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Assessing the current landscape of AI and sustainability literature: identifying key trends, addressing gaps and challenges

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Abstract

The United Nations' 17 Sustainable Development Goals stress the importance of global and local efforts to address inequalities and implement sustainability. Addressing complex, interconnected sustainability challenges requires a systematic, interdisciplinary approach, where technology, AI, and data-driven methods offer potential solutions for optimizing resources, integrating different aspects of sustainability, and informed decision-making. Sustainability research surrounds various local, regional, and global challenges, emphasizing the need to identify emerging areas and gaps where AI and data-driven models play a crucial role. The study performs a comprehensive literature survey and scientometric and semantic analyses, categorizes data-driven methods for sustainability problems, and discusses the sustainable use of AI and big data. The outcomes of the analyses highlight the importance of collaborative and inclusive research that bridges regional differences, the interconnection of AI, technology, and sustainability topics, and the major research themes related to sustainability. It further emphasizes the significance of developing hybrid approaches combining AI, data-driven techniques, and expert knowledge for multi-level, multi-dimensional decision-making. Furthermore, the study recognizes the necessity of addressing ethical concerns and ensuring the sustainable use of AI and big data in sustainability research.

Keywords: Sustainability, Artificial intelligence, Data-driven method, Topic modeling, BERTopic

Introduction

Sustainability is becoming increasingly important, particularly following the establishment of the 17 Sustainable Development Goals (SDGs) by the United Nations (UN). The call for sustainability is now more resounding and pressing than ever. The 17 SDGs emphasize the necessity for global and local efforts to confront disparities, inequalities, and their far-reaching consequences on individuals and society [37, 42, 118]. They call for action to implement measures toward a fair and equitable world, focusing on addressing social, environmental, and economic dimensions. Technological advancements, such as the Internet of Things (IoT), Information and Communication Technology (ICT), blockchain, Big Data (BD), sensors, Artificial Intelligence (AI), and data-driven methods, are increasingly regarded as promising solutions for addressing sustainability-related problems. They can integrate various aspects of sustainability, enhance collaboration among stakeholders, improve resource management, expedite innovation, foster cross-industry applications, and enable long-term sustainable planning [62, 111, 154, 336]. A systematic and collaborative approach to integrating data, technology, and AI can mitigate social and economic inequalities and reduce ecological damage. This is achieved through the development of data-driven solutions, the creation of quantitative models to optimize energy and resource usage, the implementation of policies and regulations driven by informed decision-making, online monitoring of social, environmental, and economic indicators, and the optimization of economic activities to minimize carbon emissions [30, 336, 341].

A systematic approach founded on a thorough understanding of various sustainability-related topics is lacking to the best of our knowledge. Such an approach is important for creating a comprehensive and robust framework to integrate sustainable practices, policies, guidelines, regulations, and monitoring to help achieve sustainability objectives, such as embracing carbon–neutral technology and establishing a Circular Economy (CE). There are three primary research gaps: First, at the local level, there is a lack of understanding regarding the practical implementation of new technologies and the use of AI within institutions, local businesses, healthcare, and education. It encompasses addressing local challenges, resource management, and contributing to governance, all while reducing adverse impacts on communities. Second, at the global level, it is unknown how technology and AI can effectively integrate to address global-scale problems, such as establishing a resilient and sustainable Supply Chain (SC), adopting a CE, preserving biodiversity, and mitigating climate change [142, 147, 269, 294]. Third, integrating local and global sustainability concerns within an integrated strategy remains unclear. This strategy aims for global equity, inclusive growth across all sectors, and the contribution to a healthier and more collaborative world. In addition to these existing research gaps, another critical concern pertains to the integration of AI. These concerns encompass AI regulations, ethics, the digital divide, security, AI's societal impact [97], and whether AI aligns with sustainability principles [73]. This alignment raises questions about whether AI contributes positively to sustainability or inadvertently accelerates resource depletion and reinforces biases.

To address these issues, this paper delves into the current state of AI and sustainability research, specifically focusing on the application of AI to address sustainability-related challenges at both local and global levels [276]. This exploration is carried out by answering the following research questions:

1) What is the state of research regarding AI and sustainability-related questions, trends, and collaboration between countries? A scientometric analysis of the literature sample addresses this question (see Ch. "Bibliometric Insights").
2) What are the major implementation areas of technology and AI applications for sustainability? Topic modeling is performed to answer this question (see Ch. "Bibliometric Insights").
3) How can different data-driven and AI-based methods utilized to address sustainability-related challenges be categorized? An analysis of the literature findings from

Ch. "Bibliometric Insights" is conducted to tackle this question (see Ch. "AI, ML, and Data-Driven Methods").

4) What are the dimensions of sustainable AI, considering its potential impact and implications? This question is answered by analyzing the literature results from Ch. "Semantic Analysis of Key Topics" through topic modeling (see Ch. "Sustainable Big Data and Analytics," "Sustainable AI Characteristics and Challenges," and "Sustainable Human AI Ecosystems").

Addressing these questions improves understanding of AI's status, potential, and challenges in promoting sustainable practices and solving multi-dimensional sustainability problems. This study offers a comprehensive overview of AI and sustainability literature (see Ch. "Publication Landscape Analysis"), the research collaboration among countries (see Ch. "Country-Wise Analysis"), and the current and emerging AI and data-driven approaches in sustainability research. It systematically explores AI methodologies applied across various sustainability applications (see Ch. "AI, ML, and Data-Driven Methods"), emphasizing the need for method integration to make decisions effectively and highlighting challenges with AI and its sustainable use (see Ch. "Sustainable Big Data and Analytics," "Sustainable AI Characteristics and Challenges," and "Sustainable Human AI Ecosystems").

Background: artificial intelligence for sustainability

Over the past decade, advancements in AI have made significant strides toward effectively contributing to all facets of sustainability and addressing complex sustainability-related challenges. AI encompasses a broad spectrum of capabilities, with machines programmed to think and learn human-like cognitive abilities. These capabilities include environmental perception, information processing, decision-making, and taking action to achieve specific goals [277]. According to the European Union's (EU) definition, AI entails "intelligent behavior that involves the analysis of the environment and the execution of actions, often with some degree of autonomy, to attain specific objectives" [334].

Realizing the potential of AI in achieving sustainable growth and meeting sustainability goals presents a challenge due to the multidimensionality of social, environmental, and economic sustainability issues. These challenges necessitate a comprehensive understanding of the interconnected nature of various problems [177, 280] and the collaboration of communities, nations, and diverse stakeholders. Governments, political and business leaders, innovators, scientists, and representatives from various industries worldwide are called upon to develop systematic efforts with a holistic and interdisciplinary approach to effectively address these challenges [300, 303, 342]. A collective endeavor holds the potential to foster sustainable practices in social and economic decision-making, energy consumption, resource utilization, manufacturing processes, and other sustainability-related objectives, all of which have long-term implications for overall societal well-being.

