets, prioritizing critical facilities, and stress-testing future climate scenarios.

Absorption and situational awareness layer

The absorption and situational awareness layer supports power systems during ongoing disruptions when infrastructure conditions, communication quality, and operator information may be unstable. AI-enabled anomaly detection, damage inference, outage localization, and resource allocation could help operators understand which assets are compromised and which loads require immediate protection. Research on quantitative power system resilience highlights the importance of assessing degradation and response dynamics, not only final recovery outcomes [10]. This layer therefore emphasizes real-time resilience intelligence that may help systems absorb shocks by maintaining critical services, reallocating limited resources, and avoiding unnecessary escalation.

Adaptation and transformation layer

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The adaptation and transformation layer focuses on post-event learning, adaptive reconfiguration, infrastructure hardening, and long-term climate-resilient planning. Resilience studies increasingly emphasize that recovery should not simply restore pre-event conditions when those conditions remain vulnerable to future hazards [19]. AI-supported scenario analysis could help identify where grid reinforcement, distributed energy resources, microgrids, undergrounding, vegetation management, or operational rule changes may improve future resilience. This layer connects short-term restoration experience with long-term transformation by converting disruption data into adaptive planning intelligence.

AI Capabilities for Climate-Uncertain Resilience

Predictive analytics for extreme event anticipation

Predictive analytics could support climate-uncertain resilience by characterizing extreme events, identifying vulnerable assets, and estimating plausible disruption pathways before they fully materialize. Machine learning studies on weather-related outages demonstrate how meteorological and environmental predictors can be used to estimate outage occurrence and severity, while more recent work seeks improved quantitative prediction of outages caused by extreme weather [20]. In a climate-uncertain context, however, predictive analytics should be designed to communicate uncertainty, model limitations, and scenario sensitivity rather than only producing point estimates. The framework therefore positions AI-based forecasting as a decision-support capability for preparedness, not as a deterministic substitute for resilience planning judgment.

Adaptive control and restoration under uncertainty

Adaptive control and restoration capabilities are central to the framework because climate-driven disruptions can fragment networks, degrade communications, and require rapid reconfiguration. Deep reinforcement learning has been explored for distribution system resilience under asynchronous information, suggesting that AI may support operational decisions when system knowledge is incomplete or delayed [5]. Reinforcement learning from demonstrations has also been proposed to assist service restoration in islanded microgrids, indicating how learned policies may help guide restoration under constrained conditions [21]. Within the framework, such methods would be expected to operate within safety limits, engineering constraints, and human oversight structures rather than autonomously overriding institutional decision authority.

Table 2 compares major AI techniques according to their resilience applications, strengths, and implementation limitations in climate-uncertain power systems.

Table 2. Comparative Roles of AI Techniques in Climate-Resilient Power System Operations

AI technique	Primary resilience application	Key strength	Main limitation
Machine learning	Weather-related outage prediction	Learns complex nonlinear relationships from large datasets	Performance depends on historical data quality
Deep learning	Real-time anomaly detection and fault recognition	High pattern-recognition capability	Reduced explainability for operators
Reinforcement learning	Adaptive restoration and grid reconfiguration	Learns dynamic operational strategies	Requires extensive training and validation

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Predictive analytics	Extreme-event anticipation and preparedness	Supports early-warning decision-making	Sensitive to uncertainty in climate projections
Scenario-based AI modeling	Long-term adaptation pathway analysis	Evaluates multiple plausible futures	Computationally intensive
Explainable AI	Operator decision support and governance transparency	Improves interpretability and institutional trust	May reduce model complexity or predictive performance

Learning and continuous improvement from disruptions

AI-enabled resilience should include continuous learning from disruptions so that each event improves future anticipation, response, restoration, and adaptation. Reviews of power system resilience identify the need to move beyond one-time assessment toward iterative resilience enhancement as hazards, technologies, and operating conditions evolve [22]. Outage prediction studies using storm and utility data further suggest that disruption records can be transformed into operational knowledge when systematically linked to weather, infrastructure, and response information [23]. In the proposed framework, post-event learning would update risk models, refine emergency protocols, identify maladaptive practices, and inform long-term investment decisions.

