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Review

The Impact of Novel Artificial Intelligence Methods on Energy Productivity, Industrial Transformation and Digitalization Within the Framework of Energy Economics, Efficiency and Sustainability

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Abstract

This review examines the transformative impact of innovative artificial intelligence (AI) methods on energy productivity, industrial transformation, and digitalization in the context of energy economics, energy efficiency, and sustainability. AI-based tools are revolutionizing energy systems by optimizing production, reducing waste, and enabling predictive maintenance in industrial processes. Integrating AI increases operational efficiency across various sectors, significantly contributing to energy savings and cost reductions. Using deep learning (DL), machine learning (ML), and generative AI (genAI), companies can model complex energy consumption patterns and identify efficiency gaps in real time. Furthermore, AI supports the renewable energy transition by improving grid management, forecasting, and smart distribution. The review highlights how AI-assisted digitalization fosters smart production, resource allocation, and decarbonization strategies. Economic analyses indicate that AI implementation correlates with improved energy intensity indicators and long-term sustainability benefits. However, challenges such as data privacy, algorithm transparency, and infrastructure investment remain key barriers. This article synthesizes current literature and case studies to provide a comprehensive understanding of AI's evolving role in transforming energy-intensive industries. These findings highlight AI's crucial contribution to sustainable economic development through improved energy efficiency and digital innovation.

Keywords: artificial intelligence; deep learning; machine learning; generative AI; edge computing; energy efficiency; sustainability

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1. Introduction

The impact of artificial intelligence (AI) on energy productivity began with the integration of machine learning with demand forecasting, enabling more accurate predictions of consumption patterns in the energy economy [1]. Early applications in smart grids demonstrated that AI can dynamically balance supply and demand, improving system efficiency and reducing energy waste [2]. With the rise of Industry 4.0, AI has begun to transform industrial transformation by automating energy-intensive processes and optimizing production workflows [3]. AI-powered predictive maintenance has become a key tool for preventing equipment failures, thereby improving energy efficiency and reducing operating costs. Industrial digitization has introduced large-scale data streams from

IoT sensors, laying the foundation for AI-based analytics for energy productivity [4]. As industries have become increasingly data-centric, AI techniques such as reinforcement learning have begun to optimize production scheduling and real-time energy allocation. Edge computing has fueled this transformation by enabling local, low-latency energy analysis, reducing reliance on centralized cloud systems. Digital twins have emerged as powerful tools in energy economics, enabling simulation of industrial energy consumption and supporting more sustainable design decisions [5]. From a sustainability perspective, AI-based energy optimization has contributed to reducing carbon footprints and promoting the integration of renewable energy [6]. These methods have also begun to support circular economy models, where AI helps minimize resource waste and maximize efficiency in production chains [7]. In the industrial transformation, AI-based robotics and autonomous systems have reduced human error and improved energy-conscious production processes. In politics and economics, governments and corporations have begun to recognize AI as a driver of energy productivity, encouraging research and implementation [8]. The evolution of understandable AI and ethical frameworks has addressed societal concerns, ensuring transparency and accountability for digitalization in the energy sector [9]. Together, these advances have marked a shift from reactive to proactive energy management, transforming energy efficiency into a strategic asset for industry. Today, AI sits at the intersection of energy economics, industrial digitalization, and sustainability, shaping a future where productivity and environmental responsibility converge [10].

The application of AI to energy productivity, industrial transformation, and digitalization has evolved through various phases within the fields of energy economics, efficiency, and sustainability [11]. In the 1950s and 1970s, early AI methods, such as expert systems, were primarily conceptual, with limited application in energy modeling due to computational constraints. In the 1980s, rule-based systems and optimization algorithms began supporting energy demand forecasting and efficiency planning in industry. The 1990s saw the introduction of neural networks and evolutionary algorithms, enabling more accurate load forecasting, fault detection, and efficiency optimization. In the 2000s, the development of big data and advanced sensor technologies enhanced AI-based energy monitoring, enabling industries to begin integrating digitalization into operational processes [12]. Since the 2010s, machine learning and deep learning have advanced predictive maintenance, smart grid management, and dynamic energy optimization in industry. In the mid-2000s, AI became a central element of Industry 4.0, driving the development of cyber-physical systems, intelligent automation, and resource-efficient manufacturing [13]. In the 2020s, reinforcement learning (ML) and hybrid AI models enabled real-time adaptive control of energy systems, accelerating the integration of renewable energy sources and industrial decarbonization. Current research emphasizes explainable AI and edge computing to improve transparency, trust, and energy-efficient digitalization [14]. In the future, AI is expected to underpin sustainable industrial ecosystems by balancing energy efficiency, economic growth, and carbon neutrality goals in a digitally connected global economy (Figure 1).

The influence of AI largely depends on the volume, accuracy, and detail of energy and industrial data collected via Internet of Things (IoT) and sensor networks. Furthermore, access to high-performance computers and edge devices influences the efficiency of AI's real-time processing and optimization of energy systems [15]. The degree to which AI is used to manage and integrate renewable energy sources also determines its impact on sustainability and energy efficiency. Supportive regulations, incentives, and standards enhance AI's transformative role, while fragmented policies and a lack of support can hinder its implementation and discourage potential investors, as the upfront costs (planning, construction, and implementation) are high [16]. Therefore, the willingness of industry

and governments to invest in AI-based digitalization significantly influences its impact on energy efficiency and productivity. Seamless communication (interoperability) between various devices, platforms, and industrial systems enhances AI's effectiveness in driving industrial transformation. The evolution of innovative AI methods and techniques, such as reinforcement learning, explainable AI, edge AI, and federated learning, and their relatively simple and low-cost access, are increasing the reliability and scalability of applications in the energy sector [17]. In the current geopolitical environment, robust protection of AI-based energy infrastructure against cyberthreats impacts trust, adoption, and long-term sustainability. The availability of skilled professionals capable of implementing, managing, and interpreting AI solutions is also crucial, as they can deliver significant societal and industrial benefits. The range of collaborations between industries, governments, and research institutions (from regional to global) is strengthening the dissemination of AI innovations across energy and industrial ecosystems.

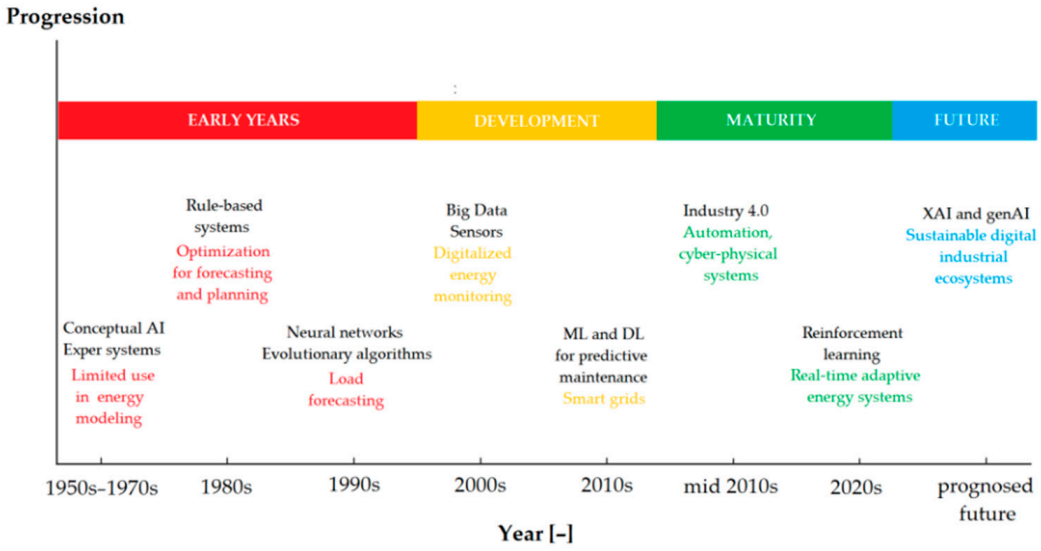


Figure 1. Milestones of development of AI methods on energy productivity, industrial transformation and digitalization (own approach). ML—machine learning, DL—deep learning, XAI—eXplainable AI, genAI—generative AI.

An important gap is the lack of standardized, high-quality datasets across industries, which limits the reliability and scalability of AI applications for energy efficiency. Many innovative AI methods require significant computing power, which can increase energy consumption and contradict sustainability goals [18]. Traditional industrial infrastructure often struggles to integrate with AI-based systems, slowing down digitalization and energy efficiency improvements and requiring significant preparation and investment. The "black box" nature of advanced AI models creates trust and accountability issues in energy economics and industrial decision-making. Decentralized and AI-based energy systems introduce new security vulnerabilities, but research into secure-by-design AI applications remains insufficient. The high upfront costs of implementing AI-based solutions prevent small and medium-sized enterprises from widely adopting them, leading to an uneven transition [19]. Current regulations have not kept pace with technological advances, leaving uncertainty about liability, compliance, and ethical standards for AI in energy management. Many successful AI demonstrations are limited to pilot projects, with limited application in large industrial or urban environments, and their scalability is difficult to predict. A lack of expertise in AI, energy systems, and digitalization slows the adoption and effective use of innovative methods in industry. Although AI is designed to increase efficiency, its

resource-intensive training and implementation can undermine long-term environmental sustainability [20].

This article aims at examination of the extent to which existing opportunities have been exploited in applying new AI methods to energy productivity, industrial transformation, and digitalization within the framework of energy economics, efficiency, and sustainability. We consider, on the one hand, the energy crisis and the need for sustainability and accelerated development of renewable energy sources, and, on the other, the impact of public awareness on the failure of electric cars, car sharing, and public transport in some countries. Therefore, from a systemic perspective, this problem is complex, and the answer may require extensive additional analysis.

2. Materials and Methods

2.1. Dataset

This bibliometric review was conducted to check the state of research, knowledge, and practice in the field of the impact of novel artificial intelligence methods on energy productivity, industrial transformation, and digitization within the framework of energy economics, efficiency, and sustainability. Well known and commonly applied bibliometric methods were used to identify and analyze recently published (i.e., up to 10 years ago, between 2016 and 2025) global scientific publications. The inclusion criteria for articles in the review were as follows: original articles and review articles in English, as well as full-text conference papers and book chapters, open source, indexed in four major bibliometric databases: WOS, Scopus, PubMed, and dblp. Exclusion criteria for the review included languages other than English, other forms of publication (reports, abstracts, etc.), and lack of full-text (open source). Research questions (RQs) were also formulated to help identify key areas including the current state of research, the origin of publications (affiliation, country, sources of funding), publication leaders, heads of research teams) and, where possible, the evolution of research topics in recent years:

- RQ1: evolution of research topics over time;
- RQ2: geographical distribution of research, publications, authors, institutions and if available,
- RQ3: publications with the highest impact and topics that may shape future research programs.

