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A Bibliometric Analysis of Artificial Intelligence and Green Information Technologies: Evaluating Future Research Trends

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ABSTRACT

Artificial intelligence (AI) has become one of the most transformative technologies of recent years. By leveraging AI, businesses can enhance their environmental interaction, perform advanced analytics, and make sustainable and equitable decisions. At this point, AI is also recognized as a key driver in the advancement of green information technologies (Green IT). Green IT focuses on enabling organizations to increase productivity and efficiency while minimizing environmental impact. This study aims to identify the key research trends at the intersection of AI and Green IT and to conduct a systematic bibliometric analysis of the existing literature. Based on 246 articles retrieved from the Web of Science database (2010–2025), the study examines the most productive countries, influential journals, and thematic clusters to provide a strategic overview for future research. It was observed that AI significantly contributes to strategies such as energy efficiency, smart grid development, and climate crisis mitigation. Notably, this paper also highlights how the synergy between AI and Green IT can lay the foundation for energy-efficient and sustainable metaverse infrastructures, where immersive technologies and intelligent systems demand green and scalable computing solutions. As one of the few bibliometric studies on this emerging convergence, the paper offers strategic insights for both academia and industry to promote environmentally responsible AI-driven digital ecosystems.

Keywords : Artificial Intelligence, Green Information Technologies, Green Computing, Digital Transformation

Yapay Zekâ ve Yeşil Bilgi Teknolojilerinin Bibliyometrik Analizi: Gelecekteki Araştırma Trendlerinin Değerlendirilmesi

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ÖZ

Yapay zekâ (YZ), son yılların en dönüştürücü teknolojilerinden biri haline gelmiştir. İşletmeler YZ'den yararlanarak çevresel etkileşimlerini artırabilir, gelişmiş analizler gerçekleştirebilir ve sürdürülebilir ve adil kararlar alabilirler. Bu noktada, YZ aynı zamanda yeşil bilgi teknolojilerinin (Yeşil BT) ilerlemesinde önemli bir itici güç olarak kabul edilmektedir. Yeşil BT, kuruluşların çevresel etkiyi en aza indirirken üretkenliği ve verimliliği artırmalarını sağlamaya odaklanır. Bu çalışma, YZ ve Yeşil BT'nin kesişimindeki temel araştırma eğilimlerini belirlemeyi ve mevcut literatürün sistematik bir bibliyometrik analizini yürütmeyi amaçlamaktadır. Web of Science veri tabanından (2010-2025) alınan 246 makaleye dayanan çalışma, gelecekteki araştırmalar için stratejik bir genel bakış sağlamak amacıyla en üretken ülkeleri, etkili dergileri ve tematik kümeleri incelemektedir. YZ'nin enerji verimliliği, akıllı şebeke geliştirme ve iklim krizi hafifletme gibi stratejilere önemli ölçüde katkıda bulunduğu gözlemlenmiştir. Özellikle bu makale, yapay zeka ve yeşil bilişim teknolojileri arasındaki sinerjinin, sürükleyici teknolojilerin ve akıllı sistemlerin yeşil ve ölçeklenebilir bilişim çözümleri gerektirdiği, enerji açısından verimli ve sürdürülebilir meta veri tabanı altyapılarının temelini nasıl oluşturabileceğini de vurgulamaktadır. Bu yeni ortaya çıkan yakınsama üzerine yapılmış birkaç bibliyometrik çalışmadan biri olan makale, hem akademiye hem de endüstriye, çevre dostu yapay zeka destekli dijital ekosistemleri teşvik etmek için stratejik içgörüler sunmaktadır.

Anahtar Kelimeler : Yapay Zeka, Yeşil Bilişim Teknolojileri, Yeşil Bilişim, Dijital Dönüşüm

INTRODUCTION

Businesses today seek to enhance their competitive advantage, innovation capacity, and operational agility by embedding advanced technologies into their organizational frameworks (Spanjol et al., 2018, par. 35). Among these technologies, artificial intelligence (AI) has emerged not only as a tool for optimization but as a transformative force redefining innovation frontiers (Akter et al., 2021, p. 259).

AI is commonly defined as an interdisciplinary field dedicated to developing systems that replicate human cognitive functions such as learning, reasoning, and problem-solving (Zhu et al., 2022, par. 79-80). As global digital ecosystems become more sustainability-oriented, the fusion of AI capabilities with environmental objectives has significantly elevated the strategic importance of Green Information Technologies (Green IT) (Ghayvat et al., 2024, p. 39032).

Crucially, this convergence holds the potential to act as a cornerstone in the development of scalable, energy-optimized metaverse infrastructures. Within immersive platforms powered by Augmented Reality (AR), Virtual Reality (VR), and Generative AI (GenAI), the imperative to reduce environmental footprints while maximizing computational efficiency has become a defining research priority. This study therefore, examines how AI-powered, environmentally conscious technologies support the realization of sustainable metaverse ecosystems and systematically maps the trajectory of academic interest using bibliometric analysis.

Green IT seeks to address key environmental goals such as improving energy efficiency, lowering carbon emissions, reducing electronic waste, and fostering digital sustainability (Aquino-Brítez et al., 2024; p. 5, Villar-Rodriguez et al., 2023, p. 6-7). When enriched by AI capabilities, these systems offer novel, intelligent approaches to environmental challenges (Palos-Sánchez et al., 2022). A growing body of research showcases how carbon-aware computing architectures—from sustainable hardware platforms to edge-based low-energy processing—can significantly improve the ecological performance of digital systems (Alzu'bi et al., 2025, p. 6-7; Huang et al., 2023, p. 36; Guo et al., 2024, p. 3930-3932). For instance, memristive nanodevices are increasingly recognized as critical enablers of ultra-efficient AI hardware (Huang et al., 2023; p. 36). Yet, despite these promising advances, a consolidated bibliometric exploration of the AI–Green IT nexus remains largely absent from the scholarly landscape.

Responding to this gap, the present study aims to investigate the intellectual structure, thematic trends, and research directions at the intersection of AI and sustainable computing through a comprehensive bibliometric analysis. Bibliometric methods are well-established tools for examining extensive scientific datasets and uncovering patterns of knowledge production, thematic clusters, and emerging research streams in fast-evolving domains (Akbarzadeh et al., 2024, p. 144; Donthu et al., 2021, p. 285-286; Mesa Fernández et al., 2021, p. 2). Accordingly, 246 peer-reviewed articles obtained from the Web of Science database were systematically analyzed to construct a knowledge map and outline prospective research trajectories.

The central research question that guides this investigation is: How is the integration of AI into environmentally aligned digital systems evolving within the global metaverse context in terms of sustainability, energy optimization, and international scholarly collaboration?

As a response, this study underscores that environmentally intelligent infrastructures, empowered by AI, not only underpin ecological sustainability but also define the architecture of future digital environments. In particular, they serve as enablers of low-carbon, adaptive systems critical to the metaverse vision. Thus, the bibliometric analysis presented here not only captures the current research landscape but also offers strategic insights for future scholarly engagement in this multidisciplinary and rapidly expanding field.

All abbreviations in this article are spelled out in full upon their first appearance, followed consistently by the abbreviation alone thereafter. A complete list of abbreviations is provided in Appendix 1.

