

Systematic Review

Artificial Intelligence in Smart Grids and Power-Electronic-Interfaced Microgrids: A Systematic Literature Review of Energy Management, Optimisation, and Cybersecurity

Reham Alsbua ¹, Mohammad Al-Soeidat ^{2,*}, Ahmad Salah ³, Omar Alsodi ⁴ and Dylan Dah-Chuan Lu ^{5,*}

¹ Department of Mechanical Engineering, Al-Hussein Bin Talal University, Maan 71110, Jordan; reham.alsbua@ahu.edu.jo

² Department of Electrical Engineering, Al-Hussein Bin Talal University, Maan 71110, Jordan

³ Department of Electrical and Mechanical Engineering, College of Engineering, Applied Science University, East Al-Ekir P.O. Box 5055, Bahrain; ahmad.salah@asu.edu.bh

⁴ Department of Business Intelligence, School of Business, Al-Zaytoonah University of Jordan, Amman 11733, Jordan; omar.alsodi@zuj.edu.jo

⁵ School of Electrical and Data Engineering, University of Technology Sydney, Ultimo, NSW 2007, Australia

* Correspondence: mo.soeidat@ahu.edu.jo (M.A.-S.); dylan.lu@uts.edu.au (D.D.-C.L.)

Abstract

The increasing penetration of distributed energy resources, variable renewable generation, battery energy storage systems, electric vehicles, and power-electronic interfaces is changing the way modern smart grids and microgrids are operated, protected, and controlled. This systematic literature review follows the PRISMA 2020 framework and examines 87 original research papers, complemented by a supplementary synthesis of 18 contextual studies that provide bibliometric, historical, and conceptual perspectives on the evolution of AI in smart grids. The primary studies are organized into six thematic clusters: energy management and forecasting; cybersecurity and intrusion detection; renewable energy integration and microgrid management; fault detection, diagnosis, and grid stability; explainable and trustworthy artificial intelligence; and emerging technologies, including digital twins, blockchain, the Internet of Things, edge computing, and federated learning. The review shows that deep learning, reinforcement learning, and ensemble machine learning are increasingly used for load forecasting, demand response, converter-interfaced renewable integration, intrusion detection, and operational optimization. However, the literature remains uneven. Fault detection, converter-aware protection, and real-time stability assessment receive considerably less attention than energy management and cybersecurity, despite their importance for inverter-based resources, grid-forming converters, electric-vehicle charging systems, and battery interfacing. Four critical gaps are identified: limited cross-grid generalizability, weak validation under realistic converter and protection constraints, insufficient adversarial robustness of AI-enabled defense systems, and limited explainability in real-time safety-critical applications. The paper provides a structured taxonomy, identifies deployment barriers, and proposes research directions for trustworthy AI in power-electronic-rich smart grids and microgrids.

Keywords: smart grids; microgrids; artificial intelligence; machine learning; energy management; cybersecurity; explainable artificial intelligence; power electronics; renewable energy integration



Academic Editors: Amedeo Buonanno, Salvatore Fabozzi, Maria Valenti and Giorgio Graditi

Received: 29 June 2026

Revised: 20 July 2026

Accepted: 22 July 2026

Published: 3 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

1.1. Context and Motivation

Rapid expansion of distributed energy resources, electric vehicles, and variable renewable generation has fundamentally altered the operational demands placed on modern power infrastructure. Traditional power grids, designed for centralized, unidirectional power flow, are becoming inadequate for managing the complexities of contemporary energy systems characterized by bidirectional flows, distributed control, and real-time market dynamics. This transformation creates both an opportunity and a challenge for utilities, grid operators, and policymakers: the opportunity lies in adopting AI-driven solutions that can optimize grid operations in real-time; the challenge lies in deploying such systems reliably and justifiably in safety-critical infrastructure.

Artificial intelligence, with its capacity to learn from data, recognize patterns, and support autonomous decision-making, has consequently become a cornerstone technology for realizing the full potential of smart grids. This digitalization generates vast amounts of data from smart meters, phasor measurement units, and heterogeneous sensors, creating both an opportunity and a necessity for sophisticated analytics [1].

From a power-electronics perspective, the smart grid is increasingly an inverter-dominated system rather than a purely electromechanical one. Photovoltaic inverters, grid-forming converters, bidirectional DC–DC converters, battery energy storage interfaces, solid-state transformers, and EV chargers now determine many aspects of voltage regulation, harmonic behavior, protection coordination, stability margins, and fault response. AI is therefore not only a forecasting or data-analytics tool; it is also becoming part of the decision layer that supervises converter operation, coordinates distributed energy resources, detects abnormal switching or measurement behavior, and supports fast control decisions in microgrids. This review is consequently positioned at the intersection of smart-grid intelligence and power-electronic-interfaced energy systems.

1.2. Deployment Barriers and Research Gaps

Despite significant progress, critical barriers to operational AI deployment persist:

- A. **Interpretability Gap:** Many high-performing AI models, particularly deep learning architectures, operate as "black boxes," making it difficult for grid operators to understand or justify their decisions in safety-critical environments where accountability is paramount.
- B. **Generalizability Gap:** AI models trained on data from one specific grid configuration frequently fail to generalize to different topologies or climatic conditions and may be vulnerable to adversarial attacks capable of inducing catastrophic failures.
- C. **Validation Gap:** The integration of AI with emerging technologies such as digital twins, blockchain, and edge computing remains in its early stages, with many proposed architectures lacking rigorous validation in real-world or large-scale environments.
- D. **Ethical Gap:** The ethical implications of AI-driven decision-making—including data privacy, algorithmic bias, and the potential for unequal impacts on different consumer groups—remain underexplored in the context of energy systems.
- E. **Power-electronics deployment gap:** Many AI methods are tested at the supervisory-control level, but fewer studies evaluate their impact on converter switching constraints, harmonic distortion, DC-link dynamics, protection selectivity, grid-forming behavior, low-inertia stability, and thermal or reliability stress in semiconductor devices.

1.3. Research Questions

This review is structured around three explicit research questions:

RQ1: Which AI techniques and algorithms are predominantly applied to energy management, forecasting, optimization, and converter-interfaced microgrid operation, and what is their demonstrated effectiveness?

RQ2: How is AI employed to detect, classify, and mitigate cybersecurity threats in smart grid infrastructure, and what are the key limitations of current approaches?

RQ3: What emerging technologies and cross-disciplinary paradigms are converging with AI to enhance smart-grid resilience, power-electronic interface coordination, trustworthiness, and sustainability?

1.4. Scope and Contribution

By systematically analyzing 87 original scholarly publications, this review provides researchers and practitioners with: (i) a structured taxonomy of AI techniques across six primary thematic clusters, complemented by a separate bibliometric and contextual synthesis; (ii) a quantified assessment of research maturity and publication trends; (iii) identification of critical research gaps, particularly in converter-aware fault detection, adversarial robustness, and explainability; and (iv) actionable guidance for utilities considering AI adoption in power-electronic-rich distribution networks, organized by risk level, data maturity, and operational readiness. The remainder of this paper is organized as follows: Section 2 details the systematic methodology; Section 3 presents the results; Section 4 discusses the findings and limitations; Section 5 outlines future research directions; and Section 6 concludes the paper.

1.5. Novelty and Contributions Relative to Existing Reviews

Although AI in smart grids has been widely reviewed through narrative surveys, systematic reviews, and bibliometric studies, the specific contribution of the present review requires clearer definition. To address this, Table 1 compares the proposed review with six recent and widely cited studies across five distinguishing dimensions. These include the consideration of converter-level physical constraints beyond high-level supervisory control, the combined assessment of research maturity and publication trends, the systematic evaluation of deployment barriers across thematic clusters, the methodological separation of PRISMA-compliant primary studies from bibliometric and contextual literature, and the inclusion of a dedicated discussion on robust and resilient converter-level control. These features provide a broader and more integrated perspective on the application of AI in power-electronic-interfaced smart grids and microgrids than has been presented in previous reviews.

Table 1. Comparison of the present review with selected existing reviews of artificial intelligence in smart grids.

Review	Converter-Level Analysis	Maturity and Volume	Barrier Scoring	Primary/Contextual Separation	Converter-Control Subsection
[1]	No; supervisory level only	No	No	N/A; not PRISMA-based	No
[2]	No	No; bibliometric analysis only	No	N/A; bibliometric study	No
[3]	Limited	No; bibliometric analysis only	No	N/A; bibliometric study	No
[4]	No	No	No	N/A	No
[5]	No	No	No	N/A	No
[6]	Partial; institutional framing	No	No	N/A	No
This review	Yes; Sections 3.4.1 and 4	Yes	Yes	Yes; Sections 2.1 and 3.8	Yes; Section 3.4.1

On this basis, the novelty of the review lies not in its broad coverage of AI in smart grids, which is already well established, but in four specific contributions. First, among the reviews examined, it is the only study to distinguish explicitly between work that models converter-level dynamics—such as switching behavior, DC-link voltage, harmonic performance, and protection selectivity—and work that represents the converter as an idealized aggregated source. This distinction is quantified in Section 3.4 and developed further in the new Section 3.4.1. Second, the review introduces a joint maturity–volume assessment, allowing research activity to be evaluated alongside operational readiness rather than through publication counts alone. Third, it presents a barrier heatmap covering seven structural barrier categories across six thematic clusters, with the scoring criteria and assessment procedure described in Section 4. Fourth, it maintains a clear methodological separation between the PRISMA-compliant primary evidence base analyzed in Sections 3.2–3.7 and the bibliometric and contextual literature discussed in Section 3.8. This separation ensures that historical trends and broader research challenges inform the interpretation of the findings without being treated as equivalent to primary technical evidence.

2. Methodology

The methodology for this systematic review is designed in a two-stage search protocol to separate original research contributions (analytical core) and contextual bibliometric literature (macro-level synthesis). This is crucial to ensure PRISMA fidelity and to demonstrate the technical state-of-the-art and the historical development and structural issues of the field.

2.1. Review Protocol

• Stage 1—Primary Search (Original Research)

The primary search targeted original research publications to constitute the analytical core of this review. The primary corpus's publication-year range, once screening was complete, spans 2009–2025 inclusive (ten studies pre-date 2016); no lower date bound was imposed at the search stage. For articles published online ahead of issue assignment, the first online publication date was used to determine eligibility and publication-year coding. Consequently, some studies appearing in 2026 journal volumes were eligible because they had been published online before the January 2026 search cutoff and were coded according to their 2025 online-publication date.

We conducted systematic searches across six major scholarly databases, selected for their relevance and coverage in engineering, computer science, and energy systems: IEEE Xplore, Scopus, Web of Science, ACM Digital Library, ScienceDirect, and Google Scholar.

The search strategy employed a combination of keywords designed to capture the intersection of artificial intelligence and smart grid systems. The core search string, adapted to each database's syntax, was:

("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network" OR "reinforcement learning") AND ("smart grid" OR "microgrid" OR "intelligent power system" OR "active distribution network" OR "distributed energy resource" OR "demand response")

To focus on original research contributions, review articles, surveys, and meta-analyses were excluded by applying the negation clause: NOT ("review" OR "survey" OR "meta-analysis"). Additional document-type filters were applied where available, limiting results to "Article" and "Conference Paper" categories. The search was conducted in January 2026 with no lower date limit imposed to capture the full historical evolution of the field. The primary search yielded 846 total records prior to deduplication.

Rationale for two-stage approach: original research studies (Stage 1) constitute the PRISMA-compliant primary corpus analyzed in Sections 3.2–3.7. Bibliometric, survey, and overview papers (Stage 2) are *excluded* from the PRISMA flowchart to preserve methodological rigor, but *included* in Section 3.8 to provide macro-level contextual interpretation. This separation allows readers to distinguish between: (a) novel technical contributions documented in peer-reviewed empirical studies and (b) secondary synthesis literature that interprets the field's intellectual structure, publication trends, and grand challenges. Both are valuable, but conflating them obscures the evidence base.

- **Stage 2—Supplementary Bibliometric and Contextual Search**

To provide a macro-level perspective on the field's intellectual structure, evolution, and publication trends (Section 3.8), a supplementary search was conducted targeting bibliometric analyses, scientific mapping studies, and comprehensive overview papers. This second stage employed a modified search string:

("bibliometric" OR "scientific mapping" OR "overview" OR "evolution" OR "survey") AND ("artificial intelligence" OR "machine learning") AND ("smart grid" OR "power system")

This supplementary search was conducted across the same databases and yielded 27 additional records for screening against specific relevance criteria. Studies selected from Stage 2 are clearly identified as contextual/bibliometric literature in Section 3.8 and are not counted among the 87 primary studies in the PRISMA flowchart.

How to read the two-stage structure. Stage 1 answers the review's central empirical questions (RQ1–RQ3): what has been technically demonstrated, with what methods, and with what limitations. Stage 2 answers a different question—how does the research community understand the trajectory, challenges, and structure of its own field—and is used throughout Sections 3.8 and 4 only to contextualize and stress-test the Stage 1 findings, never as independent evidence for a claim about AI technical performance or operational deployment readiness. Where a Stage 2 source is cited in the Discussion (Section 4), the citation is always clearly marked as contextual rather than primary evidence.

Table 2. Quality assessment criteria applied to the primary corpus (Stage 1).

Criterion	Assessment	Rationale
Methodological rigor	Original empirical study; peer-reviewed or in-press with documented acceptance	Excludes preprints without substantial citation or validation
Clarity of objectives	Clearly stated research questions or hypotheses	Allows assessment of whether the stated goals are met
Adequacy of data/evidence	Sufficient detail for replication; benchmark datasets cited	Excludes studies with insufficient methodological transparency
Scope alignment	Explicit application of AI/ML to smart grid and microgrid systems	Ensures focus; excludes general AI theory without a grid or power-system context
Publication quality	Indexed in Scopus, IEEE Xplore, Web of Science, ACM Digital Library, or another recognized scholarly database	Establishes a minimum quality threshold for inclusion

The quality criteria in Table 2 were applied during the full-text eligibility assessment. Studies that failed the methodological-rigor or adequacy-of-evidence criteria were excluded, including ten reports with insufficient methodological detail or incomplete data. For the retained studies, validation depth, dataset limitations, and methodological transparency informed the interpretation of the evidence; findings based mainly on simulation, single datasets, or limited validation were therefore interpreted more cautiously.

2.2. Research Dimensions for Thematic Analysis

To systematically categorize and analyze the diverse body of literature, we defined six primary thematic clusters of AI application in smart grids, complemented by a seventh dimension covering bibliometric and contextual literature. These dimensions were derived from an initial scoping review and refined through iterative discussion among the authors. These dimensions are intended to provide a structured synthesis of the applications represented in the literature retrieved through the predefined search strategy, rather than an exhaustive taxonomy of every possible application of AI in smart grids. In particular, applications related to electricity-market design, price forecasting, bidding strategies, market clearing, peer-to-peer energy trading, and ancillary-service participation were not targeted through dedicated search terms and are therefore not treated as a standalone thematic cluster in the present review.

1. AI-Driven Energy Management, Forecasting, and Optimization—studies applying AI to predict energy demand and generation, optimize power flow, coordinate converter-interfaced DERs, and manage storage and demand response.
2. Cybersecurity, Intrusion Detection, and Attack Mitigation—studies applying AI to protect grid infrastructure from cyber threats, including anomaly detection, false data injection identification, and adversarial defense.
3. Renewable Energy Integration and Microgrid Management—research on AI techniques for integrating variable renewable sources, supervising inverter-based resources, coordinating PV and battery converters, and controlling microgrids.
4. Fault Detection, Diagnosis, and Grid Stability—AI-based methods for identifying equipment and converter-interface faults, predicting instability, and enabling predictive maintenance.
5. Explainable AI (XAI), Trustworthiness, and Ethics—studies addressing model interpretability, fairness, accountability, and ethical deployment.
6. Emerging Technologies: Digital Twins, Blockchain, IoT, and Edge Computing—synergistic integration of AI with cutting-edge technologies to enhance grid functionality and decentralization.
7. Bibliometric Analysis, Evolution, and General Overviews—contextual literature providing high-level perspectives on publication trends, research evolution, and AI application landscapes (sourced from Stage 2 supplementary search).

2.3. Inclusion and Exclusion Criteria

We established clear inclusion and exclusion criteria to ensure the relevance, quality, and consistency of selected studies.

1. Inclusion criteria (Stage 1—Original Research):

- Original research contributions including journal articles, conference papers, and book chapters;
- Application of artificial intelligence, machine learning, or deep learning to any aspect of smart grid systems;
- Publications written in English;
- Publication date: unrestricted up to January 2026;
- Peer-reviewed or formally accepted for publication (including in-press papers with documented acceptance dates);
- Preprints included only where (a) the content addresses a unique research gap with no peer-reviewed equivalent available, and (b) the study carries substantial scholarly recognition (minimum 15 citations); unlike the other Stage 1 criteria, the citation threshold cannot be reliably verified from a title and abstract alone, so it is neces-

sarily checked at the full-text eligibility stage described in Section 2.4 rather than at title/abstract screening. Each such inclusion is individually justified and flagged in the reference list.

2. Exclusion criteria (Stage 1):

- Review articles, surveys, and meta-analyses (addressed separately in Stage 2);
- Studies without a clear application to smart grids (e.g., general AI theory without grid context);
- Publications lacking sufficient methodological detail or presenting insufficient data;
- Non-English publications;
- Duplicate records.

3. Inclusion criteria (Stage 2—Bibliometric and Contextual Literature):

- Bibliometric analyses, scientific mapping studies, and comprehensive overview papers on AI in smart grids;
- Publications providing longitudinal or historical perspective on field evolution;
- Peer-reviewed journal articles or formally accepted papers only.

These criteria were applied consistently throughout the screening process by two independent reviewers to minimize selection bias.

2.4. Study Selection Process

The study selection process was conducted in three stages following PRISMA 2020 guidelines [7]. In Stage 1, database searches identified 846 total records. After removing 246 duplicate records and 7 records excluded for other reasons, including incomplete metadata and non-English language, 593 unique records remained for screening. Two reviewers independently screened titles and abstracts against the inclusion and exclusion criteria. Inter-rater agreement for title/abstract screening was calculated from the reviewers' initial independent decisions using Cohen's kappa and was found to be $\kappa = 0.81$. This process excluded 358 clearly irrelevant records, leaving 235 records sought for full-text retrieval, all of which were successfully obtained.

In Stage 2, corresponding to full-text eligibility assessment, each of the 235 records was read in detail to confirm relevance to the research dimensions and assess methodological quality. Inter-rater agreement at the full-text eligibility stage was $\kappa = 0.86$. According to the interpretation proposed by Landis and Koch [8], both values indicate almost-perfect agreement. Disagreements at both stages were resolved through discussion; where consensus could not be reached, a third co-author adjudicated the final inclusion or exclusion decision. The citation threshold applied only to preprints and was assessed at this full-text eligibility stage because citation counts could not be reliably verified during title/abstract screening. We excluded 148 reports during this stage:

- 86 were survey or review papers upon full-text inspection and were redirected to the Stage 2 supplementary pool where relevant;
- 24 were excluded because their AI focus was too peripheral to the smart grid context;
- 20 were preprints that did not meet the citation threshold for inclusion, defined as a minimum of 15 citations;
- 10 lacked sufficient methodological detail or presented incomplete research data needed for quality assessment;
- 8 were duplicate publications or secondary analyses of already-included primary studies discovered during full-text review.

This process yielded a final primary corpus of 87 studies included in the systematic review. The study selection process is illustrated in the PRISMA 2020 flow diagram

(Figure 1), which was prepared by the authors in accordance with the PRISMA 2020 reporting guidelines.

