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Generative AI for Energy System Planning: A Theory-Driven Framework for Scenario Design, Decision Support, and Strategic Uncertainty Management

Rafael Mendoza[1*], Isabela Cruz[1], Carlos Lopez[2]

Abstract

Energy system planning must navigate deep strategic uncertainty, but traditional scenario methods are limited in scope and variety. Generative AI, with its capacity to produce novel text, data, and simulations, offers transformative potential. Current applications of generative AI in planning lack theoretical grounding and risk substituting methodological rigor with opaque, possibly biased, synthetic outputs. Without a framework, its use may add new uncertainties rather than resolve existing ones. This article develops a theory-driven framework for the principled application of generative AI in energy system scenario design, decision support, and strategic uncertainty management. The framework is constructed through conceptual synthesis of scenario planning theory, decision science, generative AI capabilities, and energy system planning practice. No empirical data are used. The framework comprises three integrated functions: generative scenario design, interactive decision support, and strategic uncertainty management. Two tables illustrate capability mappings and uncertainty handling strategies. Generative AI, when governed by a robust theoretical framework, can enhance the breadth and depth of energy planning without sacrificing rigor. Such an approach may enable more adaptive and resilient transition strategies.

Keywords Decision support, Generative AI, Energy system planning, Scenario design, Strategic uncertainty, Theory-driven framework

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Introduction

Energy system planning is increasingly shaped by interacting uncertainties surrounding decarbonization pathways, electrification, geopolitical disruption, climate risk, technology diffusion, and institutional adaptation. Energy system optimization models have become central planning instruments, yet their outputs remain sensitive to assumptions about demand, technology costs, policy ambition, behavioral change, and infrastructure constraints, which makes uncertainty assessment a core rather than peripheral planning concern [1]. Best-practice guidance for energy system modeling has emphasized transparency, scenario discipline, and careful interpretation, but conventional modeling workflows still struggle to represent surprise, ambiguity, and contested values in transition contexts [2]. As a result, planners require methods that can extend beyond deterministic forecasts without abandoning analytical rigor.

Generative AI is now entering this planning domain as a disruptive class of technologies capable of producing textual narratives, synthetic data, decision explanations, and interactive planning dialogue. Recent work on designing future

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energy systems with generative AI suggests that such tools could support ideation, model construction, and exploration of alternative system configurations when embedded in disciplined workflows [3]. Large language models have also been examined in the electric energy sector as instruments that may assist with knowledge retrieval, explanation, coding, and decision support, although their capabilities remain uneven across specialized technical tasks [4]. The planning relevance of generative AI therefore lies not only in automation, but in its potential to reshape how energy futures are imagined, represented, and debated.

The same qualities that make generative AI attractive for scenario exploration also make it risky for high-stakes planning. Generative models may produce fluent but unreliable content, and surveys of hallucination in natural language generation show that plausibility of expression cannot be equated with factual validity [5]. Broader assessments of generative AI warn that outputs may reproduce bias, obscure provenance, and create misplaced confidence when users treat generated text as authoritative knowledge rather than synthetic inference [6]. A theory-driven framework is therefore necessary because energy planning cannot rely on generative novelty alone; it must connect AI outputs to explicit assumptions, uncertainty categories, decision criteria, and governance safeguards.

This article contributes a conceptual framework that embeds generative AI within established planning theories and uncertainty management paradigms. The framework draws from energy planning under deep uncertainty, scenario planning, decision support systems, and critical generative AI scholarship to define how AI capabilities could be structured for scenario design, decision support, and strategic uncertainty management [7]. Rather than treating generative AI as a replacement for planners or models, the framework conceptualizes it as an augmenting layer that expands possibility spaces while preserving human judgment and methodological accountability. The central claim is that generative AI should be governed as a planning epistemology, not merely deployed as a technical interface.

Background

Energy system planning under deep strategic uncertainty

Energy system planning under strategic uncertainty involves decisions that must be made before future policy regimes, technology trajectories, resource conditions, market structures, and social preferences are fully knowable. Reviews of uncertainty assessment in energy system optimization show that planners often distinguish parametric uncertainty, model uncertainty, and scenario uncertainty, but these categories do not fully capture deep uncertainty where probabilities, outcomes, and values may be contested [1]. Robust and adaptive planning approaches are therefore useful because they shift attention from optimality under one forecast to performance across diverse plausible futures [8]. In this context, generative AI could be structured to support uncertainty exploration only if it remains anchored in decision theory and adaptive planning logic rather than unconstrained speculative generation.

The theory and practice of scenario design

Scenario design provides a disciplined way to reason about multiple futures, especially when strategic decisions cannot rely on prediction alone. Intuitive logics scenario planning emphasizes causal interpretation, narrative plausibility, and managerial sensemaking, while methodological augmentations have sought to strengthen causal analysis and reduce the risk of internally inconsistent storylines [9]. Scenario planning scholarship has also examined how narratives, social assumptions, and interpretive frames shape futures work, showing that scenarios are not neutral descriptions but structured devices for exploring strategic possibility [10]. A generative AI framework for energy planning must therefore preserve scenario diversity, coherence, and interpretive transparency instead of merely increasing the number of generated scenarios.

