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Review

Artificial Intelligence in Energy Economics Research: A Bibliometric Review

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Abstract: Artificial intelligence (AI) is gaining attention in energy economics due to its ability to process large-scale data as well as to make non-linear predictions and is providing new development opportunities and research subjects for energy economics research. The aim of this paper is to explore the trends in the application of AI in energy economics over the decade spanning 2014–2024 through a systematic literature review, bibliometrics, and network analysis. The analysis of the literature shows that the prominent research themes are energy price forecasting, AI innovations in energy systems, socio-economic impacts, energy transition, and climate change. Potential future research directions include energy supply-chain resilience and security, social acceptance and public participation, economic inequality and the technology gap, automated methods for energy policy assessment, the circular economy, and the digital economy. This innovative study contributes to a systematic understanding of AI and energy economics research from the perspective of bibliometrics and inspires researchers to think comprehensively about the research challenges and hotspots.

Keywords: artificial intelligence; energy economics; bibliometric analysis; network analysis

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1. Introduction

Energy economics research is not limited to issues such as agricultural energy use and biofuels but ranges from fuel economics, fossil fuel energy issues, economic analysis of the energy sector, economic and policy issues in the power sector, and techno-economic analyses of alternative energy sources. Modeling and analytical tools used in energy economics include regional and national models to assess alternative energy futures and to evaluate the consequences of alternative energy policies [1,2].

However, as the economy and society continue to evolve, traditional management tools and production technologies are not sufficient to meet the needs of the rapidly growing economy and the concept of sustainable development. Artificial intelligence (AI) has growing potential for development and is increasingly recognized as being able to make the world a better place. In our study, concerning the definition of AI, any software technology with one of the following capabilities is considered AI: machine perception, decision-making, prediction, automated knowledge extraction from data and pattern recognition, interactive communication, and logical reasoning [3]. Since the 21st century, a large amount of valuable research has emerged on the application of AI in the field of energy economics, and scholars have been combing and analyzing the results [4]. Some scholars have begun to explore the link between AI and energy [5].

AI brings advanced equipment and tools, such as robots and drones, which can improve productivity and production efficiency. AI enables systems similar to human learning and decision-making operations, which provide optimization recommendations through machine learning algorithms to reduce energy consumption. The importance of AI for energy economics research is reflected in the fact that AI is not only an important tool for energy economics research, but it is also an important object of energy economics research, and AI plays an important role in advancing energy transition, achieving global green and low-carbon goals, promoting sustainable development, and optimizing resource allocation.

The utilization of artificial intelligence in the design of energy systems has been demonstrated to enhance both sustainability and efficiency. A notable example can be found in the work of Ardakani et al., who employed multiple optimized regression and ANN models to predict long-term electrical energy consumption in both developing and developed economies [6]. Furthermore, some scholars have applied AI to develop innovative energy systems, including a hybrid algorithm of Multi-Layer Perceptron (MLP) and Firefly Optimizer for wind energy measurement [7], using ANN algorithms and statistical analysis to develop an energy decision support system for a smart city [8], and applying Random Forests and Markov Chains to construct an integrated regional energy system [9].

The development of energy systems supported by artificial intelligence and data analytics has been applied to the energy transition of companies and countries. Dimou et al. conducted scenario simulation modeling for a green energy transition project on the Greek island of Agios Efstratios, comparing it in terms of carbon emissions and economics [10]. Yin et al. discussed the positive impact of AI software development on energy transitions in 62 economies [11]. Also, Maruejols et al. revealed the direct and indirect correlation of ethnicity on the electricity consumption of rural households based on the case of a highly ethnically diverse population in Vietnam, using the tools of machine learning and Least Absolute Shrinkage and Selection Operator (LASSO) [12]. Devaraj et al. collated online news articles and comments containing the keyword "energy transition" from Korean online news platforms, and utilized machine learning methods to study media evaluation, user sentiment, and features that influence sentiment [13].

For example, in renewable energy utilization and energy transition, AI supports large-scale data processing techniques as well as a wide variety of higher-order algorithms, where smart grids and energy management systems are used to monitor and control optimal levels of energy storage and production [14]. In recent years, machine learning, as a general-purpose AI technique, has proliferated in the research literature and has been widely used in energy economics and energy finance, such as in energy price forecasting [15–17], risk management [18–21], trading strategies [22–24], and macro energy trend analysis [25–28]. Meanwhile, bibliometric analyses conducted by some scholars have shown that support vector machines (SVMs), artificial neural networks (ANNs) and genetic algorithms (GAs) are the most commonly used techniques in energy economics papers [4].

Bibliometric methods have been applied in the field of AI and energy research for keyword clustering and the analysis of research themes and research trends. In the area of engineering and technology, Iorgovan conducted a bibliometric analysis of AI and renewable energy utilization [14]. Zhang et al. conducted a bibliometric analysis and scientific mapping of AI in the field of renewable energy utilization using VOSviewer1.6.15, CiteSpace5.8.R3, and Bibliometrix4.1.1 to investigate the application of AI in the field of renewable energy [29]. Hou et al. used bibliometrics to explore the application of big data and artificial intelligence in the energy field [30]. Olu-Ajayi et al. discussed the use of statistical and artificial intelligence tools in building energy prediction [31]. In the field of energy economics and finance, Mardani et al. provided an overview of the application of DEA modeling in the field of environmental and energy economics [32], and Wang et al. examined energy policies related to green finance [33]. Singhania et al. provided a comprehensive review of the evolution of sustainable finance research and future research directions by analyzing overall publication trends, co-authorship networks, and journal co-citations, and performing by cluster analysis [34]. Qin et al. used Bibliometrix4.3.0 to analyze the characteristics of research in the field of artificial intelligence and economic development [35]. Gao et al. reviewed the application of machine learning in business and finance, discussing the application of ML in energy marketing [36].

Overall, as shown in Figure 1, most scholars focus only on the application of AI in a certain industry, and most conduct qualitative research. Bibliometric analysis is a quantitative study based on knowledge mapping, which reflects research trends and hotspots more objectively.

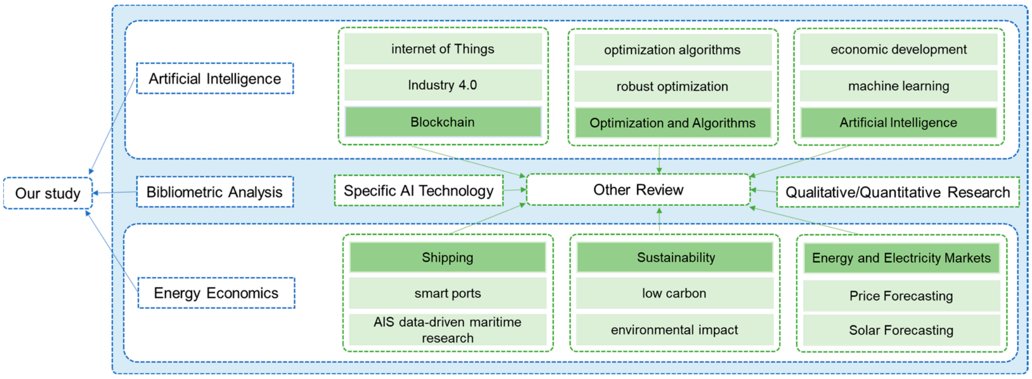

Figure 1. The novelty of the study.

These research results reflect the fact that artificial intelligence has become an important technology and research object for scholars to conduct energy economics research, but there are still limitations. From a content point of view, few scholars have analyzed the application of multiple AI technologies from a macro perspective, and most of them only focus on the application of a specific technology in a certain industry, and systematic comparative analyses are lacking. From a methodological point of view, literature studies use less quantitative research. However, quantitative research based on knowledge mapping can reflect research hotspots and trends more objectively.

In order to better understand the evolution of the application of AI in energy economics research (hereafter referred to as AI&EE) and to present a panoramic view of the field, this paper draws on bibliometric analysis to visualize and analyze research themes and trends [32–39]. The aim of this paper is to explore existing publications and comprehensively analyze the development process and research hotspots in the application of AI in energy economics. Using the bibliometric software CiteSpace as a research tool, this paper visualizes and compares the research outputs of AI technologies in energy economics between 1 January 2014 and 1 October 2024. The study is of great significance in promoting innovative international applications of AI technology in the field of energy economics and in reducing carbon emissions, and it can provide new ideas and perspectives for international research. Meanwhile, the research in this paper contributes to our systematic understanding of AI&EE.

The main contributions of this paper are as follows:

(1) First, a descriptive statistical analysis is made. The basic characteristics of the publications are presented in terms of the number of publications per year, the evolution of the topics of the publications, and the areas of research.

(2) To identify influential cited literature, countries, institutions and authors through network analysis.
(3) To identify research themes from the perspective of keywords and to perform co-occurrence analysis, cluster analysis, burst detection and timeline analysis to identify future research hotspots.
(4) To analyze future trends and challenges and limitations from current research issues.

The rest of the paper is organized as follows: Section 2 introduces the research methodology, including the bibliometric approach, data sources, search strategy and methodological framework. Subsequently, Section 3 describes the performance of the research area from four perspectives and analyzes the hot issues of current research based on keyword clustering. In addition, Section 4 provides further discussion in terms of future trends and challenges as well as limitations. Finally, Section 5 provides some conclusions.

2. Data and Methodology

The research in this paper is based on a bibliometric analysis of the application of artificial intelligence technology in energy economics.

2.1. The Definition of Energy Economics

There is no uniform concept in the academic world regarding the definition of energy economics. In this paper, energy economics is the study of economic activities, economic relations, and economic laws in the production, distribution, exchange, and consumption of energy. It involves many aspects of energy supply and demand analyses, energy price formation, energy policy formulation, energy market structure, energy efficiency, and the environmental impact of energy. In the study of energy economics, economists use a range of tools and models to perform analyses and to provide forecasts. The main research tools and models in energy economics include Computable General Equilibrium (CGE), Mathematical Programming Models, Econometric Models, Retail Net Measurement, the Energy Economics Model, Net Metering, Partial Equilibrium Models, and Techno-economic Analysis (TEA) [2].

2.2. Bibliometric Methods

In this paper, a bibliometric approach is used to visualize the analysis based on the statistics of the number of published articles and the basic background of some authors of the literature. Bibliometric methods are widely used to assess scientific results, capture scientific developments, structure scientific knowledge graphs, and identify emerging trends in specific fields [38,40,41]. CiteSpace, Ucinet, VOSviewer, and Bibliometrix are some of the most common bibliometric analysis tools used in academia.

