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Review Article

Privacy, Fairness, and Transparency in Decentralized Energy Systems: A Systematic Review of FL–GT–XAI Approaches

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Abstract

The transition toward decentralized, prosumer-driven energy systems has intensified the need for privacy-preserving analytics, fair market mechanisms, and transparent decision-making. While Federated Learning (FL), Game Theory (GT), and Explainable Artificial Intelligence (XAI) independently address these challenges, their integration within decentralized energy systems remains fragmented. This paper presents a systematic review of 52 selected peer-reviewed studies, supported by additional foundational references, published between 2020 and 2026. The review examines the applications of Federated Learning (FL), Game Theory (GT), and Explainable Artificial Intelligence (XAI) in microgrids, peer-to-peer (P2P) energy trading, and decentralized energy management systems. Using a structured methodology comprising comprehensive database searches, clearly defined inclusion and exclusion criteria, and cross-paradigm thematic synthesis, the review identifies critical gaps in the current literature. The findings reveal that existing research largely treats FL, GT, and XAI as isolated paradigms, with no study providing a unified tri-layer framework integrating privacy-preserving learning, strategic market design, and interpretable decision-making. Furthermore, most contributions rely on idealized simulations and originate from technologically advanced regions, offering limited applicability to fragile, data-scarce environments such as conflict-affected Northeastern Nigeria. Key limitations identified include insufficient support for privacy-aware market pricing, limited fairness guarantees in strategic interactions, and weak adoption of explainability in decentralized decision systems. This review represents one of the first consolidated assessments of FL–GT–XAI convergence in decentralized energy systems and contextualizes these paradigms within the operational realities of emerging and fragile regions. The synthesis highlights the urgent need for integrated architectures capable of simultaneously ensuring privacy preservation, incentive compatibility, and transparent decision support for institutional microgrids. Insights from this study provide a foundation for the development of trustworthy, equitable, and resilient decentralized energy markets.

Keywords: Decentralized energy systems, Federated learning, Game theory, Explainable AI, Peer-to-peer energy trading, Microgrids, Privacy, Energy equity.

Introduction

The global transition from centralized electricity generation to decentralized, prosumer-driven energy systems has fundamentally reshaped how energy is produced, traded, and managed [1]. The rapid deployment of distributed energy resources (DERs), including rooftop solar photovoltaics, wind turbines, battery storage systems, and electric vehicles has enabled consumers to participate actively in local energy markets as both producers and consumers (prosumers) [2]. While this transformation enhances flexibility, resilience, and sustainability, it also introduces complex challenges related to coordination, data privacy, fairness, operational uncertainty, and transparency in decision-making [3].

Peer-to-peer (P2P) energy trading, community microgrids, and local energy markets have emerged as promising paradigms for enabling decentralized energy exchange [4]. These systems allow prosumers to trade electricity directly, thereby reducing reliance on centralized utilities and improving local energy autonomy [5]. However, the operation of decentralized markets relies heavily on intelligent algorithms for load forecasting, pricing, bidding, energy scheduling, and system control [6]. Traditional centralized optimization approaches are increasingly inadequate because they face scalability limitations, expose participants to data-privacy risks, and introduce single points of failure that may compromise system resilience [7]. Consequently, there is growing interest in advanced computational frameworks capable of supporting decentralized, secure, and trustworthy decision-making.

Federated Learning (FL) has emerged as a privacy-preserving distributed learning paradigm that enables multiple participants to collaboratively train machine learning models without sharing raw data [8,9]. In energy systems, FL has demonstrated promising applications in load forecasting, anomaly detection, energy theft detection, and distributed energy management [10]. Despite these advantages, FL-based systems often lack explicit economic reasoning, fairness guarantees, and interpretability three critical requirements for building trust in decentralized energy markets [11].

Game Theory (GT) provides a complementary analytical framework for modeling strategic interactions among rational and self-interested agents. GT has been widely applied to P2P pricing mechanisms, auction-based trading, coalition formation, and demand response coordination [12]. Although these models effectively capture market dynamics and incentive structures, many GT-based designs assume complete or near-complete information sharing among participants or rely on centralized coordinators [14]. Such assumptions conflict with the privacy-sensitive and distributed nature of modern decentralized energy systems [15].

Explainable Artificial Intelligence (XAI) has recently emerged as an important paradigm for improving transparency, interpretability, and accountability in AI-driven systems [16]. In energy applications, XAI has been used to interpret forecasting models, detect anomalies, and explain control decisions [17]. However, most XAI studies operate independently of decentralized learning architectures and economic market mechanisms [18]. As a result, they provide limited insight into how transparency can be embedded within P2P energy trading, distributed optimization, or federated learning environments [19].

Although FL, GT, and XAI have each been extensively studied, their integration within decentralized energy systems remains fragmented and underdeveloped. Existing review studies typically examine these paradigms separately or focus on partial integrations such as FL combined with blockchain technologies or GT integrated with optimization models. To date, no comprehensive review has systematically examined how privacy preservation, economic fairness, and decision transparency-three foundational pillars of trustworthy decentralized energy systems can be jointly achieved within institutional microgrid environments.

This gap is particularly critical in fragile and data-scarce environments such as Northeastern Nigeria, where institutional microgrids (for example, the 12 MW hybrid microgrid at the University of Maiduguri) must operate under security constraints, infrastructural limitations, and heterogeneous user demands. In such contexts, decentralized energy markets must ensure not only technical efficiency but also privacy protection, fairness in resource allocation, and transparency in algorithmic decision-making.

To address these challenges, this review makes the following contributions.

First, it provides a systematic classification of the applications of Federated Learning (FL), Game Theory (GT), and Explainable Artificial Intelligence (XAI) within decentralized and institutional energy systems, highlighting their evolution across forecasting, market design, and decision-support domains. Second, it synthesizes methodological strengths, limitations, and contextual applicability using a comparative analytical framework. Third, it identifies key research gaps demonstrating that the simultaneous integration of privacy preservation, economic fairness, and decision transparency remains largely absent in existing literature. Finally, these insights establish a research foundation for the development of a unified FL–GT–XAI architecture tailored to the socio-technical realities of institutional microgrids in emerging economies. To guide the review, the following research questions are formulated:

RQ1: How have FL, GT, and XAI been applied in decentralized energy systems, including microgrids and peer-to-peer trading platforms?

