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Green and sustainable AI research: an integrated thematic and topic modeling analysis

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Abstract
This investigation delves into Green AI and Sustainable AI literature through a dual-analytical approach, combining thematic analysis with BERTopic modeling to reveal both broad thematic clusters and nuanced emerging topics. It identifies three major thematic clusters: (1) Responsible AI for Sustainable Development, focusing on integrating sustainability and ethics within AI technologies; (2) Advancements in Green AI for Energy Optimization, centering on energy efficiency; and (3) Big Data-Driven Computational Advances, emphasizing AI's influence on socio-economic and environmental aspects. Concurrently, BERTopic modeling uncovers five emerging topics: Ethical Eco-Intelligence, Sustainable Neural Computing, Ethical Healthcare Intelligence, AI Learning Quest, and Cognitive AI Innovation, indicating a trend toward embedding ethical and sustainability considerations into AI research. The study reveals novel intersections between Sustainable and Ethical AI and Green Computing, indicating significant research trends and identifying Ethical Healthcare Intelligence and AI Learning Quest as evolving areas within AI's socio-economic and societal impacts. The study advocates for a unified approach to innovation in AI, promoting environmental sustainability and ethical integrity to foster responsible AI development. This aligns with the Sustainable Development Goals, emphasizing the need for ecological balance, societal welfare, and responsible innovation. This refined focus underscores the critical need for integrating ethical and environmental considerations into the AI development lifecycle, offering insights for future research directions and policy interventions.

Keywords: Green AI, Sustainable AI, BERTopic, Topic modeling, Keywords co-occurrence, Sustainable development goal, Ethics, Cognitive AI, Big data

Introduction

Green AI, Sustainable AI, Zero Carbon AI, and Net Zero AI are a few terminologies used to explain efforts and practices within the broader domain of Artificial Intelligence (AI) that intend to shrink the environmental brunt of AI technologies. Green AI refers to developing and deploying artificial intelligence systems with a focus on minimizing their environmental impact [97]. Sustainable AI is an approach that emphasizes the long-term viability and responsible use of artificial intelligence technologies [54]. It includes considerations for environmental sustainability [39], ethical use of data [51], and the societal impact of AI applications towards the fulfillment of UN Sustainable Development Goals (SDGs) [84]. Zero Carbon AI aims to eliminate or offset the carbon emissions associated with developing, training, and deploying AI models and systems. This involves using renewable energy sources, improving energy efficiency, and implementing carbon offset strategies [76].

Research in Green AI focuses on developing environmentally sustainable artificial intelligence technologies [88]. Researchers aim to optimize algorithms, hardware, and data center operations to reduce energy consumption and minimize the carbon footprint of AI systems [91, 92]. Techniques such as energy-efficient model training, resource-aware algorithms, and eco-friendly hardware designs are explored [38]. The goal is to create AI solutions that deliver high performance and align with ecological considerations. This research field contributes to mitigating AI's environmental impact, promoting energy efficiency, and fostering a more sustainable future for artificial intelligence applications. Green AI aligns with global efforts to address climate change and create eco-friendly technologies [25].

Recent generative AI applications could further aggravate environmental issues as they often require substantial computational resources to train large models, leading to increased energy consumption and carbon emissions [31]. Moreover, as generative AI applications increase and become more sophisticated, the continuous need for data and model refinement could drive a cycle of energy-intensive usage, potentially overshadowing the gains made by sustainable AI initiatives.

Amidst the burgeoning research on AI applications, numerous systematic approaches seek to consolidate existing research and propose dimensions for emerging areas of study. For instance, Saad and Khamkham's [73] exploration into the synergy of AI and Green Supply Chain Management (GSCM) unveils key AI contributions to environmentally sustainable supply chains. Their systematic literature review, employing five robust processes, identifies cutting-edge technologies shaping the landscape. Focusing on healthcare, Siala and Wang [81] delve into ethical considerations in AI, proposing the "SHIFT" framework that spans Sustainability, Human-centeredness, Inclusiveness, Fairness, and Transparency. This framework acts as a compass for the ethical implementation of healthcare AI, offering insights through a systematic review that spans two impactful decades.

From our understanding of the above studies and further studies mentioned in the literature review section below, we believe these studies do not offer a holistic insight into the state of the art of literature on the applications of AI for sustainability, social good, and achieving zero carbon goals. Recognizing the number of research endeavors in these critical areas, we endeavor to fill this gap through Scientometrics [41, 59]. This approach allows us to comprehensively map and analyze the existing body of literature [57] providing a nuanced understanding of the current landscape and emerging trends in the application of AI for sustainable and socially impactful outcomes [63], including efforts towards achieving zero carbon goals. Our study, employing both thematic cluster analysis [64, 65] using keyword co-occurrences and BERTopic modeling [29], is a methodologically robust and unique approach. Thematic cluster analysis through co-occurrence mapping of keywords specified by authors offers a quantitative, frequency-based perspective, highlighting the literature's most prominent and recurrent topics. Conversely, BERTopic is essential for its capability to capture contextualized and semantic representations of words, offering a more nuanced understanding of the relationships between various themes and topics within the literature. By integrating both methods, we ensure a comprehensive analysis—capturing deep, context-driven insights with BERTopic and mapping these with empirical, frequency-based broad themes from keywords' clustering.

Precisely, we ask the following research questions (RQs):

RQ1: What are the foundational thematic clusters in Green AI and Sustainable AI literature that encapsulate the field's evolution and current trends?
RQ2: Which emerging topics in Green AI and Sustainable AI literature are poised to influence the field's trajectory significantly?
RQ3: How can the insights derived from foundational thematic clusters and emerging topics guide the development of policies and strategies for advancing sustainable AI practices?

The distinct methodologies employed for RQ1 and RQ2 cater to different analytical objectives. Thematic analysis via keywords' co-occurrences offers a macroscopic view of the field, identifying broad research areas and their relative prominence over time. Conversely, BERTopic modeling provides a microscopic view, uncovering specific, emerging discussions and their intricate relationships. This methodological triangulation strengthens the validity of our findings, offering a layered understanding that spans from overarching themes to specific emerging discussions.

This paper makes several contributions to the literature. Firstly, it offers a comprehensive mapping of the domains of Green and Sustainable AI into major thematic areas using keywords. Secondly, by implementing BERTopic analysis, the paper aims to uncover latent topics and explore semantic relationships within the literature, providing a nuanced and context-aware understanding of the interplay between AI, sustainability, social good, and zero carbon initiatives. Thirdly, by conducting a temporal analysis, the study seeks to unveil historical shifts and patterns, contributing insights into the evolving impact of AI on sustainability practices.

The structure of our paper is outlined as follows: "Literature review" section delves into the existing literature, highlighting identified gaps, followed by an explanation of the methodology used in our study. "Results and discussion" section is dedicated to the analysis and interpretation of our findings. We conclude in "Conclusions with implications" section, summarizing the main takeaways of our research and discussing their implications for stakeholders.

Literature review

The intersection of artificial intelligence (AI) and sustainability has emerged as a significant area of inquiry across various disciplines, reflecting a growing recognition of the importance of integrating sustainable practices into AI initiatives [40]. Scholars such as Jobin et al. [35] emphasize the need for ethical guidelines to govern the widespread implementation of AI technologies in society, advocating for principles that ensure sustainability and social responsibility, as articulated by Floridi et al. [24]. Conversely, Green AI research has seen considerable attention directed towards energy-efficient computing solutions, with potential implications for advancements in energy sustainability [1]. Strubell et al. [82] quantified the economic and environmental impact of AI technologies like deep learning (especially for NLP applications), of which the cost of hardware, electricity, and computing resources are the major components of financial cost while environmental cost can be attributed to the carbon footprint associated with fuel powering modern tensor processing hardware. Several actionable recommendations were also given to reduce costs and improve equity in NLP research and practice. Strubell et al. [83] presented updated estimates and broader information and provided actionable recommendations to reduce costs and improve equity in the machine learning and AI community. Pioneering work by Yokoyama et al. [98] explores innovative techniques for optimizing energy consumption in AI hardware, underscoring the potential for sustainable computing solutions to mitigate environmental impact.

Wu et al. [93, 94] delve into the environmental implications of AI, analyzing its carbon footprint across various dimensions such as data, algorithms, and system hardware. Bibri [7], on the other hand, highlights the role of green energy and smart data-driven technologies in achieving environmental objectives, emphasizing the importance of reducing energy consumption and pollution through sustainable development strategies.