Two powerful visualization software tools, namely VOSviewer [42] and CiteSpace [43], were used to mine and analyze the data. CiteSpace, which has been updated and optimized in several versions since its introduction in 2003, has received widespread attention in the academic community and has been used in quantitative research in several research areas. CiteSpace is a Java-based information visualization software that uses co-citation analysis theory and pathfinding network algorithms to measure the scientific literature in a particular field, explore the evolutionary paths and knowledge inflection points of a discipline, and identify and display new trends and developments in science. We used CiteSpace version 6.3 to set the parameters of threshold selection, pruning selection, time zone selection, minimum spanning tree, etc., to form the knowledge map and evaluate the network structure and clustering clarity based on the two indexes of modularity value (Q-value) and average profile value (S-value), and carried out multiple drawings by adjusting the parameter settings appropriately to achieve a more desirable result of the mapping.

Thus, the research power, keywords, and timeline distribution in the fields of artificial intelligence and energy economics were systematically analyzed. VOSviewer uses the VOS mapping technique to construct distance-based two-dimensional maps, which can display maps such as authors or journals satisfactorily compared with most of the bibliometric programs used [42].

2.3. Data Collection and Filtering

The scientific nature of knowledge mapping relies on authoritative databases and requires the researcher to accurately and comprehensively retrieve the entire literature on the topic under study. To ensure the scientific validity of this study, we retrieved data from the representative and authoritative Web of Science Core Collection, which is the core journal citation index database of the Institute for Scientific Information (ISI-Institute for Scientific Information) and contains more than 18,000 authoritative and high-impact academic journals. The database consists of 10 sub-datasets (8 citation indexes and 2 chemical indexes), including SCIE, SSCI, A&HCI, ESCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, CCR-Expanded, and IC [44].

In order to search the relevant literature as comprehensively as possible, we used various terms related to AI and energy economics extracted from previous studies. In order to be able to fully cover the core research literature on the application of AI in energy economics research, the following methodology was proposed after several search attempts: TS = ("AI *" OR "Artificial intelligence *" OR "Artificial intelligent *" OR "Generative AI *" OR "Big Data *" OR "Big Models *" OR "Robotics *" OR "Multimodal model *" OR "NLP *" OR "Computer Vision *" OR "LLM *" OR "Neural networks *" OR "Unsupervised learning *" OR "Supervised learning *" OR "Feature extraction *" OR "Machine learning *" OR "Deep learning *") AND TS = ("Energy *" OR "Crude Oil *" OR "Natural Gas *" OR "Gasoline *" OR "Carbon *" OR "Electricity *" OR "Solar *" OR "Wind *" OR "Renewable *" OR "Climate Policy *" OR "Energy Efficiency *" OR "Environmental Policy *" OR "Environmental Regulation *").

In WoS, all publications can be categorized into different types. The distribution of the document types is shown in Table 1. In order to improve the accuracy and scientific validity of the data, the document types were further manually selected as Articles (726; 81.39%), removing Proceedings papers (141; 15.81%), Early Access papers (54; 6.05%), Review Articles (24; 2.69%), Book Chapters (2; 0.22%), Corrections (2; 0.22%), and Editorial Material (2; 0.22%).

Table 1. Distribution of document types.

Document Type	Number	Percentage
Articles	726	81.39%
Proceedings papers	141	15.81%
Early Access papers	54	6.05%
Review Articles	24	2.69%
Book Chapters	2	0.22%
Corrections	2	0.22%
Editorial Material	2	0.22%
Book Reviews	1	0.11%

Each publication included in the Web of Science Core Collection belongs to at least one subject category. Each record corresponds to at least one Web of Science category field, which contains the subject category to which its source publication belongs. To limit the literature search to the field of economics, publications with the subject categories

Economics, Management, Business, and Business Finance were filtered. The search was again precise, and 494 documents were manually screened.

The period examined was from 1 January 2014 to 1 October 2024. The time interval chosen for the bibliometric analysis is the most recent decade, which is a representative period during which both the fields of AI and energy economics have experienced significant changes and challenges. This paper aims to explore the research trends and hotspots in the field of AI&EE during the last decade. The final data obtained included complete document record information such as the title, author, journal, abstract, keywords, references, and source journal.

2.4. The Research Framework of the Methodology

The aim of this paper is to provide a comprehensive bibliometric analysis of energy economics research and artificial intelligence. First, relevant literature was searched for in the appropriate databases according to the search strategy [45]. Next, the performance was analyzed in terms of annual publication trends, disciplinary distribution, and research areas. Then, citations, regions, institutions, and authors were studied through CiteSpace bibliometric methods and tools. Meanwhile, hotspots, future trends, and challenges in these research areas were identified. The research framework of the methodology of this paper is shown in Figure 2.

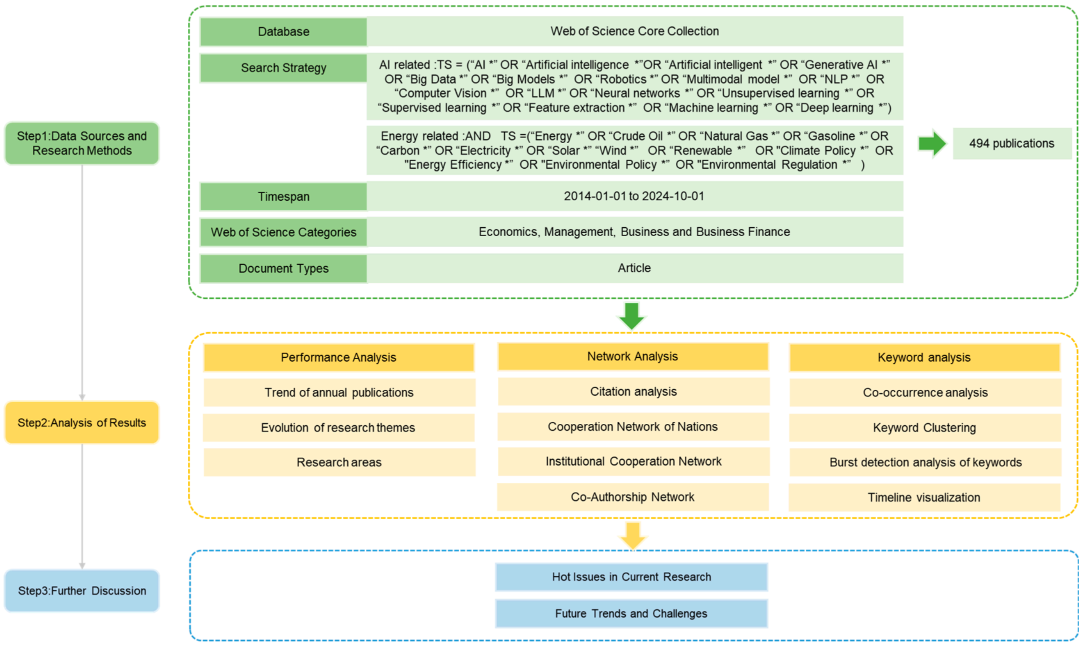

Figure 2. The research framework of the methodology used in this paper. Note: * is a wildcard, commonly used in computer programming languages to represent “any text”.

3. Bibliometric Analysis

The results of the bibliometric analysis of the application of artificial intelligence in energy economics can be obtained based on the search strategy and analysis tools. This can be demonstrated by the following three aspects: descriptive statistical analysis, network analysis, and keyword analysis.

3.1. Descriptive Statistical Analysis

3.1.1. The Annual Trends in Publications

The number of publications is an important indicator to measure the development trend of a particular field in a specific period. At the same time, we can also see more intuitively the change in the research hotness of the field, which is of great significance in analyzing the development trend in a particular field and to predict its future trend. Figure 3 shows the annual publications on artificial intelligence in energy economics research.

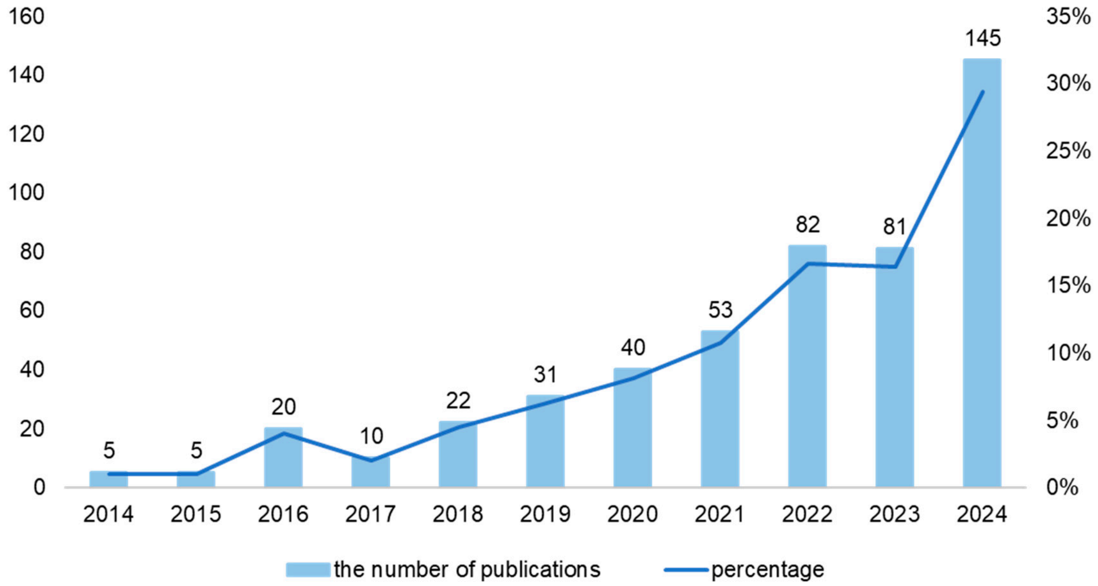

Figure 3. Trends in the number of annual publications.

From a general point of view, the number of papers published in the field of AI&EE research has shown an increasing trend over the years. Specifically, AI&EE research can be roughly divided into two developmental stages. The first stage is from 2014 to 2017; the number of papers published in this time period is generally small and the speed of publication is slow, with a total of 40 AI&EE-related papers published, and the average number of papers is 10, indicating that the importance of AI technology had not yet been taken into account in the field of energy economics during this period. The 21st United Nations Climate Change Conference passed the Paris Agreement in 2015, and therefore the number of papers published in 2016 increased significantly, with a growth rate of 300%.