Furthermore, harnessing the potential of AI for sustainable growth and achieving sustainability goals requires several prerequisites: (1) Establishing a sustainable digital infrastructure; (2) implementing and developing robust and ethical AI solutions for both local and global contexts; (3) addressing the regulatory and sustainability concerns associated with AI; and (4) ensuring the development of environmentally friendly AI and preventing monopolization of AI resources and technology. It is essential to facilitate responsible AI practices, promote transparency, and consider AI implementation's long-term social and environmental implications to maximize its positive impact.

Implementing AI methods poses various challenges, including their applicability, efficiency, performance, explainability, contextual understanding, associated risks, systematic frameworks for their application in sustainability tasks, the adaptability of their models in response to changing external factors, and user acceptability. Furthermore, the role of AI sparks essential discussions concerning its utilization in decision-making processes and the appropriate way AI should be employed. This leads to deliberations on whether AI should function as an assistant in decision-making or act autonomously as part of a multi-agent system. These concerns extend to AI-based decision-making within integrated systems, where multiple decisions across different integrated system components are exclusively determined by AI models, potentially leading to error and bias propagation. In such instances, the interrelated decision-making system could generate ripple effects that impact overall outcomes. Errors or biases originating at one stage may propagate throughout the system, influencing subsequent decisions and potentially resulting in incorrect or suboptimal results. Another essential aspect of utilizing AI is to address the trade-offs [112] associated with the three dimensions of sustainability (social, environmental, economic) at both global and local levels. This involves striving for an optimal balance between these trade-offs by leveraging AI to enhance decision-making. AI methods play a crucial role in the analysis of complex datasets, the prediction of outcomes, and the recommendation of solutions that maximize the benefits across all dimensions of sustainability [187].

Several studies focus on sustainability and AI-related research, particularly on efficient applications and challenges, including the fulfillment of SDGs [30, 70, 92, 341]. Kar et al. [152] present a systematic literature review on AI's impact on the sustainability of technical challenges, social issues, and environmental causes. Falk and van Wynsberghe [90] propose three criteria for ensuring the appropriate application of AI for sustainability: "Monitoring and information provision, sustainability analysis of the application, and an action component contributing to a sustainability goal." Nishant et al. [232] discuss the challenges and limitations of AI for sustainability, emphasizing environmental governance, industrial environmental performance, and risk reduction. Galaz et al. [97] examine the implications of AI interacting with society as a socio-technical system and using responsible AI. Khakurel et al. [159] conducted a study on the long-term impact of AI on sustainability in various dimensions in a previous literature search along with a focus group study. S. R. Wu et al. [353] discuss the impact of AI and other technologies in smart cities, SCs, and energy systems. Kopka and Grashof [172] conducted an empirical study to investigate the impact of AI on energy consumption and found that AI has the potential to both conserve and consume energy.

Various concerns related to the effective use of AI must be considered and addressed. These include AI integration, regulations, governance, the digital divide, potential threats, security, and the overall value derived from AI [97, 155]. It is imperative to assess whether AI effectively contributes to sustainability goals or if AI-based decisions unintentionally undermine these objectives. For instance, a critical evaluation of AI-based decisions should consider whether they result in the depletion of resources, favor powerful entities due to inherent design biases, or introduce contradictions in sustainability tasks. It is paramount to ensure that AI does not facilitate monopolies through biased decisions or intentional design aimed at monopolistic advantages. These pivotal issues must be addressed to guarantee that AI outcomes align with sustainable principles and benefit society [73]. Several literature reviews are available on the topic of AI and sustainability, but they are mostly focused on specific aspects such as sustainability in manufacturing [131, 134], urbanization and city planning [175], and smart and sustainable farming [11]. However, no research on the overall landscape of AI and sustainability research is currently available. A topic modeling and text analysis approach is used to study a broader range of sustainability research to address this gap.

Methods

The workflow to comprehend the current landscape of AI and sustainability research is divided into three steps and visualized in Fig. 1. First, a literature search was conducted using specific search strings that match the titles or keywords of the literature. In the second step, data and text analysis, we conducted four types of analysis: (1) A publication landscape and trend analysis was completed. (2) A country-wise analysis of countries emphasizing sustainability and AI research, as well as collaborations among countries, was performed. (3) A keyword analysis of the searched literature examined different sustainability aspects in co-occurrence network modules. The focus was identifying significant keywords and a network-based approach for analyzing the interconnection between sustainability, AI, and technology terms (co-occurrence networks). Module identification in co-occurrence networks of keywords and enrichment analysis was involved. (4) A semantic analysis of key topics involved topic modeling using the BERTopic model to distinguish key topics within the searched literature and clustering

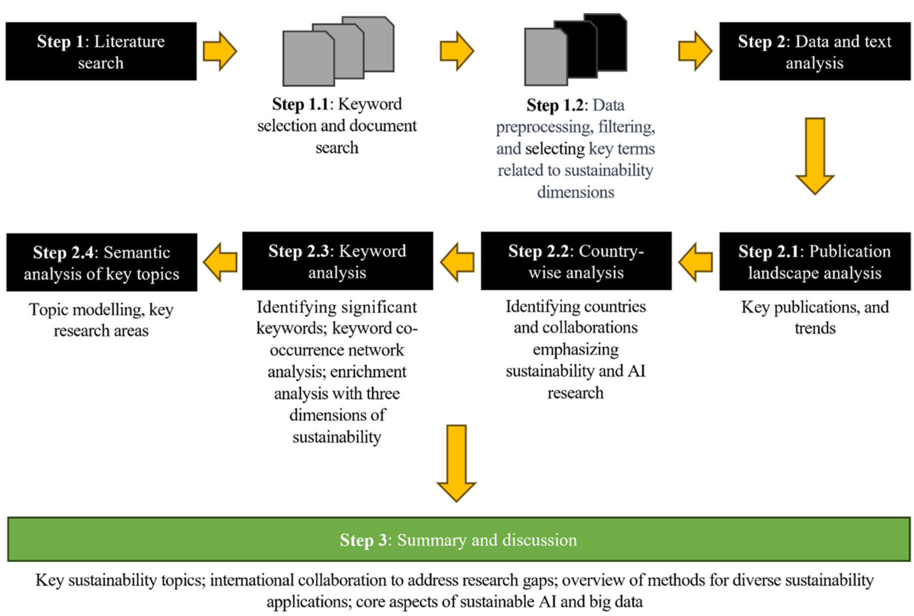

Fig. 1 A Schematic View of the Literature Analysis

identified topics and representative papers. The results obtained in steps (3) and (4) were utilized to explore various AI and data-driven methods and models applied in diverse social, environmental, and economic sustainability applications. Additionally, they were used to examine the topics that underscore fundamental AI-related concerns relevant to sustainability. Third, we summarized the results and discussed key methods and sustainable AI challenges.