RQ2: What methodological limitations and contextual constraints hinder their effective deployment, particularly in emerging and fragile regions?

RQ3: What opportunities exist for integrating FL–GT–XAI to simultaneously ensure privacy, fairness, and interpretability in real-world institutional microgrids?

These research questions provide a structured foundation for the literature review, comparative analysis, and research gap synthesis presented in the subsequent sections.

1. Methodology

This section describes the systematic approach adopted to identify, select, and synthesize the body of literature informing this review. Given that the study spans multiple intersecting domains Federated Learning (FL), Game Theory (GT), Explainable Artificial Intelligence (XAI), and decentralized energy systems a rigorous and transparent review protocol was necessary. The methodology comprises five stages: literature search strategy, selection criteria formulation, screening and eligibility assessment, data extraction, and cross-paradigm synthesis. This structured approach ensures that only high-quality, thematically aligned studies were included, thereby providing a robust foundation for the comparative and gap-mapping analyses presented in subsequent sections.

1.1 Literature Search Strategy

A systematic literature review was conducted in accordance with established structured-review principles to ensure transparency, reproducibility, and methodological rigor. The search targeted peer-reviewed journal articles and high-impact conference papers published between 2020 and 2026, reflecting the period during which FL, XAI, and advanced GT applications gained significant traction within decentralized energy research.

Relevant studies were retrieved from major academic databases, including: IEEE Xplore, Elsevier ScienceDirect, SpringerLink, Wiley Online Library, Google Scholar. Search queries were constructed using Boolean combinations of methodological and domain-specific keywords to capture interdisciplinary intersections. Representative search strings included: "federated learning" AND "microgrid", "game theory" AND "peer-to-peer energy trading", "explainable AI" AND "electricity markets", "privacy-preserving energy management", "decentralized energy systems". The search strategy was intentionally broad to encompass applications across forecasting, pricing, market design, distributed optimization, and decentralized control. Only English-language, peer-reviewed publications were included. Grey literature, dissertations, non-indexed reports, and sources lacking methodological transparency were excluded to preserve academic rigor and comparability.

1.2 Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were formulated to ensure direct alignment with the objectives of this review, which examines the intersection of decentralized energy systems and intelligent, privacy-aware computational paradigms.

Studies were included if they:

- Addressed decentralized energy environments (e.g., microgrids, P2P markets, distributed energy resources),
- Explicitly employed FL, GT, XAI, or hybrid intelligent frameworks,
- Provided sufficient methodological detail,
- Demonstrated empirical, simulation-based, or theoretical rigor.

Studies were excluded if they:

- Focused exclusively on centralized power system architectures,
- Lacked methodological transparency,
- Did not integrate computational intelligence or strategic modelling components,
- Were not peer-reviewed.

These criteria ensured that the final literature corpus was both technically robust and thematically consistent with the development of an integrated FL–GT–XAI framework, particularly relevant for institutional microgrid contexts such as the 12 MW hybrid system at the University of Maiduguri.

1.3 Study Selection Process

The study selection procedure followed a PRISMA-inspired multi-stage protocol comprising four sequential phases: identification, screening, eligibility assessment, and final inclusion. The initial database search identified 1,070 records across the selected academic databases. In addition, 24 records were obtained from other sources, including reference tracking and related literature searches, resulting in a total of 1,094 records. After removing 24 duplicate entries, 1,070 records remained for title and abstract screening. During the screening stage, studies that did not address decentralized energy systems or did not involve Federated Learning (FL), Game Theory (GT), or Explainable Artificial Intelligence (XAI) methodologies were excluded. Following this process, 310 articles were retained for full-text assessment.

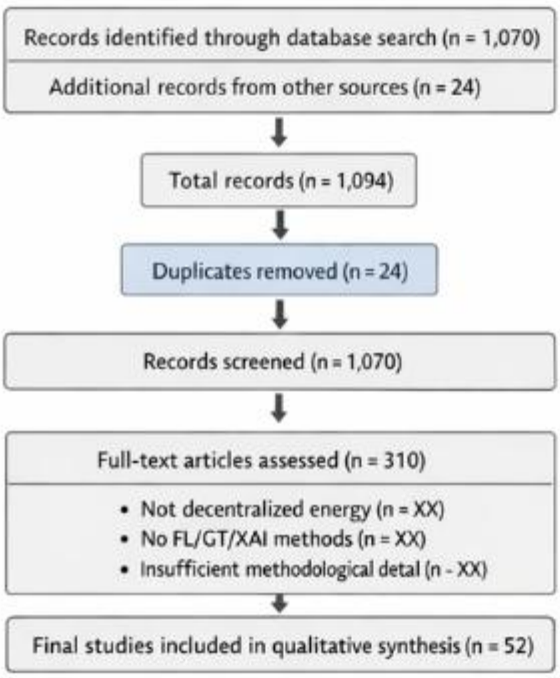

Figure 2. PRISMA-based literature identification and screening process

Full-text articles were then evaluated against the predefined inclusion and exclusion criteria to ensure methodological rigor and thematic relevance. Studies were excluded at this stage for several reasons, including lack of relevance to decentralized energy systems, absence of FL, GT, or XAI methodologies, and insufficient methodological detail. The quantitative workflow is illustrated in Figure 2. Applying the eligibility criteria resulted in the final inclusion of 52 peer-reviewed studies, which were used for qualitative and comparative synthesis in this review. This structured multi-stage filtering process minimized selection bias, enhanced methodological transparency, and ensured that the final corpus of literature provided a reliable basis for the cross-paradigm synthesis and research gap identification presented in the subsequent sections.