The second phase, from 2018 to 2024, shows that international research on AI&EE experienced a spurt of growth, with an average growth rate of 45.81%. In particular, 2024 was the year with the highest number of publications as well as the fastest growth, with a total of 145 publications in 2024 as of October 2024, representing a growth rate of 79%.

The analyses found that the timing in this area is related to international energy policy, international energy relations, and international energy markets. In particular, 2017 is known as the year of AI application, when many big events in the field of artificial intelligence emerged, such as AlphaGo's victory over Ke Jie, the human world's top-ranked chess player. Japan, Canada, Singapore, and China had begun the process of signing national AI strategies, giving strong financial support to AI. By the end of 2018, more than 20 countries had formed their own national AI strategies. In September 2021, The World Economic Forum (WEF) released the report *Accelerating the Energy Transition with Artificial Intelligence*, which provides insights into the potential of AI applications in energy transition. In 2022, the global energy market underwent drastic changes, which were reflected in the international demand for crude oil exceeding expectations and the energy crisis in Europe due to the Russia–Ukraine conflict. In the same year, OpenAI released ChatGPT, a generative AI. These factors led to a strong focus on AI&EE in academia, with an 87% increase in publications in 2024 compared with 2022.

Based on current trends, the number of publications will continue to grow in 2024. In conclusion, AI&EE has received increasing attention from academia in recent years, and the foreseeable future will be a golden period for research in this field.

3.1.2. Evolution of Research Themes

Figure 4 illustrates the evolution of research themes in the publications of the top ten countries, highlighting a clear homogenizing trend of strong continued focus on machine learning and AI across countries. Between 2014 and 2015, research efforts in pioneering countries such as China, the United States, the United Kingdom, Australia, and India focused on energy efficiency and energy forecasting, which relied on third-party forecasting and employed time-series analysis. This reflects a shift in research methodology toward learning algorithms and an increasing reliance on the data themselves rather than the variables of interest for forecasting.

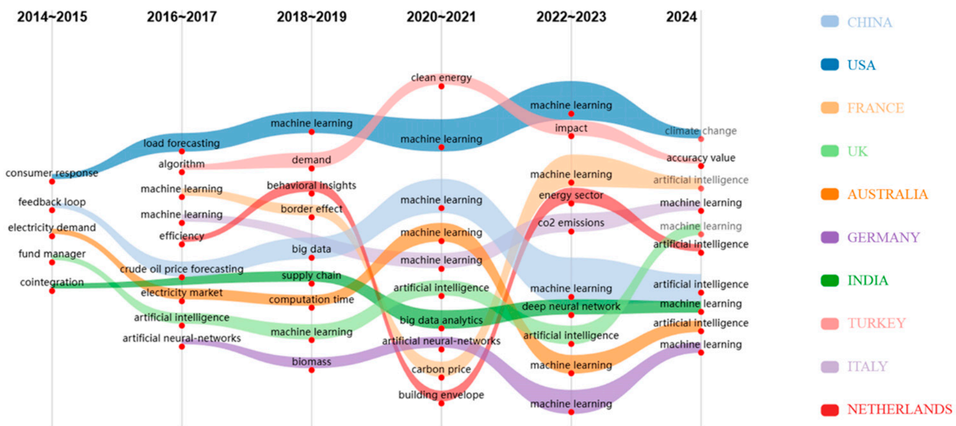

Figure 4. Evolution of research themes in the top 10 national publications.

Between 2015 and 2016, machine learning and artificial neural networks were the main research themes in France, Germany, Turkey, Italy, and the Netherlands. This marks a significant shift in the research landscape, with a clear preference for advanced research techniques and tools in energy-related research.

Beyond 2020, research themes in all countries in the graph are centered primarily around machine learning and artificial intelligence, reflecting a global convergence in the use of these technologies in energy research, with machine learning and artificial intelligence becoming a cornerstone of energy economics research.

Energy economists are increasingly recognizing the revolutionary potential of machine learning and AI in energy economics research. AI technologies provide powerful tools for data analysis, forecasting, and optimization, and the analysis of the evolution of the themes shows that the field of AI&EE research is maturing.

3.1.3. Top 10 Research Areas of Publications

Each publication covers at least one research area. The top 10 research areas are shown in Figure 5. The most popular research areas are Economics (318) and Management (156), with 64% and 32%, respectively. These are followed by Business (109), Environmental Studies (74), and Regional & Urban Planning (46). The remaining five research areas are Business, Finance (43), Energy & Fuels (43), Environmental Sciences (40), Operations Research & Management Science (35), and Social Sciences and Mathematical Methods (20). An analysis of the distribution of disciplines shows that AI is widely used in the field of energy economics, especially in economic analysis, management decision-making, and business operations. At the same time, there are fewer studies related to the integration of

AI with information systems in energy economics research, as well as insufficient research on applications in agricultural energy economics and policy making. Artificial intelligence in energy economy research is mainly concentrated in the fields of economics, management, business, and environmental studies, while less research is specialized in computer science, agricultural economics and policy, international relations, and law.

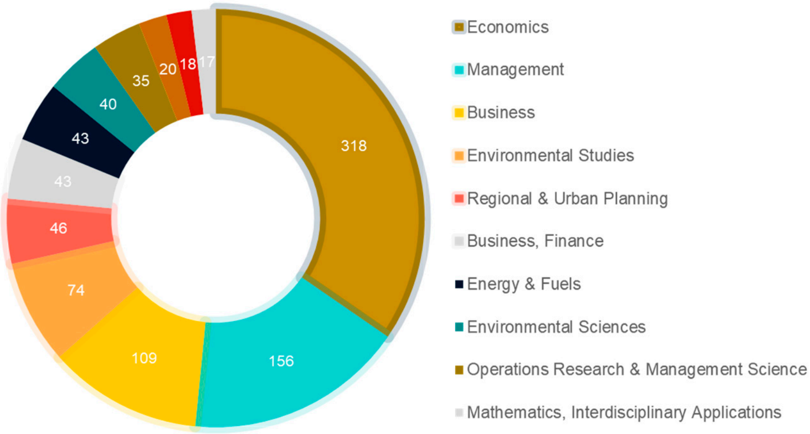

Figure 5. Number of publications in different research areas.

An overview of the distribution of journals for AI&EE-related research reveals the disciplinary configuration of the field as well as the profile and preferences of core journals. To illustrate the distribution of journals, Table 2 lists the top ten high-impact journals in terms of the percentage of published articles. The 494 papers in the field are distributed across 129 journals. These journals are authoritative in the field of economics and management and are located in Q1 or Q2 of the WoS database. They are critical knowledge aggregation and dissemination platforms in the field of AI&EE. In terms of the number of journals published, the first ranked journal is *Energy Economics* (98; 19.87%), a top journal in the field of energy economics and energy finance, with topics ranging from energy conversion and use to energy commodities and derivatives markets, followed by *Technological Forecasting and Social Change*, *Energy Policy*, and *International Journal of Forecasting* in the field of energy economics.

Table 2. Distribution of key journals.

Number	Journal	TP	Percentage	IF
1	*Energy Economics*	98	19.84%	13.6
2	*Technological Forecasting and Social Change*	44	8.91%	12.9
3	*Energy Policy*	36	7.29%	9.3
4	*International Journal of Forecasting*	29	5.87%	6.9
5	*Journal of Forecasting*	14	2.83%	3.4
6	*Business Strategy and the Environment*	12	2.43%	12.5
7	*European Journal of Operational Research*	11	2.23%	6.0
8	*Computational Economics*	11	2.23%	1.9
9	*International Review of Financial Analysis*	9	1.82%	7.5
10	*Finance Research Letters*	8	1.62%	7.4

Note: TP = number of publications; IF = 2024 journal impact factor.

3.2. Network Analysis

This section analyses publications from four perspectives: citations, regions, institutions, and authors. First, the knowledge base of the AI&EE field is analyzed through the literature co-citation network. In addition, it is analyzed from the following perspectives:

collaboration between countries, collaboration between institutions, and collaboration between authors.

3.2.1. Citation Analysis

Highly cited literature is called basic knowledge in bibliometrics, which is the classic literature in the field and can reflect the overall knowledge base of the field. Therefore, the knowledge base and knowledge structure of the research field is analyzed through the clustering of highly cited literature and co-cited literature. Literature co-citation is when two publications are simultaneously cited in another publication. The classic literature in a given field is often cited repeatedly, not only as an essential research result in the field but also as constituting the knowledge base of the field. The co-citation analysis of the literature in the field of AI&EE helps to tap the knowledge base of AI&EE research.

Table 3 lists the titles of the top 10 cited publications and their related information. The table is arranged in ascending order of citations. The co-citation analysis of the literature shows that a total of three articles possess the highest citation rate in the study of AI in energy economics. Among them, the most cited and earliest published document is the publication titled "Does energy diversification cause an economic slowdown? Evidence from a newly constructed energy". Gozgor et al. analyzed the differences in the impact of energy diversification on economic growth by constructing a new energy diversification index using the nonlinear panel autoregressive distributed lag (NPARDL) method, and found that energy diversification has a positive effect on growth in major economies in the long run, but in the short run, it has a positive effect on growth for some countries and a negative impact in all low-income economies [46]. Lau et al. published in 2023 the article titled "Introducing a new measure of energy transition: Green quality of energy mix and its impact on CO_2 emissions", which has a high citation frequency and has co-citation relationships with several articles [47]. The article adopts a new measure of energy transition, the green quality of energy mix (GREENQ), and uses systematic GMM, FGLS, and PCSE panel data techniques to examine the impact of per capita income, institutional quality, and technology in 36 OECD countries on the emissions of CO_2 from 1970–2021.

Table 3. The top 10 cited publications.