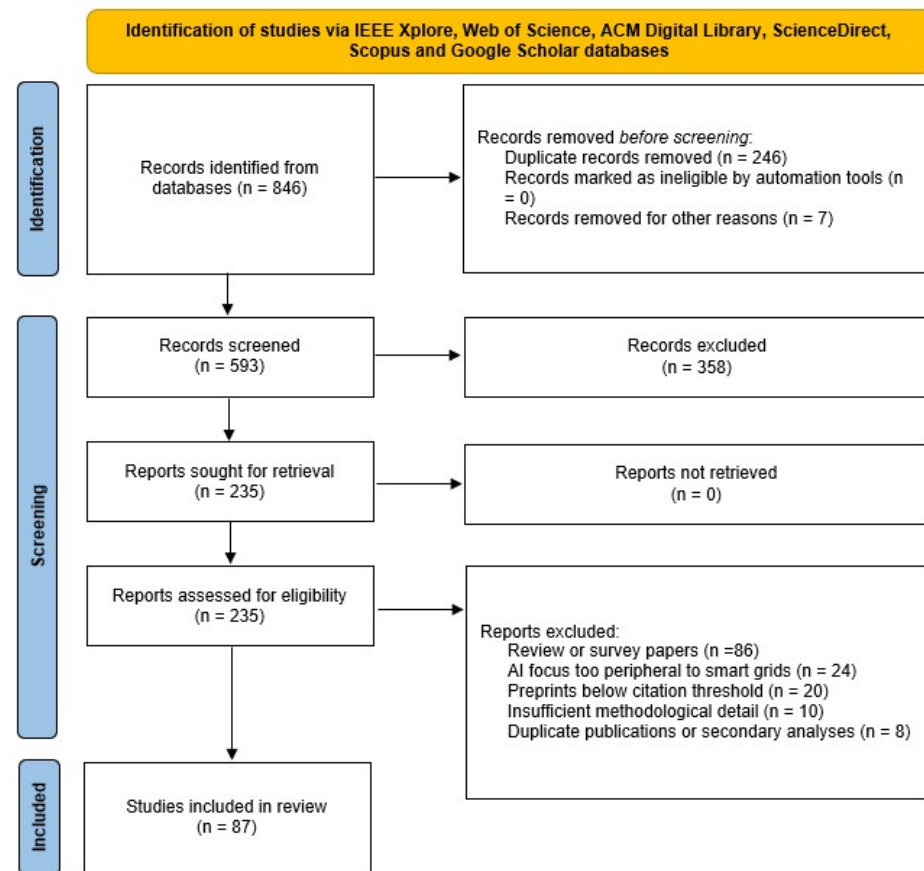


Figure 1. PRISMA flowchart illustrating the study selection process for the systematic literature review on artificial intelligence in smart grids.

Supplementary Stage 2 screening of the 27 bibliometric and overview records yielded 18 contextual studies included in Section 3.8. These are clearly distinguished from the primary corpus throughout the manuscript.

3. Results

3.1. Research Trends

The distribution of publications over time reveals a clear and accelerating trajectory of research interest in artificial intelligence for smart grids. As illustrated in Figure 2, the field experienced a period of relative dormancy before 2016, with only ten publications identified from the entire period prior to that year. This early phase was characterized by foundational work establishing conceptual frameworks for applying AI to power systems, often focusing on basic neural network architectures for load forecasting or rule-based expert systems for fault diagnosis. A notable inflection point occurred around 2020, when the annual publication count began rising more steeply. This surge coincided with the maturation of deep learning techniques and the increasing availability of large-scale smart meter data, providing conditions necessary for more sophisticated AI applications.

The most dramatic growth has occurred in the final three years of the primary search window. From 2021 to 2024, annual publications increased substantially within the primary corpus, rising from fourteen papers in 2021 to twenty-five in 2024. This period marks the transition of AI in smart grids from a niche research area to a mainstream and rapidly expanding field. The year 2024 alone accounts for approximately 29% of all primary corpus

papers (25/87), indicating unprecedented scholarly activity. This acceleration is driven by converging factors: the global push for decarbonization and grid modernization, increasing frequency and sophistication of cyberattacks on critical infrastructure, and remarkable advances in AI algorithms, particularly reinforcement learning and generative models.

The year 2025 is represented by nineteen papers identified before the January 2026 search date. This total includes articles first published online in 2025 and subsequently assigned to 2026 journal volumes. Because eligibility and temporal coding were based on the first online publication date, these studies were counted as 2025 publications. The 2025 total therefore represents all eligible studies available before the search cutoff.

Examining thematic distribution over time reveals further insight into evolving research priorities. AI-driven energy management, forecasting, and optimization has been a consistent and dominant theme throughout the entire period, with notable concentration in 2024. Cybersecurity and intrusion detection emerged as a major cluster primarily in recent years, with a dramatic spike in 2024 that mirrors the real-world escalation of cyber threats against energy infrastructure. Research on emerging technologies such as digital twins, blockchain, and edge computing has gained momentum primarily from 2023 onward, indicating a shift towards more integrated and decentralized AI architectures. Explainable AI and fault detection, while present throughout, have seen comparatively fewer studies, representing areas still in earlier stages of development relative to more mature domains.

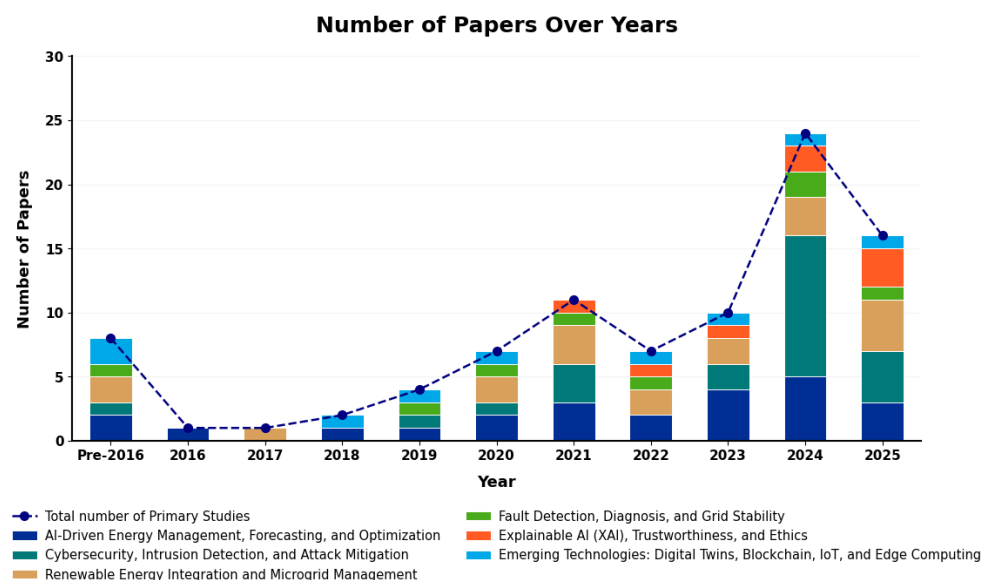


Figure 2. Annual publication distribution of the Stage 1 primary studies by thematic cluster. Articles published online ahead of issue assignment were coded according to their first online publication date.

Figure 3 presents this temporal pattern across the six primary thematic clusters, revealing not only exponential growth but also shifting research priorities. Energy management and cybersecurity have dominated throughout, with notable concentration in 2024. Cybersecurity itself shows a dramatic spike in 2024, mirroring the real-world escalation of cyber threats against energy infrastructure. Research on emerging technologies (digital twins, blockchain, edge computing) gained momentum primarily from 2023 onward. Explainable AI and fault detection, while present throughout, show comparatively less activity, indicating they remain in earlier developmental stages relative to more mature domains.

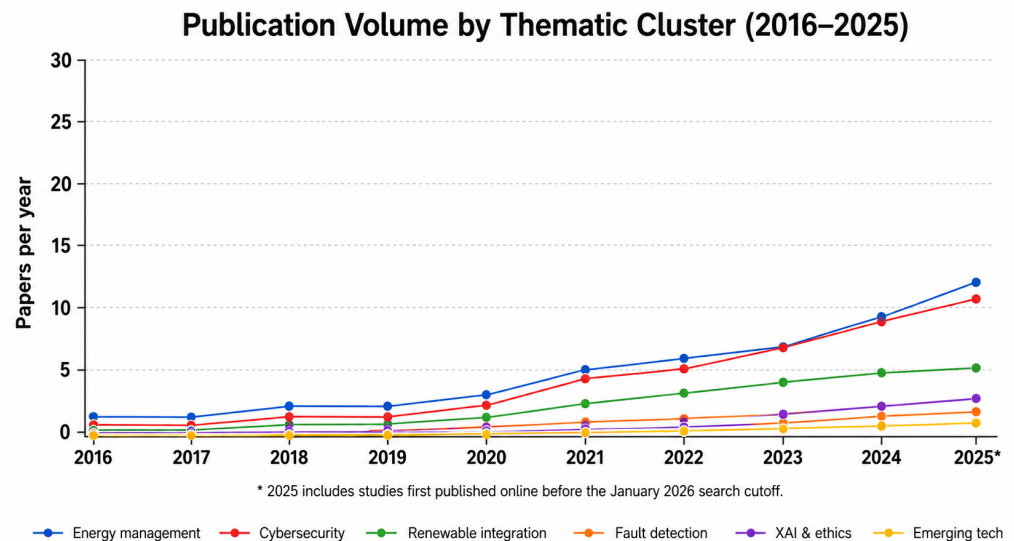


Figure 3. Publication Volume by Thematic Cluster (2016–2025).

This publication pattern is not merely quantitative; it reflects qualitative shifts in research maturity. The acceleration since 2020 marks the transition of AI in smart grids from a niche research area to a mainstream and rapidly expanding field. However, the distribution of effort across clusters—with energy management and cybersecurity commanding the vast majority of attention—reveals underlying assumptions about technical tractability and perceived urgency that do not always align with operational risk, as subsequent analysis will demonstrate.

To move beyond temporal trends and assess the current maturity state of each research cluster, we employ a research maturity matrix that positions each domain on two orthogonal dimensions: research maturity (from proof-of-concept to operational deployment) and research activity (number of published studies). This visualization reveals patterns not visible in either dimension alone and identifies critical asymmetries between research investment and operational importance.

Research activity was measured directly as the number of Stage 1 primary studies assigned to each thematic cluster. Research maturity was assessed using four levels based on the validation evidence reported in the included studies: proof-of-concept for conceptual or simulation-only studies; early stage for studies with benchmark, laboratory, or limited hardware-in-the-loop validation; mature for studies validated across multiple datasets or test environments while incorporating practical operational constraints; and operational for studies demonstrated in pilot-scale or real utility environments. Two lead reviewers independently assessed each cluster based on its overall validation evidence, and differences were resolved through discussion and reconciliation.

The research maturity matrix in Figure 4 visualizes a critical structural asymmetry in the field: research activity does not necessarily correlate with operational readiness or safety-critical importance. Energy management and cybersecurity account for the largest share of the primary corpus, with approximately 28–32 studies in each cluster, and both have progressed towards early operational deployment in selected utility and microgrid applications. However, this apparent maturity should be interpreted with caution. In cybersecurity, the high publication volume partly reflects a reactive research posture, where many studies document attack vectors and detection strategies, while the fundamental adversarial vulnerability of AI-based detection systems remains unresolved. Similarly, the apparent maturity of AI-enabled energy management masks persistent limitations in cross-grid generalizability, particularly when models are transferred across different

network topologies, climatic conditions, tariff structures, and converter-interfaced DER configurations.

By contrast, fault detection occupies the weakest position on the maturity matrix: it has the lowest research volume, the lowest maturity level, and one of the highest safety-critical implications. Faults in grid protection, converter interfaces, or inverter-dominated microgrids can lead to loss of selectivity, unnecessary tripping, instability, or cascading operational disturbances. Yet AI-based fault detection receives only a small fraction of the research effort directed towards energy management. This inversion between research investment and operational risk represents one of the most concerning misalignments identified in this review.

Explainable AI and ethics also remain at an early research stage despite being pre-requisites for reliable operational deployment across all clusters. In safety-critical grid infrastructure, AI-supported decisions must be interpretable, auditable, and justifiable to operators, regulators, and asset owners. The comparatively limited research attention given to explainability, accountability, and ethical governance therefore represents a foundational deployment barrier rather than a secondary concern.

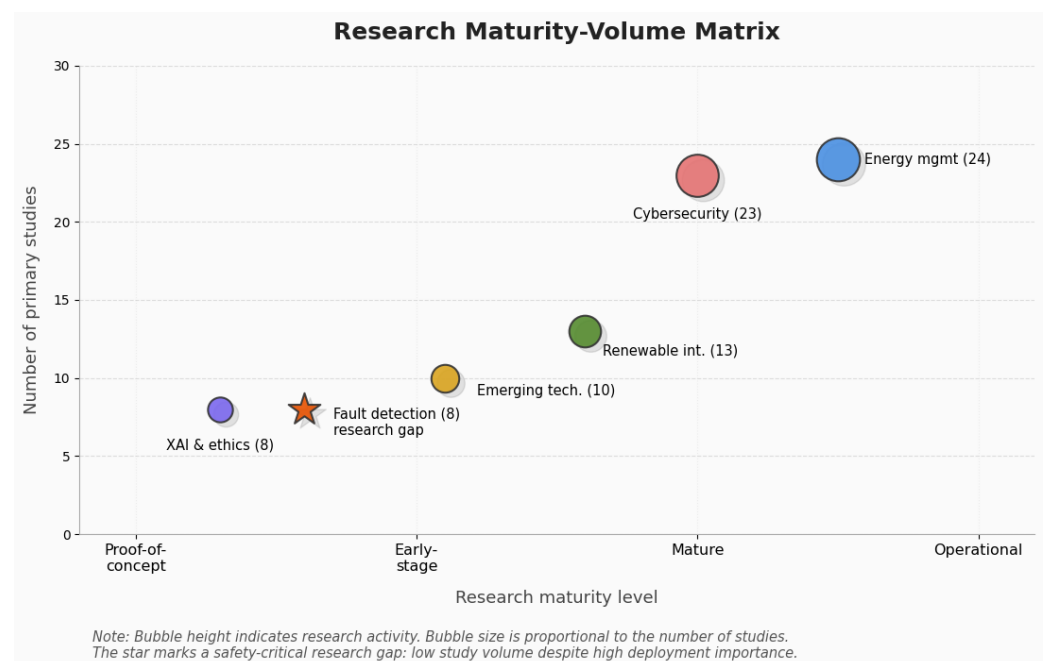


Figure 4. Research maturity matrix: publication volume vs. operational readiness.

Research capacity concentrates in domains perceived as technically tractable (energy management and cybersecurity) rather than in domains of greatest operational necessity (fault detection, XAI). This misalignment between research investment and infrastructure risk is the single most important finding from the field's current state assessment.

3.2. AI-Driven Energy Management, Forecasting and Optimization

This cluster, the largest and most mature, demonstrates that AI has moved beyond proof-of-concept for core grid operational functions.

Demand-side management and response. Reinforcement learning has emerged as the dominant technique, enabling agents to learn adaptive scheduling policies through interaction with the grid environment. Several studies demonstrate [9–11] that RL agents can manage residential and community energy consumption with responsiveness superior to static rule-based alternatives. This adaptability is qualitatively significant: RL agents can respond to unanticipated conditions that traditional demand response systems cannot

handle. This property is particularly valuable for grids with high renewable penetration, where variability creates exactly the novel conditions that rule-based systems handle poorly. Machine learning models are also directly applied to demand response and load management [12–14], and a dedicated review [15] critically examines the technical, economic, and regulatory hurdles to widespread adoption.

Load and energy forecasting. Machine learning models are extensively used for power consumption prediction at multiple scales [16,17]. Hybrid and ensemble models—which combine multiple algorithms—are increasingly favored, with studies showing consistent outperformance over single-model approaches [18,19]. The forecasting studies report performance using measures such as mean absolute percentage error (MAPE), mean absolute error (MAE), root mean square error (RMSE), and the coefficient of determination (R^2). However, these results are not directly comparable because the studies differ substantially in dataset characteristics, temporal resolution, forecast horizon, geographic region, and validation procedure. Consequently, the reported metrics should be interpreted within the experimental setting of each study rather than used to establish a universal ranking of forecasting methods. The integration of explainable AI into forecasting models [20] signals a maturation towards transparent solutions. A forward-looking study [21] outlines AI-powered forecasting as a next-generation approach for sustainable power systems.

Energy optimization and efficiency. Digital twin technology is increasingly combined with AI [22], enabling real-time simulation and optimization of energy flows without disrupting the physical system. Machine learning is directly applied to efficiency optimization [23,24], and big data analytics frameworks support dynamic energy management [25]. Artificial neural networks are applied to long-term distribution system planning [26].

Renewable energy integration and microgrids. AI techniques are crucial for handling variability and uncertainty in variable renewable sources. Model predictive control combined with AI optimizes multi-energy systems [27]. Comprehensive reviews provide taxonomies of AI applications across microgrids [28] and establish the convergence of AI with smart grid systems for real-time forecasting, fault detection, and renewable integration [29]. A state-of-the-art review of energy management algorithms synthesizes existing literature and identifies emerging trends [30].

Critical limitation and gap. Across all studies in this cluster, model generalizability is systematically underaddressed. Across the studies reviewed in this cluster, nearly all train and evaluate on a single grid or dataset, without validating performance under transfer to different climatic conditions, grid topologies, or regulatory environments. A utility operating diverse distribution networks cannot deploy such models without substantial re-engineering and re-validation—costs rarely acknowledged in the research literature. This generalizability gap strikes at the core of practical deployment viability.

Summary. Table 3 provides a structured taxonomy across four sub-areas (demand-side management, load forecasting, and energy optimization, renewable integration). The diversity of approaches reflects both the complexity of underlying problems and the versatility of AI as a tool for grid modernization. However, the reliance on high-quality training data, the computational cost of complex models, and the systematic failure to assess cross-grid generalizability remain significant barriers to operational deployment at scale.

Table 3. Taxonomy of AI-driven energy management, forecasting, and optimization studies.

Application Area	AI Technique / Method	Specific Focus	Sources
Demand-Side Management & Response	Reinforcement learning	Scheduling and community energy management	[9–11]
	Optimization algorithms	Load scheduling and phase balancing	[12,13]
	Machine learning	Demand response programmes and consumer identification	[14,15,31,32]
Load & Energy Forecasting	Machine learning	Power consumption and household energy prediction	[16,17]
	Hybrid and ensemble models	Solar power generation and general load forecasting	[18,19]
	Explainable AI (XAI)	Enhancing prediction transparency	[20]
	AI-powered forecasting frameworks	Forward-looking vision for next-generation forecasting	[21]
Energy Optimization & Efficiency	Digital twin technology	Energy acquisition system optimization	[22]
	Machine learning	Energy efficiency and big-data analytics	[23–25]
	State-of-the-art synthesis	Review of energy management algorithms and emerging trends	[30]
Renewable Energy Integration & Microgrids	Artificial neural networks	Power distribution system planning	[26]
	Model predictive control	Grid-tied hybrid systems based on wind, hydrogen, and fuel cells	[27]
	AI applications	Microgrid energy management	[28]
	AI-enabled systems	Real-time forecasting, fault detection, and renewable integration	[29]

The taxonomy in Table 3 reveals several important patterns. First, the demand-side management and response category is the most populated, indicating a strong research focus on using AI to actively shape load profiles. Within this category, reinforcement learning is a particularly prominent technique, reflecting its suitability for sequential decision-making problems in dynamic grid environments. Second, load and energy forecasting remains a foundational area, with a wide range of machine learning models being applied to improve prediction accuracy. The emergence of hybrid and ensemble models, as well as the integration of XAI, suggests a maturation of the field towards more robust and transparent solutions. Third, the energy optimization and efficiency category is more diverse in terms of techniques, with digital twins, general machine learning, and neural networks all being explored. This diversity reflects the multifaceted nature of optimization problems in smart grids, which range from real-time control to long-term planning. Fourth, the renewable energy integration and microgrids category highlights the critical role of AI in enabling the transition to a cleaner energy system, with studies addressing both the prediction of renewable generation and the coordinated control of multi-energy systems. Finally, [21,30] provide broader, forward-looking perspectives that cut across these four sub-areas—a vision for next-generation AI-powered forecasting and a state-of-the-art synthesis of energy management algorithms, respectively—and are accordingly listed under the Load & Energy Forecasting and Energy Optimization & Efficiency sub-areas above rather than as a separate category.