This is particularly relevant to the results of our review due to the quick changes in research in the areas of AI, energy transition, cybersecurity, green technologies (including Green AI), and sustainability, which have a key impact on AI-based data on energy efficiency in smart environments. Furthermore, where possible, we attempted to identify Sustainable Development Goals (SDGs) describing the publications included in the review. It is a part of a global transformation preparing society for the world of 2030 and beyond, respecting the environment and creating a better world for future generations. This method of analysis allows for a more comprehensive understanding of the areas and pace of development of past and current research, as well as economic, social, legal, and ethical trends. This indirectly also allows for AI-based business strategies and practices in the development of technologies related to AI-based data analysis for energy efficiency in smart environments that generate and distribute energy, and in the users themselves. This enables understanding and planning of further development activities in this field and allows for better matching of the potential of future researchers in technological and regulatory areas, taking into account the social context of the proposed changes (the need for social acceptance). According to paradigms of Industry 4.0 (automation, robotics, technical control throughout the entire production cycle), Industry 5.0 (humans and the environment at the center), and Industry 6.0 (empowering humans in production processes, sustainability,

and supply chain resilience), it is imperative to better understand development efforts and strengthen their potential today. Such a forward-looking interpretation of current, relevant bibliometric data will undoubtedly enrich discussions and provide a solid foundation for future research and analysis.

2.2. Methods

This study utilized a search of four bibliographic databases: Web of Science (WoS), Scopus, PubMed, and dblp. This combination of databases allowed for the broadest available search of research with global significance for the advancement of knowledge and its applications (Figure 2, Table 1). To identify the leading results of the review more quickly, appropriate filters were applied, and then further analysis steps could focus only on this selected literature, narrowing the scope of the search to articles in English. After filtering, each article was manually reviewed again by three independent experts to ensure that it met the inclusion criteria, the final sample size was determined. In the next step, key characteristics of the dataset were analyzed, such as the most frequently occurring authors and research groups, affiliations, countries, funding method (if reported), scientific fields, and topic groups. This allowed for mapping the main research achievements in the study area and identifying the most common trends. Where possible, temporal trends were observed to monitor changes over time and group publications into thematic clusters. This process highlighted important themes and subfields within the study area, including emerging ones.

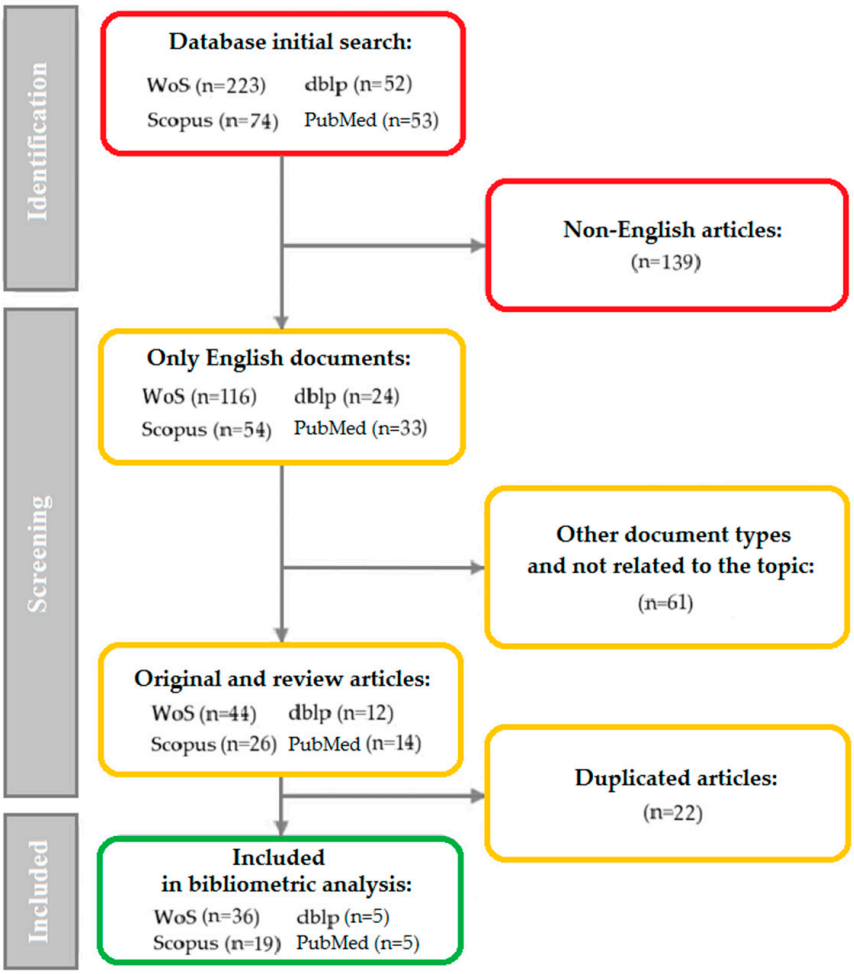


Figure 2. PRISMA 2020 flow diagram.

Table 1. Bibliometric analysis procedures (own approach).

Name of Stage	Tasks
Defining study aim(s)	Defining aim(s) of the bibliometric analysis
Selecting bibliometric database(s)	Selecting appropriate database(s), dataset(s) and developing research queries according to the aim(s) of the study
Data preprocessing/preparation	Removing duplicates and irrelevant records from the collected dataset, classification of the records to adapt them to the requirements of the ML training set
Bibliometric software selection	Selection of optimal tools from the area of bibliometric software for analysis
Data and metadata analysis	Description, keywords, type of publication, author(s), affiliation, area/topic, country, etc.
Analysis results/visualization of results (where possible)	Visualization of the results to emphasize insights
Interpretation of results and discussion	Interpreting results in the context of the research questions (RQs)

The included publications were manually assessed by three independent experts in this research area, with acceptance based on consensus among at least two of them. The included studies on the impact of novel AI methods on energy productivity, industrial transformation, and digitalization are generally credible, as most are based on peer-reviewed data sources, well-established modeling frameworks, and validated performance metrics. However, they may contain sampling errors, as case studies often focus on specific industries, regions, or energy systems, limiting the generalizability of the results. There is also a risk of methodological bias, where researchers favor specific AI models (e.g., neural networks) without sufficient comparison with alternative approaches. Data quality issues can arise, including incomplete, noisy, or outdated datasets, which can distort efficiency or sustainability results. Interpretation errors can occur when complex AI results are simplified to draw economic or policy conclusions, potentially leading to overestimation of benefits or underestimation of risks.

To facilitate replication and comparability of this review, we applied selected elements of the PRISMA 2020 Guidelines for Bibliographic Reviews (Figure 2, Supplementary Materials: PRISMA 2020 Checklist (partial only)). This allowed for a clearer structuring of the research process. The focus was on ten selected PRISMA 2020 items (presented in the Supplementary Materials):

- Item 3 (justification);
- Item 4 (objectives);
- Item 5 (eligibility criteria);
- Item 6 (information sources);
- Item 7 (search strategy);
- Item 8 (selection process);
- Item 9 (data collection process);
- Item 13a (synthesis methods);
- Item 20b (synthesis results);
- Item 23a (discussion).

This review utilized tools built-in the WoS, Scopus, PubMed, and dblp databases for bibliometric analysis. The selected review methodology allows for precise categorization by author(s), affiliations, keywords, research areas, and sources of founding, standardized across all the mentioned databases. Analytical results are presented in text and visualized to provide a coherent view tailored to the complexity of the topic.

Several methodological issues have consistently raised serious doubts about the validity of the literature on emerging AI approaches in energy productivity, industrial transformation, and digitalization. Many studies rely on small-scale case studies or simulations, limiting the generalizability of their findings to broader industrial or regional contexts. Standardized evaluation metrics are often lacking, making comparisons across AI models and applications difficult. A heavy reliance on proprietary or incomplete datasets introduces bias and raises concerns about replicability. Much of the literature emphasizes technical efficiency gains without sufficient analysis of long-term economic, social, or sustainability impacts. Publication bias favors positive results, while reporting on failed implementations or negative impacts is limited. Few studies address the interdisciplinary integration necessary for a holistic assessment of AI impact, particularly in the context of economics, policy, and environmental sustainability. The literature often lacks longitudinal analyses, which are crucial for assessing whether improvements in energy efficiency and productivity resulting from AI are sustainable in the long term. Our literature review attempts to at least partially address these methodological issues.

3. Results

3.1. Data Sources

To refine the search in the selected databases, filtered queries were used, limiting the results to English-language articles published between 2016 and 2025. The search was conducted as follows:

- In the WoS database, the "Subject" field (i.e., title, abstract, keywords, and other keywords) was used;
- In Scopus, the title, abstract, and keywords were used;
- In PubMed and dblp, manual keyword sets were used.

The databases were searched for articles using keywords such as "artificial intelligence" OR "AI," "machine learning" OR "ML," "deep learning" OR "DL" AND "energy efficiency" OR "energy productivity" OR "energy transformation" OR "energy optimisation" AND "Industry 4.0" OR "Industry 5.0" OR "Industry 6.0" AND "sustainable development" OR "sustainability" (Table 2).

Table 2. Databases search query (own version).

Parameter/Feature	Detailed Description
Inclusion criteria	Books, book chapters, articles (original, reviews, editorials), and conference proceedings, in English
Exclusion criteria	Articles, books, chapters older than 10 years, letters, conference abstracts without full text, in other languages than English
Keywords used	Artificial intelligence, machine learning, energy efficiency, energy productivity, energy transformation, energy optimization/optimization and similar
Used field codes (WoS)	"Subject" field (i.e., title, abstract, keyword plus and other keywords)
Used fields (Sopus)	Article title, abstract and keywords
Used fields (PubMed)	Manually
Used fields (dblp)	Manually
Boolean operators used	Yes
Filters used	Results were refined by year of publication, document type (e.g., articles and reviews), and subject area (e.g., industry, engineering, computer science, and physics)
Iteration/validation option(s)	The query is used iteratively, refined in subsequent iterations based on the previous results, and verified by checking whether relevant publications appear among the top results
Wildcarts and leverage truncation	Used symbol * for word variations (e.g., "energ*" for "energy" or "energetic")

In the next step the set of publications selected in the previous selection stages was further refined by manually re-selecting articles and removing irrelevant publications and duplicates to determine the final sample size. A summary of the bibliographic analysis results is presented in Table 3 and Figures 3–6. Sixty one articles (published between 2021 and 2025) were reviewed.