Freq	Label	Source	Title
20	Gozgor G (2022) [46]	*Energy Economics*	Does energy diversification cause an economic slowdown? Evidence from a newly constructed energy diversification index
20	Lau CK (2023) [47]	*Energy Economics*	Introducing a new measure of energy transition: Green quality of energy mix and its impact on CO_2 emissions
20	Sinha A (2023) [48]	*Energy Economics*	How social imbalance and governance quality shape policy directives for energy transition in the OECD countries?
19	Chishti MZ (2023) [49]	*Energy Economics*	Exploring the dynamic connectedness among energy transition and its drivers: Understanding the moderating role of global geopolitical risk
19	Shahbaz M (2023) [50]	*Energy Economics*	Financial development as a new determinant of energy diversification: The role of natural capital and structural changes in Australia

Table 3. *Cont.*

Freq	Label	Source	Title
18	Ahmad T (2021) [51]	*Journal of Cleaner Production*	Artificial intelligence in sustainable energy industry: Status quo, challenges and opportunities
16	Ghoddusi H (2019) [4]	*Energy Economics*	Machine learning in energy economics and finance: A review
12	Wang EZ (2022) [52]	*Energy Economics*	Assessing the impact of industrial robots on manufacturing energy intensity in 38 countries
12	Zhang YJ (2019) [53]	*Journal of Empirical Finance*	Forecasting crude oil prices with a large set of predictors: Can LASSO select powerful predictors?
10	Acemoglu D (2020) [54]	*Journal of Political Economy*	Robots and jobs: Evidence from US labor markets
10	Lee CC (2022) [55]	*Technological Forecasting and Social Change*	Does industrial robot application promote green technology innovation in the manufacturing industry?
10	Caldara D (2022) [56]	*American Economic Review*	Measuring geopolitical risk
10	Li YZ (2021) [57]	*Energy Economics*	The role of news sentiment in oil futures returns and volatility forecasting: Data-decomposition-based deep learning approach

Sinha et al. proposed a new energy transition indicator, an output-side indicator based on the energy ladder assumption, and analyzed the impact of social imbalances and governance quality on the drivers of energy transition using a two-step system GMM approach [48]. Chishti et al. used econometric methods such as quantile vector autoregression, cross-sectional quantile plots, wavelet quantile correlation, and nonparametric Granger causality tests, and found that green financing, green technology, and environmental policies have a positive effect on energy transition, while geopolitical risks have a negative effect [49].

Shahbaz et al. discussed the interplay between financial development and energy diversification in Australia, factoring in natural capital, structural change, economic growth, and export diversification, and revealed that financial development positively affects energy diversification, with an inverted "U"-shaped nonlinear relationship [50]. The classical literature focuses on four main research themes: energy transition, energy diversification, energy market forecasting and trading, and the development of new technologies and tools for traditional industries (e.g., industrial robotics).

The co-citation network of journals can be seen in Figure 6, which consists of five clusters corresponding to the four colors in the figure, and the top three cited journals are *Energy Economics* (1819 citations), *Energy Policy* (863 citations), and *Journal of Cleaner Production* (803 citations). All three journals are JCRQ1 (i.e., outstanding) journals.

The purple cluster relates to renewable energy and its integration into energy systems, highlighting the importance of sustainable energy solutions. The yellow cluster focuses on the application of energy in various fields, including smart grids, energy management systems, and photovoltaic power generation, emphasizing the practical utility of energy use, with strong links to the field of engineering. The red cluster covers the fields of economics, finance, and management, with special emphasis on energy economics, energy policy, and energy finance. The blue cluster is dedicated to energy policy, reflecting the role of governance and regulatory frameworks in guiding the energy sector toward sustainable development and efficiency. Finally, the green cluster represents the crosscutting areas of manufacturing, production systems management, and the development of green production materials, demonstrating efforts to improve the sustainability of industrial processes. As illustrated in Figure 6, each node symbolizes a journal, and a link between two nodes indicates that both journals appear in the same publication. The size of the node reflects the frequency of the appearance. This means that the larger the node, the more frequently the journal appeared. In contrast, the width of the links indicates the number of times the two journals appear together. In particular, in Figure 6, the nodes clustered in red are not only the largest but also have the most links, revealing a strong correlation between different research topics. This suggests that energy economics research is deeply cross-studied and rich in academic interactions with other subject areas, such as energy policy, energy applications, and renewable energy. The green engineering technology cluster is relatively independent, which implies a certain degree of research isolation in the field. Cross-research between the energy economics research and engineering technology clusters has not yet reached the desired depth, indicating that more interdisciplinary collaboration may be needed in order to promote knowledge integration and innovation.

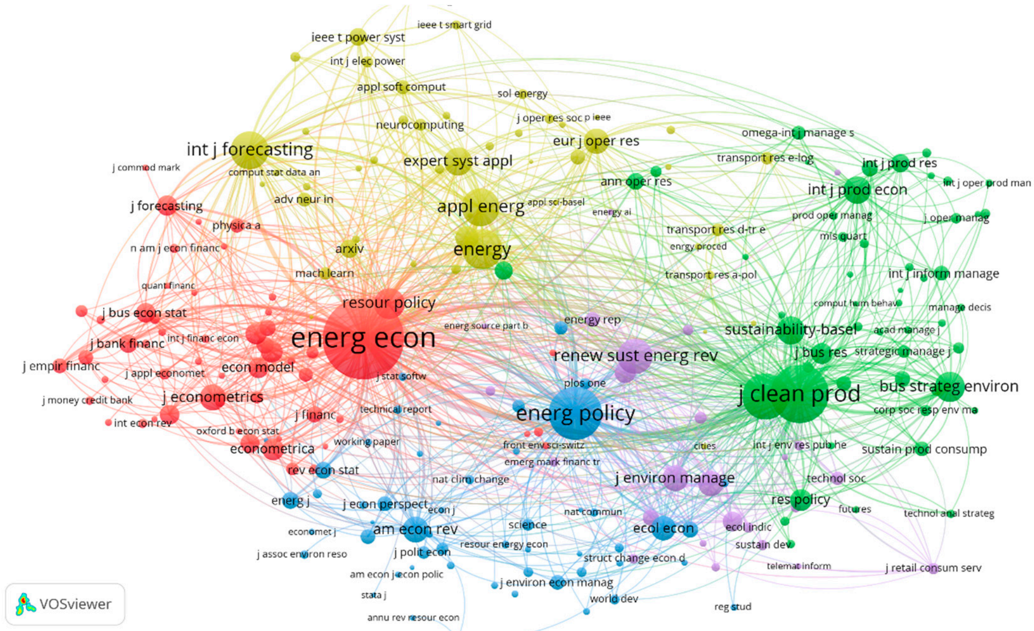

Figure 6. Co-citation of cited journals.

3.2.2. Cooperation Network of Nations

The number of publications directly reflects a country's academic impact on a particular research topic. Therefore, the types of nodes in CiteSpace are selected based on the concept of "country".

The collaborative network of countries is shown in Figure 7. Sixty-five countries participated in this study out of the 494 retrieved documents. A node represents a country, and a link between two nodes indicates that the two countries have collaborative publications. The figure has 65 nodes and 88 links in the network (with a density of 0.0423), indicating a closer collaborative network between countries. The darker the green color, the larger the node and the higher the number of publications in the corresponding country. The more extensive the links between the nodes, the closer the cooperation between the two countries.

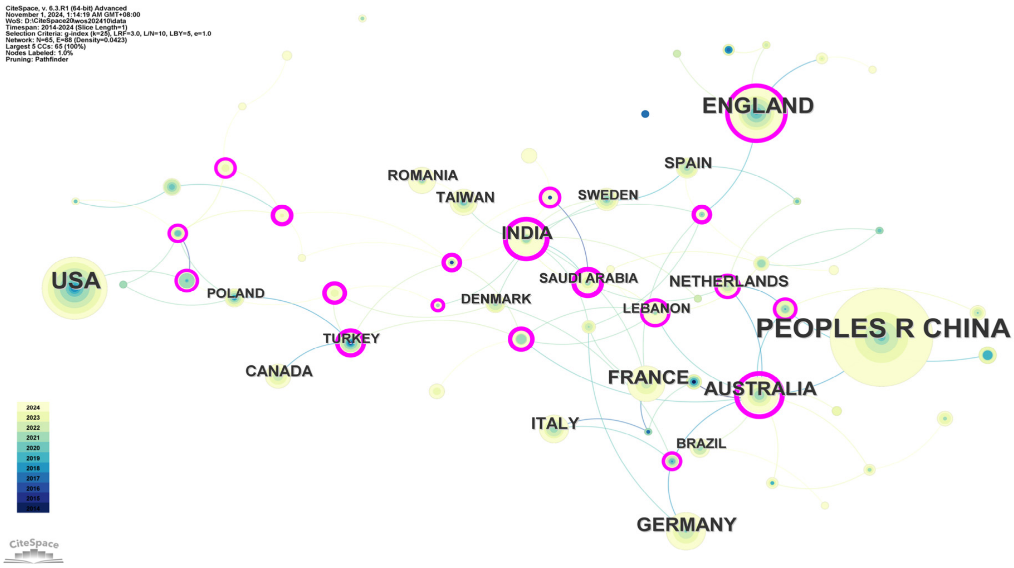

Figure 7. National cooperation network.

As shown in Table 4, China is the most productive country in this field, with 196 publications, while the United States is second, with 83 publications. England and France closely follow them, with 62 and 40 publications, respectively. In general, publications are concentrated in Asia, Europe, and North America, with an apparent geographic clustering for AI&EE. It is worth mentioning that China and the United States have the highest number of publications, with both having an early focus in the field of AI&EE but with very low centrality (0). This indicates that scholars in both countries mainly collaborate with scholars within their own countries, and there are not many cross-country collaborative achievements with other countries, so the collaborative network is rather limited.

Table 4. The top 10 countries with the highest number of publications.

No.	Frequency	Proportion	Centrality	Nation	Year
1	196	40%	0	PEOPLES R CHINA	2014
2	83	17%	0	USA	2015
3	62	13%	0.29	ENGLAND	2014
4	40	8%	0.07	FRANCE	2016
5	38	8%	0.04	GERMANY	2016
6	37	7%	0.61	AUSTRALIA	2014
7	32	6%	0.57	INDIA	2015
8	22	4%	0	ITALY	2017
9	18	4%	0.06	SPAIN	2018
10	17	3%	0.18	NETHERLANDS	2016

Furthermore, in Figure 7, the larger the circle of nodes, the higher the centrality. Nodes with purple outer circles have higher centrality. Australia, India, and Saudi Arabia are the top three countries with the highest centrality. This indicates that these countries have a lot of interactions and collaborations with other countries. Table 4 shows the top 10 countries with the highest number of publications and their related information. More than half of the countries in Table 4 have a centrality of more than 0.10. This means that they can be considered critical nodes with a significant impact.