Generative AI: technologies, affordances, and epistemology

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Generative AI includes large language models, diffusion models, synthetic data generators, and reinforcement learning from human feedback mechanisms that can produce novel outputs from learned patterns. General analyses of generative AI describe its distinctive affordances as content generation, conversational interaction, multimodal representation, and task adaptation across domains [11]. In smart energy systems, generative AI has been framed as a possible new paradigm for research and education because it may support scenario articulation, documentation, simulation assistance, and decision communication [12]. Yet its epistemological status remains unstable because generated outputs are neither direct observations nor conventional model results; they are synthetic artifacts whose validity depends on provenance, constraints, review, and contextual interpretation.

This epistemological challenge is particularly acute for scenario generation tasks, where the validity of synthetic outputs depends on how well generative models capture the underlying physical and operational constraints of energy systems. A systematic review of 228 research articles on deep generative models in energy applications found that generative adversarial networks (GANs) dominate current implementations (47.2% of studies), followed by variational autoencoders (VAEs) and diffusion-based models, with scenario generation and data augmentation representing the most mature application categories [13]. The review further identifies that while generative models can produce high-quality synthetic scenarios for uncertainty characterization, their effectiveness depends critically on proper validation against physical constraints and domain expertise, aligning directly with the framework's emphasis on human review and provenance tracking [13].

Decision support systems and AI-augmented deliberation

Decision support in energy planning requires more than producing technically optimal pathways; it requires helping planners, regulators, utilities, investors, and communities understand trade-offs under uncertainty. Scenario process reviews for socio-environmental systems show that participatory and decision-oriented scenario work can improve relevance when stakeholders are engaged in framing, interpretation, and use of future-oriented knowledge [14]. Generative AI may extend decision support by enabling interactive questioning, rapid synthesis of assumptions, and translation between technical modeling outputs and deliberative planning narratives. However, this affordance must be governed carefully because conversational systems can blur the boundary between explanation, recommendation, and persuasion.

Existing AI applications in energy planning: gaps and opportunities

AI applications in energy planning have largely emphasized forecasting, optimization, classification, control, and decision automation, while generative AI applications remain emerging and conceptually underdeveloped. Reviews of smart-grid applications of large language models suggest opportunities in grid operation, customer communication, maintenance support, and knowledge management, but they also identify limitations in reliability, data sensitivity, and domain specificity [15]. Recent integrations of large language models in smart grids similarly point to planning and operational support functions while stressing the need for evaluation, cybersecurity awareness, and human oversight [16]. The gap addressed by this article is therefore the absence of a theory-driven framework that links generative AI capabilities to scenario design, decision support, and strategic uncertainty management in long-term energy system planning. **Figure 1** illustrates how generative AI can support scenario-based energy planning by translating technical model outputs into deliberative knowledge while maintaining clear governance boundaries between explanation, recommendation, and persuasion.

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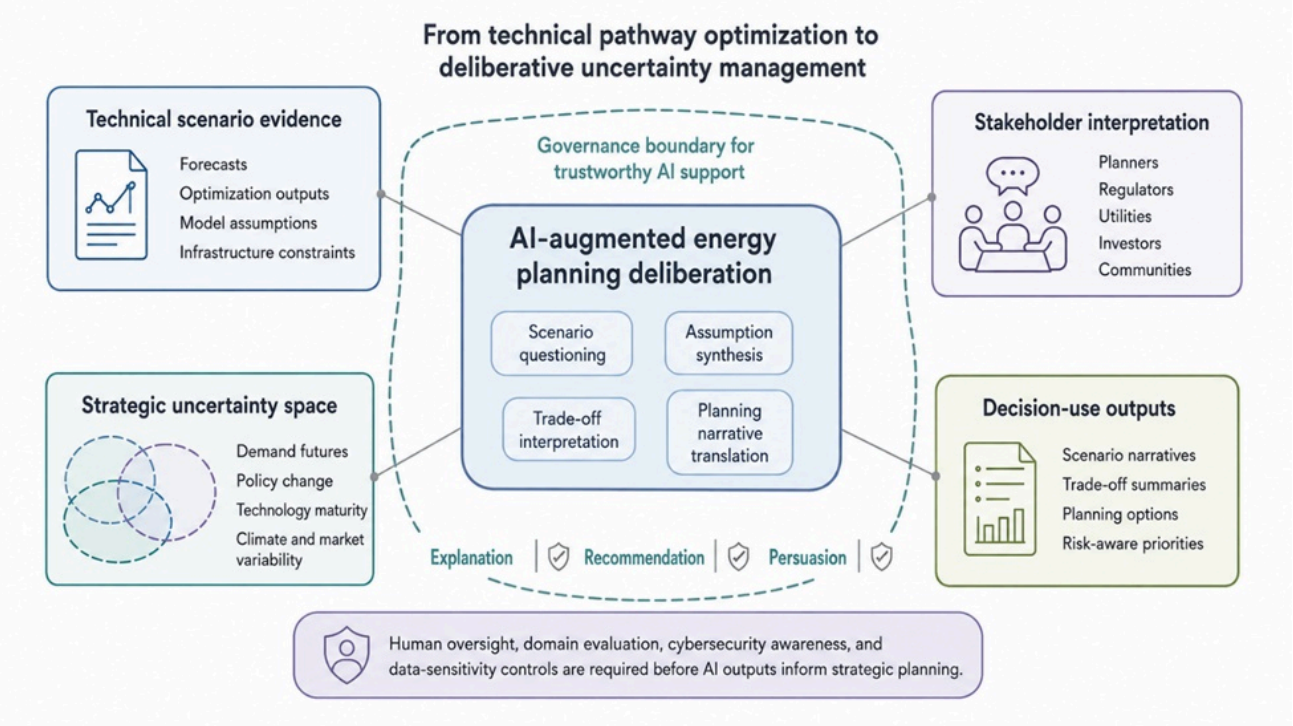