Table 3 differentiates AI-enabled resilience functions across the disruption lifecycle by clarifying their decision purpose, uncertainty burden, governance requirement, and expected resilience contribution.

Table 3. Conceptual Differentiation of AI-Enabled Resilience Functions across the Climate-Disruption Lifecycle

Resilience phase	Core system question	AI-enabled analytical function	Dominant uncertainty challenge	Required governance condition	Added resilience value
Anticipation	What disruptions are plausible, where, and with what consequences?	Climate-informed risk screening, outage likelihood estimation, vulnerability mapping, scenario stress testing	Non-stationary hazards, sparse extreme-event data, climate-model uncertainty	Transparent model assumptions, scenario pluralism, regulator-visible risk thresholds	Converts uncertain climate signals into preparedness priorities before disruption occurs
Absorption	Which parts of the system are degrading, and how can critical service be preserved?	Real-time anomaly detection, outage localization, damage inference, situational awareness, critical load prioritization	Incomplete telemetry, communication failures, rapidly changing field conditions	Human-in-the-loop operational authority, safety constraints, escalation protocols	Supports shock absorption by improving visibility and prioritizing limited response capacity
Recovery	What restoration sequence minimizes social, technical, and operational harm?	Restoration optimization, adaptive reconfiguration, crew dispatch prioritization, microgrid/islanding support	Dynamic network topology, uncertain damage extent, logistical constraints	Engineering validation, operator override, accountability for service prioritization	Links restoration speed with criticality, equity, safety, and system stability

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Adaptation	What must change so future disruptions produce less harm?	Post-event learning, adaptation pathway analysis, infrastructure investment screening, resilience metric updating	Deep uncertainty about future climate, technology, demand, regulation, and socio-economic exposure	Periodic review, public accountability, equity assessment, investment justification	Transforms disruption experience into long-term resilience strategy
Cross-phase learning	How should the system improve after every disruption?	Continuous model updating, event forensics, performance benchmarking, maladaptation detection	Data drift, institutional memory loss, inconsistent metrics	Auditable learning cycles, shared data standards, cross-agency review	Prevents resilience from remaining static under evolving climate risk

Resilience Lifecycle and Adaptive Management

Pre-event anticipation and preparation

In the pre-event phase, the framework supports anticipation by translating climate, infrastructure, and operational signals into preparedness intelligence. AI-driven risk screening could help utilities identify vulnerable corridors, substations, feeders, and generation assets before extreme events occur, while scenario stress-testing may support decisions about crew placement, spare equipment, demand-side flexibility, and distributed backup capacity. Reviews of resilience enhancement measures emphasize that pre-disruption planning must combine hardening, operational preparedness, emergency resources, and system reconfiguration options rather than relying on a single defensive strategy [24]. Within the proposed framework, pre-event AI should therefore be designed to support preparation under uncertainty, not merely to forecast isolated hazards.

During-event response and resource coordination

During extreme events, the framework positions AI as a coordination support layer for emergency response, islanded operation, critical load prioritization, and real-time system awareness. Distribution resilience research shows that extreme-weather response requires rapid integration of fault information, network status, distributed resources, and restoration constraints, especially when distribution systems become fragmented or partially observable [25]. AI could help operators prioritize hospitals, shelters, water facilities, communication hubs, and other critical loads while balancing safety, equity, and technical feasibility. However, because climate disruptions often involve incomplete data and changing field conditions, AI-generated recommendations should remain subject to operator judgment and institutional escalation procedures.

Post-event restoration and learning

In the post-event phase, AI could support restoration sequencing, damage assessment, crew dispatch prioritization, and evaluation of whether resilience measures performed as intended. Studies on sequential preventive resilience models suggest that resilience enhancement should consider not only restoration after damage but also preventive actions that reduce system degradation before failures propagate [26]. Post-event learning is therefore not limited to returning power quickly; it also involves identifying which assets failed, which assumptions were invalid, and which response protocols require revision. The proposed framework links restoration analytics to organizational learning so that disruption experience becomes a source of adaptive resilience improvement.