Literature search

A comprehensive search in the Scopus database, which offers access to high-quality publications spanning a wide spectrum of scientific, engineering, humanities, and business disciplines, was conducted. This database provided ample literature from key sustainability journals for the scientometric analysis. Although searching in additional databases might have augmented the search, we focused exclusively on Scopus due to the limitations of access and processing speed associated with other databases our university does not subscribe to. The following search string was used to search the title or keywords of the documents:

s = (sustainability OR sustainable) AND ("artificial intelligence" OR ai OR "machine learning" OR "data driven" OR data OR analytic OR forecast OR algorithm OR optimization OR "data mining")

The search was not restricted by time period, publication type, or scientific discipline. The only requirement was that the documents must be in English. In total, a sample of 1,982 documents was collected, each containing various types of metadata, including title, abstract, affiliations, and keywords. The search was restricted to the document titles and keywords aiming to collect documents that primarily focus on issues related to sustainability, particularly those that involve the applications of AI and Machine Learning (ML). The search was intended to ensure the selected documents are closely aligned with the intersection of sustainability problems and AI and ML technologies independent of any specific research area utilized. From the obtained document keywords, those conceptually linked with the three aspects of sustainability were extracted. The authors selected these keywords manually, which are important for the broader understanding of the application of AI and data-driven methods for sustainability. The selected keywords are shown in Table 1.

Keywords significance analysis

The keyword significance analysis is conducted to identify the most significant keywords with higher frequencies, ensuring their appearance is not random among the selected documents. Let a document set D with $|D|$ documents and keyword set $kw = kw_{d_1} \cup kw_{d_2} \cdots \cup kw_{|D|}$.

Let the $M = \left[m_{i,j}\right]_{i=1,2,\ldots,|kw|}^{j=1,2,\ldots,|D|}$ be a binary matrix ($m_{ij} \in \{0, 1\}$) representing the presence or absence of keywords, from kw set in document set D. The frequency of a keyword $kw_i \in kw$ is $f_{kw_i} = \sum_{j=1}^{|D|} kw_i$. The following null hypothesis was tested:

$$H0 : f_{(kw_i)} \leq f_{(kw_i)}^{random}$$

Table 1 Key terms extracted from the keywords that reflect the social, environmental, and economic aspects of sustainability

Social
Social, city, education, health, information, ethics, policy, healthcare, society, community, justice, poverty, population, gender, culture, diversity, leadership, skills, sociology, migration, livelihood, judiciary, socialization, diseases, citizen, employee, medical, law, rural, communities, heritage, equity, societies, participation, legal, housing, generations, disaster, cancer, csr, corporate social responsibility, school, sanitation, urbanization, societal, educational, ethical, municipal, personalized, humans, saving, rules, revitalization, regulations, pharmaceutical, illegal, governance, regulation, inequality, epidemic, human, life, nutrition, wealth, living, cultural, disease.
Environmental
Energy, environmental, design, urban, water, waste, food, environment, building, concrete, mining, carbon, natural, renewable, eco, urbanism, resource, power, materials, forest, transportation, land, ecological, global, transport, emission, biomass, genetic, gas, soil, emissions, co2, vehicle, grid, electric, air, tree, regional, pollution, heat, corporate, green, climate, electricity, greenhouse, conservation, recycling, groundwater, architecture, solid, crop, buildings, bio, solar, earth, chemical, biodiversity, transition, irrigation, basin, traffic, plastic, plant, ecology, river, bioeconomy, flood, environments, coastal, geographical, contaminated, yield, thermal, street, reuse, reservoir, renovation, recycled, park, oxygen, hydrogen, geographic, rehabilitation, region, pollutions, organic, lighting, hydro, harvesting, fishery, fields, congestion, combustion, chemicals, biowaste, biorefinery, biofuels, biofuel, bioethanol, bioenergy, wind, ventilation, toxicity, sterilization, sea, poultry, plastics, nitrogen, nature, nanoparticle, mountain, methane, hydrothermal, heating, habitat, geomaterials, freshwater, erosion, trees, desalination, clean, cell, biodiesel, adaptation, weather, wastes, structures, sludge, species, greenwashing, geography, geospatial, geo, fertilizer, biological, vegetation, thermoelectric, garbage, environmentally, wetland.
Economic
Industry, manufacturing, economic, business, circular, industrial, product, production, financial, finance, market, entrepreneurship, economy, industries, enterprise, economics, trade, financing, commercial, investment, profit, sales, firms, stock, income, revenues, pricing, employment, markets, capital, economies, company, firm, producer, supplier, companies, european, price, particle, logistic, trading, commerce, businesses, profits, internet, blockchain, value, products, productions, freight, retention, money, leagility, inventories, fine, digitalisation, boosted, monetisation, gdp, gross domestic product, marketing, supply chain, technology, digital, logistics, digitalization, machines, labor, infrastructure, nanotechnology, manufacture, inventory, fault, retrieval, valuation, tariff, sme, small and medium sized companies, digitisation, maintenance.

$$H1 : f_{(kw_i)} > f_{(kw_i)}^{random}$$

To test the null hypothesis, matrix entries were randomized, M, and obtaining $M_{randomized}^{b}$ where $b = \{1, 2, \ldots B = 5,000\}$. For $M_{randomized}^{b}$, $f_{kw_i}^{randomized}$ was calculated for kw_i. The p-value to test the significance of f_{kw_i} was calculated as follows:

$$p(kw_i) = \frac{\#\{f_{kw_i} > f_{kw_i}^{randomized}\}_{b=1}^{B}}{B}$$

Further, $\left|kw\right|$ hypotheses were tested. Therefore, multiple testing corrections False Discovery Rate (FDR) were applied to control the false positive results in keyword significance analysis.

Network analysis

In this analysis, network-based approaches were applied for analyzing keyword-co-occurrence analysis and country collaboration analysis by constructing networks, identifying network modules, and performing module enrichment analysis for the keyword co-occurrence network.

