



REVIEW

Integrating 5G, AI, IoT, and Digital Technologies for Sustainable Energy Systems and Smart Grid Innovations

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Received: 09 May 2026; Accepted: 21 July 2026; Published: 18 October 2026

ABSTRACT: The global Energy Transition (ET) is not only based on renewable infrastructure but also on the use of fifth-generation (5G) networks, artificial intelligence (AI) and the Internet of Things (IoT). This systematic review examines how the IoT functions as a sensing system to gather and analyze real-time data, 5G technology serves as a communication network with ultra-low latency, and AI acts as a system for autonomous control to enable autonomous decision-making and predictive analytics. From 2020 to 2026, 117 peer-reviewed publications were analyzed after filtering 889 initial records using PRISMA for a systematic literature review. On this basis, the study is carried out. The three main contributions are: (i) improved forecast of solar and wind energy resources using Machine Learning (ML) and Deep Learning (DL) models, (ii) real-time monitoring of the grid with fault detection by IoT devices and 5G communication, and (iii) automated demand response using Reinforcement Learning (RL) algorithms. Nevertheless, there are still challenging issues, such as cybersecurity threats, privacy concerns, AI systems' energy consumption, interoperability, and infrastructure limitations in developing areas. In the face of such obstacles, this study synthesizes existing Green AI frameworks that tackle energy-efficient computing, analyzes Federated Learning (FL) for privacy-preserving data analysis, synthesizes edge-cloud hybrid architectures to tackle reduced latency, bandwidth optimization, and specific policy recommendations to tackle the 5G deployment in underserved locations, such as mandatory cybersecurity certification, data governance frameworks, and public-private partnerships. Digital Twins (DTs) and Edge AI are the most promising technologies to enable predictive maintenance, self-healing grids, and low-latency operations. Together, 5G, AI, and IoT are not a solution in themselves, but rather a precondition for achieving climate goals, grid resilience, and equitable access to energy worldwide. A systematic review of 117 selected studies was conducted using PRISMA, resulting in a synthesis of existing research, key gaps, and actionable opportunities for researchers, industry practitioners, and policymakers.

KEYWORDS: Internet of Things (IoT); artificial intelligence; smart grids; 5G communication; cybersecurity; energy transition; renewable energy integration; digital twins

1 Introduction

Energy companies are transforming traditional power grids that depend on fossil fuels into ones that are wholly powered by electricity, less centralized, and more environmentally friendly. This transition

encompasses modifications in the economy, society, environment, technology, and industry. Traditional power infrastructure is currently facing significant challenges in managing the increasing electricity demand, the electrification of transportation, the development of renewable energy sources, and the reduction of economic carbon emissions [1]. In the past, power generation was mainly in one direction from a few power plants to consumers, but present energy systems require bi-directional communication, control, and adaptability in real time [2,3].

As a result, the energy transformation is contingent upon the implementation of Smart Grids (SGs). Digital communication technologies, sensors, automation, Artificial Intelligence (AI) and data analytics are being employed by SGs to establish an electrical infrastructure that is more environmentally friendly, dependable, secure, and efficient [4,5]. The International Energy Agency (IEA) considers grid and power systems of the future to be modern, intelligent, and extended, since grid systems are critical to the successful Energy Transition (ET) to clean energy sources and electrification efforts; high-performance grid infrastructure is essential to the integration of renewable energy sources [6]. Recent research has verified that SGs will facilitate the integration of renewable and non-renewable energy sources through the use of digital technologies, including the Internet of Things (IoT) and AI [7].

The target for the industry is to create more effective, automated, resilient, protected and sustainable energy systems. Reliable power supply, predictive maintenance, cost-effective operations, and effective energy management are required from enterprises. SGs can help industries save energy, improve operational scheduling, add renewable energy to their systems, and meet carbon-reduction objectives [8].

This systematic review is significant because it clarifies the complex and often overlooked associations between digital technologies and sustainable energy systems. Energy systems are becoming more complex with the introduction of scattered renewable energy sources, integrating renewables, energy storage, grid technologies, and building energy management systems to support net-zero energy systems [9]. Intelligent, interconnected infrastructure is essential to effectively manage this complexity [10].

Digital technologies are essential to the formation of a supplementary interconnected, intelligent, efficient, trustworthy and sustainable energy system. The IEA expresses the vision of digitalization having a significant positive impact on energy systems in terms of operational effectiveness, innovative services, and highly interconnected energy networks [11]. In this context, AI, IoT, Fifth Generation (5G) networks, edge computing and Digital Twins (DTs) are not stand-alone technologies, but work together as a whole digital energy management ecosystem [12].

Moreover, the topic is extremely relevant, as the ET can only be realized through additional deployment of renewable energy. The problem with renewable energy power generation is that it is, by nature, intermittent and weather-dependent. In view of this, advanced forecasting capabilities, real-time monitoring, high-speed communication and control systems are essential [13]. AI models can forecast demand and renewable energy production; IoT devices can gather real-time measurements from a variety of sensors, meters, and grid assets; and 5G networks can enable near-instantaneous communication with low latency [14].

The 5G connection is optimal for SG due to its low latency, reliability, and speed. Remote control, microgrid connectivity, real-time monitoring, electric vehicle charging, and fault diagnostics are all feasible with this technology [15]. 5G's can connect a massive number of devices with minimal response time, which is appropriate for critical energy applications [16] when compared with the current communication networks. The key requirement for the SGs is secure, flexible communication networks that enable communication between sensors, actuators, substations, control centers, and Distributed Energy Resources (DERs). The Institute of Electrical and Electronics Engineers (IEEE) SG Initiative, highlighting the potential of 5G

communication networks to enhance the tracking, management, and integration of smart grid components for flexible energy services [17].

Smart meters, sensors, actuators, and energy devices are among the technologies that facilitate real-time monitoring, all of which are underpinned by IoT. IoT can be used to track energy consumption profiles, equipment status, demand, temperature, current, and voltage for utilities and industries. The capability can help to improve decision-making and automation in energy management [18]. Green IoT is particularly important because, although it promotes sustainability, it also consumes energy. Green IoT and Edge AI technologies have the potential to contribute to sustainable digital transformation. But the energy needs of IoT and AI technologies must be controlled effectively [19].

AI applications in SG include predictive and operational optimization, data classification, anomaly detection, and decision-making. This technology can predict energy usage, predict renewable energy generation, detect electricity issues, optimize energy storage, control energy demand, and increase energy efficiency. Ref. [20] highlights the estimate of AI in the ET and also notes its energy usage, ethical issues and social impact.

To sum up, IoT provides crucial data, 5G transmits it swiftly, and AI processes it to guide strategic decisions. These technologies can be integrated to initiate a smart, resilient and sustainable energy infrastructure.

While digital technologies hold great promise for improving sustainable energy systems, challenges remain. When it comes to distributed renewable energy sources, the power supply network is not flexible enough and is very outdated. Voltage control, load management, and grid stability are issues arising from using renewable energy sources like solar and wind power, which depend on weather conditions. The demand for upgrading electricity networks is driven by the increasing use of renewable energy sources, electric vehicles, and heat pumps, according to the IEA [6]. Furthermore, compatibility issues plague it. A smart grid integrates hardware and software from multiple manufacturers, as well as various protocols, platforms, and software systems. The lack of established protocols significantly hinders the integration of technologies such as AI, IoT, 5G, cloud computing, and grid control systems. Smart infrastructure should have cybersecurity elements and be interoperable, according to the National Institute of Standards and Technology (NIST) [21]. Thirdly, the security and privacy of data are paramount. A smart grid is an intelligent system that uses the IoT to generate a deluge of real-time data on system parameters and consumers. Vulnerabilities in the grid's substations, communication networks, control systems, and smart meters might compromise grid operation and safety. The fourth point is that AI models require substantial data and processing power. Energy usage and data management are two major obstacles that this creates. Artificial intelligence systems' environmental benefits could be negated by their high energy consumption unless they are carefully designed. Finally, connectivity issues, restricted 5G rollout, grid asset shortages, a lack of trained staff, and limited investment resources further hinder the deployment of 5G in developing economies.

While there are challenges, there is much potential. This synergy of 5G, AI, IoT, edge computing, and DT can enable a smarter, more distributed, and sustainable energy system [22]. AI can help predict renewable energy, allowing the grid operators to predict when solar and wind energy will be produced [23]. IoT can help with equipment monitoring to minimize outages and optimally schedule maintenance [24]. 5G can enable high-speed communication between the sensor, the control room, Electrical Vehicles (EVs), distributed energy sources and storage [25]. Edge AI can analyze data locally without sending it to the cloud for processing and communication [26]. DT enables energy systems to create a DT that can be used to model faults, test and optimize the system, and predict maintenance needs. This can enhance reliability and lower costs [27]. In industry, they can be used for smart factories, energy-efficient manufacturing, predictive maintenance, carbon tracking, and the circular economy [28].

- The primary objective of this systematic literature review is to critically analyze and synthesize the existing body of research on the potential applications of digital technologies, including IoT, AI, and 5G, in transforming energy systems into environmentally favorable, intelligent, and sustainable systems.
- To explore the potential of 5G, AI, and the IoT to enhance decision-making in the energy system, integrate renewable power sources, and enable real-time monitoring.
- To examine the challenges and potential solutions associated with cybersecurity, interoperability, data privacy, infrastructure, and energy consumption on a large scale in the context of AI in digital energy systems.
- To discuss and plan for the development of efficient energy systems that are capable of handling the challenges of the future.

The ET towards sustainability, as experienced worldwide, underscores the importance of this research. Smart and flexible energy systems are essential for integrating large-scale renewable energy, achieving decarbonization of the energy sector, ensuring grid stability, and supporting the growth of electricity demand. This study is academically valuable because it provides insight into the latest research trends and the challenges and opportunities in this field. It provides company employees with guidance on reducing their environmental impact, enhancing operational efficiency, and conserving energy through digital technology. This report provides legislators with valuable information on data governance, cybersecurity policies, funding, and standards, all of which are essential to the development of SGs. Ultimately, this research contributes to the ongoing discourse on the use of digital technologies, including the Internet of Things, AI, and 5G, to develop energy systems that are low-carbon, resilient, intelligent, and sustainable.

The paper is organized as follows. The literature reviewed in [Section 2](#) addresses the themes of ET, SG, AI, IoT, 5G and digital technologies. [Section 3](#) outlines the methodology used in the review of the paper. [Section 4](#) discusses key technologies such as 5G communication, AI analytics for forecasting and IoT monitoring. Applications and use cases for smart grids are presented in [Section 5](#). Cybersecurity, privacy, interoperability, infrastructure, and AI power use are the challenges addressed in [Section 6](#). Finally, [Section 7](#) addresses the direction of future research, including policy implications, DT technology, edge AI, and sustainable industry practice. Finally, a summary of the study and existing research gaps is provided in [Section 8](#).

2 Literature Review

The ET, which is fundamentally altering the global energy infrastructure, is centered on decarbonization, energy efficiency enhancements, and the integration of renewable energy sources. The ET, which is also known as this transformation, is a transition from the traditional, centralized power structure reliant on fossil fuels to decentralized, low-carbon, digitalized energy systems. Digitization is a critical element of the transformation, as it enables real-time monitoring, forecasting, automation, and decision support. Recent academic studies have demonstrated that digital technologies are essential for effectively managing the complexity of contemporary energy systems. The inherent unpredictability and volatility of renewable energy sources necessitate the development of enhanced prediction, regulation, and optimization methods [23]. Digitalization improves the efficiency, responsiveness, and agility of energy systems using data-driven technological solutions.

