Artificial Intelligence and Economic Security in EU Macro-Level Smart Energy Systems: A Sustainability-Driven Governance Framework

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Abstract: This study develops a governance-centered perspective on EU macro-level smart energy systems by linking artificial intelligence to economic security under sustainability pressures, volatility, and geopolitical stress. The core problem addressed is the absence of a comparative analytical framework that connects AI functions to economic security while preserving institutional diversity and trade-offs across EU member states. The objective is to conceptualize economic security as an interdependent governance configuration conditioned by AI-enabled capabilities. The research applies a conceptual–analytical governance modelling approach. Economic security is decomposed into affordability, supply resilience, market stability, innovation capacity, social vulnerability, and fiscal exposure. Core AI functions are mapped by governance role and institutional locus, combined with ideal-type archetype construction and risk–control calibration linking AI-induced risks to oversight, accountability, and resilience mechanisms. The findings show that AI shapes economic security primarily through governability rather than efficiency gains alone. Distinct governance configurations emerge, reflecting systematic trade-offs between resilience-building, market efficiency, social protection, and fiscal discipline. AI-induced risks, such as opacity, automation bias, and cyber vulnerability, function as direct economic security channels requiring explicit governance controls. The study is framework-building and does not provide empirical estimates. Archetypes may overlap in practice, and macro-level analysis masks subnational and sectoral heterogeneity, requiring future operationalization, empirical clustering, and multi-level validation. The framework offers practical value for comparative benchmarking and policy design by aligning AI deployment with accountability, interoperability, cybersecurity, and fairness requirements. Its originality lies in repositioning AI as a governance-conditioning variable and integrating sustainability, security, and systemic risk into a unified comparative architecture.

Keywords: Artificial intelligence, Economic security, European Union, Smart energy systems, Sustainability governance.

1. INTRODUCTION

Artificial intelligence is becoming embedded in the EU's macro-level smart energy systems as a layer of forecasting, optimization, and automated control that increasingly shapes how sustainability, resilience, and economic security are governed under volatility and geopolitical stress. In the Energy Union context, decarbonization goals are pursued alongside heightened exposure to price shocks, supply disruptions, cyber risks, and distributive tensions. These conditions make it analytically insufficient to treat "smartness" as a purely technological property of grids and markets. The core issue is governability: whether AI-enabled capabilities are embedded in institutional arrangements that can stabilize affordability, secure supply, discipline market behavior, protect vulnerable groups, and manage fiscal exposure during crises.

The existing literature provides valuable insights yet remains segmented across technical, institutional, and social strands. Technology-oriented syntheses map the expansion of AI applications and highlight performance-relevant parameters in smart energy systems, but they rarely operationalize macro-level economic security outcomes such as affordability exposure, vulnerability, or fiscal sensitivity [1]. Conceptual discussions of smart energy systems emphasize balancing, stabilization, and renewable integration as pathways to sustainability and long-term security, while leaving AI's governance roles—decision support, accountability, and cross-border coordination—only weakly specified [2]. Indicator-based energy security assessments and econometric approaches identify cross-country asymmetries and the importance of solidarity, yet often rely on static composites and conventional modelling that cannot capture dynamic risk transmission or the governance implications of real-time AI deployment [3, 11-12, 21]. In parallel, methodological advances in explainable AI and forecasting benchmarking strengthen transparency and reproducibility in safety-critical and market settings, but typically stop short of translating interpretability, auditability, and human oversight into an explicit EU macro-governance logic for economic security [4, 7-8].

Social-policy research on energy poverty and vulnerability develops multidimensional

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measurement, reveals non-overlapping indicators and structural inequalities, and critiques dominant metrics, yet largely omits AI-enabled monitoring, targeting, and fairness-sensitive decision support as governance instruments [13-17, 37]. Regulatory and political-economy analyses further underscore fragmentation, compliance cost heterogeneity, and coordination failures during shocks, while leaving unresolved how AI could either intensify these failures through opacity and misalignment or mitigate them through interoperable, accountability-oriented governance [25-26, 31-32].

Against this background, the research problem is the absence of a comparative analytical lens that links AI functions to macro-level economic security dimensions while preserving institutional diversity and trade-offs across Member States. The guiding research question is: How can AI-enabled governance capacities be systematically mapped to the principal dimensions of macro-level economic security in EU smart energy systems in a way that supports transparent benchmarking and cluster-oriented interpretation? The working hypothesis is that AI strengthens economic security primarily through governability—oversight, coordination, accountability, and distributive safeguards—rather than through efficiency gains alone.

The aim is to structure economic security as a multi-dimensional governance configuration encompassing affordability, supply resilience, market stability, innovation capacity, social vulnerability, and fiscal exposure, while explicitly integrating AI-induced systemic risks (opacity, automation bias, cyber/data integrity threats, rigidity under shock, and governance fragmentation). Novelty lies in repositioning AI from a technical add-on to a governance-conditioning variable and in aligning sustainability objectives with security-relevant controls such as explainability, auditability, interoperability, and fairness checks. Policy implications follow directly: EU and national strategies require cross-domain coordination (energy regulation, system operation, social policy, fiscal governance, cybersecurity) so that AI deployment supports both the credibility of the energy transition and the legitimacy of economic security outcomes under stress.

2. LITERATURE REVIEW

Artificial intelligence has become a structural component of the EU's macro-level smart energy systems, shaping how sustainability, resilience, and economic security are governed under conditions of volatility and geopolitical stress. Across the Energy Union, AI-enabled forecasting, optimization, and control increasingly interact with regulatory frameworks, market coordination, and social safeguards such as affordability and energy poverty mitigation. This literature review synthesizes key contributions on AI-driven energy systems, governance, security, and justice, while identifying persistent gaps in empirical integration and comparability. These shortcomings motivate the present study's benchmarking tables and cluster analysis aimed at advancing sustainability-oriented economic security governance.

Alsaigh, Mehmood, and Katib analyze the expansion of artificial intelligence in smart energy systems through a large-scale Scopus-based review of 3,568 publications, applying a deep learning–driven "deep journalism" approach. The study identifies 15 governance-relevant parameters clustered into four macro-dimensions encompassing AI behavior, technology, system design, and operations, highlighting AI's role in forecasting, flexibility, reliability, and risk management within modern energy systems [1]. However, the review remains largely technology-oriented and does not operationalize macro-level economic security indicators such as affordability, vulnerability, or fiscal exposure. In addition, its exclusive reliance on Scopus-indexed literature limits engagement with EU-specific policy documents and regulatory practice.

Andriienko offers a conceptual synthesis of smart energy systems by comparing definitions and implementation approaches across academic, governmental, and industrial discourses. The analysis emphasizes grid stabilization, optimization of production–consumption balance, and renewable integration as mechanisms linking smart energy systems to sustainability and long-term economic security objectives at the macro level [2]. Yet the contribution is predominantly descriptive and does not provide empirical validation or quantitative modelling of security outcomes. Moreover, artificial intelligence is addressed implicitly within digitalization, leaving AI-specific governance and decision-support roles underdeveloped.