2.4 Data Extraction and Analytical Framework

For each selected study, a standardized data extraction template was employed to systematically capture key attributes, including: Bibliographic information, Methodological approach, Application domain (e.g., microgrids, P2P markets, forecasting, control), Algorithms and computational tools, Data sources (real-world or synthetic), Key findings and performance metrics, Identified limitations and future research directions. This structured coding process facilitated comparative tabulation and enabled systematic evaluation across paradigms.

2.5 Cross-Paradigm Synthesis and Gap Mapping

Rather than evaluating studies in isolation, a cross-paradigm synthesis was conducted to assess complementarities, fragmentation, and structural deficiencies across FL, GT, and XAI research streams. Visual analytical tools including comparative matrices and conceptual architecture diagrams were employed to: Identify methodological fragmentation, Reveal underexplored intersections (e.g., FL-enabled strategic pricing, XAI-enhanced equilibrium models), and Highlight contextual gaps relevant to institutional microgrids in fragile and data-scarce environments. This integrative synthesis directly informed the research gaps and the proposed tri-layer FL–GT–XAI framework discussed in later sections.

2. Literature Review

2.1 Intelligent Paradigms in Decentralized Energy Systems

The rapid evolution of decentralized energy systems has intensified the need for intelligent computational frameworks capable of addressing variability in renewable generation, heterogeneous prosumer behavior, privacy-sensitive consumption data, and the growing demand for transparent and accountable decision-making.

Within this context, three dominant paradigms have emerged as foundational pillars of next-generation decentralized energy architectures: Federated Learning (FL), Game Theory (GT), and Explainable Artificial Intelligence (XAI). Although each paradigm addresses distinct dimensions of decentralized coordination, their development has largely proceeded independently.

3.1.1 Federated Learning (FL)

Federated Learning (FL) enables distributed model training without centralized aggregation of raw data, thereby preserving privacy while maintaining predictive performance. In microgrid environments, FL has demonstrated effectiveness in: Load forecasting, Demand response optimization, Anomaly and energy theft detection, and Distributed energy management.

By allowing local training at the prosumer level and secure model aggregation at a coordinating node, FL mitigates risks associated with centralized data storage.

However, despite its technical strengths, the literature reveals persistent limitations. These include:

- Communication overhead under frequent model updates,
- Performance degradation under non-IID (non-independent and identically distributed) data,
- Vulnerability to inference and poisoning attacks, and
- Limited integration with market pricing and strategic decision frameworks.

Notably, most FL-based energy studies remain confined to predictive analytics rather than economic coordination or trading architectures.

3.1.2 Game Theory (GT)

Game Theory (GT) provides a structured mathematical foundation for modeling strategic interactions among self-interested prosumers in decentralized markets. It underpins mechanisms for: Peer-to-peer (P2P) pricing, Auction design, Incentive alignment, Coalition formation, and Market equilibrium computation.

GT-based frameworks contribute significantly to fairness and efficiency in decentralized electricity trading.

However, many GT models assume: Perfect or near-complete information, Fully rational agents, Stable communication infrastructure, and High coordination among participants. Such assumptions often conflict with the privacy-sensitive and infrastructure-constrained realities of institutional and community microgrids. Moreover, GT-based pricing models rarely incorporate privacy-preserving learning mechanisms or interpretability modules.

3.1.3 Explainable Artificial Intelligence (XAI)

Explainable Artificial Intelligence (XAI) enhances transparency by providing interpretable insights into model predictions and algorithmic decisions. Techniques such as SHAP and LIME enable attribution analysis, feature importance assessment, and fairness diagnostics.
In energy systems research, XAI has been applied to: Load forecasting interpretation, Electricity price anomaly detection, Renewable generation prediction, and Reinforcement learning policy explanation.

Despite its growing importance, XAI remains largely detached from decentralized market architectures. Few studies embed explainability directly within P2P trading mechanisms, and almost none integrate XAI into federated or game-theoretic frameworks. As a result, interpretability is often treated as an auxiliary post-processing step rather than a core architectural component.

3.1.4 Structural Fragmentation and Conceptual Integration

Figure 3 presents a tri-layer conceptual architecture illustrating the structural integration required to unify privacy-preserving learning (FL), strategic economic interaction (GT), and transparent decision support (XAI). While bilateral integrations have been explored such as FL-enhanced forecasting, GT-based pricing, or XAI-supported prediction analysis a complete tri-layer architecture remains absent in the literature.

This fragmentation is particularly problematic in fragile and data-scarce environments, including conflict-affected regions such as Northeastern Nigeria, where privacy, fairness, and transparency are foundational for institutional microgrid adoption and community trust.

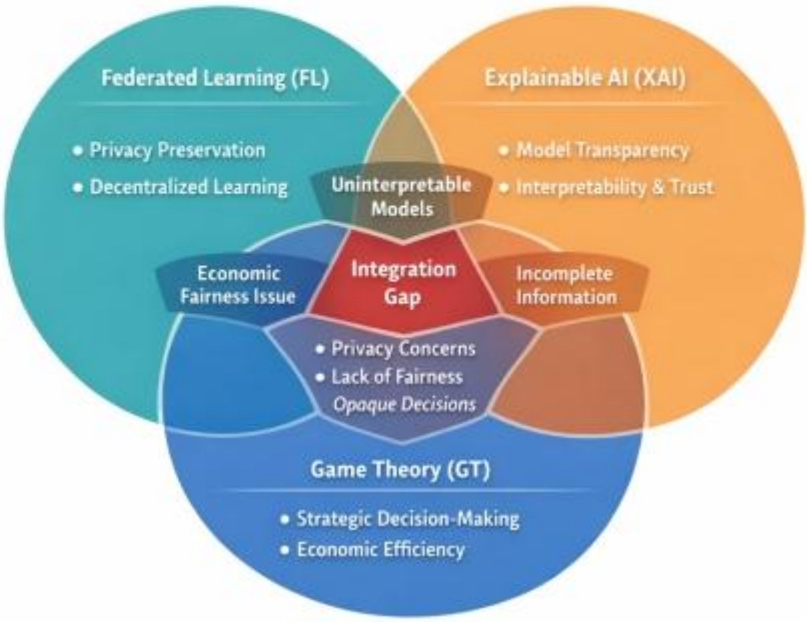

Figure 3. Conceptual framework for FL–GT–XAI integration in decentralized energy systems.

