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Research article

Bibliometric investigation of energy efficiency improvement from digitalization to smart efficiency

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Abstract: Digital technologies have become a core instrument for advancing green, low-carbon development. To address fragmented, cross-disciplinary evidence on where and how these tools deliver measurable efficiency gains, this study conducted a bibliometric analysis of 2082 Web of Science records using a reproducible toolchain and a unified terminology policy. The analysis quantified citation baselines, mapped clustered co-occurrence structures, and detected burst-driven trend evolution. The findings reveal a compact core of authors and hub institutions, a three-phase progression from measurement digitization to process digitalization and AI-enabled digital innovation, and a divergence between publication volume from per-article influence via average citation scores. The scientific value-added lies in integrating these hotspots and trends into interpretable maps that link areas of concentrated impact to existing gaps. Future efforts should prioritize interoperable data infrastructure and outcome-based incentives, scale high-return use cases through digital twins governed by large models, and establish open, replicable benchmarks to accelerate translation to measurable efficiency gains.

Keywords: energy efficiency; digital technology; innovation; bibliometric analysis; visualization

1. Introduction

Energy systems face growing pressure to reduce pollutants and greenhouse gas emissions in response to global environmental challenges such as climate change [1]. Concurrently, market imbalances, fossil-fuel depletion, increased greenhouse-gas emissions and temperatures, and sea-level rise threaten livelihoods and economic activities for roughly one billion people. The green transition of energy systems has been shown to influence mercury emissions in China [2], while the political and economic implications of peak oil continue to be explored [3]. Moreover, global carbon intensity has undergone significant changes, and a range of strategies have been proposed for mitigating climate change [4,5]. Additionally, the analysis also conducted an economic evaluation of energy subsidies [6]. Policymaking must balance energy conservation and emissions reduction with economic performance, given the existing evidence of environmental regulation impacts on potential growth [7–9]. In addition, the carbon neutrality goal is driving regional development toward a new phase characterized by green, low-carbon, and high-quality development [10,11]. Improving energy efficiency is a primary lever for reducing energy use and mitigating emissions [12,13]. However, in the long run, the most effective way to ensure that the goals of carbon peaking and carbon neutrality are realized on schedule is to boost the share of clean energy and improve energy use efficiency. Although the transition to clean energy and electrification is a long-term process, enhancing energy-use efficiency through digital technologies remains an effective pathway to green and low-carbon development across sectors [14].

Energy efficiency is influenced by multiple technological and organizational factors. Available research has included both clean energy sources such as solar and biomass, as well as conventional carriers of natural gas, oil, and coal. These works have also explored various methodologies, including the use of neural networks for clustering analysis to predict solar collector performance [15], challenges in promoting clean energy technologies in China, and the impact of technological advancements on energy efficiency [16–19]. Additionally, there has also been an analysis of environmental taxes and energy efficiency optimization methods in industrial parks [20]. Three mainstream strategies persist, namely industrial agglomeration and coordinated development [21], improvements to the reliability and operation of energy distribution systems [22,23], and retrofitting of equipment, systems, and buildings, which are typically the most viable short-term options [24–26]. Empirical studies have illustrated these approaches. For instance, Jalo et al. (2021) examined 13 small- and medium-sized industrial enterprises as case studies and found that establishing energy-efficiency networks can enhance firm-level efficiency [27]. Kamel et al. (2022) focused on the railway energy system and designed an energy storage system to facilitate energy transfer between the two networks with different average power levels, thereby improving energy efficiency by recovering most braking energy [28]. Wang et al. (2023) employed spatial econometric methods to identify potential drivers of energy efficiency [29]. Recently, digitalization has emerged as a key pathway to improving energy efficiency. The integration of artificial intelligence and data-driven technologies with the spillover effects from foreign direct investment has enabled the processing, storage, transmission, and analysis of energy data, thereby helping to optimize energy system performance. Relevant research has explored multiple dimensions of this transformation, including the integration of smart energy systems [30], synergistic benefits of energy efficiency and demand response in renewable energy systems [31], and the impact of global value chains on renewable energy consumption and carbon dioxide emissions [32]. Additionally, research has addressed the integration of residential building retrofitting technologies with renewable energy [33], the industrial agglomeration effects on factory energy efficiency [34], and innovations in renewable energy inverters [35]. The utilization of digital technologies to improve energy efficiency represents a critical and rapidly evolving research direction within the context of energy transition and climate policy. In fact, digital technologies are increasingly applied in industrial production [36]. Yang et al. (2023) integrated machine learning into operations in the metallurgy and chemical industries [37]. Ju et al. (2022) applied artificial intelligence to energy systems [38]. Technological innovation and technology adoption are essential to improving energy efficiency [39]. As a transformative approach, digital technologies enhance energy efficiency and promote sustainability by restructuring energy systems and modernizing operational models [40,41]. Manual synthesis of extensive literature is cumbersome and error-prone. In contrast, bibliometric analysis offers a systematic means to identify current research hotspots and future trends. For instance, Bornmann (2020) used a bibliometrics-based decision tree to determine whether two universities in the Leiden ranking differed substantially in their performance [42]. Chen et al. (2022) accelerated intelligent bibliometrics-driven literature analysis by leveraging deep learning for automatic literature screening [43]. In adjacent sustainability domains, a circular economy, Industry 4.0 review employing fuzzy set theory organized stage-wise decision support [44], while a bibliometric analysis of 909 Web of Science records on carbon neutrality showed rapid growth led by China and the United States and identified hotspots across technical, policy, and economic themes [45].

Due to recent sectoral and rural-systems analyses, together with the post-2017 acceleration of digital approaches and tightening net-zero commitments, a field-level synthesis is timely and necessary. Distinct from prior sector- or region-specific studies, this review consolidates dispersed evidence into a coherent, cross-disciplinary picture that links research hotspots, thematic evolution, and collaboration structures while clarifying terminology. The synthesis is consistent with earlier literature emphasizing that coordination and managerial capacity drive efficiency outcomes. At the same time, it extends prior work by indicating where influence concentrates, where cross-institutional ties remain fragmented, and which digital technologies currently anchor high-impact applications. Finally, it specifies enabling requirements, interoperable data infrastructure, and robust model governance, and highlights emerging platforms, with current grid-integration and rural-development challenges underscoring their importance [46,47].

The objective of this work is to systematically map how digital technologies contribute to energy-use efficiency by applying bibliometric analysis to records retrieved from Web of Science citation databases. The analysis quantifies publication dynamics, identifies thematic hotspots (e.g., digitization, Industry 4.0, machine learning, and artificial intelligence), and traces their evolution, leading contributors at the author, institution, and country levels, and collaboration structures. Frontier topics are further organized into application pathways linking digitalization to smart efficiency—upstream enhancement of energy quality, system-level efficiency gains through computational methods, and digitized production with demand-side participation to reduce energy waste. The objective is to provide an evidence-based knowledge map and a concise agenda for future research and practical deployment.

The rest of the article is structured as follows: Section 2 presents data sources, indicators, and bibliometric methods. Sections 3,4 presents results and discussion on the effects of digital technologies on energy efficiency, including development trends and research hotspots in this field. Finally, Section 5 presents the conclusions drawn from this work.

2. Research and data methodology

2.1. Data collection and processing

Bibliometric data were collected from the Web of Science Core Collection, a widely used global bibliographic database [48]. It is widely used by researchers and institutions for bibliometric analyses. Bibliometric approaches broaden methodological horizons by leveraging vast datasets and sophisticated analytical and visualization tools to uncover insights that would be impractical to achieve manually. Digitization refers to the conversion of analog information into digital data. Digitalization denotes the process and organizational change enabled by digital technologies, together with the new products, services, or processes enabled by digital technologies. We apply these terms consistently throughout the text, figures, and keywords in this paper. Because research in this field originated in 1990, literature published between January 1, 1990, and September 30, 2024, was selected for this work. This approach is valuable for distilling knowledge from a large body of work spanning decades and covering thousands of studies.