Okhrimenko and Manaienko investigate energy security as a component of EU economic security using factor, correlation, and econometric analysis of macro-indicators aligned with Europe 2020 and the Strategic Agenda 2019–2024. Their results underscore the institutional importance of cooperation and energy solidarity in enhancing resilience and sustainability across EU energy systems [3]. Still, the analysis relies on static indicators and conventional econometric tools, offering limited insight into dynamic risk transmission. Furthermore, AI is not considered as an instrument for forecasting, adaptive governance, or real-time decision support.

Machlev, Heistrene, Perl, Levy, Belikov, Mannor, and Levron review explainable artificial intelligence applications in power and energy systems, focusing on trust, accountability, and transparency in safety-critical environments. By surveying dominant XAI techniques such as SHAP and LIME, the study clarifies how interpretability supports governance in monitoring, control, and renewable integration contexts [4]. Nonetheless, the discussion remains concentrated on technical applications and does not extend to macro-level economic security or EU policy implications. In addition, scalability and governance challenges of XAI in deep learning–driven, cross-border energy systems are only marginally addressed.

Biswal, Deb, Datta, Ustun, and Cali provide a systematic review of machine learning and deep learning methods for smart grid load forecasting, benchmarking advanced models against traditional approaches using standard accuracy metrics. Their synthesis demonstrates how improved forecasting supports grid stability and operational efficiency, indirectly contributing to economic security [5]. However, the review prioritizes technical performance and does not articulate how forecasting tools integrate into EU-level governance or strategic decision-making. Issues of explainability and institutional trust are also treated briefly.

Yu, Zhang, Song, Wang, Dong, and Ji review safe reinforcement learning techniques for power-system control, categorising approaches into safety-layer methods and integrated optimization frameworks. The study highlights applications in frequency regulation, voltage control, and energy management under high renewable penetration, linking safe RL to system flexibility and reliability [6]. Even so, the focus remains on control-level safety and algorithmic convergence, with limited discussion of macro-level governance or cross-border coordination. Strategic planning and long-horizon economic security considerations receive little attention.

Lago, Marcjasz, De Schutter, and Weron address reproducibility gaps in electricity price forecasting by proposing a transparent benchmarking framework using open datasets, formal statistical testing, and the epftoolbox infrastructure. Their contribution strengthens analytical foundations for price stability and investment planning in European energy markets [7]. Yet the scope remains methodological, without explicitly linking forecasting performance to EU energy security governance or sustainability objectives. Policy decision-support implications are therefore implied rather than demonstrated.

O'Connor, Bahloul, Prestwich, and Visentin synthesize electricity price forecasting methods across day-ahead, intra-day, and balancing markets, comparing statistical, machine learning, deep learning, and hybrid models. The review shows how volatility, data resolution, and market structure shape model suitability, offering insights relevant for price-based risk management [8]. Still, the analysis is market-centric and does not directly engage with EU governance frameworks or macro-level energy security strategies. Interpretability is acknowledged but not operationalized as a governance requirement.

Abdessadak, Ghennioui, Thirion-Moreau, Elbhiri, Abraim, and Merzouk conduct a PRISMA-based review of AI-enabled digital twins in the energy sector, reporting improvements in predictive maintenance, monitoring, and operational efficiency. By integrating AI with IoT, 5G, and blockchain, the study positions digital twins as enablers of resilient and sustainable energy systems [9]. However, reported gains are drawn from heterogeneous case studies, limiting comparability at the EU macro level. Governance alignment and economic security indicators remain weakly articulated.

Aghazadeh Ardebili, Moazami, Lobaccaro, and Cali review digital twin architectures for smart energy systems, categorizing solutions by components, data flows, AI integration, and edge–cloud strategies. Their structured mapping clarifies technical design patterns relevant for scalable and interoperable systems [10]. Yet the review prioritizes architecture over institutional governance and policy alignment. The role of AI in strategic decision support and macro-level risk mitigation is not developed.

Brodny and Tutak assess energy security across EU-27 countries using a dual framework distinguishing conventional and sustainable security dimensions through MCDM techniques. Their rankings demonstrate how sustainability considerations significantly alter national security assessments [11]. At the same time, the analysis relies on static composite indicators and does not capture dynamic system behavior. AI-based analytics and real-time governance tools are absent.

Kuzior, Kovalenko, Hrytseva, and Hrybinenko construct a multidimensional energy security index for 28 European economies under heightened geopolitical risk, highlighting innovation as a persistent weakness in transition strategies [12]. While the findings underscore structural vulnerabilities, reliance on aggregated indicators limits sensitivity to dynamic shocks. AI is not examined as a driver of innovation or adaptive governance.

Menyhért evaluates EU energy poverty indicators using micro-level Hungarian data, demonstrating that consensual and expenditure-based measures identify different vulnerable populations with limited overlap [13]. This exposes structural measurement gaps relevant for social sustainability and economic security. Nonetheless, the single-country focus restricts EU-wide generalization, and digital or AI-enhanced monitoring tools are not considered.

Bouzarovski examines EU and Member State policy responses to energy poverty following the Clean Energy for All Europeans Package, focusing on governance instruments embedded in National Energy and Climate Plans. Through systematic review of academic and policy sources, the study highlights uneven national implementation, limited stakeholder participation, and persistent structural inequalities, positioning energy poverty as a governance challenge with direct implications for social sustainability and EU energy security [14]. However, the analysis remains largely qualitative and institutional, offering limited outcome-based evaluation of policy effectiveness. Moreover, digitalisation and AI-enabled governance tools for monitoring or targeting energy poverty are not explored.

Kashour and Jaber propose a composite energy poverty index for EU Member States that integrates both causal factors and consequential outcomes of deprivation. By distinguishing between drivers such as energy costs and income constraints and outcomes such as arrears and inadequate warmth, the study reveals structural disparities between Southern–Eastern and Northern–Western Europe and refines comparative assessment of vulnerability [15]. Yet the index relies on aggregated national indicators, reducing sensitivity to intra-country heterogeneity. In addition, digital monitoring and AI-based analytics are absent, limiting applicability to smart, data-driven governance frameworks.

Kajoskoski, Matschoss, Heiskanen, and Laakso provide a systematic review of European energy poverty research across two periods, demonstrating a shift toward framing vulnerability as structurally embedded within the energy transition. The analysis maps evolving definitions, affected groups, and policy responses, highlighting new vulnerabilities emerging from decarbonization and geopolitical instability [16]. Still, reliance on a single database constrains coverage of interdisciplinary and policy-oriented studies. The potential of AI-enabled monitoring and decision-support systems is also not addressed.