Among them, Australia has the highest centrality (0.61) with 37 publications, accounting for 35.71% of the total, which indicates that Australia has already had extensive interaction and cooperation with other countries.

3.2.3. Institutional Cooperation Network

A collaborative network analysis of the literature's issuing institutions yields Figure 8. The institutions with the highest number of articles in AI&EE are the Chinese Academy of Sciences and the Beijing Institute of Technology, with 17 and 11 articles, respectively. Other institutions with eight or more articles are the University of Chinese Academy of Sciences, Lebanese American University, Anhui University of Finance & Economics, and the University of International Business & Economics.

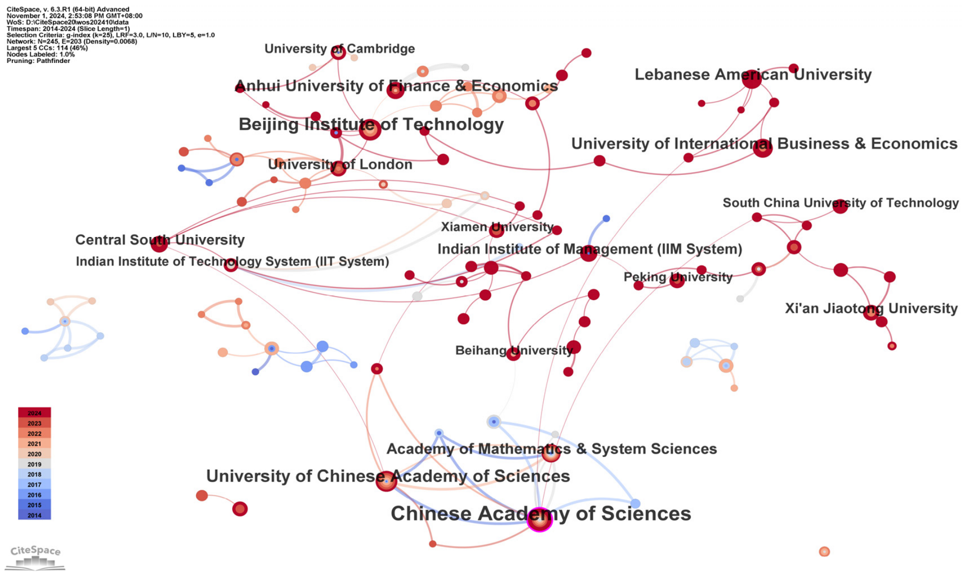

Figure 8. Collaborative networks of research institutions.

In terms of cooperation, there are 245 nodes and 203 links in the network (a density of 0.0068), indicating that there is some relationship between the issuing institutions.

A collaborative network relationship with the Chinese Academy of Sciences as the core, containing research institutions such as the University of Chinese Academy of Sciences, Academy of Mathematics & System Sciences, and South China University of Technology, is shown in Figure 8. These are focusing on issues in the forecasting of crude oil prices, forecasting the environmental performance of power companies, and stock market returns of energy companies.

Overall, there is a high intensity of cooperation and closer links between research institutions. A wide and close network of academic cooperation has been formed, with essentially all publications that have been published having been achieved through cross-institutional cooperation. However, international cooperation is not as strong, since there is a lack of transnational cooperation.

The CiteSpace calculation was applied to derive the global core institutions for research in AI&EE, as shown in Table 5. We have identified two issues that are worth paying attention to:

First, the analysis of the disciplinary attributes of the institutes shows that they are dominated by scientific and technological research institutes, supplemented by general research institutes. From an interdisciplinary perspective, the research on AI and energy economic is related to the dominant disciplines of research institutes, such as economics, environmental science, mathematics, and computing.

Second, the regional distribution needs to be balanced, and research institutions are mainly concentrated in Asia, Africa, Europe, and North America, all of which are significantly developed or developing countries with large populations. They are also mainly concentrated in the northern hemisphere, with fewer core research institutions in the southern hemisphere, suggesting that there are significant geographical differences in core research institutions.

Table 5. Core institutions.

Number	Label	Freq	Proportion
1	Chinese Academy of Sciences	17	3.44%
2	Beijing Institute of Technology	11	2.23%
3	University of Chinese Academy of Sciences	10	2.02%
4	Lebanese American University	8	1.62%
5	Anhui University of Finance & Economics	8	1.62%
6	University of International Business & Economics	8	1.62%
7	Academy of Mathematics & System Sciences	7	1.42%
8	University of London	6	1.21%
9	Central South University	6	1.21%
10	Indian Institute of Management (IIM System)	6	1.21%
	Total	87	17.61%

3.2.4. Co-Authorship Network

Due to the large number of research scholars in the field of AI&EE, this study only analyzes the information of core authors here. Core authors, as the main force promoting academic progress and scientific development in a specific field, have high paper production rates and academic influence, leading the development of a specific discipline. By analyzing the knowledge graph of published authors, the core authors in the intersection of AI and energy economics can be presented.

As shown in Figure 9, the scholar with the most publications in the field of AI in energy economics is Wang, Shouyang (8) with a total of 533 citations, forming a collaborative group with Li, Xuerong; Wei, Yunjie; Li, Yuze; and Jiang, Shangrong. They mainly focus on research themes about the prediction of crude oil prices and financial market sentiment research. High-frequency authors also include Wang, Yudong (6) and Song, Malin (6). These authors form the core authors and core research team in AI&EE and have a strong influence on the research areas of AI&EE.

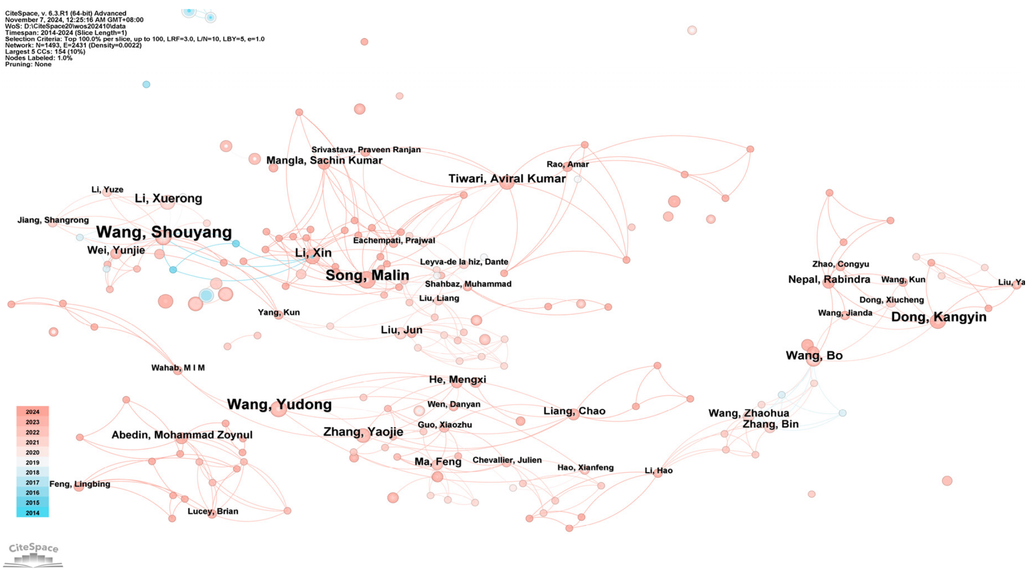

Figure 9. The collaboration network of authors.

According to the formula of Price's (Price) law, i.e., M = 0.749 × $(N_{max})^{1/2}$, N_{max} refers to the number of publications of the most prolific authors. It is derived that the threshold of prolific authors in the sample is 2.1185. According to the principle of rounding, M = 2, so the authors whose publications are more remarkable than (or equal to) 2 are considered prolific authors in this study. Statistically, it is found that the total number of articles published by high-yield authors in the sample is 67, accounting for 14%, indicating the formation of a group of core authors and research teams with high output and high impact.

3.3. Keyword Analysis

Keyword analysis helps to identify topics in a particular field. This section performs co-occurrence analysis, keyword clustering analysis, burst detection analysis of keywords, and timeline visualization to identify research hotspots, frontiers, and trends. This process uses two visualization tools, VOSviewer and CiteSpace.

3.3.1. Co-Occurrence Analysis

Co-occurrence analysis of keywords helps in understanding the research hotspots in a particular field. The nodes represent the keywords, while the node's size indicates the frequency of keyword occurrence, and the connecting line indicates the number of keyword co-occurrences, which represents the intensity of co-occurrence.

As shown in Figure 10, the top 10 keywords with the highest frequency of occurrence are "machine learning", "impact", "artificial intelligence", "model", " big data", "consumption", "neural networks", "performance", "regression", and "management", which indicate that the hot topics in the field are mainly related to these keywords. It indicates that international research in the field of AI&EE is mainly focused on reducing greenhouse gas emissions, energy modeling, and predicting future trends with the help of machine learning, neural networks, and various optimization algorithms. Mediated centrality indicates the mediating role of keywords in the graph, and keywords with high mediated centrality are the core themes of the field. In the CiteSpace tool, nodes with a mediator centrality greater than 0.1 are called vital nodes. As can be seen from Table 6, "demand", "consumption", "decomposition", and "future" series terms have become the critical nodes for research in the field of AI&EE.

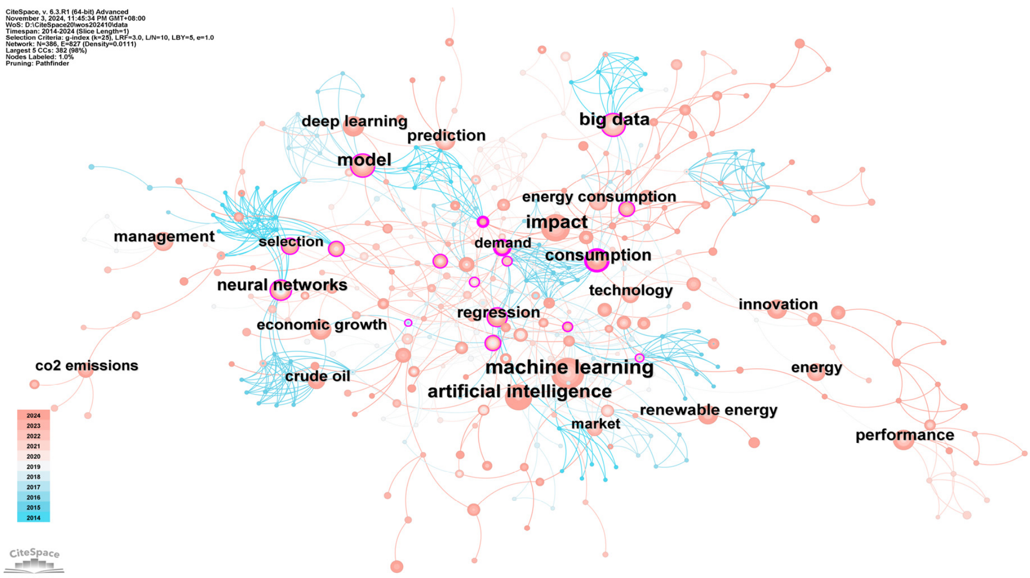

Figure 10. Visualization of the keyword co-occurrence network.