In response to RQ1, the evolution of research topics over time clearly demonstrates a path from early research on energy efficiency and optimization using classical mathematical models to the more recent integration of AI-based methods for forecasting, control, and decision support in energy systems. The timeline also reflects a gradual shift from isolated case studies to holistic analyses linking energy productivity with industrial transformation and digitalization. In response to RQ2, the geographical distribution indicates a strong contribution from countries with active clean energy programs, such as India, and European Union members, where collaboration networks between universities, research institutes, and industry are particularly extensive. High-impact publications often arise from interdisciplinary research centers and partnerships that connect AI specialists with energy economists and industrial engineers. Slowly emerging leading authors and institutions set methodological standards, shaping citation patterns and setting research priorities in different regions. Regarding RQ3, future research agendas will likely be shaped by topics such as deep learning in smart grids, reinforcement learning in adaptive energy management, and AI-based digital twins for industrial processes. Another emerging direction is the integration of AI into sustainability assessment systems, enabling precise assessment of carbon footprints and efficiency gains in real time. Digitalization and Industry 5.0/6.0 concepts will push AI research toward human-centric and resilient energy systems supported by increasing social awareness, rather than solely profit-driven optimization. New AI methods will also support cross-sectoral applications, connecting energy economics with transportation, manufacturing, and healthcare through predictive and optimization tools. Taken together, the answers to these RQs underscore that the impact of AI on energy productivity, industrial transformation, and sustainability is global and rapidly evolving, requiring coordinated attention from researchers and policymakers.

Table 3. Summary of the results of bibliographic analysis (WoS, Scopus, PubMed, and dblp).

Parameter/Feature	Value
Years of publication	Lack of publications before 2021–2025
Leading types of publication	Article (39.30%), Proceeding paper (26.20%), Book chapter (11.50%), Review article (11.50%)
Leading areas of science (there is more than one possible for a single article)	Engineering Electrical Electronic (38.18), Computer Science Information Systems (34.55%), Telecommunications (34.55%)
Leading country/countries	India (16.36%)
Leading author(s)	None prevalent
Leading affiliation(s)	None prevalent
Leading funders (where information concerning founding is available)	None prevalent
Leading Sustainable Development Goals (SDGs)	Responsible Consumption and Production, Industry Innovation and Infrastructure, Sustainable cities and Communities, Good Health and Well Being

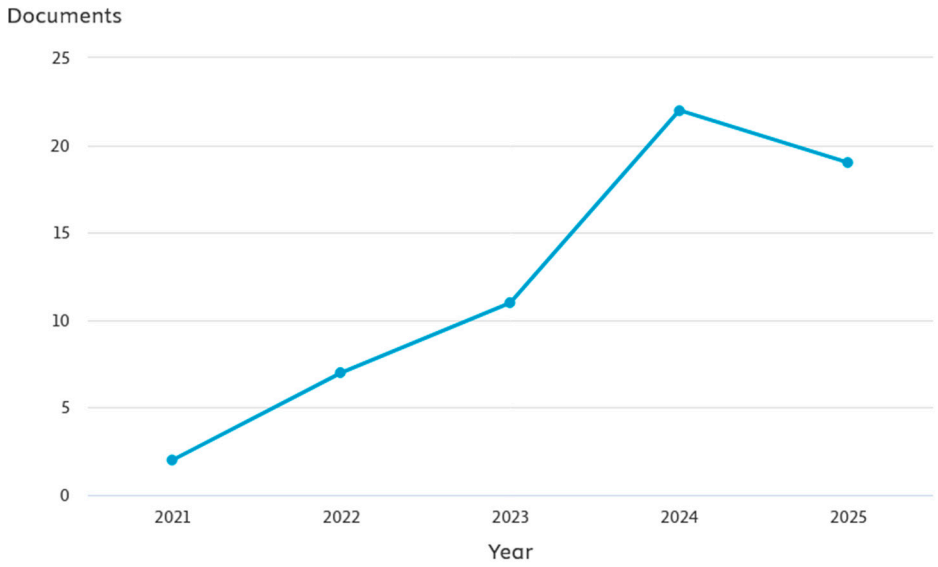


Figure 3. Results by year.

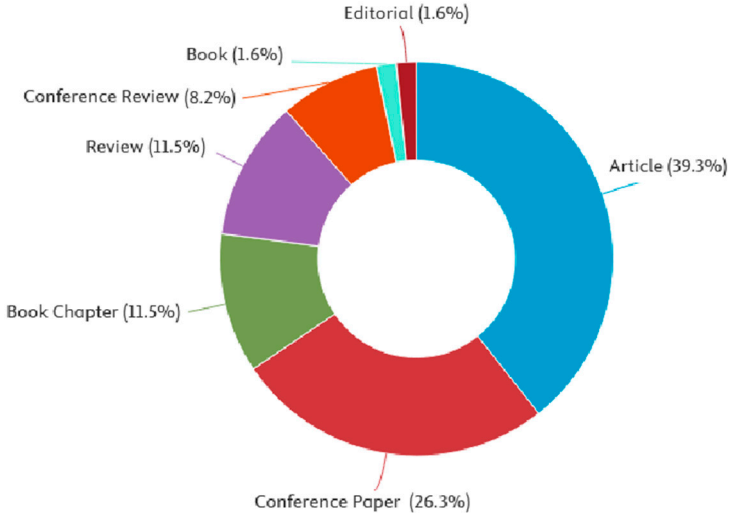


Figure 4. Results by type.

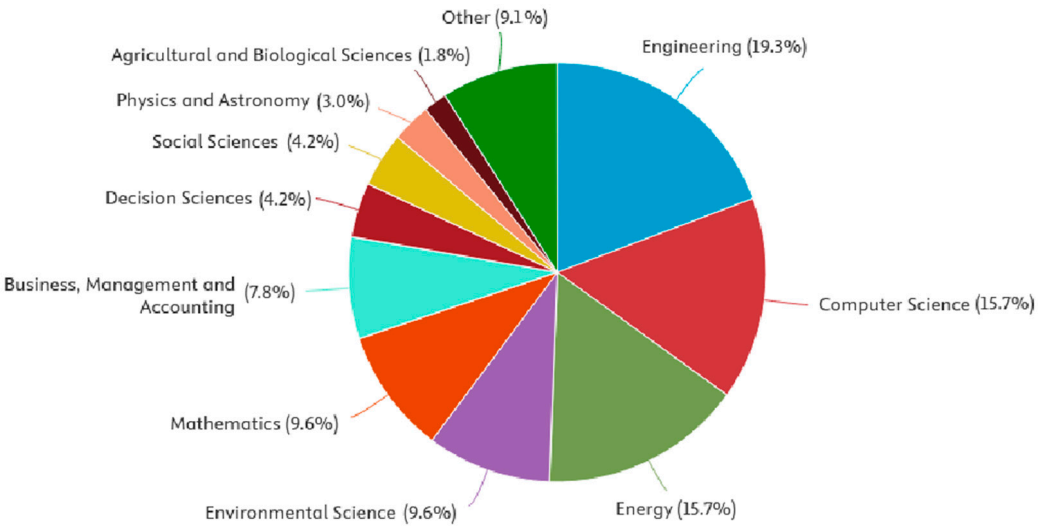


Figure 5. Results by area.

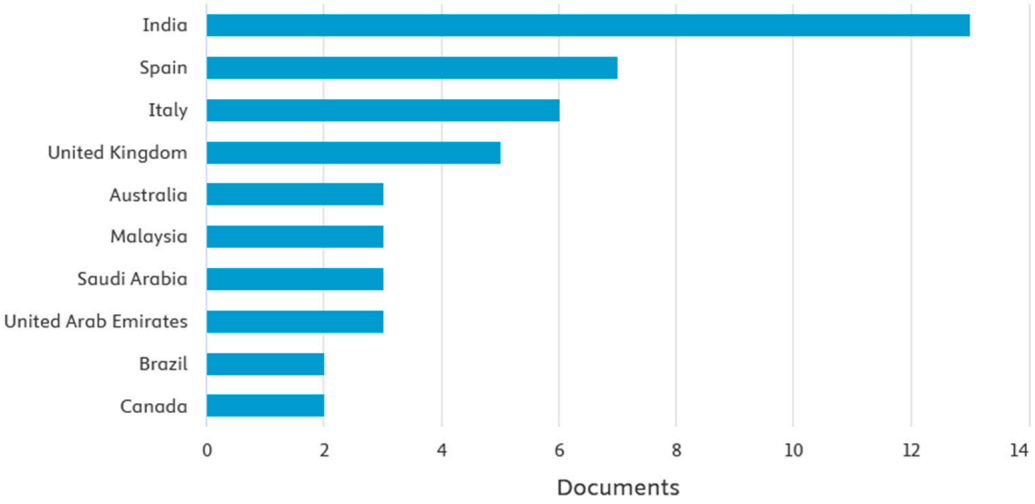


Figure 6. Results by country.

3.2. Advanced Digital Transformation in the Energy Sector

AI-based tools are transforming energy systems and industrial processes, leveraging a range of advanced technologies. ML algorithms play a crucial role, optimizing energy production by analyzing historical and current data to forecast demand, balance supply, and more effectively integrate renewable energy sources (Figure 7) [21].