Network construction

For constructing the network, the Jaccard index was used to measure the similarity between two keywords, quantifying how often these two keywords appear together in a set of documents. The Jaccard index was utilized to establish both keyword co-occurrence and collaboration networks. The method follows network modules and performs module enrichment analysis for the keyword co-occurrence network. Let a document set D with $|D|$ documents and keyword set $kw = kw_{d_1} \cup kw_{d_2} \cdots \cup kw_{|D|}$. A keyword-document matrix $[\mathrm{m_{ij}}]_{i=1,2,\ldots|kw|}^{j=1,2,\ldots,|D|}$ was created, and $m_{ij} \in \{0,1\}$. The value of $m_{ij} = 1$ if the keyword k_i is mentioned in the document d_j in their keywords. The Jaccard index measures the similarity between the two keywords.

$$ji(kw_a, kw_b) = \frac{||m_{kw_a,\cdot} \cap m_{kw_b,\cdot}||_{/||0,0||}}{||m_{kw_a,\cdot} \cup m_{kw_b,\cdot}||_{/||0,0||}}$$

Similarly, a country-based analysis was created for computing similarity based on their common co-occurrence by constructing matrix $[m_{ij}]_{i=1,2,\ldots|c|}^{j=1,2,\ldots,|D|}$, and $m_{ij} \in \{0,1\}$, where D is a document set with $|D|$ documents and $c = \{c_1, c_2, \ldots, c_{|c|}\}$ are $|c|$ countries.

$$ji(c_a, c_b) = \frac{||m_{c_a,\cdot} \cap m_{c_b,\cdot}||_{/||0,0||}}{||m_{c_a,\cdot} \cup m_{c_b,\cdot}||_{/||0,0||}}$$

The keyword co-occurrence and country collaboration network are created as follows: Let G be an undirected weighted graph $G = (V, E, w), w : E \to R$ where the V are the vertices and E are the edges. The number of vertices is equal to the keywords $|kw|$ (or country $|c|$), and

$$E(i,j) = 1, \text{if } ji(\mathrm{kw}_a, \mathrm{kw}_b) > \alpha \left(ji(c_a, c_b) > \alpha \textit{ for country collaboration}\right)$$

$$w(i,j) = ji(kw_a, kw_b)(ji(c_a, c_b) \textit{for country collaboration network}).$$

Module detection

We utilized the multi-level modularity optimization algorithm developed by Blondel et al. [44] to partition the constructed weighted keyword co-occurrence and country collaboration networks. This algorithm groups nodes that exhibit greater proximity and similarity compared to other nodes. The multi-level algorithm outperforms alternative module detection algorithms, offering faster processing times and superior results.

An adjusted modularity optimization approach was employed for the country collaboration network using multi-level module detection to optimize the modules. In this approach, a small fraction ($\nu = 0.0001$) from edge weights, i.e., $w(i,j) = max(w(i,j) - \nu, 0)$ was iteratively subtracted. The multi-level module detection algorithm for weighted graphs was run until the modularity reached its maximum value or until 2% of the total edge weights became zero. This approach prioritizes countries into the same modules, which shows stronger collaboration and emphasizes stronger collaboration based on the Jaccard index value.

Module enrichment analysis

Module enrichment analysis is used to identify modules in the keyword co-occurrence network that are enriched for a specific set of keywords or annotations (in this case, different aspects of sustainability). This can be useful for understanding the characteristics of different modules in the co-occurrence network and identifying important modules for a particular phenomenon. Module enrichment analysis was applied to identify whether various sustainability keywords were significantly represented in a module obtained from the keyword co-occurrence network (G). The following hypotheses were tested:

H0: The presence of observed keyword pattern expressing sustainability aspect s_a in module m_i is by chance.

H1: The observed number of keywords expressing sustainability aspect s_a in module m_i is significantly higher than the expected number by chance.

The Fisher exact test was applied to test the hypotheses, comparing the significance of the association between two sets. In this case, we evaluated the association between sustainability aspects and modules identified in the keyword co-occurrence network by assessing the presence or absence of keywords expressing a particular sustainability aspect in a module of the keyword co-occurrence network. The contingency table illustrating the presence and absence of the keyword pattern (as shown in Table 1) of each sustainability aspect in a module is presented in Table 2, described as follows:

Let $\mathrm{N} = |V(G) \cup s|$ be the total keywords representing the union of vertices of the co-occurrence network and all terms from the sustainability aspects (see Table 1), where $\{\mathrm{s_{social}}, \mathrm{s_{environmental}}, \mathrm{s_{economic}}\}$ are sustainability aspects and $s = s_{social} \cup s_{environmental} \cup s_{economic}$, and a module $m_i \subset V(G)$. The values of the contingency table are defined as:

$$\mathrm{N_{11}} : \text{are the number of pattern matches of keywords from } \mathrm{s_a} \text{in } \mathrm{m_i}$$

$$\mathrm{N_{12}} : \text{are the number of keywords in } \mathrm{s_a} \text{ do not match with keywords in } \mathrm{m_i}$$

$$\mathrm{N_{21}} : \text{are the number of keywords in } \mathrm{m_i} \text{ do not match with keywords in } \mathrm{s_a}$$

$$\mathrm{N_{22}} : \text{are the remaining keywords not present in } \mathrm{m_i} \text{ and not with keywords in } \mathrm{s_a}$$

The test calculates the probability of obtaining the observed outcome, assuming the null hypothesis is true. The probability of N_{11} sustainability aspect keyword pattern matches with keywords in a module:

$$p = \frac{\binom{N_{1.}}{N_{11}}\binom{N_{2.}}{N_{21}}}{\binom{N}{N_{.1}}}$$

The probability p follows a hypergeometric distribution, representing the likelihood of observing an overlap of sustainability aspect-related keyword patterns within the module when randomly drawing keywords from the data.

Table 2 Contingency table

	In sustainability aspect s_a	Not in sustainability aspect s_a	Sum
In module m_i	N_{11}	N_{12}	$N_{1.}$
Not in module m_i	N_{21}	N_{13}	$N_{2.}$
	$N_{.1}$	$N_{.2}$	N

Semantic analysis

Topic modeling is employed for the semantic analysis of publication texts, combining the title, keywords, and abstract. For the topic modeling of the obtained literature, the BERTopic [107] approach was applied to identify key research themes related to sustainability. For the topic modeling, our objective is to explore topics that can be comprehended best through semantic analysis while maintaining diversity and coherence. We have opted for BERTopic as our method of choice to achieve this goal due to its effectiveness with large corpora. Several studies have demonstrated that BERTopic outperforms other methods in capturing contextual information and generating coherent topics. Furthermore, BERTopic has proven effective in various assessments compared to different topic modeling techniques [84, 98, 332].