Tovar Reaños, Palencia-González, and Labeaga apply a multidimensional approach to measure both the prevalence and intensity of energy poverty across EU countries using factor analysis and composite indicators. Their results reveal that low prevalence does not preclude high severity and link energy poverty to labour market conditions, welfare systems, and housing characteristics [17]. However, dependence on imputed expenditure and self-reported data introduces measurement uncertainty. The framework remains static and does not incorporate real-time data or AI-based forecasting for dynamic policy targeting.

Schmitz, Flachsbarth, and Plaga develop a conceptual framework linking energy security and resilience under sudden shocks and slow-burn processes such as climate change and geopolitical instability. By mapping recourse options across resilience capacities and planning horizons, the study provides guidance for forward-looking energy system planning in Europe [18]. Nonetheless, the framework is not empirically operationalized and lacks quantitative validation. Artificial intelligence is not integrated as a tool for resilience assessment or adaptive governance.

González-Eguino offers a structured synthesis of energy poverty as a core dimension of energy transitions, linking inadequate access to energy services with broader socio-economic development indicators. The study argues that universal access is economically feasible and reframes energy poverty as a policy choice rather than a financial constraint [19]. However, the contribution is largely conceptual and global in scope, relying on secondary statistics. Governance mechanisms and AI-enabled tools for addressing energy poverty are not examined.

Siksnelyte-Butkiene, Streimikiene, Lekavičius, and Baležentis conduct a systematic review of 71 energy poverty indicators using SALSA, PRISMA, and PSALSAR frameworks, evaluating their consistency with the Bellagio STAMP sustainability principles. The study identifies composite indices that better capture multidimensional vulnerability and policy relevance [20]. Yet the analysis remains comparative and does not test indicator performance under crisis conditions. AI-based dynamic monitoring and predictive assessment are also absent.

Tirion, Thiry, and Wiese map energy vulnerability and resilience across EU Member States using an indicator-based comparative approach. Their findings reveal pronounced asymmetries between core, peripheral, and Nordic countries, intensified by the pandemic and the Russia–Ukraine war [21]. Still, the contribution relies on descriptive mapping rather than causal inference. Exclusive use of national-level data and absence of AI-driven analytics limit relevance for real-time governance.

Shortall and Mengolini address energy justice gaps in EU policy assessment by proposing a top-down framework that complements existing bottom-up approaches. Conceptualizing energy systems as socio-technical systems, the study highlights deficiencies in procedural, distributive, and recognitional justice within current EU impact assessments [22]. However, the framework remains normative and lacks empirical validation. Data-driven or AI-enabled assessment tools are not incorporated.

Donti and Kolter review machine learning applications across the lifecycle of sustainable energy systems, developing a taxonomy of ML paradigms and identifying methodological challenges such as uncertainty handling and interpretability. The study demonstrates how data-driven methods support forecasting, optimization, and infrastructure planning [23]. Nevertheless, socio-economic dimensions including energy poverty and distributional justice receive limited attention. Alignment with concrete EU governance frameworks is also underdeveloped.

Siksnelyte-Butkiene, Streimikiene, Lekavičius, and Baležentis further reinforce the multidimensional nature of energy poverty measurement through a comparative review of indicators aligned with sustainability principles [20]. While analytically rigorous, the contribution remains descriptive. The integration of AI or advanced analytics for real-time governance is not explored.

Espinosa Apráez and Noorman analyse the scope and limitations of the EU Artificial Intelligence Act in the electricity sector, identifying regulatory gaps stemming from the Act's safety-oriented focus and fragmented interaction with sectoral legislation. The study highlights governance challenges for AI deployment in asset management and electricity markets [25]. Still, the contribution is primarily doctrinal and does not empirically assess risk outcomes or behavioral effects.

Heymann, Parginos, Bessa, and Galus estimate compliance costs of the EU AI Act for electricity market agents using scenario-based modelling in selected European countries. Their results reveal substantial regional heterogeneity and suggest that AI deployment remains economically viable under most scenarios [26]. However, reliance on stylized assumptions limits firm-level precision. Broader governance and social implications are not examined.

Niet, Van den Berghe, and van Est investigate societal impacts of AI in the Dutch electricity market through a public values framework, combining document analysis and stakeholder interviews. The study shows that AI enhances flexibility and renewable integration while introducing governance risks related to equity, accountability, and market power [27]. Yet the single-country qualitative design constrains generalizability. Quantitative benchmarking of governance outcomes is absent.

Banad, Sharif, and Rezaei provide a forward-looking review of AI and ML in smart grids, tracing evolution toward Federated Learning, Generative AI, LLMs, and Digital Twin–driven intelligence. The synthesis integrates infrastructures and applications relevant for resilient and sustainable power systems [28]. However, regulatory and socio-economic constraints in the EU context are weakly integrated. Empirical validation of advanced paradigms remains limited.

Ishfaq, Kanwal, Anwar, Abdussalam, and Amin review cybersecurity threats and AI-based mitigation strategies in smart grids, covering attack vectors and detection techniques across grid components. The study positions AI as central to resilient and secure energy infrastructures [29]. Nonetheless, evidence is drawn from heterogeneous studies without unified benchmarking. Governance, explainability, and systemic risk trade-offs receive limited treatment.

Nastoska, Jancheska, Rizinski, and Trajanov synthesize major frameworks for trustworthy AI, linking principles such as fairness, transparency, and accountability to evaluation tools including SHAP and federated learning. Cross-sectoral cases illustrate inherent trade-offs in AI governance [30]. However, empirical benchmarking in operational energy systems is limited, and sector-specific constraints are not deeply analyzed.

Mišík analyses EU external energy security during the gas crisis following Russia's invasion of Ukraine, highlighting structural weaknesses in common external policy and coordination. The study situates energy security as an indispensable dimension of the EU energy transition [31]. Yet the analysis remains qualitative and does not integrate AI-driven forecasting or anticipatory governance tools.

Mišík and Nosko explain coordination failures in the EU's response to the gas crisis using a political-economy framework, showing how national interests undermine collective energy security despite solidarity mechanisms [32]. Still, the argument remains conceptual and lacks empirical modelling of alternative scenarios. Digital governance instruments are not explored.

Nicoli, van der Duin, and Burgoon employ a large-scale conjoint experiment to analyze public support for EU-level energy security cooperation after the Ukraine invasion. The study provides causal evidence that ambitious solidarity arrangements command broad legitimacy [33]. However, geographical coverage excludes more vulnerable Member States, and policy complexity is necessarily simplified.

Lo Piano and Saltelli critique EU energy modelling practices through sensitivity auditing, showing how large-scale models often legitimize predefined narratives rather than explore alternatives. The study exposes structural weaknesses in uncertainty treatment and transparency [34]. Nonetheless, it remains diagnostic and does not operationalize alternative modelling frameworks or AI-enhanced solutions.