This implicates the use of AI, IoT, and advanced communication technologies. For example, AI can play a role in the ET by providing precise forecasts of energy demand and renewable energy sources and by optimizing energy system operation, as noted in [29]. In the same vein, the IoT enables real-time data collection from smart instruments, grid assets, and DERs, thereby enhancing monitoring and control capabilities [30]. The development of SGs that can include DERs is an additional benefit of digitization. This

enables bidirectional communication and enhances grid resilience. A significant amount of data analytics and communication technology is required to ensure the seamless and efficient operation of SGs [31]. The digital energy ecosystem is a novel paradigm emerging at the intersection of energy systems and digital technology. In this ecosystem, intelligent systems optimize energy generation, delivery, and consumption by connecting all of the objects.

5G communication technology represents a breakthrough in the rollout of next-generation energy systems. 5G provides low latency, high-speed connectivity, and extensive device connectivity, enabling real-time energy management and SG technologies [32]. This technological progress enables energy systems to rapidly adapt to demand/supply variations, especially in systems with a significant share of renewables. 5G is the backbone of communication between the sensors, substations, control centers and DERs in smart grids. This connectivity permits real-time monitoring, fault detection and remote operation of the grid. As highlighted by [33], new communication technologies such as 5G play a role in the energy digital transformation and grid efficiency.

Moreover, 5G enables the deployment of new tools, such as EVs, microgrids, and distributed generation, which contribute to a more responsive, adaptable, and scalable grid and support sustainable energy systems [34]. With its enhanced data processing, predictive analytics, and decision-making capabilities, AI is revolutionizing energy systems. To maximize operational efficiency, SGs use a range of artificial intelligence technologies, such as Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) [35]. AI is also making significant strides in energy forecasting, which involves predicting future power consumption and renewable energy production. The grid system is rendered more dependable and efficient through the implementation of ML methodologies, including decision trees and Support Vector Machines (SVM), for fault detection and load forecasting [36]. The use of DL techniques, such as Artificial Neural Networks (ANNs) and Long Short-Term Memory (LSTMs), enables the capture of more complex nonlinear correlations in the data, rendering them highly suitable for renewable energy forecasting [37].

Deep Q Networks (DQNs) and Q-learning are two RL algorithms that have been employed in energy scheduling and demand response due to their ability to make decisions in complex contexts [38]. Additionally, to address energy scheduling and resource allocation concerns in a cost-effective and resource-efficient manner, optimization techniques such as Quantum Particle Swarm Optimization (QPSO) and genetic algorithms are implemented [39]. Hybrid AI approaches are integrating AI with IoT and edge computing technologies to further optimize system performance. This enables predictive maintenance and real-time data analysis [40]. These methods enhance the system's stability and reduce the frequency of disruptions. The functions of the numerous AI methods in enhancing energy prediction, optimization, and security are summarized in Table 1.

Table 1: AI methods used in energy systems and their respective applications.

AI Technique	Method/Model	Application in Energy Systems	Key Benefits	Reference
Machine Learning (ML)	SVM, Decision Trees	Load forecasting, fault detection	Improves prediction accuracy and grid stability	[41]
Deep Learning (DL)	ANN, CNN, LSTM	Renewable energy forecasting (solar/wind)	Handles complex data, improves forecasting	[42]

(Continued)

Table 1 (continued)

AI Technique	Method/Model	Application in Energy Systems	Key Benefits	Reference
Reinforcement Learning (RL)	Q-Learning, DQN	Demand response, grid control optimization	Real-time adaptive decision-making	[43]
Optimization Algorithms	Genetic Algorithm, PSO	Energy management, storage optimization	Cost reduction and efficiency improvement	[44]
Hybrid AI Models	AI + IoT + Edge AI	SG automation, predictive maintenance	Improves reliability and performance	[45]
Anomaly Detection	Clustering, Autoencoders	Fault detection, cybersecurity	Enhance system security	[46]
Forecasting Models	Time-series ML, LSTM	Demand and renewable forecasting	Balances supply and demand	[47]

To understand the theoretical underpinnings of the intelligent analytics layer, it is essential to formalize the core mathematical frameworks driving these models. In renewable energy forecasting using DL architectures such as LSTM networks, temporal dependencies in weather data streams are captured via a series of gating mechanisms. At any given time step t , the forget gate f_t , input gate i_t , and cell state C_t are formulated as given in Eqs. (1)–(3):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (3)$$

where σ represents the activation function, W and b are the weight matrices and biases, x_t is the multi-variate weather/load vector, and h_{t-1} is the hidden state from the previous sequence layer.

Correspondingly, automated demand response and grid optimization problems solved via RL are modeled as Markov Decision Processes (MDPs). The goal is to maximize the expected cumulative discounted reward R_t , ensuring real-time adaptive grid control as represented in Eq. (4):

$$R_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \quad (4)$$

where r is the localized operational reward function (balancing cost reduction and grid voltage margins), and $\gamma \in [0, 1]$ is the temporal discount factor.

To provide a more granular perspective on the comparative performance of these localized forecasting methods, Table 2 summarizes empirical benchmarks across data granularity, computational overhead, and standardized error metrics.

The IoT is integral to digital energy systems, enabling real-time monitoring and data acquisition from energy infrastructure. Energy production, consumption, and system status are measured in real time by IoT sensors, smart meters, and actuators. In the world of utilities and industries, IoT can help track key parameters such as voltage, current, temperature, and load, enabling real-time monitoring, informed

decision-making, predictive maintenance, and effective energy management [47]. It is an integral part of sustainable development. Moreover, IoT enables the deployment of decentralized energy sources in SGs, as it can provide uninterrupted information on their operational status. This capability can improve the coordination and control of the system and promote intelligent control mechanisms that dynamically adjust to changes in demand and supply [48].

Table 2: Comparative performance benchmarking of machine learning models for renewable forecasting.

Model Type	Ideal Data Granularity	Typical RMSE Range	Key Limitations	Angular Focus
Traditional ML (SVM/RF)	Hourly/Daily	12%–18%	Struggles with sudden weather shifts	Baseline load forecasting
Deep Learning (LSTM/GRU)	Sub-hourly/Minutes	4%–8%	High dependency on massive historical datasets	Intermittent wind/solar tracking
Hybrid AI (CNN-LSTM)	Seconds/Minutes	2%–5%	Extreme computational training overhead	Real-time dynamic grid balancing

But with IoT comes issues with energy, security and interoperability. To face these concerns, the Green IoT framework has been proposed to build energy-efficient IoT solutions and minimize the environmental impact of IoT [49]. Combining 5G, AI and IoT technologies will provide a robust foundation in the development of intelligent and sustainable energy systems. The technologies work together to capture real-time data, deliver prompt and secure 5G connectivity, and facilitate data analysis for valuable insights [50,51]. This synergy enables functions such as real-time energy monitoring, predictive maintenance, automated control, and optimal energy distribution. Further, it increases SGs' ability to incorporate renewable energy, boost efficiency and guarantee good performance.

The conceptual framework for this integration is illustrated in Fig. 1, which shows the interplay among 5G, AI, IoT, and the smart grid for sustainable ETs.

Although a lot of research has been carried out in the fields of SGs, AI and energy systems based on IoT, most of the existing literature concentrates on these technologies separately and not on their full integration in a smart energy system. Very few works focus on the cooperative operation of 5G communication, IoT-based data collection systems and AI-based data analytics frameworks for energy management in an end-to-end system to achieve real-time, intelligent and adaptive energy management. In addition, while many research papers focus on the technical advantages of such technologies, there is a significant lack of literature on practical considerations for large-scale deployment, including cybersecurity, interoperability, infrastructure, and the growing energy consumption of AI-driven systems. The link between emerging technological opportunities and industrial applications, especially within Industry 5.0 and sustainable circular energy systems, remains underexplored. Furthermore, new concepts such as DT and edge computing are not fully adopted in smart energy systems. Thus, there is an urgent need in the current literature for a holistic, integrated method that encompasses all these technological advances while accounting for pragmatic challenges and opportunities for future growth.

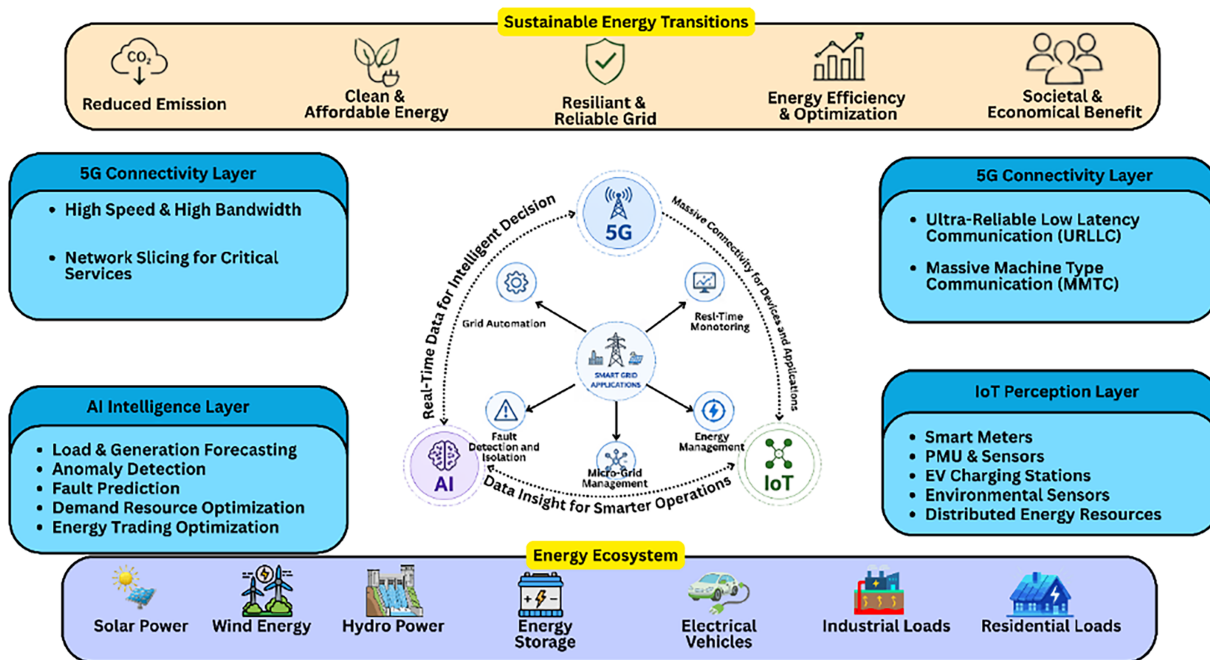


Figure 1: Integration of 5G, AI, and IoT in energy systems: a conceptual framework for sustainable ETs.

3 Methodology

This survey uses a systematic literature review and Bibliometric analysis to examine the roles of digital technologies, including 5G, AI, and IoT, in Sustainable Energy systems and SGs. Since this study is not based on new experimental results, a review is suitable for pinpointing the key themes, technology trends, research needs, and future research topics in the field. Therefore, the selected approach is the systematic identification, screening, selection, classification, and analysis of the literature, which will help the study generate a holistic perspective on digital transformation in energy systems. This aligns with the paper's objective, which focused on the integrated use of digital technologies in SGs, renewable energy integration, real-time monitoring, and sustainable ET. This systematic review was designed, conducted, and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [52], and the completed PRISMA 2020 checklist is provided as Supplementary Material.

3.1 Research Design

A qualitative systematic review approach and bibliometric mapping are used in the study. The systematic review helps to analyze the content of the selected publications, and the bibliometric analysis helps to identify research trends, keywords, publication trends, and Technology clusters. This is suitable, as the issue involves various associated technologies, including 5G, AI, IoT, edge computing, DT, SGs, and renewable energy systems.