Recognizing the transformative potential of AI in addressing sustainability challenges, Pedemonte [60] and Vinuesa et al. [89] discuss both the opportunities and risks associated with integrating AI into the pursuit of SDGs 2030. Scholars such as Van Wynsberghe [86] and Duan et al. [18] advocate for redefining AI within the context of sustainable development, encapsulating this paradigm shift with the concept of "Green AI." This framework prioritizes innovative outcomes while considering computational costs, promoting resource reduction throughout the entire AI life cycle [76].

Amidst these discussions, the energy sector explores novel energy sources and innovative solutions, including solar and water-based energy generation [15] and the application of AI in modeling energy systems [37]. However, the burgeoning energy consumption of AI poses challenges, necessitating efforts to enhance energy efficiency in model training approaches [88]. Novel AI hardware architectures targeting the Internet of Things (IoT offer promising avenues for reducing energy footprints while maintaining learning accuracy (Wheeldon et al. 2019) [38].

Furthermore, Galaz et al. [25] shed light on the widespread adoption of AI technologies in global agriculture, forestry, and marine management, highlighting governance gaps in AI principles from a sustainability perspective. This multifaceted exploration of the interface between AI and sustainability underscores the complexities and opportunities in shaping a more environmentally conscious and socially responsible technological landscape.

Artificial Intelligence (AI) is going to have an impact on all aspects of human life. In some aspects the impact is already made. The potential of AI to contribute to UN SDGs is being enthusiastically explored by researchers from almost all fields. However, is AI (technologies that come under the umbrella of AI) sustainable? If not, how can it be useful in the pursuit of SDGs? While there is heavy excitement about the explorations of AI's ability to bring wonders to all spheres of life, which can be partly attributed to its possibility to contribute substantially to SDGs, equal enthusiasm and dedicated efforts should be there to ponder the above two questions that are of enormous gravity. Van Wynsberghe [86] argued that two equitable branches, viz. 'AI for sustainability' and 'sustainability of AI' should be the key to defining, developing, and practicing 'Sustainable AI.' The increasing demand for AI as a tool for augmenting existing key infrastructures is transforming AI itself as an infrastructure, and societies might sooner or later be trapped in different kinds of lock-ins, be it carbon lock-ins [8, 77] or lock-ins of dependencies or interdependencies from which there is no escape [67]. Falk & van Wynsberghe [22] observed that the terms 'Sustainable AI' and 'Sustainability of AI' are overused to such an extent that various stakeholders are required to be reminded about the actual meaning behind 'AI for sustainability.' Without acknowledging the importance of ensuring the sustainability of AI, the idea of 'AI for sustainability' is counterintuitive, and movements or efforts (no matter how organized they are) in that direction might end up counterproductive.

Thus, all these works suggest that the primordial responsibility of stakeholders of AI or sustainable AI (as most of us would like to call ourselves) is to argue, strive, and ensure that the plethora of environmental risks associated with AI should be at the core of the ethical analysis and efforts for the development of ethical, legal and regulatory frameworks. It is important to acknowledge that unsustainable methods exist for AI that might be marketed under the label of sustainable AI. Proper mechanisms should be in place to check such tendencies, and synergetic-focused efforts should be there to recognize, fund, and nurture sustainable methods of AI. However, more insightful information for various stakeholders and more suggestions of actionable recommendations can be of help to them in promoting sustainable AI, which in turn can be vital for efforts in exploring and directing AI for sustainability. Inspired by this, we intend to systematically explore the relevant literature related to Green and Sustainable AI research through the usage of an integrated framework for thematic and topic modeling analysis. Previous explorations that highlight the importance of constituent methods are briefly discussed next.

Given the multifaceted nature of Green and Sustainable AI research, conducting thematic and BERTopic modeling analyses is imperative to comprehensively understand and navigate this rapidly evolving landscape [3]. By systematically categorizing and examining thematic clusters, researchers can uncover nuanced relationships and patterns that may not be apparent through traditional literature review methods alone [53]. Additionally, by leveraging advanced natural language processing techniques, BERTopic modeling provides a deeper understanding of the intricate interplay between different concepts and themes, facilitating a data-driven approach to uncovering latent topics within the literature [29]. Together, thematic and BERTopic modeling analyses offer a robust framework for synthesizing and interpreting the vast and diverse body of literature on Green and Sustainable AI, ultimately contributing to advancing knowledge and developing sustainable AI solutions.

Methodology

In pursuit of our specific research questions, this study aims to analyze Green and Sustainable AI research using a unique combination of Scientometrics and BERTopic analyses. Figure 1 illustrates the study's broad methodology, outlining the sequential steps taken to ensure the robustness of the analytical process. While thematic and topic modeling analyses have been applied independently, there is a growing interest in integrating these methodologies to provide a comprehensive understanding of the field [3, 87]. Our proposed research builds upon this foundation by leveraging thematic analysis to identify overarching concepts and topic modeling to explore granular research themes. This integrated approach provides a comprehensive understanding of Green and Sustainable AI research.

Data

In the initial phase of our study, we adhered to the PRISMA protocol [55, 64] and systematically gathered scholarly articles from the Scopus database on November 19, 2023. The period covered in this study spans between 2016 and 2023. The starting point of 2016 is chosen as it follows the formal adoption of the SDGs in late 2015. The search query encompassed diverse terms related to sustainable AI, green AI, and ethical considerations in AI, resulting in 448 records. Documents of the type article, book, book chapter, conference paper, and review are included. However, we removed the editorial, note, erratum, and short survey from the analysis. Further, records with missing authors, abstracts, and non-English language documents are also excluded. Following the elimination of unrelated documents, 397 records were retained for analysis. The core content of these records, including titles, abstracts,

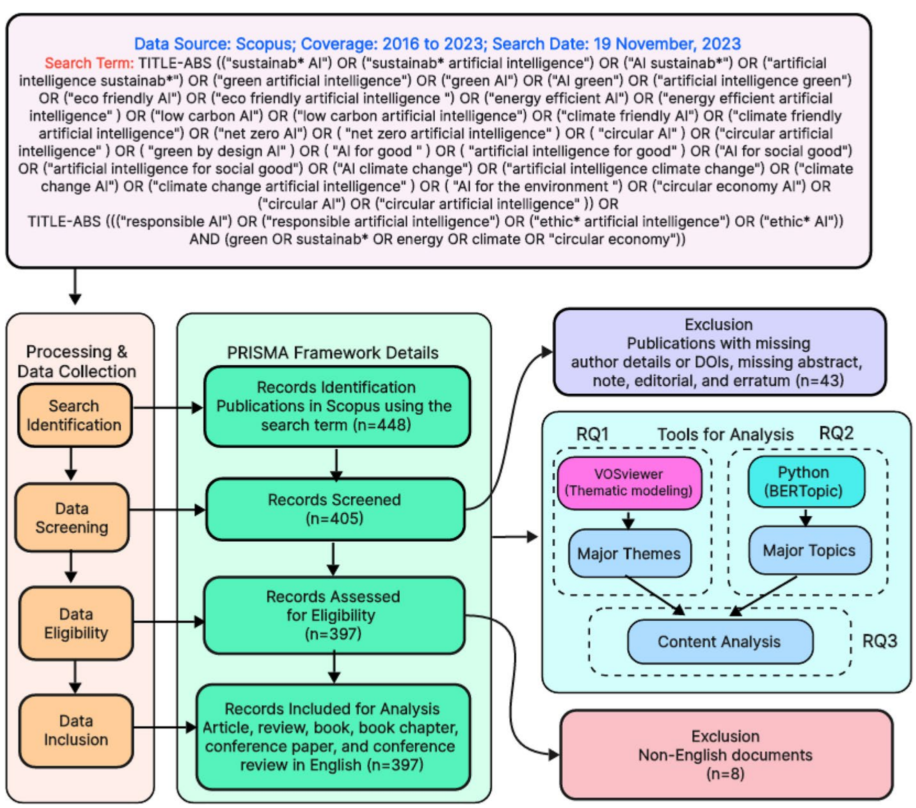

Fig. 1 Research Methodology

and author-specified keywords, was utilized for descriptive analysis, thematic cluster analysis, and topic modeling analysis [27, 59].

For data organization, sorting, listing, and graphical representation, we employed "MS Excel." In the Scientometric analysis, we adopted a comprehensive set of metrics to dissect scholarly publications' performance, collaboration dynamics, and impact, as defined and presented in Pattnaik et al. [56, 58, 59].