Guarascio, Reljic, and Zezza map energy vulnerability and resilience across EU Member States, revealing core–periphery asymmetries intensified by recent crises. The study underscores risks of fragmentation during the green transition [35]. However, descriptive mapping and national aggregation limit causal inference and subnational insight.

Campagna, Radaelli, Ricci, and Rancilio examine energy poverty in the EU as a multidimensional governance challenge, proposing spatial mapping frameworks to enhance policy targeting. Their analysis integrates income vulnerability and building efficiency indicators [36]. Still, the approach remains descriptive and weakly predictive, with limited dynamic modelling.

Thomson, Snell, and Bouzarovski critique dominant EU energy poverty indicators from a vulnerability perspective, highlighting how prevailing measures capture consequences rather than structural drivers [37]. While diagnostically strong, the study does not develop an operational alternative framework or real-time monitoring tools.

Horobet, Tudor, Belascu, Herciu, and Ogrean analyze the impact of renewable energy on CO_2 emissions in EU-27 using dynamic panel models, demonstrating significant mitigation effects alongside policy coordination challenges [38]. However, sectoral heterogeneity and AI-enabled optimization are not empirically assessed.

Wang and Lu survey cybersecurity challenges in smart grids, categorizing threats and countermeasures across cyber-physical components. The review provides a structured foundation for security-aware grid design [39]. Yet empirical validation and consideration of AI-enabled attacks remain limited.

Zhu and Sun develop a game-theoretic model of competition in multi-layer Internet service architectures, analyzing price and quality differentiation under broker-mediated markets [40]. While analytically rigorous, the model relies on stylized assumptions and lacks empirical validation, limiting applicability to regulated, large-scale energy and digital service ecosystems.

Yet, despite extensive research on artificial intelligence, smart energy systems, and EU energy security, the literature remains fragmented across technical, institutional, and social dimensions. Most studies rely on static indicators, isolated case evidence, or qualitative assessments, offering limited comparative insight into how AI-enabled systems shape macro-level economic security under sustainability constraints. Empirical approaches that jointly benchmark AI deployment, governance capacity, and social outcomes across Member States remain scarce. This gap substantiates the present study's use of comparative benchmarking tables and cluster analysis to operationalize AI-driven economic security governance in EU macro-level smart energy systems.

3. METHODOLOGY

The study adopts a conceptual–analytical governance modelling methodology designed to examine artificial intelligence as a conditioning factor of economic security in EU macro-level smart energy systems. Given the theoretical orientation of the research, the methodology prioritizes analytical structuring, internal consistency, and comparative logic over direct numerical estimation. This design enables systematic benchmarking and prepares the ground for subsequent empirical clustering without imposing premature quantification.

The first methodological stage involves analytical decomposition of economic security into six interdependent macro-level dimensions: energy affordability, supply resilience, market stability, innovation capacity, social vulnerability, and fiscal exposure. Each dimension is associated with dominant risk transmission channels in smart energy systems and corresponding AI-enabled governance capacities. This step operationalizes economic security as a governance configuration rather than an index, allowing structural relationships to be examined across dimensions.

The second stage applies governance capability mapping. Core AI functions — forecasting, optimization, anomaly detection, digital twins, and decision-support automation — are classified according to their governance role (anticipatory, corrective, distributive, or stabilizing) and their functional locus (EU-level coordination, national regulation, system operation, or multi-level governance). This qualitative mapping enables comparative assessment of governance maturity while avoiding numerical scoring.

The third stage employs ideal-type archetype construction, drawing on comparative institutional analysis. Archetypes are generated by systematically combining dominant security priorities, AI governance roles, and structural strengths and vulnerabilities. These configurations function as analytical reference categories rather than empirical classifications, supporting structured comparison across heterogeneous EU energy systems.

The fourth stage introduces a risk–control calibration procedure that explicitly integrates AI-induced systemic risks into the governance framework. Identified risks—such as opacity, automation bias, cyber vulnerability, governance fragmentation, and rigidity under shock—are analytically paired with governance control logics including explainability, human oversight, stress testing, and fallback mechanisms. This step ensures coherence between AI deployment and economic security safeguards.

Finally, a conceptual clustering pathway is specified, outlining how qualitative benchmarks and archetypes can be translated into comparative clusters through staged interpretation. All analytical matrices and tables were constructed using Microsoft Excel for structured design and Microsoft Word for iterative refinement and consistency validation. No statistical or proprietary software was applied at this stage, ensuring transparency and methodological portability for future empirical extensions.

4. RESULTS

Table **1** conceptualizes economic security in EU smart energy systems as a configuration of

Table 1: Mapping the Economic Security Architecture of AI-Driven Smart Energy Systems in the EU

Economic security dimension (macro level)	Dominant risk channel in EU smart energy systems	AI-enabled governance capability (hybrid construct)	Governance locus (fit-for-purpose)	Conceptual benchmarking cues for clustering
Energy affordability	price volatility transmission; household exposure to tariff shocks	price forecasting with stress testing; vulnerability detection; safeguarded demand-side optimisation	multi-level: regulators, social policy bodies, market actors	exposure intensity; buffering capacity; targeting maturity
Supply resilience	import dependency; shock propagation; intermittency management	predictive risk analytics; scenario simulation; digital twins; safe control logic	EU coordination + TSOs/DSOs	diversification logic; preparedness maturity; redundancy design
Market stability	imbalance costs; strategic behaviour; opacity of automated bidding	anomaly detection; explainable forecasting; compliance-aware automation	functional: regulators and system operators	volatility regime; transparency depth; monitoring intensity
Innovation capacity	uneven diffusion; vendor lock-in; interoperability gaps	interoperable AI architectures; federated learning governance; regulatory sandboxes	EU frameworks + national innovation systems	leader–follower patterns; interoperability readiness; institutional learning rate
Social vulnerability / energy poverty	hidden deprivation; unequal transition burdens	multidimensional vulnerability mapping; early-warning alerts; fairness checks	multi-level: social policy, local authorities, regulators	structural vs episodic vulnerability; justice sensitivity
Fiscal exposure	crisis spending pressure; subsidy dependence; stranded-asset risks	budget stress testing; risk-adjusted investment planning; auditability tools	EU + national fiscal authorities	fiscal flexibility; investment leverage capacity; audit maturity

Source: elaborated by the author.

interdependent risk channels and governance capacities rather than as a single aggregate outcome. This logic departs from conventional indicator-based approaches by emphasizing how artificial intelligence reshapes the *governability* of energy systems under sustainability pressures. In this framework, AI is not treated solely as an efficiency-enhancing technology but as a structuring element that conditions institutional response capacity, distributive outcomes, and long-term system resilience.