3.2 Data Sources and Search Strategy

The literature was collected from academic platforms and journals, mainly in the form of peer-reviewed articles, specifically related to SGs, ET, AI, IoT, 5G communication, and sustainable energy systems. Predefined keywords and eligibility criteria guided the systematic search process. This search-and-selection workflow is summarized in Fig. 2.

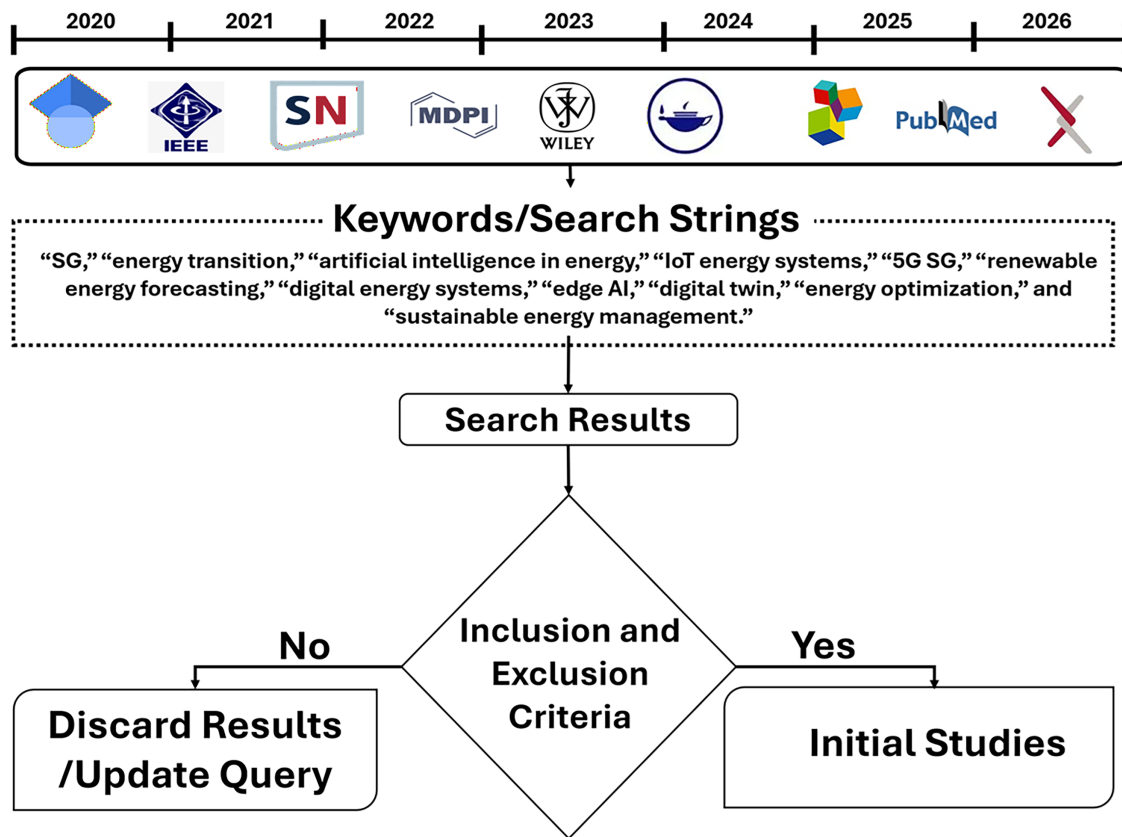


Figure 2: Defining search strings and strategy.

3.3 Inclusion and Exclusion Criteria

The selected studies are related to digital technologies in energy systems, SG applications, renewable energy integration, AI-based energy forecasting, energy monitoring using the IoT, energy management using 5G communication, cybersecurity, and sustainable energy management. Recent peer-reviewed journal articles and review studies relevant to the digital transformation of energy systems were prioritized. We filtered out studies that were not energy-related, only general ICT technologies with no energy applications, lacked clear methodological or technological relevance, and did not mention SGs, sustainability, AI, IoT, or digital energy systems. Study selection was done using explicit inclusion and exclusion criteria. A detailed discussion of these criteria is provided in [Fig. 3](#).

3.4 Literature Screening and Selection Process

The choice of literature went through four phases. Firstly, the relevant articles were identified by using the keywords. For the second stage, studies were included or excluded based on their titles and abstracts. Abstracts of selected papers were reviewed to determine their relevance in the third stage. Finally, the most relevant papers were organized into subcategories based on the technology they focus on, such as AI, IoT, 5G, SGs, DT, cybersecurity, and sustainable ET. To achieve the objectives of the study, a multi-phase research design was followed. This methodological framework is shown in [Fig. 4](#).

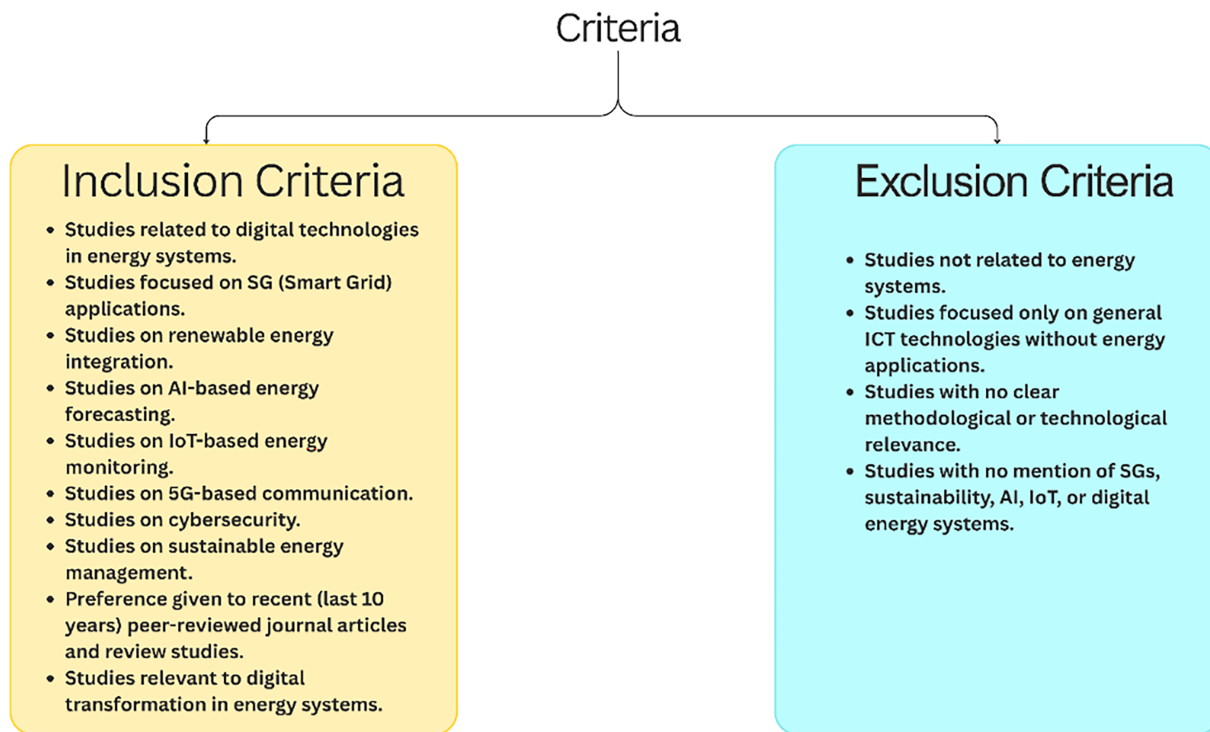


Figure 3: Inclusion and exclusion criteria.

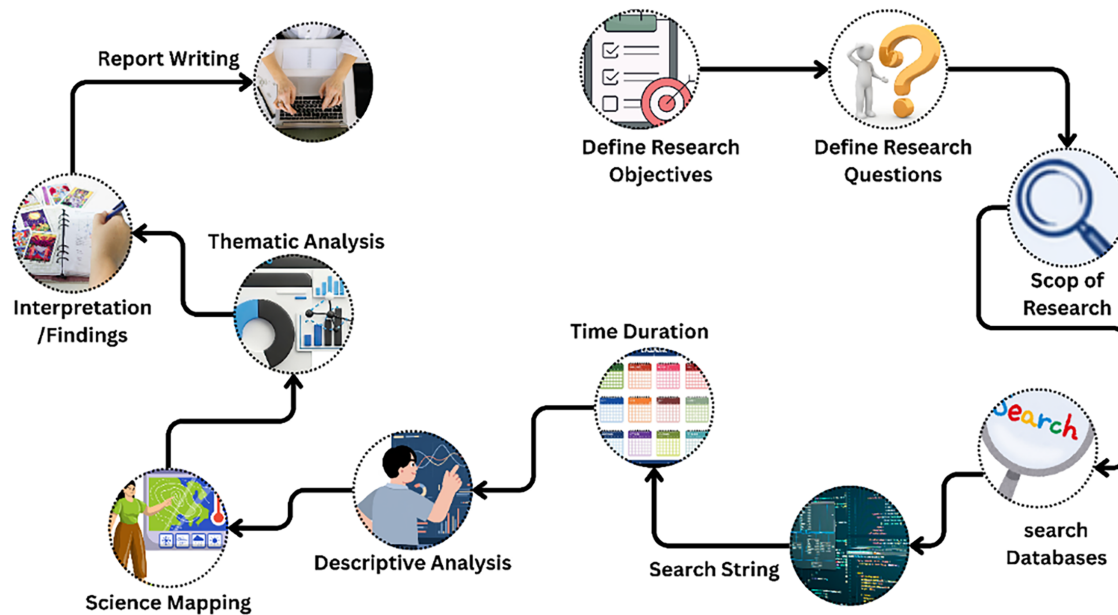


Figure 4: Methodology for systematic review and bibliometric analysis of research on SGs and digital technologies.

The selected studies were reviewed and classified according to their main technological applications and domains in smart energy systems. The studies have an impact in the fields of AI, IoT, 5G communication and their integration within SGs and sustainable energy systems. The chosen studies provide a mix of conceptual, recent and applied aspects of the digital transformation of the energy sector. Details on the selected studies,

including technological orientation and application areas, as well as their main contributions, are provided in [Table 3](#).

Table 3: Overview of selected studies and their focus areas in SG and energy technology applications.

Study	Technology Focus	Application Area	Key Contribution
[53]	IoT, Edge AI	Smart manufacturing, energy monitoring	Introduced Green IoT and Edge AI for sustainable and energy-efficient systems
[20]	AI	ET, policy, forecasting	Highlighted the AI role in energy optimization and renewable integration
[54]	AI, IoT, Digital Tech	SGs, sustainability	Provided a bibliometric analysis of digital technologies in SGs
[37]	AI, ML	Renewable energy forecasting	Applied ML models for solar and wind prediction
[55]	IoT	Energy management systems	Developed an IoT-based real-time energy monitoring framework
[56]	AI, Big Data	SG optimization	Used big data analytics for efficient energy distribution

Database search in Scopus, Web of Science, IEEE Xplore, MDPI, Elsevier, Springer, Taylor and Francis, ACM, Sage, SSRN and Heliyon-Cell is done with predefined sets of keywords of 5G, AI, IoT, smart grids and sustainable energy systems, and a total of 889 records are identified. After the identification phase, 193 records were excluded, and 696 records went on to screening. Titles and abstracts were screened during the screening phase. It led to the elimination of 278 records because they lacked a smart grid application, were not related to energy systems, or did not cover the technologies included in the study (5G, AI, IoT). The remaining 418 full-text articles were then screened based on eligibility criteria using abstract and title; 213 were excluded because there was insufficient specification of the integration of digital technologies in energy systems, methodological or technological focus was missing, or the articles were not peer-reviewed. A total of 205 studies met the preliminary inclusion criteria and underwent full-text screening for eligibility, of which 117 studies were included in the final review. The overall identification, screening, eligibility, and inclusion process is summarized in the PRISMA 2020 flow diagram [Fig. 5](#).