Thematic analysis

The thematic analysis serves as a valuable tool for identifying overarching themes. It involves recognizing, examining, structuring, explaining, and documenting patterns discovered in data collection [53]. Braun and Clarke [12] emphasized the importance of thematic analysis as a foundational approach, providing researchers with indispensable skills applicable across various qualitative methodologies. Numerous scholars have argued that thematic analysis, an integral process to many qualitative methodologies, should not be viewed as a distinct method but as a tool to support researchers in their analysis [11, 33, 72].

For our thematic cluster analysis, we utilized VOSviewer, a software application designed for constructing and visualizing bibliographic networks [85]. The foundation of our thematic cluster analysis rests on the authors' specified keywords. Each node in the analysis represents a distinct author-specified keyword. The lines connecting nodes indicate the frequency of co-occurrence of keywords. In contrast, the color of a node often indicates the cluster or group to which a keyword belongs, with each color representing a different thematic cluster or set of closely related topics [27, 59]. This clustering is usually based on the similarity of the keywords' co-occurrence patterns, suggesting they are frequently discussed in the literature. The distance between nodes in the visualization is also significant. Generally, a shorter distance between two nodes implies a stronger or more frequent co-occurrence, indicating that those keywords are often mentioned together in the same articles or contexts, thus suggesting a closer relationship or a higher degree of topic relevance.

Topic modeling

Using topic modeling allows researchers to augment their toolkit for exploratory analysis and literature review processes [9, 28, 32]. Asmussen and Møller [5] discuss using topic modeling and machine learning for literature reviews. Nikolenko et al. [52] highlight topic modeling for qualitative studies and propose a new quality metric (tf-idf coherence) and an interval semi-supervised approach to make topic modeling more effective for specific subtopics. BERTopic is a topic modeling approach that leverages pre-trained BERT (Bidirectional Encoder Representations from Transformers) embeddings for more accurate and contextually rich topic representations [29]. Egger and Yu [21] evaluated the performance of four topic modeling techniques (latent Dirichlet allocation (LDA), non-negative matrix factorization (NMF), Top2Vec, and BERTopic. One of the main advantages of BERTopic over traditional topic modeling approaches, such as Latent Dirichlet Allocation (LDA), is its ability to capture semantic meanings and contextual relationships within text data more effectively.

We employ the sophisticated BERTopic in Python, leveraging transformers and Class-Tf-idf-Transformer to create condensed clusters, ensuring a streamlined generation of easily comprehensible topics while preserving essential words in the descriptions [29]. We apply the BERTopic modeling technique to extract and analyze meaningful topics within Green and Sustainable AI, contributing to a comprehensive understanding of the field. Following data extraction, a meticulous preprocessing step enhances the quality and uniformity of the dataset, involving text-cleaning procedures, natural language processing (NLP) techniques, and tokenization. The employment of sentence embeddings generated using the "all-mpnet-base-v2" model from Sentence Transformer and dimensionality reduction using Uniform Manifold Approximation and Projection (UMAP) further refines the dataset for meaningful topic extraction and visualization [47].

For the main topic modeling task, the "all-MiniLM-L6-v2" model from Sentence Transformer is employed, and the BERTopic model is instantiated, incorporating embedding, representation, vectorization, and c-Tf-idf models. Probability calculations for topic assignments enrich the interpretability of the results, ensuring a robust and reliable study outcome. The BERTopic model is fitted to the preprocessed text content, extracting five distinct topics and corresponding probabilities for each document. The generated topics are analyzed for coherence, and the distribution of articles across topics is examined, providing insights into the degree of association between articles and identified topics. This comprehensive and advanced approach in our topic modeling analysis ensures the reliability and robustness of our study findings.

The findings from both the Scientometric analysis (VOSviewer) and BERTopic modeling are synthesized to distinguish between foundational and evolving areas of research and explore how they interact to shape future research directions and policy-making in sustainable AI. This methodological integration offers a multidimensional understanding of the field, bridging the gap between broad thematic insights and detailed topical nuances.

Results and discussion

Building on our comprehensive methodology, we present a concise yet thorough exploration of our key findings, shedding light on the evolving landscape of scholarly contributions and advancements in the realm of Green and Sustainable AI research.

Thematic cluster analysis based on keyword co-occurrences (RQ1)

Thematic clustering analysis carried out in this study indicates that contemporary Green and Sustainable AI research is focused on three specific clusters. Figure 2 illustrates the co-occurrence network showing the three clusters.

Cluster 1 (red): responsible AI for sustainable development

Figure 2 depicts keywords constituting Cluster 1, while Table 1 shows the top-cited articles representing the cluster. As displayed in the figure, a wealth of terms such as sustainable development, decision-making, ethics, ethical technology, behavioral research, and environmental impact reflect a concerted focus on leveraging artificial intelligence to address complex environmental and developmental challenges. It encapsulates a vision where AI not only automates but also innovates in ways that promote ecological

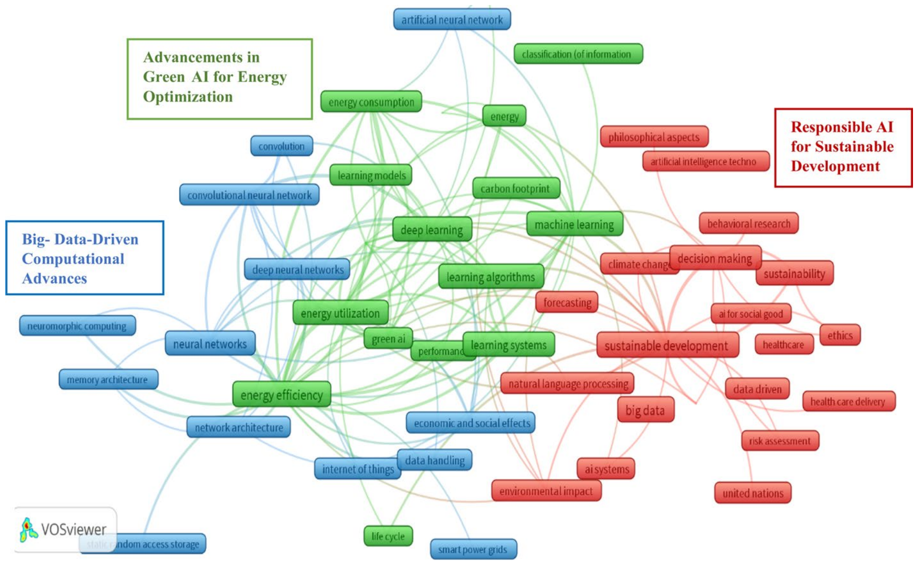

Fig. 2 Thematic Clusters based on keywords co-occurrences

Table 1 Top cited articles of Cluster 1

Citations	Author(s)	Paper title	SDG Focus
110	Floridi et al. [24]	"How to design AI for social good: seven essential factors"	10 REDUCED INEQUALITIES; 16 PEACE, JUSTICE AND STRONG INSTITUTIONS
97	Tomašev et al. [84]	"AI for social good: unlocking the opportunity for positive impact."	All SDGs
82	Galaz et al. [25]	"Artificial intelligence, systemic risks, and sustainability"	10 REDUCED INEQUALITIES
47	Doorn [18]	"Artificial intelligence in the water domain: Opportunities for responsible use"	6 CLEAN WATER AND SANITATION
33	Gupta et al. [30]	"Assessing whether artificial intelligence is an enabler or an inhibitor of sustainability at the indicator level"	All SDGs

balance and social welfare [90]. The interplay between AI and natural language processing implies a potential for developing sophisticated tools that show promise for creating advanced tools for environmental monitoring and policy analysis that can help make sustainable efforts more transparent and responsible [18, 25]. The inclusion of healthcare denotes the potential of AI in advancing precision medicine and global health initiatives, which are integral to achieving the United Nations' Sustainable Development Goals [17]. This synergy between AI and ethical frameworks is critical for shaping technologies that support equitable and sustainable futures.