1. CONCEPTUAL FRAMEWORK

1.1. The Concept of AI

AI creates value in today's organizations not only by enhancing productivity but also by enabling agile decision-making and responsiveness to evolving customer needs (Ooi et al 2025, p. 80). As a transformative technology, AI plays a critical role in supporting innovation and strategic adaptability (Mustak et al., 2021, p. 392). AI broadly refers to the scientific pursuit of creating systems that emulate human cognition—including reasoning, adaptive learning, communication, planning, and complex problem resolution (Debrah et al., 2022, p. 137). These capabilities are now deeply integrated into enterprise ecosystems, enabling intelligent automation, context-aware data interpretation, and operational agility (Tabbakh et al., 2024, p. 6). Beyond its technical scope, AI is also considered a conceptual and disciplinary framework aimed at replicating human-like intelligence (Laleni et al., 2024, p. 154). Its applications range from data-driven decision support tools to emerging GenAI models (Alzu'bi et al., 2025, p. 7; Machado et al., 2024, p. 514). Over time, the definition and scope of AI have evolved alongside technological advancements (Welsh, 2019, p. 28). Foundational contributions such as Turing's early algorithmic theory Turing, (1937) and his subsequent proposal of the Turing Test (Turing, 1950) laid the groundwork for philosophical and technical inquiries into machine intelligence. The formal term "AI" was introduced during the Dartmouth Conference in 1956 by John McCarthy and colleagues (McCarthy et al., 2006; Paesano, 2021), later expanded by various scholars. In contemporary organizational ecosystems, AI functions as a driver of digital transformation, not only enhancing decision support systems but also fostering the development of carbon-conscious computing environments (Zhou et al., 2020; p. 2932; Zavieh et al., p. 2). Through the intelligent orchestration of digital assets—including network layers, storage mechanisms, and processing units—AI enables eco-efficient IT architectures with improved sustainability outcomes (Zhu et al., 2022, p. 84).

1.2. The Concept of Green Computing

Green computing is an interdisciplinary approach that seeks to reduce the environmental impact of information technologies through their design, usage, and management, while aligning with broader sustainability goals (Tabbakh et al., 2024, p. 2). It promotes the creation of smart, low-impact computing systems designed to optimize energy use, reduce greenhouse gas output, and shrink the overall digital carbon footprint (Alzu'bi et al., 2025, p. 7).

In this context, particular attention has been paid to the energy consumption and CO_2 emissions of Deep Learning (DL) models, which often require extensive computational resources (Henderson al., 2020, p. 3). Assessing the ecological impact of intelligent computing frameworks has gained prominence, particularly given the widespread deployment of large-scale models.

Green computing is widely examined through a multidimensional sustainability lens—integrating social, environmental, and economic perspectives (Alzu'bi et al., 2025; p. 7 Desheng et al., 2021, p. 129). Green technologies (greentech), as part of this paradigm, offer holistic solutions that merge domain-specific knowledge with sustainability-centric design. In recent years, applied research has increasingly focused on developing performance metrics and evaluation frameworks for assessing sustainability in IT systems (Bracarense et al., 2022, p. 4-6; Al Sallami et al., 2023, p. 139).

Moreover, emerging hardware technologies—such as spintronics-based artificial neural networks (ANNs)—demonstrate high accuracy in addressing sustainability challenges with significantly lower energy consumption (Kumar et al., 2024, p. 1522). These advancements signal a transition toward environmentally responsive digital architectures, forming the backbone of sustainable metaverse infrastructures as well.

1.3.Artificial Intelligence and Green Computing

Deploying intelligent computing solutions to confront environmental and societal challenges has notably broadened their relevance within sustainable digital systems. Scholarly work increasingly highlights how intelligent automation contributes to environmental resilience by enabling resource-conscious operations and informed sustainability strategies (Yigitcanlar et al., 2021, p. 9). For example, Ooi et al., (2025, p. 83) highlight how GenAI can reduce energy consumption, lower carbon emissions, and enhance data center efficiency.

While AI adoption varies by organizational size and sector, small and medium-sized enterprises (SMEs) often encounter greater structural and financial barriers (Lee et al., 2019, p. 2). Nonetheless, AI offers considerable benefits—including increased productivity, operational cost reduction, and the creation of new green business models. Alzu'bi et al., (2025, p. 10) demonstrate that localized edge-intelligent platforms enable greener production processes in SMEs by lowering energy intensity and mitigating environmental stressors.

Beyond firm size, factors such as digital maturity, technological competence, and organizational learning capacity play critical roles in AI integration. El Yaacoub et al., (2024, p. 2667) argue that AI systems equipped with continuous learning capabilities reduce processing costs and contribute positively to environmental performance. Similarly, Huang et al., (2023, p. 37) underscore the importance of low-power computing architectures that contribute to climate-conscious digital infrastructure.

Recent studies stress the need for comprehensive models that combine AI and Green IT within a unified sustainability framework. Tabbakh et al., (2024, p. 2) propose such a model, emphasizing energy reduction, carbon footprint mitigation, and environmentally conscious design as central goals.

The role of AI in green computing extends beyond software. Ghayvat et al., (2024, p. 39039) developed an AIoMT architecture based on edge computing and the TEMS algorithm, which ensures system-level energy efficiency. On the software side, Naumann et al., (2011, p. 296) the Greensoft Model offers guidance for sustainable software engineering, while Beghoura et al. (2017, par. 30-34) advocate for incorporating energy consumption metrics—such as green efficiency evaluated via random forest algorithms—into software development cycles.

From a hardware perspective, carbon-optimized system designs now play a vital role in minimizing the ecological footprint of AI-driven operations. Technologies like Resistive Random Access Memory (RRAM), as examined by Huang et al., (2023, par. 30-32) and Grossi et al., (2019, p. 1282), demonstrate low energy consumption in DL tasks. Akbarzadeh et al. (2024, p. 154) provide empirical examples of how such savings at the hardware level directly reduce AI's carbon footprint. Additionally, Ghayvat et al. (2024) illustrate how edge AI and intelligent data workflows contribute to green computing goals.

Finally, Al Sallami et al., (2023, p. 140) reinforce the relevance of developing sustainable AI frameworks by aligning AI design and deployment with environmental priorities such as energy efficiency and reduced emissions.

Taken together, these advancements highlight a strengthening synergy between AI and Green IT, increasingly seen as a cornerstone in the shift toward sustainable and scalable digital infrastructures—especially within metaverse ecosystems. As immersive technologies continue to evolve and require substantial computational resources, the need for AI-driven optimization methods, energy-efficient hardware, and carbon-aware computing frameworks becomes more pressing (Tabbakh et al., 2024, p. 10; Nambi et al., 2021, p. 103700). Recent studies featured in Sustainable Computing: Informatics and Systems and Nature Communications emphasize the importance of embedding sustainability principles into the core design of AI-enabled systems, particularly those supporting extended reality (XR), digital twins, and decentralized virtual environments (Liu et al., 2019, p. 173995). Within this context, intelligence-enabled sustainable architectures embody not just technological progress but a strategic alignment with long-term ecological objectives. As such, the integration of AI and Green IT outlines a promising pathway for building next-generation digital infrastructures capable of meeting net-zero computing targets in the emerging landscape of the sustainable metaverse.

2. METHODOLOGY

2.1. Research Objectives and Significance

This study aims to systematically explore the scientific literature on the integration of green computing technologies and AI through a bibliometric analysis. The objective is to identify research productivity, collaborative networks, key thematic areas, and emerging trends in this interdisciplinary domain. Given the increasing scholarly interest in AI–Green IT convergence, particularly within the context of sustainable digital transformation, the study seeks to contribute in two primary ways:

- To provide academics with a comprehensive overview of the current literature and a framework for identifying future research directions,
- To offer industry stakeholders insights into the adoption of AI-driven solutions for energy efficiency, data center optimization, and sustainable infrastructure development.

Within this scope, the central research question of the study is formulated as follows: How does the integration of AI into green computing technologies evolve within the global digital ecosystem in terms of sustainability, energy efficiency, and scientific collaboration? In seeking to answer this question, the study analyzes 246 research articles retrieved from the Web of Science database and presents the current research landscape of the relevant literature through indicators such as the most influential authors, institutions, countries, journals, keywords, and thematic clusters. Accordingly, the evaluation of the findings obtained through the bibliometric analysis aims to provide a foundation that can contribute to knowledge-based decision-making processes in the context of sustainable digital transformation.

2.2.Bibliometric Analysis Approach

Bibliometric analysis is a robust methodological approach that enables the systematic and quantitative investigation of the structure, evolution, and impact of scientific knowledge. It facilitates the mapping of research domains, the identification of key publications and authors, and the detection of conceptual clusters within a given field (Mesa Fernández et al 2021, p. 2 ; Donthu et al., 2021, p. 287-289).