The BERTopic approach follows four main steps: (1) Generating embeddings, (2) dimensionality reduction, (3) clustering, and (4) c-TF-IDF-based topic extraction from the clusters. The "sentence-transformers" library transforms the input text into numerical representations (embeddings) optimized for semantic similarity. The "all-minilm-l6-v2" sentence transformer model, which maps the input text of each document into a 384-dimensional numerical vector, was used. The model then applies Uniform Manifold Approximation and Projection (UMAP) for dimensionality reduction ($n = 20$) and uses hdbscan for clustering, selecting the number of clusters. The "BERTopic" python package automatically generates the topic representation through c-TF-IDF-based extraction of the most important keywords from the clustering solution. Additionally, the coherence was enhanced, and stopwords were reduced in the extracted topics by using the "KeyBERTInspired" representation model in BERTopic. From the topics identified by BERTopic, hierarchical Ward clustering was applied to the topic-term c-TF-IDF matrix to find clusters of common topics resulting from the topic modeling process.

Topic optimization

We utilize the topic coherence measure Coherence (C_V) to optimize and fine-tune topics. The measure involves varying the parameters of the number of neighbors [3, 5, 8, 10, 15, 20, 25, 30] for the "UMAP" function and the minimum cluster size parameter for "hdbscan" clustering (from 3 to 30). We perform topic modeling for each combination, where the BERTopic hdbscan automatically selects the number of clusters and computes the C_V coherence [268]. The results are evaluated based on the C_V score and the number of topics obtained from the topic modeling. Additionally, we manually evaluate the topic keywords to assess if the topics identified by the selected model uniquely represent themes in sustainability and AI research.

Significance analysis of projection of the clustered embeddings

For comparing differences between clusters obtained by the hdbscan algorithm in "BERTopic." We analyze the UMAP-reduced 2D projection of document embeddings to assess the statistical significance of clusters. We applied the non-parametric N-statistic method [35] to test the null hypothesis regarding the equality of distributions of data points in two clusters. The method is described as follows: Let X and Y be the p-dimensional

UMAP reduced embeddings of documents in clusters i and j with samples m and n, respectively, and F_{CL_i} and G_{CL_j} are these clusters' distribution functions. The null and alternative hypotheses are expressed as follows: $H0 : F_{CL_i} = G_{CL_j}$,H1 : $F_{CL_i} \neq G_{CL_j}$

The N-statistic for the comparison is defined as follows:

$$T_{m,n} = \frac{mn}{m+n} m \left[\frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} ||X_i - Y_j|| - \frac{1}{2m^2} \sum_{i=1}^{m} \sum_{j=1}^{m} ||X_i - X_j|| - \frac{1}{2n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} ||Y_i - Y_j|| \right]$$

Bibliometric insights

Publication landscape analysis

The literature search obtained 1982 papers, including research articles, review papers, books and book chapters, conference papers, and editorials. Table 3 shows the different journals that publish papers on sustainability and AI-based applications.

The largest fraction belongs to other categories, including a mix of conference papers, journal papers, and others, but no category exceeds the top 30 journals. Tables 4 and 5 display the categories of top review papers, research articles, and collaborations based on their citations. The top articles belong to various subject areas or topics of sustainability and are sourced from different journals.

Table 3 Number of papers of top 30 journals

Journals	#Publications	Journals	#Publications
Sustainability (Switzerland)	227	IFIP Advances in Information and Communication Technology	11
Journal of Cleaner Production	70	Environmental Science and Pollution Research	11
Sustainable Cities and Society	40	Energies	11
Lecture Notes in Computer Science	27	ACM International Conference Proceeding Series	11
Geopolitics, History, and International Relations	22	International Conference on Artificial Intelligence, Management Science and Electronic Commerce (2021)	11
Science of the Total Environment	19	Technology in Society	10
Journal of Self-Governance and Management Economics	19	CEUR Workshop Proceedings	10
Sustainable Energy Technologies and Assessments	14	Advances in Intelligent Systems and Computing	10
Advances in Science, Technology and Innovation	14	Studies in Computational Intelligence	9
Technological Forecasting and Social Change	13	Lecture Notes in Networks and Systems	9
Economics, Management, and Financial Markets	13	IOP Conference Series: Earth and Environmental Science	9
Renewable and Sustainable Energy Reviews	12	Frontiers in Environmental Science	9
Resources, Conservation and Recycling	11	Sustainable Computing: Informatics and Systems	8
Philosophical Studies Series	11	Resources Policy	8
International Journal of Production Research	11	IEEE Access	8
Other	1217		

Table 4 Top papers based on citations (A and B) and number of collaborations (C)

Title	#	References
A. Articles		
Green, circular, bio economy: a comparative analysis of sustainability avenues	517	D'Amato et al. [66]
Evaluating sustainability transitions pathways: bridging analytical approaches to address governance challenges	296	Turnheim et al. [331]
Sustainable supplier management—a review of models supporting sustainable supplier selection, monitoring and development	279	Zimmer et al. [369]
A hybrid decision support system for sustainable office building renovation and energy performance improvement	277	Juan et al. [144]
A systematic literature review on machine learning applications for sustainable agriculture supply chain performance	235	R. Sharma et al. [291]
Artificial intelligence and business models in the sustainable development goals perspective: a systematic literature review	229	Di Vaio et al. [74]
Convergence of blockchain and artificial intelligence in IoT network for the sustainable smart city	227	Singh et al. [298]
Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities	220	Bag et al. [32]
Role of multiple stakeholders and the critical success factor theory for the sustainable supplier selection process	210	Kannan [151]
Bridging sustainable business model innovation and user-driven innovation: a process for sustainable value proposition design	208	Baldassarre et al. [34]
Big data and predictive analytics for supply chain sustainability: a theory-driven research agenda	188	Hazen et al. [116]
Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0	174	Çınar et al. [58]
Comparing systems approaches to innovation and technological change for sustainable and competitive economies: an explorative study into conceptual commonalities, differences and complementarities	172	Coenen and Díaz López [60]
Investigating a serious challenge in the sustainable development process: analysis of confirmed cases of COVID-19 (new type of Coronavirus) through a binary classification using artificial intelligence and regression analysis	169	Pirouz et al. [255]
B. Review papers		
The role of artificial intelligence in achieving the Sustainable Development Goals	589	Vinuesa et al. [341]
Achieving sustainable performance in a data-driven agriculture supply chain: a review for research and applications	376	Kamble et al. [150]
Statistical machine learning methods and remote sensing for sustainable development goals: a review	141	Holloway and Mengersen [120]
The narrative of sustainability and circular economy—A longitudinal review of two decades of research	141	Schöggl et al. [284]
Artificial intelligence in sustainable energy industry: status Quo, challenges and opportunities	137	Ahmad et al. [5]
Unleashing the convergence amid digitalization and sustainability towards pursuing the Sustainable Development Goals (SDGs): a holistic review	135	Del Río Castro et al. [70]
Digitalization to achieve sustainable development goals: steps towards a Smart Green Planet	134	Mondejar et al. [221]
Sustainable cyber-physical production systems in big data-driven smart urban economy: a systematic literature review	97	Andronie et al. [23]
Industry 4.0 technologies for manufacturing sustainability: a systematic review and future research directions	93	Jamwal et al. [132]
Using satellite imagery to understand and promote sustainable development	92	Burke et al. [47]