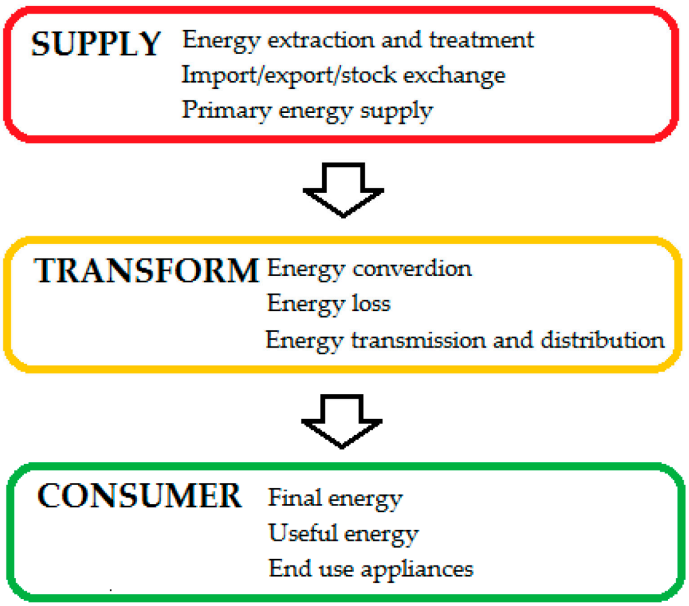


Figure 7. Simplified energy supply chain (own version based on [2]).

Predictive analytics based on deep learning (DL) enables early detection of anomalies in equipment operation, reducing downtime and extending asset life. Reinforcement learning (RL) methods dynamically optimize control systems in factories and power plants, adapting energy consumption to changing conditions (Figure 8) [22].

DTs technologies create virtual replicas of machines and processes, enabling continuous monitoring, performance optimization, and scenario testing without disruption. IoT sensors provide AI systems with detailed data on energy flows, temperatures, vibrations, and pressures, improving the accuracy of waste detection and performance monitoring (Figures 9 and 10) [23,24].

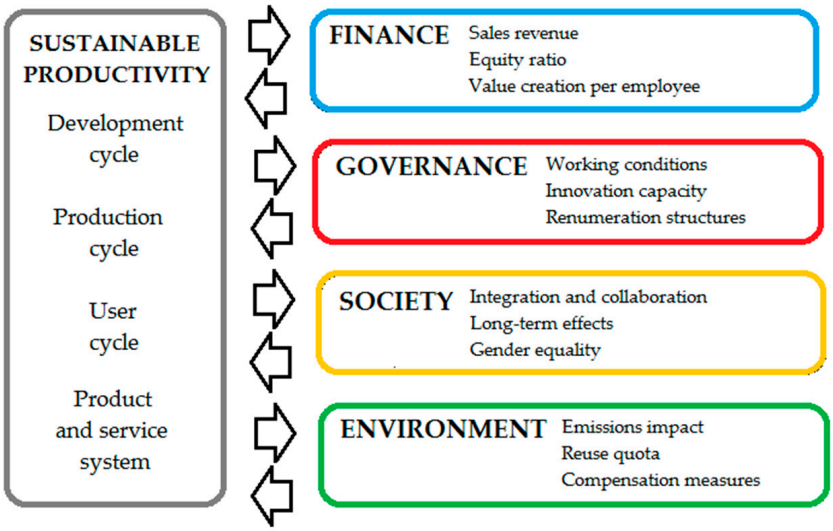


Figure 8. Factors influencing energy consumption within sustainable resilient manufacturing (own version based on [2]).

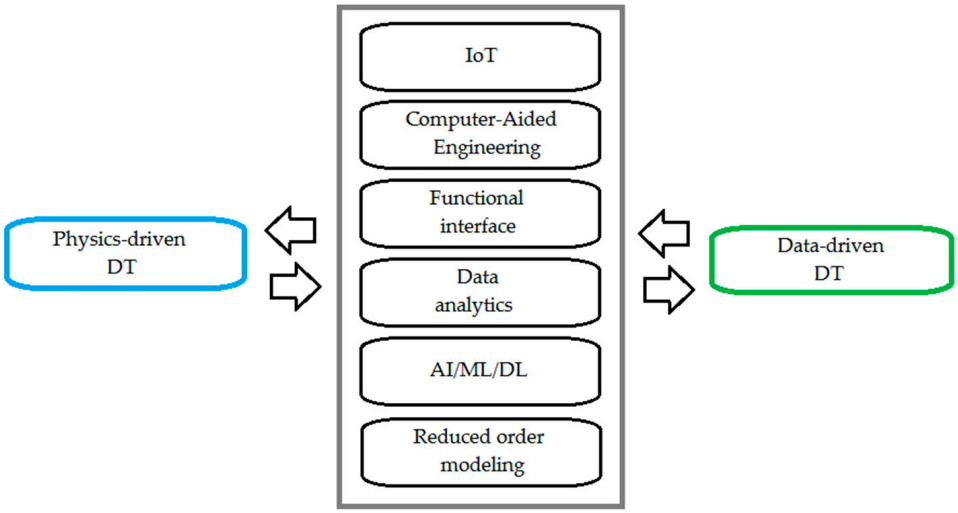


Figure 9. Sample DTs infrastructure (own version based on [1]).

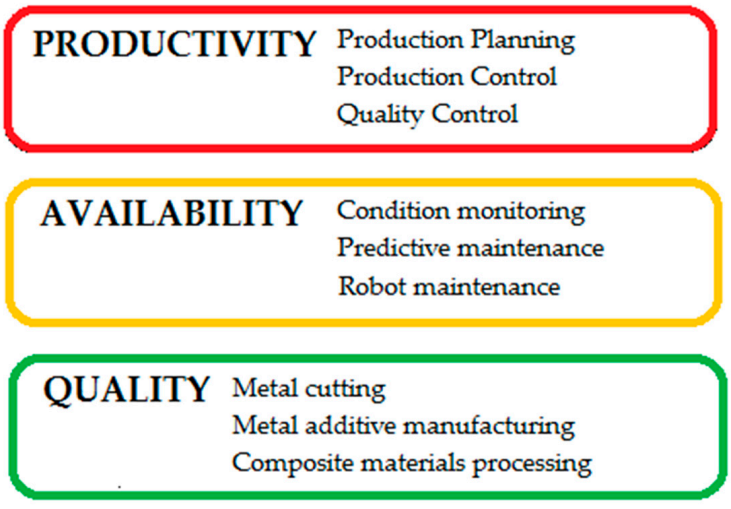


Figure 10. Key current areas of AI-based DTs in sustainable manufacturing (own version based on [1]).

Edge AI causes that this data is processed locally (in real time), reducing latency and energy consumption compared to cloud-based solutions. Vision systems further enhance predictive maintenance by analyzing thermal images, visual inspections, and wear patterns of industrial equipment. Natural language processing (NLP) powers energy management platforms that can interpret human queries, generate reports, and recommend optimization strategies. Together, these technologies enable a shift toward smarter, cleaner, and more sustainable industrial ecosystems where energy consumption is minimized, productivity is maximized, and environmental impact is significantly reduced [25,26].

3.3. Integrating AI Increases Operational Efficiency Across Various Sectors, Significantly Contributing to Energy Savings and Cost Reductions

AI integration in the industrial and service sectors increases operational efficiency of the entire system by enabling data-driven decision-making and real-time optimization. In manufacturing, AI-based predictive maintenance reduces unplanned downtime and extends equipment life, directly reducing energy consumption and repair costs [27]. In logistics, ML algorithms optimize routing and fleet management, minimizing fuel consumption and improving delivery efficiency. Smart grids use AI to forecast demand and dynamically balance loads, reducing energy consumption and shaping integration with renewable energy sources. In buildings, AI-based systems autonomously manage heating, cooling, and lighting, achieving significant energy reductions. In agriculture, AI-based precision farming optimizes irrigation, fertilizer use, and machine scheduling, reducing resource waste and energy costs. The financial services and IT sectors benefit from AI-based workload management, which reduces server energy demand through efficient data processing and cloud optimization. In the healthcare sector, AI is improving hospital operations, from patient flow to energy-efficient equipment use [28–35]. Retail and commercial businesses are leveraging AI to optimize supply chains and intelligently manage inventory, reducing both operating costs and energy consumption. The Green AI paradigm focuses on using less energy-intensive AI methods, while the eXplainable AI (XAI) paradigm focuses on human-readable decision-making from AI systems. Collectively, these sector-wide applications demonstrate that AI is a key enabler of energy efficiency, cost reduction, and sustainable growth in the global economy [36]. This clearly impacts national economies, including small and medium-sized enterprises (SMEs).

New AI methods have delivered measurable energy savings across multiple sectors. Logistics applications, such as AI-based HVAC (heating, ventilation, and air conditioning) control in cold storage facilities, have seen annual electricity consumption reductions of up to 30% (~850,000 kWh/year). In industrial energy systems, AI-powered predictive maintenance and process optimization have demonstrated a 10–20% reduction in operational energy consumption, resulting in lower costs and carbon emissions. In agriculture, AI-optimized irrigation systems, such as Netafim's, have reduced water consumption by 50% while also reducing the energy required for pumping and distribution. Greenhouse automation projects, such as iGrow, have seen a 92.7% increase in net profit and a 10.15% increase in yield, achieved in part by improved energy and input efficiency. AI-based predictive building control in institutional facilities has achieved 23.9% lower natural gas consumption and 6.3% lower winter heating demand. In construction and building operations, AI-based digital twins and intelligent control systems can reduce material consumption by up to 40% and achieve 20–30% energy savings compared to conventional methods. Indoor agriculture research has shown that AI can reduce the energy intensity of lettuce production from ~9.5 kWh/kg to ~6.42 kWh/kg, representing a significant improvement in food system sustainability. In wind energy logistics, AI/ML tools are expected to reduce installation and transportation costs by 10% globally, indirectly reducing emissions associated with heavy equipment use and transportation. AI-based monitoring in ports and supply chains,

such as Awake.AI, provides tools to quantify and reduce CO_2 emissions from Scope 1–3 sources, helping cities achieve their climate goals. Statistical evidence to date shows that AI contributes not only incremental but also double-digit percentage improvements in energy savings and emissions reductions, confirming its role as a key driver of energy efficiency, industrial transformation, and sustainable development.

3.4. Using ML, DL, and genAI Companies Can Model Complex Energy Consumption Patterns

ML enables companies to analyze massive datasets from sensors, meters, and industrial processes, uncovering complex energy consumption patterns that are difficult to detect with traditional methods. Using anomaly detection algorithms, ML can identify real-time performance gaps, such as unexpected demand spikes or equipment inefficiencies [37]. DL enhances this process by using neural networks to model nonlinear relationships between variables, increasing the accuracy of energy demand forecasting and predictive maintenance. DL also supports renewable energy integration by forecasting solar and wind energy generation variability with increased precision, enabling to more efficiently balance supply and demand [38]. GenAI introduces a new dimension by creating synthetic scenarios and simulations of energy systems, helping companies test different operational strategies without physical risk. GenAI can generate digital twins of entire energy grids, enabling scenario analysis for demand response, storage optimization, and outage management. Together, ML, DL, and genAI enable smart distribution systems to dynamically allocate resources, reducing losses and improving reliability [39]. These technologies also enable utilities to more seamlessly integrate distributed renewable energy sources, such as rooftop solar PV and microgrids, into national systems. Real-time analytics from AI-based models ensure grid stability even with high renewable energy deployments, while reducing costs and emissions [40]. The synergy of ML, DL, and genAI accelerates the transition to renewable energy, enabling the creation of more resilient, efficient, and adaptive energy ecosystems (Figure 11) [41–43].