When applied rigorously, bibliometric methods can offer theoretical insights and methodological contributions. For example, Chappin & Ligtvoet, (2014, p. 718) and Liu et al., (2019, p.173991) showed that sustainability-related technological transitions have primarily been examined from a technical standpoint, with limited attention to social dimensions.

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2.3. Data Collection and Analysis Process

This study utilizes bibliometric analysis to examine the academic literature on the integration of green computing and AI. Data were sourced exclusively from the Web of Science Core Collection, chosen for its inclusion of high-impact, peer-reviewed journals and its methodological reliability in citation indexing (Donthu et al., 2021, p. 285). To ensure consistency, the study considered only English-language journal articles, excluding book chapters, conference proceedings, editorials, and other non-article formats (Aria & Cuccurullo, 2017, p. 967).

The search strategy included the following keywords: "Green IT", "Green Computing", "Sustainable IT", "Energy-efficient Computing", "Eco-friendly Computing", "Green Cloud Computing", "Green Software", "Artificial Intelligence", "AI", "Machine Learning", "Deep Learning", "Neural Networks", "Natural Language Processing", "Generative AI", "AI Integration".

The search query was structured as: TS = (("Green IT" OR "Green Computing" OR "Sustainable IT" OR "Energy-efficient computing") AND ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks"))

From 449 initial records (2010–2025), 246 articles were selected after data cleaning. Analysis was performed using VOSviewer (v1.6.20), R programming (v4.3.2), and the Bibliometrix R package (v4.2.0). These tools enabled the visualization of co-authorship networks, keyword co-occurrence, and publication trends. To improve clarity, countries with fewer than five publications were excluded from the co-authorship network visualizations [44]. Through this structured process, the study aims to deliver a comprehensive understanding of the current research landscape and to identify emerging directions at the intersection of green computing and AI.

3. FINDINGS

3.1. Temporal Distribution of Publications in Green IT & AI Integration (2010–2025)

To provide a clearer view of the publication dynamics over time, Figure 1 illustrates the annual distribution of the 246 articles examined in this study, covering the period from 2010 to mid-2025. The results indicate a sharp increase in publication activity beginning in 2020, marking a transition from early conceptual interest to an established research trajectory. While the number of publications remained minimal between 2010 and 2014, the first noticeable growth occurred in 2015 and continued steadily. A significant acceleration is observed in 2021, with articles increasing from 15 in 2020 to 28. This upward trend continued, peaking in 2024 with 69 publications—nearly double the volume of the previous year (2023:

36 articles). As of June 2025, 28 articles have already been published, indicating that the year's final total is likely to align with or exceed that of 2023. This sharp post-2020 growth can be attributed to several factors: the widespread digitalization accelerated by the COVID-19 pandemic, the deepening convergence between AI applications and environmentally focused innovation policies (Tunçsiper et al., 2025, p. 29; Huang et al. 2023, p. 34-35; Al Sallami et al., 2023, p. 138-139). Overall, this trend reflects not only a quantitative surge but also the rising acknowledgment of intelligent, sustainability-driven computing systems as a strategically significant and forward-looking research domain within global environmental discourse.

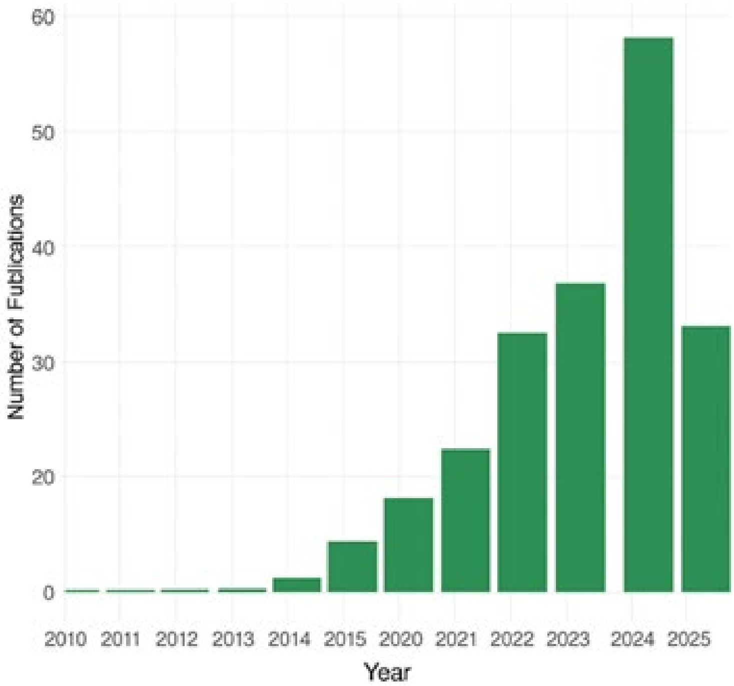

Figure 1: Distribution of publications by year (2010–2025)

3.2. Top Contributing Institutions in Green IT & AI Research

To identify institutional research hubs within the domain, Figure 2 presents the top ten institutions contributing to the domain of intelligent and sustainability-driven computing research based on publication volume (n = 246). The Chinese Academy of Sciences (15 publications) and Stanford University (10 publications) emerge as the most prolific institutions. A strong regional pattern is evident: the majority of these institutions are located in Asia and North America. Notable Asian contributors include Huazhong University of Science & Technology (9), Sungkyunkwan University (8), and the Indian Institute of Technology System (7). In Europe, the University of Cambridge (7) and the Swiss Federal Institutes of Technology Domain (6) represent prominent contributors.

Indicating a growing research orientation toward environmentally responsive digital systems within emerging innovation hubs. The Middle East is represented by King Abdulaziz

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University (7), reflecting an increasing institutional focus on carbon-aware computing as part of the region's expanding innovation ecosystem.

These patterns align with observations by Yaseen et al. (2025, p. 46), who noted a strategic shift among Asia-Pacific institutions toward AI-driven ecological innovation and climate-aligned computational strategies. Importantly, institutions like CAS, Stanford, and Cambridge are well-positioned to lead in resource-intensive AI experimentation. Meanwhile, emerging economies—such as China, India, and Saudi Arabia—are advancing national priorities focused on low-emission tech infrastructures, signaling the emergence of new regional champions in sustainable digital innovation.

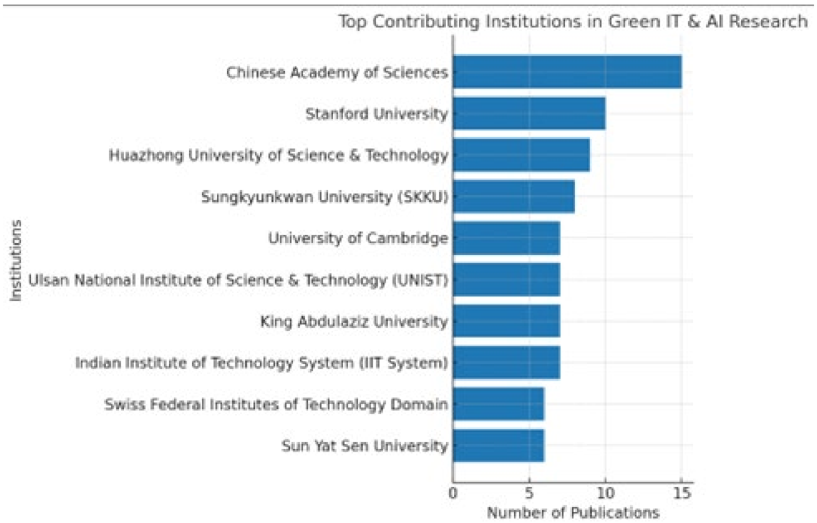

Figure 2: Top contributing institutions in Green IT & AI research (2010 – 2025).

3.3. Countries with the Most Studies and Collaboration Networks

This section examines the global research landscape in sustainable intelligent computing through country-level bibliometric indicators and international co-authorship network metrics.

As shown in Figure 3, countries differ significantly in their publication activity on Green IT and AI integration. The analysis incorporates both quantitative data—such as publication and citation counts—and structural network characteristics to capture the breadth and depth of international scholarly engagement.