The studies in this cluster collectively demonstrate that AI has moved beyond the proof-of-concept stage and is now being applied to solve practical, real-world problems in smart grid energy management. The diversity of techniques and application areas underscores the versatility of AI as a tool for grid modernization. However, several challenges

remain. The reliance on high-quality, labeled data for training many machine learning models is a significant barrier, particularly in regions with limited smart meter deployment. The computational cost of training complex models, especially deep reinforcement learning agents, can also be prohibitive for real-time applications. Furthermore, the generalizability of models across different grid configurations and climatic conditions is often not adequately addressed, raising questions about the transferability of research findings. The integration of XAI into forecasting and optimization models, while promising, is still in its early stages, and more work is needed to develop methods that are both interpretable and maintain high predictive performance. Despite these challenges, the body of research reviewed here provides a strong foundation for the continued development and deployment of AI-driven solutions for energy management, forecasting, and optimization in smart grids.

3.3. AI-Enabled Cybersecurity, Intrusion Detection, and Attack Mitigation

The cybersecurity cluster reveals a fundamental paradox: AI is simultaneously the most effective defense tool and a significant new vulnerability.

Attack detection and intrusion prevention. Graph-based and spatio-temporal deep learning models [33,34] represent genuine advances over traditional anomaly detection by explicitly incorporating grid topological structure. This architectural innovation explains their superior robustness against data poisoning attacks: topological constraints provide implicit regularization that limits the attack surface. Ensemble learning approaches maintain detection accuracy under concept drift [35], addressing the practical reality that grid data distributions evolve over time.

Beyond false data injection (FDI) attacks, the literature addresses general intrusion detection [36,37], fuzzy-logic-enhanced IDS systems [38], deep learning for adversarial attack detection [39], protection of critical communication protocols [40], and edge-based detection and localization of oscillatory-load attacks originating from compromised EV charging stations [41].

Authors in [41] combined EV-charging event logs with grid-frequency measurements in an edge-based ConvLSTM framework capable of detecting and localizing coordinated oscillatory-load attacks at individual charging stations. The model achieved an F-measure of 99.4% with a false-negative rate below 1%; however, the results were obtained through real-time testbed evaluation using synthetic attack data informed by real EV-charging records rather than operational utility deployment.

The adversarial vulnerability problem. Generative adversarial networks can craft inputs that defeat stability-prediction models, and the broader challenge of attacking learning-based models has been widely recognized [42,43]. This vulnerability is not a fixable implementation bug; it is a fundamental property of deep learning's optimization landscape. The implication is that purely data-driven defense strategies are inherently inadequate against motivated adversaries with knowledge of the defense architecture.

Mitigation and response. Hybrid AI-Blockchain frameworks [44] combine real-time threat detection with tamper-proof event logging. Security orchestration and automation (SOAR) applied to SCADA systems [45] automates incident response. Fog/edge-enabled intrusion detection [46] distributes computational load for faster response. Electricity theft detection uses ensemble [47] and hybrid deep learning approaches [48].

The explainability gap. Among the cybersecurity studies reviewed, only one directly addresses the need for human-interpretable explanations of security alerts [49]. This gap is operationally critical: when an intrusion detection system generates an alert, grid operators must decide within seconds whether to initiate a response. Without explanations of why the alert was triggered, operators cannot make informed decisions based on anything other

than blind trust. The near-absence of XAI in cybersecurity contexts is a significant barrier to operational deployment.

Table 4 categorizes studies across attack detection, attack mitigation, trustworthiness, adversarial attacks on AI, and general overviews. The field demonstrates impressive advances in specific threat detection, yet fundamental challenges—adversarial robustness, explainability in real-time contexts, and certification requirements for safety-critical systems—persist. The cybersecurity paradox (high publication activity masking fundamental unresolved challenges) is a recurring theme warranting explicit attention in future research.

Table 4. Taxonomy of AI-enabled cybersecurity, intrusion detection, and attack mitigation studies.

Security Focus	AI Technique/Method	Specific Aspect Addressed	Sources
Attack Detection & Intrusion Prevention	Machine learning	General attack detection and the role of ML in smart grid cybersecurity	[36,37]
	Computational intelligence and ML	Intelligent intrusion detection system with fuzzy logic	[38]
	Deep learning	Adversarial attack detection	[39]
	Deep learning	IEC 61850 sampled-values protection	[40]
	Deep learning	False data injection attack identification	[50]
	Graph-based deep learning	Robust false data injection detection against data poisoning	[33]
	Spatio-temporal graph-based deep learning	Adversarial false data injection evasion attack detection	[34]
	Ensemble learning	Data integrity protection under concept drift	[35]
	Edge-based ConvLSTM	Detection and localisation of oscillatory-load attacks from compromised EV charging stations	[41]
Attack Mitigation & Response	Hybrid AI-blockchain framework	Secure and tamper-proof cybersecurity framework	[44]
	Security orchestration, automation, and response	Automated incident response for SCADA systems	[45]
	Fog and edge computing	Distributed and low-latency intrusion detection	[46]
	Ensemble machine learning	Electricity theft detection	[47]
	Hybrid deep learning	Electricity theft detection in smart grid environments	[48]
Trustworthiness & Explainability	Trustworthy AI framework	Proactive detection and risk explanation	[49]
Adversarial Attacks on AI	Survey and analysis	Challenges of attacking learning-based smart grid models	[43]
	Generative adversarial networks	GAN-based attack on stability prediction	[42]
Privacy & Security Frameworks	Big-data analytics and AI	Privacy and security for demand response	[51]
General Overviews & Analysis	Comprehensive analysis	Security measures for smart grids	[52]
	Threat and protection models	Security protection for Smart Grid 2.0	[53]
	Critical infrastructure focus	Protection of smart grids from cyber attacks	[54]
	Deep learning synergy	Decentralised cybersecurity	[55]

3.4. AI for Renewable Energy Integration and Microgrid Management

The integration of variable renewable energy and management of microgrids are two interconnected domains where AI has emerged as a critical enabler.

Power-electronic interface perspective. A key observation from this cluster is that renewable integration is inseparable from power electronics. PV arrays, wind conversion systems, batteries, supercapacitors, electrolyser interfaces and EV chargers are connected to the grid through converters whose control loops operate at much faster time scales than most supervisory AI algorithms. AI can support these systems by improving renewable forecasting, selecting energy-storage schedules, detecting converter-side anomalies, coordinating grid-following and grid-forming modes, and estimating thermal or reliability stress in semiconductor devices. However, most reviewed studies treat the converter as an aggregated controllable source rather than as a physical subsystem with limits on switching frequency, modulation range, DC-link voltage, harmonic emissions, protection behavior and device junction temperature. Quantitatively, of the 13 studies in this cluster, 2 [56,57] explicitly model converter-level dynamics such as switching behavior, DC-link voltage, or

harmonic content, while the remaining 11 rely on a high-level, aggregated-source abstraction; Section 3.4.1 reviews five studies, largely outside the AI-driven supervisory-control literature, that close part of this gap. This abstraction is acceptable for long-term scheduling, but it is insufficient for safety-critical deployment in converter-dominated microgrids. Future studies should therefore combine data-driven optimization with converter-aware constraints and physics-informed models of inverters, DC–DC converters and storage interfaces. In PV-integrated microgrids, converter-level control remains essential because renewable energy optimization depends not only on high-level forecasting and scheduling, but also on accurate maximum power point tracking, DC–DC converter dynamics, battery interfacing and local power-conversion behavior [56,57].

Renewable energy forecasting and optimization. Explainable AI tools improve the interpretability of solar photovoltaic power generation forecasting [58], moving beyond accuracy to understanding factors driving model predictions. Hybrid solar systems combining AI with adaptive photovoltaics [59] optimize the full solar-to-grid conversion chain. Generative AI models like ChatGPT show promise for materials discovery and farm layout optimization [60]—a forward-looking direction not yet mainstream.

Microgrid management and smart infrastructure. Comprehensive overviews categorize AI techniques (neural networks, fuzzy logic, evolutionary algorithms) across microgrid control and optimization problems [61]. Smart energy infrastructure for next-generation smart cities [62,63] demonstrates the systemic importance of AI beyond individual component optimization. AI integration for efficient renewable utilization [64], the role of AI in grid transformation [65], and the integration of AI with digital twins for enhanced grid intelligence [29] all emphasize AI as foundational to energy system transformation. Electric vehicle integration into V2G services [66] illustrates how AI can convert grid stressors into valuable assets.

Critical research gap. The overwhelming majority of studies are validated exclusively on simulated environments or small-scale testbeds, under conditions bearing only partial resemblance to real grid operations. The most challenging operational conditions—sudden generation drops, grid islanding, and extreme weather—are precisely the conditions hardest to simulate accurately and most dangerous to mishandle. Closing this validation gap requires both larger testbeds and a fundamental cultural shift toward treating the simulation-to-reality gap as a central research problem rather than an implementation detail.

Table 5 organizes studies across renewable integration, microgrid management, and cross-cutting themes. While AI's potential is clearly demonstrated, the gap between simulated validation and operational readiness remains significant.

Table 5. Taxonomy of AI for renewable energy integration and microgrid management studies.

Application Area	AI Technique/Focus	Specific Domain/Outcome	Sources
Converter-Level Integration	DC–DC converter design and MPPT	PV-battery converter dynamics and maximum-power-point tracking	[56,57]
	Forecasting and optimization	Solar photovoltaic power generation	[58,59]
	Forecasting and optimization	General grid optimization and efficiency	[65,67]
	Forecasting and optimization	Energy supply and demand balancing	[68]
Microgrid Management	Generative AI	ChatGPT and other generative AI applications	[60]
	Hybrid systems	Integration and management of hybrid renewable sources	[61]
	Smart infrastructure	Smart energy infrastructure for smart cities	[62,63]
	Electric vehicles	Role of AI in large-scale electric vehicle adoption	[66]
Cross-Cutting Themes	General AI techniques	Smart grids and renewable energy systems	[64]

3.4.1. Converter-Level Robustness and Resilient Control: Bridging AI and Physics-Based Approaches

Section 3.4 shows that most studies on AI-enabled renewable-energy integration and microgrid management represent power-electronic converters as aggregated and ideally controllable sources, rather than as physical subsystems subject to switching, thermal, dynamic, and protection constraints. Of the 13 studies included in this cluster, only two explicitly model converter-level dynamics, whereas the remaining 11 operate predominantly at the supervisory-control level. To place this limitation in a broader control-theoretic context, this subsection considers five studies that directly address converter-level robustness, resilience, power regulation, and transient stability, several of which were identified during the peer-review process.

Robust control under model uncertainty. The H_∞ robust-control design for a three-phase voltage-source inverter presented in [69] formulates voltage regulation as a disturbance-rejection problem. Rather than assuming a fully known nominal converter model, the proposed method explicitly limits the influence of parameter uncertainty, external disturbances, and unmodeled dynamics on output-voltage tracking. This approach differs from much of the AI-driven renewable-integration literature reviewed in Section 3.4, where controllers are commonly validated under a limited set of deterministic simulation conditions without a formal robustness bound.

Resilience under cyber-physical attacks. The resilient-control framework developed for a building-scale DC microgrid in [70] extends the robustness problem beyond parametric uncertainty to include malicious manipulation of measurement and actuation signals. This work is closely related to the adversarial-robustness barrier identified in Section 4. However, unlike most studies in the cybersecurity cluster, which focus primarily on communication networks, intrusion detection, or system-level data integrity, Section 3.3 addresses resilience directly at the converter and DC-bus levels. It therefore provides an important link between cyber-resilience and the physical control layer of converter-dominated microgrids.

Interlinking-converter architectures for hybrid microgrids. The study in [71] proposes an energy-storage-based interlinking architecture, referred to as the *Power Lever*, for regulating power exchange between AC and DC subgrids within a microgrid community. By employing a partially rated, high-gain converter topology, the proposed architecture addresses the efficiency and cost limitations associated with conventional fully rated interlinking converters. A subsequent study [72] further extends this line of research through a dynamic circuit-based unified power-regulation strategy for hybrid AC/DC/DS microgrids. The proposed approach integrates steady-state power sharing with transient inertia support, thereby addressing the limited treatment of converter-aware transient behavior identified in Section 3.4.

Transient stability of grid-forming inverters. The study in [73] develops a port-controlled Hamiltonian energy-reshaping method to improve the transient stability of grid-connected grid-forming inverters. This study is particularly relevant to the low-inertia and grid-forming stability challenges discussed in Sections 1.1 and 1.2. In contrast to purely data-driven control approaches, the method embeds the physical energy structure of the converter within the control design and provides an explicit stability-oriented formulation. It therefore represents one of the comparatively few studies to combine converter-level physical modeling with a formal transient-stability objective.

Taken together, these studies demonstrate that an established body of robust and resilient control research already addresses several of the deployment barriers identified in this review, particularly those associated with model uncertainty, cyber-physical attacks, transient behavior, and converter-level stability. Importantly, these contributions remain only weakly connected to the mainstream AI-driven microgrid-management literature.

Most do not rely on black-box data-driven models; instead, they incorporate explicit physical models, uncertainty descriptions, disturbance bounds, or stability constraints.

The comparison with the 13 studies reviewed in Section 3.4 therefore suggests that the converter-aware validation gap does not arise solely from a lack of suitable control techniques. Rather, it reflects limited integration between two research communities: AI-based supervisory energy management and physics-based robust or resilient converter control. Bridging these areas is likely to be more productive than treating them as separate research directions. Future work should therefore investigate hybrid architectures in which AI supports forecasting, scheduling, adaptation, or anomaly detection, while converter-level safety, robustness, and stability are retained through formally designed control laws and physics-informed constraints.

3.5. Fault Detection, Diagnosis, and Grid Stability

This thematic cluster remains the smallest in the revised primary corpus, comprising eight studies [29,74–80]. These studies cover high-speed fault detection, fault classification, and localization, grid-stability prediction, predictive reliability, and credibility assessment of machine-learning-based transient-stability evaluation. Related physics-based converter-control studies are discussed separately in Section 3.4.1 and are not included in this cluster count. Given the limited evidence base, the observations below should be interpreted as a preliminary but consistent indication rather than a conclusive finding. Nevertheless, the comparatively limited research activity warrants attention because fault detection plays a critical role in preventing severe grid failures.

High-speed fault detection. A frequently overlooked dimension is computational infrastructure [75]. Even at grid sampling rates of 800,000 samples per second, their AI platform performs inference fast enough to enable real-time fault detection—a hardware-software co-design necessity often neglected in purely algorithmic research.

Fault classification and localization. Machine learning applied to smart meter data enables fault type identification and feeder location estimation [76], extracting significant value from already-deployed infrastructure. Practical applicability depends on data quality and coverage—regions with limited metering cannot replicate reported accuracy.

A fault-location method for unbalanced active distribution networks using sparse hybrid measurements was proposed in [74]. The method extends fault intelligence beyond fault-type classification by estimating fault locations under limited measurement availability, although its application depends on prior knowledge of measurement placement. An augmented K-NN method for fault detection and classification using an enhanced distance-weighting procedure was developed in [79]. However, the method was evaluated using a relatively limited simulated fault dataset, and broader field validation is still required.

Ensemble models and comparative analysis. Comparative analysis has been used to compare K-NN, SVM, and decision tree algorithms for stability prediction, providing practitioners with direct performance benchmarks [77]. StarNet [78] uses ensemble methods to improve predictive reliability and enable automation—a step towards autonomous grid operation where AI directly influences control actions.

An incremental dataset-recognition approach was introduced in [80] to assess the credibility of machine-learning-based transient-stability predictions under stochastic and changing operating conditions. Rather than relying only on prediction accuracy, the framework also examines whether the trained model remains dependable when the operating conditions differ from those represented in the training data. However, the approach has so far been evaluated mainly for transient-stability assessment, and its applicability to other fault-diagnosis and protection tasks still requires further investigation.

Integrated perspectives. Fault detection can also be positioned within a coordinated suite of AI capabilities, emphasizing that isolated single-function AI systems should give way to integrated, multi-objective architectures [29].

Research gap analysis. The small size of this cluster relative to energy management and cybersecurity reveals a critical misalignment. Fault events are rare, making large labeled datasets difficult to assemble. Nevertheless, AI-based approaches may support earlier identification of developing abnormal conditions and provide additional time for preventive maintenance and operational intervention. Future research must address data scarcity through simulation-based augmentation, transfer learning, and physics-informed neural networks that supplement limited empirical fault data with domain knowledge. This domain warrants significantly increased research investment.

Table 6 categorizes the limited literature by application area and AI technique. The observed gap between safety-critical importance and research investment represents an important preliminary finding from this cluster and warrants confirmation through a broader evidence base.

Table 6. Taxonomy of fault detection, diagnosis, and grid stability studies.

Application Area	AI Technique/Method	Specific Focus	Sources
Fault Detection & Diagnosis	AI inference and high-performance hardware	High-speed fault detection using hardware–software co-design	[75]
	Machine learning with augmented K-NN	Fault detection and classification using an enhanced distance-weighted algorithm	[79]
	Data-driven classification using smart-meter measurements	Fault detection, classification, and feeder localization	[76]
	Sparse hybrid-measurement fault-location method	Fault localization in unbalanced active distribution networks under limited measurement availability	[74]
Grid Stability & Reliability	Comparative machine-learning analysis	Comparison of K-NN, SVM, and decision-tree algorithms for smart-grid stability prediction	[77]
	StarNet ensemble model	Predictive reliability and automation of smart-grid stability assessment	[78]
	Incremental dataset recognition and credibility evaluation	Credibility assessment of machine-learning-based transient-stability predictions under stochastic operating conditions	[80]
Integrated/Cross-Domain	Multi-function AI framework	Simultaneous forecasting, fault detection, renewable-energy integration, and optimization	[29]

3.6. Explainable AI (XAI), Trustworthiness, and Ethics

As AI becomes embedded in critical grid decision-making, transparency, accountability, and ethical governance have become pressing concerns. This cluster addresses these dimensions, though research investment remains disproportionately low.

XAI methods and applications. Interpretable prediction frameworks for decentralized grids [81] combine machine learning with explainable AI. XAI tools (SHAP, LIME) reveal which input features drive solar forecasting models [58], enabling validation and actionable insights. The fusion of intelligence modeled with XAI [20] demonstrates that accuracy and interpretability are not mutually exclusive. A conceptual architecture for XAI in smart grid systems [82] provides foundational guidance for incorporating explainability across grid functions.

Critical limitation: All four studies apply XAI to forecasting—the least safety-critical application. Explainability in real-time control decisions, security alerts, and protection relay operations—where stakes are highest and time for human review is shortest—remains almost entirely unaddressed.

Accountability and governance. Accountability is increasingly treated as a governance problem rather than merely a research challenge because existing regulatory frameworks do not fully accommodate AI-driven decision-making in safety-critical contexts. Novel risks of large language models in grid operations, including hallucination, prompt injection, and biased recommendations, extend the ethical concern to emergent AI technologies [83,84].

Ethical and social dimensions. Researchers have called for ethical and social challenges to be considered alongside technical development and have situated smart-grid ethics within broader urban AI concerns, including surveillance, citizen participation, and power concentration [85,86]. Both papers are theoretical rather than empirical; evidence on actual distributional impacts of AI deployment across income groups, communities, and employment is lacking.

Table 7 organizes studies across XAI methods, accountability, and ethical implications. The relative neglect of this cluster—despite its importance—and the dominance of theoretical over empirical research both represent significant gaps.

Table 7. Taxonomy of explainable AI, trustworthiness, and ethics studies.

Focus Area	AI/XAI Technique or Concept	Specific Aspect Addressed	Sources
XAI Methods & Applications	Interpretable machine learning and XAI	Decentralised smart grid prediction	[81]
	XAI tools, including SHAP and LIME	Solar photovoltaic power generation forecasting	[58]
	Fusion of intelligent modeled and XAI	Transparent smart grid electricity prediction	[20]
	General XAI framework	Conceptual architecture for explainable smart grid systems	[82]
Accountability & Reliability	Accountability framework	Legal, regulatory, and technical dimensions of AI-enabled grid services	[83]
	Threat modeled and validation	Risks of using large language models in smart grid operation and decision support	[84]
Ethical & Social Implications	Ethical and social challenges	Consideration of social impacts in smart grid research and deployment	[85]
	Ethical reflections	AI in smart cities, with emphasis on smart grid applications	[86]

3.7. Emerging Technologies: Digital Twins, Blockchain, IoT, and Edge Computing

AI increasingly integrates with digital twins, blockchain, IoT, and edge computing in synergistic ways that amplify capabilities. Digital twins provide safe virtual environments for AI learning; blockchain enables decentralized, transparent transactions; IoT generates the sensory data fueling AI; and edge computing enables low-latency inference.