Floridi et al. [24] tackled the ongoing challenges in applying AI for social benefits by pinpointing seven important ethical considerations that support efforts to reduce inequality and promote justice and strong community leadership, contributing to SDG 10 (Reduced Inequalities) SDG 16 (Peace, Justice, and Strong Institutions). These factors are (1) falsifiability and incremental deployment, (2) safeguards against the manipulation of predictors; (3) receiver-contextualized intervention; (4) receiver-contextualized explanation and transparent purposes; (5) privacy protection and data subject consent; (6) situational fairness; and (7) human-friendly semanticization. Their analysis was supported by 27 case examples, and best practices for each of these factors that can serve as preliminary guidelines for well-designed AI4SG were presented. Tomašev et al. [84] provided a set of guidelines for establishing successful long-term collaborations between AI researchers and application domain experts. These guidelines are vital as the AI for Social Good (AI4SG) movement requires interdisciplinary collaboration centered on AI towards the address of 17 SDGs. Also, some existing AI projects were analyzed concerning the guidelines to identify key opportunities for future AI projects. Focussing on SDG 10 (Reduced Inequalities), Galaz et al. [25] argued that despite the growing interest and investment in the deployment of AI technologies for domains like agriculture, forestry, marine resources exploration, etc., that are critical for sustainability, systemic risk assessment of these technologies remains underexplored. An overview of the progress of these technologies in these critical domains was provided, and possible systemic risks such as algorithmic bias and allocative harms, unequal access and benefits, cascading failures and external disruptions, and trade-offs between efficiency and resilience were identified. Limitations in current governance in addressing AI sustainability risks were also highlighted.

Prioritizing SDG 6 (Clean Water and Sanitation), Doorn [18] emphasized the relatively underdeveloped usage of AI techniques in the water domain and the need for attempts to develop insights about 'responsible AI.' The literature review identified four application categories, viz. modeling, prediction and forecasting, decision support and operational management, and optimization. Three insights were provided, like the general use of AI, multi-objective optimization (ensure pluralism and dynamism of values), and the use of theory-guided data science. The synergetic effort from data scientists, professionals, domain experts, and experts from social sciences and humanities for pursuing 'responsible AI' was also recommended. Finally, Gupta et al. [30] evaluated the impact of AI on 17 SDGs through an expert panel discussion. Key issues associated with AI for the pursuit of a prosperous future, such as data privacy, were discussed, and indicator-level assessment of digitalization and AI at the indicator level of SDGs was highlighted. It also recommended the development of 'Easy-to-use' standard tools to guide AI practitioners in the evaluation of the impact of AI and also to foster collaboration across disciplines to ensure responsible, ethics-driven, inclusive, and context-aware AI applications for sustainable development.

Cluster 2 (green): advancements in green AI for energy optimization

Figure 2 depicts the thematic network of Cluster 2, while Table 2 presents the top articles representing the cluster. The themes delve into the synergistic relationship between artificial intelligence and sustainable energy practices, as evidenced by keywords like energy efficiency, deep learning, energy utilization, energy consumption, and green computing. The cluster emphasizes the development of algorithms that perform with high accuracy and operate with minimal energy demands, aligning computational progress with environmental imperatives. The prominence of 'green AI' indicates a systematic approach to reducing the computational cost of algorithm

Table 2 Top Cited Articles of Cluster 2

Citations	Author(s)	Paper title	SDG focus
64	Yigitcanlar et al. [97]	"Green artificial intelligence: Towards an efficient, sustainable and equitable technology for smart cities and futures"	11 SUSTAINABLE CITIES AND COMMUNITIES 12 RESPONSIBLE CONSUMPTION AND PRODUCTION
59	Xue et al. [96]	"A CMOS-integrated compute-in-memory macro based on resistive random-access memory for AI edge devices"	7 AFFORDABLE AND CLEAN ENERGY 9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
33	Zhu et al. [102]	"Green AI for IIOT: energy efficient, intelligent edge computing for industrial internet of things"	7 AFFORDABLE AND CLEAN ENERGY 9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
27	Wheeldon et al. [91, 92]	"Learning automata based energy-efficient AI hardware design for IOT applications: learning automata based AI hardware"	7 AFFORDABLE AND CLEAN ENERGY
26	Yuan et al. [100]	"Reconfigurable MoS2Memtransistors for Continuous Learning in Spiking Neural Networks"	7 AFFORDABLE AND CLEAN ENERGY 9 INDUSTRY, INNOVATION AND INFRASTRUCTURE

training and inference, which is essential for sustainably scaling AI applications. Furthermore, 'green computing' mirrors the industry's shift towards sustainable hardware, where energy-efficient processors and storage solutions are pivotal. This cluster may also explore the lifecycle analysis of AI models, considering the embodied energy from development to deployment, to ensure a holistic approach to sustainability in technology.

Among the representative works, Yigitcanlar et al. [97] attempted to highlight the fundamental limitations in mainstream AI system conceptualization and practice via literature analysis. They advocated the need for a consolidated green AI approach to ensure a smooth transition towards smart cities aligning with SDG 11 (Sustainable Cities and Communities). Appropriate government intervention, popularization of AI ethical principles viz. "transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, sustainability, dignity, and solidarity" [35], development of suitable AI ethical frameworks and regulation guidelines as well as enforcement mechanisms, engagement of public and other vital stakeholders for ensuring that green AI approach that encompasses ethical frameworks, regulation guidelines, enforcement systems, etc., aligns well with SDG 12 (Responsible Consumption and Production). Next, Xue et al. [96] reported the development of a non-volatile compute-in-memory macro that can outperform existing schemes in terms of multi-bit dot product, increased input–output parallelism, reduced cell-array area, improved accuracy, and reduced computing latency and energy consumption. This work contributes to SDG 7 (Affordable and Clean Energy) and SDG 9 (Industry, Innovation, and Infrastructure) by developing energy-efficient AI hardware for edge devices, reducing the environmental footprint of AI. This advantage is vital for manufacturing energy-efficient artificial intelligence edge devices, making a direct technological contribution to green AI.

Conversely, the third work in the list addressed the challenge caused by high energy consumption for performing AI computation tasks in IIoT (Industrial Internet of Things) due to the requirement for high-end servers [101]. An intelligent edge computing framework with a heterogeneous architecture was proposed to offload most AI tasks from servers. A novel optimization algorithm was also proposed for scheduling tasks, and an overall reduction of energy consumption of up to 70–80% is estimated on the usage of different strategies, thereby contributing to green AI through technology for energy efficiency improvement contributing to SDG 7 and SDG 9.

On the other hand, Wheeldon et al. [91, 92] dealt with energy-efficient AI hardware design for IoT based on learning automata (propositional logic) aligning with SDG 7. The potential to lower energy consumption than state-of-the-art AI hardware and to outperform the robustness and accuracy of state-of-the-art machine learning algorithms was determined on an extensive evaluation of single and multi-class machine learning datasets. Contributing to SDGs 7 and 9, Yuan [100] introduced a mem transistor with gate-tunable dynamic learning behavior that can adjust its learning capabilities, making it more flexible for AI tasks. Heightened reconfigurability, diverse learning curves, simplified spike-timing-dependent plasticity, and continuous learning are the claimed advantages that offer unique hardware accelerator opportunities for energy-efficient AI and machine learning, especially for neuromorphic computing.

Cluster 3 (blue): Big Data-driven computational advances

Figure 2 depicts the thematic network of Cluster 3, while Table 3 shows the highly cited articles representative of the cluster. Cluster 3 encompasses a range of keywords like neural networks, convolutional neural networks, deep neural networks, learning systems, big data, and data-driven, indicative of high-level computational innovations and their integration into societal frameworks. These technologies are adept at processing and extracting valuable insights from big data, reflecting their integration into societal frameworks. This cluster focuses on the technological aspects of computational methods, such as the intricacies of neural network design or the efficiencies introduced by

Table 3 Top Cited Articles of Cluster 3

Citations	Author(s)	Title	SDG focus
273	Bag et al. [6]	"Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities"	12 RESPONSIBLE CONSUMPTION AND PRODUCTION
134	Sharma et al. [79]	"Recent advances in machine learning research for nanofluid-based heat transfer in renewable energy system"	7 AFFORDABLE AND CLEAN ENERGY
36	Kwon et al. [42]	"Large-area pixelized optoelectronic neuromorphic devices with multispectral light-modulated bidirectional synaptic circuits"	7 AFFORDABLE AND CLEAN ENERGY 9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
4	Li et al. [44]	"AI for social good: AI and big data approaches for environmental decision-making"	13 CLIMATE ACTION
3	Sapignoli [75]	"The mismeasure of the human: big data and the 'AI turn' in global governance"	10 REDUCED INEQUALITIES 16 PEACE, JUSTICE AND STRONG INSTITUTIONS

neuromorphic computing. It also critically assesses their socio-economic ramifications, particularly in handling and analyzing large datasets for informed decision-making. The role of AI in smart power grids, exemplified by big data analytics, transcends technical performance, potentially revolutionizing energy distribution and consumption patterns. This, in turn, could profoundly impact economic structures and resource allocation. Furthermore, the cluster implies a research trajectory exploring the ethical dimensions of AI, privacy concerns related to big data, and the digital divide, thereby ensuring that technological advancements contribute to inclusive and equitable societal development.