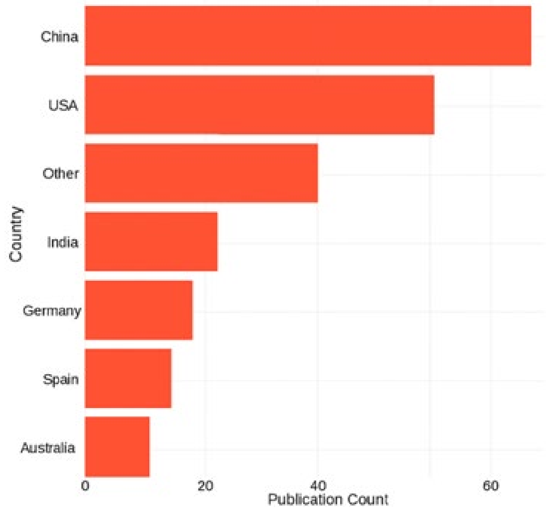

Figure 3: Publication distribution by country

To complement this, Table 1 presents key bibliometric indicators, including total documents, citations, citations per publication, and international collaboration scores (total connection power). Although the United States and United Kingdom dominate in terms of research output and academic influence, countries like India and Malaysia distinguish themselves with remarkably high citation efficiency, pointing to influential research despite fewer published studies. In contrast, countries such as Denmark, Russia, and Singapore show modest publication volumes and limited collaborative links. These findings underscore the potential for strengthening international partnerships and enhancing cross-border research capacity.

Table 1: Country-based bibliometric indicators in Green IT & AI integration

Country	Documents (n)	Citations	Citation per Document	Total Connection Power
United States	29	360	12.41	10
United Kingdom	14	325	23.21	7
India	9	269	29.89	3
China	8	84	10.50	1
Egypt	5	105	21.00	0
South Korea	5	63	12.60	1
Taiwan	3	65	21.67	0
Denmark	2	4	2.00	0
Russia	2	12	6.00	2
Singapore	2	33	16.50	0
Australia	1	3	3.00	1
Canada	1	21	21.00	0
Japan	1	36	36.00	0
Malaysia	1	185	185.00	1
UAE	1	31	31.00	0

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3.4. Country-Level Analysis in the Field of Green Computing and AI Integration

This section evaluates the scientific contributions of countries to the field of Green Computing and AI integration by considering both quantitative and qualitative indicators. The analyses are based on publication counts, total citations, average citations per document, and total link strength, which reflects the level of international collaboration.

3.4.1. National Publication Performance and Academic Impact

Table 1 presents the bibliometric indicators by country. According to the data, the United States (USA) leads the field with 29 publications and 360 citations. The United Kingdom and India also stand out, with 14 and 9 publications respectively. These countries demonstrate strong performance both in terms of productivity and international collaboration. Notably, although countries such as Malaysia (185.00), Japan (36.00), and the United Arab Emirates (31.00) have only one publication each, their exceptionally high citation-per-document averages indicate high-impact, outlier contributions. These can be considered as examples of "high-impact exceptional contributions. Notably, the paper by Ooi et al., (2025), which focuses on the potential of GenAI in sustainable metaverse infrastructures, has received 185 citations, making it the most cited study among the 246 articles analyzed (Tunçsiper et al., 2025, p. 36). Despite originating from Malaysia—a country with only one publication in the dataset—this work significantly skews the average citation impact, highlighting it as a high-impact outlier in the domain.

3.4.2. Network Structure and Collaboration Intensity

Within the framework of network analysis, key metrics such as the number of nodes, the number of edges, network density, and average node degree were calculated. Table 2, along with Figures 4 and 5, presents these metrics corresponding to the respective network structures.

Table 2: Network Statistics

Figure	Nodes	Edges	Density	Average Degree
Figure 4	8	9	0.321	2.25
Figure 5	8	9	0.321	2.25

Table 2 compares the key structural metrics of the two network visualizations presented in Figures 4 and 5.

3.4.3. Central Countries in International Cooperation

The central positions of countries within the collaboration network were evaluated based on degree, betweenness, and closeness centrality metrics. The United States and the United Kingdom emerge as key actors shaping the structure of the network, given their high centrality values. The centrality scores of countries within the collaboration network are presented alongside their publication outputs. These centrality metrics help to identify the strategic positions of countries within the network in terms of collaboration and influence capacity. Although countries like China and India have shown increasing publication volumes, the citation impact of their studies remains moderate in comparison to high-performing outliers. This suggests a gap between quantity and quality in knowledge production, calling for more targeted investments in high-impact, collaborative research.

Table 3: Central countries and strongest collaborations

Country	Degree	Betwenness	Closeness	Documents
United States	12	33.0	0.0071	29
United Kingdom	10	39.5	0.0092	14
India	8	4.5	0.0076	9
Egypt	7	1.5	0.0069	5
South Korea	7	0.5	0.0068	5
China	6	0.0	0.0057	8

3.4.4. Most Intensive International Collaborations

The strongest collaboration ties between countries are presented in Table 4. The United States stands out for its intensive research collaborations with a wide range of countries.

Table 4: Strongest country collaborations

	From	To	Weight	Years
1	United Kingdom	United States	50	2017-2025
2	China	United States	39	2023-2025
3	India	United States	36	2022-2025
4	South Korea	United States	31	2020-2024
5	Egypt	United States	25	2022-2024
6	Taiwan	United States	19	2020-2024

3.4.5. International Collaboration Map

Figure 4 illustrates the network structure of collaborations among countries with at least five publications. The size of the nodes represents publication volume, while the thickness of the edges indicates the number of co-authored publications.

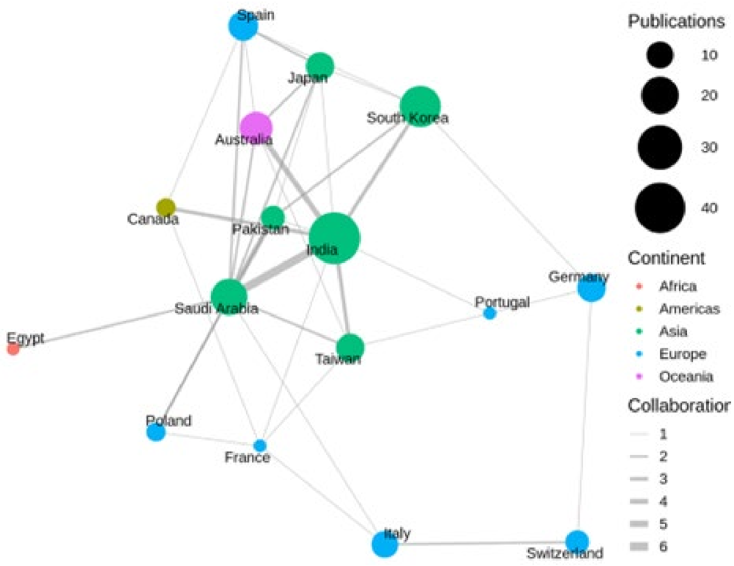

Figure 4: International collaboration network in the field of green computing and AI integration (countries with ≥5 publications)

This network graph displays international collaboration among countries contributing at least five publications. The size of each node reflects the number of publications, while edge thickness indicates the volume of co-authored articles. Node colors represent regional classifications, including Asia, Europe, and Developing Countries. An international collaboration network among countries with at least five publications on green IT and AI integration. Node sizes represent publication volume; link thickness reflects co-authorship intensity between countries. Figure 4 illustrates the collaboration network among countries that have contributed at least five publications on the integration of green computing and AI. Node sizes represent the total number of publications per country, while edge thickness indicates the number of co-authored publications between country pairs. When the distribution of academic collaborations among the most contributing countries is examined, it is evident that nations such as China, the United States, and Germany occupy central positions within the network. Türkiye, on the other hand, appears to have established strong partnerships, particularly with European countries. It is worth noting that some underrepresented institutions, such as King Fahd University of Petroleum & Minerals and UCSI University, produced some of the most cited papers in the dataset. This indicates a shift in research influence beyond traditional academic centers, especially in the Asia-Pacific and MENA regions.