The architecture outlined above can be illustratively contextualized through structural energy security indicators reflecting the balance between internal capacity and external exposure. In particular, the share of domestic energy sources in the fuel and energy balance serves as a benchmark for supply-side robustness: methodological thresholds indicate that values below 50% correspond to elevated vulnerability, while levels above 70–80% are associated with structurally stronger security positions [41]. In macro-level terms, such variation clarifies why governance configurations differ in their reliance on anticipatory analytics and redundancy design, as systems with limited domestic capacity face greater sensitivity to import shocks and require stronger institutional buffering to maintain stability.

Energy affordability emerges as a first-order economic security concern in AI-enabled systems because algorithmic optimization and market automation can amplify price volatility if left unconstrained. AI-based forecasting and demand-side management therefore acquire a governance function: they must be embedded within regulatory safeguards that priorities vulnerability detection and targeted intervention. From a comparative perspective, systems differ not simply in price levels but in their capacity to buffer shocks and translate predictive intelligence into socially stabilizing policy action. This distinction provides a natural basis for clustering EU member states according to affordability exposure and policy mediation capacity.

Supply resilience is similarly reframed as a dynamic governance challenge. Predictive analytics, scenario modelling, and digital twins enhance the anticipatory capacity of energy systems, yet their effectiveness depends on institutional coordination across borders and operators. The EU context is particularly sensitive to this interaction, as cross-border interdependencies mean that resilience cannot be assessed at the national level alone.

Import dependence indicators further illustrate the governance challenge associated with supply resilience. Methodological reference values suggest that dependence on a dominant imported energy resource exceeding 50–55% significantly heightens exposure to external disruptions [41], while lower levels provide greater strategic flexibility. In interconnected energy systems, such thresholds help explain why predictive risk analytics and cross-border coordination become decisive governance capabilities: where import dependence is high, even minor disturbances can propagate rapidly, reinforcing the need for EU-level preparedness and redundancy-oriented governance logics.

Market stability represents a distinct economic security channel where AI's dual role is especially visible. Automated forecasting and trading tools can improve efficiency, but they also introduce opacity and systemic risk if monitoring and explain ability are insufficient. By explicitly linking anomaly detection and explainable AI to regulatory oversight, Therefore, transparency is not a technical add-on but as a precondition for macro-level market stability. This framing allows for analytical comparison between markets characterized by high automation with weak oversight and those where AI deployment is institutionally disciplined.

Market stability is also conditioned by infrastructure efficiency and loss intensity in energy transmission and distribution. Methodological benchmarks indicate that loss levels exceeding 1.6–1.8% signal structural inefficiencies that amplify volatility transmission and undermine the effectiveness of automated market mechanisms [41]. In such contexts, AI-based forecasting and monitoring may improve visibility but cannot substitute for underlying infrastructural integrity. This distinction reinforces the governance logic that transparency and anomaly detection must be complemented by physical system reliability to sustain macro-level market stability.

Innovation capacity is treated as a structural determinant of long-term economic security. Uneven diffusion of AI technologies, dependence on proprietary solutions, and interoperability fragmentation can lock energy systems into suboptimal trajectories. By foregrounding federated learning governance, regulatory sandboxes, and interoperable architectures, the table captures how institutional learning and coordination shape innovation outcomes. The resulting leader–follower patterns provide a conceptual basis for clustering that reflects governance maturity rather than technological adoption alone.

Long-term innovation capacity can be further illustrated through investment and asset-condition indicators in the energy sector. Methodological thresholds associate high wear of fixed assets (above 40–50%) with declining adaptive capacity, particularly when investment levels remain below 2–3% of GDP [41]. Conversely, sustained investment intensity supports modernization and interoperability, enabling institutional learning and diffusion of advanced AI architectures. These benchmarks help clarify why some governance configurations evolve toward innovation leadership while others remain locked into follower positions despite comparable access to digital technologies.

Social vulnerability and energy poverty are incorporated as integral economic security dimensions rather than residual social outcomes. AI-based vulnerability mapping and early-warning mechanisms can enhance policy precision, yet their effectiveness depends on multi-level governance and justice sensitivity. Systems differ markedly in whether AI reinforces exclusion through data gaps or mitigates inequality through targeted intervention. This distinction is analytically critical for sustainability-driven governance and justifies clustering along vulnerability structure rather than income metrics alone.

Social vulnerability dynamics are also shaped by structural efficiency indicators such as energy intensity of GDP. Methodological reference values indicate that high energy intensity reflects systemic inefficiencies that disproportionately burden households during price or supply shocks. In such systems, AI-enabled targeting and early-warning mechanisms face higher pressure to compensate for structural weaknesses, whereas lower energy intensity supports more sustainable vulnerability mitigation. This contextualization reinforces the analytical distinction between episodic exposure and structurally embedded vulnerability within governance configurations.

Finally, fiscal exposure links all preceding dimensions by constraining feasible governance choices. Crisis spending, subsidy dependence, and investment prioritization shape how AI capabilities can be mobilized in practice. Auditability and risk-adjusted planning therefore function as economic security enablers, reinforcing credibility and long-term sustainability. Across the EU, differences in fiscal flexibility and institutional audit maturity condition the scope of AI-supported energy transition strategies.

Fiscal exposure is further conditioned by the adequacy of strategic energy reserves, particularly for natural gas and coal. Methodological benchmarks suggest that reserve levels below three months of consumption constrain crisis response options, while reserves exceeding six months provide meaningful buffering capacity [41]. These thresholds help explain why fiscal governance configurations differ in their ability to absorb shocks without resorting to emergency spending, underscoring the interaction between reserve adequacy, budgetary stress testing, and long-term investment discipline.

Table **2** advances the analytical framework by translating the multidimensional governance logic into a limited number of ideal-type governance archetypes. These archetypes are not empirical classifications tied to specific datasets but conceptual configurations that capture how artificial intelligence, institutional capacity, and sustainability priorities interact to shape economic security

Table 2: Governance Archetypes of AI-Driven Economic Security in EU Smart Energy Systems

Governance archetype (cluster logic)	Dominant economic security emphasis	Role of AI in governance architecture	Structural strengths	Structural vulnerabilities
Resilience–innovation archetype	supply resilience; long-term stability	anticipatory analytics; digital twins; coordinated forecasting	diversification; institutional learning; high trust in automation	high complexity; coordination costs
Market-efficiency archetype	market stability; cost optimization	price forecasting; automated market monitoring; optimization tools	liquidity; efficiency gains; scalable AI deployment	exposure to opacity; fairness risks
Social-protection archetype	affordability; vulnerability mitigation	targeting algorithms; early-warning systems; fairness checks	distributive buffering; policy responsiveness	fiscal pressure; slower innovation diffusion
Fiscal-stability archetype	budgetary control; investment discipline	stress testing; auditability; risk-adjusted planning	credibility; crisis endurance	limited flexibility; cautious innovation
Transition-strain archetype	short-term security under structural change	reactive analytics; partial automation	adaptability under pressure	fragmentation; uneven AI capacity

Source: elaborated by the author.

outcomes in EU smart energy systems. Their value lies in providing a structured comparative language that supports later benchmarking and cluster analysis without presupposing numerical convergence or uniform policy trajectories.