Digital twins. An AI-enabled digital twin has been presented for energy efficiency optimization, enabling risk-free identification of inefficiencies and testing of optimization strategies [87]. A digital-twin-based intelligent authorization method has also been proposed for B5G-enabled grids, using virtual simulation of access requests before granting permissions—a security application complementing the operational use case [88].

Blockchain integration. Hybrid AI–blockchain frameworks can combine real-time threat detection with tamper-proof security event logging. Blockchain-integrated AI has

also been proposed for peer-to-peer energy trading, with AI optimizing buyer–seller matching and price prediction, while broader surveys describe AI–blockchain convergence across multiple smart-grid applications [44,89,90].

IoT and edge computing. IoT sensors and smart meters generate the high-volume, granular data fueling AI models [91]. A case study documents IoT–AI integration for smart city development with grid applications [92]. Advanced communication (5G RAN slicing) is critical for supporting AI applications [93]. Federated learning [94] is particularly significant: it enables privacy-preserving distributed model training where local edge nodes train on local data and only share model updates—simultaneously addressing data privacy and communication bandwidth constraints.

Critical gap. No study demonstrates the integration of more than two technologies in a coherent, end-to-end validated architecture. The full potential of the AI-digital twin-blockchain-edge computing ecosystem remains unrealized. Furthermore, the computational and energy costs of operating these multi-technology systems are rarely reported, raising questions about economic viability and net environmental benefit.

Table 8 categorizes studies by technology domain. The convergence trend is clear, but seamless integration at operational scale remains an open engineering challenge.

Table 8. Taxonomy of emerging technologies: digital twins, blockchain, IoT, and edge computing studies.

Technology Domain	Specific Technology/Technique	Application/Focus	Sources
Digital Twins	AI-enabled digital twins	Energy efficiency optimization in smart grids	[87]
	Digital twin for authorisation	Intelligent authorisation in B5G-enabled smart grids	[88]
Blockchain	Hybrid AI–blockchain framework	Security framework for threat detection and tamper-proof logging	[44]
	Blockchain-integrated AI framework	Energy efficiency and sustainability through peer-to-peer energy trading	[89]
	Blockchain and AI survey	General overview of smart grid applications in the AI era	[90]
IoT & Edge Computing	IoT and AI	General overview of smart grid applications	[91]
	IoT and AI case study	Sustainable smart city development with a smart grid focus	[92]
	5G and smart RAN slicing	Communication enhancement for smart grid applications	[93]
	Federated learning with edge–cloud computing	Secure and efficient model training with privacy preservation	[94]
Cross-Cutting/ Enabling IT	General IT infrastructure	Role of information technology in developing smart grids for efficient power distribution	[95]

To facilitate direct comparison across the thematic clusters, Table 9 presents a study-level evidence-synthesis matrix for a representative subset of the reviewed literature. The selected studies reflect the main application areas, AI and control approaches, validation environments, and levels of power-electronic representation identified in the primary corpus. In particular, the matrix distinguishes studies that represent converters through aggregated supervisory abstractions from those that explicitly model converter dynamics or employ hardware-in-the-loop or field-based validation. It also summarizes the principal evaluation metrics and reported limitations, thereby providing a transparent basis for the subsequent assessment of research maturity, deployability, and remaining methodological gaps.

Table 9. Evidence-synthesis matrix for a representative cross-cluster subset of studies, illustrating differences in data source, AI or control approach, validation setting, power-electronic modeled depth, evaluation metrics, and principal limitations.

Ref.	Cluster	AI/Control Technique	Validation Setting	PE Modelling Depth	Reported Metric	Principal Limitation
[9]	Energy mgmt.	Reinforcement learning	Simulation	Aggregated	Reward/adaptability (no single metric)	No cross-grid transfer test
[18]	Energy mgmt.	Hybrid/ensemble ML	Simulation	Aggregated	MAPE	Single-dataset validation
[33]	Cybersecurity	Graph-based deep learning	Simulation	N/A	Detection accuracy under poisoning	Not tested against adaptive adversary
[42]	Cybersecurity	GAN-based attack	Simulation	N/A	Attack success rate	Defensive countermeasure not proposed
[58]	Renewable/microgrid	XAI (SHAP/LIME) + ML	Simulation	Aggregated	Forecast accuracy + feature attribution	XAI limited to forecasting, not control
[75]	Fault detection	AI inference on dedicated hardware	Hardware-in-the-loop	Converter-aware (sampling-rate validated)	Inference latency at 800 kSa/s	Single hardware platform, not field-tested
[76]	Fault detection	ML on smart-meter data	Field data (retrospective)	Aggregated	Classification accuracy	Requires dense metering coverage
[77]	Fault detection/stability	K-NN, SVM, decision tree (comparative)	Simulation	Aggregated	Classification accuracy (comparative)	No field validation
[78]	Fault detection/stability	StarNet ensemble	Simulation	Aggregated	Predictive reliability score	No field validation
[79]	Fault detection	Augmented k-NN	Simulation	Aggregated	Classification accuracy	Small simulated fault set
[74]	Fault detection	Sparse hybrid-measurement estimation	Simulation	Aggregated (network-level)	Location error	Assumes measurement placement is known
[69]	Converter control (3.4.1)	H ∞ robust control	Simulation (converter-level)	Converter-aware (physics-based)	Disturbance rejection bound	Not validated against cyberattack scenarios
[70]	Converter control (3.4.1)	Resilient control under attack	Simulation (building-scale DC microgrid)	Converter-aware (physics-based)	Resilience under attack scenario	Building-scale only, not utility-scale
[71]	Converter control (3.4.1)	Partially rated interlinking converter	Simulation	Converter-aware (physics-based)	Efficiency/cost vs. fully rated ILC	Not yet field-deployed
[73]	Converter control (3.4.1)	PCH energy-reshaping control	Simulation	Converter-aware (physics-based)	Transient stability margin	Grid-connected only; islanded case not covered
[44]	Cybersecurity/emerging tech	Hybrid AI-blockchain	Simulation	N/A	Detection + logging integrity	Adversarial robustness not tested at scale
[49]	Cybersecurity/XAI	Trustworthy-AI framework	Simulation	N/A	Risk-explanation quality (qualitative)	Only cybersecurity study addressing explainability
[80]	XAI/trustworthiness (3.6)	Credibility evaluation for ML-based TSA	Simulation (stochastic operation modes)	N/A	Scene-specific credibility index	Evaluated on transient stability assessment only, not other AI tasks

As shown in Table 9, most of the selected studies rely on simulation-based validation and aggregated representations of the underlying power-electronic interfaces. Only a limited subset explicitly incorporates converter-level physical dynamics, hardware-in-the-loop testing, or field measurements. This imbalance supports the review’s conclusion that methodological maturity at the supervisory level has advanced more rapidly than operational validation at the converter and deployment levels.

3.8. Bibliometric and Contextual Synthesis of AI in Smart Grids: Supplementary Secondary Literature

This section draws on the Stage 2 supplementary bibliometric search described in Section 2.1, and its scope and purpose differ deliberately from those of Sections 3.2 through

3.7. The studies presented here—bibliometric analyses, scientific mapping papers, comprehensive overview articles, and forward-looking perspective pieces—were excluded from the primary PRISMA-guided corpus to preserve the methodological integrity of the original research synthesis in the preceding sections. Their inclusion here serves an explicitly defined and complementary purpose: to provide a macro-level intellectual framework within which the primary findings can be contextualized, interpreted, and positioned relative to the long-term trajectory of the field. None of the studies in this section are counted among the 87 primary studies, and they are clearly distinguished as supplementary contextual literature throughout.

The studies assembled in this supplementary synthesis occupy a unique and indispensable role in the broader research ecosystem. Rather than advancing specific technical contributions, they provide the structural scaffolding upon which the field organizes its understanding of itself: its origins, its growth, its tensions, and its trajectory. This meta-level perspective is not merely complementary to the primary findings—it is essential for interpreting their significance. Understanding that the grand challenges of AI in smart grids were articulated more than a decade ago and remain substantially unresolved [96] fundamentally changes how we read the incremental technical advances documented in the primary corpus. Similarly, understanding the quantitative contours of publication growth [3,97] allows us to assess whether the concentration of research in certain thematic clusters reflects genuine scientific progress or simply the gravitational pull of popular topics. This section organizes the supplementary literature into four sub-themes: bibliometric and scientific mapping, historical evolution and conceptual development, general overviews of AI techniques and applications, and grand challenges and broader implications.

3.8.1. Bibliometric and Scientific Mapping Studies

Quantitative bibliometric analyses constitute perhaps the most objectively grounded form of meta-knowledge available to a research community. By applying systematic, data-driven methods to publication records, citation networks, and keyword co-occurrence patterns, these studies reveal structures that are invisible to narrative synthesis alone. Two major bibliometric studies are of particular relevance to the findings of this review.

A bibliometric analysis and scientific mapping study presents [97] a comprehensive bibliometric analysis and scientific mapping of AI in smart grids, examining publication volume trends, geographic and institutional distributions of research output, leading authors, and the co-occurrence of keywords across the indexed literature. Its keyword co-occurrence analysis reveals the emergence of distinct research clusters corresponding closely to the thematic dimensions identified in the present review: energy management and forecasting, cybersecurity, renewable integration, and explainable AI all appear as discernible nodes in the co-occurrence network. Importantly, the same study identifies a small set of highly influential papers that have served as intellectual anchors for the field, with disproportionate citation counts reflecting their role in establishing foundational frameworks and benchmark datasets. This citation concentration phenomenon has implications for the primary findings of this review: the most-cited papers in the corpus may reflect field consensus, but they may also reflect citation habits and availability bias rather than true methodological superiority.

A 20-year bibliometric-based overview extends [3] this perspective significantly by offering a 20-year bibliometric-based overview of the role of AI in smart grids, providing a longitudinal analysis that traces the field's intellectual evolution from its earliest foundations through its current state. The 20-year timeframe captures the full arc from early, narrowly focused applications—primarily rule-based expert systems and basic neural networks for load forecasting—through the deep learning revolution of the 2010s to the current period characterized by reinforcement learning, explainable AI, and the integration

of AI with emerging technologies. This overview observes a progressive diversification of research themes, with new sub-topics such as cybersecurity and ethics emerging primarily after 2018. This diversification pattern is consistent with and validates the thematic structure of the present review, which documents seven distinct research clusters rather than the two or three that would have characterized the field a decade earlier. The longitudinal perspective also reveals a recurring pattern: technological innovation consistently precedes conceptual consolidation, with practical AI applications appearing in the literature several years before the field develops shared vocabulary, evaluation benchmarks, or regulatory frameworks for those applications. This lag between innovation and consolidation is particularly visible in the domains of explainable AI and ethics, which continue to trail technical development by a substantial margin.

Complementing these broad bibliometric analyses, a domain-specific bibliometric study of blockchain applications in smart grids [2] demonstrates how emerging digital technologies are forming specialized research communities within the wider smart-grid ecosystem. In addition, a comprehensive review of deep learning applications in smart grids [1] highlights the rapid expansion of deep learning across forecasting, fault diagnosis, renewable energy integration, and grid optimization, reinforcing the central role of deep learning identified throughout the primary corpus.

The bibliometric evidence from both studies collectively validates a central finding of this review: that the field of AI in smart grids is not merely growing but structurally maturing, with increasingly specialized sub-communities developing distinct methodological traditions, publication venues, and intellectual genealogies. This maturation is a positive development, but it also carries risks: as sub-communities become more specialized, cross-disciplinary synthesis becomes harder, and important connections between, for example, cybersecurity and explainability research may go unexplored.

3.8.2. Historical Evolution and Conceptual Development

To understand the current state of AI in smart grids, it is necessary to understand where the field came from and how its foundational concepts have evolved over time. Several studies provide this historical grounding.

Reference [98] provides a foundational overview of the smart grid concept, tracing its evolution from early automated power-system visions to modern data-driven grids. This paper situates the role of AI within a broader historical narrative, explaining how the progressive instrumentation of the power grid with sensors, smart meters, and communication infrastructure created a fundamentally new kind of data environment: one characterized by high volume, high velocity, and high variety, and thus inherently suited to machine learning approaches that could not have been practically deployed on earlier, less data-rich grids. The value of this historical perspective is that it establishes AI adoption in smart grids not as an arbitrary technological fashion but as a structurally determined response to the grid's own digital transformation. Understanding this causal relationship is important for anticipating the next wave of AI adoption: as grids become further instrumented—with phasor measurement units, IoT sensors, and electric vehicle charging stations generating ever-larger data streams—the demand for AI-based analytics will continue to intensify regardless of any deliberate policy choice to promote AI.

An applied historical overview examines [99] the evolution of smart grids from a more applied perspective, focusing specifically on how AI is being deployed in the context of highly digitized power grids with high penetration of renewable energy. This paper bridges the gap between earlier historical smart-grid framing and the contemporary technical literature reviewed in Sections 3.2 through 3.7, providing a practitioner-oriented narrative of how AI has moved from academic research into operational deployment. This

overview identifies several enabling conditions for this transition: the maturation of cloud computing infrastructure capable of hosting complex AI models, the standardization of grid communication protocols that enable interoperability between AI systems and grid devices, and the increasing willingness of regulators and utilities to pilot AI-based applications in controlled operational environments. This paper also identifies a critical and frequently overlooked bottleneck: the shortage of skilled personnel who possess both power engineering expertise and AI competence. This human capital constraint is not captured in any of the primary research studies reviewed in Sections 3.2 through 3.7, representing a gap that future sociotechnical research must address.

A deliberately provocative critical evaluation of the current state of grid intelligence poses the central question: how smart is the smart grid, actually? [100] This paper serves as a necessary and important corrective to the often-optimistic framing of both the primary research literature and the bibliometric overview studies. The study systematically compares the ambitious vision of a fully autonomous, self-healing, demand-responsive smart grid against the empirical reality of grid operations in major industrialized economies, finding a substantial and persistent gap between aspiration and achievement. Several factors contribute to this gap: the fragmented and heterogeneous nature of existing grid infrastructure, which was not designed with AI integration in mind; the slow pace of utility investment and regulatory adaptation; the conservatism of grid operators who are understandably reluctant to delegate control functions to AI systems that cannot be fully understood or audited; and the shortage of high-quality, labeled operational data needed to train and validate AI models under realistic conditions. This critical assessment is directly relevant to the discussion in Section 4, which similarly emphasizes that the dominant narrative of AI as a transformative technology for grid modernization must be tempered by sober recognition of the structural, institutional, and epistemic barriers to real-world deployment. The contribution of this line of work to the review is not merely cautionary: by precisely articulating what the smart grid is not yet, it implicitly defines what the research community must achieve to close the gap.

The broader context for these historical and critical perspectives is provided by a guest editorial [101], which, introducing a Special Issue on AI and data analytics for smart grids with high penetrations of renewables, offers a curated overview of the field's state-of-the-art at the time of its publication. Guest editorials of this kind perform an important function in the research ecosystem: by assembling and framing a collection of high-quality contributions around a shared theme, they help define the boundaries of a sub-field and signal which research directions the community considers most promising. This framing—emphasizing the challenges of integrating variable renewables through AI-driven forecasting, dispatch optimization, and demand flexibility—is fully consistent with the primary findings in Section 3.2 and reinforces the centrality of these themes to the field's self-understanding.

3.8.3. General Overviews of AI Techniques and Applications

A substantial portion of the supplementary literature comprises general overview papers that survey the landscape of AI techniques applied to smart grids, while these papers do not advance original empirical findings, they serve several important functions: providing accessible entry points for researchers new to the domain, mapping the AI toolbox available for grid applications, and identifying patterns of technique adoption and performance that are not visible in any single primary study. Four such overview papers are of particular relevance.

A broad-scope overview presents [102] a broad-scope overview of AI applications and prospects in smart grids, synthesizing the development of both the AI and smart grid

fields and analyzing applications across three major domains: power load forecasting, fault diagnosis, and grid security. This paper is notable for its genuinely integrated treatment of these domains, recognizing that AI in smart grids is not a collection of independent applications but a set of interrelated capabilities that must ultimately function in coordination. The distinction drawn between AI as a tool for optimization—improving the efficiency of existing processes—and AI as an enabler of new capabilities—allowing the grid to perform functions that were previously impractical—is conceptually important and maps directly onto the taxonomy of applications documented in the primary corpus. The paper also identifies a recurring tension between model complexity and operational practicality that pervades the primary literature: the most accurate AI models are often the least interpretable and the most computationally demanding, creating trade-offs that are particularly acute in real-time grid applications.

A practically oriented catalogue provides [4] a practically oriented catalogue of AI techniques applicable to smart grid problems, covering neural networks, fuzzy logic systems, expert systems, and evolutionary algorithms, while predating many of the deep learning advances documented in the primary corpus, this paper retains value as a structured reference that situates newer techniques within a longer history of AI application to power systems. It is useful for understanding the conceptual continuities between early AI research in power systems—which was dominated by expert systems and fuzzy logic in the 1990s—and the contemporary deep learning era. Many of the fundamental problem types identified in this earlier work—pattern classification, sequential decision-making, and optimization under uncertainty—remain the same; what has changed is the scale, the data richness, and the algorithmic sophistication with which they are addressed.

A forward-looking perspective offers [5] a forward-looking perspective on the role of AI in advancing smart grid technologies, identifying key trends that will shape the field over the coming decade. Several of the trajectories identified in this perspective are fully consistent with and supported by the primary findings of this review: the increasing dominance of deep learning for time-series forecasting, the growing importance of reinforcement learning for adaptive control, the rising prominence of explainable AI as a prerequisite for operational trust, and the convergence of AI with digital twins and edge computing for distributed intelligence. The paper also identifies several emerging trends that receive less attention in the primary corpus: the potential of neuromorphic computing to enable extremely energy-efficient AI inference on edge devices; the application of causal inference methods to move beyond correlation-based AI toward models that can reason about the underlying mechanisms of grid behavior; and the possibility of using AI to actively co-design grid infrastructure rather than merely optimize its operation. These emerging directions, noted in this perspective but largely absent from the primary literature, represent concrete recommendations for future research priorities.

A historical and institutional perspective examines [6] the role of AI in the transition from conventional power systems to modernized smart grids from a historical and institutional perspective. This paper argues that AI has not merely been a tool for grid optimization but a genuinely enabling technology whose availability has made certain forms of grid modernization possible that would otherwise be impractical or uneconomical. The examples provided—including AI-driven demand response that makes it economically viable to integrate variable renewables without proportional investment in conventional backup generation—connect directly to the primary findings in Sections 3.2 and 3.4. The institutional dimension of this transition, however, receives relatively little attention in the primary corpus: how utilities, regulators, and market operators have adapted their processes and governance structures to accommodate AI-driven capabilities is a question that remains largely unexplored in original research.

3.8.4. Grand Challenges and Broader Implications

The most intellectually significant subset of the supplementary literature comprises studies that step back from technical specifics to engage with the grand challenges, systemic implications, and broader societal dimensions of AI in smart grids. These papers collectively define what is ultimately at stake in this research domain and establish the criteria by which progress should be judged.

A grand-challenge paper remains [96], more than a decade after its publication, the most influential single statement of the grand challenges facing AI in smart grids. This paper, published in the Communications of the ACM, framed the vision of a fully intelligent smart grid as a "grand challenge" for AI comparable in ambition and difficulty to other historic AI challenges such as chess or the Turing test. The challenges identified in this work span power systems engineering, telecommunications, and AI itself: managing the complexity of millions of simultaneous demand response interactions, providing real-time control under extreme reliability and latency constraints, handling the heterogeneity of grid actors and devices, and ensuring security and privacy across a distributed cyber-physical system. The enduring relevance of these challenges, which remain substantially unresolved despite a decade of intensive research, is itself a significant finding of this review. The primary literature documents impressive advances in specific technical capabilities, but the fundamental barriers to the vision articulated in that work have not been overcome. This gap between local technical progress and global challenge resolution underscores the importance of the structural and institutional barriers identified in historical and critical overviews [99,100]: the obstacles to a fully intelligent smart grid are not primarily algorithmic but architectural, institutional, and social.