3.4.6. The Temporal Development of International Research Collaborations

Figure 5 presents annual collaboration trends between 2019 and 2025. A noticeable increase in contributions from Asian and developing countries is observed in the post-pandemic period.

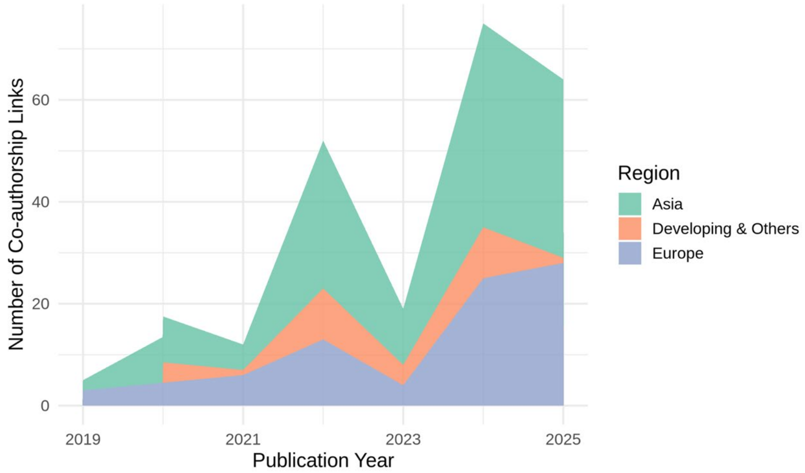

Figure 5: Temporal evolution of international collaborations (2019-2025)

This area chart illustrates the annual progression of international co-authorship in the field of Green IT and AI between 2019 and 2025. The colored areas represent cumulative contributions from Asia, Europe, and Developing & Other regions. The chart reveals how regional collaboration patterns have shifted over time, particularly highlighting the growing participation of Asian and developing countries in the post-pandemic period. The presence of institutions from Saudi Arabia and the UAE with single but impactful publications—such as Tabbakh et al., (2024, p. 5)—reflects growing interest from the Middle East in sustainable AI infrastructures. These cases underscore the rising influence of Gulf countries in shaping regional research trajectories on green computing and AI.

3.4.7. Network Summary of the Highest Contributing Countries

Table 5 presents the core network metrics for a fully connected collaboration network formed by the six most contributing countries. A notable increase in collaborative activities is observed after 2015, marking a shift toward more diversified and intensified international partnerships. The steep rise in contributions from Asia, particularly from countries like China and India, indicates a regional leadership in sustainable technology research. Meanwhile, developing countries show a steady integration into the global research landscape. This trend accelerated significantly after 2020, suggesting that the post-pandemic period played a pivotal role in amplifying global collaborations in this domain. The structural characteristics of the network formed among the top six contributing countries are summarized below (Table 5).

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Summary of the network density and connection structure among the top six contributing countries. Although all countries exhibit equal degree centrality, the disparities in their publication volumes are noteworthy (Table 6).

Table 5: The structural characteristics of the network formed among the top six contributing countries

Metrics		Value
1	Total Countries	6
2	Total Connections	15
3	Network Density	1
4	Average Degree	5

Table 6: Key network metrics among the top six contributing countries

Country	Degree Centrality	Documents
United States	5	29
United Kingdom	5	14
India	5	9
China	5	8
Egypt	5	5
South Korea	5	5

Countries' contributions to the literature are categorized into four distinct phases (Table 7).

3.4.8. Temporal Participation of Countries in the Literature

Countries' contributions to literature are categorized into four distinct phases (Table 7), allowing for a period-based analysis of the field's progression.

The temporal segmentation of contributing countries was revised to reflect recent developments in the field. In addition to previously defined periods such as "Early Adopters (2011–2015)" and "Mid Period (2016–2019)", the classification now includes two new categories: "Recent Entrants (2020–2022)" and "Latest Contributors (2023+)". This update provides a more granular view of the evolving landscape of international collaborations, particularly capturing the surge in contributions from emerging countries during and after the COVID-19 pandemic.

Accordingly, Figure IV and Tables 6 and 7 related temporal analyses present the following updated periods:

- Early Adopters (2011–2015): Countries with initial contributions at the early stage of the field.
- Mid Period (2016–2019): Countries entering during the growth phase, marked by increasing productivity and institutional investment.

- Recent Entrants (2020–2022): Countries that joined the field amidst the global shift toward digital and green technologies.
- Latest Contributors (2023+): The newest participants, reflecting ongoing expansion of the research network.

Table 7: Temporal patterns in country contributions (2011-2023+)

Entry Period	Number of Countries	Total Documents	Average Documents per Country
Early Adopters (2011–2015)	2	17	8.5
Mid Period (2016–2019)	2	43	21.5
Recent Entrants (2020–2022)	7	20	2.86
Latest Contributors (2023+)	3	3	1.0

Table 7 presents the years of initial contribution for each participating country, grouped into four distinct phases. This classification reveals the temporal dynamics of national engagement in the Green IT and AI literature.

3.5. Most Cited Publications and Publication Dynamics

3.5.1. Citation Patterns and Leading Contributions in the Field of Green Computing and AI

The citation distribution of the 246 publications evaluated in the field of Green Computing and AI integration is visualized as a histogram in Figure 6. The results indicate that the vast majority of studies received between 0 and 20 citations, while only a limited number of works have surpassed the threshold of 100 citations. This pattern suggests that the field is still in its developmental phase, although a few studies have achieved interdisciplinary impact. Figure 6 illustrates the citation distribution (n = 246 publications), revealing a positively skewed structure where a small number of influential papers account for a disproportionately high number of citations.

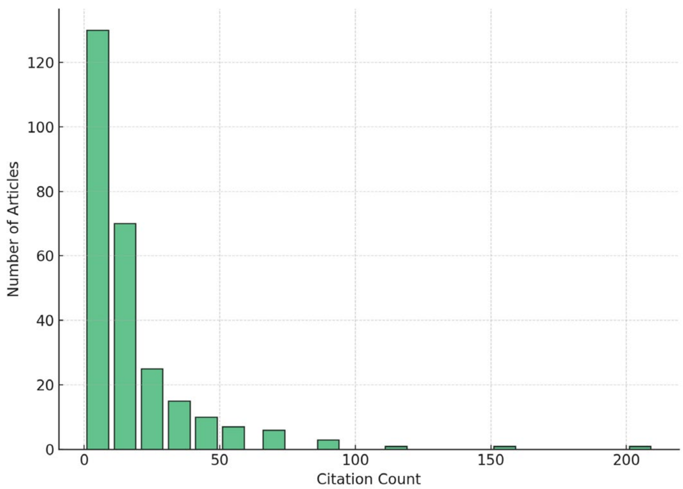

Figure 6: Citation count distribution

Among these publications, the study titled "Towards the Systematic Reporting of the Energy and Carbon Footprints of Machine Learning" by Henderson et al. (2020, p. 1-2) stands out as the most highly cited article, with a total of 225 citations. This finding reflects the growing academic interest in systematically reporting the energy consumption and carbon footprint associated with machine learning applications. Moreover, it indicates that the field is increasingly evolving within the framework of environmental sustainability, highlighting a shift from purely technical efficiency to broader ecological concerns.

3.5.2. Trends in Annual Citation Growth within the Green IT and AI Literature

The citation distribution of the evaluated studies was analyzed using the histogram presented in Figure 6. The majority of articles reviewed in this study received relatively low citation counts, while a few pioneering works attained significantly higher citation levels. This indicates that the field is still in a developmental phase, with certain foundational studies emerging as key reference points.

The most highly cited study in this field is the article by Henderson et al., (2020, p. 1-2) titled "Towards the Systematic Reporting of the Energy and Carbon Footprints of Machine Learning", which stands out with 225 citations. This reflects the significant academic interest in systematically reporting the environmental impacts—particularly energy consumption and carbon emissions—of machine learning applications.

Another highly cited work is Ooi et al., (2025, par. 79-83) titled "The Potential of Generative Artificial Intelligence across Disciplines: Perspectives and Future Direction," which has received 185 citations to date. This study outlines the role of GenAI in enabling sustainability across digital infrastructures and is recognized as a leading work in the emerging literature on Green AI.