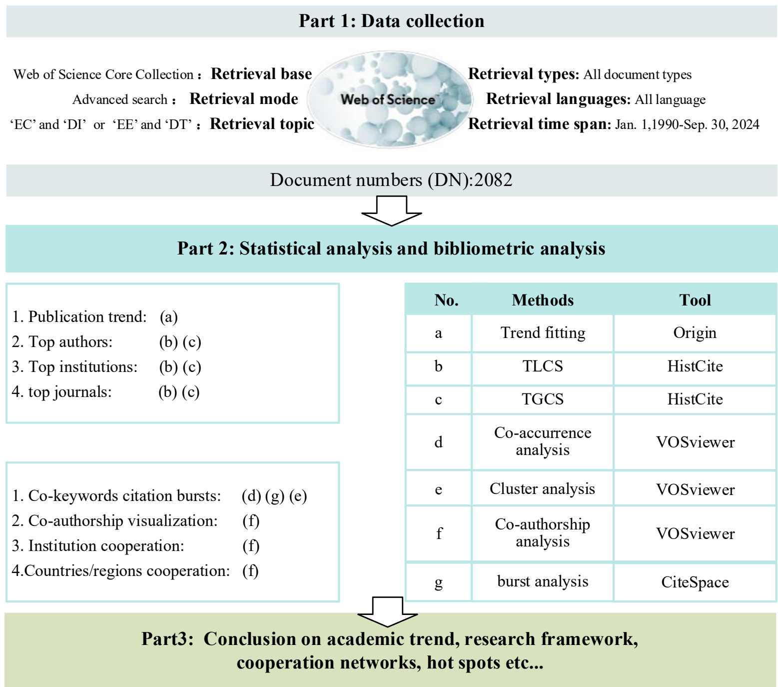


Figure 1. Literature search strategy and methods.

The literature search strategy for "energy efficiency" and "digital technologies" is shown in Figure 1; first, the database and topics were identified, and then Advanced Search was used for data collection. Queries used here were "energy efficiency and digital technologies or energy conservation and digitalization" to capture the broadest relevant set of records; language was set to "All languages" and the document type to "All document types". Date range was restricted to "January 1, 1990, to September 30, 2024". We then exported full records and cited references in CSV, RIS, or plain-text format. The exported records included metadata fields such as title, author, institution, year of publication, source journal, and references. Finally, we conducted bibliometric analyses and visualizations on the exported records, analyzed the data, and derived conclusions using bibliometric methods. This analysis yields insights into publication trends, research frameworks, collaboration networks, and topical issues in energy efficiency and digital technologies. Following the above strategies, a total of 2082 valid publications were found. Among these, the three main document types were articles, proceedings papers, and reviews; other types included letters and editorial materials.

2.2. Model-building overview

The software suite includes HistCite, VOSviewer, and CiteSpace, which supported the bibliometric analysis. HistCite computed global and local citation indicators (TGCS/TLCS) and generated historiographic maps to establish citation baselines; VOSviewer constructed and clustered co-keyword, co-authorship, and co-citation networks and reported total link strength (TLS); CiteSpace performed temporal analyses, including annual time-slicing, citation/keyword burst detection, and evolution mapping to identify emerging topics. The workflow was as follows: (i) exporting Web of Science Core Collection records as plain text, CSV, or RIS; (ii) deduplicating by DOI; (iii) cleaning and normalizing author, affiliation, and keyword fields with a curated thesaurus; (iv) applying a unified terminology policy distinguishing digitization, digitalization, and digital innovation; (v) running the three tools with the parameters in Table 1; (vi) documenting interface outputs in Figure 2; and (vii) exporting high-resolution figures with accompanying data for downstream analysis.

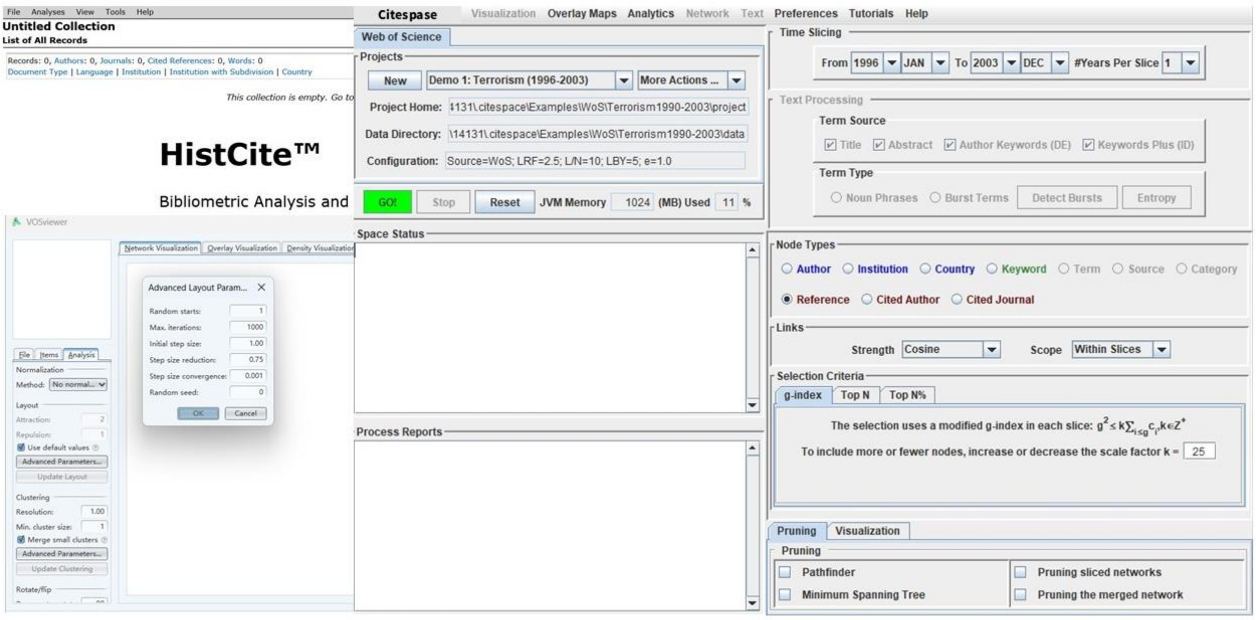


Figure 2. User interface of the three tools HistCite, VOSviewer, and CiteSpace.

Table 1. Essential parameter settings of the three tools HistCite, VOSviewer, and CiteSpace.

Setting	Value
HistCite	
Impact metrics	TLCS and TGCS reported
Reporting thresholds	TLCS ≥ 5, TGCS ≥ 30
Historiograph step	1 year per step
VOSviewer	
Normalization	Association-strength
Counting method	Full (topics)
Key thresholds	Authors docs ≥ 3, keyword occurrences ≥ 5, references cited ≥ 20
Clustering	Resolution: 1.00
CiteSpace	
Time slicing	1996–2024, 1 year per slice
Term sources	Keywords
Node types	Keywords, cited references
Selection	g-index, k: 25
Links/Scope	Cosine/within slices
Pruning	Pathfinder and MST
Cluster labeling	LLR
Burst detection	γ: 1.0, min duration: year, Top N per slice: 20

2.3. Indicators, networks, and temporal analysis

Citation indicators included TGCS/TLCS and their per-article average A_TGCS/A_TLCS to separate publication volume from influence per paper. Average publication year (APY) characterizes recency, and TLS summarizes co-occurrence connectivity. Core authors were identified with Price's law threshold using explicit rounding. Co-keyword, co-authorship, and co-citation networks were constructed under association-strength normalization with full counting as the main specification and fractional counting in checks. The minimum keyword occurrence threshold was 5, yielding 304 items for visualization; analogous settings were used for co-authorship and co-citation networks. Communities were detected with modularity-based clustering and visualized with force-directed layouts; overlay coloring reflected APY. Annual time-slicing and burst detection highlighted periods of rapid growth and emerging topics.