Table 6. Top 10 keywords in terms of centrality.

Number	Freq	Centrality	Keyword	Year
1	22	0.35	demand	2015
2	34	0.3	consumption	2015
3	11	0.28	decomposition	2014
4	15	0.2	future	2018
5	31	0.2	regression	2014
6	13	0.19	big-data analytics	2015
7	12	0.19	artificial neural network	2018
8	34	0.15	neural networks	2014
9	18	0.15	efficiency	2017
10	17	0.14	algorithm	2016

3.3.2. Keyword Clustering

Based on the analysis of the co-occurrence and mutation of keywords in AI&EE, this paper uses the keyword clustering atlas to sort out the hotspots of the research and the degree of concentration of the research in order to further understand whether the hotspots of the research in AI&EE are familiar or not. The keywords are clustered according to the log-likelihood rate, with a total of 20 clusters, and the results are shown in Figure 11.

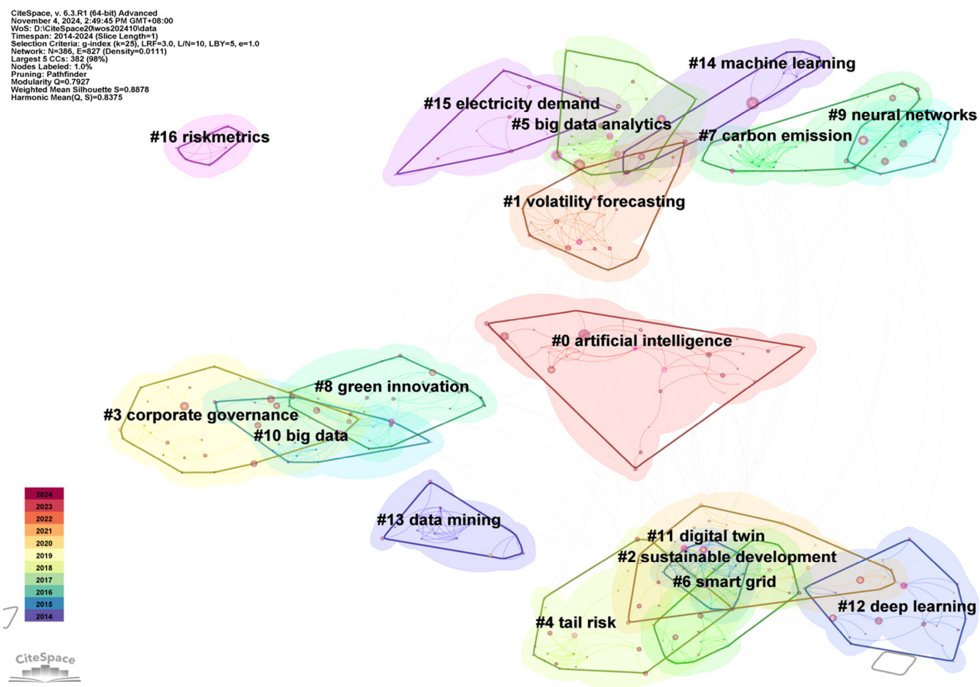

Figure 11. Keyword clustering graph.

The clustering module value of Q = 0.7927 means that the clustering structure is significant, and the average profile value of S = 0. 0.8878, which is greater than 0.7, means that the clustering is convincing. The clusters are classified and organized according to the principle of homogeneity, which is shown in Table 7. We divide the above 20 clusters into four main research themes: artificial intelligence and the energy market, sustainable development and environmental policy, energy consumption and demand management, and socio-economic impacts.

Table 7. Four main research topics.

Focus	ID	Cluster	Size	Silhouette	Year	Typical Keywords and Their Centrality
Artificial Intelligence and the Energy Market	#0	artificial intelligence	35	0.841	2019	artificial intelligence (26.41; 1.0×10^{-4}); energy transition (15.57; 1.0×10^{-4}); renewable energy (11.1; 0.001); Bayesian networks (8.74; 0.005); portfolio diversification (8.74; 0.005)
	#1	volatility forecasting	31	0.901	2019	volatility forecasting (13.9; 0.001); crude oil market (9.93; 0.005); artificial neural networks (9.22; 0.005); time-series forecasting (7.23; 0.01); artificial intelligence (6.6; 0.05)
	#4	tail risk	25	0.815	2017	tail risk (6.08; 0.05); Bayesian extreme learning machine (6.08; 0.05); oil–food–renewable energy market (6.08; 0.05); crude oil shocks (6.08; 0.05); precious metal forecasting (6.08; 0.05)
	#5	big-data analytics	25	0.936	2017	big-data analytics (12.4; 0.001); energy efficiency (9.55; 0.005); carbon emission efficiency (8.56; 0.005); heterogeneity (6.62; 0.05); electricity demand (5.28; 0.05)
	#6	smart grid	25	0.811	2018	smart grid (11.42, 0.001); electricity market (11.42; 0.001); privacy (11.42; 0.001); risk management (7.72; 0.01); quantile regression (7.72; 0.01)
	#9	neural networks	20	0.955	2016	neural networks (12.8; 0.001); energy intensity (11.11; 0.001); crude oil (8.75; 0.005); correlation (5.54; 0.05); choice models (5.54; 0.05)
Artificial Intelligence and the Energy Market	#10	big data	20	0.91	2018	big data (12.86; 0.001); smart cities (8.17; 0.005); imperfect quality components (5.93; 0.05); bidirectional fixed-effect model (5.93; 0.05); smart energy communities (5.93; 0.05)
	#11	digital twin	20	0.941	2015	digital twin (12.14; 0.001); market research (8.42; 0.005); patents (8.42; 0.005); multivariate forecasting (6.06; 0.05); decomposition (6.06; 0.05)
	#12	deep learning	20	0.9	2020	deep learning (14.65; 0.001); energy price forecasting (11.04; 0.001); carbon tax (11.04; 0.001); regression analysis (7.35; 0.01); parameter instability (7.35; 0.01)
	#13	data mining	16	0.956	2017	data mining (8.3; 0.005); artificial intelligence (AI) (8.3; 0.005); technological implications (7.86; 0.01); information technology (IT) (7.86; 0.01); correlation analysis (7.86; 0.01)
	#16	riskmetrics	7	1	2015	riskmetrics (10.83; 0.001); leveraging (10.83; 0.001); genetic programming algorithm (10.83; 0.001); higher-order neural network (10.83; 0.001); multilayer perceptron neural network (10.83; 0.001)
	#19	Gaussian processes	1	0	2014	Gaussian processes (13.29; 0.001); gradient-boosting machines (10.52; 0.005); load forecasting (10.52; 0.005); machine learning (0.23; 1.0); artificial intelligence (0.15; 1.0)
Sustainable Development and Environmental Policy	#2	sustainable development	29	0.728	2020	sustainable development (17.2; 1.0×10^{-4}); Industry 4.0 (12.03; 0.001); carbon emissions (5.64; 0.05); information technology (5.45; 0.05)
	#3	corporate governance	29	0.931	2021	corporate governance (9.43; 0.005); o13 (5.81; 0.05); big-data economy (4.71; 0.05); tfp (4.71; 0.05); wind (4.71; 0.05)
	#7	carbon emission	24	0.96	2017	carbon emission (12.7; 0.001); CO_2 emissions (12.53; 0.001); green investment technology (6.33; 0.05); adaptive management (6.33; 0.05); thresholds (6.33; 0.05)
	#8	green innovation	23	0.901	2023	green innovation (14.31; 0.001); digital transformation (14.26; 0.001); digital finance (12.45; 0.001); environmental regulation (12.45; 0.001); green technology innovation (9.51; 0.005)

Table 7. *Cont.*

Focus	ID	Cluster	Size	Silhouette	Year	Typical Keywords and Their Centrality
Energy Consumption and Demand Management	#14	machine learning	14	0.952	2016	machine learning (39.53; 1.0×10^{-4}); energy poverty prediction (10.49; 0.005); eco-innovation (5.24; 0.05); iot (5.24; 0.05); atfp (5.24; 0.05)
	#15	electricity demand	11	0.828	2021	electricity demand (8.86; 0.005); energy consumption structure (8.15; 0.005); copula function model (8.15; 0.005); multi-factor dynamic support vector machine model (8.15; 0.005); advanced index (8.15; 0.005)
Socio-economic Impacts	#17	theory of planned behavior	4	1	2017	theory of planned behavior (11.7; 0.001); compliance behavior (11.7; 0.001); IT relatedness (11.7; 0.001); compliance knowledge (11.7; 0.001); compliance support system (11.7; 0.001)
	#18	operational improvement	3	1	2016	operational improvement (12.11; 0.001); customer demand anticipation (12.11; 0.001); customer attendance (12.11; 0.001); attendance strategies (12.11; 0.001); relationship (12.11; 0.001)

Moreover, based on the principle of homogeneity, the four organized clustering results can be divided into the following five major research themes:

1. **Artificial Intelligence Forecasting for Energy Markets—Energy price forecasting**

One of the most important forecasts in energy market price forecasting is that of crude oil prices, and oil price movements and shocks can have a significant impact on financial markets and the real economy [58]. Oil price is an important reference factor for the government's macro forecasting and policy decision-making, as well as an important reference standard for investors' asset allocation. Zhang et al. selected a large number of predictors based on the LASSO method (LASSO) and the elastic net method (elastic net) to predict the return of oil prices [53].