Long-term transformational adaptation

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Long-term transformational adaptation extends resilience beyond event response toward structural change in infrastructure, planning, governance, and technology deployment. Microgrids are frequently discussed as resilience resources because they may support islanding, local energy continuity, and flexible recovery when central grid infrastructure is disrupted [27]. Yet transformational adaptation also requires decisions about asset relocation, vegetation management, climate-informed design standards, digital infrastructure, and distributed energy integration. In the framework, AI could support these decisions by exploring alternative adaptation pathways, but final choices should be guided by public accountability, engineering feasibility, and social priorities.

Application Domains in Climate-Uncertain Power Systems

Wildfire-resilient grid operations

In wildfire-prone regions, the framework could support resilience by integrating weather forecasts, vegetation conditions, asset health, topography, and grid loading into ignition-risk and outage-risk intelligence. Research on vegetation management and LiDAR-derived tree height data demonstrates how environmental and asset-adjacent information can improve utility outage prediction, which is directly relevant to wildfire-sensitive grid operations [11]. AI-enabled systems could support proactive de-energization, targeted inspection, vegetation prioritization, and safer restoration sequencing after fire danger declines. Because de-energization can also create public health and equity risks, wildfire-related AI tools should be embedded in transparent governance procedures that justify trade-offs and protect critical customers.

Flood and storm resilience for coastal and inland infrastructure

For coastal and inland infrastructure exposed to floods, hurricanes, and severe storms, the framework could combine climate projections, hydrological forecasts, asset elevation data, outage histories, and field reports to support resilience decisions. Energy system modeling that incorporates hurricane risk demonstrates the need to represent extreme weather as a planning concern rather than as an external shock outside energy system analysis [12]. AI could assist with substation vulnerability screening, post-storm damage inference, repair prioritization, and identification of restoration bottlenecks. The framework also encourages utilities to connect storm analytics to long-term adaptation decisions, such as relocation, elevation, redundancy, and distributed backup planning.

Heatwave and demand-surge management

Heatwaves create a distinctive resilience challenge because they simultaneously increase electricity demand, stress grid equipment, reduce thermal efficiency, and heighten public health risks. Research on electricity infrastructure vulnerability under long-term growth and extreme heat shows that climate-driven heat exposure can interact with urban demand growth and infrastructure constraints [28]. AI could support heatwave resilience by forecasting localized demand surges, identifying transformer and feeder overload risks, and coordinating demand-side measures such as pre-cooling, targeted conservation requests, and flexible load scheduling. These actions should be designed to avoid shifting risk onto vulnerable households that depend on cooling for health and safety.

Compound and cascading event resilience

Compound and cascading events challenge conventional resilience planning because hazards may interact across energy, water, transportation, communication, and public health systems. Climate impact studies show that renewable energy supply, demand, and infrastructure performance can all be affected by changing climate conditions, making future system behavior dependent on multiple interacting stressors [1]. AI could help detect emerging cascades by integrating cross-sector signals, outage patterns, weather evolution, and infrastructure interdependencies. However, compound-event resilience requires governance arrangements that clarify data sharing, emergency authority, responsibility allocation, and protection of sensitive infrastructure information.

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Governance Integration and Policy Implications

Resilience governance and institutional decision-making

The proposed framework requires governance integration because AI-generated resilience intelligence has practical consequences for investment prioritization, emergency response, ratepayer costs, and public safety. Comprehensive reviews of power system resilience show that resilience is not only a technical property but also a planning and decision-making challenge involving definitions, metrics, enhancement strategies, and stakeholder priorities [29]. Regulatory bodies and utilities could use the framework to connect climate stress testing, resilience investment cases, and operational decision protocols. Without such institutional embedding, AI risks becoming a technical advisory tool that produces information without clear authority, accountability, or implementation pathways.

Table 4 consolidates the governance requirements needed to ensure that AI-generated resilience intelligence becomes accountable decision support rather than an opaque technical recommendation.