2.4. Validation, robustness, and reproducibility

Records from the Web of Science were obtained, deduplicated by DOI, and normalized for authors, affiliations, and keywords using a curated thesaurus and a unified terminology policy. Citation indicators were computed; co-keyword, co-authorship, and co-citation networks were constructed with association-strength normalization under full counting. Communities were detected and visualized with force-directed layouts, and annual time-slicing with burst detection was used to trace thematic evolution. HistCite provided citation baselines and historiography, VOSviewer produced and clustered the networks and reported TLS, and CiteSpace carried out time-sliced co-citation/keyword analyses. Robustness was examined along standard dimensions. Full versus fractional counting was contrasted for author and institution outputs; minimum co-occurrence thresholds and clustering resolution were varied within reasonable ranges, and random seeds were changed to check the stability of community assignments. Raw TGCS was compared with field/year-normalized citation indicators to reduce age and domain effects, and early versus late time slices were contrasted to verify the observed three-stage evolution. These procedures follow recommended practices for bibliometric model testing and reporting [49–51] and are consistent with prior applications that combine network clustering with temporal/burst analysis in renewable-energy and carbon-neutrality mappings [52,53] and in biofuel and energy-security bibliometrics [54,55]. To support reproducibility, full search strings, thesaurus mappings, deduplication and disambiguation rules, and the main parameter settings for HistCite, VOSviewer, and CiteSpace are supplied in the supplementary material. Exported node/edge tables and high-resolution figures are also provided so that results can be regenerated or extended.

3. Results

3.1. Descriptive statistics and quantitative analysis

3.1.1. Publication output and trend growth

The growth in journal publications directly reflect the expansion of scientific knowledge, as increased research output indicates advancements in scholarly understanding within a field [56,57]. Figure 3 presents the annual publication and citation trends for research on energy efficiency and digital technologies based on Web of Science data from 1996 to 2024. The chart reveals consistent year-by-year growth, starting with only one publication in 1996 and gradually increasing to 10 by 2000. After 2015, annual publications surged and exceeded 100 per year. In addition, Figure 4 shows how the number of journal articles on energy efficiency and digital technologies has varied over time. In this figure, the time series can be segmented into three periods: an embryonic stage (1996–2007), a development stage (2008–2017), and a prosperity stage (2018–2024). In the embryonic stage, annual publications grew slowly and remained below 50. In the development stage, annual output grew rapidly and approached and then exceeded 100 per year. In the prosperity stage, annual publications on energy efficiency and digital technologies exceeded 250 for the first time, and the growth rate accelerated relative to the development stage. Research on energy efficiency initially focused on improving energy-use practices and environmental regulations. However, with the emergence of Industry 4.0 in 2013, scholars began to explore the role of digital technologies in enhancing energy efficiency. This shift catalyzed a significant increase in research activity from 2017 onward. The integration of advanced technologies such as the Internet of Things, big data analytics, and artificial intelligence has enabled more precise energy management and optimization. Additionally, growing global emphasis on sustainability, stricter environmental policies, and economic pressures have further spurred the adoption of digital solutions in energy efficiency research. As a result, the convergence of digital transformation and energy efficiency has become a pivotal area for addressing both environmental challenges and industrial competitiveness.

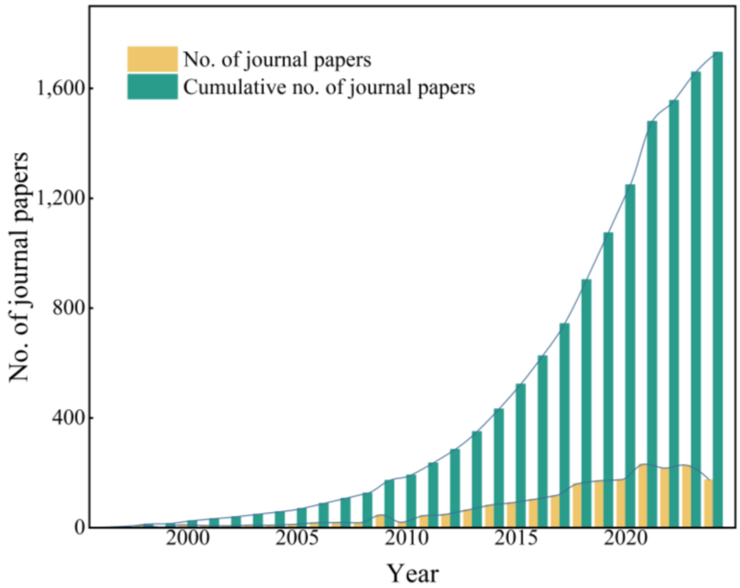


Figure 3. Number of publications and citations regarding energy efficiency and digital technologies based on Web of Science from 1996 to 2024.

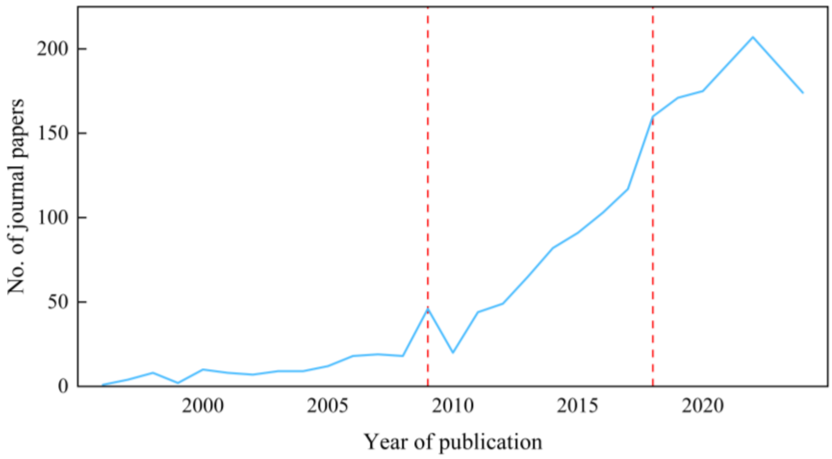


Figure 4. Research on energy efficiency and digitalization technology based on the number of journal papers.

3.1.2. Identification of candidates for core authorship

Calculating the publication count for each author can be challenging, as each publication typically involves multiple authors and contributions vary significantly, so raw counts may not reflect true scholarly contribution. The core author group was identified using Price's law, in which the total number of papers published by scientists who have published more than $0.749N_{max}^{0.5}$ papers is equal to half of the total number of papers. Table 2 shows the top 20 most prolific authors based on publication records. According to this table, Kim from Pohang University of Science and Technology (South Korea) is the most prolific author, with 16 publications. Because publications are typically co-authored and individual contributions vary, we computed per-author publication totals under the full-counting rule (e.g., each paper counts as 1 for every co-author). To identify a compact yet representative set of core authors, we applied Price's law threshold to productivity and an analogous rule to citation impact. The threshold number of publications can be obtained using the formula as follows:

$$TP_n = 0.749 \cdot \sqrt{N_{\max}} \tag{1}$$

where $N_{\max}$ is the number of publications of the most prolific author, and TP_n is the productivity threshold for core authors. Next, we derived the minimum TGCS threshold. Mitra achieved the highest total number 944 of TGCS. Based on Price's law, the lowest number of TGCS is

$$TP_s = 0.749 \cdot \sqrt{M_{\max}} \tag{2}$$

where $M_{\max}$ refers to the maximum TGCS, and TP_s refers to the minimum TGCS threshold. Finally, 144 core author candidates were identified based on the defined criteria. These authors dominate the literature output and citation metrics, significantly influencing the field's development. Notably, scholars from Stanford University, including Mitra, Shulaker, and Hills, have achieved high TGCS, reflecting their significant impact on related disciplines. Collaboration among core authors has enhanced academic innovation and research depth, thereby driving advancements in cutting-edge technologies. For example, the collaboration between Mitra and Shulaker has been associated with significant progress in engineering and computer science, highlighting the critical role of interdisciplinary collaboration in fostering technological breakthroughs and academic excellence.