Figure 1. Governed Generative AI–Augmented Deliberation for Long-Term Energy Planning Under Uncertainty

Conceptual Foundation

A theory-driven approach to generative AI integration

A theory-driven approach begins from the premise that planning technologies should be organized around the structure of decision problems rather than the novelty of available tools. Energy transition planning has already required transdisciplinary modeling frameworks that connect technical pathways with stakeholder participation, policy timing, and adaptive governance [17]. Generative AI should therefore be guided by concepts from decision theory, sensemaking, anticipatory governance, and scenario methodology, because these theories define what counts as a useful planning output. In this framework, AI is valuable only when it improves the planner's ability to structure uncertainty, compare alternatives, and reason transparently about future conditions. The resulting archetype is summarized in **Figure 2.**

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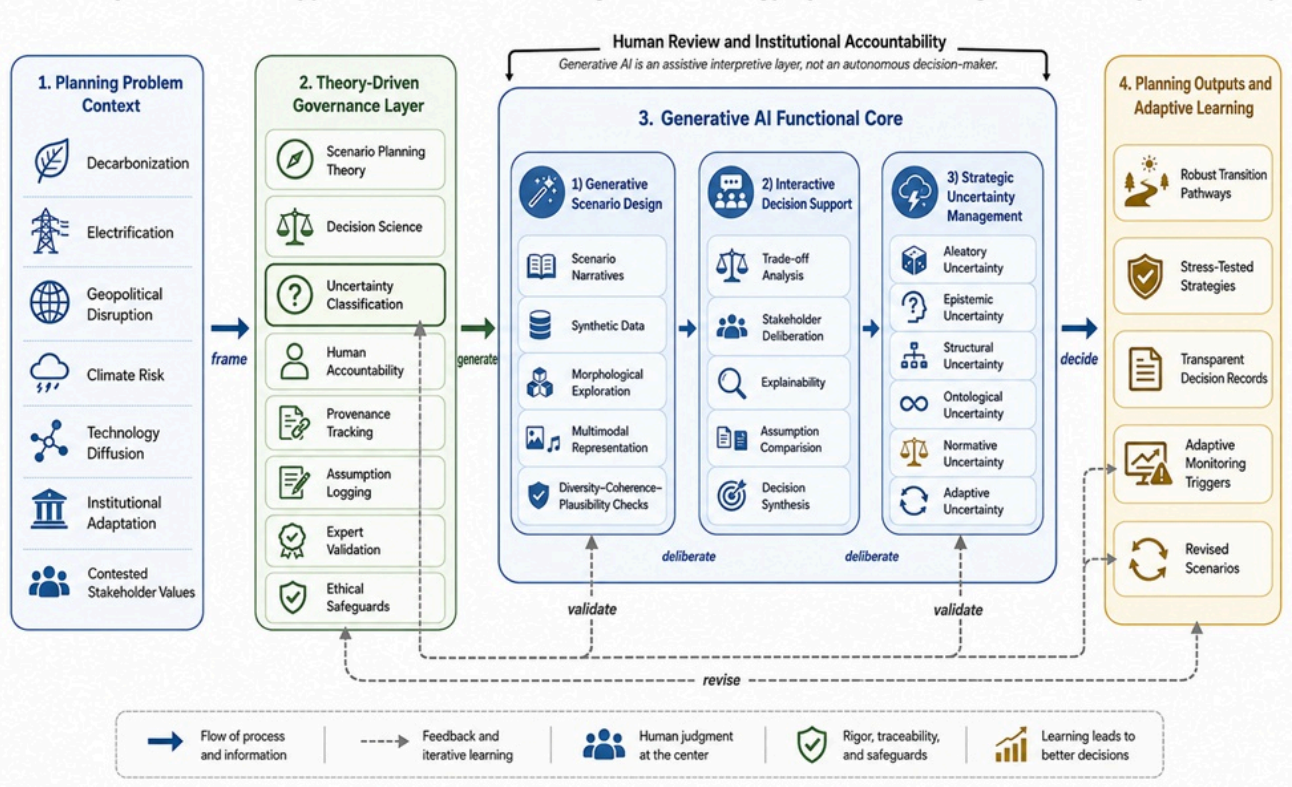

Figure 2. Theory-Driven Archetype for Generative AI–Augmented Energy System Planning Under Strategic Uncertainty

Generative AI as a boundary object in planning

Generative AI can be conceptualized as a boundary object because it may help connect quantitative energy models, qualitative scenario narratives, stakeholder deliberation, and policy interpretation. Scenario planning and foresight research has emphasized the need to improve both theoretical grounding and practical usability, especially when scenarios must travel across organizational and disciplinary boundaries [18]. Generative AI could assist by translating model assumptions into narratives, converting stakeholder concerns into scenario variables, and producing alternative framings for deliberation. Its boundary-object role should remain mediated by human review, because the same flexibility that enables translation may also conceal inconsistencies or value-laden assumptions.