Table 4. Governance Matrix for Translating AI Outputs Into Resilience Decisions

AI output type	Primary decision user	Decision domain	Risk if unguided	Governance safeguard	Suitable evidence standard
Climate-risk forecast	Utility planners, regulators	Asset hardening, investment timing, climate stress testing	Overconfidence in single-scenario forecasts; underinvestment in low-probability high-impact risks	Scenario comparison, uncertainty disclosure, periodic stress-test review	Robustness across multiple plausible climate and demand futures
Outage likelihood map	Distribution operators, emergency managers	Crew pre-positioning, vegetation management, emergency preparation	False precision, geographic bias, neglect of socially vulnerable customers	Model validation by region, equity overlay, operator review	Historical performance plus stress testing under synthetic extreme events
Real-time anomaly alert	System operators	Fault detection, situational awareness, emergency escalation	Alarm fatigue, missed failures, inappropriate escalation	Confidence scoring, explainable alert logic, operator override	Low-latency performance with documented false-positive and false-negative rates
Restoration recommendation	Operators, field coordinators	Switching, dispatch, critical load restoration, microgrid activation	Unsafe switching, inequitable restoration priority, conflict with field realities	Engineering constraints, safety validation, human authorization	Simulation validation plus practitioner review under emergency exercises
Adaptation pathway analysis	Regulators, utilities, public agencies	Long-term infrastructure planning, distributed energy deployment,	Lock-in to costly or maladaptive investments	Adaptive pathways, public accountability,	Performance across climate scenarios, socio-economic

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		relocation, undergrounding		cost-risk-equity review	futures, and technology pathways
Resilience performance metric	Regulators, utilities, stakeholders	Investment evaluation, performance reporting, policy compliance	Narrow measurement of resilience as outage duration only	Multi-dimensional metrics including critical service continuity, recovery equity, adaptability, and learning	Transparent metric definitions and repeatable reporting protocols
Post-event learning report	Utilities, regulators, emergency agencies	Protocol revision, model updating, institutional learning	Blame avoidance, incomplete data capture, failure to revise assumptions	After-action review, auditable datasets, cross-institutional lessons learned	Documented linkage between event evidence, model revision, and policy or operational change

Regulatory and policy enablers for AI-enabled resilience

Regulatory and policy mechanisms could enable AI-supported resilience by requiring climate-informed planning, transparent resilience metrics, auditable AI decision-support systems, and periodic review of adaptation pathways. Reviews of power system resilience metrics show that inconsistent measurement approaches can make it difficult to compare resilience investments, evaluate preparedness, or justify long-term adaptation strategies [9]. Climate stress testing mandates, resilience performance standards, and AI transparency requirements may therefore help align technical innovation with public oversight. The framework also suggests that regulators should distinguish between AI used for advisory risk intelligence and AI used for operational control, because these uses require different levels of validation, explainability, and human authority.

Table 5 identifies major governance principles necessary for responsible deployment of AI-enabled resilience systems under climate uncertainty.

Table 5. Governance Principles for AI-Enabled Energy Resilience Systems

Governance principle	Purpose in resilience governance	Example implementation mechanism	Expected resilience benefit
Transparency	Clarifies how AI recommendations are generated	Explainable decision-support interfaces	Improves institutional trust and operator confidence
Human oversight	Prevents unsafe autonomous decision-making	Human-in-the-loop operational approval	Enhances safety and accountability
Adaptive learning	Ensures resilience improves after disruptions	Periodic post-event model updating	Supports continuous resilience enhancement
Equity consideration	Protects vulnerable populations during disruptions	Critical-load and social vulnerability prioritization	Improves fairness in resilience outcomes

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Data interoperability	Enables integration of climate and grid datasets	Shared resilience data standards	Strengthens cross-system situational awareness
Regulatory accountability	Aligns AI deployment with public oversight	Auditable resilience reporting frameworks	Enhances legitimacy of resilience investments

Figure 2 illustrates how AI outputs should move through uncertainty translation and institutional governance before becoming operational, regulatory, or adaptation decisions.