VOSviewer was used to analyze collaboration patterns among authors studying energy efficiency and digital technologies [58]. Figure 5 illustrates the co-authorship network for 2016–2024. To ensure comprehensive coverage of authors, a threshold of two publications was set for inclusion in the co-authorship analysis. Initially, 596 authors were identified; after excluding unrelated items, 64 remained for further analysis. As shown in Figure 5(a), the network partitions into seven distinct color clusters, each representing a group of collaborating authors. For example, the red cluster includes prominent researchers such as Mitra, Hills, Shulaker, and Gielen. Structurally, the map exhibits a hub-and-spoke topology, with a small set of hubs concentrating links and acting as brokers between communities, while several peripheral clusters maintain few external ties. This centralization implies that knowledge diffusion relies on a handful of gatekeepers and that cross-cluster spillovers are limited. In Figure 5(b), the size of the circles corresponds to the link weight of authors, while the color gradient (purple to yellow) indicates the average citation scores of their publications. Notably, authors with higher link weights, such as Hills, Mitra, Wei, and Wong, also tend to have higher average citation scores. In contrast, clusters such as Tan's demonstrate weaker collaboration and lower citation metrics, suggesting relative isolation. Figure 5(c) further explores the temporal dimension of research activity, with circle size representing the average publication output of authors, and the color gradient (blue to yellow) indicating the transition from earlier to more recent research frontiers. It is evident that authors with strong collaborative networks and high citation scores are often associated with earlier research periods, whereas those with lower citation scores tend to be more active in recent years. This suggests topic diversification and the entry of new teams rather than consolidation around a single core group. Table 3 summarizes the link counts and total link strengths of the top ten authors. Mitra is the most collaborative author, followed by Hills, with 18 links and a TLS of 28. Wei stands out with the highest average citation score of 212, while Shen L, ranked ninth, is notable for having the most recent publication year. However, both Table 3 and Figure 5 indicate the absence of a stable core author collaboration group in this field, reflecting a fragmented research landscape. More funding should be given to teams that bridge different research groups, encouraging co-PIs from different clusters to work together on shared data and benchmarks.

Table 2. Top 20 influential authors based on records.

Ranking	Authors	Records	TLCS	TGCS	Institution
1	Kim	16	0	141	Pohang University of Science and Technology
2	Chen	12	0	142	Beijing Institute of Technology
3	Zhang	12	1	417	Peking University
4	Kim	11	1	45	Stevens Institution of Technology
5	Mitra	11	29	944	Stanford University
6	Shulaker	11	21	885	Stanford University
7	Hills	10	15	823	Stanford University
8	Wong	10	16	260	Stanford University
9	Lee	9	1	42	Seoul National University
10	Zhang	9	2	96	Delft University of Technology
11	Benini	8	1	83	Swiss Federal Institution of Technology
12	Gielen	8	5	97	Katholieke University Leuven
13	Kim	8	5	27	Seoul National University
14	Yang	8	2	47	Huazhong University of Science and Technology
15	Li	7	1	104	University of Pittsburgh
16	Wang	7	0	68	National University of Singapore
17	Yang	7	2	64	Taiyuan University of Technology
18	Yu	7	1	87	Georgia Institute of Technology
19	Lee	6	2	36	Sungkyunkwan University
20	Lian	6	5	85	York University

Table 3. Link and total link strength of the top 10 authors.

RO	Authors	Cluster number	Links	Total link strength	AC	APY
Top 1	Mitra	1	17	49	85.82	2016
Top 2	Hill	1	16	28	82.30	2017
Top 3	Shulaker	1	15	36	91.78	2016
Top 4	Gielen	8	12	27	12.12	2015
Top 5	Wei	6	12	19	212.00	2014
Top 6	Verhelst	1	11	13	8.25	2015
Top 7	Tan	3	10	11	34.00	2018
Top 8	Wang	6	9	10	68.00	2015
Top 9	Shen	3	9	17	5.67	2020
Top 10	Van	2	7	8	98.00	2016

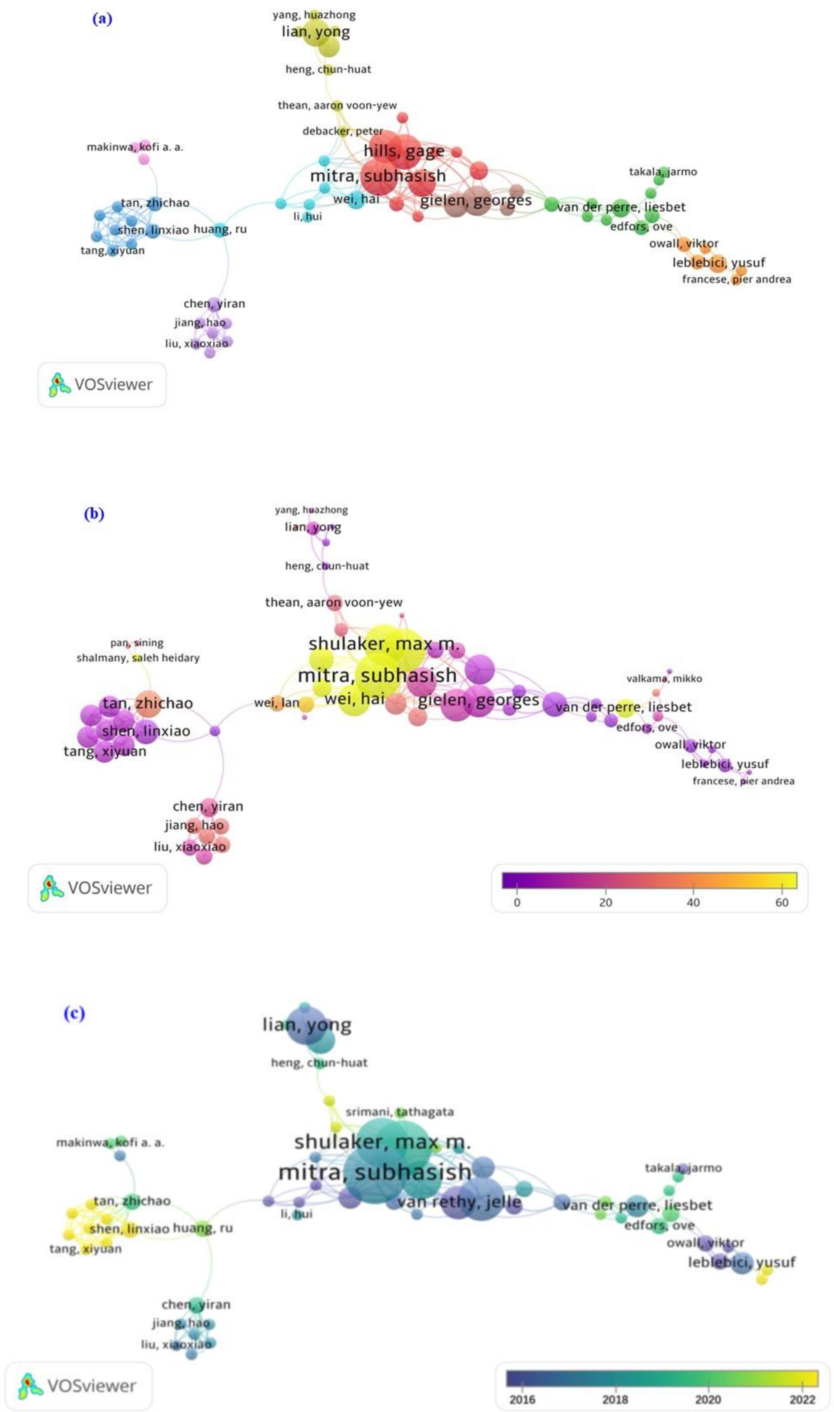


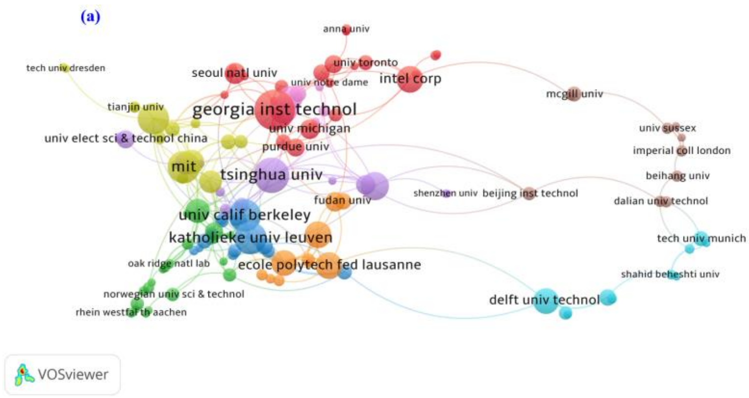
Figure 5. Authors' cooperation network in energy efficiency and digital technologies innovation research: (a) link weight view: heavier edges indicate stronger co-authorship and are typically associated with larger, more cohesive clusters; (b) citation overlay: node color encodes citation score; (c) recency overlay: node color encodes average publication year.