Managing the epistemic risks of generative outputs

The epistemic risk of generative outputs arises from the possibility that synthetic content may appear coherent while lacking traceable evidence, internal consistency, or planning relevance. Studies of hallucination in natural language generation make clear that generated statements require verification because language fluency can mask factual error or unsupported inference [5]. Broader critiques of generative conversational AI also stress that the technology raises governance concerns for research, practice, and policy when users cannot determine the source, reliability, or bias structure of outputs [19]. The framework therefore treats provenance tracking, assumption logging, scenario review, and domain expert validation as integral design requirements rather than optional safeguards.

Framework Components: Generative AI in Scenario Design

AI-Augmented morphological and narrative scenario generation

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AI-augmented scenario generation could be structured to expand the morphological space of energy futures by combining variables such as technology costs, policy regimes, demand flexibility, infrastructure constraints, social acceptance, and climate stressors. Reviews of scenario planning show that different scenario types serve different purposes, including exploration, strategy testing, communication, and learning, so generative AI should not produce scenarios without first specifying the intended planning function [20]. Large language models may enable narrative elaboration around model-based pathways, while generative tools can propose alternative combinations of drivers that human planners might otherwise overlook [4]. The framework therefore positions generative AI as a disciplined scenario-expansion mechanism rather than a scenario-authoring authority.

Synthetic data for rare and extreme events

Synthetic data generation could support planning for rare and extreme events by producing plausible stress conditions for grid resilience, demand shocks, supply interruptions, policy reversals, or compound climate-energy disruptions. Energy modelers have argued that scenarios should explore extremes more systematically, because central cases often underrepresent the conditions most relevant for robust long-term planning [21]. Generative AI may enable structured stress-test inputs, such as synthetic time series or event narratives, that help planners examine vulnerabilities under low-probability, high-impact futures. These outputs would still require careful calibration, expert review, and documentation because synthetic events can easily become speculative artifacts if they are not connected to physical, institutional, and historical constraints.

Ensuring diversity, coherence, and plausibility in AI-generated scenarios

The framework requires AI-generated scenarios to satisfy diversity, coherence, plausibility, and decision relevance before they enter planning deliberation. Scenario scholarship has warned that the methodological “black box” of scenario planning can obscure how assumptions are selected, combined, and validated, which makes transparency especially important when generative systems contribute to future construction [22]. Human-AI interaction loops should therefore require planners to define scenario axes, review causal links, reject incoherent storylines, and compare outputs against established energy-model assumptions. As shown in **Table 1**, different generative AI capabilities should be matched to specific planning tasks and uncertainty dimensions rather than treated as interchangeable tools.

Table 1. Mapping Generative AI Capabilities to Scenario Design Tasks and Uncertainty Dimensions

Generative AI Capability	Planning Task	Uncertainty Dimension Addressed	Quality Control Mechanism
Natural language scenario generation	Producing alternative transition narratives from defined drivers, constraints, and policy assumptions	Ontological uncertainty about future social, institutional, and market configurations	Expert review of causal consistency, explicit assumption registers, and comparison with established scenario logics
Synthetic time series creation	Stress-testing demand, renewable output, storage behavior, or disruption sequences under unusual operating conditions	Aleatory uncertainty in variable renewable supply, load volatility, and extreme event timing	Physical plausibility checks, sensitivity analysis, and exclusion of generated patterns that violate engineering constraints
Interactive conversational planning	Supporting workshop dialogue, clarification of trade-offs, and iterative reframing of planning questions	Epistemic uncertainty arising from incomplete understanding of stakeholder preferences and model assumptions	Facilitator moderation, transcript auditing, and separation between generated suggestions and agreed decisions

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Multimodal scenario representation	Converting technical pathways into text, diagrams, maps, and stakeholder-facing summaries	Ambiguity in how different actors interpret the same transition pathway	Cross-stakeholder readability review and traceability from visual or narrative outputs back to source assumptions
Retrieval-augmented generation	Linking scenario narratives to approved documents, model outputs, and prior planning assumptions	Epistemic uncertainty related to evidence availability and source provenance	Source citation requirements, retrieval logs, and rejection of unsupported claims
Generative sensitivity framing	Proposing alternative parameter combinations and neglected driver interactions for model exploration	Structural uncertainty about which variables and relationships define the planning problem	Modeler screening, scenario-set balance checks, and documentation of included and excluded drivers
Synthetic stakeholder personas	Exploring how different actor groups may perceive costs, risks, fairness, and implementation barriers	Interpretive uncertainty in social acceptance and institutional response	Ethical review, avoidance of demographic stereotyping, and validation through real stakeholder deliberation

Framework Components: Decision Support

Interactive scenario exploration and trade-off analysis

Conversational generative AI could support real-time scenario exploration by allowing planners to ask how assumptions, constraints, or policy priorities alter the interpretation of future pathways. Large language model studies in the electric energy sector suggest that these systems may assist with explanation, summarization, and domain-specific reasoning, but they also require careful task framing because their performance varies across technical contexts [4]. In planning workshops, generative AI could be used to compare trade-offs among reliability, affordability, emissions reduction, land use, equity, and resilience in language accessible to different participants. The framework limits this role to interpretive decision support, meaning that AI may help structure deliberation but should not independently determine planning choices.