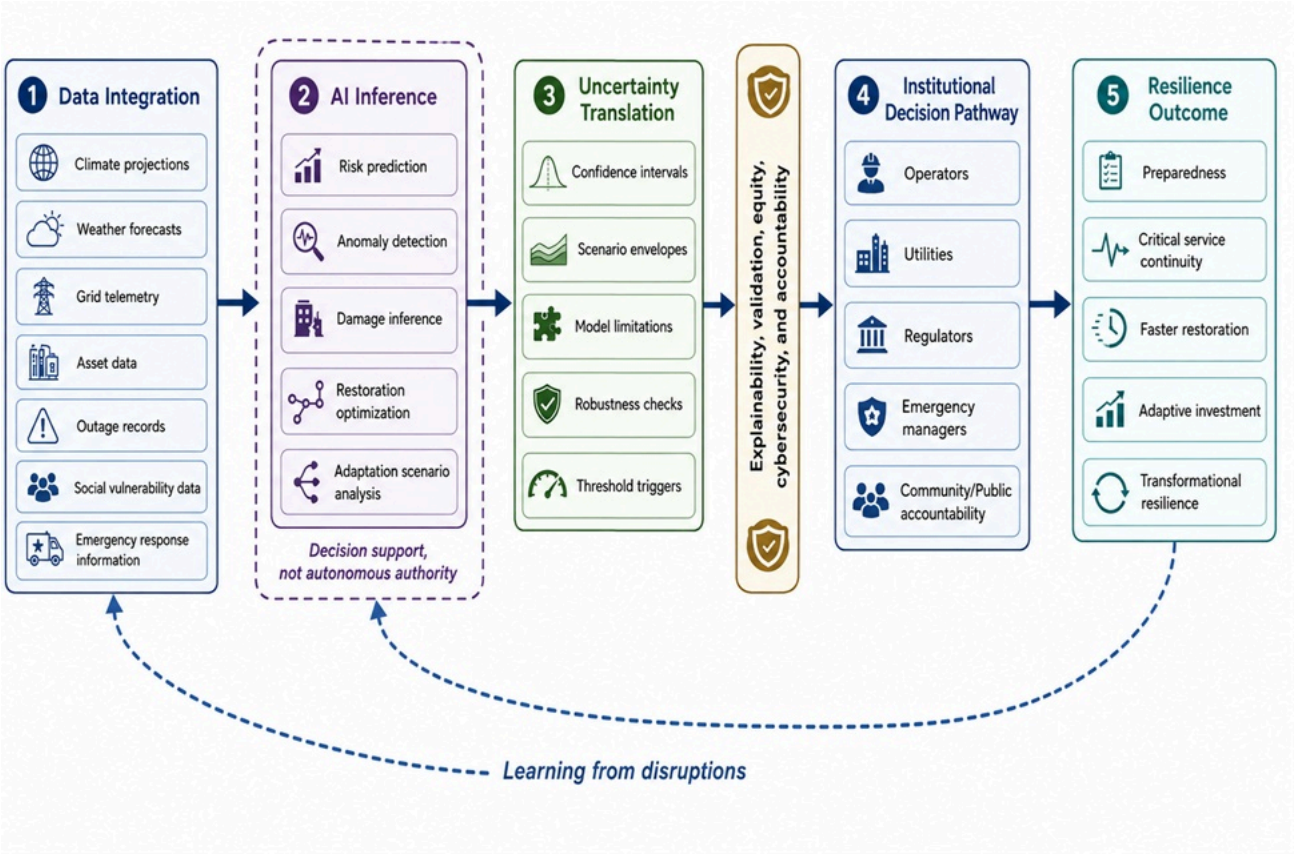


Figure 2. Decision-Use Pathway for AI-Enabled Resilience Under Climate Uncertainty

Evaluation Strategy for the Conceptual Framework

Conceptual coherence and resilience theory alignment

The framework should first be evaluated for conceptual coherence, including whether its anticipation, absorption, adaptation, and recovery dimensions align with established resilience theory. Reviews of smart grid resilience measurement emphasize that resilience assessment remains challenged by inconsistent definitions, system boundaries, and evaluation methods [6]. A coherent conceptual framework should therefore clarify what forms of disruption it addresses, which decisions AI is intended to support, and how resilience capabilities differ across lifecycle phases. This evaluation would be theoretical rather than empirical, assessing whether the framework provides a logically consistent bridge between AI capabilities and resilience engineering.