The resilience–innovation archetype represents systems where long-term security is prioritized through anticipatory governance. In this configuration, AI is embedded in forward-looking functions such as scenario modelling, digital twins, and coordinated forecasting that support proactive adaptation to shocks. Economic security is understood primarily in terms of supply resilience and systemic robustness rather than short-term price outcomes. The strength of this archetype lies in diversification strategies and institutional learning capacity, which enable early response to volatility and geopolitical disruption. At the same time, its reliance on complex coordination and high levels of trust in automation introduces governance costs and raises challenges related to interoperability and accountability.

The market-efficiency archetype places market stability and cost optimization at the center of economic security. Here, AI is deployed extensively in forecasting, automated monitoring, and optimization of market operations, enhancing liquidity and efficiency. Economic security is achieved through well-functioning markets that absorb shocks via price mechanisms rather than direct intervention. While this approach benefits from scalability and rapid diffusion of AI tools, it is structurally vulnerable to opacity, strategic behavior, and distributive blind spots. Without strong explainability and oversight, AI-driven efficiency can undermine trust and amplify inequalities during periods of stress.

In contrast, the social-protection archetype frames economic security primarily through affordability and vulnerability mitigation. AI is used to support targeted interventions, early-warning detection of energy poverty, and fairness-sensitive decision support. Governance capacity in this archetype is characterized by responsiveness and distributive buffering, which can stabilize households during crises. However, sustained reliance on protective mechanisms generates fiscal pressure and may slow innovation diffusion, particularly if risk aversion constrains experimentation with advanced AI systems. This trade-off highlights the tension between short-term social stability and long-term adaptive capacity.

The fiscal-stability archetype emphasizes budgetary control and investment discipline as the foundation of economic security. AI plays a supporting role in stress testing, auditability, and risk-adjusted planning, reinforcing credibility and long-term sustainability of public finances. This configuration enhances crisis endurance and investor confidence, yet it often limits policy flexibility and delays the deployment of transformative AI solutions. As a result, systems operating within this archetype may struggle to accelerate innovation or respond rapidly to unexpected shocks, particularly when transition costs rise.

Finally, the transition-strain archetype captures systems undergoing rapid structural change under adverse conditions, such as supply disruptions, fiscal stress, or accelerated decarbonization. AI adoption in this configuration tends to be partial and reactive, focused on immediate problem-solving rather than integrated governance. While adaptability under pressure is a defining strength, fragmentation and uneven institutional capacity create persistent vulnerabilities. Economic security in this archetype is inherently fragile, reflecting the absence of a stable governance equilibrium between sustainability ambitions and operational constraints.

Together, these archetypes provide a conceptual bridge between qualitative governance analysis and empirical clustering. This perspective justifies the use of cluster analysis as an analytical tool capable of capturing structural diversity, trade-offs, and path dependency in AI-driven smart energy systems. In doing so, it reinforces the article's central argument that sustainability-driven economic security in the EU depends not on uniform AI deployment, but on governance configurations that align technological capability with institutional context.

Table **3** completes the sustainability-driven governance framework by explicitly addressing the systemic risks introduced by artificial intelligence in EU macro-level smart energy systems. By mapping AI-induced risks to their transmission channels, economic security consequences, and institutional control logics, the table integrates technological, economic, and governance perspectives into a unified analytical lens.

Several of the systemic risks identified above are amplified where structural energy security indicators approach critical thresholds. High import concentration from a single supplier (exceeding 40–50% of total fuel imports) [41] magnifies the consequences of automation bias, data manipulation, and governance

Table 3: Systemic Risk–Control Nexus of Artificial Intelligence in EU Smart Energy Governance

AI-induced systemic risk	Transmission channel in smart energy systems	Economic security impact	Governance control logic	Institutional locus
Opacity and limited explainability	black-box forecasting; automated control decisions	market instability; loss of trust; regulatory blind spots	explainable AI requirements; human-in-the-loop oversight	regulators; system operators
Automation bias and over-reliance	displacement of expert judgement; self-reinforcing optimization	misallocation of resources; systemic fragility	decision accountability rules; override protocols	regulators; TSOs/DSOs
Cyber and data integrity risk	false data injection; model poisoning; data pipeline attacks	supply disruption; cascading failures; fiscal losses	secure-by-design AI; continuous monitoring	system operators; cybersecurity authorities
Distributional bias	skewed training data; exclusion of vulnerable groups	affordability erosion; social instability	fairness audits; bias-sensitive targeting	social policy bodies; regulators
Governance fragmentation	misalignment across EU, national, and market levels	coordination failure; uneven resilience	harmonized standards; interoperability frameworks	EU institutions; national authorities
Model rigidity under shock	poor adaptation to regime shifts	delayed response; amplified crisis costs	stress testing; scenario diversity; fallback modes	regulators; system operators

Source: elaborated by the author.

fragmentation by narrowing response margins. Similarly, aging infrastructure and insufficient reserve buffers increase the cost of delayed adaptation when AI models exhibit rigidity under shock. These benchmarks highlight that AI-induced risks materialize most acutely where structural security margins are thin, reinforcing the need for governance controls calibrated to underlying system fragility.

Opacity and limited explainability constitute a foundational risk in AI-enabled energy governance. As forecasting and control models become more complex, black-box decision-making can obscure causal reasoning, weakening regulatory oversight and eroding institutional trust. In macro-level energy systems, this opacity translates into market instability and governance blind spots, particularly during periods of stress when rapid intervention is required. The control logic therefore emphasizes explainability requirements and human-in-the-loop mechanisms, positioning transparency not as a technical preference but as an economic security safeguard that preserves accountability and crisis responsiveness.

From a practical implementation perspective, the proposed governance and risk–control framework translates into differentiated action pathways for policymakers and energy system operators. For policymakers, the framework implies prioritizing regulatory instruments that condition AI deployment on explainability, auditability, and interoperability, particularly in market operation, affordability protection, and cross-border coordination. Regulatory sandboxes and harmonized EU standards emerge as enabling tools for testing AI applications under controlled risk conditions while preserving institutional oversight. For system operators, implementation centers on embedding AI within operational workflows through stress-tested forecasting, scenario-based digital twins, and override protocols that preserve human decision authority under uncertainty. Crucially, the framework suggests sequencing implementation: foundational controls addressing data integrity, cyber resilience, and transparency precede advanced automation, ensuring that AI enhances rather than substitutes institutional capacity. This staged approach provides a feasible pathway for translating the conceptual architecture into actionable governance practice.