While the preceding discussion outlined the chronological execution steps, it is essential to emphasize the specific scientific rigor and operational advantages that our refined research protocol delivers. Standard selection roadmaps often focus heavily on screening volumes, sometimes diluting selection clarity. Conversely, our structured methodology funnel, conceptualized in [Fig. 6](#), moves away from a loose roadmap into a high-utility integrated filtering matrix. The core strategic advantages of using this unbiased protocol are direct cross-functional reproducibility and the elimination of selective reporting bias through explicit exclusion criteria. This ensures that the qualitative synthesis presented is derived from a flawless data loop. Furthermore, instead of a simple counting chart, [Fig. 6](#) explicitly links our systematic methodology to its major scientific contributions. By vertically filtering 889 initial records through strict boundaries down to 117 core high-impact papers, this study yields definitive value across three main contribution blocks: the crystallization of an end-to-end grid synergy architecture; the formulation of a tactical troubleshooting matrix to solve the eight categorized smart grid operational bottlenecks; and the integration of digital asset life-cycle management into an Industry 5.0 circular grid management roadmap.

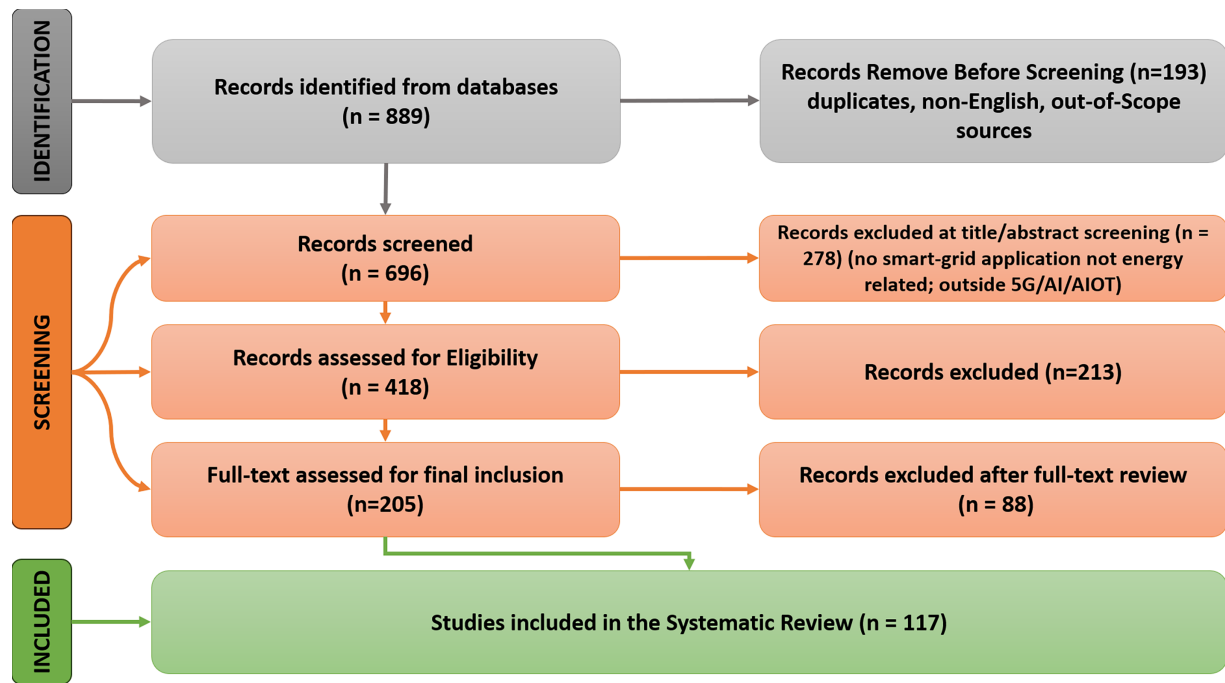


Figure 5: PRISMA 2020 flow diagram of the study identification, screening, eligibility, and inclusion process.

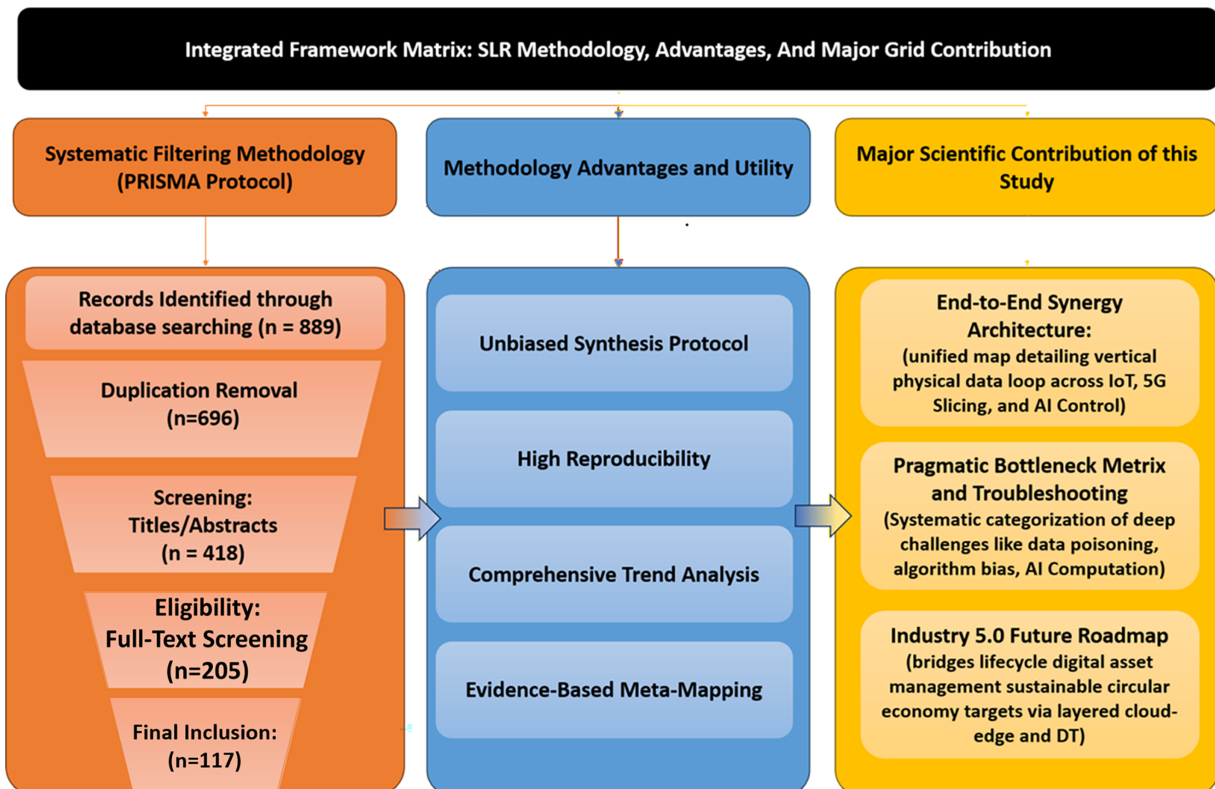


Figure 6: Integrated framework matrix mapping the systematic methodology funnel, its intrinsic advantages, and derived major scientific grid contributions.

3.5 Bibliometric Analysis of Publication Trends

A bibliometric analysis of publication trends was conducted to provide a picture of the evolution and state of the art of research on digital technologies in sustainable energy systems. This is the distribution of 117 peer-reviewed articles by the publisher and by year of publication from 2020 to 2026. Three important trends are seen in these statistics. For one, the number of research outputs has increased during the period, and the number of published papers in 2020 is approximately 5. The number of papers on the convergence of 5G, AI, and IoT for smart grid applications has tripled in 2024 to more than 35. Third, the rollout of 5G infrastructure worldwide and the emergence of AI models for predicting renewable energy sources will be at a definite inflection point in 2023–2024. The number of 2026 cases is low at the end of the year, as these are not yet finalized. The fact that MDPI, Elsevier, and Springer dominate the list, as do preprint repositories, suggests that literature is being rapidly disseminated in this rapidly evolving field, but has yet to undergo peer review. Fig. 6 shows the publication trends (2020–2026) of peer-reviewed literature on the integration of 5G, AI, and IoT in sustainable energy systems, by publisher. A total of 117 publications were analyzed. Most output is from MDPI, Elsevier and Springer, and has significantly increased since 2023. A bibliometric analysis was conducted to identify publication trends, leading publishers, and temporal trends.

The overall trajectory of the research from 2020 to 2026 clearly demonstrates a paradigm shift. Initial publications (2020–2022) focused heavily on isolated component digitalization, such as simple smart meter telemetry or stand-alone forecasting algorithms. However, the inflection point observed in 2023–2024 highlights an escalating research trend toward deep vertical integration, moving swiftly from cloud-bound reactive systems to decentralized, low-latency Edge-AI solutions and synchronized DT systems for automated self-healing grids. The publication output of the major academic publishers from 2020 to 2026 is shown in Fig. 7.

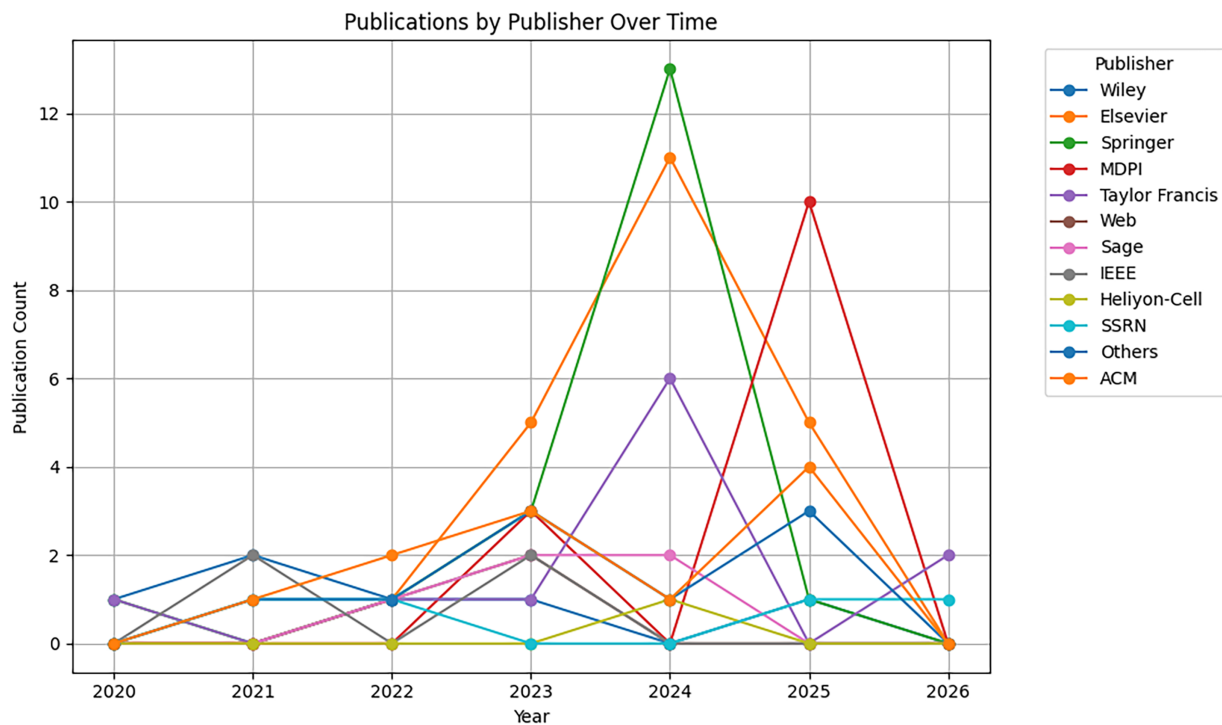


Figure 7: Distribution of publications by publisher and year (2020–2026), illustrating the growing research output on 5G, AI, and IoT applications in sustainable energy systems.