Generative AI for multi-stakeholder deliberation

Generative AI may enable more inclusive deliberation by summarizing technical documents, translating modeling assumptions into plain language, and generating alternative explanations for stakeholders with different expertise. Participatory scenario process research shows that decision relevance improves when scenario development includes diverse knowledge holders and when outputs are designed for actual decision contexts rather than detached analytical exercises [14]. In energy planning, generative AI could help bridge the communication gap between modelers, regulators, community representatives, and infrastructure operators. This function should be governed through transparent records of prompts, outputs, revisions, and human judgments so that deliberative support does not become hidden agenda-setting.

Decision recommendations and explainability

Generative AI may suggest robust strategies by synthesizing scenario implications, identifying recurrent vulnerabilities, and explaining why certain options appear resilient across multiple futures. However, work on generative AI for sustainable smart environments emphasizes that user-centric decision-making requires transparency, contextual appropriateness, and careful alignment between AI-generated recommendations and real operational constraints [23]. In this framework, recommendations must be explainable in terms of scenario assumptions, uncertainty types, trade-off criteria, and planning objectives. Generative AI should therefore function as an explanation and synthesis layer that

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supports accountable human judgment rather than as an autonomous planning authority. As shown in **Figure 3**, generative AI can support multi-stakeholder energy planning by translating complex scenario evidence into accessible explanations, synthesizing recurrent vulnerabilities across futures, and documenting the human judgments that shape recommendations. The figure emphasizes that AI should act as a transparent deliberative and explanatory layer, not as an autonomous planning authority.