3.2 Thematic Synthesis of Reviewed Literature

Table 3.1 summarizes over 50 peer-reviewed studies spanning peer-to-peer (P2P) energy trading, microgrid modeling, federated learning, game-theoretic pricing, and explainable AI applications.

The literature can be organized into five dominant thematic clusters that collectively define current research trajectories in decentralized energy systems.

3.2.1 Peer-to-Peer Energy Trading and Community Microgrids

Early and contemporary studies demonstrate the feasibility of P2P energy markets for improving local resilience, reducing transmission losses, and enhancing consumer participation. Empirical pilots such as the Brooklyn Microgrid and various European community energy

projects illustrate operational viability. However, most implementations originate from technologically advanced regions and assume stable regulatory frameworks and digital infrastructure. Transferability to low-income, fragile, or infrastructure-constrained contexts remains limited. African-focused studies are comparatively sparse and rarely incorporate advanced pricing mechanisms or distributed intelligence.

3.2.2 Microgrid Modelling in African and Conflict-Prone Regions

Studies focusing on Sub-Saharan Africa, particularly Northeast Nigeria, emphasize persistent energy access deficits, high solar resource potential, and grid unreliability. Techno-economic modelling tools such as HOMER, MILP optimization, and GIS-based resource assessment dominate this literature. Although these studies strongly advocate decentralized microgrids, they largely exclude advanced computational paradigms such as P2P trading, federated learning, or explainable AI. Consequently, there is a structural disconnect between techno-economic feasibility research and intelligent market design.

3.2.3 Federated Learning Applications in Energy Systems

FL research within energy domains demonstrates improved privacy protection and competitive forecasting performance relative to centralized models. Applications include demand forecasting, distributed optimization, and anomaly detection. Nevertheless, most implementations remain proof-of-concept simulations conducted under controlled conditions. Integration with economic decision-making layers, strategic pricing models, or interpretability mechanisms remains minimal. The scalability of FL under heterogeneous prosumer behaviour and unreliable communication networks also remains underexplored.

3.2.4 Game-Theoretic Market Design and Strategic Pricing

GT-based research addresses equilibrium pricing, coalition stability, and incentive compatibility in P2P energy markets. These models enhance fairness and economic efficiency. However, they often rely on idealized assumptions of complete information and rational agent behaviour. Furthermore, GT models rarely incorporate privacy-preserving learning or explainability modules, limiting their applicability in real-world decentralized environments.

3.2.5 Explainable AI and Trustworthy Energy Systems

XAI research underscores the growing need for transparency in AI-driven forecasting and decision systems. Interpretability tools help diagnose bias, validate predictions, and enhance user trust. Yet applications of XAI in decentralized trading architectures remain rare. Most implementations focus on centralized forecasting tasks rather than embedding interpretability within distributed market operations. This omission weakens trust, regulatory compliance, and adoption potential in community microgrids.

3.3 Transition to Comparative Analysis

Collectively, the reviewed literature demonstrates significant technical progress within individual paradigms but reveals structural fragmentation across privacy, fairness, and interpretability dimensions.

Table 3.1 consolidates the methodological characteristics, findings, and limitations of the 52 selected studies. The subsequent section builds upon this synthesis by conducting a cross-paradigm comparative analysis to identify systemic gaps and inform the development of an integrated FL–GT–XAI framework.

Table 3.1 – Summary of Reviewed Literature

S/N	Author(s)	Year	Region / Context	Domain	System Type	Method / Model	Algorithms / Tools	Data Source	Key Findings	Identified Gaps / Limitations
20	Tushar et al.	2020	Global	P2P Trading	Distributed networks	Systematic review	Literature synthesis	Secondary	Comprehensive P2P taxonomy	Limited developing-region focus
21	Mezquita et al.	2022	EU	P2P + Blockchain	Community MG	Blockchain marketplace	Smart contracts	Simulation	Transparent energy exchange	Scalability & energy overhead
22	Wu et al.	2022	Asia	Energy community	Microgrid + Blockchain	Distributed coordination	Blockchain	Simulation	Beyond bilateral P2P	Limited pricing fairness analysis
23	Moradi et al.	2023	Multi-region	Market design	Local energy market	Hybrid decentralized market	MILP + pricing model	Simulation	Joint energy-reserve trading	No privacy-preserving learning
24	Gasca et al.	2025	EU	Fairness	Energy communities	Comparative framework	Welfare metrics	Case studies	Fairness comparison	No AI integration
25	Adewole et al.	2023	Nigeria	P2P adoption	Residential	Survey-based analysis	Statistical models	Field survey	Financial motivation critical	No computational modeling
26	Karaki & Al-Fagih	2024	Global	Game Theory	Smart grids	Evolutionary game	Replicator dynamics	Simulation	Strategic adaptation improves stability	Ideal rationality assumptions
27	Krayem et al.	2023	Middle East	GT-P2P	Rooftop PV MG	Non-cooperative game	MATLAB	Simulation	Efficient P2P pricing	Requires full information
28	Tushar et al.	2020	Global	Coalition GT	P2P MG	Coalition formation	Game theory	Simulation	Stable prosumer groups	No privacy layer
29	Zhao et al.	2023	China	Stackelberg + RL	Multi-MG	Stackelberg game + MARL	Deep RL	Simulation	Improved trading efficiency	Black-box learning
30	Yu et al.	2024	China	Stackelberg pricing	Community MG	Leader-follower model	Optimization	Case study	Stable price equilibrium	No explainability
31	Izanlo et al.	2024	EU	GT + Network constraints	P2P MG	MILP + GT	MILP	Simulation	Network-aware P2P	Computational complexity
32	Luo et al.	2022	Asia	Distributed GT	Community MG	Distributed	Game theory	Simulation	Ownership-aware trading	No learning integration