Similarly, Jiang et al., (2020, p. 210) have made a significant impact with their DL-based energy optimization model for multi-channel intelligent environments, cited 124 times. Their model combines green computing principles with efficient resource allocation in edge computing, a critical area for sustainable systems.

Zhu et al., (2022, p. 79-80) in their article "Green AI for IIoT: Energy Green AI for IIoT: Energy efficient intelligent edge computing for industrial Internet of Things (IoT)," emphasize the integration of AI with industrial IoT for achieving low-power operations, accumulating 62 citations. This reflects the broader industrial and academic attention toward AI-supported smart infrastructure.

The citation trends also reveal that some early contributions—particularly those from 2010 and 2011—still retain foundational value, as evidenced by their high citation averages

(Figure 8). These early works continue to influence contemporary research agendas, reinforcing their role in defining the theoretical and technical pillars of the field.

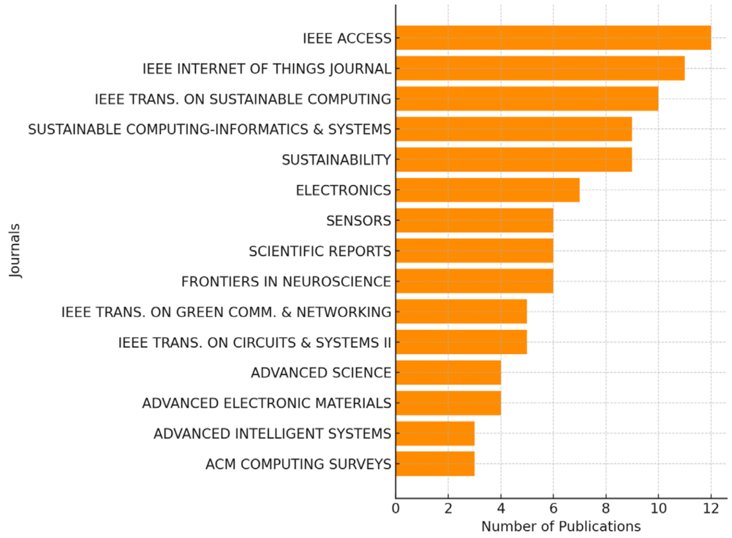

Figure 7: Top journals by number of publications

Based on the results presented in Figure 7, IEEE (Institute of Electrical and Electronics Engineers) Access (12 publications), IEEE Internet of Things Journal (JIOT) (11 publications), and IEEE Transactions on Sustainable Computing (10 publications) emerge as the leading journals in terms of publication volume within this field. These findings highlight IEEE's prominent role in advancing research at the intersection of sustainable computing and AI.

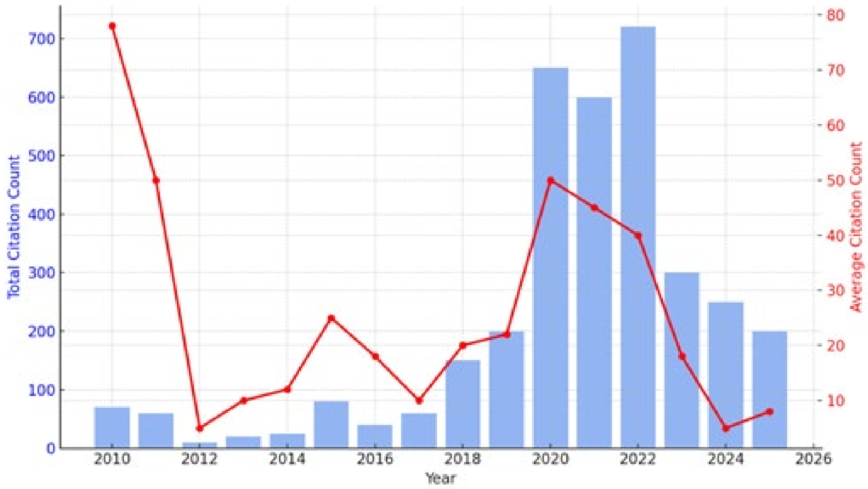

Figure 8: Annual citations trends

The dual-axis chart presented in Figure 8 illustrates the evolution of citation dynamics between 2010 and 2025. The blue bars represent the total number of citations per year, while the red line indicates the average number of citations per article. A significant increase is observed during the 2020–2022 period, coinciding with the accelerated adoption of AI-enabled green technologies in the academic landscape. It can be stated that citation rates have shown a gradual decline after 2022, likely due to recency and citation lag. Publications from 2010 and 2011 received high citation counts, indicating that these early studies have become foundational references in the field. In contrast, although the number of publications increased during the 2013–2016 period, the average citation rates remained relatively low. The high citation levels of pioneering articles such as Jiang et al., (2020) and Ooi et al., (2025) suggest a growing demand for applied, solution-oriented AI research in green computing domains.

3.6. Keyword Analysis

The most frequently used keywords in the field of "Green Computing and AIare presented as a Word Cloud in Figure 9. Among the most prominent terms are "green computing" (43), "sustainable computing" (33), "DL" (30), "machine learning" (30), "energy efficiency" (26), and "AI" (21). These findings indicate that the primary focus areas in the field are sustainable computing, energy efficiency, and AI technologies. In the word cloud, the core concepts and research trends within the field are visually emphasized. When the prominent terms are examined, it becomes evident that "green computing" and "sustainable computing" constitute the foundational concepts of the domain. Following these, "DL" and "machine learning" appear as sub-concepts nested within the broader theme of AI technologies. The term "energy efficiency" reflects a central focus on sustainability, while "AI" represents the overarching technological framework underpinning the field.

Figure 9: Network map of keywords

3.7. Scope and Limitations of the Study

The present study explores the intersection of AI and Green IT through a bibliometric approach. Its scope is defined by articles indexed in the Web of Science database between 2000 and 2024. Publications written in English were selected, which naturally excludes studies published in other languages. The dataset was analyzed using R-Bibliometrix and VOSviewer software. While these tools are widely accepted and effective for mapping research trends and networks, alternative software or methods could lead to slightly different outcomes.

This research also has several limitations that should be noted. First, focusing on a single database means that relevant studies indexed in sources such as Scopus, IEEE Xplore, or Google Scholar were not considered. Second, citation-based indicators are dynamic and change over time; therefore, the results should be viewed as a snapshot rather than a permanent picture of the field. Third, the analysis centers on quantitative indicators such as publication and citation counts, without conducting an in-depth qualitative evaluation of article content.

These limitations restrict the generalizability of the findings to the entire body of literature on AI and Green IT. Nevertheless, the study offers a structured overview of the intellectual landscape, highlights current research patterns, and identifies collaboration networks. In this respect, the results provide useful guidance for future research and contribute to the ongoing discussion on sustainable digital transformation.

4. DISCUSSION

This study evaluates the integralin of Green Computing and AI through a comprehensive bibliometric analysis. The results identified three dominant thematic clusters: energy-efficient AI hardware, federated and edge computing for sustainability, and carbon-aware AI model deployment. These clusters reflect a growing scholarly focus on environmentally aligned computing strategies. The findings also highlight that this intersection has become a fast-growing, multidisciplinary research area, aligning with earlier studies that noted the acceleration of AI-based green Technologies (Henderson et al., 2020, p. 1-2).

The analysis revealed that China and the United States lead in research output and collaboration strength, consistent with previous bibliometric research highlighting the pivotal roles of North American and East Asian institutions in sustainable AI, underscoring the necessity of standardized energy and carbon reporting practices for AI models, which continues to influence evaluation frameworks in current literatüre.

IEEE journals emerged as the most active publication venues, particularly in themes such as sustainability, machine learning, and energy efficiency. This is further supported by

Villar-Rodriguez (2023, p. 5), who emphasized the role of GenAI in enabling holistic sustainability, responsible AI applications, and energy-aware policy development.