Table 4 (continued)

Title	#	References
Sustainable supply chain management towards disruption and organizational ambidexterity: a data driven analysis	86	Bui et al. [45]
Urban energy planning procedure for sustainable development in the built environment: a review of available spatial approaches	75	Torabi Moghadam et al. [322]
Decision support systems for sustainable manufacturing surrounding the product and production life cycle—A literature review	73	Zarte et al. [362]
COVID-19 and healthcare system in China: challenges and progression for a sustainable future	69	Sun et al. [309]
Nanotechnology and artificial intelligence to enable sustainable and precision agriculture	68	Zhang et al. [365]
Trends in predictive biodegradation for sustainable mitigation of environmental pollutants: recent progress and future outlook	61	Singh et al. [296]

Table 5 Papers ordered based on collaborations

A. Top collaborations	#collaboration countries	References
Digitalization to achieve sustainable development goals: Steps towards a Smart Green Planet	12	Mondejar et al. [221]
Intelligent approaches for sustainable management and valorisation of food waste	10	Said et al. [275]
A computational view on nanomaterial intrinsic and extrinsic features for nanosafety and sustainability	10	Mancardi et al. [208]
A machine learning driven multiple criteria decision analysis using LS-SVM feature elimination: Sustainability performance assessment with incomplete data	10	Ijadi Maghsoodi et al. [126]
Foodomics: A Data-Driven Approach to Revolutionize Nutrition and Sustainable Diets	9	Ahmed et al. [6]
Predicting sustainable arsenic mitigation using machine learning techniques	8	Singh et al. [299]
Deploying digitalisation and artificial intelligence in sustainable development research	7	Leal Filho et al. [188]
Guest Editorial Artificial Intelligence and Deep Learning for Intelligent and Sustainable Traffic and Vehicle Management (VANETs)	7	Gupta et al. [110]
A strategic review on sustainable approaches in municipal solid waste management and energy recovery: Role of artificial intelligence, economic stability and life cycle assessment	7	Naveenkumar et al. [229]
Economic analysis of sustainable exports value addition through natural resource management and artificial intelligence	7	Wang et al. [344]

Figure 2 shows the number of publications per year. The earliest paper is from 1995 and discusses the "community option model" to provide the outcome of policies and actions for community development and management. The subsequent years show a slow growth in the number of publications until 2017; afterward, the rise in the number of publications is higher. Just after the year 2018, the frequency of publication is in triple digits, showing the maturation and application of data-driven technology. AI has reached a level where it can be utilized systematically with expertise and necessary resources for various applications and multiple disciplines with sustainability-related topics at the center.

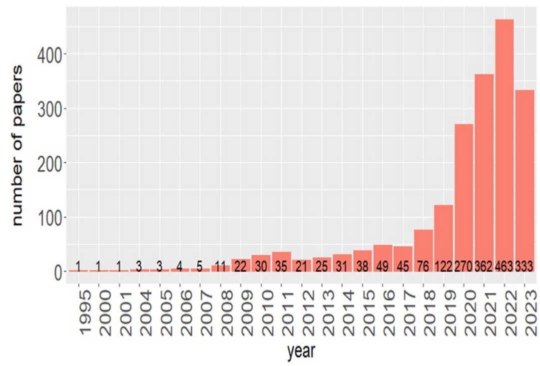

Fig. 2 Number of publications over the years related to sustainability and AI

The next result is the representation of social, environmental, and economic aspects in the current literature's keywords. For this analysis, all keywords from the literature were extracted, duplicates eliminated, and keywords (including open compound words) and subparts of compound words relevant to the general concept of sustainability were manually selected. These selected keywords are categorized into one of three aspects, as presented in Table 1. Thus, the social, environmental, and economic aspects were defined. These three categories of words are used to search for patterns in the titles and keywords.

The proportion of different aspects of sustainability using keywords in Table 1 is as follows: Let us consider a set of documents $D = \{d_1, d_2, \ldots\}$ with $|D|$ documents. There is also a set $k_a = \{kw_1, kw_2, \ldots\}$ with $\left|k_a\right|$ words related to aspect a. Let $P\left(kw_i, d_j\right)$ be a pattern search function that returns 1 if it finds a match for kw_i in $d_j(keywords)$, and 0 otherwise. The proportion for aspect a is calculated as follows:

$$\text{Total count for aspect a in D: a} = \sum_{i=1}^{|k_a|} \sum_{j=1}^{|D|} P\left(kw_i, d_j\right)$$

It was searched for patterns related to each aspect in the titles and keywords of documents for different years. The year-wise counts for each aspect of sustainability are presented in Fig. 3. There has been a consistent upward trend in publications related to sustainability, AI, and data-driven approaches. The keywords in these publications have been categorized into social, environmental, and economic groups, and there has been a proportional increase in the count of keywords in all three categories. The results reveal a consistently higher count of environmental-related keywords since 2004.

In contrast, social-related and economic-related keywords have been less prominent than environmental-related ones, indicating a lower representation in the papers. Until 2015, they were closely matched in the count. However, from 2016 onward, there has been a significant and consistent increase in the count of economic-related keywords compared to social-related keywords. The social dimension is complex, and implementing AI in this area presents a substantial challenge, necessitating greater expertise, domain knowledge, investments, systematic data collection, and implementation trials that benefit society. The increasing number of publications underscores the subject's importance, emerging trends, and diversity within the field.

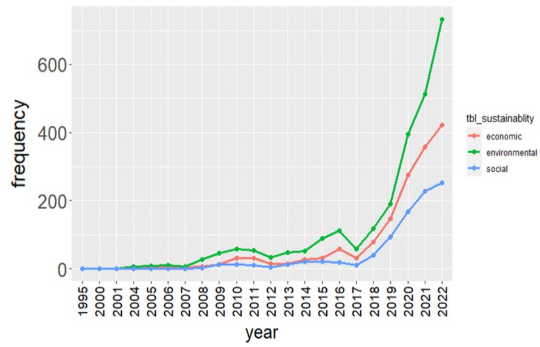

Fig. 3 Frequency of the terms related to the triple bottom line of sustainability (social, economic, and environmental)

Country-wise analysis

The initial step in analyzing global research on AI-based applications for sustainability involves examining the country affiliations of the authors who have contributed to the research papers. This examination provides insight into the scope and prevalence of sustainability research. In cases where multiple authors are listed on a paper and share the same country affiliations, they were treated as a single instance for that specific country. This approach streamlines the analysis by ensuring each paper is associated with a unique country affiliation, thereby preventing potential bias. Table 6 displays the leading countries with a minimum of 20 publications among the 102 countries with at least one publication.