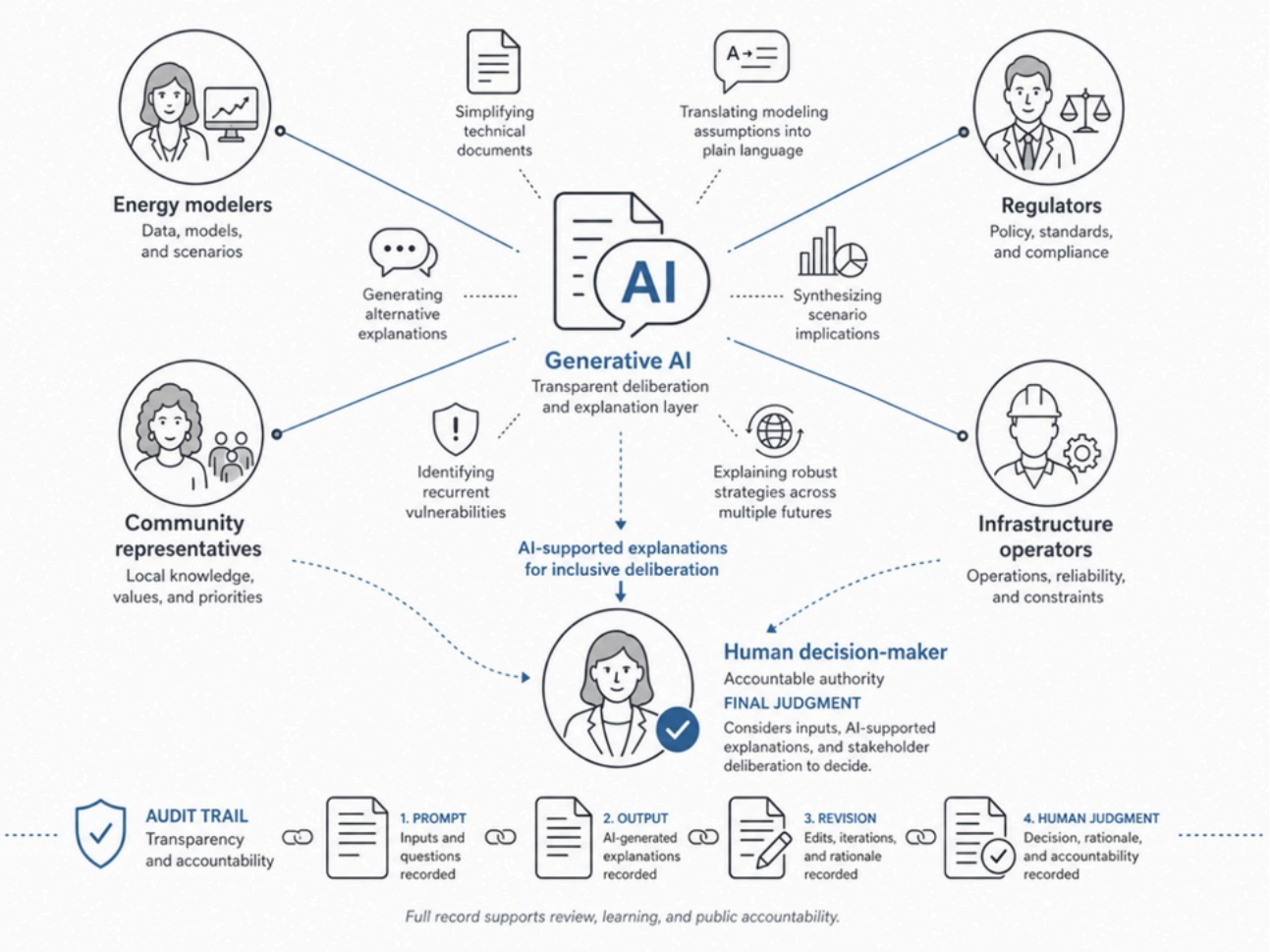

Figure 3. Generative AI as an Explainable Deliberation Layer for Scenario-Based Energy Planning

Strategic Uncertainty Management

Classifying uncertainty types in energy transitions

The framework classifies strategic uncertainty in energy transitions into aleatory, epistemic, and ontological forms because each type requires a different planning response. Aleatory uncertainty refers to variability in phenomena such as renewable output, demand fluctuation, fuel prices, outage timing, and weather-linked stressors, while epistemic uncertainty concerns incomplete knowledge about technologies, costs, behavioral responses, and institutional capacities [1]. Ontological uncertainty is deeper because it concerns the possible emergence of qualitatively new futures, such as unexpected geopolitical alignments, new market designs, disruptive storage breakthroughs, or changing social meanings of energy security [24]. This classification matters because generative AI should not be used as if all uncertainty can be reduced through more information; some uncertainty must instead be explored through alternative narratives, stress tests, and adaptive pathways.

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Generative AI for epistemic uncertainty reduction vs. ontological exploration

Generative AI can be used in two distinct ways: to reduce epistemic uncertainty by synthesizing known evidence and to explore ontological uncertainty by generating alternative future logics that cannot be assigned reliable probabilities. In the first role, retrieval-augmented language models and structured synthesis tools may help planners compare assumptions, identify missing evidence, or clarify the implications of model inputs, although such uses require source control and expert verification [6]. In the second role, generative AI may support strategic foresight by producing alternative narratives, institutional configurations, and disruption pathways that extend beyond the boundaries of established model cases [18]. The framework therefore separates evidence-oriented generation from imagination-oriented generation, because confusing these roles would risk presenting speculative futures as validated knowledge.

Tailoring generative AI to uncertainty management strategies

Different uncertainty types call for different generative AI applications, and the framework tailors the AI role to the planning phase rather than applying one general-purpose tool across all tasks. Synthetic data generation may help explore aleatory variability by producing stress-test inputs, but such outputs must remain constrained by physical plausibility and engineering review [21]. Conversational and narrative generation may help manage epistemic and ontological uncertainty by surfacing assumptions, reframing contested futures, and enabling stakeholders to examine transition pathways from multiple perspectives [10]. As shown in **Table 2,** the framework differentiates uncertainty handling strategies by planning phase, AI role, and limitation so that generative AI supports uncertainty management without overstating its epistemic authority.

Table 2. Strategic Uncertainty Handling with Generative AI: Types, Strategies, and Limitations

Uncertainty Type	Planning Phase	Generative AI Role	Uncertainty Management Strategy	Key Limitation
Aleatory uncertainty	Stress testing and resilience screening	Generate synthetic operating conditions, disruption sequences, or renewable variability cases	Explore robustness across variable conditions rather than optimize for a single expected future	Synthetic variability may misrepresent physical constraints if not checked against domain knowledge
Epistemic uncertainty	Assumption review and evidence synthesis	Summarize evidence, compare model assumptions, identify knowledge gaps, and support sensitivity framing	Reduce uncertainty through better documentation, expert review, and targeted information gathering	Generated synthesis may appear authoritative even when evidence is incomplete or uneven
Structural uncertainty	Model design and scenario architecture	Suggest alternative causal structures, driver combinations, and omitted system relationships	Broaden model framing and expose hidden assumptions before formal modeling begins	AI may generate plausible but non-actionable causal structures without theoretical discipline
Ontological uncertainty	Strategic foresight and exploratory scenario design	Create alternative future narratives, institutional logics, and disruption pathways	Explore futures that cannot be reliably predicted or probabilistically bounded	Outputs may become speculative fiction unless linked to planning questions and plausibility criteria

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Normative uncertainty	Stakeholder deliberation and policy choice	Translate value conflicts into alternative planning frames and decision criteria	Make trade-offs explicit across equity, reliability, affordability, and decarbonization goals	AI may flatten political disagreement into neutral-sounding language
Adaptive uncertainty	Monitoring and pathway revision	Regenerate scenarios when signals, thresholds, or planning assumptions change	Support dynamic adaptive planning and periodic strategy re-evaluation	Frequent regeneration may create planning instability if not governed by clear trigger rules

Adaptive pathways and AI-driven re-evaluation

Generative AI could support dynamic adaptive planning by periodically regenerating scenarios when monitoring indicators suggest that an existing pathway is becoming less plausible or less robust. Adaptive policy pathway approaches already emphasize sequencing, trigger points, and revision mechanisms, which are especially relevant when energy transition decisions unfold across decades rather than single investment cycles [17]. A generative AI layer may help planners reinterpret weak signals, update narratives, and compare whether emerging conditions require incremental adjustment or strategic redirection. However, AI-driven re-evaluation should be governed through predefined review intervals and decision thresholds so that planning remains adaptive without becoming reactive or unstable.