4.1.Key Challenges in Green AI

Figure 10 and Table 8 have been developed based on an evaluation of specific challenges encountered in integrating Green IT with AI, as identified through both the literature and the analysis of the reviewed studies, including keywords and the most highly cited publications. The most prominent issue is the high energy consumption and carbon footprint associated with large-scale AI models and data centers (Henderson et al., 2020, p. 4-5; Laleni et al. 2024, p. 157). Figure 10 maps the primary technical and systemic challenges facing the integration of AI and Green IT. Data is aggregated from keyword co-occurrence analysis and highly cited studies (Henderson et al., 2020; Laleni et al. 2024; Kumar et al., 2024; Zhou et al., 2021). Table 8 presents the distribution of challenge categories based on their frequency of occurrence in the literature. The most commonly emphasized issues include high carbon emissions, limitations in model scalability, and constraints related to hardware optimization, as reflected in multiple high-impact studies (Ghayvat et al., 2024; Zhou et al., 2021).

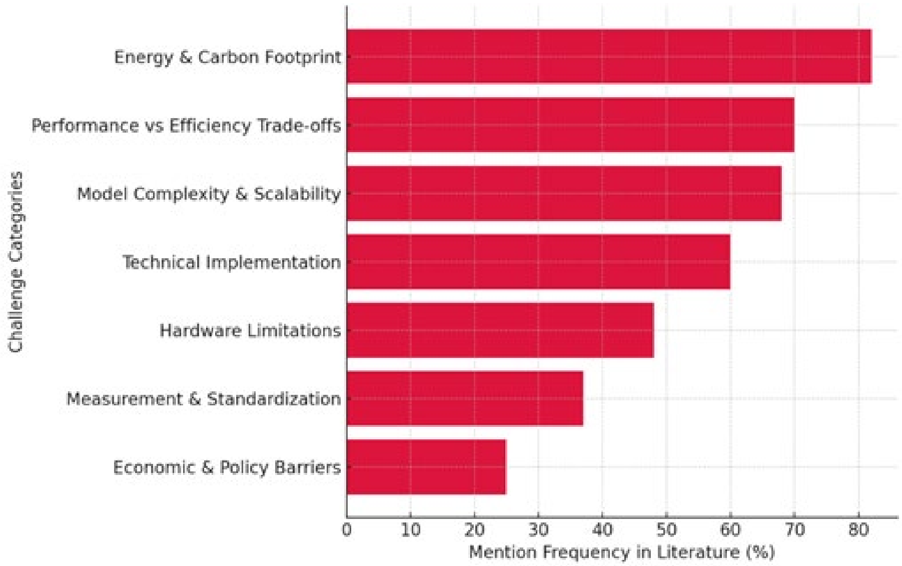

Figure 10: Key challenges in Green AI

Table 8: Key challenge categories in Green AI

Challenge Category	Description	Frequency in Literature (%)
Energy & Carbon Footprint	High energy consumption of large AI models and data centers	85
Model Complexity & Scalability	Computational complexity of DL models	65
Hardware Limitations	Limited energy-efficient hardware options	45
Performance vs Efficiency Trade-offs	Balancing AI performance with environmental impact	70

In data center energy management, Ghayvat et al., (2024, p. 39039) proposed the Time and Energy Minimization Scheduler (TEMS) using AIoMT to enable local energy-optimized computing. Their model highlights the necessity of balancing dynamic cooling and power allocation across IoT and cloud systems.

DL model complexity and limited scalability remain central concerns. Zhou et al. (2021, p. 2934) argue that large-scale AI models require significant computational resources, compromising sustainability. Automated scaling solutions, although under development, are still experimental and often lack energy optimization features.

Regarding hardware limitations, Grossi et al., (2019, p. 1286) introduced the use of RRAM to optimize energy efficiency in DL, while Liu et al., (2019, p. 173994) recommended model compression and quantization for energy-efficient edge deployments. These strategies are particularly useful for edge AI systems with constrained resources.

Frameworks like TensorFlow Lite and Open Neural Network Exchange (ONNX), though promising, still require standardization. Huang et al., (2023, p. 35) and Ooi et al., (2025, p. 91) explored energy-aware deployment techniques involving Graphics Processing Unit (GPU) and Tensor Processing Unit (TPU) optimization. However, existing solutions like NVIDIA MIG and AMD ROCm face scalability issues.

Network infrastructure loads, especially in federated AI training, are another challenge. While CDN and caching strategies are proposed, most solutions are still nascent. Laleni et al., (2024, p. 157-158) and Yang et al., (2022, p. 3-4) emphasized real-time energy tracking via APIs and dashboards for sustainable AI workflows. Mucha, (2024, p. 6) evaluated the viability of real-time AI systems embedded in hardware, suggesting that Magnetoresistive Random Access Memory (MRAM)-based neuromorphic designs Xue et al., (2025, p. 4-5) offer low-power inference potential. These architectures are critical for scalable edge AI deployments.

The performance-efficiency trade-off was highlighted by who stressed the importance of maintaining AI accuracy while minimizing environmental impact (Henderson et al., 2020, p. 1-2). Standardization of green AI remains a key issue. Al Sallami et al., (2023, p. 139) emphasized incorporating environmental metrics into AI evaluation frameworks to promote resilience. Similarly, Aquino-Brítez, (2024, p. 11) warned that performance-oriented national incentives may conflict with sustainability goals.

4.2. Technical Complexity of Green AI Challenges

Figure 11 presents the challenge areas by technical complexity and impact level. Kumar et al., (2024, p. 1527-1528) proposed real-time cooling prediction and renewable energy integration as strategic solutions for data centers. AI model deployment efficiency can be enhanced by techniques such as knowledge distillation and compression, particularly on edge systems. TensorFlow Lite and ONNX are widely used but still maturing. Dynamic GPU/TPU allocation and load balancing in heterogeneous hardware environments remain active research areas (Ooi et al., 2025, p. 89; Kumar et al., 2024, p. 1527-1528). In federated learning, Zhu et al., (2022, p. 9) demonstrated significant energy savings and communication efficiency in IIoT applications. Penev et al., (2024, p. 7) developed a sustainability tracking framework compatible with real-time AI workflows, while Guo et al., (2024, p. 39131) designed APIs for carbon-aware AI inference. Scalability and sustainability integration is essential. Auto-scaling and hybrid architecture design are promising but require advanced middleware and adapters for energy-efficient IT integration. Legacy system retrofitting remains a major challenge. Carbon-aware AI models represent a growing solution. Choi et al., (2018, p. 678) and Zavieh et al., (2024, p. 3-4) advocated for carbon sensitivity in model design, while Vergallo & Mainetti, (2024, p. 6) showed energy savings from carbon-aware deployment strategies. Zhu et al., (2022, p. 81) reported efficiency gains in green manufacturing via energy-optimized IIoT systems. Song et al., (2024b, p. 39111) emphasized phased deployment for risk reduction in AIoT environments. Yu et al., (2024, p. 38990–38992) explored quantum-assisted hybrid algorithms to optimize energy in low-power AI systems. For multi-cloud workloads, introduced orchestration models for energy-aware inter-cloud transfers and model migration, minimizing carbon footprints while maintaining performance (Alzu'bi et al., 2025, p. 6).