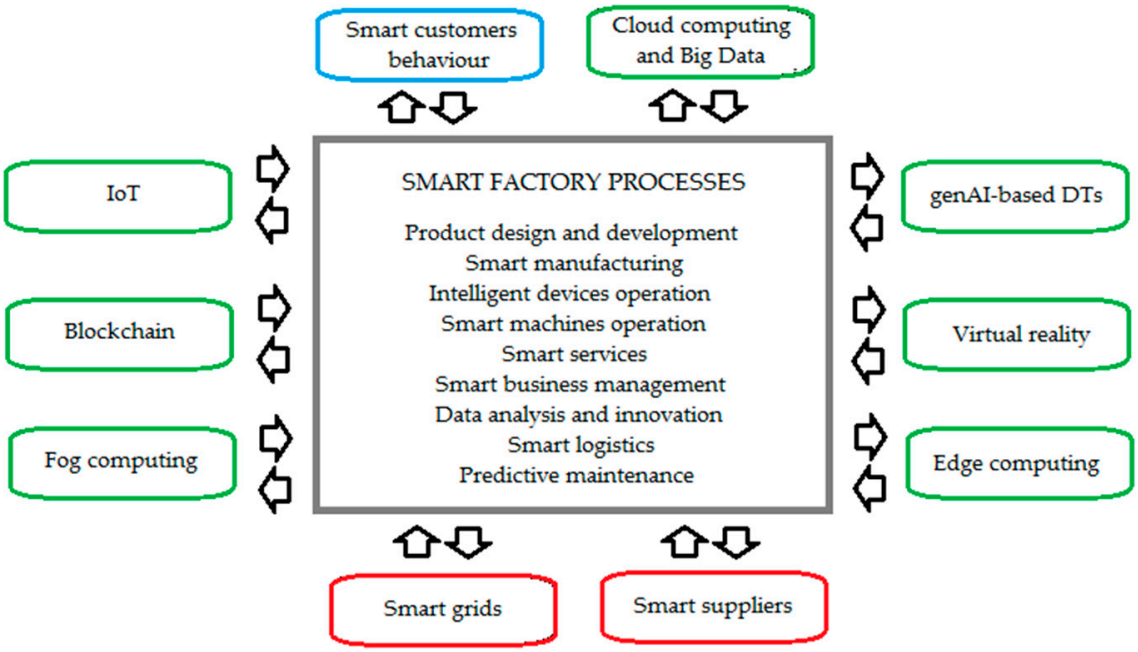


Figure 11. Synergy of technologies and approaches within sustainable smart factory (own version based on [2]).

3.5. AI-Assisted Digitalization Fosters Smart Production, Resource Allocation, and Decarbonization Strategies

AI-powered digitalization supports smart manufacturing by enabling monitoring and optimization of industrial processes in real time, ensuring minimal energy waste and maximum production efficiency [44]. Using advanced analytics, AI systems dynamically allocate resources to match supply with demand while minimizing downtime and overproduction. AI-based predictive maintenance further reduces energy intensity, extending equipment life and preventing costly breakdowns [45]. In asset management, AI-based platforms optimize raw material consumption, recycling, and supply chain logistics, contributing to the implementation of circular economy practices. This efficiency directly supports decarbonization strategies by reducing the carbon footprint in energy-intensive industries. Economic analyses show that companies implementing AI experience measurable improvements in energy intensity, meaning they generate more energy with less energy [46]. Smart grids and dedicated decentralized energy management systems based on AI facilitate the integration of sources of renewable energy, further accelerating the achievement of carbon reduction goals [47]. Over time, these technologies not only reduce operating costs but also provide resilience to volatile energy markets. Research also suggests that AI implementation correlates with long-term sustainability benefits, including increased competitiveness and compliance with climate policies [48]. AI-assisted digitalization aligns industrial transformation with global sustainability goals, making energy systems cleaner, smarter, and more economically viable (Figure 12) [49].

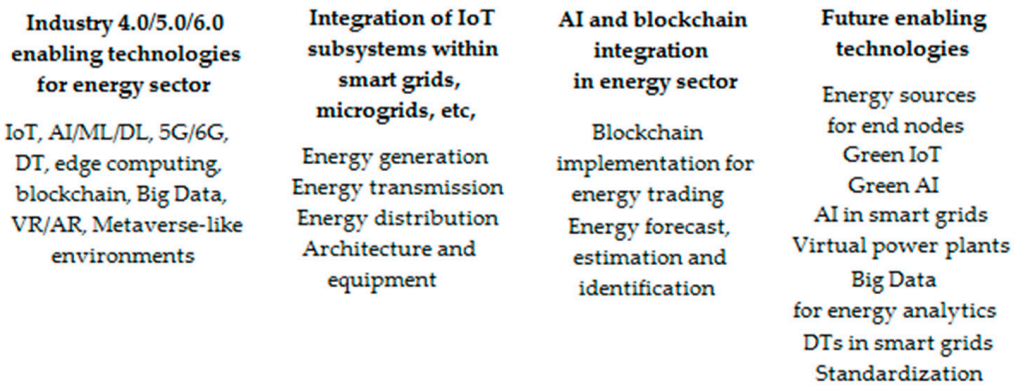


Figure 12. Key issues in sustainable energy management (own version based on [2]).

3.6. Risks and Advantages

New AI methods for energy productivity, industrial transformation, and digitalization, despite their transformative potential, carry a number of risks. One major issue is data dependency, as low-quality or biased datasets can lead to erroneous forecasts and suboptimal energy strategies. The use of complex, black-box AI models creates problems with interpretation and accountability, making it difficult for decision-makers and operators to justify or trust decisions regarding critical infrastructure. High implementation costs and unequal access can lead to disparities, where only well-funded regions or companies benefit from AI-driven efficiency gains, exacerbating inequalities. Furthermore, increasing digitalization exposes energy systems to cybersecurity threats, where attacks on AI-controlled networks can have serious social and economic consequences. There is also the risk of excessive automation, limiting human oversight and potentially omitting contextual knowledge needed in crisis situations. AI-based optimization may prioritize short-term efficiency or economic benefits over long-term sustainability goals, risking misalignment with broader climate and societal goals (Table 4, Figure 13).

Table 4. Summary of advantages and risks of using Ai in the energy sector.

Advantages	Risks
Improved energy forecasting (demand, prices, renewable generation)	Data privacy and security vulnerabilities
Enhanced grid stability and reliability through real-time monitoring	Algorithmic bias leading to unfair or inefficient decisions
Optimization of energy dispatch and load balancing	High initial investment and implementation costs
Integration of renewable and distributed energy resources	Over-reliance on black-box models with limited explainability
Predictive maintenance reducing downtime and costs	Cybersecurity threats to critical infrastructure
Dynamic pricing and market efficiency improvements	Integration challenges with legacy systems
Support for decarbonization and sustainability goals	Potential job displacement in traditional grid management

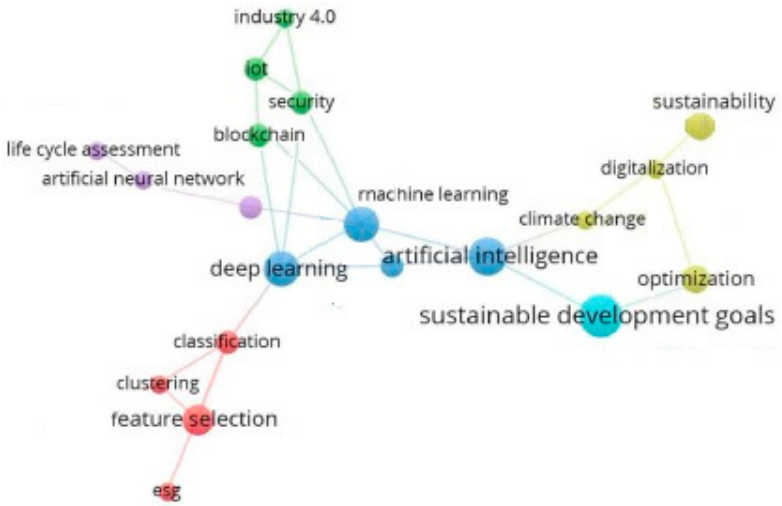


Figure 13. Keyword co-occurrence map (all four databases).

Several examples of projects from the logistics, construction, and agriculture sectors, illustrating the impact of innovative AI methods on energy efficiency, industrial transformation, and digitalization in the context of energy economics, efficiency, and sustainability, include CEVA Logistics/BeeBryte, GE Vernova—AI/ML for Wind Turbine Logistics Costs, Grow Autonomous Greenhouse Control(iGrow), Smart Droplets Project (a part of the European Green Deal), AgMonitor Platform (for water and energy efficiency in agriculture), Netafim and Smart AgriHubs.

4. Discussion

The primary outcome of this work is a bibliometric analysis that maps the impact of emerging AI methods on energy efficiency, industrial transformation, and digitalization. This analysis indicates a clear upward trend in the number of publications over the past decade, reflecting the growing role of AI in energy economics and sustainability. It identifies clusters of research topics, including AI for smart grids, predictive maintenance, renewable energy integration, and industrial applications of digital twins. High-impact research is concentrated in regions with ambitious energy transition policies, particularly in Europe and India, where research-industry collaboration is strongest. The literature also highlights a shift away from efficiency-oriented research toward a broader framework that connects AI with decarbonization, resilience, and circular economy principles. Citation

patterns show that interdisciplinary work, combining AI with economics and sustainability science, achieves the greatest impact and shapes new research agendas. The trend analysis highlights the growing importance of explainable AI and cybersecurity in addressing the threats accompanying large-scale digitalization. At the same time, bibliometric data reveal a gap in research on equity and access, as most studies focus on technologically advanced economies. The synthesis shows that AI-based methods deliver consistent, double-digit improvements in energy efficiency and emissions reductions, but their scalability depends on the regulatory, ethical, and infrastructural context. This bibliometric analysis provides a comprehensive synthesis of current knowledge and future directions, making it a crucial foundation for policymaking and research in the areas of energy productivity, industrial transformation, and sustainable development.