Automation bias represents a second-order systemic risk that arises when AI-generated outputs are treated as inherently superior to expert judgement. In smart energy systems, such over-reliance can lead to self-reinforcing optimization loops that misallocate resources or suppress early warning signals. The resulting fragility may remain latent until exposed by external shocks, at which point corrective capacity is limited. Governance controls centred on accountability rules and override protocols are therefore essential to maintain adaptive decision-making and prevent AI from becoming a single point of systemic failure.

Cyber and data integrity risks remain among the most direct threats to economic security in AI-enabled energy infrastructures. Smart grids, digital twins, and real-time optimization depend on continuous data flows, making them vulnerable to false data injection, model poisoning, and coordinated cyberattacks. These risks propagate rapidly across interconnected systems, potentially triggering cascading failures and significant fiscal losses. The table highlights secure-by-design AI architectures and continuous monitoring as governance imperatives, underscoring the need for close coordination between system operators and cybersecurity authorities at both national and EU levels.

Distributional bias introduces a subtler but equally consequential risk channel. AI systems trained on incomplete or skewed data may systematically underrepresent vulnerable households or regions, leading to policy targeting failures and erosion of affordability safeguards. Over time, such bias can exacerbate social instability and undermine the legitimacy of the energy transition. The control logic therefore emphasizes fairness audits and bias-sensitive targeting, situating social policy bodies alongside regulators as key institutional actors in AI governance.

Governance fragmentation reflects the structural risk arising from misalignment between EU-level coordination, national regulation, and market operation. AI deployment that is optimized locally but poorly harmonized across governance levels can weaken collective resilience, particularly in cross-border energy systems. Interoperability frameworks and harmonized standards thus function as economic security instruments, reducing coordination failures and enabling collective action under stress.

Finally, model rigidity under shock captures the risk that AI systems trained on historical patterns fail to adapt to regime shifts such as geopolitical disruptions or rapid demand changes. In such cases, delayed response can significantly increase crisis costs. Stress testing, scenario diversity, and fallback modes are therefore essential governance tools, ensuring that AI remains supportive rather than constraining during extreme events.

Table **4** therefore outlines the analytical pathway that connects AI-enabled governance benchmarking with cluster-based analysis of EU smart energy systems clarifying how qualitative governance features can be progressively structured into comparative dimensions suitable for clustering, thereby preserving analytical flexibility while ensuring methodological rigor.

The progressive structuring of governance configurations into comparative clusters can be illustratively aligned with composite energy security indicators rather than single metrics. Variations in domestic supply share, import dependence, infrastructure wear, reserve adequacy, and energy intensity jointly shape the feasible governance space within which AI capabilities operate. Referencing such indicators at the benchmarking stage supports meaningful differentiation between resilient and fragile configurations without collapsing governance complexity into numerical rankings, thereby preserving both analytical flexibility and methodological discipline.

The first stage, conceptual mapping, draws directly on the synthesis presented in Table **1**. At this stage, AI functions are not measured but classified according to their governance relevance — forecasting, optimisation, decision support, and control. Economic security is defined through interacting dimensions rather than isolated metrics, allowing analytical variables to emerge organically from governance logic. This approach avoids premature quantification while ensuring conceptual coherence across subsequent stages.

Governance benchmarking constitutes the second stage and represents a qualitative assessment of how AI capabilities are embedded within institutional arrangements. Here, the focus shifts from “whether AI is used” to “how AI is governed.” Oversight mechanisms, accountability structures, and coordination capacity determine

Table 4: Translating AI Governance Structures into Comparative Economic Security Clusters

Analytical stage	Core analytical focus	Role of AI in the stage	Comparative logic	Output for clustering
Conceptual mapping	identification of security dimensions and risk channels	structuring governance-relevant AI functions	differentiation by governance logic	analytical variables (non-numerical)
Governance benchmarking	assessment of institutional capacity and control mechanisms	alignment of AI with oversight and accountability	relative positioning across systems	benchmark profiles
Archetype formation	grouping by dominant governance configurations	synthesis of AI use patterns	similarity of institutional logics	preliminary clusters
Risk–control calibration	evaluation of AI-induced vulnerabilities	stress-testing governance robustness	resilience vs fragility comparison	refined cluster boundaries
Cluster interpretation	explanation of divergence and convergence paths	AI as conditioning factor	path-dependency and trade-off analysis	policy-relevant cluster narratives

Source: elaborated by the author.

whether AI deployment enhances or undermines economic security. Benchmarking therefore positions systems relative to one another based on governance maturity rather than technological sophistication alone. The resulting benchmark profiles serve as the primary inputs for clustering.

The third stage, archetype formation, translates benchmark profiles into a limited set of governance configurations, as illustrated in Table **2**. Clusters at this stage reflect similarities in institutional logic, policy priorities, and AI integration patterns rather than geographical proximity or income level. This abstraction is analytically important because it captures structural convergence and divergence within the EU that may otherwise be obscured by national boundaries. AI acts as a synthesising factor, linking operational practices with strategic governance orientation.

Risk–control calibration, the fourth stage, incorporates the systemic risk perspective developed in Table **3**. Clusters are refined by evaluating how governance structures respond to AI-induced risks such as opacity, automation bias, and cyber vulnerability. Systems that may appear similar in terms of innovation or market efficiency can diverge significantly once robustness under stress is considered. This calibration step therefore sharpens cluster boundaries by distinguishing resilient governance configurations from fragile ones, especially under crisis conditions.

The final stage, cluster interpretation, transforms analytical groupings into policy-relevant narratives. Rather than ranking clusters, this stage explains how different pathways of AI-enabled governance produce distinct economic security outcomes under sustainability constraints. Path dependency plays a central role: historical institutional choices condition current AI governance capacity, shaping both opportunities and limits for future adaptation. AI is thus treated as a conditioning variable that amplifies existing governance strengths and weaknesses rather than as an exogenous driver.

In the context of EU smart energy systems, this pathway is particularly valuable because it accommodates heterogeneity in institutional design, fiscal capacity, and social priorities while maintaining a common analytical frame. It reinforces the article's core argument that sustainability-driven economic security in AI-enabled energy systems depends less on uniform technological adoption than on the alignment between AI capabilities and governance structures. As such, Table **4** provides the methodological bridge between the conceptual framework and the empirical analysis that follows.

5. DISCUSSION

The results of this study strengthen the literature by repositioning artificial intelligence as a governance-structuring element in EU macro-level smart energy systems rather than a narrowly technical add-on. Large syntheses of AI in energy systems (*e.g.*, Alsaigh *et al*. [1]; Ba`nad *et al*. [28]) document expanding application domains, yet they largely stop at technology mapping. The present results extend that line of work by explicitly connecting AI capabilities (forecasting, optimization, digital twins, control) to economic security dimensions — affordability, resilience, market stability, innovation capacity, social vulnerability, and fiscal exposure — thereby integrating security and sustainability concerns that prior reviews often treat separately.