In these results, institutions or universities in the United States are affiliated with the most publications by authors, followed by China, India, the United Kingdom, Germany, and other countries. One interesting observation is that these are larger economies and higher-income countries investing in sustainability-related research. Next, the number of publications per million population was compared to the Gross Domestic Product (GDP) based on Purchasing Power Parity (PPP). Population and GDP (PPP) data for 2022 were gathered from the World Bank website (databank.worldbank.org). This data could only be obtained for 91 countries. The visualization of GDP (PPP) on the x-axis and the logarithmic value of publications per million population on the y-axis is presented in Fig. 4. This visualization highlights the focus on sustainability-related applications and research. Countries such as Norway, Ireland, Finland, Denmark, Sweden, Cyprus, and Macao, which fall within the high to middle range of GDP (PPP), exhibit higher publication rates per million population. In contrast, lower-income or densely populated countries tend to have significantly lower publication rates per million. This consideration is particularly important for implementing locally relevant sustainability initiatives.

The finding pertains to country-wise publication trends, revealing that countries with more advanced industrial economies or higher per capita incomes tend to exhibit more publications. This could be attributed to the rise of Industry 4.0 (I4.0), research investment, adopting and addressing sustainability, especially for economic and environmental dimensions, alternative energy sources with less carbon footprint, and the UN's SDGs. However, comparing publications per million population versus GDP per capita reveals that many larger economies lag significantly behind, which is also the case

Table 6 Country-wise publication distribution

Country	#Publications	Country	#Publications
United States	333	Japan	37
China	276	Poland	34
India	268	Hong Kong	34
United Kingdom	193	South Africa	32
Germany	123	Portugal	32
Italy	111	Ireland	31
Saudi Arabia	105	Finland	30
Spain	98	Brazil	30
Australia	88	Denmark	29
Canada	76	Greece	28
Malaysia	74	Belgium	27
South Korea	69	Switzerland	26
Taiwan	65	Romania	26
France	65	Mexico	26
Pakistan	58	Slovakia	24
Norway	57	Austria	24
Iran	57	Vietnam	22
Netherlands	48	Hungary	21
Sweden	47	Czech Republic	21
Egypt	41	Singapore	20
Turkey	40	Indonesia	20
United Arab Emirates	39	Colombia	20
Russian Federation	37		

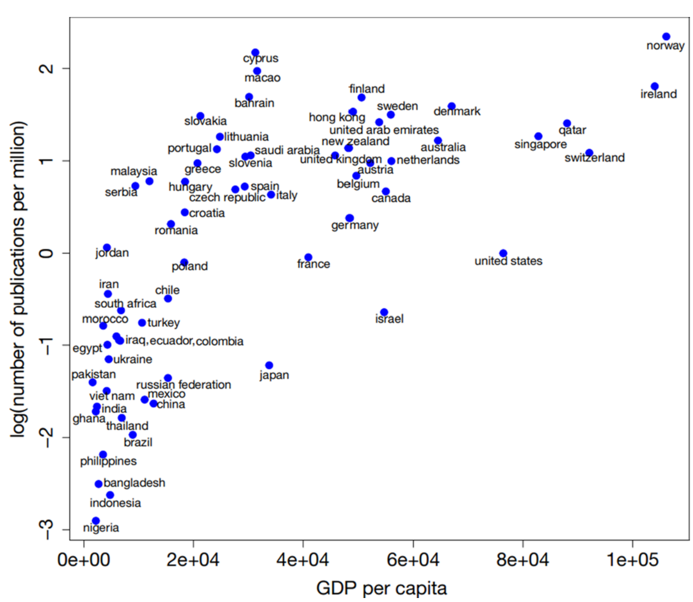

Fig. 4 GDP per capita vs number of publications per million

for underdeveloped countries. This analysis does not reflect the actual status but only reflects AI and sustainability research papers from the Scopus database. AI and sustainability research must be emphasized to understand various local sustainability challenges, particularly aligning with the demography. Otherwise, the full potential of AI-based approaches for sustainability may remain underutilized. Demography and population growth are important factors when investing in sustainability-related research and applications. Bhargava [39] discusses the implications of rapid population growth and emphasizes its inclusion in sustainability research.

Next, the collaboration network from the country-document binary matrix using the Jaccard index for collaborative analysis was constructed. As discussed in the method section, countries with at least three collaborations and a Jaccard index value greater than $\alpha > 0.01$ were selected. Next, module detection algorithms were applied. Seven cooperation modules were obtained from the module detection analysis. The module of countries' collaborations is shown in Fig. 5. Countries collaborate with their specific module and with other countries. The relative weight measured as the Jaccard index is higher for countries within the same module.

Sustainability is interdisciplinary and necessitates collaboration on various issues, particularly regional and global ones. The modules identified from collaboration networks of countries based on the Jaccard index reveal three main findings: the collaboration among large economies, the collaboration among European countries, and the collaboration among neighboring or closely situated countries. The collaboration network