Despite the limited research available, it is already clear that the energy transition holds enormous potential. We must prepare for this both technologically, actively adapting old methods and techniques, and developing new, more energy-efficient ones. However, it seems that the greatest work lies ahead in the area of social awareness: ensuring that people and their communities are willing and able to use this to their benefit. In this area, the incentive of saving on energy bills will likely resonate most strongly and motivate people to make the effort. For businesses, this is a much smaller problem, but it is still related to the pace of digitalization and therefore highly dependent on the industry. Companies relying on electronic communications, new media or computational simulations will need to undergo a full digital and energy transformation faster, more effectively, and more comprehensively [50–52].

The bibliometric analysis indicates that India is leading the way in AI application in the energy sector, driven by rapidly growing electricity demand and a commitment to integrating renewable energy sources. Compared to Europe and North America, where AI often focuses on grid stability and energy efficiency optimization, India emphasizes scalable and low-cost AI solutions for managing diverse energy sources and rural electrification. China is seeing strong growth in AI-based energy projects, particularly in smart grids and renewable energy forecasting, but Indian research places a greater emphasis on practical implementation in emerging markets. Developed economies, on the other hand, typically achieve higher efficiency gains per project thanks to advanced infrastructure, while India demonstrates broader societal impact by expanding AI applications to underserved regions. Comparative data suggests that AI deployment in Europe could improve grid efficiency by as much as 15–20%, and AI-based demand forecasting in India reduced power outages in several states by almost 30%. These results highlight global regional differences, demonstrating that developed countries lead the way in technological advancement.

New cross-domain metrics can bridge AI research, energy economics, and sustainability, introducing new ways to assess the broader impact of AI methods. Benchmarks of AI model energy consumption allow researchers to quantify and compare the computational resources required by different algorithms, highlighting the trade-offs between accuracy and efficiency. AI regulatory policy variables reflect the impact of governance frameworks, compliance costs, and ethical constraints on AI deployment in energy-intensive sectors, linking digitalization with policy-driven sustainability. Quantitative assessment of Green AI methods provides standard metrics for measuring carbon footprint reductions achieved through model optimization, lightweight architectures, or renewable energy-based computing. Together, these metrics enable linking AI technical choices to macro-level outcomes in energy productivity, where efficient algorithms reduce overall industrial energy demand. They also reflect the role of AI-based automation in industrial transformation, enabling smarter and less energy-intensive production processes. Integrating these indicators into the energy economics and efficiency framework ensures that digitalization is not only

technologically advanced, but also environmentally sustainable and aligned with global climate goals.

4.1. Technological and Economical Influence

In the past, early AI methods such as expert systems and rule-based optimization were used in energy economics to improve forecasting and efficiency planning, although their impact was limited by computational power and narrow application areas. In the 1990s and early 2000s, neural networks, evolutionary algorithms, and the development of big data analytics enabled more accurate energy demand modeling, predictive maintenance, and improved optimization of industrial processes [53]. The proliferation of IoT sensors and digital monitoring systems in the 2000s increased data availability, allowing AI tools to play a key role in energy consumption balancing and efficiency tracking. Today, ML and DL models play a crucial role in energy efficiency, providing real-time information on consumption patterns, reducing waste, and optimizing the integration of renewable energy [53]. ML and DTs now support adaptive control in industrial systems, enabling the creation of smart factories, predictive fault detection, and dynamic energy allocation. AI-based smart grids are revolutionizing energy distribution, facilitating decarbonization and increasing resilience to fluctuations in renewable energy production [54]. Economic analyses show that current AI implementation improves energy intensity, reduces carbon footprint, and aligns with sustainable development goals. In the future, genAI will model complex energy systems and create scenario-based strategies for industrial decarbonization and efficiency optimization. Quantum computers and neuromorphic AI can further accelerate energy simulations and real-time resource allocation. The future of AI in energy economics will focus on creating resilient, sustainable, and digitally integrated ecosystems that balance productivity, cost-effectiveness, and environmental responsibility [55].

4.2. Societal and Ethical Influence

In the past, the social and ethical impact of early AI on energy economics was limited because its applications were narrow and focused primarily on technical forecasting [56–58]. However, concerns about job losses and automation began to emerge. With the rise in digitalization in the 2000s, AI-based productivity tools in industry raised issues of data privacy, workforce retraining, and equal access to technological benefits [59]. Today, the widespread use of ML/DL in energy and industrial systems brings both social benefits, such as lower energy costs and reduced emissions, and ethical risks, including algorithmic bias, cybersecurity vulnerabilities, and uneven global implementation [60]. Smart grids and AI-assisted energy systems enhance sustainability, but also raise concerns about oversight and control over consumer energy consumption. The digital divide poses ethical challenges as wealthier countries and companies adopt AI more quickly, potentially exacerbating inequalities in access to sustainable energy [61]. On the societal front, AI has created opportunities for green jobs, innovation, and improved public health through reduced pollution [62]. Today's ethical debates emphasize transparency, accountability, and the need for XAI in critical infrastructure such as energy systems [63]. In the future, AI could democratize access to clean energy by enabling decentralized microgrids, but only if regulatory frameworks ensure equity and inclusiveness [64]. Future ethical challenges will also include balancing automation with human employment, as well as ensuring the equitable distribution of sustainability benefits across societies [65]. Ultimately, the social and ethical impact of AI on the energy and industrial transformation will depend on governance, global cooperation, and prioritizing human-centered sustainability alongside technological advances [66,67].

The implementation of innovative AI methods for energy productivity, industrial transformation, and digitalization raises significant social, ethical, and legal issues in the context of energy economics, efficiency, and sustainability. From a societal perspective, AI-based energy optimization can reduce carbon footprints, but it can also lead to job losses in traditional energy sectors, as seen in the automation of smart grid operations. From an ethical perspective, relying on AI for critical infrastructure raises concerns about algorithmic bias in energy allocation, which can lead to unequal access to optimized resources for marginalized communities. For example, predictive AI models used in smart cities sometimes prioritize urban centers with high energy consumption over rural areas, exacerbating inequalities. From a legal perspective, issues of liability and accountability arise in the event of failures in AI-driven energy systems, such as power outages caused by automated errors in the demand-response system. Data privacy is another concern, as digitalization requires vast amounts of consumer energy consumption data, increasing the risk of surveillance and abuse. A specific example is the controversy surrounding smart meters in Europe, where citizens have expressed concerns about the continuous monitoring of household energy consumption. Ethical dilemmas also arise in balancing energy efficiency and sustainability, as AI can recommend cost-effective solutions that are not environmentally sustainable, such as over-reliance on gas instead of renewable energy sources. Social justice issues are becoming more prominent in industrial transformation, where wealthy companies may deploy AI-powered digital twins to achieve sustainability, while small businesses struggle to compete, creating an uneven technological environment. While innovative AI methods promise transformative benefits in energy efficiency and sustainability, they also require robust legal governance, ethical oversight, and socially inclusive policies to ensure equitable benefits.

4.3. Legal Influence

New AI methods are increasingly shaping the legal framework for energy economics, as policymakers adapt regulations to regulate their impact on productivity and sustainability. Regulations are beginning to recognize AI-based optimization tools that increase energy efficiency across industries by reducing waste and improving system reliability. In the midst of industrial transformation, legal standards define how AI can automate processes while ensuring compliance with labor, safety, and environmental regulations [68–71]. Regulators are also establishing requirements for data management and transparency, as the digitalization of energy systems relies on reliable AI models. Improving energy productivity based on AI raises issues of intellectual property rights, particularly regarding the ownership of algorithms and optimization results [72,73]. Regulators must also address liability issues, for example, when AI-driven industrial systems cause failures or inefficiencies that impact energy sustainability [74–76]. Digitalization in energy markets requires legal clarity regarding data sharing, cybersecurity, and interoperability, as cross-sectoral AI applications develop. International law plays a role in harmonizing AI standards in the energy sector to prevent technological and trade imbalances between regions [77]. The Sustainable Development Goals influence legal instruments that encourage or mandate AI deployment in renewable energy integration, demand response, and smart grid management [78,79]. AI's legal impact in this area balances innovation with responsibility, ensuring that technological advances in the energy economy promote efficiency, resilience, and long-term sustainability [80].

5. Conclusions

AI makes a key contribution to sustainable economic development by optimizing energy efficiency across industries, reducing waste, and reducing operating costs. Through

predictive analytics, AI enables accurate energy demand forecasting, allowing for better supply balance and the integration of the sources of renewable energy. AI-based smart grid systems increase resilience and flexibility, ensuring stable energy distribution even with fluctuating renewable energy supplies. In manufacturing, AI-based automation and process optimization minimize energy consumption while maintaining or increasing efficiency. DTs and AI simulations help companies test and refine low-emission strategies without costly real-world experiments. In transportation, AI supports route optimization, fleet electrification, and road traffic management, which contributes to lower emissions and fuel consumption. By enabling precision agriculture, AI reduces water, fertilizer, and energy consumption, thereby sustainably improving food security. From an economic perspective, AI-based digital innovations are creating new business models, green jobs, and investment opportunities in clean technologies. Research indicates that AI implementation correlates with long-term improvements in energy efficiency, competitiveness, and carbon reduction. AI acts as a catalyst for linking economic growth with environmental sustainability, making it a key component of the global green transformation.