A focused examination provides [103] a more focused examination of challenges and opportunities in applying AI to critical power infrastructure, with particular attention to the unique requirements of safety-critical systems. The paper distinguishes clearly between the requirements of AI in consumer applications—where errors are inconvenient but rarely catastrophic—and AI in critical infrastructure—where errors can cascade into widespread outages, physical damage, or security breaches. This distinction has profound implications for the design and validation of AI systems for grid applications: accuracy metrics that are perfectly acceptable for a recommendation algorithm may be entirely insufficient for an AI-based protection relay. This work argues that the field currently lacks adequate frameworks for specifying, testing, and certifying the reliability of AI systems in safety-critical grid contexts—a gap that is directly relevant to the thin state of research on fault detection and grid stability documented in Section 3.5. The development of such frameworks, likely involving collaboration between AI researchers, power engineers, and regulatory bodies, represents a high-priority direction for future work.

A systemic perspective raises [104] a question that is notable both for its originality and its systemic importance: how are the massive energy demands of AI itself reshaping the future of the smart grid? This paper inverts the conventional framing—in which AI is purely a tool for optimizing the grid—to consider AI as an increasingly significant consumer of the energy resources the grid must manage. The exponential growth of AI training and inference workloads has made data centers among the fastest-growing categories of electricity demand in many industrialized economies, creating a feedback loop in which AI-driven grid modernization must increasingly account for the energy appetite of the AI systems it deploys. This work argues that this feedback loop has not been adequately integrated into smart grid planning frameworks and that the net environmental benefit of AI-based grid optimization cannot be assumed without explicit accounting for the energy cost of the AI systems themselves. This perspective is absent from the primary

research corpus reviewed in Sections 3.2 through 3.7, representing a significant conceptual gap in the field's self-understanding.

A structured framework provides [105] a structured framework for evaluating the impact of AI on three dimensions that are central to the smart grid policy agenda: sustainability, resilience, and efficiency. This paper makes a valuable methodological contribution by moving beyond the binary question of whether AI "works" toward a multi-dimensional assessment of how AI performs across the full range of objectives that grid modernization is meant to serve. The framework distinguishes between efficiency gains—which are well-documented in the primary literature—and resilience improvements—which require demonstrating that AI-based systems perform adequately under conditions of stress, failure, and attack—and sustainability contributions—which require accounting for the full lifecycle environmental and social impacts of AI deployment. This multi-dimensional framing is directly relevant to the practical implications discussed in Section 4: grid operators, policymakers, and researchers all need evaluation tools that go beyond narrow accuracy metrics to assess the holistic value and risk profile of AI systems.

A real-world case study provides [106] a grounding counterpoint to the theoretical and policy-oriented perspectives of the other studies in this sub-theme, presenting a real-world case study of building smart grids on AI. This paper is significant for its empirical grounding: rather than arguing abstractly about the potential of AI, it documents the practical experience of attempting to deploy AI-based systems in an actual operational grid environment. The lessons drawn from this experience—including the difficulties of obtaining reliable training data, the challenges of integrating AI outputs into existing operational workflows, and the importance of operator trust and engagement—correspond directly to the structural barriers identified in critical and historical overviews [99,100]. Case studies of this kind are underrepresented in the primary literature, and their expansion represents an important direction for future research: the field needs more empirical documentation of what happens when AI leaves the laboratory and enters operational deployment.

An environmental sustainability perspective rounds [107] out this sub-theme with a discussion of environmental sustainability and the role of AI and smart grid sensors in enabling more sustainable energy operations. This paper situates smart grid AI within the broader context of environmental governance, arguing that the full potential of AI for sustainability can only be realized when it is embedded in a system of sensors, communication infrastructure, and policy frameworks that collectively enable transparent, accountable, and equitable energy management. The environmental dimension of smart grid AI is frequently invoked in research abstracts and introductions but rarely examined with the depth and specificity it deserves, making this contribution a valuable exception.

3.8.5. Synthesis and Implications for the Primary Findings

As stated in Section 2.1, the following synthesis is used only to contextualize the Stage 1 findings and is not treated as independent primary evidence. The supplementary bibliometric literature reviewed in this section provides three layers of context that materially enrich the interpretation of the primary findings in Sections 3.2 through 3.7.

At the quantitative level, bibliometric evidence confirms [3,97] that the publication trends and thematic distribution observed in the primary corpus are representative of the broader field rather than artifacts of our specific search and selection process. The exponential growth pattern, the dominance of energy management and cybersecurity as research themes, and the relative underrepresentation of explainability and ethics are all corroborated by the bibliometric evidence.

At the structural level, historical and critical overview papers indicate that the gap between research output and operational deployment is a persistent feature of the field [96,99,100]. This

structural inertia suggests that incentive realignment—not merely additional research—may be necessary to close the deployment gap.

As shown in Table 10, recent grand-challenge literature introduces [103–105] several dimensions that are largely missing from the primary corpus. These include the energy consumption of AI systems, multi-dimensional assessments of AI value that extend beyond narrow accuracy-based metrics, and the certification requirements for safety-critical AI applications. Together, these dimensions represent not only gaps in the existing research but also potential blind spots that may threaten the long-term sustainability of the research agenda if they remain unaddressed.

Table 10. Taxonomy of bibliometric analysis, evolution, and general overviews of AI in smart grid studies.

Focus Area	Type of Analysis/Perspective	Specific Contribution	Sources
Bibliometric & Scientific Mapping	Domain-specific bibliometric analysis	Scientific mapping of blockchain applications in smart grids and their research evolution	[2]
	Quantitative analysis	Publication trends, leading authors and institutions, and keyword co-occurrence	[97]
	20-year longitudinal overview	Evolution of research themes over two decades	[3]
Historical Evolution & Conceptual Development	Practical perspective	Curated overview of AI and data analytics for smart grids with high renewable penetration	[101]
	Historical overview	Development of the smart grid concept from early origins to modern grid architectures	[98]
	Practical perspective	AI application in highly digitized grids with high renewable energy penetration	[99]
	Critical evaluation	Assessment of the current level of “smartness” in modern grids	[100]
General Overviews of AI Applications	Comprehensive review	Deep learning techniques, applications, challenges, and future research directions for smart grids	[1]
	Comprehensive overview	AI applications in load forecasting, fault diagnosis, cybersecurity, and smart grid operation	[102]
	General overview of techniques	Neural networks, fuzzy logic, expert systems, and evolutionary algorithms	[4]
	Forward-looking perspective	Future directions for AI-enabled smart grid technologies	[5]
	Transition perspective	Role of AI in the transition from conventional grids to modernized smart grids	[6]
Grand Challenges & Broader Implications	Grand challenge	Fundamental challenges for AI in realizing the smart grid vision	[96]
	Challenges and opportunities	Critical power infrastructure, safety, robustness, and explainability	[103]
	Energy demands of AI	Feedback loop between AI as a grid optimization tool and AI as a consumer of grid resources	[104]
	Sustainability, resilience, and efficiency	Framework for evaluating the impact of AI on sustainability, resilience, and operational efficiency	[105]
	Real-world case study	Practical application of AI to a specific smart grid problem	[106]
	Environmental sustainability	Role of AI and smart grid sensors in enabling sustainable grid operation	[107]

The studies in this supplementary synthesis collectively show that the research community has consistently identified similar structural challenges, including deployment gaps, limited interpretability, ethical uncertainty, and institutional inertia. The persistence of these challenges, despite more than a decade of growing research activity, suggests that resolving them will require more than incremental technical improvements. A broader reorientation is needed in validation methods, research incentives, regulatory alignment, and governance frameworks. This conclusion provides the basis for the critical discussion in Section 4 and the future research agenda presented in Section 5.

4. Discussion

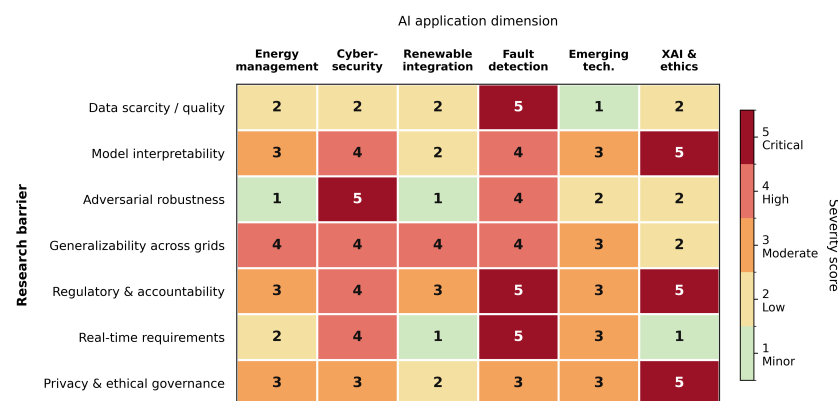
The synthesis of 87 primary studies across six primary thematic clusters indicates that reliable operational deployment remains incomplete across all application domains. Simulation-based and small-scale validation remain dominant, while generalizability, adversarial robustness, explainability, ethical governance, and cross-domain integration are insufficiently addressed. The following subsections interpret these evidence-based limitations and examine their implications for trustworthy AI deployment in smart grids and

microgrids. Three overarching patterns emerge from the cross-cluster analysis. First, AI has demonstrably moved from a peripheral experimental tool to a central enabling technology across virtually all dimensions of smart grid operation, yet the transition from proof-of-concept to reliable operational deployment remains incomplete in every cluster examined. Second, the field exhibits a structural imbalance between technical ambition and practical grounding: the dominant research paradigm prioritizes algorithmic novelty demonstrated on simulated or small-scale testbeds, while the operational conditions, institutional constraints, and human factors that govern real-world deployment receive systematic and sustained underattention. Third, the most consequential research questions—concerning model trustworthiness, adversarial robustness, ethical governance, and cross-domain integration—are precisely those receiving the least research investment, a misalignment that poses a significant long-term risk to the credibility and utility of the entire research program. The following subsections develop these observations through detailed analysis of each thematic cluster before addressing theoretical and practical implications, study limitations, and future research priorities.

While Section 3 documents what AI research is being conducted across smart grids, Section 4 addresses a prior question: what are the structural barriers preventing research from translating into reliable operational deployment? To map these barriers systematically, we identify seven categories of challenges—data scarcity, model interpretability, adversarial robustness, generalizability, regulatory frameworks, real-time computational requirements, and privacy/ethical governance—and assess their severity across the six primary research clusters.

The barrier-severity scores shown in Figure 5 were assigned using a predefined three-indicator rubric. For each combination of thematic cluster and barrier category, two lead reviewers independently considered: (i) the prevalence of the barrier within the reviewed studies, (ii) its potential operational consequence if unresolved, and (iii) the difficulty of mitigation under realistic deployment conditions. These indicators jointly informed an ordinal score from 1 to 5, where 1 denotes a minor barrier, 2 a manageable barrier, 3 a moderate barrier, 4 a critical barrier, and 5 a catastrophic deployment blocker. Differences between the independent assessments were resolved through discussion and reconciliation. The final reconciled barrier scores are presented directly in Figure 5, while the scoring criteria and reconciliation procedure are described above.

Figure 5 presents a research barrier heatmap, where color intensity reflects barrier severity (green: minor; yellow: manageable; orange: moderate; red: critical; dark red: catastrophic blocker). This visualization reveals both cluster-specific vulnerability profiles and cross-cutting challenges that affect all domains.



Scale: 1 = minor concern; 5 = critical blocker. High scores indicate barriers requiring targeted research before broad operational deployment.

Figure 5. Research barrier heatmap.

The heatmap reveals four critical patterns:

Pattern 1: Fault detection faces critical barriers across nearly all dimensions. Data scarcity (5/5) and real-time performance requirements (5/5) are catastrophic blockers. Generalizability (4/5), regulatory frameworks (5/5), and interpretability (4/5) are all severe. This cluster-wide concentration of critical barriers explains both the small research volume and the persistent gap between laboratory prototypes and operational deployment.

Pattern 2: Cybersecurity's adversarial robustness vulnerability (5/5) is unmatched; while intrusion detection algorithms achieve high accuracy on standard benchmarks, the fundamental vulnerability to adversarial attack creates a security paradox: improving detection capabilities simply refines the attack surface for sophisticated adversaries. This challenge is neither algorithmic nor amenable to simple solutions.

Pattern 3: Generalizability is a widespread challenge (3–4/5 severity across all clusters). Models trained on single grids do not reliably transfer to different topologies, climates, or regulatory contexts. This is the single most pervasive limitation preventing deployment at scale.

Pattern 4: Regulatory and accountability barriers are critical (5/5) for fault detection and XAI, yet receive minimal attention in the primary research literature. Utilities and regulators face fundamental ambiguity about liability when AI-driven decisions cause adverse outcomes—a governance gap that must be resolved before large-scale autonomous AI deployment.

These barriers are not primarily algorithmic limitations. They are structural, institutional, and epistemic challenges that additional research alone cannot overcome without parallel progress in regulatory frameworks, data infrastructure, and organizational practices.

4.1. Discussion of AI-Driven Energy Management, Forecasting and Optimisation

The energy management and forecasting cluster, the largest and most mature in the primary corpus, provides strong evidence that AI has moved well beyond the proof-of-concept stage for core grid operational functions. The convergence of findings across demand-side management, load forecasting, and energy optimization studies supports a clear conclusion in response to **RQ1**: The evidence reviewed in response to RQ1 indicates that reinforcement learning is widely applied and particularly suitable for sequential decision-making in demand-side management, while deep learning, hybrid, and ensemble models are prominent in high-dimensional forecasting tasks. However, differences in datasets, application contexts, evaluation metrics, and validation procedures prevent a reliable universal ranking of these techniques.

The reinforcement learning literature on demand-side management is especially instructive. The collective evidence from the reviewed studies demonstrates [9–11] that RL agents can learn adaptive scheduling policies that outperform static, rule-based alternatives across a range of residential and community energy contexts. This adaptability is qualitatively significant: traditional demand response programs require explicit programming of responses to predefined scenarios, making them brittle in the face of unanticipated conditions. RL agents, by contrast, can respond to conditions they have never explicitly encountered, provided the state space of the training environment was sufficiently rich. This property is particularly valuable for grids with high renewable penetration, where the variability and unpredictability of generation create exactly the kind of novel conditions that rule-based systems handle poorly.

The forecasting literature reveals a clear trend toward hybrid and ensemble architectures that combine the strengths of multiple algorithms. Hybrid models often outperform single-algorithm approaches on standard benchmarks, although the reported improvements are specific to the datasets and validation settings used in the individual studies [18,19]. The

integration of XAI into forecasting models is a particularly important development [20]: it indicates that the research community is beginning to recognize that prediction accuracy is a necessary but not sufficient condition for operational deployment and that interpretability is an independent and equally important requirement.

However, a critical and consistent limitation across this cluster demands direct attention: the near-universal failure to assess model generalizability. Of the 22 studies reviewed in this cluster, the overwhelming majority train and evaluate their models on data from a single grid, region, or dataset and do not attempt to validate performance under transfer to different climatic conditions, load profiles, grid topologies, or regulatory environments. This omission is not a minor technical detail—it strikes at the core of whether the optimistic accuracy figures reported in these studies are meaningful for the utilities that most need them. A utility operating a diverse portfolio of distribution networks across multiple geographic regions cannot deploy a model validated on a single network without substantial re-engineering and re-validation, costs that are rarely acknowledged in the research literature. The practical implication is that the energy management literature, despite its volume and technical sophistication, currently offers limited directly actionable guidance for operational deployment at scale.

4.2. Discussion of AI-Enabled Cybersecurity, Intrusion Detection and Attack Mitigation

The cybersecurity cluster presents the most intellectually complex pattern in the primary corpus, and its findings in response to RQ2 reveal a fundamental paradox at the heart of AI-based grid security: AI is simultaneously the most effective tool available for detecting sophisticated cyberattacks and a significant new vulnerability that adversaries can exploit. This paradox is not a peripheral complication but a structural feature of the AI-in-cybersecurity relationship that has profound implications for how AI-based security systems are designed, validated, and deployed.

On the defensive side, the evidence is compelling. Graph-based and spatio-temporal deep learning models represent a genuine advance over prior approaches by explicitly incorporating the topological structure of grid measurement networks into the detection architecture [33,34]. Traditional anomaly detection methods treat measurements as independent signals; graph-based models recognize that the relationships between measurements—determined by the physical connectivity of the grid—carry diagnostic information that independent analysis discards. This architectural innovation explains the superior robustness of graph-based models against data poisoning attacks, where an adversary corrupts training data to create blind spots in the detection system: the topological constraints of the grid provide a form of implicit regularization that limits the attack surface available for poisoning. Ensemble learning adds a complementary capability by maintaining detection accuracy under concept drift, addressing the practical reality that grid data distributions evolve over time as the system changes and as attackers adapt their strategies [35].

On the offensive side; however, GAN-based attack studies and broader adversarial-AI surveys demonstrate that every AI-based defense system creates a new attack surface [42,43]. Adversaries who understand the architecture of a detection model can craft inputs—adversarial examples—that are indistinguishable from legitimate grid measurements to a human analyst but cause the model to misclassify them as benign. This vulnerability is not a fixable bug in a specific implementation; it is a fundamental property of the optimization landscape in which deep learning models are trained. The implication is that a purely data-driven defense strategy—one that relies solely on the learned decision boundary of a trained model—is inherently inadequate for a motivated adversary with knowledge of the defense system. Hybrid AI-blockchain and trustworthy-AI frameworks represent important steps toward more resilient architectures, but they remain at the proof-

of-concept stage and have not been validated against sophisticated adversarial attacks at operational scale [44,49].

A secondary finding of significant importance concerns the near-absence of explainability in cybersecurity AI. Among the 23 cybersecurity studies reviewed, only one directly addresses the need for human-interpretable explanations of security alerts [49]. This gap matters enormously in operational practice: when an AI-based intrusion detection system generates an alert, a grid security operator must decide within seconds whether to treat it as genuine and initiate a potentially disruptive response or dismiss it as a false positive. Without an explanation of why the alert was generated—which features triggered the detection, what attack pattern they correspond to, and how confident the model is—the operator has no basis for making this decision other than blind trust in the AI system. The current literature's neglect of explainability in cybersecurity contexts is therefore not an academic oversight but a practical barrier to operational deployment that must be addressed as a research priority.

4.3. Discussion of AI for Renewable Energy Integration and Microgrid Management

The renewable energy integration and microgrid management cluster reveals a field navigating a productive but unresolved tension between the breadth of AI's potential applications and the depth of its validated performance in practice. The primary corpus documents credible advances in solar forecasting using XAI tools [58], AI-driven control of hybrid multi-energy systems [27], and the strategic deployment of AI across smart city energy infrastructure [62]. Forward-looking work on generative AI in renewable energy opens [60] a genuinely new frontier, suggesting that large language and generative models could accelerate materials discovery for photovoltaics, optimize wind farm layouts, and generate synthetic training data for grid models—capabilities that, if realized, would represent a qualitative shift in the relationship between AI and renewable energy technology.

However, the most significant finding from this cluster is not a technical result but a structural observation: the overwhelming majority of proposed AI frameworks are validated exclusively on simulated environments or small-scale testbeds, and the conditions under which they are tested bear only partial resemblance to the operational conditions of real-world grids. This validation gap is particularly consequential in the context of renewable integration, where the most challenging conditions—sudden generation drops due to cloud cover or wind lulls, grid islanding events, and extreme weather-driven demand spikes—are precisely the conditions that are most difficult to simulate accurately and most dangerous to handle incorrectly. The studies that do address real-world deployment, such as studies of European smart city infrastructure, tend to operate [62] at a high conceptual level without providing the empirical performance data that utilities would need to make informed adoption decisions. Closing this validation gap requires not just larger or more realistic testbeds but a fundamentally different research culture: one that values empirical grounding as highly as algorithmic novelty and that treats the gap between simulation and reality as a central research problem rather than an implementation detail.

4.4. Discussion of Fault Detection, Diagnosis and Grid Stability

The fault detection cluster is the smallest thematic cluster in the primary corpus, comprising only eight studies, and this quantitative fact is itself among the most significant findings of this review. Grid fault detection and protection are among the most safety-critical functions in power system operations: failures in protection systems can cause equipment damage, widespread outages, and cascading failures with severe economic and social consequences. The relative neglect of this domain by AI researchers—compared to

the extensive literature on demand response, load forecasting, and intrusion detection—represents a significant misalignment between research investment and operational risk.