Framework Integration and Planning Workflow

The full planning cycle with generative AI

The full planning cycle begins with problem framing, proceeds through uncertainty classification, scenario generation, model integration, deliberative interpretation, strategy selection, and adaptive monitoring. Bottom-up energy system models provide detailed representations of technologies, sectors, and constraints, but reviews show that their classification and practical use depend heavily on modeling purpose, temporal resolution, spatial scale, and data assumptions [25]. Within this cycle, generative AI could support early-stage framing, scenario elaboration, assumption comparison, stakeholder communication, and post-decision monitoring. The framework therefore embeds generative AI across the planning workflow as an assistive interpretive layer rather than a replacement for formal modeling or institutional decision-making.

Human-AI collaboration protocols

Human-AI collaboration protocols are necessary because generative AI can influence how planning questions are framed, which uncertainties are made visible, and which futures appear credible. Research on generative AI in education and management highlights a paradox: the same tools that may expand creativity and accessibility may also weaken critical judgment if users outsource reasoning to fluent machine-generated outputs [26]. In energy planning, modelers should define constraints, planners should specify decision contexts, stakeholders should review interpretive relevance, and domain experts should validate technical plausibility. These protocols would be expected to preserve human accountability while using generative AI to support exploration, translation, and structured deliberation.

Validation and stress-testing of AI-generated outputs

Validation of AI-generated planning outputs should focus on conceptual coherence, traceability, decision relevance, and robustness rather than predictive accuracy or performance metrics. Energy transition scenario reviews demonstrate that model-based scenarios are often shaped by national context, model structure, policy assumptions, and technology representation, so AI-generated additions must be tested against these existing constraints [27]. Stress-testing should examine whether generated narratives contradict model assumptions, whether synthetic data violate physical plausibility,

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and whether recommendations depend on unsupported claims. The framework therefore requires validation as a multi-layered process involving expert review, source auditing, scenario comparison, and stakeholder interpretation.

Integration with existing energy models and tools

Integration with existing energy models and tools should proceed through controlled interfaces rather than unrestricted AI access to planning systems. Formal energy system modeling practice already emphasizes documentation, reproducibility, transparency, and clear communication of uncertainty, and these principles become even more important when generative AI is used to interpret or extend model outputs [2]. Generative AI could connect to models such as MARKAL, TIMES, capacity expansion tools, dispatch simulations, or corporate planning dashboards by translating assumptions, generating scenario narratives, and helping users interrogate trade-offs. It should not alter model structures, input datasets, or policy conclusions without version control, expert approval, and documented rationale.

Governance, Epistemology, and Ethical Guardrails

Ethical use of generative AI in high-stakes planning

Ethical use of generative AI in high-stakes planning requires explicit safeguards against misinformation, manipulation, over-reliance, and the amplification of embedded biases. Scientific knowledge mapping of generative AI in the energy economy field suggests growing interest in the technology's research potential, but such expansion also increases the need for critical governance of how AI-generated outputs are used in decision contexts [28]. In energy system planning, an AI-generated scenario can influence investment priorities, infrastructure siting debates, and policy legitimacy, even if it is framed as exploratory. The framework therefore treats ethical governance as a core planning function, requiring transparency about AI roles, limits, assumptions, and human responsibility.

Transparency, provenance, and documentation standards

Transparency standards should require that every AI-generated planning artifact be linked to its prompt, source materials, model version, assumptions, review history, and final human decision status. Multidisciplinary analyses of generative conversational AI emphasize that policy and practice risks increase when users cannot distinguish between generated synthesis, sourced evidence, and unsupported extrapolation [19]. For planning institutions, provenance documentation could include generation logs, model cards, scenario lineage records, uncertainty labels, and records of rejected or revised outputs. Such standards would help prevent generative AI from becoming a hidden epistemic infrastructure that shapes planning conclusions without visible accountability.

Evaluation Strategy for the Framework

Theoretical coherence and contribution to planning theory

The framework can be evaluated conceptually by examining whether it coherently connects generative AI capabilities to established theories of scenario planning, decision support, and uncertainty management. Scenario planning and foresight scholarship has called for stronger theory development and improved practice, particularly in relation to how scenarios support strategic reasoning rather than merely describe possible futures [18]. This framework contributes by defining generative AI not as a generic automation tool but as a structured planning layer with roles in possibility generation, assumption articulation, deliberation support, and adaptive revision. Its theoretical coherence depends on maintaining the distinction between generated possibilities, validated evidence, and accountable decisions.