Bag et al. [6] addressed the research gap concerning the limited research on reasons for the adoption of big data analytics-powered AI by manufacturing firms. It used institutional theory and resource-based view theory to explain the configuration of tangible resources and workforce skills to drive technological enablement and improve sustainable manufacturing practices to develop circular economy capabilities mapping to SDG 12 (Responsible Consumption and Production). Primary data was collected from 219 automotive and allied manufacturing companies in South Africa. Insights regarding institutional pressures' role in adopting big data analytics-powered artificial intelligence and its effect on sustainable development capability, the moderating effects of organizational flexibility, and industry dynamism were also discussed. On the other hand, Sharma et al. [79] reviewed the applications of different machine-learning techniques for nanofluid-based renewable energy systems aligned with SDG 7 (Affordable and Clean Energy). Artificial neural network-based model prediction using contemporary commercial software is the most sought-after technique. Apart from well-known neural networks, fuzzy and gene-based techniques, ensemble machine learning techniques such as boosted regression, K-means, KNNs, CatBoost, and XGBoost are also gaining popularity. A major concern was identified in users' lack of understanding about the functioning of neural networks and fuzzy-based algorithms (black box techniques). Kwon et al. [42] reported the development of a fully light-driven and scalable optoelectronic energy-efficient neuromorphic circuit using a heterostructure phototransistor and photovoltaic divider, directly contributing to SDG 7 (Affordable and Clean Energy) and SDG 9 (Industry, Innovation, and Infrastructure). Multispectral light-modulated bidirectional synaptic circuits were used for precise, color-sensitive brain-like functions and for recognizing patterns directly through hardware.

Contributing to achieving SDG 13 (Climate Action) and a more sustainable future, Li et al. [44] wrote an editorial piece that attempted to review works published in their special issue as well as addressed four pertinent questions related to the (i) conditions for and (ii) appropriate usage of AI and big data to facilitate environmental decision making, (iii) the extent to which AI and big data serve those at risk of environmental pollution, and (iv) ownership and governance of AI and big data. Important principles of AI for Social Good that may help to distinguish good and bad environmental decisions based on AI and big data technologies were also highlighted. Finally, Sapignoli [75] offered some reflections on the possible effect of 'AI turn,' associated with efforts of the UN for the theme 'AI for Good,' on human rights practices. It is argued that creating new foundations of human belonging and being is in progress, along with efforts of intervention and establishing policies. Four possible emergent phenomena are speculated to be encountered by anthropologists viz. (1) a growing role of data technicians and experts in terms of capacities and the ethical answerability of global governance mapping to SDG 16 (Peace, Justice, and Strong Institutions) (2) a greater share of participation and responsibility of the private sector for human rights and global governance and possible trade-offs of public image (of corporates) over profitability (3) the effect of automatic decision making (that appears invisible) on the targeted population confirming to SDG 10 (Reduced Inequalities) (4) the scenario in which computational calculation and algorithmic interpretation defines our identities and its dynamics with the addition of new data.

BERTopic modeling analysis (RQ2)

BERTopic is crucial for capturing contextualized and semantic representations of words, providing a more nuanced comprehension of the relationships among different themes and topics in literature. The topical content, the association among topics, and the relative significance of respective topics are presented in this section. Table 4 displays the topics and the top words representing each topic (top 10 words based on probability).

Table 4 Topic labels, top words, and exemplary articles

Topic	Keywords and their probability scores	Representative documents	APY
Topic 0: Ethical Eco-Intelligence AI & Sustainability	ai (0.3651), intelligence (0.2762), artificial intelligence (0.2721), sustainability (0.2423), ethics (0.2085), environmental (0.2040), intelligence ai (0.1937), artificial intelligence ai (0.1923), sustainable development (0.1842), ai social (0.1834)	Gao & Liu [26], Conte et al. [16], Shin & Shin [80], Masih and Kaur (2022), Bolte et al. [10]	2021.3
Topic 1: Sustainable Neural Green Computing	energy (0.3421), energy efficient (0.2507), memory (0.2419), computing (0.2347), efficiency (0.2285), deep learning (0.2160), green (0.2118), machine (0.2115), green ai (0.2023), neural network (0.2004)	Ajagekar et al. [2], Yu et al. [99], Mehonic [48], Wu et al. [95], Ferro et al. [23]	2021.9
Topic 2: Ethical Healthcare Intelligence	healthcare (0.4932), health care (0.3660), oral health (0.3224), ai healthcare (0.2951), ethical issues (0.2885), ai health care (0.2718), ai health (0.2637), healthcare decision making (0.2562), healthcare decision (0.2562), ethics ai (0.2472)	Capasso and Umbrello [13], Ducret et al. [20], Richie [66], Pennestrì and Banfi [61], Katirai [36]	2022.0
Topic 3: AI Learning Quest	students (0.4965), behavioral intention (0.4141), ai (0.3773), artificial intelligence (0.3531), intelligence (0.3478), teaching ai (0.3450), learn ai (0.3253), ai steam (0.2956), intention learn ai (0.2956), intention learn (0.2956)	Sanusi et al. [74], Polas et al. [62], Lin et al. [45], Chai et al. [14], Hsu et al. [34]	2022.1
Topic -1: Cognitive AI Innovation	ai, intelligence, artificial intelligence, data, models, dementia, health, cognitive, development, framework	Rutkowski et al. [68–71], Arvind & Sindhu Madhuri [4]	2021.8

This table shows the topic labels, the top 10 words based on probability, and exemplary articles. Topic-1: Cognitive AI doesn't report the probability score as it constitutes the noise of the BERTopic model. Here, APY = Average Publication Year, calculated as the ratio between the sum product of years of publications and the number of publications upon the total number of publications

Topic 0, “Ethical Eco-Intelligence AI and Sustainability,” is the most prominent topic, representing approximately 44% of the corpus. Topic 1, “Sustainable Neural Computing,” is the 2nd highest prominent topic, with approximately 32%. Topic 2, “Ethical Healthcare Intelligence,” and Topic 3 “, AI Learning Quest,” are the 3rd highest prominent topics, with 3% of the total research output.

The distance between data points on the plot confirms the distinctness of the topics [78]. Figure 3 in Appendix shows the inter-topic distance map, confirming the distinctness of the topics.

Topic 0: Ethical eco-intelligence AI and sustainability

This topic contributes to ongoing discussions about sustainable technological progress and responsible AI use. For example, Gao and Liu’s [26] exploration of the ethical eco-intelligence landscape investigated how technology readiness, perceived usefulness, and green consciousness impact users’ inclination to adopt AI Sports. Through the analysis of 670 valid questionnaires using cross-sectional surveys and structural equation modeling, the study disclosed that technology readiness directly influences users’ perceived usefulness of AI Sports. Additionally, it revealed that green awareness significantly affects perceived usefulness, bringing attention to a research gap in consideration of green consciousness in this specific context. Emphasizing the pivotal role of perceived usefulness, the study highlights its significance in predicting users’ willingness to embrace AI Sports for sustainable development, thereby offering valuable insights into the ethical discourse of eco-intelligence. Conte et al. [16] stress the imperative to optimize strategies for sustainable technological advancement, focusing on the escalating production of productivity-enhancing technologies. Their work highlights the critical role of AI in this context, presenting results from laboratory investigations dedicated to the responsible use of AI for sustainable technological improvement. Shin and Shin [80] propose a human-centered AI approach within Topic 0, offering both a theoretical foundation and practical guidelines to achieve green and sustainable AI. Their goal is to make a substantial contribution to discussions surrounding the environmentally conscious use of AI, advocating for a more sustainable and greener approach. Bolte et al. [10] highlight the distinctive nature of ‘Sustainable AI’ within Topic 0, emphasizing its focus on the ecological costs of AI often overlooked in policy discussions. They discussed a joint report on Sustainability Criteria for Artificial Intelligence, positioning it as the first AI ethics document centralizing sustainability considerations. The authors critique current approaches, advocating for an ‘ethics of desirability’ framework and a reconceptualization of sustainability as a property of complex systems. They offer directions for further research, questioning the effectiveness of current conceptual approaches in bringing about a paradigm shift in AI ethics, particularly concerning ecological concerns.