						equilibrium				
33	Sarker et al.	2024	Asia	FL + XAI	Smart grid	Attention-based FL	Deep learning + SHAP	Smart meter	Improved accuracy + interpretability	No economic modeling
34	Su et al.	2021	China	Secure FL	Smart grid	Edge-cloud FL	Secure aggregation	Simulation	Privacy-preserving training	Communication overhead
35	Wen et al.	2022	China	FL forecasting	Solar MG	Distributed FL	LSTM + FL	Solar data	Accurate solar forecasting	No market integration
36	He et al.	2023	China	FL + GT	Blockchain energy	Incentive mechanism	Game-theoretic FL	Simulation	Secure collaborative FL	Limited microgrid realism
37	Zhang et al.	2022	Global	GT-FL	General FL	Robust DP-FL	Differential privacy	Simulation	Joint privacy & strategy	Not energy-specific
38	Liu et al.	2025	Global	Blockchain + FL	P2P trading	Integrated framework	Smart contracts	Simulation	Privacy-preserving P2P	High infrastructure need
39	Baur et al.	2024	Global	XAI review	Load forecasting	Survey	SHAP, LIME	Literature	Interpretability taxonomy	Limited distributed focus
40	Cifci	2025	EU	XAI smart grid	Decentralized grid	Interpretable ML	ML + XAI	Case study	Transparent grid predictions	No GT/FL link
41	Pesenti & O'Sullivan	2025	EU	XAI pricing	Electricity markets	DNN + XAI	SHAP	Market data	Explainable price forecasts	No decentralized learning
42	Miskiw & Staudt	2024	EU	XAI + RL	Market simulation	Explainable DRL	Deep RL	Simulation	Interpretable trading agents	Not federated
43	Våle et al.	2025	EU	Forecast interpretability	Balancing market	ML interpretability	Feature attribution	Market data	Transparency improves trust	Limited to forecasting
44	Li et al.	2024	China	RL bidding	Energy storage	Temporal DRL	Deep RL	Market simulation	Adaptive bidding improves returns	Black-box decision
45	Zheng et al.	2024	China	Privacy RL	Energy market	Multi-agent RL	MARL	Simulation	Privacy-aware trading	No XAI integration
46	Yang et al.	2020	Global	Energy-aware FL	IoT	Energy-efficient FL	FL optimization	Simulation	Reduced FL energy cost	Not energy-market focused
47	Li et al.	2020	Global	FL survey	General	Systematic review	FL taxonomy	Literature	FL system classification	Not domain-specific
48	Nguyen et al.	2021	Global	FL survey	IoT	Comprehensive review	FL architectures	Literature	IoT FL taxonomy	No microgrid link

49	Rahman et al.	2022	Asia	Blockchain FL	Smart grid	Blockchain + FL	Secure protocol	Simulation	Secure trading	Scalability limits
50	Zhao et al.	2020	Global	Non-IID FL	General	FL under heterogeneity	SGD	Simulation	Non-IID challenges identified	Not energy-focused
51	Morstyn et al.	2020	UK	P2P federation	Community MG	Platform design	Optimization	Pilot data	Prosumers form federated plants	No FL/XAI
52	Paudel et al.	2020	Asia	Network P2P	Smart grid	Auction + constraints	Game theory	Simulation	Network-aware trading	No privacy layer
53	Mengelkamp et al.	2021	EU	Microgrid markets	Community MG	Regulatory review	Case study	Pilot projects	Governance critical	No AI integration
54	Wang et al.	2022	China	Multi-agent GT	Microgrid	Strategic optimization	GT	Simulation	Efficient sharing	No interpretability
55	Long et al.	2020	UK	Community P2P	MG	Distributed pricing	Optimization	Case data	Reduced retailer dependence	Limited fairness analysis
56	Arrieta et al.	2020	Global	XAI theory	General	Taxonomy	Conceptual	Literature	Responsible AI framework	Not energy-specific
57	Rudin	2021	Global	Interpretable ML	General	Glass-box models	Interpretable ML	Conceptual	Advocates interpretable models	Not decentralized context
58	Rai	2020	Global	XAI principles	General	Conceptual	Trust frameworks	Literature	Explainability essential	No energy focus
59	Bussmann et al.	2021	EU	XAI regulation	Energy & finance	Regulatory analysis	XAI tools	Case studies	Compliance importance	Not microgrid-specific
60	Lundberg et al.	2020	Global	SHAP	ML	Global explanation	Tree SHAP	Case studies	From local to global XAI	Computational cost
61	Vázquez-Canteli & Nagy	2021	Global	RL demand response	Smart grid	RL survey	RL taxonomy	Literature	RL potential in DR	Transparency issues
62	Fang et al.	2021	Global	Smart grid review	Grid systems	Comprehensive survey	Multi-domain	Literature	Smart grid evolution	No FL-GT integration
63	Zhou et al.	2021	Global	Blockchain P2P	Distributed energy	Review	Blockchain	Literature	Blockchain enables trust	Energy & latency cost
64	Sousa et al.	2025	Europe (Portugal)	Renewable energy communities	Solar PV + Battery storage community	Techno-economic integration analysis	PV–Battery optimization modelling	Case study data from renewable energy	Integration of new members with PV and storage increases economic benefits and	Does not incorporate AI-driven pricing, federated learning, or game-theoretic coordination