3.1.3. Features of affiliated research institutions

Core authors are critical nodes in academic collaboration networks, strengthening inter-institutional ties and facilitating cross-institutional research progress [59,60]. Table 4 presents the top ten influential institutions by publication volume. Georgia Institute of Technology ranks first with 27 publications, followed by Tsinghua University (22 publications) and Massachusetts Institute of Technology (MIT) (21 publications). But MIT leads in total local citation score. The analysis shows that while global citation scores correlate with publication volume, institutional strength is a key driver of research quality, as local impact does not necessarily translate into global influence, and rankings of institutions do not always align with those of individual authors. The partnerships among institutions are shown in Figure 6. These 151 institutions were divided into nine clusters, as indicated by nine distinct colors in Figure 6(a). The size of each circle corresponds to the publication output of the institutions, with larger circles reflecting higher publication volumes. The connecting lines represent collaborations, with shorter lines indicating stronger partnerships. The largest cluster, represented in red, includes Georgia Institute of Technology, which ranks first in both publications and link strength. The second largest cluster, green, contains 21 organizations, including Zhejiang University, University of Cambridge, University of Oxford, and Oak Ridge National Laboratory. The blue cluster, with 17 organizations, includes key contributors such as the University of California, Berkeley, Katholieke Universiteit Leuven, and Lund University. Combining the network visualization in Figure 6(a) with the density visualization in Figure 6(b), it is evident that the blue cluster exhibits tighter academic collaboration, especially among European institutions such as Katholieke Universiteit Leuven and the University of Bologna; the University of California, Berkeley, is also a central contributor within this cluster. Additionally, several strong academic collaboration clusters exist in Asia, with key institutions like the University of the Chinese Academy of Sciences, Nanyang Technological University, and University of Science and Technology Beijing. The analysis reveals that while the field of energy efficiency and digital technologies has seen exponential growth in research, key institutions and authors have shown limited collaboration. Connector projects that pair hubs with neighboring clusters (e.g., cross-cluster grants) should be encouraged. These projects should require shared datasets, testbeds, and basic interoperability deliverables in institutional collaborations. Cross-region partnering should be included as an evaluation criterion, so that strong local communities translate into broader, faster diffusion rather than parallel silos.

Table 4. Top ten influential institutions based on records.

Ranking	Institutions	Records	TLCS	TGCS	Country
1	Georgia Institute of Technology	27	3	965	USA
2	Tsinghua University	22	8	303	Mainland, China
3	Massachusetts Institute of Technology	21	27	878	USA
4	Katholieke Universiteit Leuven	20	7	187	Belgium
5	University of California, Berkeley	20	13	510	USA
6	Nanyang Technological University	19	11	434	Singapore
7	University of Chinese Academy of Sciences	17	0	228	China
8	Ecole Polytechnique Federale de Lausanne	16	6	590	Switzerland
9	Intel Corporation	16	7	376	USA
10	National Chiao Tung University	16	1	107	Taiwan, China



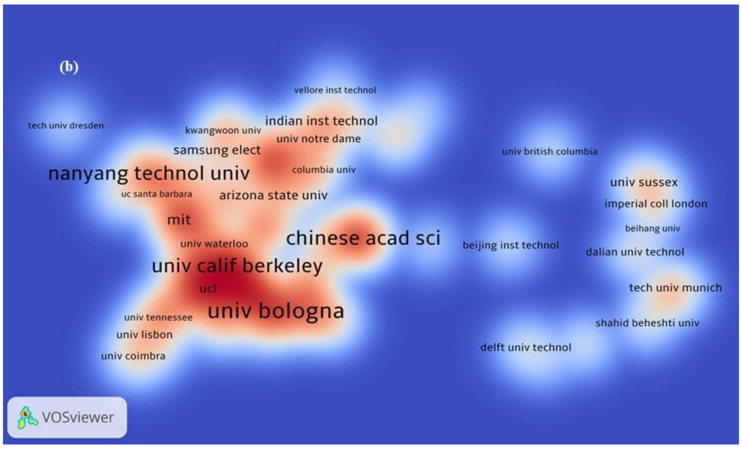


Figure 6. Visualization map of research institutions on energy efficiency and digital technologies innovation: (a) link weight view: stronger edges indicate tighter inter-institutional collaboration and are typically associated with larger, more cohesive clusters; (b) density view: color gradient encodes local concentration of influential institutions.

3.1.4. Literature sources and research fields

Analyzing literature sources is essential to identify high-impact journals and influential publishing platforms [61]. Assessing publication trends enables researchers to identify key journals in a field with significant visibility and scholarly impact. The top ten journals are listed in Table 5. According to this table, the top ten journals account for 17.5% of publications, meaning that 17.5% of articles are concentrated in the top 1.08% of journals. Journal records are assessed by indexes such as TLCS, TGCS, A_TLCS, and A_TGCS. Specifically, A_TLCS is the ratio of total local citation score to records, and the index A_TGCS is the ratio of TGCS to records. The journal *IEEE Journal of Solid-State Circuits* ranked 1 in publication number with 64, total local citation score of 84, TGCS of 2161, A_TLCS of 1.31, and A_TGCS of 33.77. *IEEE Transactions on Circuits and systems I-Regular Papers* ranked fourth in publication count but second in TLCS and A_TLCS, indicating its substantive influence in this field. *Sustainability* ranked sixth by publication count, but its TLCS is zero. This is interpreted here as limited within-corpus connectivity. Similarly, the TLCS of *Energies*, *Sensors*, and *Nuclear Instruments and Methods in Physics Research Section A-Accelerators*, *Spectrometers*, *Detectors and Associated Equipment* ranked among the lowest, which indicates limited within-corpus connectivity. It is worth noting that the journal *Medical Physics* ranked eighth in the number of articles published, while it ranked first in A_TLCS with 40.07. This indicates that the journal *Medical Physics* is highly valued in other research fields. In fact, the top 10 journals account for 17.5% of outputs, indicating a Bradford-type concentration around a small set of hubs. Publication counts show where work is placed, whereas A_TLCS and A_TGCS capture per-article influence; using both avoids conflating volume with impact. A TLCS of zero does not imply lack of "cooperation"; instead, it reflects within-corpus citations and may be driven by recency, so collaboration should be assessed via co-authorship and affiliation networks. Device and circuit outlets tend to anchor low-power and design streams, while systems and application outlets host digitalization topics. Targeting A_TGCS-strong venues maximizes cross-field reach, whereas A_TLCS-strong venues shape core technical debates. These findings emphasize the importance of distinguishing between publication quantity and academic influence. Journals with high A_TLCS/TGCS ratios may serve as strategic targets for researchers seeking interdisciplinary collaboration, while those with low scores highlight opportunities for fostering deeper thematic alignment.

Table 5. Top ten journals based on records.