3.6 Analytical Framework

The analytical framework of this study is founded on four pillars: data acquisition, communication, intelligence, and decision-making. The IoT, 5G communications, AI, and software gateways comprise layers one through four. This approach enables the research to examine collaborative efforts among various technologies to enhance energy efficiency, reliability, and sustainability, and to integrate renewable energy sources.

3.7 Methodological Justification

The systematic review and bibliometric approach are suitable for this topic, as it is interdisciplinary and fast-moving. One experimental approach alone would not address the technological, industrial and sustainability aspects of 5G, AI and IoT in energy systems. As such, this methodology enables a broader, systematic understanding of the research progress, challenges and opportunities in smart energy systems.

4 Key Technological Components

The transition from conventional power systems to sustainable and intelligent energy systems has been significantly accelerated by the integration of cutting-edge digital technologies. 5G networks, AI, and the Internet of Things are pioneering the development of real-time measurements and monitoring, predictive analytics, autonomous decision-making, and energy efficiency. Like the frosting on a cake, these technologies form a smart energy system; the IoT collects data, 5G enables fast connections, and AI intelligently optimizes and processes data [4,20]. In this section, we examine the role and impact of these technologies in energy systems.

5G communication networks will significantly improve future SGs. 5G's vast connectivity, low latency, and high bandwidth enable energy system activities to occur in real time, in contrast to previous wireless technologies. This enables the efficient monitoring and control of energy systems, particularly those that integrate a significant number of renewable energy sources. Some examples of the applications where low latency is a key requirement are fault detection and grid protection and control, where a slight delay in data transmission can lead to instability or failure in the system [57,58]. With high bandwidth, large quantities of data can be transferred from IoT devices, sensors, and smart meters on the grid [59]. Moreover, 5G is also able to provide massive machine type communication (mMTC), which can connect thousands of devices in an SG.

In addition, 5G will facilitate real-time management of EVs and energy storage, as well as solar panels, wind farms and DERs. This improves the tractability of the grid and allows demand response [34,60]. Finally, SGs are not possible without efficient communication networks such as 5G.

Another important feature of 5G is “network slicing”, which involves creating distinct virtual networks for various energy applications, which provide certain Quality of Service (QoS) guarantees. This enhances the reliability and security of critical energy applications. To summarize, 5G is the communication infrastructure of SGs and offers high-speed, reliable and scalable data transfer. AI is a crucial technology in the ET process, providing predictive modelling, optimization and decision-making. One such critical energy case study of AI in SGs is energy forecasting, which attempts to predict electricity usage and renewable energy generation.

Optimization and forecasting are achieved through RL, DL, and ML. The utilization of ML techniques, such as decision trees and SVMs, to forecast load and identify faults improves grid stability and efficiency [61]. DL models, such as ANNs, CNNs, and LSTMs, have enabled the prediction of solar and wind power output by comprehending nonlinear patterns in energy data [62,63]. RL can be employed to develop control strategies that facilitate the energy system's learning and adaptation to a variety of situations. These are employed

in applications such as grid optimization, energy scheduling, and demand response, where decisions must be made in real time. Furthermore, to enhance the efficiency of energy management, storage, and cost-effectiveness, optimization techniques such as particle swarm optimization and evolutionary algorithms are implemented [64].

Predictive maintenance, which uses AI to analyze sensor data for anomalies and potential equipment failures in the grid, is another application of AI in the field. As a result, the cost of repairs and downtime is reduced. Having said that, AI applications require substantial data and computational capacity, which can lead to higher energy consumption. Therefore, it is clear that energy-efficient AI models, also known as Green AI, are essential for sustainability [65].

Smart energy systems employ IoT devices to collect and monitor data. Real-time data is collected on a variety of variables, including voltage, current, temperature, energy consumption, equipment status, and more, using IoT sensors, smart instruments, and actuators. All of this information can assist in optimizing and regulating energy systems by providing a comprehensive understanding of the system [18,66]. IoT can help utilities monitor the grid in real time, identify inefficiencies, and resolve issues as they arise. For example, smart meters can enable charge management and demand response by providing consumption data. Additionally, sensors in distribution and transmission networks monitor operations and detect outliers [67,68].

Another prospective application of the IoT is the automation of control systems for energy supply management, distributed generation control, and resource optimization. The IoT and its role in the optimization and analysis of data for sustainable and intelligent energy systems [69]. Some of the challenges associated with the use of IoT devices include security, interoperability, and power consumption. The concept of green IoT has been introduced to address these concerns. This concept involves creating IoT devices with minimal environmental impact and low energy consumption [70,71]. In this section, we examine the comparison between AI and IoT in energy systems to determine their unique characteristics and their collaborative capabilities. The main points of comparison and cooperation between the two technologies are summarized in Table 4.

Table 4: Comparison of AI and IoT technologies in energy system optimization.

Criteria	Artificial Intelligence (AI)	Internet of Things (IoT)	Integrated Role in Energy Systems	Reference
Primary Function	Data analysis, prediction, decision-making	Data collection and sensing	IoT collects data, AI analyzes and optimizes decisions	[72]
Key Techniques	ML, DL, RL	Sensors, smart meters, connected devices	AI models use IoT-generated real-time data	[18]
Application in SGs	Load forecasting, fault detection, demand response	Real-time monitoring, asset tracking	Enables automated and intelligent grid management	[73]
Role in Energy Optimization	Predictive optimization, energy scheduling	Real-time energy consumption tracking	Improves efficiency through data-driven control	[74]

(Continued)

Table 4 (continued)

Criteria	Artificial Intelligence (AI)	Internet of Things (IoT)	Integrated Role in Energy Systems	Reference
Data Handling	Processes large datasets, pattern recognition	Generates continuous real-time data streams	Supports real-time analytics and adaptive systems	[75]
Smart city load forecasting	LSTM predicts future electricity demand from past load data	Smart meters and sensors collect real-time energy data	IoT provides data, while AI forecasts demand to optimize energy use and reduce peak load	[76]
Energy Efficiency Impact	Reduces waste through optimization algorithms	Enables monitoring and control of energy usage	Combined systems significantly improve efficiency	[77]
Challenges	High computational cost, data dependency	Security risks, device interoperability	Integration complexity and cybersecurity concerns	[78]

The maximum potential of SGs can be realized when these technologies are seamlessly integrated. For instance, when 5G networks transmit data at high speeds and with reliability, IoT devices can capture energy network data in real time, and AI algorithms can process it to provide insights and assist in decision-making [68,79,80]. This integration enables the implementation of numerous advanced technologies, including generation and distribution optimization, real-time energy monitoring and control, predictive maintenance and defect diagnosis, renewable energy integration, load balancing, and demand response [29]. The integration of these technologies enables the operation of energy systems in a more sustainable, resilient, and efficient manner. Additionally, SGs can be engineered to self-adapt and self-heal, thereby enabling them to adjust to fluctuations in both supply and demand [81]. A visual representation is included to further illustrate the revolutionary impact of 5G on energy infrastructure. As illustrated in Fig. 8, 5G technology has numerous potential applications in grid operations due to its high bandwidth and low latency.

To further investigate architectural trends in the smart grid communication network, Table 5 presents a technical comparison of distinct computing deployment models across key operational dimensions.

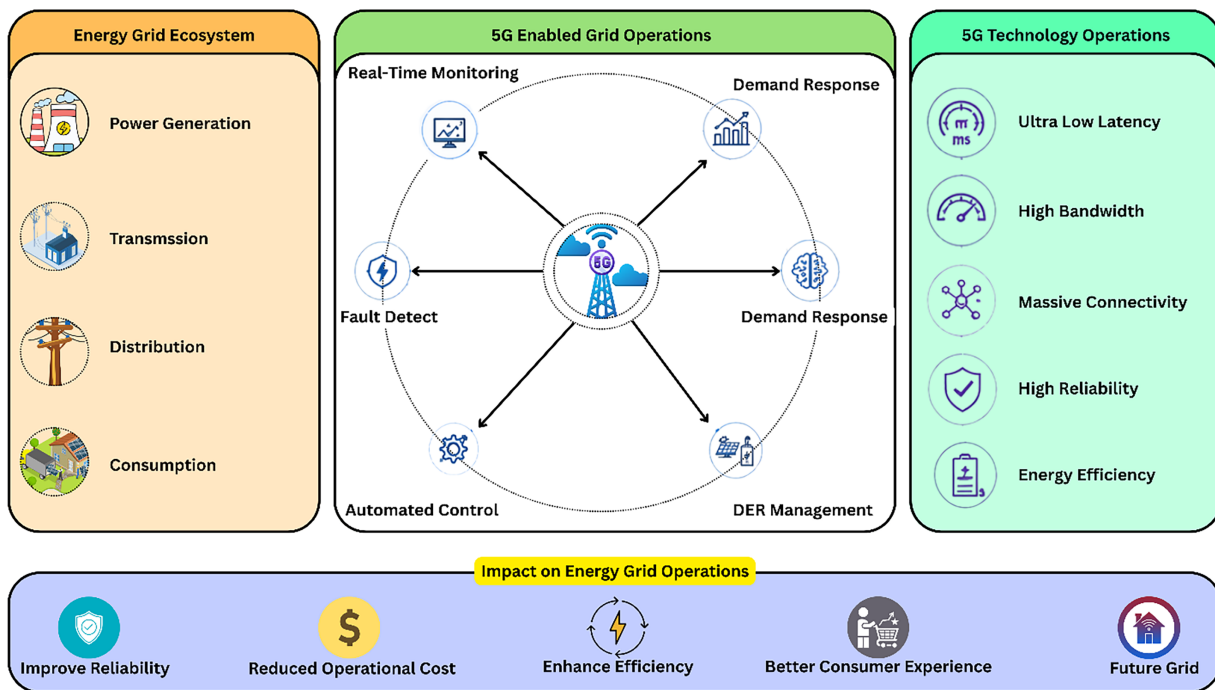


Figure 8: Energy grid operations and the function of 5G technology.

Table 5: Strategic trade-offs between cloud-centric and edge-AI grid management architectures.