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Stakeholder validation through expert and practitioner engagement

Stakeholder validation could be pursued through expert elicitation, utility planning workshops, emergency management exercises, and regulatory sandbox discussions, without treating such engagement as experimental evidence in the present article. Broad reviews of resilience analysis emphasize that resilience assessment involves technical, organizational, and decision-making dimensions that cannot be captured by engineering models alone [13]. Practitioners could assess whether the framework reflects operational realities such as crew constraints, communication failures, regulatory obligations, customer vulnerability, and mutual assistance coordination. Such validation would help refine the framework's terminology, governance assumptions, and decision-use pathways before operational testing.

Transferability across regions and power system archetypes

The framework's transferability should be assessed across regions with different climate hazards, grid structures, market arrangements, and institutional capacities. Power outage estimation research across highly affected United States contexts illustrates that outage vulnerability and resilience needs vary across jurisdictions, infrastructure conditions, exposure profiles, and utility service territories [30]. The framework should therefore be adaptable to vertically integrated utilities, liberalized electricity markets, islanded systems, microgrids, and active distribution networks. Transferability does not imply uniform implementation; rather, it means that the framework's lifecycle logic and AI-governance architecture can be customized to local climate risks and institutional settings.

Limitations

Conceptual abstraction and the need for empirical grounding

The primary limitation of this article is that the framework remains conceptual and has not been tested in utility operations, pilot projects, emergency exercises, or simulation environments. Although resilience reviews provide a strong theoretical basis for organizing resilience capabilities, they also show that implementation requires context-specific assumptions, metrics, and validation procedures [16]. The framework therefore should be interpreted as a conceptual architecture rather than an operationally verified model. Future work must examine whether its layers, lifecycle phases, and governance mechanisms remain useful when applied to real grid data, institutional constraints, and climate hazard contexts.

Data, computational, and institutional feasibility barriers

AI-enabled resilience also faces feasibility barriers related to data quality, climate-model translation, grid observability, computational demands, cybersecurity, and institutional adoption. Active distribution system resilience research highlights the growing complexity of integrating distributed resources, control functions, and restoration strategies under uncertain operating conditions [17]. In practice, utilities may lack interoperable climate and grid datasets, validated AI models for extreme events, or regulatory incentives to adopt adaptive resilience planning. These barriers mean that the proposed framework requires gradual development, careful governance, and sustained collaboration among engineers, climate scientists, regulators, communities, and AI researchers.

Conclusion

This article developed an AI-enabled energy resilience framework for climate-uncertain power systems. The framework addresses the full resilience lifecycle by connecting anticipation, absorption, adaptation, and recovery with AI-supported sensing, prediction, learning, and decision support. Its central contribution is to conceptualize AI as a resilience intelligence layer rather than a disconnected technical tool. This orientation helps reposition resilience as an adaptive, climate-informed, and institutionally embedded process.

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The framework emphasizes that AI must be embedded within resilience governance structures if it is to support systemic adaptive capacity. Forecasts, anomaly alerts, restoration recommendations, and scenario analyses become meaningful only when they are linked to accountable decision pathways. Human oversight, regulatory transparency, and institutional learning are therefore not external constraints on AI-enabled resilience but core design requirements. This is especially important when decisions affect public safety, service continuity, vulnerable customers, and long-term infrastructure investment.

The framework is versatile across diverse climate hazards, including wildfires, storms, floods, heatwaves, and compound events. It can inform operational decisions such as resource positioning, critical load prioritization, adaptive restoration, and situational awareness during disruptions. It can also inform long-term investment strategies by helping planners evaluate hardening, decentralization, flexibility, and transformational adaptation options under uncertain futures. Its value lies in connecting immediate resilience action with long-term climate adaptation.

Future research should move from conceptual development toward collaborative validation, field pilots, and policy engagement. Utilities, regulators, climate scientists, AI researchers, emergency managers, and affected communities should work together to test how AI-enabled resilience intelligence can be responsibly implemented. Such work should examine technical performance, institutional usability, equity implications, and governance safeguards. Bridging the gap between framework and practice is essential for strengthening power system resilience in an era of accelerating climate change.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Received: 07 Nov 2022 Revised: 13 Jan 2023 Accepted: 30 Jan 2023
Published online: 15 November 2023

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