								community	improves community energy sharing efficiency	
65	Li et al.	2024	China	Energy storage bidding	Market-integrated MG	Temporal-aware deep reinforcement learning	Deep RL	Market simulation data	Adaptive bidding increases storage profitability	Black-box decision process; no explainability
66	Zhang et al.	2024	China	Electricity spot markets	Grid-connected renewables	Strategic bidding analysis	Game-theoretic modeling	Empirical market data	Participation ratio affects market efficiency	Limited privacy consideration; centralized assumptions
67	Zheng et al.	2024	China	Multi-agent RL + Privacy	Energy markets	Privacy-preserving MARL	Multi-agent RL	Simulation	Improved decentralized coordination	No XAI; no federated learning integration
68	Mustapha et al.	2026	Nigeria	P2P + GT Pricing	Residential Solar MG	Comparative pricing simulation	Stackelberg GT, ATOU	Real household load data	7.4% cost reduction, improved fairness	No FL, no XAI, no privacy layer
69	Wang et al.	2023	China	Federated Learning for Energy Forecasting	Smart Grid	Distributed learning framework	FL + LSTM neural networks	Smart meter datasets	FL improves load forecasting accuracy while preserving user data privacy	Does not integrate market pricing or game-theoretic coordination
70	Zhang et al.	2023	China	P2P Energy Trading	Microgrid Energy Market	Blockchain-enabled trading platform	Smart contracts + decentralized optimization	Simulation	Secure and transparent P2P trading platform improves transaction trust	High computational overhead and limited scalability
71	Khorasany et al.	2020	Australia	Local Energy Markets	Community Microgrids	Market-clearing framework	Double auction mechanism	Simulation	Demonstrates efficient decentralized electricity trading and improved market liquidity	No privacy-preserving learning or explainability mechanisms

3.4 Comparative Paradigm Distribution and Research Trends

3.5

A structured analysis of the 52 reviewed studies reveals a pronounced methodological concentration around peer-to-peer (P2P) trading mechanisms and game-theoretic (GT) pricing strategies. Approximately 45–50% of the reviewed works employ classical, Stackelberg, coalition, Bayesian, or evolutionary game-theoretic models to formalize strategic interactions among prosumers in decentralized electricity markets. These studies primarily focus on equilibrium computation, incentive alignment, coalition formation, and network-constrained pricing optimization.

Federated Learning (FL)-based research accounts for approximately 25–30% of the literature. These contributions are predominantly applied to load forecasting, anomaly detection, demand response coordination, and privacy-preserving distributed optimization. While FL demonstrates strong capability in handling non-IID energy datasets and decentralized computation, its integration with market pricing and strategic interaction layers remains limited.

Explainable Artificial Intelligence (XAI) represents the smallest thematic cluster (10–15%). XAI applications are largely confined to interpretability in load forecasting, electricity price anomaly detection, and reinforcement learning transparency. However, XAI rarely extends into P2P pricing architectures or multi-agent economic decision-making frameworks. Notably, only a marginal fraction of studies (<5%) demonstrate partial integration across two paradigms (e.g., FL + GT or FL + XAI). No study within the reviewed corpus presents a fully integrated FL–GT–XAI tri-layer framework tailored to decentralized microgrids.

Geographically, empirical implementations are heavily concentrated in Europe and East Asia, particularly China, Germany, and the United Kingdom. African applications remain severely underrepresented despite high renewable energy potential and urgent energy access needs.

Overall, the distribution analysis reveals a technically rich yet structurally fragmented research landscape characterized by isolated methodological silos rather than unified intelligent energy architectures.

3.6 Methodological Fragmentation Across Paradigms

Despite rapid innovation in decentralized energy research, the reviewed literature exhibits clear methodological fragmentation across computational paradigms.

3.5.1 Federated Learning (FL)

FL studies prioritize privacy preservation and distributed model training. However, they frequently operate independently of economic pricing mechanisms or strategic behavior modeling. Most FL implementations remain technically oriented, focusing on forecasting or anomaly detection without integration into decentralized market layers.

3.5.2 Game Theory (GT)

GT-based frameworks rigorously model strategic pricing, fairness allocation, coalition formation, and equilibrium stability. Nevertheless, many models assume complete or near-complete information visibility among agents, centralized data access, or ideal communication conditions. Such assumptions conflict with privacy-preserving decentralized architectures, particularly in infrastructure-constrained regions.

3.5.3 Explainable AI (XAI)

XAI enhances transparency and trust but is typically applied post hoc to forecasting or reinforcement learning models. It is rarely embedded directly within pricing engines or federated learning pipelines. Consequently, most decentralized trading mechanisms remain black-box systems lacking interpretability guarantees. This fragmentation suggests that while each paradigm addresses a critical dimension of decentralized energy systems privacy (FL), strategic interaction (GT), and transparency (XAI) their isolated deployment limits holistic system performance.

An integrated architecture is therefore required to unify distributed intelligence, economic equilibrium, and explainability within a coordinated framework.

3.6 Geographic and Contextual Imbalance

A significant geographic imbalance is evident across the reviewed studies. The majority of P2P pilot projects, blockchain-enabled trading platforms, and GT-based simulations are situated in technologically advanced regions characterized by stable digital infrastructure, high smart-meter penetration, and mature regulatory frameworks.

In contrast, decentralized energy systems in Sub-Saharan Africa and conflict-affected regions receive limited empirical attention. Although regulatory reforms such as Nigeria's Electricity Act (2023) increasingly enable decentralized generation and trading, practical implementations of intelligent pricing mechanisms remain scarce. Regions such as Northeastern Nigeria face infrastructural instability, security constraints, limited digital penetration, and heterogeneous prosumer participation. Most existing computational models assume stable communication networks, abundant data availability, and consistent agent participation assumptions that are misaligned with developing-region realities. Bridging this contextual mismatch is therefore not merely an academic challenge but a socio-technical imperative for equitable energy transition.

3.7 Identified Research Gaps and Positioning

An integrated synthesis of the reviewed literature reveals five cross-cutting gaps emerging at theoretical, methodological, and contextual levels.

3.7.1 Gap 1: Absence of Fully Integrated FL–GT–XAI Architectures

While bilateral integrations (e.g., GT-based pricing, FL-based forecasting, XAI-based interpretability) are documented, no study provides a unified framework that simultaneously:

- Employs federated learning for distributed demand or load modeling,
- Utilizes game-theoretic equilibrium mechanisms for decentralized pricing,
- Embeds explainability mechanisms within pricing and allocation systems.

The lack of tri-layer integration prevents holistic optimization of privacy, fairness, and transparency.