Evaluation Metric	Cloud-Centric Architecture	Edge-AI Deployment	Hybrid Layered Model
Latency Boundary	High (100 ms–500 ms)	Ultra-low (<5 ms)	Dynamic (5 ms–50 ms)
Bandwidth Consumption	High (Continuous raw streaming)	Low (Local filtering)	Optimized (Summary batching)
Privacy Preservation	Low (Centralized storage vulnerability)	High (Data remains localized)	Controlled (Federated partitions)
Primary Use Case	Macro-capacity planning & simulation	Immediate localized fault isolation	Regional demand-side response

5 Applications in Real-World Energy Systems

The integration of 5G, AI, and IoT into energy systems is now in progress, a concept previously only theoretical. The power grid is becoming increasingly intelligent and capable of adapting to the evolving requirements of the contemporary energy complex, driven by these technological advancements. Digital technologies are facilitating the integration of renewable energy sources, enhancing operational efficiency, and enabling real-time control and monitoring in practical contexts. We provide significant case studies and SG pilot projects that demonstrate the practical application of these technologies. The energy industry has numerous applications for 5G, AI, and the Internet of Things. To monitor the status of various IoT components, including consumers, substations, generation, and transmission, SG systems use IoT sensors. The data is transmitted to centralized or decentralized platforms via rapid communication networks, such

as 5G, to optimize system operation. Subsequently, artificial intelligence algorithms are implemented for analysis. Smart meters are one example of how many urban energy systems are using IoT to monitor power consumption. Utility companies can use these to implement demand-side management strategies that enhance efficiency and reduce peak demand. AI enables more effective resource planning and management by predicting energy demand and identifying usage trends [18,82].

Another area in which renewable energy systems can benefit from AI is predicting solar and wind power generation. By leveraging historical and real-time data from various sensors, artificial intelligence models can effectively manage the grid by predicting future demand and supply. IoT sensors monitor environmental variables, such as temperature, wind speed, and solar intensity, to ensure that forecasting models remain up to date [83,84]. The IoT monitors the performance of manufacturing apparatus, while artificial intelligence detects anomalies and forecasts problems [85]. As a result, predictive maintenance is now feasible, reducing expenses and disruptions. Industry 5.0 is being employed to construct sustainable and intelligent industrial systems by integrating the Internet of Things and artificial intelligence [86].

The knowledge and experience gained from the experimental SG initiatives are invaluable for integrating digital technologies. Renewable energy sources, communication technology, and control systems may need to be integrated into these projects to make power systems resilient and efficient. One notable breakthrough in these programs is the use of real-time energy management systems. These systems are enabled by 5G networks, which enable high-speed communication across different parts of the grid. This improves the reliability and stability of the energy system by allowing it to react quickly to changes in energy demand and supply. Using this information, AI systems control energy distribution, load balancing, and demand response initiatives [87].

DT is one of the most significant contributions to SG technology. Digital siblings, which are digital representations of the system, can be generated to optimize, monitor, and simulate the performance of a physical energy system. DT, which leverages data from IoT, 5G networks, and AI to simulate and predict system behavior, can assist operators in enhancing system performance and risk management [88]. DT can simulate the operation of renewable energy systems, such as solar panels, wind turbines, and energy storage devices. This has the potential to enhance energy generation, anomaly detection, and maintenance task planning [60]. In addition, DTs facilitate decision-making by monitoring system performance in real time and even predicting future performance [89].

Fig. 9 illustrates the architecture of a DT system that integrates real-time IoT data, AI analytics, and high-speed communication networks, enabling the monitoring and optimization of energy systems in real time. This approach optimizes the system's dependability, efficiency, and predictive maintenance capacity.

6 Challenges and Limitations

There are numerous technological, operational, and socioeconomic impediments to the widespread implementation of 5G, AI, and the Internet of Things in SGs, despite their immense potential to revolutionize energy systems. For next-generation energy systems to be sustainable, scalable, secure, and dependable, these challenges must be effectively addressed. Here, we critically address cybersecurity, privacy, AI equity, and scalability.

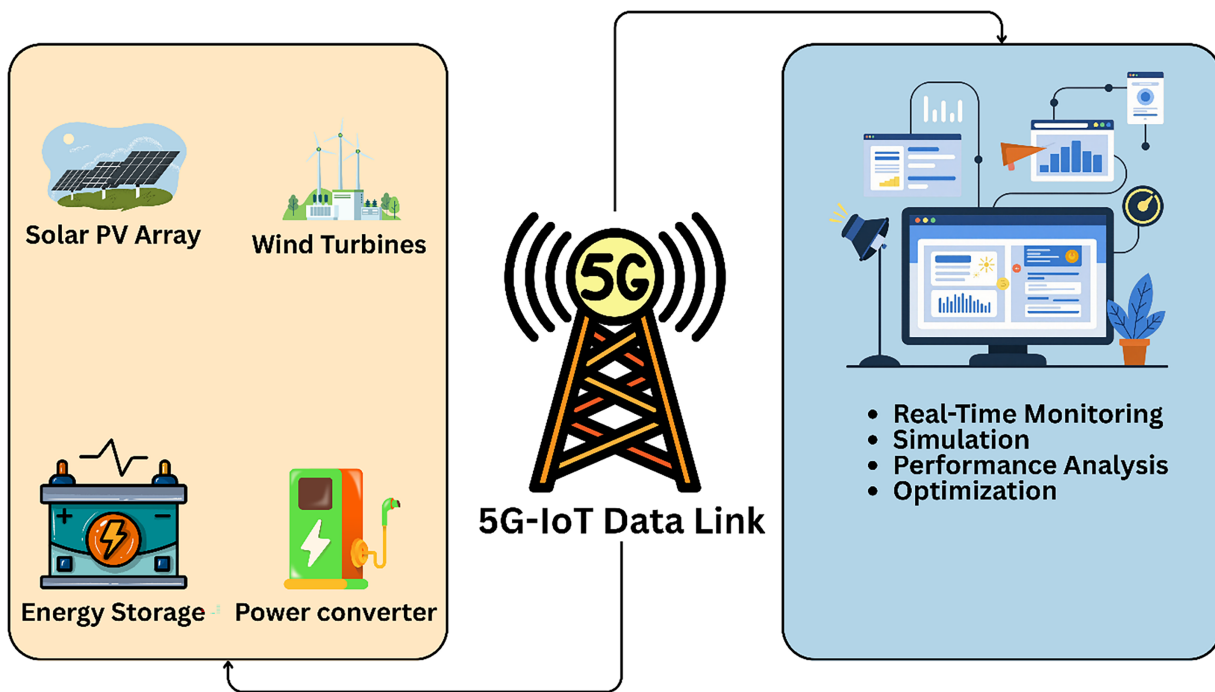


Figure 9: Digital twin framework for real-time monitoring and optimization of renewable energy systems.

6.1 Cybersecurity Threats in IoT-Enabled Smart Grids

SGs incorporating IoT devices are more susceptible to cybersecurity risks. IoT devices, including smart meters, sensors and actuators, are often resource-constrained and may lack robust security protocols, making them vulnerable to cyber threats. They communicate with each other and with the grid via networks such as 5G, thereby increasing the energy system's vulnerability [90]. Common cybersecurity issues in SGs include data breaches, denial-of-service (DoS) attacks, malware injection and control system access [91]. These can cause system instability, data theft, and even blackouts. For instance, a cyber-attack on communication systems could delay or manipulate real-time data, impacting grid decision-making and stability [92].

Further, incorporating AI brings its own security challenges, as ML algorithms can be susceptible to adversarial attacks and data poisoning, in which malicious data is injected to manipulate the system [93]. The need for secure communication systems and AI-based security mechanisms to secure smart energy systems [94].

To combat these threats, it is crucial to use measures such as secure authentication, end-to-end encryption, intrusion detection, and blockchain technology for trustless transactions. System updates, vulnerability scanning, and compliance with cybersecurity standards are of the utmost importance. Fig. 10 shows the cybersecurity framework for IoT-enabled smart grids, which consists of security measures (such as secure device management, secure communication, data protection, access control, threat detection, policies), governance frameworks (such as regulations, compliance, risk management, policies), and security outcomes (such as confidentiality, integrity, availability, privacy, trust, compliance) with continuous improvement.

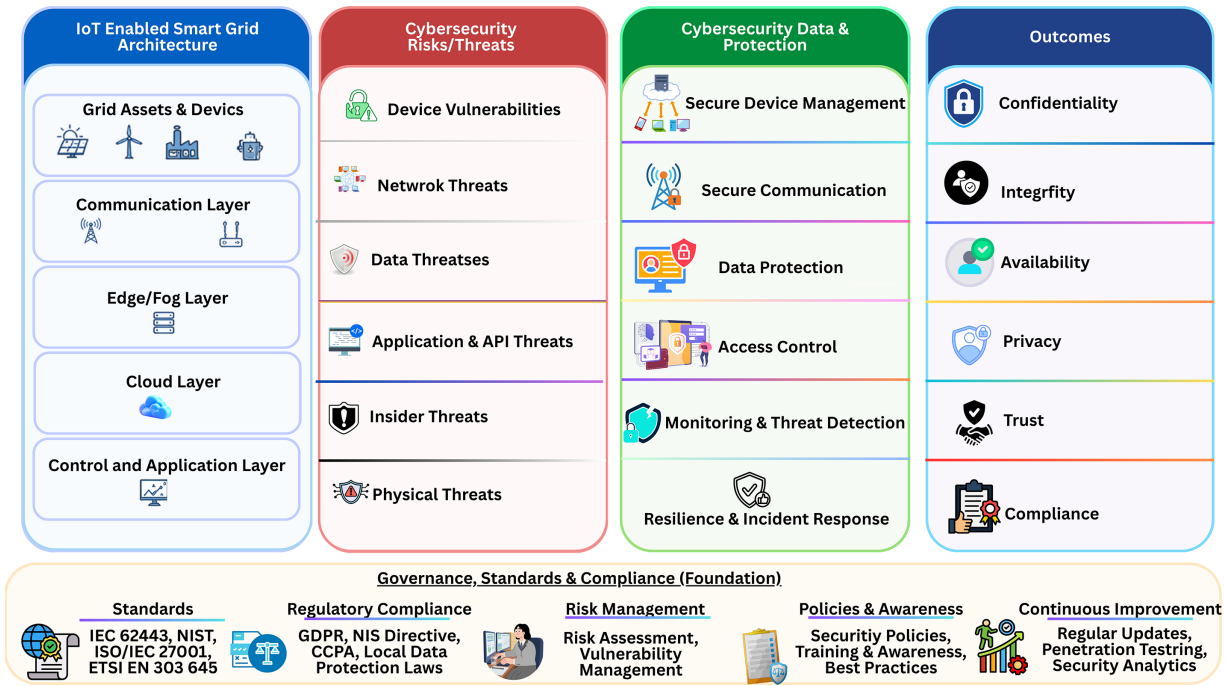


Figure 10: Cybersecurity and data privacy considerations in IoT-based SGs.

6.2 Data Privacy and AI Fairness Issues

The integration of these IoT and AI technologies into energy management systems involves substantial data. This data contains sensitive information about consumers' energy consumption. This may lead to data privacy and security concerns [95]. For instance, smart meters can provide valuable insights into customer activity; however, this data could be exploited and result in privacy violations. There are numerous concerns regarding AI in energy systems, including privacy, transparency, impartiality, and bias. Historical data is used to train AI algorithms; however, the algorithms must be accurate and representative to be effective. Biased or non-representative historical data may lead to inaccurate or unfair forecasts [96,97]. For example, inaccurate energy forecasts may lead to inefficient demand response or an unequal distribution of energy.

Despite AI's potential to improve the optimization of energy systems, it is imperative also to consider ethical considerations, including responsibility, transparency, and justice. The complexity of artificial intelligence models, which are also referred to as "black-box models," exacerbates this challenge [98]. To resolve these concerns, it is imperative that we establish and rigorously adhere to data governance principles that use privacy-protecting algorithms and anonymization. Furthermore, XAI has the potential to enhance transparency and ensure that decisions are both equitable and comprehensible.