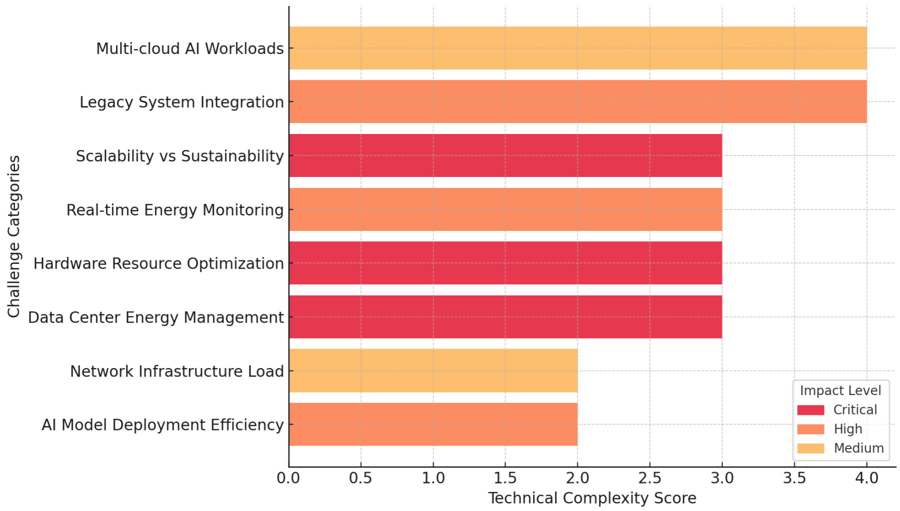

Figure 11: Technical complexity levels of Green IT_AL challenges

4.3.Emerging Topics in Green AI

To guide future directions, the bibliometric analysis also examined emergent themes (Figure 12). Topic frequency and clustering of frontier concepts in Green AI, such as neuromorphic systems and federated learning. Developed through bibliometric topic extraction (Machado et al., 2024, p. 512-515; Nambi et al., 2021; Song et al., 2024b).

Neuromorphic computing ranked highest with 76 mentions, with a strong emphasis on low-power, brain-inspired hardware. Yang et al., (2022, p. 1-5) and Mucha, (2024, p. 2-4) highlighted the potential of memristor crossbars and MRAM designs for sustainable edge AI. Machado et al., (2024, p. 512-515) provided additional support for energy-efficient neuromorphic systems.

The carbon footprint theme (20 mentions) emphasizes emission measurement and life cycle metrics in AI development. Zavieh et al., (2024, p. 7) underscored the necessity of standardized carbon tracking (Song et al., 2024b, p. 39107). Blockchain, ranked third, featured in 19 papers, focusing on green consensus protocols and secure distributed AI.

Federated learning (15 mentions) gained prominence for energy efficiency and privacy preservation in distributed environments. Zhu et al., (2022, p. 82) confirmed its effectiveness in green IIoT contexts. Transformer architectures were also identified as an emerging area, especially for their energy optimization in LLMs (Song et al., 2024a, p. 7)

Promising research avenues include energy-aware neuromorphic AI co-design, standardized sustainability metrics, green blockchain via Proof-of-Stake, and federated green AI for bandwidth and energy efficiency.

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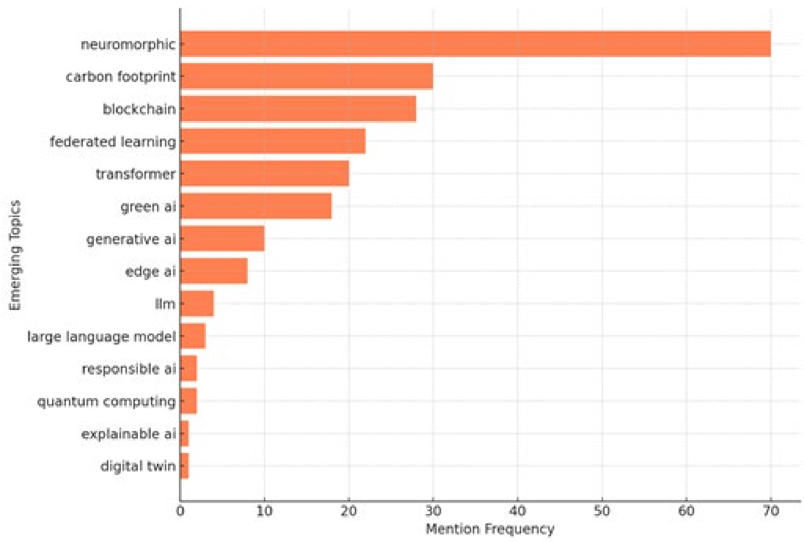

Figure 12. Emerging topics in the field of green computing and AI

5. CONCLUSION

5.1. Theoretical Contributions

This study contributes to the growing body of research at the intersection of green computing and AI by offering a systematic bibliometric overview of 246 academic articles. It identifies the evolution of scholarly interest in GenAI-supported sustainability applications and highlights key conceptual clusters, including energy efficiency, green cloud infrastructure, carbon-aware computing, and environmental data governance.

By revealing thematic hotspots—such as compute-in-memory architectures (Huang et al., 2023, p. 34) federated learning models (Alzu'bi et al., 2025, p. 6), and carbon-optimized AI deployments—the study strengthens the theoretical foundation for Green AI as a multidisciplinary field. It also fills a literature gap by focusing on the environmental dimensions of immersive digital infrastructures, particularly in metaverse ecosystems, which have received limited attention in sustainability frameworks.

Moreover, the study contributes methodologically by applying bibliometric techniques to map co-authorship networks, keyword co-occurrence, and global publication trends, providing a macro-level understanding of how green computing and AI research has developed and where it is headed.

5.2. Practical Implications for Sustainable Metaverse

As immersive technologies such as VR, AR, digital twins, and GenAI become more integrated into societal functions, their environmental impact must be critically assessed. The study demonstrates that integrating AI with green computing strategies—such as edge computing, renewable-energy-based data centers, and carbon-aware monitoring tools—is pivotal for creating environmentally sustainable metaverse ecosystems.

Use cases such as GenAI-supported supply chain simulations, AI-powered energy optimization in healthcare, and sustainable agricultural systems highlight the breadth of practical applications. AIoMT systems leveraging MEC and TEMS algorithms exemplify scalable, low-carbon solutions (Ghayvat et al., 2024, p. 39031). These advancements signal that sustainable metaverse infrastructures are not only possible but already emerging through AI-enablement. Nonetheless, gaps remain. The literature points to the lack of comprehensive life cycle assessments, limited transparency in energy use data, and underdeveloped standards for AI hardware sustainability (Villar-Rodriguez et al., 2023, p. 6). Addressing these limitations will be critical for the real-world implementation of sustainable digital systems. Although this study provides a comprehensive bibliometric overview of the intersection between AI and Green IT, it is not without limitations. The reliance on a single database and the focus on citation-based indicators mean that the findings should be interpreted with caution. Nevertheless, within these limitations, the results highlight key trends and collaboration networks that may guide future research in sustainable digital transformation (Donthu et al., 2021; Zupic & Čater, 2015).

5.3. Future Research Agenda

Building on the bibliometric findings, several avenues for future research emerge:

- Sectoral Applications: Greater emphasis should be placed on domain-specific investigations, particularly in energy-intensive sectors such as manufacturing, logistics, and healthcare.
- Technological Innovation: Future studies should explore the development of energy-efficient GenAI algorithms, next-generation AI chips, and low-power federated learning frameworks.
- Policy and Governance: There is a need to establish ethical standards, regulatory frameworks, and metrics to evaluate the sustainability performance of AI systems.
- Interdisciplinary Collaboration: Research integrating environmental science, computer engineering, and digital ethics is essential to advancing green AI holistically.
- Data Quality and Standardization: The impact of AI on sustainability is directly tied to data quality, transparency, and cross-sector interoperability (Kumar et al., 2024, p. 1526).

Furthermore, expanding bibliometric analyses to include alternative databases and interdisciplinary journal sources could reveal additional insights and thematic nuances overlooked by single-database studies.

Finally, based on technology diffusion models, Redwine ve Riddle (1985), it is anticipated that Green AI integration will reach technological maturity and broad industrial adoption within the next 15–20 years. As immersive platforms continue to scale, the findings of this study confirm that AI and green computing technologies will play a transformative role in designing the low-carbon digital ecosystems of the future.

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Appendix 1: Abbreviations

AI – Artificial Intelligence

ANNs – Artificial Neural Networks

AR – Augmented Reality

DL – Deep Learning

GenAI – Generative Artificial Intelligence

GPU – Graphics Processing Unit

IEEE – Institute of Electrical and Electronics Engineers

IoT – Internet of Things

IT – Information Technology

JIOT – IEEE Internet of Things Journal

MRAM – Magnetoresistive Random Access Memory

ONNX – Open Neural Network Exchange

RRAM – Resistive Random Access Memory

TPU – Tensor Processing Unit

VR – Virtual Reality