Table 3 provides a comparative assessment of validation approaches applicable to theory-driven generative AI frameworks for energy planning.

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Table 3. Validation Strategies for Theory-Driven Generative AI Frameworks in Energy System Planning

Validation Type	Methodology	Evaluation Criteria	Application to Proposed Framework
Theoretical coherence	Conceptual synthesis and comparative analysis	Internal consistency, logical completeness, mapping between AI capabilities and planning functions	Assess whether framework components (scenario design, decision support, uncertainty management) form an integrated logical structure
Expert validation	Delphi panels, structured interviews with energy planners and modelers	Perceived usefulness, clarity of roles, completeness of coverage, operational feasibility	Test whether framework clarifies AI roles and prevents inappropriate reliance on generated outputs
Planning exercise validation	Simulation games, workshop-based scenario generation tasks	Quality of generated scenarios, diversity of explored futures, traceability of assumptions	Compare planning outcomes with and without framework guidance under controlled conditions
Case study application	Retrospective application to documented planning processes	Ability to explain past decisions, identify missed alternatives, improve documentation	Apply framework to historical energy planning cases to assess counterfactual value
Comparative benchmarking	Side-by-side comparison with alternative scenario methods	Scenario diversity, coherence, relevance to decision contexts, resource efficiency	Compare framework performance against conventional scenario planning and unguided AI use
Stress testing	Extreme condition testing, adversarial input evaluation	Robustness to unusual assumptions, handling of edge cases, failure mode identification	Test whether framework constraints prevent generation of physically implausible or logically inconsistent scenarios

Expert and practitioner validation

Future validation could use Delphi panels, expert workshops, planning exercises, simulation games, and structured practitioner reviews, without treating such activities as evidence that the framework has already been empirically proven. Robust climate and energy policy design research demonstrates the value of comparing strategies across possible net-zero futures, which suggests that expert review should test whether the framework improves strategic reasoning under uncertainty [29]. Practitioners could examine whether the framework clarifies AI roles, prevents inappropriate reliance on generated outputs, and improves the documentation of uncertainty assumptions. Such validation would be expected to refine the framework's operational protocols while preserving its conceptual and theory-driven character.

Transferability across Planning Contexts and scales

The framework is transferable across national, regional, utility, and corporate energy planning contexts because it organizes generative AI use around planning functions rather than a single model or institutional setting. Global transition studies show that consumer preferences, policy choices, and technology adoption pathways interact in complex ways, reinforcing the need for planning approaches that can represent multiple behavioral and institutional futures [30]. At national scale, the framework may support long-term transition pathways; at regional scale, it may assist infrastructure and resilience planning; and at corporate scale, it may help utilities explore investment and risk strategies. Transferability nevertheless requires contextual adaptation because uncertainty categories, stakeholder legitimacy, data availability, and governance capacity differ across planning environments.

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Limitations

Conceptual abstraction and need for operational tools

The framework remains conceptually abstract and requires operational tools, workflow templates, governance checklists, and software interfaces before it can be implemented in planning practice. Reviews of model-based energy transition scenarios show that even conventional scenario tools vary substantially in scope, assumptions, and interpretation, which means a generative AI framework cannot be operationalized through a single universal procedure [27]. Practical application would require clear prompt protocols, approved source repositories, validation rubrics, documentation templates, and role definitions for planners, modelers, stakeholders, and governance bodies. The framework should therefore be understood as a theory-driven architecture for future development rather than a fully specified software system.

The evolving nature of generative AI capabilities

A second limitation is that generative AI capabilities are evolving rapidly, and any framework developed around current technologies may require frequent revision. General accounts of generative AI show that its applications, interfaces, and risks continue to shift as models become more multimodal, interactive, and embedded in organizational systems [6]. Energy-specific uses may also change as large language models, diffusion models, synthetic data tools, and decision-support interfaces become more specialized for planning contexts [12]. The framework therefore requires further validation and periodic updating so that its governance principles remain stable while its technical implementation adapts to new capabilities.

Conclusion

This article developed a theory-driven framework for integrating generative AI into energy system planning under strategic uncertainty. The framework positions generative AI as an augmenting layer that supports scenario design, interactive decision support, and uncertainty management without replacing formal modeling, expert judgment, or institutional accountability.

The central argument is that generative AI offers transformative potential only when its use is structured by planning theory, decision science, and explicit uncertainty classification. Without such structure, the same tools that broaden imagination may also introduce hallucination, bias, opacity, and false confidence into high-stakes planning processes.

The two tables provide practical conceptual tools for applying the framework. **Table 1** aligns generative AI capabilities with planning tasks and uncertainty dimensions, while **Table 2** differentiates uncertainty handling strategies across aleatory, epistemic, structural, ontological, normative, and adaptive uncertainty.

Future work should develop operational protocols, software implementations, expert validation exercises, and real-world planning pilots to refine the framework. Interdisciplinary collaboration among energy modelers, planners, AI researchers, decision scientists, and governance scholars will be essential for realizing the benefits of generative AI while protecting the rigor and legitimacy of energy transition planning.

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