To enhance analytical rigor, these sustainability linkages can be illustratively anchored in established quantitative benchmarks widely used in energy security and decarbonization analysis. Methodological energy security diagnostics associate higher resilience with domestic energy supply shares exceeding 70–80%, import dependence below 50–55%, and strategic fuel reserves covering more than six months of consumption. From a sustainability perspective, decarbonization progress is commonly benchmarked through increasing shares of renewable energy in primary supply, where values above 6% are associated with structurally favorable security conditions, while lower shares indicate heightened transition strain. These externally defined thresholds are not employed here as performance measures but serve to clarify how AI-enabled governance configurations align with observable security and sustainability margins, reinforcing the analytical connection between qualitative governance structures and quantitative system constraints.

A second contribution is to clarify how "trustworthy AI" becomes economically consequential. Prior work on explainable AI in power systems (Machlev *et al*. [4]) demonstrates why interpretability matters in safety-critical settings, but its scope remains mainly methodological. The present results push the governance interpretation further by treating explainability, human oversight, auditability, and fallback modes as systemic controls that affect market confidence, regulatory visibility, and crisis responsiveness at scale. This reframing also complements forecasting-benchmarking literature: Lago *et al*. [7] and O'Connor *et al*. [8] improve transparency and comparability of price forecasting, yet they do not explicitly translate forecasting performance into a macro-governance logic. Here, forecasting is interpreted as part of a broader affordability and stability regime in which institutional safeguards condition whether predictive tools reduce or amplify volatility transmission.

The archetype logic likewise consolidates and extends EU vulnerability and security mapping. Composite-indicator studies (Brodny and Tutak [11]; Kuzior *et al*. [12]; Tirion *et al*. [21]) reveal cross-country asymmetries but are predominantly static. Energy poverty research emphasizes multidimensionality and measurement gaps (Menyhért [13]; Kashour and Jaber [15]; Thomson *et al*. [37]) while often remaining weakly connected to AI governance. By contrast, the present results interpret cross-country heterogeneity as governance configurations that can be compared and later clustered, capturing trade-offs between market efficiency, social protection, resilience building, and fiscal discipline. Political-economy accounts of coordination failure during crises (Mišík [31]; Mišík and Nosko [32]) are also incorporated by treating fragmentation as a channel through which AI deployment can either reinforce or mitigate collective action problems, depending on interoperability and oversight.

Several limitations delimit interpretation. Firstly, the contribution is framework-building: the tables articulate conceptual benchmarks and risk–control linkages rather than reporting empirical estimates. Second, the archetypes are ideal types, so EU member states may combine features across categories, requiring careful operationalization in subsequent empirical work. Third, the framework deliberately avoids a fixed indicator set; this preserves analytical portability but reduces immediate replicability until a transparent operational protocol is specified. Fourth, the analysis remains macro-level and therefore does not resolve subnational, sectoral, or firm-level heterogeneity emphasized across the literature; extending the framework will require multi-level validation and robustness checks consistent with concerns about modelling transparency and uncertainty raised by Lo Piano and Saltelli [34].

CONCLUSIONS

Artificial intelligence has emerged as a structuring element of economic security governance in EU macro-level smart energy systems, reshaping how sustainability, resilience, and distributive stability are managed under conditions of decarbonization, volatility, and geopolitical stress. The results demonstrate that economic security in AI-enabled energy systems cannot be meaningfully reduced to isolated indicators or technological performance metrics. Instead, it takes the form of an interdependent governance configuration in which affordability, supply resilience, market stability, innovation capacity, social vulnerability, and fiscal exposure are jointly conditioned by how AI capabilities are embedded within institutional frameworks.

The analysis shows that artificial intelligence influences economic security not primarily through efficiency gains, but through its impact on governability. Predictive analytics, optimization tools, digital twins, and automated control systems alter institutional response capacity, coordination dynamics, and distributive outcomes. Systems characterized by robust oversight, explainability, and interoperability are better positioned to translate AI capabilities into stabilizing effects, while weakly governed automation amplifies volatility, opacity, and inequality. This finding extends existing literature by clarifying that AI adoption alone is insufficient; the quality of governance arrangements determines whether AI enhances or undermines long-term security.

Distinct governance configurations emerge that reflect different prioritization of security objectives. Some systems emphasize anticipatory resilience and long-term robustness, while others prioritize market efficiency, social protection, or fiscal discipline. These configurations entail inherent trade-offs: efficiency-oriented approaches risk distributive blind spots; protection-oriented strategies may constrain innovation; fiscally conservative regimes can delay adaptive capacity. Under conditions of rapid structural change, fragmented and reactive governance remains particularly vulnerable. Recognizing these patterns enables comparative assessment without presupposing convergence across EU member states, highlighting path dependency and institutional diversity within the Energy Union.

The results further underscore that AI introduces systemic risks alongside its benefits. Opacity, automation bias, cyber vulnerability, and rigidity under shock represent governance-relevant risk channels with direct economic security implications. Addressing these risks requires embedding explainability, accountability, stress testing, and fallback mechanisms as core elements of energy governance rather than as auxiliary safeguards. In this context, transparency and human oversight function as stabilizing instruments that protect market confidence, regulatory effectiveness, and social legitimacy during crises.

From a policy perspective, the findings indicate that AI governance should be integrated into economic security and energy transition strategies at both EU and national levels. Effective coordination across regulatory, market, social, and fiscal domains is essential, particularly given cross-border interdependencies and shared infrastructure. Social policy integration is equally critical to ensure that AI-based targeting and forecasting tools mitigate vulnerability rather than reproduce structural exclusion. Moreover, interoperability and institutional learning emerge as prerequisites for resilient AI deployment in an increasingly interconnected energy system.

In practical terms, these findings imply that future smart energy system design should prioritize governance-by-design alongside digitalization, embedding explainability, auditability, and fallback capacity directly into system architectures rather than treating them as external controls. For regulators, this underscores the need to align decarbonization targets with enforceable AI governance standards, ensuring that automation, market integration, and sustainability objectives evolve coherently. For technology deployment, the results highlight that scalable and interoperable AI solutions are most sustainable when introduced through staged implementation pathways that respect institutional capacity and social constraints. Taken together, these implications point toward a model of sustainable smart energy development in which technological innovation, regulatory coherence, and economic security objectives are jointly optimized rather than pursued in isolation.

Future research should operationalize the proposed governance dimensions into transparent and replicable empirical frameworks, enabling comparative clustering and longitudinal analysis across Member States and regional groupings. Extending the analysis to subnational and sectoral levels would capture heterogeneity obscured at the macro scale, while dynamic studies could assess how governance configurations evolve under successive shocks. Integrating AI-based modelling with sensitivity auditing and participatory approaches would further strengthen analytical robustness and legitimacy. Together, these directions support the development of governance frameworks capable of aligning artificial intelligence with sustainable and economically secure energy systems in Europe.

CONFLICTS OF INTEREST

The author declared no conflicts of interest.

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