The evolution of research topics points the way to the latest integration of AI-based methods for forecasting, control, and decision support in energy systems, as well as holistic analyses linking energy productivity with industrial transformation and digitalization. The geographical distribution indicates a strong contribution from countries with active clean energy programs and strong networks of universities and partnerships that connect AI specialists with energy economists and engineers, such as EU members and India. Future research programs will be shaped by the integration of AI with sustainability assessment systems, enabling precise assessment of carbon footprints and efficiency gains in real time. Cross-sectoral applications will be important, linking energy economics with transportation, manufacturing, and healthcare using predictive and optimization tools with a global reach and open to evolution.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
DL	Deep learning
GenAI	Generative AI
ML	Machine learning
XAI	eXplainable AI

References

1. Huang, Z.; Shen, Y.; Li, J.; Fey, M.; Brecher, C. AI-Driven Digital Twins. *Sensors* **2021**, *21*, 6340. [CrossRef]
2. Singh, R.; Akram, S.V.; Gehlot, A.; Buddhi, D.; Priyadarshi, N.; Twala, B. Energy System 4.0: Digitalization of the Energy Sector with Inclination towards Sustainability. *Sensors* **2022**, *22*, 6619. [CrossRef]
3. Ghobakhloo, M.; Fathi, M. Industry 4.0 and opportunities for energy sustainability. *J. Clean. Prod.* **2021**, *295*, 126427. [CrossRef]
4. Rojek, I.; Macko, M.; Mikołajewski, D.; Saga, M.; Burczynski, T. Modern methods in the field of machine modeling and simulation as a research and practical issue related to Industry 4.0. *Bull. Pol. Acad. Sci. Tech. Sci.* **2021**, *69*, e136719. [CrossRef]
5. Sepasgozar, S.M.E. Differentiating Digital Twin from Digital Shadow: Elucidating a Paradigm Shift to Expedite a Smart, Sustainable Built Environment. *Buildings* **2021**, *11*, 151. [CrossRef]
6. Xi, T.; Benincá, I.M.; Kehne, S.; Fey, M.; Brecher, C. Tool wear monitoring in roughing and finishing processes based on machine internal data. *Int. J. Adv. Manuf. Technol.* **2021**, *113*, 3543–3554. [CrossRef]
7. Moretti, M.; Rossi, A.; Senin, N. In-process monitoring of part geometry in fused filament fabrication using computer vision and digital twins. *Addit. Manuf.* **2021**, *37*, 101609. [CrossRef]
8. Borowski, P.F. Digitization, digital twins, blockchain, and industry 4.0 as elements of management process in enterprises in the energy sector. *Energies* **2021**, *14*, 1885. [CrossRef]
9. Rangel-Martinez, D.; Nigam, K.D.P.; Ricardez-Sandoval, L.A. Machine learning on sustainable energy: A review and outlook on renewable energy systems, catalysis, smart grid and energy storage. *Chem. Eng. Res. Des.* **2021**, *174*, 414–441. [CrossRef]
10. Rojek, I.; Mikołajewski, D.; Kotlarz, P.; Tyburek, K.; Kopowski, J.; Dostatni, E. Traditional Artificial Neural Networks Versus Deep Learning in Optimization of Material Aspects of 3D Printing. *Materials* **2021**, *14*, 7625. [CrossRef] [PubMed]
11. Alavikia, Z.; Shabro, M. A comprehensive layered approach for implementing internet of things-enabled smart grid: A survey. *Digit. Commun. Netw.* **2022**, *8*, 388–410. [CrossRef]
12. He, B.; Liu, L.; Zhang, D. Digital Twin-driven Remaining Useful Life Prediction for Gear Performance Degradation: A Review. *J. Comput. Inf. Sci. Eng.* **2021**, *21*, 030801. [CrossRef]
13. Heo, T.W.; Khairallah, S.A.; Shi, R.; Berry, J.; Perron, A.; Calta, N.P.; Martin, A.A.; Barton, N.R.; Roehling, J.D.; Roehling, T.; et al. A mesoscopic digital twin that bridges length and time scales for control of additively manufactured metal microstructures. *J. Phys. Mater.* **2021**, *4*, 034012. [CrossRef]
14. Jazdi, N.; Ashtari Talkhestani, B.; Maschler, B.; Weyrich, M. Realization of AI-enhanced industrial automation systems using intelligent Digital Twins. *Procedia CIRP* **2021**, *97*, 396–400. [CrossRef]
15. Guo, Y.; Wan, Z.; Cheng, X. When Blockchain Meets Smart Grids: A Comprehensive Survey. *High-Confid. Comput.* **2022**, *2*, 100059.
16. Rojek, I.; Mroziński, A.; Kotlarz, P.; Macko, M.; Mikołajewski, D. AI-Based Computational Model in Sustainable Transformation of Energy Markets. *Energies* **2023**, *16*, 8059. [CrossRef]
17. Bayer, B.; Diaz, R.D.; Melcher, M.; Striedner, G.; Duerkop, M. Digital twin application for model-based doe to rapidly identify ideal process conditions for space-time yield optimization. *Processes* **2021**, *9*, 1109. [CrossRef]
18. Ma, X.; Cheng, J.; Qi, Q.; Tao, F. Artificial intelligence enhanced interaction in digital twin shop-floor. *Procedia CIRP* **2021**, *100*, 858–863. [CrossRef]
19. Hardt, M.; Schraknepper, D.; Bergs, T. Investigations on the Application of the Downhill-Simplex-Algorithm to the Inverse Determination of Material Model Parameters for FE-Machining Simulations. *Simul. Model. Pract. Theory* **2021**, *107*, 129–148. [CrossRef]
20. Xu, J.; Guo, T. Application and research on digital twin in electronic cam servo motion control system. *Int. J. Adv. Manuf. Technol.* **2021**, *112*, 1145–1158. [CrossRef]
21. Zhou, Y.; Xing, T.; Song, Y.; Li, Y.; Zhu, X.; Li, G.; Ding, S. Digital-twin-driven geometric optimization of centrifugal impeller with free-form blades for five-axis flank milling. *J. Manuf. Syst.* **2021**, *58*, 22–35. [CrossRef]
22. Zhang, D.Y. Artificial intelligence and computational pathology. *Lab. Investig.* **2021**, *101*, 412–422.
23. Rojek, I.; Mikołajewski, D.; Mroziński, A.; Macko, M. Machine Learning- and Artificial Intelligence-Derived Prediction for Home Smart Energy Systems with PV Installation and Battery Energy Storage. *Energies* **2023**, *16*, 6613. [CrossRef]
24. Yiping, G.; Xinyu, L.; Gao, L. A Deep Lifelong Learning Method for Digital-Twin Driven Defect Recognition with Novel Classes. *J. Comput. Inf. Sci. Eng.* **2021**, *21*, 031004. [CrossRef]
25. Ganser, P.; Landwehr, M.; Schiller, S.; Vahl, C.; Mayer, S.; Bergs, T. Knowledge-Based Adaptation of Product and Process Design in Blisk Manufacturing. *J. Eng. Gas Turbines Power* **2022**, *144*, 011023. [CrossRef]
26. Su, S.; Zhao, G.; Xiao, W.; Yang, Y.; Cao, X. An image-based approach to predict instantaneous cutting forces using convolutional neural networks in end milling operation. *Int. J. Adv. Manuf. Technol.* **2021**, *115*, 1657–1669. [CrossRef]
27. Alguri, K.S.; Chia, C.C.; Harley, J.B. Sim-to-Real: Employing ultrasonic guided wave digital surrogates and transfer learning for damage visualization. *Ultrasonics* **2021**, *111*, 106338. [CrossRef]
28. Song, Z.; Hackl, C.M.; Anand, A.; Thommessen, A.; Petzschmann, J.; Kamel, O.; Braunbehrens, R.; Kaifel, A.; Roos, C.; Hauptmann, S. Digital Twins for the Future Power System: An Overview and a Future Perspective. *Sustainability* **2023**, *15*, 5259. [CrossRef]