Topic 1: Sustainable neural computing

Our next topic spearheads discussions on enhancing energy efficiency and environmental friendliness in neural computing systems. Representative articles offer insights through innovative approaches and practical demonstrations, contributing to ongoing efforts for greener AI applications. For instance, Ajagekar et al. [2] make a notable contribution by introducing an AI-based control framework for greenhouses, demonstrating a significant 57% reduction in energy consumption compared to traditional methods. This underscores the potential impact of advanced AI techniques on sustainable agricultural practices. Yu et al. [99] contribute valuable insights into sustainable neural computing by exploring the energy efficiency of AI models in medical applications. Their study highlights the XGB algorithm as a leader in accuracy, run time, and energy efficiency, emphasizing the importance of energy-efficient AI models in medical contexts and promoting environmentally friendly neural computing applications. Mehonic [48] addresses energy challenges in AI-driven applications by advocating for post-CMOS technologies, particularly memristor technology, as a solution for energy-efficient AI systems. This perspective emphasizes the need for hardware innovations to meet the unsustainable energy demands of current AI systems, aligning with the overarching goal of sustainable neural computing. Wu et al. [95] showcase the ALL-resistive neuromorphic computing (ARNC) platform, presenting a tangible example of a system optimized for energy-efficient AI-Inference. This platform integrates Restive-gate FinFET memory with features such as 4-bit-per-cell RG-FinFET memory arrays, ReLU with linear output responses, and an ADC with low power consumption. Their work contributes to the field by offering a practical demonstration that advances sustainable neural computing efforts. Finally, Ferro et al. [23] contribute to the sustainable neural computing dialogue by evaluating the energy efficiency of machine learning algorithms. Their study identifies factors influencing energy consumption in ML algorithms, emphasizing the importance of parameter choices in adopting greener strategies for AI. This research adds valuable insights to the discourse on energy-efficient neural computing and the pursuit of environmentally friendly AI applications.

Topic 2: Ethical healthcare intelligence

Topic 2 delves into the ethical considerations and sustainable deployment of AI in healthcare, addressing issues such as nudging, environmental impact, oral health, laboratory medicine, and governmental investments. For example, Capasso and Umbrello [13] spotlight the ethical challenges in AI-driven healthcare, advocating for the value-sensitive design approach to align systems with ethical values. Ducret et al. [20] explore the potential positive impacts and challenges of AI in oral health, emphasizing the need for a systematic assessment to guide evidence-based sustainable deployment. Richie [66] uniquely emphasizes the environmental impact of AI in healthcare, proposing health, justice, and resource conservation as criteria for ethical and sustainable AI. Pennestrì and Banfi [61] focus on ethical challenges in pathology and laboratory medicine, underscoring the importance of defining ethical norms for AI technologies. Katirai [36] offers a case study on Japan's AI investments, revealing uneven attention to ethical principles and emphasizing the urgency of a comprehensive approach to address the ethical complexity of digital health technologies in healthcare. Together, these insights contribute to the ongoing discourse on responsible and ethically sound AI practices in the healthcare sector.

Topic 3: AI learning quest

Topic 3 investigates the multifaceted landscape of AI learning methodologies, encompassing various dimensions such as teacher perceptions, educational techniques, instructional design, student perceptions, and interdisciplinary application. Sanusi et al. [74] delve into teachers' perceptions and behavioral intentions to teach AI, considering factors like AI anxiety, perceived usefulness, and confidence. Their findings emphasize the influence of AI for social good and confidence in the relationships in the proposed model, highlighting the importance of incorporating AI-related aspects into teacher professional programs. Polas et al. [62] explore the influence of AI technologies on education in the post-COVID-19 context, particularly focusing on green AI and its significance in education 4.0. Lin et al. [45] address the challenges of teaching AI in schools, presenting effective instructional design components based on experienced teachers' perspectives, including obstacles to teaching AI, interactive design thinking processes, and orienteering AI knowledge for social good. Chai et al. [14] shift the focus to students, examining their perceptions of learning AI. Their research model integrates the theory of planned behavior and self-determination theory, revealing the interrelationships among factors like AI knowledge, programming efficacy, autonomy, AI for social good, and learning resources. The findings offer insights into designing AI curricula that consider students' needs and satisfaction. Hsu et al. [34] contribute by evaluating the learning effectiveness of the MIT App Inventor platform and its Personal Image Classifier tool in an interdisciplinary AI-STEAM course. The study confirms the course's suitability for 7th-grade students, showcasing significant progress in electromechanical concepts and image recognition knowledge. The research provides valuable guidance for the development of sustainable AI-STEAM courses, emphasizing factors like active learning and self-efficacy. Together, these articles offer comprehensive perspectives on AI learning, encompassing both educators and students, and contribute to the ongoing quest for effective and sustainable AI education.

Topic-1: Cognitive AI innovation

The final topic unfolds with a series of papers by Rutkowski et al., focusing on the application of AI for social good in early-onset dementia prediction. Rutkowski et al. [68] present an efficient machine learning method, including EEG-wearable-based signal analysis, achieving promising results with 90% median accuracies for random forest and fully connected neural network classifier models. Building on this, Rutkowski et al. [71] report developments in EEG-derived theta-band fluctuations examination, emphasizing the social benefits of AI application in early-onset dementia prognosis. In Rutkowski et al. [70], the authors extend their work, employing machine learning algorithms for neuro-biomarker development to enhance the well-being of individuals with disabilities. They discuss a pilot study using EEG-based passive brain-computer interfaces to forecast mild cognitive impairment, showcasing the critical utilization of AI for early-onset dementia prognosis. Rutkowski et al. [69] delve into the practical application of machine learning for elderly adult dementia onset prediction, reporting promising results in facial emotion implicit-short-term-memory learning experiments with median accuracies near 90%. Their work establishes a behavioral and cognitive biomarker candidate for dementia diagnostics. Arvind & Sindhu Madhuri [4] introduce an AI-based innovation detection model for complex data communication systems, emphasizing its revolutionary approach to identifying opportunities for innovation. The model utilizes AI-assisted data mining to automate the detection of patterns and correlations in large datasets, aiding organizations in identifying areas for innovation, such as new product development in healthcare and tailored services in the retail sector. Overall, these contributions advance the intersection of cognitive AI innovation and social good, particularly in enhancing healthcare outcomes and fostering innovation in various sectors.

Temporal evolution of topic trends

The yearly temporal evolution of topics based on the number of articles published on each topic within Green AI research is visualized in Fig. 4 in Appendix. It is observed that more publications belong to topic-0 (Ethical Eco-Intelligence) and topic-1 (Sustainable Neural Computing), and these topics are the most active research strands. The topical trends derived from the number of articles in each topic and their year of publication are depicted in Fig. 5 in Appendix.

A closer examination of the figures reveals that the evolution of Green and Sustainable AI topics unveils a dynamic landscape shaped by shifting priorities and emerging trends over time. Cognitive AI Innovation emerged as a focal point from 2016 onwards, witnessing steady growth before surging in prominence by 2023, reflecting an intensified focus on pioneering AI approaches tailored to sustainability challenges. Concurrently, Ethical Eco-Intelligence garners increasing attention, particularly from 2018 onwards, indicating a growing recognition of the ethical imperatives inherent in eco-intelligence applications, with exponential growth seen in recent years. Sustainable Neural Computing experiences gradual but notable growth, with spikes in 2021 and 2023, signaling a rising interest in sustainable computing solutions driven by neural networks.

Moreover, our analysis reveals a growing intersection between ethics, healthcare, and AI, exemplified by the ascent of Ethical Healthcare Intelligence, showing sporadic mentions but a notable increase in recent years. Finally, the narrative unfolds with AI Learning Quest, initially demonstrating modest mentions but experiencing an uptick from 2020 onwards, underscoring a burgeoning interest in AI-driven learning initiatives within the sustainability domain. Together, these extracted topics illuminate the multifaceted evolution of Green and Sustainable AI research, reflecting the field's increasing complexity and the diverse avenues of inquiry driving advancements in sustainable technological innovation.

Conclusions with implications

Thematic analysis using keywords co-occurrence and BERTopic modeling were employed in tandem in our study to analyze Green and Sustainable AI literature, each contributing distinct methodological strengths. The thematic analysis offered a structured and systematic approach to identifying explicit themes, ensuring that the primary areas of research were clearly defined and understood (RQ1). In contrast, BERTopic modeling brought a nuanced depth to the analysis by leveraging context-aware natural language processing techniques (RQ2). This method was particularly adept at uncovering the subtle, often overlooked relationships between topics, adding a layer of sophistication to the thematic structure identified by thematic analysis.