Within the existing literature, one distinctive contribution is a high-performance AI inference platform that addresses the frequently overlooked computational dimension of real-time fault detection [75]. The demonstration that AI inference can operate at the millisecond timescales required for grid protection—specifically, maintaining performance at sampling rates of 800,000 samples per second—is a crucial proof of feasibility that enables the subsequent algorithmic research to be taken seriously as a candidate for operational deployment. Without such hardware-level validation, the accuracy figures reported by algorithm-focused studies, however impressive, remain purely academic.

Ensemble-based stability prediction and comparative algorithm analysis provide a solid, if narrow, evidence base [77] for the algorithmic dimension of fault detection and stability prediction. What these studies collectively fail to address is the data scarcity problem that is arguably the most fundamental barrier to progress in this domain. Fault events are inherently rare in well-maintained grids—a property that makes the grid reliable but simultaneously makes it extremely difficult to assemble the large, labeled fault datasets that deep learning models require. The performance figures reported in the existing studies are almost uniformly based on simulated or synthetic fault data, and the degree to which performance on simulated faults translates to performance on real events—which are often more complex, ambiguous, and idiosyncratic than simulations assume—is an open and critical question. Future research must specifically address these data scarcity challenges through transfer learning, physics-informed simulation, and cross-utility data-sharing protocols.

4.5. Discussion on Explainable AI, Trustworthiness and Ethical Considerations

The XAI and ethics cluster is the second smallest in the primary corpus, and its relative neglect by the research community is a cause for substantive concern that extends beyond the usual call for more interdisciplinary research. The reason is structural: without explainability, accountability, and ethical governance, the entire AI-in-smart-grids research enterprise is building on a foundation that regulators, operators, and the public may ultimately refuse to accept. All the technical advances documented in Sections 3.2 through 3.5 depend, for their operational realization, on a degree of institutional trust that the current research culture has done little to earn.

The XAI literature reviewed here establishes a clear principle [20,58,81,82]: that prediction accuracy and interpretability are not mutually exclusive and that models can be designed to provide both. This is an important corrective to the common assumption that explainability necessarily comes at the cost of performance. However, all four studies apply XAI to forecasting applications—the most benign and least safety-critical of the AI functions documented in this review. Explainability in the context of real-time control decisions, security alerts, and protection relay operations—where the stakes are highest and the time available for human review is shortest—remains almost entirely unaddressed in the primary corpus. This is precisely the gap that most urgently needs to close.

Accountability and LLM-risk studies introduce dimensions that extend beyond technical AI research into legal and regulatory territory [83,84]. A key gap is not primarily a research problem but a governance problem: existing regulatory frameworks for grid operations were not designed to accommodate AI-driven decision-making, and no clear framework currently exists for assigning responsibility when an AI-based demand response system or protection relay makes a decision that leads to an adverse outcome. Resolving this gap requires collaboration between power engineers, AI researchers, legal scholars, and regulators—a form of interdisciplinary engagement that the research community has

not yet meaningfully organized. This concern also extends to the specific risks of large language models in grid operations, where hallucination, prompt injection, and biased recommendations become novel threat vectors that are not addressed by existing grid security frameworks [84]. Given the rapid proliferation of LLM-based tools in enterprise applications, this is a concern that may move from theoretical to operational much faster than the research community is currently prepared for.

The ethical and social dimensions of AI in smart grids reveal a further and deeper gap [85,86]: the near-complete absence of empirical research on how AI deployment actually affects different stakeholder groups, including low-income consumers, communities in proximity to AI-optimized generation facilities, and workers whose roles are affected by grid automation. The existing ethical literature is almost entirely theoretical, consisting of frameworks, principles, and calls to action rather than documented impacts. This theoretical character is understandable given the early stage of operational AI deployment, but it means that the ethical case for—and against—specific AI applications in smart grids currently rests on assertion rather than evidence.

4.6. Discussion on Emerging Technologies: Digital Twins, Blockchain, IoT and Edge Computing

The emerging technologies cluster documents a clear and significant trend: AI in smart grids is increasingly being designed not as a standalone capability but as one component of an integrated technological ecosystem that combines digital twins, blockchain, federated learning, IoT sensing, and edge computing. This integration trend is driven by genuine functional complementarity: digital twins provide safe simulation environments for AI learning and validation; blockchain provides the trust substrate necessary for AI-driven peer-to-peer energy trading; federated learning enables privacy-preserving distributed model training across multiple utilities; and edge computing enables low-latency AI inference without the bandwidth and latency penalties of centralized cloud processing.

The partial integrations documented in the primary corpus—AI with blockchain [44,89], AI with digital twins [87,88], and federated learning with edge-cloud collaboration [94]—all demonstrate the feasibility and functional value of pairwise technology integration. The federated learning contribution is particularly significant because it simultaneously addresses two of the most critical barriers to AI adoption: data privacy and communication bandwidth. By training AI models locally on edge devices and sharing only model parameters rather than raw data, federated learning enables collaborative intelligence across the entire grid without requiring any utility to expose sensitive consumer or operational data to external parties.

However, a critical gap persists: no study in the primary corpus demonstrates the integration of more than two technologies in a coherent, end-to-end architecture validated at operational scale. The full potential of the AI-digital twin-blockchain-edge computing ecosystem will only be realized when these technologies are seamlessly combined in a unified architecture that addresses interoperability, data synchronization, security, and latency simultaneously. The engineering challenges involved in achieving this integration are substantial and currently underaddressed in the research literature. Furthermore, the computational and energy costs of operating these multi-technology systems are rarely reported, raising questions about their economic viability and their net environmental benefit—a concern directly relevant to sustainability dimensions highlighted in the supplementary synthesis [105].

4.7. Connecting Themes: Cross-Cluster Insights

Beyond the cluster-specific observations above, several cross-cutting insights emerge from a synthetic reading of the full primary corpus that are not visible within any single thematic cluster.

- **The interpretability-security nexus.** The cybersecurity and XAI clusters, typically treated as independent research domains, are in fact deeply interlinked. AI-based intrusion detection systems that cannot explain their alerts are not merely less trusted—they are operationally less effective, because operators who cannot understand an alert cannot verify it, cannot prioritize it appropriately, and cannot learn from it. The adversarial vulnerability of opaque deep learning models is further compounded by the absence of explainability: a model that cannot explain why it classified an input as benign cannot help operators identify when its judgment has been manipulated. Bringing XAI methods into cybersecurity AI is therefore not a secondary enhancement but a core architectural requirement.
- **The data-deployment paradox.** Across all technical clusters, the most data-rich and computationally sophisticated studies tend to be the least operationally grounded. The inverse relationship between algorithmic complexity and deployment readiness is a paradox that the research community has not directly confronted. High-performance deep learning models trained on large, curated datasets frequently fail when exposed to the messy, incomplete, and distribution-shifted data of real operational environments. More research investment in robust, low-data, and transfer-learning approaches—even if they produce lower accuracy on benchmark datasets—may ultimately advance operational deployment faster than continued refinement of state-of-the-art models on idealized data.
- **The ethics-deployment gap.** The ethical literature identifies data privacy, algorithmic bias, and social equity as central concerns for AI deployment in smart grids, but these concerns are almost entirely absent from the technical studies in energy management, cybersecurity, and renewable integration clusters. This disconnect means that the technical solutions being advanced in the primary corpus are designed without explicit consideration of the ethical constraints they will ultimately face in deployment. Integrating ethical requirements—including fairness constraints, privacy budgets, and equity impact assessments—into the design of AI systems from the outset, rather than applying them as post hoc filters, should be a standard research practice.
- **Validation depth and evaluation scope.** A further cross-cutting distinction concerns not only where the reviewed methods are validated but also which dimensions of performance are evaluated. The representative evidence presented in Table 9 shows a strong concentration on simulation-based validation and task-specific performance measures, including MAPE, classification accuracy, detection rate, and attack success rate. By contrast, only a smaller subset reports deployment-oriented dimensions such as inference latency, formal disturbance-rejection bounds, resilience under attack, transient-stability margins, or explanation quality. Scalability and adversarial resilience are more frequently identified as limitations than evaluated directly. The converter-level studies reviewed in Section 3.4.1 partially address this limitation by extending evaluation beyond predictive accuracy to disturbance rejection, cyber-physical resilience, converter efficiency, and transient stability. Deployment readiness therefore cannot be inferred from accuracy alone; it requires evidence concerning robustness, latency, scalability, adversarial resilience, explainability, and validation under progressively more realistic conditions, ranging from simulation to hardware-in-the-loop or laboratory testing and field deployment.
- **Risk tolerance and interpretability across application types.** Forecasting AI, control AI, and cybersecurity AI have different operational risk profiles and therefore require different levels of interpretability and tolerance for implementation uncertainty. Forecasting models are commonly used in advisory, scheduling, or receding-horizon applications, where prediction errors can often be mitigated through updated forecasts,

operating reserves, or human intervention. Their tolerance for uncertainty is therefore generally higher than that of autonomous closed-loop control, although inaccurate forecasts may still produce significant operational and economic consequences. Control AI, particularly converter-level and grid-forming control, has substantially lower tolerance for uncertainty because an erroneous action may propagate through the physical system on sub-second or millisecond timescales. Cybersecurity AI presents asymmetric error consequences: false-positive alerts may increase operator workload, whereas false negatives or successful adversarial evasion may allow malicious activity to remain undetected. Despite these differences, the XAI literature reviewed in Section 3.6 remains concentrated primarily on forecasting, while explainability is rarely incorporated into control and cybersecurity applications. This pattern suggests an inverse alignment between operational risk and current interpretability provision and reinforces the broader finding that research investment and methodological maturity are not yet proportionate to safety-critical deployment needs.

4.8. Theoretical Implications

The synthesis presented in this review carries three principal theoretical implications that extend beyond the specific domain of AI in smart grids.

- **The limits of the data-driven paradigm.** The dominant paradigm in AI research—learning from data without incorporating domain knowledge—has produced remarkable results in perception, language, and game-playing tasks. In the smart grid context; however, this paradigm encounters structural constraints that are unlikely to be overcome by scaling alone. Grid data are sparse in fault events, heterogeneous across configurations, sensitive to distribution, and governed by physical laws that pure data-driven models do not respect. The theoretical implication is that hybrid approaches combining physics-informed models with data-driven learning represent not merely a pragmatic compromise but a principled theoretical advance for physical infrastructure domains. The emerging literature on physics-informed neural networks and constraint-aware reinforcement learning provides the conceptual foundation for this shift, but it remains far from mainstream adoption in the smart grid research community.
- **AI as a sociotechnical, not merely technical, system.** The persistent failure to close the deployment gap documented across all thematic clusters suggests that conceptualizing AI purely as a technical artifact—defined by its architecture, training procedure, and benchmark performance—is fundamentally inadequate for infrastructure applications. AI systems deployed in smart grids are embedded in social and institutional contexts that co-determine their effectiveness, their trustworthiness, and their distributional consequences. Theoretical frameworks that treat organizational behavior, regulatory structure, operator cognition, and consumer behavior as boundary conditions rather than integral components of the AI system are likely to produce insights that do not transfer from the laboratory to operational deployment. The theoretical implication is a call for sociotechnical AI frameworks that model the human and institutional dimensions of AI deployment as first-class research objects, not implementation afterthoughts.
- **The adversarial equilibrium problem.** The cybersecurity literature reveals that AI-based defense and AI-based attack co-evolve in an adversarial equilibrium: improvements in detection capability create selection pressure for more sophisticated attacks, which in turn drive further defense innovations. This dynamic is structurally different from the optimization problems that dominate the energy management and forecasting literature, and it requires different theoretical tools—game theory, mechanism

design, and robust optimization—that are not yet mainstream in the smart grid AI literature. Developing theoretical frameworks that treat the AI-in-cybersecurity problem as an adversarial game rather than a classification or optimization problem would substantially advance both the scientific understanding and the practical design of secure AI systems for grid infrastructure.

4.9. Practical Implications

4.9.1. Implementation Roadmap for Utilities

The findings of this review support a phased, risk-stratified adoption posture tailored to utility maturity and data availability:

- **Phase 1 (Immediate, 0–12 months)—Low-Risk AI Applications:**
- **Load forecasting**—highest evidence quality, lowest deployment risk
 - Data requirement: Sufficient smart-meter or AMI coverage, historical depth, data completeness, and temporal resolution to support locally validated forecasting;
 - Expected outcome: improved forecasting accuracy relative to the utility’s existing baseline, with the magnitude established through local validation;
 - Success criteria: The model should be evaluated over an appropriately long held-out period before operational deployment;
 - Organizational requirement: Data science team with ML expertise; forecast accuracy monitoring dashboard.
- **Demand response optimization**—moderate risk, high business value
 - Data requirement: AMI data with customer coverage and temporal resolution appropriate to the intended demand-response application;
 - Expected outcome: measurable peak-load and consumer-cost reductions, quantified through a utility-scale pilot;
 - Success criteria: Pilot on single distribution substation before network-wide rollout; independent verification of cost savings claims;
 - Organizational requirement: Advanced meter reading (AMR) vendor partnership; SCADA integration.
- **Phase 2 (Medium-term, 12–36 months)—Moderate-Risk Applications with Human-in-the-Loop:**
- **Anomaly detection for fraud/theft**—high business impact; model explainability essential
 - Data requirement: Historical consumption data + known fraud incidents for model training
 - Expected outcome: improved identification of non-technical losses, subject to false-positive monitoring and human review.
 - Success criteria: **Human operator review required** for all alerts before investigation dispatch; monthly false-positive rate audit.
 - Organizational requirement: Fraud analytics team; integration with customer service for alert investigation.
- **Cybersecurity and intrusion detection**—not recommended for autonomous operation
 - Data requirement: Network traffic logs; SCADA historian data
 - Expected outcome: earlier and more reliable identification of known attack patterns; no universal detection rate is assumed.
 - Success criteria: AI-generated alerts inform human security analysts; final decision to isolate/respond remains with security ops center

- Organizational requirement: CISO approval; incident response runbooks; integration with SIEM (Security Information and Event Management)
- **Phase 3 (Long-term, 36+ months)—Advanced Applications with Proven Track Record:**
- **Fault detection and predictive maintenance**—highest technical complexity; requires proven generalisability
 - Prerequisites: Successful completion of Phase 1 and 2; demonstrated model performance on diverse equipment types
 - Expected outcome: earlier identification of incipient faults and a potential reduction in unplanned outages; these are aspirational objectives requiring field validation.
 - Success criteria: Cross-utility validation; deployment of physics-informed models, not pure data-driven.
 - Organizational requirement: Investment in high-fidelity sensor networks; collaboration with equipment manufacturers.
- **Real-time grid control (if at all)—only after regulatory clarity achieved**
 - Prerequisites: Regulatory approval; demonstrated trustworthiness framework; real-time performance validation.
 - Organizational requirement: Completely separate control systems; automatic fall-back to human-operated grid on AI system failure.

4.9.2. Regulatory and Compliance Alignment

The following as shown in Table 11 regulatory frameworks govern or will govern AI deployment in energy systems:

Table 11. Relevant regulatory and standardisation frameworks for AI-enabled smart grid systems.

Framework	Scope	Implication for AI Systems
NERC CIP (Critical Infrastructure Protection)	Cybersecurity for bulk electric system-connected infrastructure	AI-based detection and control-support systems must not introduce new cyber vulnerabilities. Their decisions, alerts, and data exchanges should be traceable through audit trails.
IEC 62351	Information security for power system communication networks	Communication data used by AI systems should comply with encryption, authentication, and secure information-exchange requirements.
EU AI Act	AI risk classification and transparency requirements for high-risk applications	AI-enabled smart grid control, monitoring, and decision-support tools may require documented risk assessment, human oversight, auditability, and transparent system behavior.
IEEE 2700	Application of AI and autonomous systems to power and energy systems	Provides guidance on safety validation, performance metrics, cybersecurity requirements, and operational reliability for AI applications in power and energy systems.
Regional grid codes and market rules	Grid operation, reliability, interconnection, and market participation requirements	AI-driven demand response, forecasting, dispatch, and converter-control applications should comply with response-time, reliability, validation, and market-audit requirements.

- **Utility Actions:**

1. Designate an AI governance officer responsible for regulatory compliance and ethical auditing.
2. For each AI deployment, document: (a) regulatory jurisdiction(s); (b) applicability of AI Act/NERC/IEEE standards; (c) required audit trails and monitoring.
3. Develop data governance policies aligned with EU GDPR or equivalent (even if outside EU, privacy-by-design is emerging best practice).

4. Establish vendor contracts requiring: data lineage documentation, model explainability, IP ownership clarity.

4.9.3. Data Infrastructure as a Foundation

The most consequential investment a utility can make is not in AI algorithms, but in data infrastructure:

1. Smart-meter and AMI coverage: Utilities should progressively expand metering coverage and improve data quality. The required coverage should be determined by the network characteristics and intended AI application rather than by a universal percentage threshold.
2. Data governance: Establish clear ownership, access, retention, and deletion policies; implement anonymization for cross-utility data sharing.
3. Cross-utility data sharing: Collaborate on federated learning agreements (see Section 3.7) to enable model training without exposing raw consumer data.
4. Data quality auditing: Regular checks on meter accuracy, missingness, and outliers; document and handle data quality issues explicitly in AI model evaluation.

4.9.4. For Policymakers and Regulators

Three regulatory priorities emerge:

1. Accountability frameworks—Develop clear assignment of responsibility when AI-driven decisions cause adverse outcomes (blackouts, consumer harm). Current utility liability frameworks assume human operators; AI complicates assignment.
2. Data governance standards—Actively incentivize privacy-preserving data sharing (federated learning, differential privacy) through regulatory relief or subsidy.
3. Ethical standards—Incorporate fairness, transparency, and equity audits as preconditions for AI system certification, not voluntary post-deployment assessments.

4.10. Limitations of This Review

Notwithstanding the rigor of the methodology described in Section 2, this review is subject to several limitations that should inform the interpretation of its findings.

- **Database and language coverage.** The primary search was conducted across six major scholarly databases and restricted to English-language publications, while these databases provide broad international coverage, research published in other languages or indexed in specialized regional repositories may have been missed. Research programs in China, Germany, Japan, and South Korea—all of which have significant national smart grid initiatives—may be underrepresented, introducing a potential geographic and linguistic bias whose magnitude cannot be precisely quantified.
- **Search string sensitivity.** Despite efforts to design a comprehensive search string incorporating terms for microgrids, distributed energy resources, and demand response, the search is inherently bounded by the vocabulary choices made at protocol design. Studies using unconventional terminology, discipline-specific nomenclature, or emerging concepts not yet established in indexed vocabulary may have been missed. A formal sensitivity analysis of the search string was not conducted, which represents a methodological gap relative to best-practice SLR standards.
- **Preprint inclusion.** A small number of studies meeting explicit citation threshold criteria were included despite being available only as preprints at the time of the search. Each such inclusion was individually justified, but this introduces a degree of methodological flexibility. Readers should independently verify the current publication status of these works, as peer review outcomes may have changed since the search date.

- **Temporal limitation.** The search was conducted in January 2026, and the field is evolving at a pace that makes any systematic review a snapshot in time. High-impact studies published after the search date are not represented. The 2025 figures reported in Section 3.1 necessarily underrepresent the complete 2025 literature, as the search captured only publications available before the January 2026 cutoff. Because the search was conducted in January 2026 while this manuscript is being submitted in June 2026, studies published in the intervening five months are not reflected in the corpus, the PRISMA flow diagram, or the quantitative trend analysis in Section 3.1; at the corpus's current growth rate (Figure 2), this window plausibly contains an additional 10–15 eligible studies, and the 2025–2026 segment of Figure 2 should be read as a lower bound rather than a complete count.
- **Thematic cluster imbalance.** The number of included studies varies substantially across thematic clusters, ranging from eight studies in fault detection to over twenty in energy management and cybersecurity. This imbalance reflects the actual distribution of research activity in the field rather than any artifact of the search process. However, conclusions drawn from smaller clusters—particularly fault detection and XAI—rest on a thinner evidence base and should be interpreted with proportionally greater caution.
- **Subjectivity in screening.** Despite two independent reviewers and clearly defined criteria, the screening and eligibility assessment process retains an inherent element of interpretive judgment. Different reviewers might have reached different conclusions about borderline cases. This risk was mitigated through structured consensus procedures and explicit documentation of exclusion rationales but cannot be entirely eliminated.
- **Scope limitation—electricity markets.** AI applications to electricity-market design, bidding strategy, and price formation are not treated as a standalone thematic cluster in this review; relevant studies are captured incidentally within the Energy Management (Section 3.2) and Emerging Technologies (Section 3.7, peer-to-peer trading) clusters but were not targeted by dedicated search terms. This cluster may therefore be underrepresented, and we identify it as a candidate eighth cluster for a follow-on review in Section 5.
- **Certainty of cluster-level conclusions.** Because the fault-detection (8 studies) and XAI/ethics (8 studies) clusters rest on markedly fewer primary studies than energy management (24) or cybersecurity (23), the conclusions drawn about these two smaller clusters—including the 'critical gap' framing in Sections 3.5 and 3.6—carry proportionally lower statistical and evidentiary certainty and should be treated as preliminary signals warranting further investigation rather than as settled findings.