3.7.2 Gap 2: Centralized Information Assumptions in Decentralized Markets

Many GT-based pricing frameworks assume full visibility of prosumer demand or generation data. Such assumptions contradict the privacy-sensitive nature of decentralized microgrids. Privacy-preserving computation within strategic pricing environments remains underdeveloped.

3.7.3 Gap 3: Limited Integration of Equity and Interpretability Metrics

Although fairness is frequently discussed conceptually, rigorous quantitative evaluation using metrics such as Gini coefficients, Lorenz curves, or distributional fairness indices is rare. Furthermore, explainability tools (e.g., SHAP, LIME) are seldom embedded within decentralized trading architectures. As a result, most pricing mechanisms lack transparent justification for allocation decisions and do not systematically evaluate distributive equity.

3.7.4 Gap 4: Overreliance on Simulation and Limited Real-World Validation

The majority of reviewed works rely on synthetic datasets or controlled simulations. Empirical studies grounded in field measurements remain scarce. The absence of real usage patterns and heterogeneous prosumer behaviour reduces the external validity of many proposed frameworks.

3.7.5 Gap 5: Underrepresentation of African and Conflict-Prone Contexts

Empirical implementations in Sub-Saharan Africa remain minimal. Existing studies rarely incorporate infrastructural instability, communication constraints, digital literacy limitations, or socio-economic diversity into model design. This contextual underrepresentation limits the global applicability of decentralised intelligent energy frameworks.

3.8 Research Positioning

In response to the identified gaps, this study positions itself at the intersection of distributed learning, strategic market design, and explainable decision systems. Specifically, it proposes a unified FL–GT–XAI architecture tailored to institutional microgrids operating under infrastructure-constrained and data-scarce conditions.
The contribution is threefold:

1. **Federated Learning Layer:**

A privacy-preserving load forecasting and behavior modeling framework designed to operate under non-IID data distributions.

2. **Game-Theoretic Pricing Layer:**

An incentive-compatible pricing mechanism incorporating strategic prosumer interaction and local market constraints.

3. **Explainability Layer:**

An embedded XAI module (e.g., SHAP/LIME-based) providing transparent price attribution, fairness diagnostics, and stakeholder interpretability. By integrating privacy preservation, strategic equilibrium, and transparent decision support, the proposed framework directly addresses the structural incompleteness of existing decentralized energy research.
This positioning advances decentralized energy systems beyond isolated methodological applications toward coordinated, trustworthy intelligent architectures.

4. Comparative Analysis and Synthesis

This section synthesizes insights from the reviewed literature by comparing Federated Learning (FL), Game Theory (GT), and Explainable AI (XAI) across thematic dimensions critical to decentralized energy systems. Instead of analyzing studies in isolation, the discussion highlights cross-cutting issues that affect the viability, acceptability, and scalability of peer-to-peer (P2P) energy trading and distributed microgrid management.

4.1 Thematic Comparison

4.1.1 Privacy

Privacy consistently emerges as a primary driver for incorporating FL into decentralized energy management. FL limits data exposure by allowing local model training and global aggregation without raw data exchange, thereby mitigating risks associated with centralized storage. However, most implementations still rely on a trusted aggregator and provide incomplete protection against inference attacks, gradient leakage, or malicious model manipulation. In contrast:

- GT-based and blockchain-based trading models typically assume high transparency and full information availability, often overlooking the privacy needs of prosumers with sensitive consumption patterns.

- XAI-focused studies improve system transparency but rarely embed privacy-preserving features, revealing an underlying tension between explainability and confidentiality.

Overall, the literature lacks integrated approaches that balance privacy, transparency, and strategic interaction in decentralized markets.

4.1.2 Fairness

Fairness considerations are most visible in GT and auction-based frameworks, where equilibrium strategies, welfare metrics, and incentive-compatible pricing aim to ensure equitable participation. Yet, fairness is often narrowly defined, limited to price fairness, payoff balance, or coalition stability and rarely extends to algorithmic fairness in learning models.

- FL studies seldom address fairness across participants, despite heterogeneity in household load patterns that can distort model performance.
- XAI studies provide a basis for identifying biased or unfair outcomes but rarely operationalize fairness-aware explanations or corrective mechanisms.

This creates a critical gap: fairness is not systematically linked to predictive modelling or decision automation in decentralized energy systems.

4.1.3 Interpretability

Interpretability remains the least developed of the three thematic dimensions. Although XAI methods such as SHAP and LIME are increasingly used in traditional forecasting tasks, their application in decentralized or federated environments is very limited. Most FL and GT configurations operate as opaque decision engines, offering stakeholders little insight into:

- how prices are formed,
- why energy is allocated in specific ways, or
- how individual behavior influences collective outcomes.

This lack of interpretability undermines trust, especially in emerging markets where users often demand transparent justification for automated decisions. Moreover, regulators require explainability for compliance and auditability, yet most reviewed models provide only superficial or post-hoc explanations.

4.1.4 Scalability

Scalability challenges manifest differently across paradigms:

- FL enhances computational scalability by distributing learning but suffers from communication overhead, slow convergence under non-IID data, and device heterogeneity.
- GT models often struggle with scalability due to the complexity of computing equilibria in large, heterogeneous populations.
- Blockchain-based P2P markets improve traceability but face significant latency, throughput, and energy consumption constraints.

Very few studies provide holistic scalability analyses that jointly consider learning efficiency, economic performance, and system stability under realistic deployment conditions. This gap is particularly relevant for community microgrids in low-resource settings.

4.2 Key Findings

4.2.1 Methodological Fragmentation

A central finding is the methodological fragmentation across the literature. Most studies optimize within a single paradigm learning, economics, or transparency while neglecting interactions among them. As a result:

- FL studies optimize privacy and prediction accuracy but ignore market incentives.
- GT models optimize prices and interaction strategies but assume unrealistic information availability.
- XAI tools improve transparency but are rarely embedded within operational decision pipelines.