The bibliometric analysis of Green and Sustainable AI research in this study identifies three pivotal thematic clusters, each representing a unique facet of the field's evolution (RQ1). Responsible AI for Sustainable Development (Cluster 1) underscores a commitment to integrating sustainable development and ethical frameworks into AI. This cluster reflects a focus on developing AI technologies that are environmentally conscious and ethically aligned, with significant advancements in energy-efficient hardware and computing technologies. The cited works within this cluster demonstrate a dedication to responsible innovation, advocating for AI that promotes ecological balance and societal welfare, thereby contributing to a more sustainable future. Advancements in Green AI for Energy Optimization (Cluster 2) emphasizes technological enhancements aimed at minimizing AI's energy consumption. This cluster highlights the synergy between AI and sustainable energy practices, focusing on green computing and energy-efficient algorithms. It points towards a paradigm shift in AI development, prioritizing computational efficiency and environmental sustainability. The cluster's discourse centers around practical strategies for reducing the computational cost of AI, showcasing a commitment to environmental stewardship in the realm of technology. Big Data-Driven Computational Advances (Cluster 3) explores the intersection of AI with big data, emphasizing both the technological advancements and the socio-economic and environmental implications. This cluster captures a broad spectrum of research, from enhancing computational methods to understanding the societal impacts of AI, including ethical considerations and privacy concerns. The publications in this cluster highlight the importance of a balanced approach that navigates technological innovation alongside societal needs and environmental concerns, advocating for a comprehensive and responsible development of AI technologies.

Our study harnesses BERTopic modeling to dissect the vast domain of Green and Sustainable AI literature, unveiling five distinct topics (RQ2). Ethical Eco-Intelligence AI and Sustainability (Topic 0) signifies the growing field of ethical considerations in AI with a focus on eco-intelligence. Studies within this topic delve into the intricacies of user perception and the imperative role of green consciousness in technology adoption. Findings underscore the necessity of integrating ethical deliberations with technological readiness and usefulness, particularly in niche areas like AI Sports. Sustainable Neural Computing (Topic 1) emerges as a pivotal theme, concentrating on the development of energy-efficient and environmentally friendly neural computing systems.

Representative studies present groundbreaking methods and applications, such as energy-saving AI frameworks for greenhouses and medical applications, underscoring the sector's potential to reduce energy consumption. The emphasis on innovative hardware technologies like memristor technology and the ALL resistive neuromorphic computing platform points to a critical direction in sustainable technology, aiming for substantial energy reductions in AI operations. Ethical Healthcare Intelligence (Topic 2) addresses the ethical quandaries and sustainable deployment strategies in AI-driven healthcare. Diverse studies cover a range of issues, from nudging and environmental impacts to specific healthcare domains like oral health and laboratory medicine. The discourse pivots around aligning AI with ethical norms, emphasizing systematic assessments and the need for comprehensive ethical frameworks. It brings to light the multifaceted challenges and opportunities in realizing ethical and sustainable AI in healthcare. AI Learning Quest (Topic 3) explores the evolving landscape of AI education and learning methodologies. Studies on this topic shed light on perceptions, intentions, and methodologies from both the educators' and students' perspectives. They underscore the importance of integrating AI into educational curricula and teaching methodologies while aligning with concepts of social good and sustainability.

When examining the results of RQ1, RQ2, and RQ3, the intersection and divergence of themes and topics provide the following insights and recommendations for the Green and Sustainable AI landscape:

1. The intersection of Ethics and Sustainability: Both methodologies demonstrate the significant overlap between ethical considerations and sustainability in AI. The Responsible AI for Sustainable Development (Cluster 1) from RQ1, along with "Ethical Eco-Intelligence (Topic 0)" and "Ethical Healthcare Intelligence (Topic 2)" from RQ2. While thematic analysis categorizes this as a core theme, BERTopic modeling provides specific insights into smaller discussion topics in healthcare and healthcare ethics. This aligns with SDG 3 (Good Health and Well-being) through its focus on healthcare and healthcare ethics and with SDG 16 (Peace, Justice, and Strong Institutions) by advocating for ethical frameworks and systematic assessments (RQ3).
2. AI and Big Data for Societal Impact: Big Data-Driven Computational Advances (Cluster 3)" suggests the use of AI and big data to address technological innovation while considering socio-economic and societal needs. Improving socio-economic impact through technological advancements supports SDG 8 (Decent Work and Economic Growth) and SDG 9 (Industry, Innovation, and Infrastructure). Within this, BERTopic modeling reveals the emerging trend "Learning Quest," which is aligned to SDG 4 (Quality Education), such as enhancing educational curricula with ethical AI considerations (RQ3).
3. Advancements in Green AI Technologies and Energy Optimization: The emphasis on reducing energy consumption and enhancing green computing in "Advancements in Green AI for Energy Optimization" (Cluster 2) with "Sustainable Neural Computing" (Topic 1) supports SDG 7 (Affordable and Clean Energy) and SDG 12 (Responsible Consumption and Production) through the promotion of energy-efficient algorithms and hardware. Technology firms and university researchers should focus on green computing technologies to build energy-efficient algorithms and hardware, with policymakers incentivizing developments. Such strategies align with SDG 9 (Industry, Innovation, and Infrastructure) and SDG 13 (Climate Action) by fostering innovation in service of environmental stewardship (RQ3).

Implications for various stakeholders

International bodies like the UN

While AI can be of tremendous use in various vital applications like crisis interventions, its effect on human rights practices should be rigorously researched to stay on track toward 'AI for good.' The UN and similar bodies should guide the integration of sustainable development and ethical frameworks into AI, as emphasized in Cluster 1: Responsible AI for Sustainable Development. This cluster indicates a focus on leveraging AI for complex environmental and developmental challenges, underscoring the need for an integrated approach to ethics and sustainable development in AI policy-making (Fig. 3 and Table 1 in the document).

The following aspects should be addressed.

- The scenario in which the dominance of technologists and technology-developing firms (including private ones) in deciding the legal, ethical, and governance aspects of AI should be cautiously tackled, and there should be a substantial effort to assign roles, accountability and responsibility among technology experts, tech firms, legal and ethical experts, anthropologists, administrative experts.
- Deployment of AI technology in crisis interventions and other applications should be decided after a rigorous study of the effect of automatic decision-making on targeted populations to avoid possible compromise in human rights.
- The effect of dynamics (growth) of auto-generated data on automatic interpretations and decision-making should be carefully considered before making policies and guidelines for constituent nations regarding AI.
- A concerted green AI approach should be encouraged based on green AI principles and recommendations towards 'AI for social good' from relevant evolving literature, as mainstream design, development, and governance principles and laws are not sufficient for pursuing green or sustainable AI for humanity.

National level policymakers

The multitude of possibilities offered by AI should be embraced, but mechanisms to curb its negative impact and possible misuse should be in place well before humanity encounters harmful effects. National policymakers must address the ecological and energy consumption challenges of AI as highlighted in Cluster 2: Advancements in Green AI for Energy Optimization and the socio-economic implications as depicted in Cluster 3: Big Data-Driven Computational Advances. The recommendations should include formulating and enforcing robust, green, AI-compliant ethical, legal, and regulatory frameworks, fostering an industrial ecosystem for energy-efficient hardware, and ensuring that national strategies align with these global sustainability goals. The following suggestions can be considered.

- As green and sustainable AI requires formulation of more diligent, global green AI or sustainable AI-compliant ethical, legal, and regulatory frameworks compared to existing insufficient frameworks (in some countries) for traditional AI, concerted efforts to ensure the formulation and enforcement of such frameworks should be there.
- An R&D, as well as an industrial ecosystem, should be fostered to develop and market heavy computation competent and compliant energy-efficient hardware for AI devices and systems that can make significant contributions towards techno-economic-environmental pillars of green or sustainable AI.