5. Future Research Directions

The findings of this review indicate that future research should move beyond isolated algorithmic improvements and focus more strongly on validation, robustness, explainability, and deployment in power-electronic-rich smart grids and microgrids. Seven priority directions are identified.

Generalizability and transfer learning. Future studies should develop AI models that can be transferred across different grid topologies, climatic conditions, regulatory environments, and levels of renewable energy penetration. This is particularly important for converter-dominated networks, where operating conditions can vary significantly between systems. Cross-grid validation should become a standard requirement rather than an optional extension. The converter-level robust and resilient control literature reviewed in Section 3.4.1 offers a concrete test bed for generalizability claims, since converter behavior

is among the dimensions most sensitive to grid topology, climatic operating range, and protection-coordination practice.

Adversarial robustness and certified cybersecurity. AI-based intrusion detection and protection systems should be designed with formal robustness guarantees against false data injection, data poisoning, and adversarial evasion attacks. Standardized adversarial benchmarks for smart grid AI are needed to support fair comparison between methods and to improve confidence in safety-critical deployment.

Explainability under real-time constraints. Explainable AI should be extended beyond forecasting applications to real-time protection, converter control, cybersecurity alerting, and fault diagnosis. Future models should provide operator-actionable explanations within the time constraints required by smart grid and microgrid operation.

Privacy-preserving collaborative learning. Federated learning and edge-based AI should be further investigated to enable collaborative model training across utilities while preserving consumer privacy and reducing communication requirements. This is especially relevant for smart meters, EV charging networks, distributed storage systems, and microgrid controllers.

Large-scale empirical deployment studies. More research is needed on real-world AI deployment in operational grid environments. Longitudinal studies across multiple utilities, microgrids, and renewable-energy-rich distribution networks would help close the gap between simulation-based performance and practical reliability.

Ethical, regulatory, and accountability frameworks. Future work should address the social, regulatory, and institutional dimensions of AI deployment. This includes accountability for AI-assisted operational decisions, fairness in demand response programs, privacy protection, and certification requirements for safety-critical grid applications.

Electricity-market-aware AI. Future research should examine AI applications in electricity-market design, market-price forecasting, bidding strategy, market clearing, peer-to-peer energy trading, ancillary-service participation, and the coordination of distributed energy resources across physical and market layers. Particular attention should be given to explainability, strategic manipulation, fairness, regulatory compliance, and the integration of market decisions with network stability and power-electronic operating constraints. A dedicated systematic review using market-specific search terms would also be valuable because this application area was not comprehensively captured by the present search strategy.

Overall, future research should treat robustness, explainability, and regulatory compatibility as design requirements from the beginning, rather than as post-processing additions after model development.

6. Conclusions

This systematic literature review examined 87 primary research studies on artificial intelligence in smart grids and microgrids, complemented by a supplementary synthesis of 18 bibliometric and contextual studies. The review shows that AI has become a central enabling technology for energy management, load forecasting, renewable energy integration, cybersecurity, and emerging digital grid architectures. Deep learning, reinforcement learning, ensemble learning, digital twins, blockchain, edge computing, and federated learning are increasingly used to improve the flexibility, intelligence, and resilience of modern power systems.

The analysis also shows that the literature is unevenly developed. Energy management and cybersecurity are the most mature and active research areas, whereas fault detection, explainable AI, and real-time safety-critical deployment remain underdeveloped. This imbalance is particularly important for power-electronic-interfaced grids, where inverter-

based resources, EV chargers, battery systems, and converter-dominated microgrids require fast, reliable, and explainable decision-making.

In relation to RQ1, reinforcement learning is particularly suitable for sequential demand-side scheduling, while deep, hybrid, and ensemble models report strong forecasting performance. However, differences in datasets, forecast horizons, evaluation metrics, and validation procedures prevent a universal ranking and limit claims of operational effectiveness. Regarding RQ2, machine learning and graph-based deep learning methods are widely applied to intrusion and false-data-injection detection, although adversarial robustness and explainability remain limited. Regarding RQ3, digital twins, blockchain, federated learning, and edge computing are the principal converging technologies, but their end-to-end integration and operational validation remain incomplete.

The main conclusion is that AI has considerable potential to support the transition towards smarter, cleaner, and more resilient power systems, but large-scale deployment still depends on solving challenges related to generalizability, adversarial robustness, explainability, data quality, and governance. Therefore, the next stage of research should prioritize validated, trustworthy, and regulation-ready AI systems that can operate reliably in real smart grid and microgrid environments. The findings provide a structured evidence base for future research and practical deployment of trustworthy AI-enabled smart grids while highlighting the critical need to bridge AI-driven supervisory intelligence with converter-aware control, cyber resilience, and real-world validation.

Author Contributions: Conceptualization, R.A., M.A.-S., and O.A.; methodology, R.A., M.A.-S., A.S., D.D.-C.L., and O.A.; software, R.A., M.A.-S., and O.A.; validation, R.A., M.A.-S., and A.S.; formal analysis R.A. and M.A.-S.; investigation, M.A.-S.; resources, A.S.; data curation, R.A., M.A.-S., A.S., and O.A.; writing—original draft preparation, R.A., M.A.-S., and O.A.; writing—review and editing, R.A., M.A.-S., A.S., and D.D.-C.L.; visualization, R.A., M.A.-S., A.S., and O.A.; supervision, M.A.-S. and A.S.; project administration, D.D.-C.L.; funding acquisition, A.S. and D.D.-C.L.; All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. This systematic literature review is based on previously published studies, and all data supporting the reported findings are available within the cited literature.

Acknowledgments: During the preparation of this manuscript, the authors used ChatGPT-Plus for language editing, improvement of clarity, LaTeX formatting support, and manuscript polishing. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Massaoudi, M.; Abu-Rub, H.; Refaat, S.S.; Chihi, I.; Oueslati, F.S. Deep Learning in Smart Grid Technology: A Review of Recent Advancements and Future Prospects. *IEEE Access* **2021**, *9*, 54558–54578. <https://doi.org/10.1109/ACCESS.2021.3071269>.
2. Lampropoulos, G. Blockchain in Smart Grids: A Bibliometric Analysis and Scientific Mapping Study. *J* **2024**, *7*, 19–47. <https://doi.org/10.3390/j7010002>.
3. Huang, Y.; Huo, S.; Dong, Y. Exploring the Role of AI in Smart Grids: A 20-Year Bibliometric-Based Overview. *Int. J. Gen. Syst.* **2026**, *55*, 523–554. <https://doi.org/10.1080/03081079.2025.2547187>.
4. Jiao, J. Application and prospect of artificial intelligence in smart grid. *IOP Conf. Ser. Earth Environ. Sci.* **2020**, *510*, 022012. <https://doi.org/10.1088/1755-1315/510/2/022012>.

5. Gupta, V. Artificial Intelligence (AI) Applications and Techniques in Smart Grid. In *Proceedings of the ISGW 2018 Compendium of Technical Papers*; Springer: Singapore, 2020; pp. 223–233. https://doi.org/10.1007/978-981-32-9119-5_19
6. Mahmud, A.R. The Role of Artificial Intelligence in Advancing Smart Grid Technologies. *Eur. J. Sci. Mod. Technol.* **2025**, *1*, 1–13. [https://doi.org/10.59324/ejsmt.2025.1\(3\).01](https://doi.org/10.59324/ejsmt.2025.1(3).01).
7. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. <https://doi.org/10.1136/bmj.n71>.
8. Landis, J.R.; Koch, G.G. The Measurement of Observer Agreement for Categorical Data. *Biometrics* **1977**, *33*, 159–174. <https://doi.org/10.2307/2529310>.
9. Dasgupta, D.; Mondal, A.; Chakrabarti, P.P. Smart Scheduling of Home Appliances Using Happiness Aware Scalable Reinforcement Learning Agent. In *Proceedings of the Soft Computing and Its Engineering Applications*; Patel, K.K., Santosh, K., Gomes de Oliveira, G., Patel, A., Ghosh, A., Eds.; Springer: Cham, Switzerland, 2025; pp. 377–391. https://doi.org/10.1007/978-3-031-88042-1_29.
10. Rocha, H.R.; Honorato, I.H.; Fiorotti, R.; Celeste, W.C.; Silvestre, L.J.; Silva, J.A. An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes. *Appl. Energy* **2021**, *282*, 116145. <https://doi.org/10.1016/j.apenergy.2020.116145>.
11. Zhou, S.; Hu, Z.; Gu, W.; Jiang, M.; Zhang, X.P. Artificial intelligence based smart energy community management: A reinforcement learning approach. *Csee J. Power Energy Syst.* **2019**, *5*, 1–10. <https://doi.org/10.17775/CSEEJPES.2018.00840>.
12. Pathak, A.K.; Chatterji, D.S.; Narkhede, M.S. Artificial intelligence based optimization algorithm for demand response management of residential load in smart grid. *Int. J. Eng. Innov. Technol. (IJEIT)* **2012**, *2*, 136–141.
13. Nagathimmaiah, P.; Lalitha, S.V.N.L. Artificial intelligence based phase balancing in the smart grid. *Aip Conf. Proc.* **2024**, *2512*, 020103. <https://doi.org/10.1063/5.0117013>.
14. Raspopov, D.; Belousov, P. Development of methods and algorithms for identification of a type of electric energy consumers using artificial intelligence and machine learning models for Smart Grid Systems. *Procedia Comput. Sci.* **2020**, *169*, 597–605. <https://doi.org/10.1016/j.procs.2020.02.204>.
15. Khan, M.A.; Saleh, A.M.; Waseem, M.; Sajjad, I.A. Artificial Intelligence Enabled Demand Response: Prospects and Challenges in Smart Grid Environment. *IEEE Access* **2023**, *11*, 1477–1505. <https://doi.org/10.1109/ACCESS.2022.3231444>.
16. Tiwari, S.; Jain, A.; Yadav, K.; Ramadan, R. Machine Learning-Based Model for Prediction of Power Consumption in Smart Grid. *Int. Arab. J. Inf. Technol. (IAJIT)* **2022**, *19*, 323–329. <https://doi.org/10.34028/iajit/19/3/5>.
17. Souhe, F.G.Y.; Mbey, C.F.; Boum, A.T.; Ele, P. Forecasting of Electrical Energy Consumption of Households in a Smart Grid. *Int. J. Energy Econ. Policy* **2021**, *11*, 221–233. <https://doi.org/10.32479/ijeeep.11761>.
18. Bhutta, M.S.; Li, Y.; Abubakar, M.; Almasoudi, F.M.; Alatawi, K.S.S.; Altimania, M.R.; Al-Barashi, M. Optimizing solar power efficiency in smart grids using hybrid machine learning models for accurate energy generation prediction. *Sci. Rep.* **2024**, *14*, 17101. <https://doi.org/10.1038/s41598-024-68030-5>.
19. Ahamed, A.; Tarafder, M.T.R.; Rimon, S.T.H.; Hasan, E.; Al Amin, M. Optimizing Load Forecasting in Smart Grids with AI-Driven Solutions. In *Proceedings of the 2024 IEEE International Conference on Data and Software Engineering (ICoDSE)*, Gorontalo, Indonesia, 30–31 October 2024; pp. 182–187. <https://doi.org/10.1109/ICoDSE63307.2024.10829903>.
20. Janjua, J.I.; Ahmad, R.; Abbas, S.; Mohammed, A.S.; Khan, M.S.; Daud, A.; Abbas, T.; Khan, M.A. Enhancing smart grid electricity prediction with the fusion of intelligent modeling and XAI integration. *Int. J. Adv. Appl. Sci.s* **2024**, *11*, 230–248. <https://doi.org/10.21833/ijaas.2024.05.025>.
21. Ahmed, A.A.; Nassar, Y.F.; Abdulla, N.M.; Bashir, A.M. AI-Powered Energy forecasting: ANext-Gen approach for smart grids and sustainable power systems. *Eurasian J. Theor. Appl. Sci. (EJTAS)* **2025**, *1*, 1–15. <https://doi.org/10.32213/w4zdxg34>.
22. Jing, Z.; Wang, Q.; Chen, Z.; Cao, T.; Zhang, K. Optimization of energy acquisition system in smart grid based on artificial intelligence and digital twin technology. *Energy Inform.* **2024**, *7*, 121. <https://doi.org/10.1186/s42162-024-00425-0>.
23. Nayyef, Z.T.; Abdulrahman, M.M.; Kurdi, N.A. Optimizing Energy Efficiency in Smart Grids Using Machine Learning Algorithms: A Case Study in Electrical Engineering. *Shifra* **2024**, *2024*, 46–54. <https://doi.org/10.70470/SHIFRA/2024/006>.
24. Cestero, J.; Delle Femine, C.; Muro, K.S.; Quartulli, M.; Restelli, M. Optimizing Energy Management of Smart Grid Using Reinforcement Learning Aided by Surrogate Models Built Using Physics-Informed Neural Networks. *Appl. Energy* **2025**, *401*, 126192. <https://doi.org/10.1016/j.apenergy.2025.126192>.
25. Diamantoulakis, P.D.; Kapinas, V.M.; Karagiannidis, G.K. Big Data Analytics for Dynamic Energy Management in Smart Grids. *Big Data Res.* **2015**, *2*, 94–101. <https://doi.org/10.1016/j.bdr.2015.03.003>.
26. Soliman Qudaih, Y.; Mitani, Y. Power Distribution System Planning for Smart Grid Applications using ANN. *Energy Procedia* **2011**, *12*, 3–9. <https://doi.org/10.1016/j.egypro.2011.10.003>.
27. Chen, X.; Cao, W.; Zhang, Q.; Hu, S.; Zhang, J. Artificial Intelligence-Aided Model Predictive Control for a Grid-Tied Wind-Hydrogen-Fuel Cell System. *IEEE Access* **2020**, *8*, 92418–92430. <https://doi.org/10.1109/ACCESS.2020.2994577>.

28. Altin, N.; Eyimaya, S.E. Artificial Intelligence Applications for Energy Management in Microgrid. In Proceedings of the 2023 11th International Conference on Smart Grid (icSmartGrid), Paris, France, 4–7 June 2023; pp. 1–6. <https://doi.org/10.1109/icSmartGrid58556.2023.10170860>.
29. Iyaniwura, A.A.; Mayaki, C.S. Artificial Intelligence-enabled smart grid systems for real-time load forecasting, fault detection, renewable energy integration and optimization. *Glob. J. Eng. Technol. Adv.* **2025**, *24*, 191–208. <https://doi.org/10.30574/gjeta.2025.24.3.0272>.
30. Klaimi, J.; Rahim-Amoud, R.; Merghem-Boulahia, L.; Jrad, A. Energy management algorithms in smart grids: State of the art and emerging trends. *Int. J. Artif. Intell. Appl. (IJAIA)* **2016**, *7*, 25–45. <https://doi.org/10.5121/ijaia.2016.7403>.
31. Chaurasia, K.; Kamath, H.R. New approach using artificial intelligence-machine learning in demand side management of renewable energy integrated smart grid for smart city. In Proceedings of the International Conference on Innovative Computing & Communication (ICICC), Delhi, India, 20–21 February 2021. <https://doi.org/10.2139/ssrn.3833753>.
32. Jain, N.; Pillai, B.; Singh, N. Green IoT-based smart grid: implementing intelligent demand-response systems for energy sustainability. In Proceedings of the 2025 2nd International Conference on Research Methodologies in Knowledge Management, Artificial Intelligence and Telecommunication Engineering (RMKMATE), Chennai, India, 7–8 May 2025; pp. 1–6. <https://doi.org/10.1109/RMKMATE64874.2025.11042574>.
33. Takiddin, A.; Ismail, M.; Atat, R.; Davis, K.R.; Serpedin, E. Robust Graph Autoencoder-Based Detection of False Data Injection Attacks Against Data Poisoning in Smart Grids. *IEEE Trans. Artif. Intell.* **2024**, *5*, 1287–1301. <https://doi.org/10.1109/TAI.2023.286831>.
34. Takiddin, A.; Ismail, M.; Atat, R.; Serpedin, E. Spatio-temporal Graph-Based Generation and Detection of Adversarial False Data Injection Evasion Attacks in Smart Grids. *IEEE Trans. Artif. Intell.* **2024**, *5*, 6601–6616. <https://doi.org/10.1109/TAI.2024.3464511>.
35. Mohammadpourfard, M.; Weng, Y.; Pechenizkiy, M.; Tajdinian, M.; Mohammadi-Ivatloo, B. Ensuring cybersecurity of smart grid against data integrity attacks under concept drift. *Int. J. Electr. Power Energy Syst.* **2020**, *119*, 105947. <https://doi.org/10.1016/j.ijepes.2020.105947>.
36. Ozay, M.; Esnaola, I.; Yarman Vural, F.T.; Kulkarni, S.R.; Poor, H.V. Machine Learning Methods for Attack Detection in the Smart Grid. *IEEE Trans. Neural Netw. Learn. Syst.* **2016**, *27*, 1773–1786. <https://doi.org/10.1109/TNNLS.2015.2404803>.
37. Diaba, S.Y. The Role of Machine Learning Algorithms in Smart Grid Cybersecurity. In Proceedings of the 2024 International Workshop on Artificial Intelligence and Machine Learning for Energy Transformation (AIE), Vaasa, Finland, 20–22 May 2024; pp. 1–7. <https://doi.org/10.1109/AIE61866.2024.10561386>.
38. Khan, S.; Kifayat, K.; Kashif Bashir, A.; Gurtov, A.; Hassan, M. Intelligent intrusion detection system in smart grid using computational intelligence and machine learning. *Trans. Emerg. Telecommun. Technol.* **2021**, *32*, e4062. <https://doi.org/10.1002/ett.4062>.
39. Ness, S. Adversarial Attack Detection in Smart Grids Using Deep Learning Architectures. *IEEE Access* **2025**, *13*, 16314–16323. <https://doi.org/10.1109/ACCESS.2024.3523409>.
40. Ustun, T.S.; Hussain, S.M.S.; Yavuz, L.; Onen, A. Artificial Intelligence Based Intrusion Detection System for IEC 61850 Sampled Values Under Symmetric and Asymmetric Faults. *IEEE Access* **2021**, *9*, 56486–56495. <https://doi.org/10.1109/ACCESS.2021.3071141>.
41. Saredidine, K.; Sayed, M.A.; Torabi, S.; Atallah, R.; Assi, C. Edge-based detection and localization of adversarial oscillatory load attacks orchestrated by compromised EV charging stations. *Int. J. Electr. Power Energy Syst.* **2024**, *156*, 109735. <https://doi.org/10.1016/j.ijepes.2023.109735>.
42. Efatinasab, E.; Brighente, A.; Rampazzo, M.; Azadi, N.; Conti, M. GAN-GRID: A novel generative attack on smart grid stability prediction. In *Proceedings of the European Symposium on Research in Computer Security*; Springer: Berlin/Heidelberg, Germany, 2024; pp. 374–393. https://doi.org/10.1007/978-3-031-70879-4_19.
43. Sánchez, G.; Elbez, G.; Hagenmeyer, V. Attacking Learning-based Models in Smart Grids: Current Challenges and New Frontiers. In Proceedings of the 15th ACM International Conference on Future and Sustainable Energy Systems, New York, NY, USA, 4–7 June 2024; e-Energy '24; p. 589–595. <https://doi.org/10.1145/3632775.3661984>.
44. Ghadi, Y.Y.; Mazhar, T.; Shahzad, T.; Jaghdam, I.H.; Khan, S.; Khan, M.A.; Hamam, H. A hybrid AI-Blockchain security framework for smart grids. *Sci. Rep.* **2025**, *15*, 20882. <https://doi.org/10.1038/s41598-025-05257-w>.
45. Mir, A.W.; Ramachandran, R.K. Implementation of Security Orchestration, Automation and Response (SOAR) in Smart Grid-Based SCADA Systems. In *Proceedings of the Sixth International Conference on Intelligent Computing and Applications*; Dash, S.S., Panigrahi, B.K., Das, S., Eds.; Springer: Singapore, 2021; pp. 157–169. https://doi.org/10.1007/978-981-16-1335-7_14.
46. Tariq, N.; Alsirhani, A.; Humayun, M.; Alserhani, F.; Shaheen, M. A fog-edge-enabled intrusion detection system for smart grids. *J. Cloud Comput.* **2024**, *13*, 43. <https://doi.org/10.1186/s13677-024-00609-9>.
47. Kulkarni, Y.; Z, S.H.; Ramamritham, K.; Somu, N. EnsembleNTLDetect: An Intelligent Framework for Electricity Theft Detection in Smart Grid. In Proceedings of the 2021 International Conference on Data Mining Workshops (ICDMW), Virtual, 7–10 December 2021; pp. 527–536. <https://doi.org/10.1109/ICDMW53433.2021.00070>.