This isolation limits real-world applicability, where decentralized energy platforms must simultaneously address privacy, economic efficiency, fairness, and interpretability.

4.2.2 Privacy–Utility Trade-offs

Several FL and differential privacy studies demonstrate that stronger privacy often reduces model accuracy, communication efficiency, or market performance. However, these trade-offs are seldom quantified in energy market contexts, leaving practitioners without actionable guidance on balancing privacy protection against economic or operational utility. Existing work also underestimates the risks of privacy leakage in high-resolution smart meter data, especially in sensitive or insecure regions.

4.2.3 Weak Adoption of Explainability

Despite growing attention, explainability remains underutilized in decentralized energy applications. Most AI-driven models treat XAI as an optional post-processing tool rather than a foundational requirement. Consequently:

- Trading mechanisms remain opaque,
- Users cannot understand or contest decisions, and
- Regulators lack insight into system logic.

This weak adoption of explainability poses major risks for trust, acceptance, and long-term sustainability of decentralized energy initiatives.

4.3 Implications for Decentralized Energy Markets

4.3.1 Operational Implications

Operationally, the absence of integrated FL–GT–XAI frameworks results in poorly coordinated forecasting, pricing, and control strategies. Systems that lack fairness and transparency may experience:

- reduced prosumer engagement,
- unstable trading participation,
- inefficient resource utilization, and
- increased volatility in distributed generation networks.

In high-uncertainty environments such as weak grids or hybrid microgrids, these shortcomings can significantly reduce system performance.

4.3.2 Regulatory Implications

Regulators increasingly prioritize transparency, accountability, and explainability in algorithmic decision systems. Current decentralized energy models especially those based on GT or machine learning rarely provide sufficient auditability. This mismatch can hinder regulatory approval, create compliance vulnerabilities, and undermine consumer protection in future P2P energy markets. Data protection laws further require privacy-preserving mechanisms, yet many systems depend on centralized data sharing.

4.3.3 Socio-Economic Implications in Emerging Markets

In emerging markets such as Sub-Saharan Africa, decentralized energy systems operate within contexts characterized by:

- institutional fragility,
- low digital literacy,
- limited trust in centralized authorities, and
- socio-economic heterogeneity.

Black-box or opaque AI-driven solutions risk being rejected by communities. Conversely, systems that are fair, transparent, and privacy-aware can promote:

- greater prosumer participation,
- better alignment with local norms,
- reduced technology mistrust, and
- more equitable distribution of energy benefits.

These insights underscore the importance of integrated FL–GT–XAI frameworks for inclusive and sustainable microgrid development.

5. Synthesis of Identified Research Gaps

The systematic review and comparative analysis presented in Sections 3 and 4 highlight critical limitations in existing research on decentralized energy systems, particularly in microgrids, P2P energy trading, federated learning (FL), game-theoretic pricing (GT), and explainable AI (XAI). The synthesis below consolidates these gaps to justify the need for an integrated approach.

5.1 Fragmented Paradigm Integration

Most studies optimize a single objective-forecasting accuracy, market pricing, or interpretability without considering interactions across learning, strategic behaviour, and transparency. This fragmentation limits practical deployment in real-world microgrids, where privacy, fairness, and explainability must be addressed simultaneously.

5.2 Limited Adoption of Privacy-Preserving Learning

Although FL has demonstrated potential for decentralized load forecasting and anomaly detection, its use in market mechanisms, P2P trading, and prosumer behaviour modelling remains scarce. Existing implementations often assume ideal network conditions and homogeneous data distributions, which are unrealistic for low-resource or conflict-affected contexts such as Northeastern Nigeria.

5.3 Absence of Strategic Incentive Models in Distributed Settings

Game-theoretic frameworks typically require complete information and rational agent behaviour. Few studies combine GT with FL-informed forecasting to design privacy-aware, incentive-compatible trading mechanisms, leaving a gap in strategic alignment for heterogeneous prosumers.

5.4 Weak Integration of Explainable AI

While XAI improves transparency in AI-driven systems, most applications are limited to centralized forecasting or optimization. Very few studies embed XAI into distributed learning or market frameworks, reducing stakeholder trust, regulatory compliance, and adoption potential.

5.5 Scarcity of Context-Specific Research

Few studies account for the socio-technical realities of emerging and conflict-affected regions. Key challenges such as intermittent grid access, prosumer heterogeneity, low digital literacy, and security constraints remain largely unaddressed. Existing frameworks often rely on synthetic data or simulations, limiting real-world applicability. These gaps collectively highlight the need for a unified FL–GT–XAI framework capable of providing privacy-preserving, incentive-compatible, and transparent decision support in microgrid environments particularly in low-resource, high-risk contexts.

6. Conclusion

This study provides a comprehensive review of decentralized energy systems with a focus on federated learning, game-theoretic pricing, and explainable AI. The review reveals a fragmented literature landscape where most studies address forecasting, trading, or interpretability in isolation. Critical gaps include:

- insufficient integration across learning, economic, and transparency paradigms,
- limited adoption of privacy-preserving analytics,
- lack of strategic incentive alignment in distributed P2P settings, and
- minimal context-specific evidence for low-resource or conflict-affected regions.

To address these gaps, this study motivates the development of an integrated FL–GT–XAI framework. Such a framework would:

1. Enable privacy-preserving forecasting and prosumer behaviour modelling,
2. Support fair, incentive-compatible market mechanisms,
3. Provide transparent and explainable decision support to stakeholders, and
4. Enhance trust, adoption, and operational resilience in microgrids.

This synthesis establishes a foundation for future work that includes real-world validation, community-scale deployment, digital-twin simulations, and regulatory alignment, thereby advancing the state-of-the-art in decentralized, inclusive, and trustworthy next-generation energy systems.

Author Contributions

The author has significantly contributed to the study's conception, design, data collection, analysis, and interpretation. All authors were involved in writing the manuscript or critically reviewing it for its intellectual value. They have reviewed and approved the final version for submission and publication and accept full responsibility for the content and integrity of the work.

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