Ranking	Journal	Records	TLCS	TGCS	A_TLCS	A_TGCS
1	*IEEE Journal of Solid-State Circuits*	64	84	2161	1.31	33.77
2	*IEEE Access*	36	8	799	0.22	22.19
3	*Energies*	32	0	148	0.00	4.63
4	*IEEE Transactions on Circuits and systems I-Regular Papers*	31	23	487	0.74	15.71
5	*IEEE Transactions on Very Large-Scale Integration (VLSI) Systems*	27	12	556	0.44	20.59
6	*Sustainability*	25	0	182	0.00	7.28
7	*IEEE Transactions on Circuits and Systems II-Express Briefs*	21	7	130	0.33	6.19
8	*Medical Physics*	14	6	561	0.43	40.07
9	*Sensors*	14	0	119	0.00	8.50
10	*Nuclear Instruments & Methods in Physics Rection A-accelerators Spectrometers Detectors and Associated Equipment*	13	0	147	0.00	11.31

3.1.5. Country/region collaboration analysis

Scientific investigation is moving toward internationalization, and collaboration in scientific research between countries or regions plays a key role in promoting knowledge sharing and technological innovation [62]. Cross-regional collaboration not only promotes the complementarity of academic resources but also facilitates the global dissemination and application of advanced technological achievements. Bibliometric methods enable the analysis of global research collaboration networks, revealing the distribution of research power, patterns of collaboration, and their impact on the development of the field. We used VOSviewer to create visual maps of national and regional links and to explore major partnerships among 85 countries or regions, as shown in Figure 7. At a threshold value of 2, there were 67 countries. After dropping scattered countries like New Zealand, Wales, Romania, Ecuador, and South Africa, 54 valid countries remained. The network map was based on document weights, and the density map was based on total link strength weights. The map contained four clusters (red, yellow, green, and blue), with 334 links and a total link strength of 741. As shown in Figure 7(a), the first cluster was red, which contains 22 items, including the United States, the United Kingdom, Australia, Italy, Germany, Spain, and Switzerland. The green cluster ranked second and contained 19 items, such as China, India, Singapore, France, and South Korea. Combining the network visualization in Figure 7(a) with the density visualization in Figure 7(b), it can be inferred that the red and green clusters had a stronger academic collaboration; specifically, the United States, Germany, England, Italy, and France formed an academic collaboration group on energy efficiency and digital technologies. In addition, another collaboration group led by China formed within the red cluster, including South Korea, Singapore, India, and Canada. The bibliometric analysis reveals the distribution of global research power and highlights key collaboration patterns between major countries and regions. Strong academic collaborations, particularly among countries like the United States, Germany, China, and South Korea, are driving advancements in fields such as energy efficiency and digital technologies, indicating the increasing significance of international partnerships in shaping the future of global research. This pattern implies three risks: corridor dependence, where knowledge flows are concentrated along a few US-Europe and East/South Asia routes; limited brokerage between blocks, where few connectors mean slower method transfer; and geographic under-representation at the periphery, which narrows evidence diversity. Strengthening cross-bloc bridges (e.g., pairing Asia-centered teams with trans-Atlantic consortia) and elevating mid-degree “broker” countries (such as Singapore or Canada) would reduce siloing and speed diffusion of practices in energy efficiency and digital technologies.

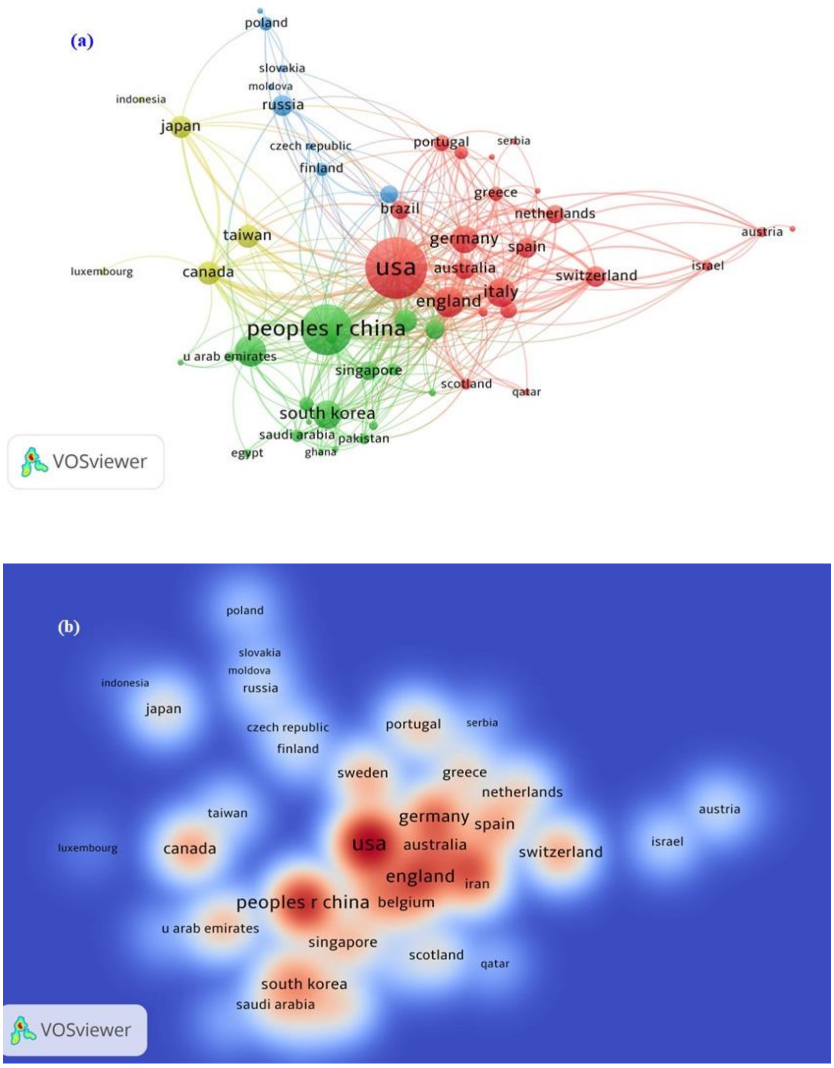


Figure 7. Visualization map of research countries on energy efficiency and digital technologies innovation: (a) link-weight view: thicker edges denote stronger cross-country collaboration, and larger hubs form cohesive clusters; (b) density view: red hotspots mark areas with a high local concentration of influential countries.

3.2. Visualization and analysis of hotspot investigation

3.2.1. Visual analysis of collaborative co-keywords

The synergistic analysis of keywords can reveal the core hotspots of the research field, the correlations between themes, and their evolutionary trends [63]. By analyzing the frequency and co-occurrence patterns of keywords, researchers can gain insights into major research directions, potential cross-disciplinary collaborations, and dynamic changes in the field. Bibliometric data show 3481 keywords involved in this research. The co-occurrence threshold of the keywords was set to 5; finally, 304 items were obtained for visualization purposes. In Figure 8(a), larger nodes and shorter inter-node distances indicate higher term frequency and stronger similarity, respectively. The red cluster contains 101 items; "energy efficiency" is the largest node, followed by "performance", “internet”, “technology”, “sustainability”, “digital twin”, and “consumption”. The cluster reveals key areas for the convergence of energy and digital technologies, providing an important academic foundation for advancing low-carbon energy technologies. In Figure 8(b), the transition from blue to yellow indicates that research is gradually shifting from basic technologies to applied technologies. The “yellow hotspots” indicate that future research may focus on digital energy management and smart technology applications in the context of Industry 4.0. In addition, links and total link strength for the top ten keywords are reported in Table 6. APY denotes the average publication year, and TLS denotes total link strength. The keywords with the highest frequency were “energy efficiency” and “design”. Low-frequency keywords such as “sustainability” and “management”, despite low frequency, have a total link strength of 145 and 162, respectively, indicating that they still have strong academic relevance to other keywords that are potential secondary hotspots. They could be an important direction for future research. In conclusion, the analysis underscores the growing importance of digitalization and sustainability in the energy sector. Future research should focus on the application of advanced technologies, such as machine learning and augmented reality, to enhance energy efficiency and promote innovative solutions for the challenges posed by climate change and technological advancement. The co-occurrence of digital twins, machine learning, and augmented reality with management and sustainability points to a practical path, embedding digital tools in management and demand-side practices to deliver efficiency gains. APY values indicate that later-year topics sit at the frontier, while high-TLS bridges show where cross-cluster diffusion can be accelerated even when raw frequency is modest.

Table 6. Link and total link strength of the top 10 occurrence keywords.