- Especially address the assignment of roles, responsibilities, and legal liabilities of technologists, tech firms, and other vital stakeholders within the nation in compliance with international guidelines and norms provided by agencies like the UN.
- Concerns raised in connection with the social and individual level impacts of AI and anything applicable to specific localities or regions should be specifically addressed rather than trying to fit them into a common template. However, efforts to integrate such issues into one umbrella to provide better solutions in the long run have to continue.
- Pressing issues like data security, privacy, and issues raised by automatic interpretation for decision-making in governance-related applications should be given topmost priority. AI deployments for such applications should be attempted only after rigorous study and upon approval of human rights experts, anthropologists, judicial mechanisms, etc.
- To ensure progress toward green AI, special public–private partnership models should be in place rather than relying on traditional PPP models.
- Relevant government agencies and law enforcement agencies should build an expertise pool and upgrade it with the pace of technological advancement of AI to ensure misuse affecting socio-techno-economic-environmental fronts of green or sustainable AI.
- Public awareness about the possible positive and negative impacts or misuse should be increased and upgraded with the evolution of technology, and feedback should be taken into account to estimate the level of social acceptance before any serious decision-making.

Technology firms

For technology firms, the BERTopic modeling analysis (RQ2) emphasizes the importance of understanding the nuanced relationships between various themes and topics in Green and Sustainable AI (Table 4). Firms should focus on legal liability, policy alignment, and the development of energy-efficient and innovative hardware. They need to be at the forefront of adopting and promoting green AI principles, ensuring their strategies and products contribute to the broader goals of sustainable and ethical AI.

With the possible invasion of AI into almost all spheres of life, technology firms will be key stakeholders to bear the responsibility of and reap the maximum benefits of the technology. Technology firms should consider at least the following suggestions for their responsible contribution towards the Green and Sustainable AI initiative.

- As more power and responsibility are expected to be bestowed on AI technology firms, more legal liability and answerability are also bound to be there, and firms should be very careful to formulate their own organizational policies and employee legal bindings in alignment with the national and global laws and regulations.

- As the profit-reputation trade-off is forewarned in such a scenario, top management should exhibit prudence and maturity to keep away greed while eyeing to maximize profit. It should make a conscious effort to keep employees motivated against any possible illegal or criminal activities.
- Along with the advancement of algorithms and software, data generation and storage technologies, as energy efficient computational hardware requirements are also vital and there is a market potential for such development, traditional hardware technology firms and AI firms can consider diversification or expansion strategies to grab the opportunity.
- As a myriad of new business opportunities, including those in 'governance' is there, the ability to hire human resources, capacity building, and achieve flexibility and readiness very swiftly to embrace a plethora of opportunities that can drastically materialize and to the ability to abide by the commitment towards green or sustainable AI will be a key determinant of success in coming times.

Limitations of this study

Several factors constrain our study. Firstly, the scope of literature based on the database selected could limit comprehensiveness, as the exclusion of certain journals, conferences, or languages might overlook relevant research in the field. Secondly, while the combination of thematic cluster and BERTopic modeling provides a robust analysis, each method has inherent limitations in capturing the complexities of the field, potentially leading to an oversimplification of some aspects. Also, the subjective nature of interpreting themes and topics, even with advanced modeling techniques, could introduce biases or misinterpretations, underscoring the need for critical review and validation by experts in the field. Additionally, as this study uses citations to the publications related to identified thematic clusters and topics as a proxy for impact, this study is prone to all the possible limitations of citation analysis such as possible citation biases such as affirmative citation bias that leads to proliferation of misconceptions too among the well-received ideas as well as subjugation of criticisms or non-affirmative research [43], practices such as lack of attribution or palimpsestic syndrome [49] misattributions of citations or obliteration by incorporation [46, 50]. These limitations highlight the importance of considering this study as a snapshot in time in a rapidly evolving landscape of AI research (Additional file 1).

Appendix

See Figs. 3, 4, 5.

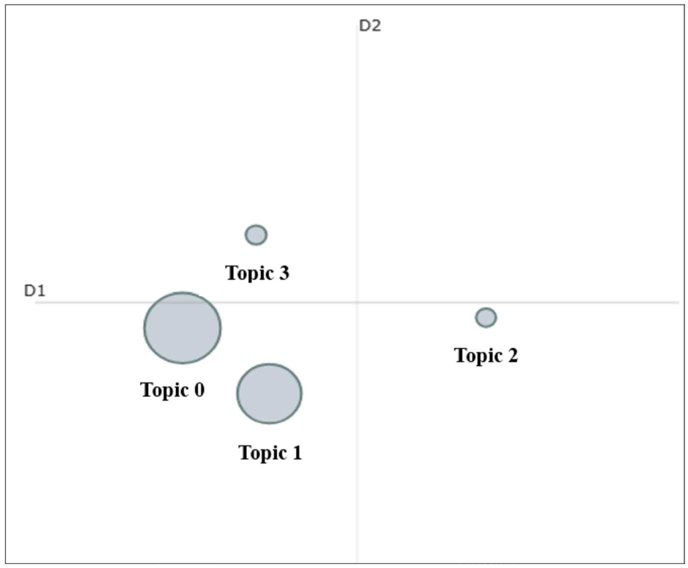

Fig. 3 Inter-topic distance map (excluding noise)

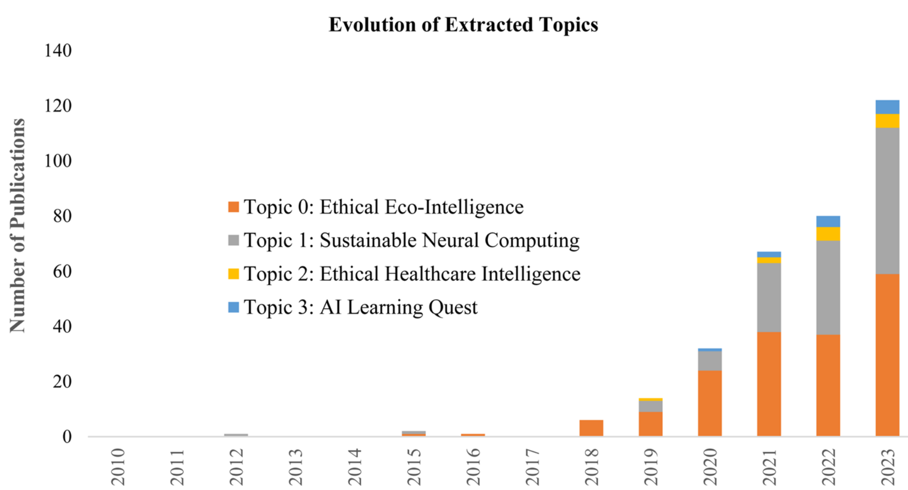

Fig. 4 Evolution of extracted topics (including noise)

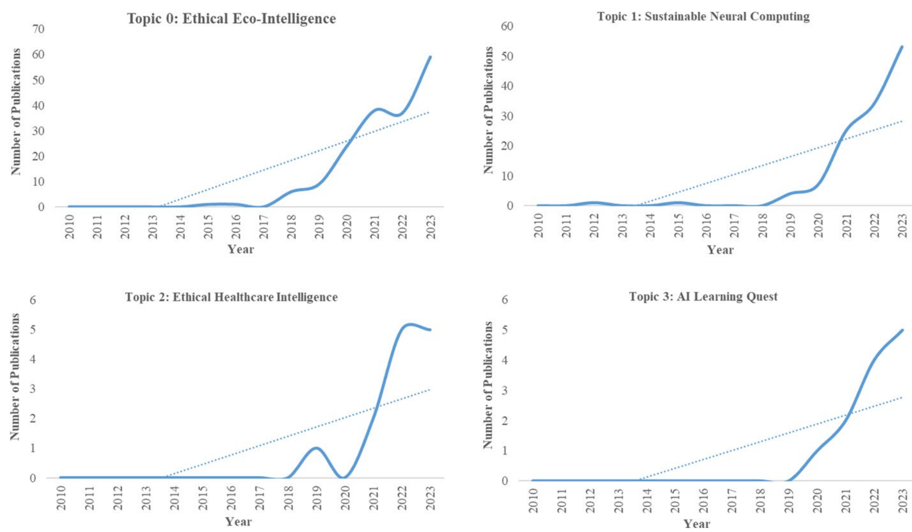

Fig. 5 Publication trend of extracted topics

Supplementary Information

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Additional file 1. Dataset used in this study.

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Author contributions

RR, DP, HL contributed to the conception and design of the work, interpretation of data. CK contributed to the data acquisition, curation, and analysis. RR, DP, HL, CK, KG, and PN have drafted the work and substantively revised it. All authors read and approved the final manuscript.

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Availability of data and materials

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Declarations

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Consent for publication

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Competing interests

The authors declare that they have no competing interests.

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