Predicting energy price tools can be subdivided into three categories: The first category includes traditional methods such as autoregressive integrated moving average models and generalized autoregressive conditional heteroskedasticity. The second category is artificial intelligence methods, such as artificial neural networks, deep learning [59], and LSTM [60]. The third category is the heterogeneous autoregressive (HAR) model.

Yang et al. constructed a novel kernel-based generalized stochastic-interval multilayer perceptron (KG-iMLP) method based on the D(K) distance of the kernel function for predicting high-volatility interval-valued returns of crude oil. In the empirical analysis of the weekly and daily returns of WTI crude oil, the proposed method is demonstrated to have excellent forecasting performance, which is able to provide stable and accurate forecasts for both point and interval values [61].

The current focus of crude oil price forecasting has shifted from deterministic to uncertainty indicators due to the emergence of various uncertainty indices associated with financial and energy markets. Tissaoui et al. use a new machine learning tool approach, XGBoost modeling, applied to the SVM and ARIMAX (p,d,q) models to examine the impact of natural gas prices and other uncertainty indicators on the ability to predict oil prices [62].

2. **Artificial Intelligence Innovation for Energy Systems in Businesses and Industries**

Artificial intelligence (AI) has great potential to improve energy system efficiency and to reduce energy system costs. Currently, enterprises are applying AI to optimize enterprise workflows, streamline enterprise operational procedures, and serve enterprise customers as well as to assist in operational decision-making. While AI has the potential to save energy in the process of enterprise digital transformation, it is inherently characterized by high energy consumption. The Zhang et al. study listed Chinese manufacturing enterprises, finding that the widespread application of AI can significantly reduce the energy intensity of enterprises, with one additional unit of industrial robots per 100 workers reducing the energy intensity (EI) of the enterprise by about 2.5%, a reduction that is more pronounced in high-energy-consuming, non-labor-intensive, and state-owned enterprises [63]. Wang et al. discussed the relationship between AI adoption rates and corporate green innovation efficiency in Chinese energy firms from the perspectives of CEOs and boards of directors, concluding that energy firms with higher AI adoption rates have stronger positive impacts on green innovation [64].

Industrial robotics is a key technology for Industry 4.0 and the artificial intelligence revolution. The International Federation of Robotics (IFR) defines an industrial robot as an automatically controlled, reprogrammable, programmable multipurpose manipulator for industrial automation applications [65]. The application of industrial robots can promote technological progress in manufacturing, significantly improve industrial productivity and energy efficiency, reduce carbon intensity, and realize energy savings and emission reductions. Bennedsen et al. investigated the carbon-reducing effect of the application of industrial robots, combining fixed effects with nonparametric neural network regression, and found the existence of an Environmental Kuznets Curve (EKC) in production emissions [66].

3. **Socio-economic impacts**

Artificial intelligence has infrastructural spillover properties, and employment and labor markets are important research themes in the AI&EE field. In the short term, AI can replace some low-skilled employees, thus reducing the market demand for labor, creating a substitution effect in the labor force, and reducing the share of labor income. In the long run, AI can expand the demand for highly skilled employees and increase the share of labor income. Thus, AI technology can reshape the job market by replacing workers and creating jobs [54].

Niet et al. examined the socio-economic impacts of AI integration in the EU electricity market and showed that AI improves the sustainability, reliability, and affordability of the market. However, AI increases the complexity of the electricity market and its dependence on digital infrastructure, which may pose potential risks in terms of cybersecurity, privacy, and technological autonomy. Due to the high cost of running and improving AI programs, AI is not widely used in the EU electricity market, despite the fact that AI can reduce the burden of grassroots staff on complex electricity market tasks [67].

4. **Energy transition in economic sectors**

Energy transition is an important research theme in the current energy field. With economic and social development, the large-scale development and utilization of fossil energy has brought about problems such as resource depletion, climate change, and geopolitical conflicts. Energy transition refers to the replacement of the main source of energy from fossil energy to non-fossil energy and the formation of green production methods and lifestyles. The current application of artificial intelligence has been widely used in the fossil energy sector but is characterized by complexity and high cost, which is a contributing factor in energy transition [68]. Zhao et al. investigated whether artificial intelligence can facilitate the transition of economies from traditional fossil energy to renewable energy (RE), and the results of the study showed that in the short and medium term, AI has a negative impact on the increase in the share of renewable energy, while in the long term, AI increases the share of renewable energy in the total amount of energy and accelerates the transition to RE [69]. Zhao et al. also discuss the asymmetry of the impact of AI on renewable energy development across economies, while finding that its post-financing can play an effective moderating role [70].

5. **Climate change and carbon emissions**

The rapid development, upgrading, and wide-scale application of AI will inevitably have an impact on climate change, and several scholars have discussed the interplay between the application of AI and climate change and energy use.

Zhou et al. explored the impact of adopting industrial robots on pollution emissions and energy efficiency in various provinces and regions in China [71]. Zhong et al. investigated the dual role of AI applications on the environment and climate change and studied the synergistic effect of AI in reducing pollutants and carbon emissions using the system generalized method of moments (SYS-GMM) [72].

In discussing the impact of advances brought about by information and science and technology on carbon emissions, some studies have suggested that AI has a dampening effect on carbon emissions; however, because the application of AI requires a high level of technology and advanced computing hardware, it may have a negative impact on carbon emissions and energy use. Therefore, Zhong et al. attempted to discuss whether the impact of AI on carbon emission reduction is positive or negative and used quantile regression and the PSTR model to study the impact of AI on carbon emission in 66 countries, finding that the carbon emission reduction effect of AI only exists in high-carbon emission and high-income countries [73].

3.3.3. Burst Detection Analysis of Keywords

The burst detection feature analyses keywords that produce significant changes in a short period and can show the start and end time of the keyword. Table 8 lists the top 20 keywords with the strongest citation bursts.

Table 8. Top 20 keywords with the strongest citation bursts.

Keywords	Year	Strength	Begin	End	2014–2024
demand	2015	3.62	2015	2019	
neural networks	2014	5.14	2016	2019	
artificial neural networks	2016	4.13	2016	2020	
time series	2016	3.43	2016	2020	
regression	2014	2.68	2016	2018	
algorithm	2016	2.56	2016	2021	
consumption	2015	2.04	2017	2018	
big data	2014	3.77	2018	2020	
neural network	2018	2.75	2018	2021	
electricity demand	2018	2.3	2018	2020	
artificial neural network	2018	2.05	2018	2021	
prices	2018	2.05	2018	2019	
system	2018	2.03	2018	2020	
prediction	2019	3.33	2019	2021	
power	2019	2.2	2019	2021	
dynamics	2020	3.59	2020	2021	
big data analytics	2015	2.29	2020	2022	
inference	2020	2.05	2020	2021	
ICT	2021	2.07	2021	2022	
investment	2022	2.98	2022	2024	

Note: Red represents strong citation bursts. Blue and light blue mean no strongest citation bursts in the period.

The keyword "neural networks" in 2014 with showed the highest burst strength (5.14), indicating that AI plays an increasingly important role in energy economic and is gradually becoming a research frontier. Notably, the keyword "investment" has an intensity value of 2.98, which appears prominently in 2022, and is expected to continue to receive academic attention beyond 2024, which is related to the increasing global focus on sustainable energy investments.

3.3.4. Timeline Visualization

Analyzing the evolutionary path of a research area enables researchers to have a clearer picture of the development of the research topic and the direction of development, and the research trend of the topic can also be predicted based on the evolutionary path. We can understand the evolution of the research topic by analyzing the temporal naming and frequency of keywords. In this section, a timeline analysis of keywords from 2014 to 2024 is conducted with CiteSpace. The time slice is set to 1, and the timeline review of the keywords is shown in Figure 12. The Timeline function of CiteSpace enables such visual analysis of the evolution path, and at the same time, relevant keywords can also be clustered into themes—in this case, into 17 keyword cluster labels.

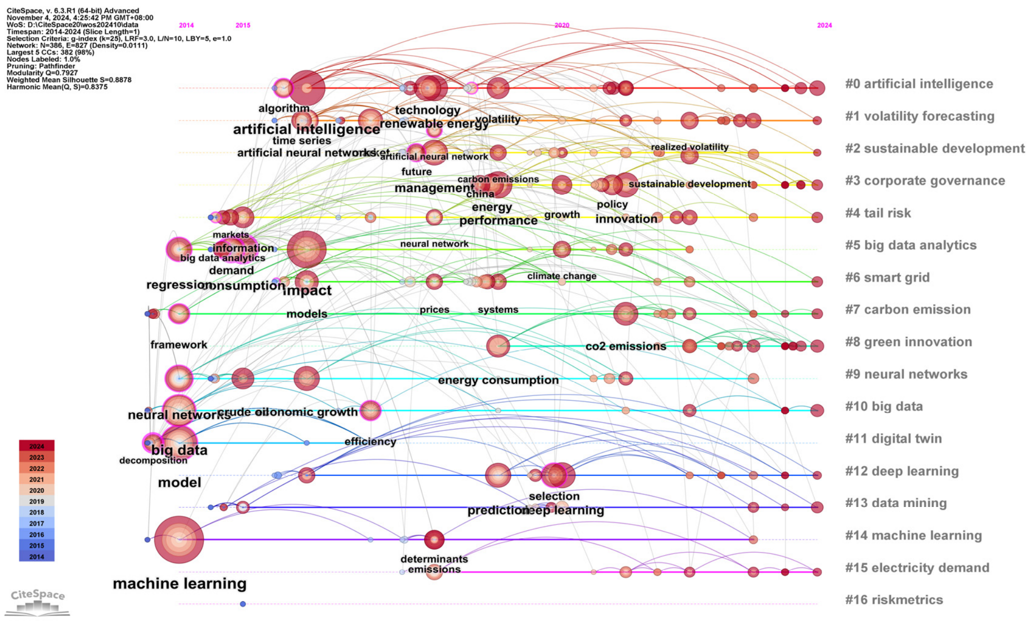

Figure 12. Timeline chart.

The concept of "#0 artificial intelligence" is a crucial research direction. The results of the timeline graph reflect a clear trend of homogenization, where there is strong continuity of national attention to machine learning and AI. We categorized the evolution of research themes into three phases:

The first phase is from 2014 to 2015. This was the initial phase of AI&EE research, with work focused on energy efficiency and energy forecasting. These studies relied on third-party forecasting and used time-series analysis. The keywords "regression" and "big data analytics" both appeared for the first time in 2014.