48. Mbey, C.F.; Bikai, J.; Yem Souhe, F.G.; Foba Kakeu, V.J.; Boum, A.T. Electricity Theft Detection in a Smart Grid Using Hybrid Deep Learning-Based Data Analysis Technique. *J. Electr. Comput. Eng.* **2024**, 2024, 6225510. <https://doi.org/10.1155/2024/6225510>.
49. Munir, M.S.; Shetty, S.; Rawat, D.B. Trustworthy artificial intelligence framework for proactive detection and risk explanation of cyber attacks in smart grid. *arXiv* **2023**, arXiv:2306.07993. <https://doi.org/10.48550/arXiv.2306.07993>.
50. Merza, M.E.; Hussein, S.H.; Ali, Q.I. Identification scheme of false data injection attack based on deep learning algorithms for smart grids. *Indones. J. Electr. Eng. Comput. Sci.* **2023**, 30, 219–228. <https://doi.org/10.11591/ijeecs.v30.i1.pp219-228>.
51. Reka, S.S.; Dragicevic, T.; Venugopal, P.; Ravi, V.; Rajagopal, M.K. Big Data Analytics and Artificial Intelligence Aspects for Privacy and Security Concerns for Demand Response Modelling in Smart Grid: A Futuristic Approach. *Heliyon* **2024**, 10, e35683. <https://doi.org/10.1016/j.heliyon.2024.e35683>.
52. Wasumwa, S.A. Safeguarding the Future: A Comprehensive Analysis of Security Measures for Smart Grids. *World J. Adv. Res. Rev.* **2023**, 19, 847–871. <https://doi.org/10.30574/wjarr.2023.19.1.1387>.
53. Nguyen, L.H.; Nguyen, V.L.; Hwang, R.H.; Kuo, J.J.; Chen, Y.W.; Huang, C.C.; Pan, P.I. Toward Secured Smart Grid 2.0: Exploring Security Threats, Protection Models, and Challenges. *IEEE Commun. Surv. Tutor.* **2025**, 27, 2581–2620. <https://doi.org/10.1109/COMST.2024.3493630>.
54. Zaman, D.; Mazinani, M. Cybersecurity in Smart Grids: Protecting Critical Infrastructure from Cyber Attacks. *Shifra* **2023**, 2023, 86–94. <https://doi.org/10.70470/SHIFRA/2023/010>.
55. Verma, S.; Rao, A. A short report on deep learning synergy for decentralized smart grid cybersecurity. *Front. Artif. Intell.* **2025**, 8, 1557960. <https://doi.org/10.3389/frai.2025.1557960>.
56. Al-Soeidat, M.; Aljarajreh, H.; Khawaldeh, H.; Lu, D.; Zhu, J. A Reconfigurable Three-Port DC–DC Converter for Integrated PV-Battery System. *IEEE J. Emerg. Sel. Top. Power Electron.* **2020**, 8, 3423–3433. <https://doi.org/10.1109/JESTPE.2019.2941595>.
57. Al-Soeidat, M.; Lu, D.; Zhu, J. An Analog BJT-Tuned Maximum Power Point Tracking Technique for PV Systems. *IEEE Trans. Circuits Syst. II Express Briefs* **2019**, 66, 637–641. <https://doi.org/10.1109/TCSII.2018.2865804>.
58. Kuzlu, M.; Cali, U.; Sharma, V.; Güler, Ö. Gaining Insight Into Solar Photovoltaic Power Generation Forecasting Utilizing Explainable Artificial Intelligence Tools. *IEEE Access* **2020**, 8, 187814–187823. <https://doi.org/10.1109/ACCESS.2020.3031477>.
59. Mamodiya, U.; Kishor, I.; Garine, R.; Ganguly, P.; Naik, N. Artificial intelligence based hybrid solar energy systems with smart materials and adaptive photovoltaics for sustainable power generation. *Sci. Rep.* **2025**, 15, 17370. <https://doi.org/10.1038/s41598-025-01788-4>.
60. Rane, N.L. Contribution of ChatGPT and Other Generative Artificial Intelligence (AI) in Renewable and Sustainable Energy. *J. Adv. Artif. Intell.* **2024**, 2, 1–26. <https://doi.org/10.18178/JAAI.2024.2.1.1-26>.
61. Talaat, M.; Elkholy, M.H.; Alblawi, A.; Said, T. Artificial intelligence applications for microgrids integration and management of hybrid renewable energy sources. *Artif. Intell. Rev.* **2023**, 56, 10557–10611. <https://doi.org/10.1007/s10462-023-10410-w>.
62. Şerban, A.C.; Lytras, M.D. Artificial Intelligence for Smart Renewable Energy Sector in Europe—Smart Energy Infrastructures for Next Generation Smart Cities. *IEEE Access* **2020**, 8, 77364–77377. <https://doi.org/10.1109/ACCESS.2020.2990123>.
63. Kulkarni, G.R.; Tamta, M.K.; Kumar, A.; Nomani, M.Z.M.; Singh, C.; Pallathadka, H. The Role of Artificial Intelligence (AI) in Creating Smart Energy Infrastructure for the Next Generation and Protection Climate Change. In *Proceedings of the Second International Conference in Mechanical and Energy Technology*; Yadav, S., Haleem, A., Arora, P.K., Kumar, H., Eds.; Springer: Singapore, 2023; pp. 457–464. https://doi.org/10.1007/978-981-19-0108-9_47.
64. Novati, N.D.; Maulina, S.D.; Smith, S. Smart Grids: Integrating AI for Efficient Renewable Energy Utilization. *Int. Trans. Artif. Intell.* **2024**, 3, 1–11. <https://doi.org/10.33050/italic.v3i1.644>.
65. Mossavar-Rahmani, F.; Zohuri, B. Artificial Intelligence Integration Driven Smart Grid Alternative Transforming the Future With Renewable, and Non-renewable Energy Sources. *Int. J. Adv. Eng. Manag. Res.* **2024**, 9, 14–25. <https://doi.org/10.51505/ijaemr.2024.9402>.
66. Ahmed, M.; Zheng, Y.; Amine, A.; Fathiannasab, H.; Chen, Z. The Role of Artificial Intelligence in the Mass Adoption of Electric Vehicles. *Joule* **2021**, 5, 2296–2322. <https://doi.org/10.1016/j.joule.2021.07.012>.
67. Bose, B.K. Artificial Intelligence Techniques in Smart Grid and Renewable Energy Systems—Some Example Applications. *Proc. IEEE* **2017**, 105, 2262–2273. <https://doi.org/10.1109/jproc.2017.2756596>.
68. Ahmad, T.; Zhang, D.; Huang, C.; Zhang, H.; Dai, N.; Song, Y.; Chen, H. Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities. *J. Clean. Prod.* **2021**, 289, 125834. <https://doi.org/10.1016/j.jclepro.2021.125834>.
69. Rasool, M.A.U.; Khan, M.M.; Ahmed, Z.; Saeed, M.A. Analysis of an H_∞ Robust Control for a Three-Phase Voltage Source Inverter. *Inventions* **2019**, 4, 18. <https://doi.org/10.3390/inventions4010018>.
70. Nasir, M.; Gao, F.; Khan, M.M.; Ahmed, Z.; Ali, K. Resilient control of a building scale DC microgrid in the presence of attacks. *Electr. Power Syst. Res.* **2026**, 254, 112586. <https://doi.org/10.1016/j.epsr.2025.112586>.
71. Lin, P.; Du, L.; Zhang, H.; Zhu, M.; Ma, J.; Wang, P. Power Lever: To Transform Interlinking Architecture in Hybrid AC/DC Microgrids Community. *IEEE Trans. Ind. Electron.* **2026**, 73, 6984–6997. <https://doi.org/10.1109/TIE.2025.3629388>.

72. Lin, P.; Meng, Q.; Zhu, M.; Ghias, A.M.Y.M.; Blaabjerg, F. Dynamic Circuit-Based Unified Power Regulation for Hybrid AC/DC/DS Microgrids: A Comprehensive Approach to Static and Transient Control. *IEEE Trans. Ind. Electron.* **2026**, *73*, 522–533. <https://doi.org/10.1109/TIE.2025.3585029>.
73. Yuan, L.; Hu, M.; Su, M.; Liu, Z.; Sun, Y.; Dong, Z.Y. PCH Theory-Based Energy Reshaping Control for Transient Stability Enhancement of Grid-Connected Grid-Forming Inverters. *IEEE Trans. Ind. Electron.* **2026**, 1–13. <https://doi.org/10.1109/TIE.2026.3690734>.
74. Jia, H.; Zhang, C.; He, L.; Li, J.; Zhu, L.; Zhou, Q.; Shuai, Z.; Sun, X. A Novel Fault Location Method for Unbalanced Active Distribution Networks With Sparse Hybrid Measurements. *IEEE Trans. Smart Grid* **2026**, *17*, 1056–1068. <https://doi.org/10.1109/TSG.2025.3631276>.
75. Sun, L.; Muguira, L.; Jiménez, J.; Lázaro, J.; Yong, W. High Performance Platform to Detect Faults in the Smart Grid by Artificial Intelligence Inference. *IEEE Trans. Smart Grid* **2024**, *15*, 504–512. <https://doi.org/10.1109/TSG.2023.3271001>.
76. Souhe, F.G.Y.; Boum, A.T.; Ele, P.; Mbey, C.F.; Kakeu, V.J.F. Fault Detection, Classification and Location in Power Distribution Smart Grid Using Smart Meters Data. *J. Appl. Sci. Eng.* **2023**, *26*, 23–34. [https://doi.org/10.6180/jase.202301_26\(1\).0003](https://doi.org/10.6180/jase.202301_26(1).0003).
77. Bashir, A.K.; Khan, S.; Prabadevi, B.; Deepa, N.; Alnumay, W.S.; Gadekallu, T.R.; Maddikunta, P.K.R. Comparative Analysis of Machine Learning Algorithms for Prediction of Smart Grid Stability. *Int. Trans. Electr. Energy Syst.* **2021**, *31*, e12706. <https://doi.org/10.1002/2050-7038.12706>.
78. Chhabra, A.; Singh, S.K.; Kumar, S.; Singh, M.; Chauhan, U.; Arora, S.; Alhalabi, W.; Arya, V.; Alsulami, B.S.; Hsu, C.H.; et al. Improving Predictive Reliability and Automation of Smart Grids Using the StarNet Ensemble Model. *Sci. Rep.* **2026**, *16*, 9592. <https://doi.org/10.1038/s41598-025-31479-z>.
79. Hosseinzadeh, J.; Masoodzadeh, F.; Roshandel, E. Fault detection and classification in smart grids using augmented K-NN algorithm. *SN Appl. Sci.* **2019**, *1*, 1627. <https://doi.org/10.1007/s42452-019-1672-0>.
80. Liu, J.; Liu, J.; Lin, K.; Ding, T.; Ren, C.; Yan, R.; Zhao, Y. Enhancing credibility of transient stability assessment under stochastic operation modes in power systems: An incremental dataset recognition approach. *Electr. Power Syst. Res.* **2026**, *253*, 112435. <https://doi.org/10.1016/j.epsr.2025.112435>.
81. Cifci, A. Interpretable Prediction of a Decentralized Smart Grid Based on Machine Learning and Explainable Artificial Intelligence. *IEEE Access* **2025**, *13*, 36285–36305. <https://doi.org/10.1109/ACCESS.2025.3543759>.
82. Alfayan, M.; Hagra, H. Towards an Explainable Artificial Intelligence approach for smart grid systems. *Discov. Artif. Intell.* **2025**, *5*, 40. <https://doi.org/10.1007/s44163-025-00261-5>.
83. Volkova, A.; Patil, A.D.; Javadi, S.A.; de Meer, H. Accountability challenges of AI in smart grid services. In Proceedings of the Thirteenth ACM International Conference on Future Energy Systems, New York, NY, USA, 28 June–1 July 2022; e-Energy '22; pp. 597–600. <https://doi.org/10.1145/3538637.3539636>.
84. Li, J.; Yang, Y.; Sun, J. Risks of Practicing Large Language Models in Smart Grid: Threat Modeling and Validation. *arXiv* **2024**, arXiv:2405.06237. <https://doi.org/10.48550/arXiv.2405.06237>.
85. Robu, V.; Flynn, D.; Andoni, M.; Mokhtar, M. Consider ethical and social challenges in smart grid research. *Nat. Mach. Intell.* **2019**, *1*, 548–550. <https://doi.org/10.1038/s42256-019-0120-6>.
86. Wang, B. Ethical Reflections on the Application of Artificial Intelligence in the Construction of Smart Cities. *J. Eng.* **2024**, *2024*, 8207822. <https://doi.org/10.1155/2024/8207822>.
87. Ahmed, M.; Khan, M.R. Artificial Intelligence-Enabled Digital Twins for Energy Efficiency in Smart Grids. *Rev. Appl. Sci. Technol.* **2025**, *4*, 580–615. <https://doi.org/10.63125/12kp9w74>.
88. Lopez, J.; Rubio, J.E.; Alcaraz, C. Digital Twins for Intelligent Authorization in the B5G-Enabled Smart Grid. *IEEE Wirel. Commun.* **2021**, *28*, 48–55. <https://doi.org/10.1109/MWC.001.2000336>.
89. Singh, K.; Goyal, S.; Rajawat, A.S.; Waked, H.N. A Blockchain-Integrated AI Framework for Enhancing Energy Efficiency and Sustainability in Smart Grids. *Procedia Comput. Sci.* **2025**, *258*, 2302–2311. <https://doi.org/10.1016/j.procs.2025.04.485>.
90. Salama, R.; Altrjman, C.; Al-Turjman, F. Smart Grid Applications and Blockchain Technology in the AI Era. *NEU J. Artif. Intell. Internet Things* **2023**, *1*, 59–63. <https://doi.org/10.54878/jaiit.755>.
91. Salama, R.; Altrjman, S.; Al-Turjman, F. Internet of Things and AI in Smart Grid Applications. *NEU J. Artif. Intell. Internet Things* **2023**, *1*, 44–58. <https://doi.org/10.54878/jaiit.754>.
92. Alwar, B.; Edgardo, H.; Faustino, E. Integrating IoT and Artificial Intelligence for Sustainable Smart City Development: A Case Study Approach. *ITEJ Inf. Technol. Eng. Journals* **2024**, *9*, 80–90. <https://doi.org/10.24235/itej.v9i2.137>.
93. Carrillo, D.; Kalalas, C.; Raussi, P.; Michalopoulos, D.S.; Rodríguez, D.Z.; Kokkonien-Tarkkanen, H.; Ahola, K.; Nardelli, P.H.; Fraidenraich, G.; Popovski, P. Boosting 5G on Smart Grid Communication: A Smart RAN Slicing Approach. *IEEE Wirel. Commun.* **2023**, *30*, 170–178. <https://doi.org/10.1109/MWC.004.2200079>.
94. Su, Z.; Wang, Y.; Luan, T.H.; Zhang, N.; Li, F.; Chen, T.; Cao, H. Secure and Efficient Federated Learning for Smart Grid With Edge-Cloud Collaboration. *IEEE Trans. Ind. Inform.* **2022**, *18*, 1333–1344. <https://doi.org/10.1109/TII.2021.3095506>.

95. Khaleel, M.M.; Abuali, T.; Alsharif, A. The Role of IT in Developing Smart Grids for Efficient Energy Distribution. *Open Eur. J. Appl. Sci. OEJAS* **2025**, *1*, 65–80. Available online: <https://easdjournals.com/index.php/oejas/article/view/18> (accessed on 10 May 2026).
96. Ramchurn, S.D.; Vytelingum, P.; Rogers, A.; Jennings, N.R. Putting the ‘smarts’ into the smart grid: a grand challenge for artificial intelligence. *Commun. ACM* **2012**, *55*, 86–97. <https://doi.org/10.1145/2133806.2133825>.
97. Lampropoulos, G. Artificial Intelligence in Smart Grids: A Bibliometric Analysis and Scientific Mapping Study. *J. Mechatronics, Electr. Power, Veh. Technol.* **2023**, *14*, 11–34. <https://doi.org/10.14203/j.mev.2023.v14.11-34>.
98. Cecati, C.; Mokryani, G.; Piccolo, A.; Siano, P. An Overview on the Smart Grid Concept. In Proceedings of the 36th Annual Conference of the IEEE Industrial Electronics Society (IECON 2010), Glendale, AZ, USA, 7–10 November 2010; pp. 3322–3327. <https://doi.org/10.1109/IECON.2010.5675310>.
99. Kang, C.; Kirschen, D.; Green, T.C. The Evolution of Smart Grids. *Proc. IEEE* **2023**, *111*, 691–693. <https://doi.org/10.1109/JPROC.2023.3284213>.
100. Lo Cascio, E.; Girardin, L.; Ma, Z.; Maréchal, F. How Smart is the Grid? *Front. Energy Res.* **2021**, *9*, 637447. <https://doi.org/10.3389/fenrg.2021.637447>.
101. Jiang, T. Guest Editorial: Artificial Intelligence and data analytics for smart grids with high penetrations of renewables. *IET Energy Syst. Integr.* **2021**, *3*, 223–226. <https://doi.org/10.1049/esi2.12040>.
102. Mahadik, S.; Gedam, M.; Shah, D. Environment Sustainability with Smart Grid Sensor. *Front. Artif. Intell.* **2024**, *7*, 1510410. <https://doi.org/10.3389/frai.2024.1510410>.
103. Cheng, L.; Yu, T. A new generation of AI: A review and perspective on machine learning technologies applied to smart energy and electric power systems. *Int. J. Energy Res.* **2019**, *43*, 1928–1973. <https://doi.org/10.1002/er.4333>.
104. Islam, S.N.; Biswas, A. Artificial Intelligence for Critical Power Infrastructure: Challenges and Opportunities. *Appl. IT Eng.* **2023**, *1*, 1–9. <https://doi.org/10.25163/engineering.1110397>.
105. Zohuri, B.; Mossavar-Rahmani, F.; Abedi-Varaki, M. Powering Artificial Intelligence: How Artificial Intelligence’s Massive Energy Demands Are Reshaping the Future of Smart Grid. *J. Energy Power Eng.* **2025**, *19*, 91–99. <https://doi.org/10.17265/1934-8975/2025.03.002>.
106. Taherdoost, H.; Le, T.V.; Slimani, K. Advancing Smart Grids With Artificial Intelligence for Advancing Sustainability, Resilience, and Efficiency. *J. Control Sci. Eng.* **2026**, *2026*, 9001391. <https://doi.org/10.1155/jcse/9001391>.
107. You, S.; Li, H.; Liu, S.; Sun, K.; Zhao, Y.; Xiao, H.; Dong, J.; Su, Y.; Wang, W.; Cui, Y.; et al. Build Smart Grids on Artificial Intelligence – A Real-world Example. In *Applications of Big Data and Artificial Intelligence in Smart Energy Systems*; Chapter 8; River Publishers: Aalborg, Denmark, 2023; pp. 193–220.

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.