RO	Keywords	Cluster number	Links	Total link strength	Occurrences	APY
Top 1	Energy efficiency	1	187	466	164	2018
Top 2	Design	2	197	553	144	2017
Top 3	Performance	1	118	216	72	2016
Top 4	Coms	3	88	166	65	2016
Top 5	Efficiency	1	93	183	61	2017
Top 6	Internet	1	110	245	44	2019
Top 7	Technology	4	102	189	42	2017
Top 8	Lower power	3	52	89	38	2015
Top 9	management	1	83	162	33	2020
Top 10	Sustainability	1	73	145	31	2020

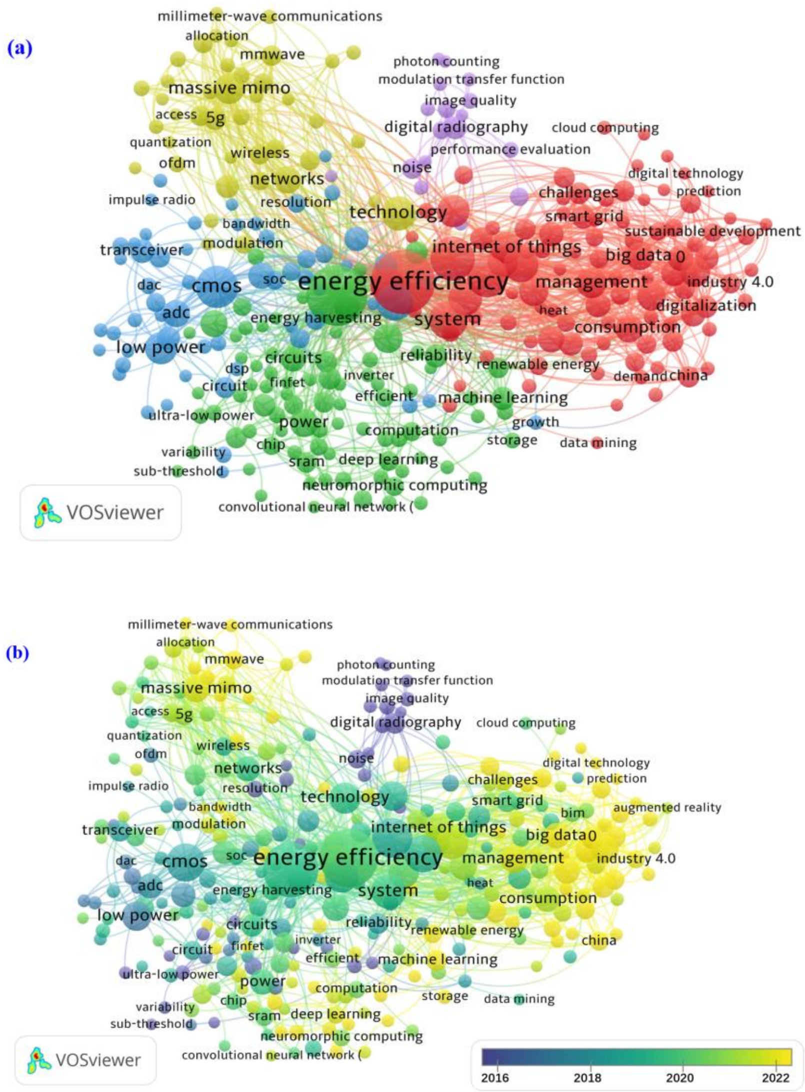


Figure 8. Co-occurrence map of keywords: (a) network map of keywords: node size represents the frequency of occurrence, and color represents clustering; (b) overlay map of keywords: node size represents frequency of occurrence, and node color represents average year of publication.

3.2.2. Cluster analysis of high-frequency keywords

The utilization of high-frequency keywords can, to some extent, serve as an indicator of the current research focus. Clustering analysis of high-frequency keywords not only helps reveal the knowledge structure of the investigation field but also reveals the intrinsic connection between research topics and cross-disciplinary characteristics [64,65]. The distribution characteristics and clustering patterns of keywords are analyzed in depth by visualization methods. Table 7 shows 10 software-generated keyword clusters (#0–#9) ranked by keyword count; labels are retained as given, and a brief thematic focus is provided for each cluster. The results show that “digitization” (#0) and “low power consumption” (#1) are the two clusters with the highest number of keywords. Among them, “digitization” (#0) contains 94 keywords, and the main research focuses on Industry 4.0, scenario applications, and concrete 3D printing, reflecting the central position of digital technologies in energy efficiency research. This indicates that with the acceleration of industrial digitalization, digital technologies are playing an important role in the fields of energy efficiency optimization, process reengineering, and smart manufacturing. Meanwhile, "low power consumption" (#1) contains 91 keywords, and the research direction primarily focuses on technologies such as delayed phase-locked loops and thermometers to binary decoders. This indicates that low-power technology is a key breakthrough points in the traditional energy field and provides important support for sustainable development and energy conservation. From the application point of view, the wide application of low-power technologies reflects researchers' continued focus on improving the efficiency of energy devices and reducing energy consumption. In addition, other clusters such as "massive MIMO" (#2) and "phase change" (#7) represent directions for exploring emerging technologies in energy efficiency research. Overall, the pattern reveals a bridging gap: many studies optimize either components or digital processes, but few connect the end-to-end chain.

Table 7. Keywords clustering results for journal papers.

Cluster number	Keyword clusters	Number of keywords	Main research focus
#0	Digitization	94	Industry 4.0; Scenarios; concrete 3D printing
#1	Lower power	91	Delay locked loop; thermometer to binary decoder
#2	Massive MIMO	88	Hybrid precoding; time-domain processing
#3	Random access memory	60	Random access memory; computer architecture
#4	Analog relational preprocessor	47	Building energy saving; carbon nanotube
#5	Autonomous flowmeter	47	Leakage control; smart metering system
#6	Digital radiography	45	High resolution; emerging imaging technology
#7	Phase-change	26	Autoradiography; optical storage media
#8	Pixel detector	18	Design; pixel detector
#9	Photonic internet	14	Future internet; global network; built energy saving

3.2.3. Analysis of the evolution of research trends

The appearance of bursts of keyword citations usually indicates that a particular investigation topic has received widespread academic attention over a short period of time. These bursts highlight key areas of intense investigation, signaling evolving research priorities and shifting intellectual focuses in the field [66]. They usually represent hot research directions or innovative themes in the field. Period-specific research frontiers can thus be identified, and future trajectories inferred [67]. CiteSpace was used to detect bursty keywords and explore intensively researched directions across periods. Figure 9 lists the detected hotspot keywords; the top 22 burst terms reflect fast-growing topics in research on energy efficiency and digital technologies. The red represents the period when the citation burst happened. The "*digital radiography*" exhibited the earliest burst in this field of research. The longest burst was for "ADC" (application data center), spanning 2006–2017. According to

Figure 9, the 22 keywords can be divided into three research frontiers: early, mid-term, and late research frontiers. Keywords in the early research frontier included *digital radiography*. This phase benefited from the "Digital 1.0" era, marked by the rise of personal computers. The mid-term front includes application data center, digital signal processing, wireless sensor networks, logic, low-power design, and energy efficiency. In 2006, the policy slogan "energy conservation and emissions reduction" was introduced, and digital technologies were gradually applied to industrial production to promote energy efficiency. The recent research frontier features energy harvesting, circuits, power, 5G, and artificial intelligence. This indicates that the latest digital technologies, including 5G and artificial intelligence, have been widely used in the field of industrial production and have become an effective way to improve energy efficiency. This analysis underscores the dynamic nature of research in this domain, showing how early foundational technologies have paved the way for more advanced innovations, and highlights the critical role of emerging digital technologies in driving the next generation of energy-efficient industrial solutions. Although not among the highest-amplitude bursts in Figure 9, "sustainability" and "management" emerge as cross-cutting themes whose co-occurrence rises over time and bridges multiple clusters. Sustainability links efficiency gains to broader outcomes, including emissions reduction, resource intensity, and system reliability, while management capabilities (e.g., data governance, skills development, change management, and model-lifecycle practices) condition whether technical potential is converted into realized performance. These patterns imply that policy should value not only kilowatt-hour savings but also flexibility and emissions metrics, and that firms should pair technology deployment with governance and capability playbooks to de-risk scaling. Remaining gaps include limited multi-year evidence on durability and rebound effects and heterogeneous reporting across sites. Future work would benefit from field- and year-normalized indicators, standardized reporting, and causal evaluations that connect managerial interventions to sustainability trajectories.