The second phase is from 2015 to 2016. Machine learning and artificial neural networks became major research themes. This marked a major shift in AI&EE. Energy economists tended to adopt more advanced research techniques and tools during this period. The keywords "time series", "consumption", and "algorithm" all appeared for the first time in 2016.

The third phase is from 2020 to the present. Research in this phase is more specialized, and the models are more complex. Research themes are centered around machine learning and artificial intelligence, reflecting a global convergence in the use of these technologies in energy research, which has become a cornerstone of energy economics research.

Artificial intelligence technologies provide powerful tools for energy data analysis, forecasting, and optimization, and the analysis of keyword timeline graphs suggests that the field of artificial intelligence and energy economics research is maturing.

4. Further Discussion

To better understand the evolution of AI&EE research themes, we can categorize the results of above-mentioned analysis into the following six future trends and two challenges.

4.1. Future Trends

4.1.1. Energy Supply-Chain Resilience and Security

As international political changes, the issue of energy supply-chain security is becoming a future research trend in the field of AI&EE. Resources supply-chain security is mainly related to the international situation and geopolitics. Given the long-term energy interdependence between the EU and the Russian Federation, Ilie et al. discussed the long-term energy security of the EU 27 and the dependency of the EU on imports of gas, oil, and petroleum products from the Russian Federation [74]. Deng et al. analyzed the impacts of the outbreak of the Russia–Ukraine war on the risk-related systems of oil, food, and renewable energy through a time-varying QVAR model and constructed a risk early-warning system for oil–food–renewable energy by using an ATT-CNN-LSTM model, which found that the outbreak of the Russia–Ukraine war promoted the development of renewable energy and enhanced the food-renewable energy correlation [75]. Zhong, Yufei et al. discussed how developing the use of artificial intelligence in energy market uncertainty could disrupt global supply chains [76].

In energy supply-chain resilience, AI can perform risk management tasks, identifying and assessing potential risks in the energy supply chain, such as natural disasters and market volatility. In the logistics and distribution part of the energy supply chain, self-driving vehicles, drones, and robots can conduct automated inspections to monitor and maintain the critical infrastructure of the energy network. In quantifying supply-chain resilience, AI can simulate different market and operational scenarios to assess the performance and resilience of the supply chain in the face of various shocks.

4.1.2. Social Acceptance and Public Participation

Social awareness and acceptance of AI technologies in the energy sector is a key factor in the mass commercialization of AI. New technologies in the energy sector also need to be aligned with the preferences of mass society and require public acceptance and participation for their widespread deployment and operation. Conversely, public acceptance of and participation in AI can also positively feed back into the diffusion and application of AI technologies in the energy sector. In order to assess public acceptance of fusion, Cabelkova et al. used big-data techniques as a criterion for social acceptance through participant interviews, internet news, newspapers and magazines, and the rate of support for the technology was assessed [77]. Enhancements that can be made include popularizing AI in teaching and publicizing it through mass media in order to increase public awareness of AI applications in the energy sector.

4.1.3. Economic Inequality and the Technology Gap

The acquisition and application of AI technology has a high threshold, requiring a high level of technological development and long-term sustained infrastructure investment, which naturally precludes low-income countries and less profitable firms from entering the AI space. In terms of the impact path, the aggregation of AI in these high-income countries and strong profitability firms in realizing the cumulative benefits of resources will lead to the gradual accumulation of additional benefits from AI in these individuals, such as customer service capabilities, productivity, and energy intensity. Ultimately, this will lead to unequal economic development, and this inequality, at the firm level, manifests itself in the nature of firms, such as monopolies and non-monopolies and state-owned and non-state-owned firms. At the national level, it is manifested in the imbalance of economic development between countries and regions, and from 2017, major economies began to develop AI as their main national development strategy, and AI competition will become more and more intense. Few articles have studied the inter-individual economic development gap brought about by AI development from the field of energy. Sinha et al. developed a policy framework for realizing the energy transition by considering social imbalance and regulatory effectiveness, with social imbalance dampening the positive impacts of energy-transition drivers [48].

The high threshold of AI will bring about a gradual increase in both the technology gap and the knowledge gap. The technology gap will lead to an unequal distribution of benefits in the energy economy. Rikap et al. discuss the knowledge monopoly of the State Grid Corporation of China (SGCC), a leader in AI applications in the energy sector, using big-data techniques [78]. SGCC relies on public research institutions and public funding as well as on innovation and energy policies to grow from being a global knowledge monopoly.

4.1.4. Automated Methods for Energy Policy Assessment

In the energy policy field, traditional assessment methods often rely on expert experience and qualitative analysis, which limit the objectivity and accuracy of policy assessment to some extent. The automated approach to energy policy assessment is mainly reflected in the ability of AI to simulate different policy scenarios and to assess the potential impact of these policies on the energy market and the socio-economic sector. Through machine learning algorithms, AI can process and analyze large amounts of historical and real-time data and identify the relationship between policy changes and energy market responses, thus predicting the possible consequences of policy changes. This automated approach not only improves the efficiency of policy assessment but also enhances the accuracy and reliability of the results. Neto-Bradley et al. used a tree-ensemble-based machine learning predictive analytics approach to identify targets for clean-cooking policy interventions [79]. This suggests that automated methods can be used not only as a tool for in-depth analysis but also to provide policymakers with more specific guidance for action.

4.1.5. Circular Economy (CE)

The circular economy is a model for economic growth, the core of which is emissions reduction and reuse and resource mobilization, and it is characterized by low consumption, low emissions, and high productivity. Vigorous efforts have been made to develop a circular economy and significantly increase the utilization and recycling rates of key materials such as steel, cement, fertilizers, and plastics. Anwar et al. explore how two technologies, artificial intelligence (AI) and digital twins (DT), are contributing to consumption transformation and sustainable development for a circular economy in agriculture [80].

4.1.6. Digital Economy

The digital economy can affect economic development significantly. Meanwhile, the impact of the digital economy on the environment and resources is an important research topic for future studies. Wang et al. found that AI will have a significant positive impact on the strategy of the high-quality development of energy (HED) in the areas with a developed digital economy [81]. Lai et al. used China's National Big Data Comprehensive Pilot Zone (NBD-CPZ) as a quasi-natural experiment and found that the impact of the digital economy on urban eco-efficiency was more significant in resource-based and high-energy-intensity cities [82].

4.2. Challenges

4.2.1. Government and Administrative Support

According to Duan et al., with regard to AI, legal issues have become a significant challenge [83]. The role of the government is crucial, especially in terms of how the government develops adequate policies, regulations, and legal frameworks to guide and prevent misuse of the technology.

4.2.2. Policy, Law, and Intellectual Property Protection

One of the main problems with AI research in energy economics is the lack of accessible data, which hampers research conducted for the public good; hence, there is a need for an AI data-sharing platform. Therefore, legislative and regulatory measures are needed to facilitate data sharing and digital transformation among individuals, universities, businesses, and governments. Another issue is the ethical issues raised by AI and the lack of sound legal provisions for AI in the law; hence, the recommendation for ethical audits of high-risk AI systems that should be used for environmental issues. From a legal perspective, Mylrea et al. explored the privacy laws, torts, and precedents relevant to smart-energy technology opportunities and examined the challenges involved [84].

5. Conclusions

This paper presents a bibliometric analysis of relevant publications in AI&EE from different perspectives, revealing their essential characteristics, knowledge structures, hotspots, and trends. First, a performance analysis was conducted to present the essential characteristics of the publications, including the annual indicators, thematic evolution, and research areas. Then, to identify collaborations in the research area, analyses were conducted from four perspectives: citations, countries, institutions, and authors. Next, co-occurrence analysis, keyword clustering analysis, burst detection analysis of keywords, and timeline visualization were performed to identify research hotspots, frontiers, and trends. Finally, further discussions were conducted.

5.1. Key Findings

Based on the results of the bibliometric analysis, the key findings are summarized as follows:

(1) Descriptive statistical analysis reveals that the number of publications in AI&EE has been increasing year by year. There is strong continued interest in machine learning and artificial intelligence across countries. The most popular research areas are economics (318) and management (156). The top-ranked journal is *Energy Economics*, followed by *Technology Forecasting and Social Change*, *Energy Policy*, and *International Journal of Forecasting* in the field of energy economics.

(2) In network analysis, the most influential and most cited articles are those by Gozgor et al., Lau et al., and Sinha et al. China is the country with the most achievements, with Australia and India and other countries collaborating most closely. Chinese Academy of Sciences and Beijing Institute of Technology are the most influential institutions. The scholar with the most publications in the field of AI&EE is Shouyang, Wang (8), with a total of 533 citations.

(3) The keyword analysis demonstrates that the hotspots of AI&EE research are concentrated on “ machine learning”, “ impact”, “ artificial intelligence”, “model”, and so on. The keyword “investment”, with a strength of 2.98, emerged in 2022, and it

is expected that academic attention will continue beyond 2024. The current prominent research themes are energy price forecasting, artificial intelligence innovations in energy systems, socio-economic impacts, energy transition, and climate change. Based on the timeline analysis, the resulting 17 clusters can be considered as the core directions of current AI&EE research.

(4) Potential future research directions include energy supply-chain resilience and security, social acceptance and public participation, economic inequality and the technology gap, automated methods for energy policy assessment, the circular economy, and the digital economy. Future challenges include governmental and administrative support as well as legal and intellectual property protection. The results of the survey provide some suggestions for future research.

5.2. Limitations

This paper provides a comprehensive analysis of publications related to AI&EE from 2014 to 2024. It can help scholars interested in AI&EE research to better understand the field's evolution and to reflect on it from multiple perspectives. At the same time, this paper has some limitations. A single database source and the use of specific search settings may have resulted in some publications being missed. This paper focuses on presenting a panoramic view of the field rather than analyzing the details in depth. Therefore, the discussion in this paper has some limitations.

In the future, we should work on researching and developing new AI-based techniques. We will consider using additional databases, more loosely defined terms for data collection, and alternative bibliometric analysis methods. In addition, more advanced methods for comprehensive analyses, such as machine learning and text mining, will be further employed. In the future, we will continue to focus on developing AI&EE research.

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Abbreviations

AI	Artificial intelligence
EE	Energy economics
PSTR	Panel smooth transition model
RE	Renewable energy
LSTM	Long short-term memory
WTI	West Texas intermediate
EU	The European Union
QVAR	Quantile vector autoregression

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