6.3 Challenges in Scaling across Different Infrastructure Environments

A challenge in the rollout of digital energy technologies is scaling solutions across areas with varying levels of infrastructure readiness. While developed regions may be equipped with modern communication and grid, many developing regions may have traditional systems with limited digital features [99]. 5G communication networks, which are essential for providing real-time communication for SGs, come at a cost and will require infrastructure upgrades. The full potential of 5G-powered SGs cannot be achieved in areas with poor connectivity. Similarly, the implementation of IoT systems demands skilled personnel, a telecommunications network, and electricity, and in some cases, these may not be available [100].

Also, there is a need for interoperability: devices, platforms, and communication technologies must communicate efficiently. Without standards, compatibility issues can arise, restricting system performance and flexibility. A crucial aspect of the deployment of digital energy systems is infrastructure upgrades and standardization [101,102]. Furthermore, the difficulty and expense of implementing and operating cutting-edge technologies, such as AI and IoT systems, can be too high for utilities and industries, particularly in developing economies [103]. A shortage of skilled technicians and AI, IoT and SG experts also prevents deployment.

To overcome these challenges, governments and industry need to prioritize better infrastructure development, policy frameworks, standards and training. Edge and cloud-edge computing models can also help to minimize the need for cloud computing, improving scalability. The main challenges and the proposed solutions are summarized to give a one-stop resource for researchers and practitioners. Table 6 presents the eight categories of challenges, their effects on energy systems, and specific solutions, along with relevant literature.

Table 6: Challenges and solutions for the integration of 5G, AI, and IoT in sustainable ETs.

Challenge Category	Key Issues	Impact on Energy Systems	Proposed Solutions	Reference
Cybersecurity Risks	Vulnerabilities in IoT devices, data breaches and network attacks	Threats to SG stability and reliability	Implementation of encryption, secure communication protocols, and AI-based threat detection	[104]
Data Privacy Concerns	Sensitive user data from smart meters and IoT devices	Risk of misuse of consumer energy data	Data anonymization, strict data governance policies, and regulatory frameworks	[105]
High Energy Consumption of AI	Large-scale computation and data center energy usage	May offset sustainability benefits	Development of energy-efficient AI (Green AI), edge computing to reduce cloud dependency	[106]
Infrastructure Limitations	Lack of 5G coverage, outdated grid systems	Limits the adoption of smart technologies in developing regions	Investment in smart infrastructure, expansion of 5G networks, and modernization of grids	[107]
Interoperability Issues	Integration challenges between different devices and platforms	Reduces system efficiency and scalability	Standardization of protocols and open architecture for IoT and SGs	[108]
Scalability Challenges	Difficulty in expanding pilot projects to large-scale systems	Slows down real-world implementation	Modular system design and cloud-edge hybrid architectures	[109]

(Continued)

Table 6 (continued)

Challenge Category	Key Issues	Impact on Energy Systems	Proposed Solutions	Reference
Lack of Skilled Workforce	Shortage of expertise in AI, IoT, and SGs	Delays deployment and innovation	Training programs, interdisciplinary research, and capacity building	[110]
Regulatory and Policy Barriers	Lack of clear policies for AI and IoT in energy systems	Uncertainty in adoption and investment	Development of supportive policies, global standards, and governance frameworks	[111]

7 Future Directions

The vision of 5G, AI, and IoT for sustainable energy systems is still in its infancy, and there are numerous opportunities for further research, technology development, and policy initiatives. Although the preceding sections have shown the potential of these digital technologies, several areas still need to be explored to enable large-scale, secure and equitable implementation. In this section, a number of potential future directions are identified, including policy recommendations, new technologies (DT and edge AI), new capabilities for AI-based predictive analytics, and solutions to address current implementation challenges.

7.1 Policy Recommendations for Accelerating Adoption

To enable the use of 5G, AI, and IoT in energy systems, both technological innovation and favorable policies are required. National and international policymakers need to create regulatory frameworks, investment incentives, and standards to ensure interoperability, security, and sustainability.

Many existing policy settings in many countries were crafted for the traditional, centralized, fossil-fueled energy system and, as such, are not well aligned with the decentralized, digital nature of SGs. To overcome this, new policies need to clearly define data governance and ownership policies for IoT energy systems, clarifying the ownership of data collected by smart meters and sensors, and the policies for sharing and monetizing such data [112]. Also, it is important to ensure that there are mandatory, up-to-date cybersecurity protocols and certifications for IoT devices, 5G communication components, and AI systems used in critical energy systems. Policies should also include interoperability guidelines requiring SG components to be based on standardized communication protocols to prevent vendor lock-in and enhance compatibility, such as IEC 61850, OpenADR, and MQTT [113]. Lastly, governments should offer incentives for developing Green AI and energy-efficient computing, including tax credits or research grants, to promote low-carbon AI models and edge computing that avoid the cloud.

Substantial investment and infrastructure upgrades are needed in many areas, especially in developing countries, to support 5G-ready SGs. Governments should focus on public-private partnerships for 5G deployment in rural and marginalized areas, as connectivity is deeply linked to energy access; governments could invest in infrastructure in exchange for certain levels of service from grid operators [114]. Additionally, investments in grid modernization should focus on digital technologies such as IoT sensors, smart meters, and AI-based control systems rather than simply grid hardening. Training programs must be developed to enable engineers, technicians, and policymakers to adapt to the management of AI and IoT, facilitating this transition [29]. Meanwhile, there is a need to inspire universities to create interdisciplinary degrees with energy systems and data science/cybersecurity.

Finally, because energy systems will become increasingly transboundary and because digital technologies are not yet harmonized, international coordination and harmonization are needed. Future efforts should be made to coordinate 5G spectrum for the use of SG technologies on a cross-border level, allowing cross-border energy markets and grid operations. Governments should also establish international standards for AI ethics in energy to mitigate algorithmic bias, transparency and accountability concerns, possibly building on the EU's Ethical Guidelines for Trustworthy AI [115] with energy-specific considerations. Similarly, the energy sector could adopt threat intelligence-sharing platforms for cybersecurity, enabling utilities to share information on cyberattacks and vulnerabilities while protecting critical data.

7.2 The Future Role of Digital Twins in Energy Grid Management

DT is one of the most exciting technologies for the future of smart energy systems, where a physical asset (a power station, a transmission network, or an entire grid) is virtually replicated and kept up to date using real-time data from IoT sensors for simulation, prediction, and optimization. DT allows a shift from static modelling based on historical data to dynamic, real-time simulation, unlike present grid management, which is primarily based on historical data and offline modelling [116,117]. This enables predictive fault detection, in which operators use real-time sensor data to compare it with the twin's normal behavior and detect early signs of problems, such as abnormal temperature or vibration in a transformer, milliseconds before they occur. In addition, DT enables “what-if” simulations, helping operators assess the effects of various contingencies, such as cloud cover blocking solar panels or cyberattacks, and explore response strategies without affecting physical assets. DT also enables asset optimization by simulating the wear and tear on costly assets, such as substations, and helping operators balance short- and long-term benefits.

The integration of DT with AI and 5G presents an opportunity for self-organizing, self-healing grids, a promising research frontier. AI-powered DT could go beyond simulation to suggest or even implement corrective measures; for example, if a DT detects a voltage problem, an AI agent could automatically control tap changers or capacitor banks [29]. Also, the ultra-low latency of 5G enables edge-level DT, where multiple DT instances for various grid components (such as microgrids or distribution feeders) interact to achieve global optimization while meeting local constraints. Future research should also consider lifecycle DT that models energy assets from cradle to grave, thereby promoting the circular economy through optimal repair, refurbishment and recycling.

There are obstacles to overcome when using DT. The computing resources required for DT of large grids for high-fidelity simulations are significant, and reduced-order modelling needs to be carried out to ensure an optimal balance between fidelity and speed. Additionally, for synchronizing physical assets and their DT, an accurate clock and communication are necessary. At the same time, 5G can help in this regard; however, more research is required to address the missing data and delays. Finally, trust in these systems requires the development of validation procedures and uncertainty quantification techniques to increase confidence in decisions made based on a DT.

7.3 Expected Advancements in AI for Predictive Analytics and Automation

AI technologies are advancing rapidly, and several trends are poised to shape smart energy systems over the coming decade. On the front of future energy forecasting, new AI systems will extend beyond point forecasts to probabilistic forecasts, offering probability distributions to enable risk-based decision-making by grid operators. There will also be spatio-temporal models, such as graph neural networks (GNNs), that model correlations among geographically dispersed renewable energy sources and integrate diverse data streams, such as satellite images, drone data, and social media, to improve forecasts.

RL has the potential to play a crucial role in real-time grid operation, but safety requirements constrain its use. Key areas for future research include safe RL approaches that employ methods such as constrained policy optimization to ensure constraints on voltage and thermal limits are satisfied even while exploring. Moreover, multi-agent RL is being investigated to coordinate DERs, enabling distributed agents to communicate with one another rather than relying on a central controller. For efficiency, transfer learning and meta-learning are being investigated to transfer policies across grids, reducing the need for retraining.

As AI takes on a more prominent role in energy management, transparency and fairness are crucial. This includes XAI for power systems, such as attention-based methods that explain the most significant features used to make a particular forecast or control action. Moreover, future work needs to ensure fairness audits in demand response programs to avoid unintentional discrimination against low-income customers. Finally, the use of privacy-preserving AI, especially federated learning, will enable powerful analysis across multiple datasets while safeguarding customer data privacy.

7.4 Edge Computing and Distributed Intelligence

Many existing SG technologies rely on a cloud-centric architecture, leading to latency, bandwidth, and privacy concerns, and driving the trend toward edge computing, where data is processed locally, and is a natural fit for 5G. Future SGs are likely to have AI capabilities built into edge devices such as smart meters and substation controllers to facilitate local anomaly detection that can detect abnormal events such as a voltage anomaly or a device malfunction in milliseconds, rather than relying on cloud-based analytics. In addition to immediate action, edge AI supports data compression and filtering by pre-processing sensor data to send only summaries back to the cloud, thereby reducing bandwidth. These devices should also facilitate incremental learning, enabling them to update their models in response to local conditions, even when offline.

Cloud and edge should not be the only intelligence structures for the future, but a hierarchical intelligence model that leverages the cloud-edge partnership. This model is structured into three layers: Tier 1 (device/edge), for millisecond-level responses with lightweight models; Tier 2 (fog/regional), for second-to-minute planning and coordination; and Tier 3 (cloud), for planning, global model training, and simulations. This model can be supported by 5G network slices with different QoS levels for each tier, enabling the prioritization of critical real-time data over non-critical analytics.

However, research challenges arise in edge AI applications for energy systems. The biggest challenge is hardware constraints, which means that model compression techniques like quantization and pruning, as well as new hardware such as neuromorphic chips, are needed to make AI possible on low-end hardware. Security is also an important factor, since edge devices are physically accessible and thus vulnerable to attacks, and they require secure execution environments and remote attestation. Finally, federated learning across thousands of grid devices is a difficult distributed systems problem that demands efficient communication protocols and fault tolerance.

7.5 Addressing the Energy Consumption of Digital Technologies

One of the main difficulties of digitizing energy systems is that they consume energy; training AI algorithms and operating IoT and 5G networks can counteract some of the benefits of digitization. To overcome this, Green AI and sustainable computing should be a focus of future research and practice. This includes energy-efficient model design, where models are selected for lower energy consumption, even if it leads to slightly lower accuracy, and carbon-efficient computing, which shifts the scheduling of computationally intensive tasks to periods of lower carbon intensity. Additionally, the establishment of standardized lifecycle assessment methods is crucial for estimating the overall carbon emissions associated

with using AI, IoT, and 5G for energy applications, accounting for the energy consumption of the digital system and the operational energy savings achieved.