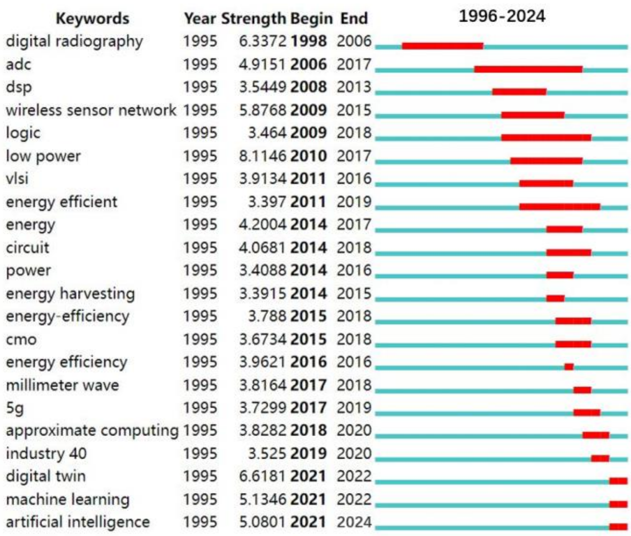


Figure 9. Keyword citation bursts, 1996–2024. Top 22 terms ranked by burst strength; red bars mark the active burst periods; Begin/End give the interval boundaries.

4. Discussion

4.1. Indicators and terminology

Indicator selection determines what is seen as "influence" and how network structure is inferred. A_TGCS/A_TLCS and their per-article forms separate publication volume from influence intensity, yet raw TGCS/LCS remain sensitive to field size and citation windows; thus, field and year-normalized indicators offer a more comparable baseline over time and across domains. APY and TLS, respectively, summarize temporal recency and co-occurrence connectivity, but APY can overweight rapidly expanding subfields, and TLS can conflate frequency with breadth. Price's law provides a pragmatic threshold for identifying core authors, although the square root rule is heuristic and benefits from sensitivity checks. A unified terminology policy that distinguishes digitization, digitalization, and digital innovation reduces ambiguity and improves cross-study comparability, while publishing exact definitions and parameter values enhances reproducibility.

4.2. Data sources and coverage

Findings reflect what the Web of Science indexes. Although coverage is broad, language and regional biases remain, and some outlets, such as engineering proceedings or local journals, may be under-represented, which can raise the apparent influence of older items. Metadata quality also matters; missing DOIs, inconsistent initials, and variant institutional names require cleaning, and some name ambiguities will persist, especially for common surnames and multi-affiliation records. Using additional databases (e.g., Scopus, Dimensions, IEEE Xplore) and reporting how results compare across sources can reduce database-specific artifacts.

4.3. Network modeling, counting, and visualization

Analytical settings shape productivity, centrality, and community boundaries. Full counting is simple but can overweight multi-author papers; fractional counting provides a lower-bound view and is useful for robustness checks. Co-occurrence and co-authorship networks depend on minimum-frequency thresholds and association-strength normalization, and cluster assignments can change with the resolution parameter or random seeds. Force-directed layouts in VOSviewer and CiteSpace are designed for readability; they aid interpretation but are not ground truth. Reporting parameter choices and testing reasonable ranges is important for credible network claims.

4.4. Interpretation of results

The record shows a stepwise shift from the digitization of measurements to process-level digitalization and, more recently, to AI-based applications such as advanced analytics and digital twins in industrial energy management. Output and influence are concentrated in a small set of authors and institutions, while cross-institution collaboration is patchy, which limits the spread of effective practice. Topics converge on Industry 4.0 and AI-driven optimization, where measurable efficiency gains are most often reported; at the same time, regions and institutions with weaker links appear underserved and represent scope for future work.

4.5. From description to stronger evidence

Bibliometric patterns are descriptive and should not be read as causal effects. Estimating the impacts of specific digital interventions calls for complementary designs, such as experiments, quasi-experiments, or baseline case studies. Moving beyond metadata to full-text mining can more precisely link methods to outcomes. Side-by-side reporting of fractional versus full counting and normalized versus raw citation indicators can bound estimates, and sensitivity checks over thresholds, resolution, and seeds can improve robustness. Open, replicable benchmarks that pair datasets with code would help institutions test and adopt approaches more consistently.

5. Conclusions

In this work, a bibliometric investigation of energy efficiency and digital technologies was carried out using HistCite, VOSviewer, and CiteSpace to examine the effects of digital technologies on energy efficiency. The main findings are summarized as follows.

(1) The knowledge base has transitioned from early digitization of measurements and records to process-level digitalization, and more recently to digital innovation, including artificial intelligence or machine learning analytics and digital twins that reconfigure operations and industrial energy management.

(2) Output and impact are highly skewed; a compact core of authors and institutions anchors publications and citations, yet inter-institutional collaboration remains fragmented, limiting the diffusion and expansion of effective practices.

(3) Topic convergence centers on high-impact application areas such as industrial energy management, Industry 4.0, and artificial intelligence or machine learning enabled optimization, indicating where digital technologies most effectively translate into measurable efficiency gains.

6. Managerial implications

For firms and utilities, a staged pathway is advisable: first, focus on high-return use cases such as condition-based maintenance, anomaly detection, and advanced process control; then, scale through digital twins for energy-intensive assets; and finally, institute robust model-governance practices, covering data quality, performance monitoring, cybersecurity, and versioning, before portfolio-wide deployment. Capability building in data, controls, and MLOps, together with cross-functional teams and change-management routines, is essential to convert technical potential into realized savings; influence metrics (e.g., A_TLCS/A_TGCS) and collaboration maps can guide partner selection and knowledge transfer.

7. Practical/social implications

These patterns carry several practical implications. For policy, priority should be placed on interoperable data infrastructure (e.g., standards and open protocols), mission-oriented consortia that connect leading hubs with lagging regions, and incentive schemes that reward not only kilowatt-hour savings but also flexibility and emissions outcomes. The phased pathway recommended for firms and utilities in the managerial implications section can similarly guide practical deployment, focusing on high-return use cases and scaling through digital twins for energy-intensive assets. At the interface between research and practice, replicable benchmarks (e.g., open datasets with code) and cross-disciplinary teams can accelerate translation from algorithms to operational impact.

8. Prospects

Several steps can mitigate these concerns in subsequent work. Triangulating multiple databases (e.g., Scopus, Dimensions, IEEE Xplore) would broaden coverage; applying fractional counting alongside full counting would bound estimates; adopting field- and year-normalized citation indicators would reduce age and domain biases; and reporting sensitivity analyses over network thresholds, resolution parameters, and random seeds would increase robustness. Extending from metadata to full-text mining could map methods to outcomes more precisely, while causal evaluations could assess the realized efficiency gains of specific digital interventions. Together, these extensions would convert descriptive regularities into decision-relevant evidence for policy and industrial practice.

Use of AI tools declaration

While preparing this work, the authors used ChatGPT to improve language and readability. After employing this tool/service, the authors reviewed and revised the content as necessary and assumed full responsibility for the final publication.

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Conflict of interest

The authors declare no potential conflict of interest with respect to the research, authorship, and/or publication of this article.

Author contributions

Author Wanchang Chen: conceptualization, methodology, formal analysis, writing—review & editing. Author Xue Zhang: writing—original draft, formal analysis, visualization. Author Youqing Fan: investigation, writing—review & editing. Author Kai Yang: conceptualization, supervision, writing—review & editing. Author Hua Wang: investigation, formal analysis, supervision. Author Qingtai Xiao: investigation, visualization, funding acquisition, supervision, project administration, writing—review & editing.

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