29. Lv, Q.; Zhang, R.; Sun, X.; Lu, Y.; Bao, J. A digital twin-driven human-robot collaborative assembly approach in the wake of COVID-19. *J. Manuf. Syst.* **2021**, *60*, 837–851. [CrossRef] [PubMed]
30. Conrad, C.; Al-Rubaye, S.; Tsourdos, A. Intelligent Embedded Systems Platform for Vehicular Cyber-Physical Systems. *Electronics* **2023**, *12*, 2908. [CrossRef]
31. Różanowski, K.; Piotrowski, Z.; Ciolek, M. Mobile Application for Driver's Health Status Remote Monitoring. In Proceedings of the 9th International Wireless Communications and Mobile Computing Conference (IWCMC), Sardinia, Italy, 1–5 July 2013; pp. 1738–1743.
32. Jannasz, I.; Sondej, T.; Targowski, T.; Mańczak, M.; Obiała, K.; Dobrowolski, A.P.; Olszewski, R. Relationship between the Central and Regional Pulse Wave Velocity in the Assessment of Arterial Stiffness Depending on Gender in the Geriatric Population. *Sensors* **2023**, *23*, 5823. [CrossRef]
33. Martinez-Ruedas, C.; Flores-Arias, J.-M.; Moreno-Garcia, I.M.; Linan-Reyes, M.; Bellido-Outeiriño, F.J. A Cyber–Physical System Based on Digital Twin and 3D SCADA for Real-Time Monitoring of Olive Oil Mills. *Technologies* **2024**, *12*, 60. [CrossRef]
34. Mikołajczyk, T.; Kłodowski, A.; Mikołajewska, E.; Walkowiak, P.; Berjano, P.; Villafañe, J.H.; Aggogeri, F.; Borboni, A.; Fausti, D.; Petrogalli, G. Design and control of system for elbow rehabilitation: Preliminary findings. *Adv. Clin. Exp. Med.* **2018**, *27*, 12, 1661–1669. [CrossRef]
35. Zhao, Z.; Shen, L.; Yang, C.; Wu, W.; Zhang, M.; Huang, G.Q. IoT and digital twin enabled smart tracking for safety management. *Comput. Oper. Res.* **2021**, *128*, 105183. [CrossRef]
36. Pan, Y.; Zhang, L. A BIM-data mining integrated digital twin framework for advanced project management. *Autom. Constr.* **2021**, *124*, 103564. [CrossRef]
37. Huynh, H.N.; Altintas, Y. Modeling the Dynamics of Five-Axis Machine Tool Using the Multibody Approach. *J. Manuf. Sci. Eng.* **2021**, *143*, 021012. [CrossRef]
38. Rojek, I.; Kotlarz, P.; Dorożyński, J.; Mikołajewski, D. Sixth-Generation (6G) Networks for Improved Machine-to-Machine (M2M) Communication in Industry 4.0. *Electronics* **2024**, *13*, 1832. [CrossRef]
39. Psarommatis, F. A generic methodology and a digital twin for zero defect manufacturing (ZDM) performance mapping towards design for ZDM. *J. Manuf. Syst.* **2021**, *59*, 507–521. [CrossRef]
40. Joseph, A.J.; Kruger, K.; Basson, A.H. *An Aggregated Digital Twin Solution for Human-Robot Collaboration in Industry 4.0 Environments*; Springer International Publishing: Cham, Switzerland, 2021; pp. 135–147.
41. Autiosalo, J.; Ala-Laurinaho, R.; Mattila, J.; Valtonen, M.; Peltoranta, V.; Tammi, K. Towards integrated digital twins for industrial products: Case study on an overhead crane. *Appl. Sci.* **2021**, *11*, 683. [CrossRef]
42. Węgrzyn-Wolska, K.; Rojek, I.; Dostatni, E.; Mikołajewski, D.; Pawłowski, L. Modern approach to sustainable production in the context of Industry 4.0. *Bull. Pol. Acad. Sci. Tech. Sci.* **2022**, *70*, e143828. [CrossRef]
43. Cirullies, J.; Schwede, C. On-demand Shared Digital Twins—An Information Architectural Model to Create Transparency inCollaborative Supply Networks. In Proceedings of the 54th Hawaii International Conference on System Sciences, Honolulu, HI, USA, 5–8 January 2021; pp. 1675–1684.
44. Tipary, B.; Erdős, G. Generic development methodology for flexible robotic pick-and-place workcells based on Digital Twin. *Robot. Comput.-Integr. Manuf.* **2021**, *71*, 102140. [CrossRef]
45. Wang, P.; Luo, M. A digital twin-based big data virtual and real fusion learning reference framework supported by industrial internet towards smart manufacturing. *J. Manuf. Syst.* **2021**, *58*, 16–32. [CrossRef]
46. Zhang, X.; Liu, L.; Wan, X.; Feng, B. Tool Wear Online Monitoring Method Based on DT and SSAE-PHMM. *J. Comput. Inf. Sci. Eng.* **2021**, *21*, 034501. [CrossRef]
47. Chakraborty, S.; Adhikari, S.; Ganguli, R. The role of surrogate models in the development of digital twins of dynamic systems. *Appl. Math. Model.* **2021**, *90*, 662–681. [CrossRef]
48. Rojek, I.; Kowal, M.; Stoic, A. Predictive compensation of thermal deformations of ball screws in cnc machines using neural networks. *Teh. Vjesn.-Tech. Gaz.* **2017**, *24*, 1697–1703.
49. Chakraborty, S.; Adhikari, S. Machine learning based digital twin for dynamical systems with multiple time-scales. *Comput. Struct.* **2021**, *243*, 106410. [CrossRef]
50. He, B.; Cao, X.; Hua, Y. Data fusion-based sustainable digital twin system of intelligent detection robotics. *J. Clean. Prod.* **2021**, *280*, 124181. [CrossRef]
51. Rezaei Aderiani, A.; Wärmefjord, K.; Söderberg, R. Evaluating different strategies to achieve the highest geometric quality in self-adjusting smart assembly lines. *Robot. Comput.-Integr. Manuf.* **2021**, *71*, 102164. [CrossRef]
52. He, B.; Li, T.; Xiao, J. Digital twin-driven controller tuning method for dynamics. *J. Comput. Inf. Sci. Eng.* **2021**, *21*, 031010. [CrossRef]
53. Rojek, I. Hybrid Neural Networks as Prediction Models. In *Artificial Intelligence and Soft Computing, Lecture Notes in Artificial Intelligence*; Rutkowski, L., Scherer, R., Tadeusiewicz, R., Zadeh, L.A., Zurada, J.M., Eds.; Springer: Berlin/Heidelberg, Germany, 2010; pp. 88–95.

54. Wang, Q.; Jiao, W.; Wang, P.; Zhang, Y. Digital Twin for Human-Robot Interactive Welding and Welder Behavior Analysis. *IEEE/CAA J. Autom. Sin.* **2021**, *8*, 334–343. [CrossRef]
55. Denkena, B.; Pape, O.; Krödel, A.; Böß, V.; Ellersiek, L.; Mücke, A. Process design for 5-axis ball end milling using a real-time capable dynamic material removal simulation. *Prod. Eng.* **2021**, *15*, 89–95. [CrossRef]
56. Singgih, I.K. Production Flow Analysis in a Semiconductor Fab Using Machine Learning Techniques. *Processes* **2021**, *9*, 407. [CrossRef]
57. Ward, R.; Sencer, B.; Jones, B.; Ozturk, E. Accurate prediction of machining feedrate and cycle times considering interpolator dynamics. *Int. J. Adv. Manuf. Technol.* **2021**, *116*, 417–438. [CrossRef]
58. Mourtzis, D.; Angelopoulos, J.; Panopoulos, N. Development of a PSS for Smart Grid Energy Distribution Optimization based on Digital Twin. *Procedia CIRP* **2022**, *107*, 1138–1143. [CrossRef]
59. Heo, E.; Yoo, N. Numerical Control Machine Optimization Technologies through Analysis of Machining History Data Using Digital Twin. *Appl. Sci.* **2021**, *11*, 3259. [CrossRef]
60. May, M.C.; Overbeck, L.; Wurster, M.; Kuhnle, A.; Lanza, G. Foresighted digital twin for situational agent selection in production control. *Procedia CIRP* **2021**, *99*, 27–32. [CrossRef]
61. Malik, A.A.; Brem, A. Digital twins for collaborative robots: A case study in human-robot interaction. *Robot. Comput.-Integr. Manuf.* **2021**, *68*, 102092. [CrossRef]
62. Domalewska, D. A longitudinal analysis of the creation of environmental identity and attitudes towards energy sustainability using the framework of identity theory and big data analysis. *Energies* **2021**, *14*, 647. [CrossRef]
63. Han, X.; Chen, Y.; Feng, Q.; Luo, H. Augmented Reality in Professional Training: A Review of the Literature from 2001 to 2020. *Appl. Sci.* **2022**, *12*, 1024. [CrossRef]
64. Garavand, A.; Aslani, N. Informatics in Medicine Unlocked Metaverse phenomenon and its impact on health: A scoping review. *Inform. Med. Unlocked* **2022**, *32*, 101029. [CrossRef]
65. Sayed, K.; Abo-Khalil, A.G.; Eltamaly, A.M. Wind Power Plants Control Systems Based on SCADA System. In *Control and Operation of Grid-Connected Wind Energy Systems*; Springer: Cham, Switzerland, 2021; pp. 109–151.
66. Ahmadpour, A.; Mokaramian, E.; Anderson, S. The effects of the renewable energies penetration on the surplus welfare under energy policy. *Renew. Energy* **2021**, *164*, 1171–1182. [CrossRef]
67. Kulkarni, V.; Sahoo, S.K.; Mathew, R. Applications of Internet of Things for Microgrid. In *Microgrid Technologies*; Wiley: Hoboken, NJ, USA, 2021; pp. 405–428.
68. Hua, H.; Qin, Z.; Dong, N.; Qin, Y.; Ye, M.; Wang, Z.; Chen, X.; Cao, J. Data-driven dynamical control for bottom-up energy Internet system. *IEEE Trans. Sustain. Energy* **2021**, *13*, 315–327. [CrossRef]
69. Han, D.; Zhang, C.; Ping, J.; Yan, Z. Smart contract architecture for decentralized energy trading and management based on blockchains. *Energy* **2020**, *199*, 117417. [CrossRef]
70. Damisa, U.; Nwulu, N.I.; Siano, P. Towards Blockchain-Based Energy Trading: A Smart Contract Implementation of Energy Double Auction and Spinning Reserve Trading. *Energies* **2022**, *15*, 4084. [CrossRef]
71. Kumari, A.; ChintukumarSukharamwala, U.C.; Tanwar, S.; Raboaca, M.S.; Alqahtani, F.; Tolba, A.; Sharma, R.; Aschilean, I.; Mihaltan, T.C. Blockchain-Based Peer-to-Peer Transactive Energy Management Scheme for Smart Grid System. *Sensors* **2022**, *22*, 4826. [CrossRef]
72. Al Moti, M.M.M.; Uddin, R.S.; Hai, M.A.; Bin Saleh, T.; Alam, M.G.R.; Hassan, M.M.; Hassan, M.R. Blockchain Based Smart-Grid Stackelberg Model for Electricity Trading and Price Forecasting Using Reinforcement Learning. *Appl. Sci.* **2022**, *12*, 5144. [CrossRef]
73. Wang, X.; Xie, Z. Research on the Application of Blockchain Technology in Logistics Industry. *Adv. Econ. Bus. Manag. Res.* **2020**, *XXIX*, 1339–1349.
74. Gajić, D.B.; Petrović, V.B.; Horvat, N.; Dragan, D.; Stanisavljević, A.; Katić, V.; Popović, J. A Distributed Ledger-Based Automated Marketplace for the Decentralized Trading of Renewable Energy in Smart Grids. *Energies* **2022**, *15*, 2121. [CrossRef]
75. Rocha, H.R.O.; Honorato, I.H.; Fiorotti, R.; Celeste, W.C.; Silvestre, L.J.; Silva, J.A.L. An Artificial Intelligence based scheduling algorithm for demand-side energy management in Smart Homes. *Appl. Energy* **2021**, *282*, 116145. [CrossRef]
76. Albarakati, A.J.; Boujoudar, Y.; Azeroual, M.; Jabeur, R.; Aljarbouh, A.; El Moussaoui, H.; Lamhamdi, T.; Ouaaline, N. Real-time energy management for DC microgrids using artificial intelligence. *Energies* **2021**, *14*, 5307. [CrossRef]
77. Nair, D.R.; Nair, M.G.; Thakur, T. A Smart Microgrid System with Artificial Intelligence for Power-Sharing and Power Quality Improvement. *Energies* **2022**, *15*, 5409. [CrossRef]
78. Chen, C.; Hu, Y.; Karuppiah, M.; Kumar, P.M. Artificial intelligence on economic evaluation of energy efficiency and renewable energy technologies. *Sustain. Energy Technol. Assess.* **2021**, *47*, 101358.
79. Goia, B.; Cioara, T.; Anghel, I. Virtual Power Plant Optimization in Smart Grids: A Narrative Review. *Futur. Internet* **2022**, *14*, 128. [CrossRef]

80. Dhanalakshmi, J.; Ayyanathan, N. A systematic review of big data in energy analytics using energy computing techniques. *Concurr. Comput. Pract. Exp.* **2022**, *34*, e6647. [CrossRef]
81. 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. [CrossRef]

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