Recent hardware developments are promising avenues to reduce the energy use of these digital systems. Examples include energy-harvesting IoT devices that harness ambient energy sources (such as solar, thermal or vibration) to power their operation, removing the need for battery changes and thus lowering the lifecycle carbon impact. Also, 5G Redcap is a new standard for IoT devices that do not require the full performance of 5G, offering reduced cost and energy consumption without compromising many grid-sensing use cases. Lastly, backscatter communication can enable ultra-low-power sensors that reflect rather than transmit data, helping make sensors that last for decades without requiring maintenance. A conceptual map is offered to bring together the future potential of digital technologies in energy systems. Fig. 11 illustrates the synergistic interaction among AI, IoT, and 5G, each contributing to sustainable ETs through predictive analytics, real-time monitoring, and intelligent control, respectively.

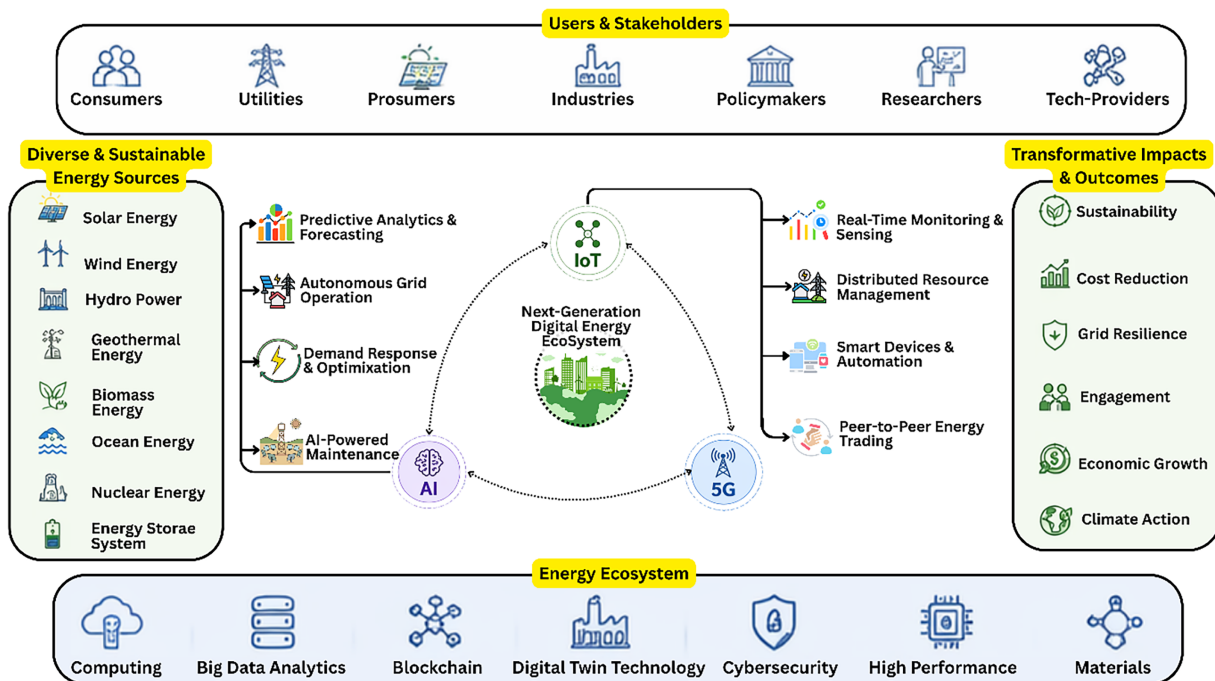


Figure 11: Future vision for digital energy systems: the next generation of AI, IoT, and 5G in sustainable energy management.

8 Conclusion

8.1 Synthesis of Key Findings

Unlike standard singular tech reviews, this comprehensive study introduces three major structural and theoretical contributions to the field of smart grid digital transformations:

1. **End-to-End Synergy Architecture:** It establishes a unified, cross-functional analytical map detailing how the physical data loop moves flawlessly across the IoT perception layer, 5G ultra-reliable low-latency network slicing, and AI cognitive control systems.
2. **Socioeconomic and Operational Troubleshooting:** It identifies and categorizes eight pragmatic bottleneck boundaries, such as algorithmic bias in XAI, data poisoning in smart grids, and the computational

energy penalty of large DL clusters, and proposes actionable technical engineering and governance solutions for each.

3. Future Industrial Roadmap Integration: It successfully bridges the gap between digital asset life-cycle management and sustainable circular-economy targets through hierarchical cloud-edge analytics, federated learning topologies, and DT frameworks tailored for Industry 5.0 grid scaling.

To provide a structured overview of the digital grid paradigm transformation analyzed in this paper, the core concluding insights are summarized below:

1. The Digital-Energy Dependency: The traditional one-way power grid is architecturally incapable of handling the variable load profiles of decentralized DERs, EVs, and proactive prosumers.
2. The Strategic Triad Synergy: Digitalization is not an elective enhancement but a fundamental requirement; the IoT serves as the baseline sensing system, 5G establishes the ultra-low-latency communication grid slicing pipelines, and AI serves as the core predictive cognitive layer.
3. Quantifiable Operational Benefits: Empirical literature confirms that the seamless integration of these advanced technologies yields precise renewable energy forecasting models, reduces grid maintenance overhead through automated anomaly detection, and maximizes adaptive balancing via RL-based demand response loops.
4. The Digitization Carbon Trade-Off: A critical paradox exists in which the computational footprints, data center infrastructure, and continuous network-processing energy demands of large-scale DL frameworks risk undermining the net-positive sustainability gains achieved through grid optimization.
5. Pragmatic Obstacle Boundaries: Universal deployment remains constrained by severe cybersecurity risks (such as data poisoning and edge-node intrusion), proprietary device interoperability deadlocks, and acute regional infrastructure investment disparities in developing economies.
6. The Evolution Matrix: The future trajectory of smart grid control systems will depend heavily on the maturity of lifecycle DT simulators, privacy-preserving federated learning loops, low-power hardware extensions like 5G RedCap, and supportive multi-sector data governance policies.

8.2 Research Gaps Identified

The present study reveals several major gaps that need to be explored. Existing studies on AI model fairness and accountability focus more on the accuracy and efficiency of models than on algorithmic bias, transparency, and model explainability. At the same time, important questions regarding equitable response programs and the verifiability of the AI recommendations remain largely unanswered. In terms of cybersecurity for AI-enabled grids, most studies focus on AI as a means of threat detection rather than as a potential threat itself, and the adversarial ML and security implications of federated learning and edge AI architectures are underexplored. Another gap is in net sustainability accounting, where there is no common approach to estimating the net positive carbon impacts of digital energy deployments, including the energy use associated with IoT devices, 5G networks, AI services, and computing, as well as the energy saved by their use. There are also issues of fragmentation in policy integration across sectors, as energy policy, digital infrastructure regulation, data privacy legislation, and cybersecurity standards have been formulated in isolation and are difficult to govern in an integrated fashion. In addition, equity and access are rarely discussed, and questions remain about whether 5G-enabled SGs will amplify current inequities and about how the advantages of digitalization can be fairly shared among high- and low-income communities, as well as between urban and rural areas.

8.3 Implications for Stakeholders

There are specific implications for three major audiences for this study. The paper offers a map for researchers to see where the current landscape stands and what is known and not yet known, as well as a list of research questions in computer science, electrical engineering, energy policy and social science that could be explored in doctoral dissertations and collaborative projects. The takeaway for industry players is that the digital revolution in the energy sector has already begun, and companies that don't invest in AI, IoT and 5G risk falling behind. Cybersecurity planning and staff training, interoperability standards work, pilot projects, and DT provide low-risk ways to experiment before scaling up technology adoption. This study demonstrates to policymakers that the energy and digital transitions are mutually dependent. Investments need to be connected to renewable generation and grid digitalization, and spectrum needs to be allocated for 5G for both consumer broadband and SG applications. Data governance must be mindful of innovation, privacy and security, and international coordination regarding standards and threat intelligence is imperative for interconnected energy systems.

8.4 Limitations of This Study

The limitations of this research need to be recognized. First, this study is not based on primary experimental research but on a systematic literature review. This method provides a broad synthesis but does not yield original quantitative results or validate them through controlled experiments. Secondly, the methodology section mentions bibliometric analysis, but it was not completed due to scope limitations; this should be included in future studies, and keyword co-occurrence mapping should be used. Third, the study is largely based on English-language academic literature, with the risk that relevant work in other languages or in industry 'gray literature' might not have been covered.

8.5 A Final Reflection

This sustainable ET is sometimes incorrectly described as a purely physical and engineering problem, when the real issue is scaling up solar panels, wind turbines, and batteries. The real challenge is in coordination, complexity, and control: managing millions of DERs in real time, dealing with the intermittency of supply and the variability of demand, and ensuring the security of the grid, with billions of connected devices. Digital technologies like 5G, AI, IoT, DT and edge computing are thus not a sidecar to the ET but the very central nervous system, thinking power and immune system. If they don't, renewable energy won't be able to be integrated at scale, grids won't be robust enough to defend against new threats, and a low-carbon, equitable, resilient energy future will remain out of reach. Digitalization, however, has its own set of dangers: cybersecurity vulnerabilities, privacy erosion, algorithmic bias and a considerable amount of energy usage. The way forward is for well-informed, critical and purposeful integration to be guided by deep research, considered policy and a dedication to equity. The fusion of 5G, AI, and IoT into intelligent, adaptive energy systems is no longer a vision. Still, unfolding reality—and the question is no longer “if”, but “how well and for whom.”

8.6 Concluding Statement

To conclude, this paper has shown that by combining 5G, AI and IoT in a single digital ecosystem, it is possible to unlock transformative potential for sustainable energy systems and SG innovation. They facilitate real-time monitoring, prediction, autonomous control, and effective incorporation of renewables. Yet numerous obstacles in cybersecurity, data privacy, interoperability, infrastructure investments, and energy use for digital technology must be addressed to realize this potential. Future research should focus on AI fairness, adversarial robustness, net sustainability accounting, and equitable access. The message is

clear for researchers, industry, and policymakers: Digital and ETs are now inseparably intertwined. It will be none of these technologies alone, but a combination of these technologies, intelligently, responsibly, and inclusively, that will bring success.

Acknowledgement: Not applicable.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: Ateeq Ur Rehman and Sunawar Khan performed the original writing part, software, and methodology; Ateeq Ur Rehman performed the rewriting, investigation, design methodology, and conceptualization; Salil Bharany perform related work part and managed results and discussions; Tariq Shahzad and Sunawar Khan performed the related work part and manage results and discussions; Sunawar Khan performed the rewriting, design methodology, and visualization; Ateeq Ur Rehman and Rizwan Tariq performed rewriting, design methodology, and visualization; Ateeq Ur Rehman conceptualization, data curation, formal analysis, resources, and supervision. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The data generated and analyzed during this study consist of the extracted literature characteristics, bibliometric analysis results, and synthesized datasets derived from publicly available publications and weblinks. These data are included within this published article and its supplementary materials. Any additional data supporting the findings of this study are available from the corresponding authors upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: Given their roles as Guest Editors of this journal, Ateeq Ur Rehman and Salil Bharany had no involvement in the peer review of this article and had no access to information regarding its peer review. Full responsibility for the editorial process for this article was delegated to another journal editor. The authors declare no other conflicts of interest.

Supplementary Materials: The supplementary material is available online at <https://www.techscience.com/doi/10.32604/ee.2026.085322/sl>.

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