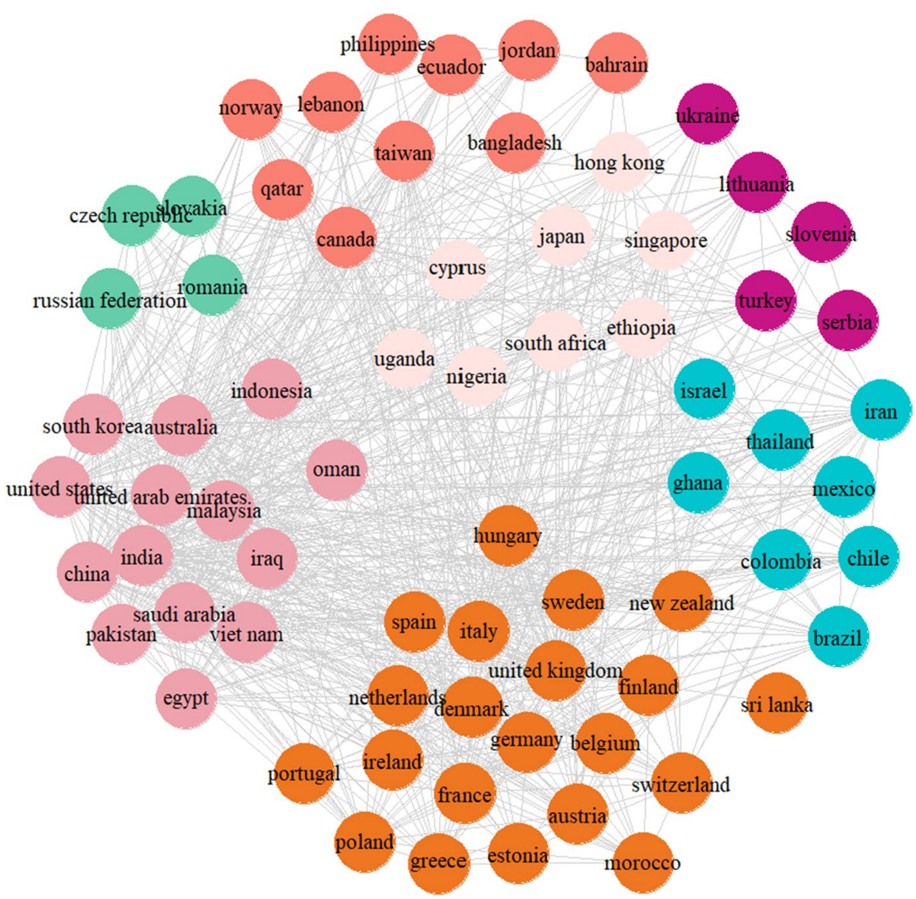

Fig. 5 Collaboration among 70 countries related to sustainability and AI research

consists of only 70 countries, as a minimum of three collaborative publications had to occur for inclusion. The major emphasis is understanding how the AI applications of sustainability-related research are distributed worldwide. As several studies have highlighted, overcoming the digital divide and lack of infrastructure and human resource expertise in underdeveloped countries requires investment in research, education, and collaboration to enhance research in these regions. Achieving social, environmental, and economic sustainability is equally important and a priority for underdeveloped nations. With sufficient research on the social, environmental, and economic dimensions and a comprehensive understanding of the system, the advantages of sustainability tasks will be achievable only through collaborative efforts [96].

Keyword analysis

The keyword analysis highlights the significance of various technologies in conjunction with sustainability concepts, their application areas, and their interrelationships. The keyword analysis began with a pool of 5723 unique keywords. When the significance analysis was applied to identify the most meaningful keywords, it narrowed them to 67 (see Table 7). These keywords encompass sustainability-related concepts and technology/data-driven methods.

Table 13 (see Appendix) displays the keywords in each of the 14 modules detected in the co-occurrence network. Enrichment analysis was conducted to identify sustainability-related aspects within these modules. This analysis revealed that 11 out of the 14 modules were enriched with at least one aspect related to sustainability. Figure 6 illustrates the co-occurrence network and labeled nodes with a degree greater than 20.

Table 8 shows the outcomes of the enrichment analysis, highlighting the significant modules that contained enrichment for at least one aspect. Notably, the findings indicate that not all modules were uniformly enriched with all three aspects (social, environmental, and economic). Seven modules significantly represent the environmental and economic aspects. The key terms in Table 8 (column 4) represent key sustainability terms. The results reveal variations in the distribution of sustainability-related aspects throughout the network of keywords.

The keywords and co-occurrence analysis focus on two important aspects: First, identifying common key terms, which highlight a central subject's association with other key terms, and second, identifying current and emerging trends. The results shown in Table 7 highlight keywords that emphasize sustainability-related themes and keywords that emphasize technology and data-driven methods. The top two keywords can be understood in terms of sustainability or sustainable topics with AI applications. "Sustainable development" is a major abstract keyword that emphasizes that significant publications related to the search criteria actively consider or try to align with the principles of sustainable development and demonstrate the widespread recognition of the importance of sustainability in that field of research. However, the global sustainability objectives can conflict with the various objectives of these studies.

Further research is warranted where each work addressing sustainability is critically evaluated for global sustainability questions. Keywords such as smart and sustainable cities, I4.0, renewable and sustainable energy, and agriculture have gained considerable attention by being discussed by different research groups. However,

Table 7 Top significant keywords

Sustainability keywords	Frequency	q value	Technology, AI, & data analysis terms	Frequency	q value
Sustainable development	152	5E-05	Decision support system	99	5E-05
Sustainable development goals	75	5E-05	Big data	90	5E-05
Smart city	62	5E-05	Internet of things	84	5E-05
Industry 40	48	5E-05	Deep learning	62	5E-05
Environmental sustainability	33	5E-05	Neural network	31	5E-05
Circular economy	30	5E-05	Support vector machine	38	5E-05
Renewable energy	26	5E-05	Optimization	36	5E-05
Sustainable cities	23	5E-05	Blockchain	30	5E-05
Covid 19	23	5E-05	Big data analytics	24	5E-05
Decision making	23	5E-05	Data mining	22	5E-05
Climate change	21	5E-05	Random forest	21	5E-05
Agriculture	20	5E-05	Digitalization	19	5E-05
Sustainable manufacturing	20	5E-05	Multi objective optimization	15	5E-05
Energy	19	5E-05	Sustainable ai	14	5E-05
Resilience	19	5E-05	Digital technologies	13	5E-05
Energy efficiency	17	5E-05	Prediction	13	5E-05
Sustainable agriculture	17	5E-05	Multi criteria decision making	13	5E-05
Life cycle assessment	17	5E-05	Cloud computing	13	9.9995E-05
Smart manufacturing	16	5E-05	Data analytics	12	0.0002
Energy consumption	16	5E-05	Classification	12	1E-04
Decision support	16	5E-05	Data driven approach	12	5E-05
Social sustainability	15	5E-05	Data science	11	0.0003
Sustainable design	14	5E-05	Gis	11	0.0003
Innovation	14	5E-05	Simulation	10	0.00035
Governance	13	5E-05			
Sdgs	13	5E-05			
Security	13	5E-05			
Sustainable supply chain	13	5E-05			
Supply chain	13	5E-05			
Ethics	12	5E-05			
Systematic literature review	12	5E-05			
Supply chain management	12	9.9995E-05			
Urban sustainability	12	9.9995E-05			
Environment	11	0.00014999			
Digital transformation	11	0.00014999			
Urban planning	11	0.00019999			
Sustainable SCM	11	0.00019999			
Sustainable concrete	11	0.00014999			
Smart sustainable cities	11	0.00024999			
Smart grid	11	0.00024999			

this trend could lead to emerging issues if trade-offs exist with global sustainability goals. The keywords covering data-driven technologies show that "decision support system" is the key term followed by BD, IoT, Deep Learning (DL), neural network, sustainable AI, optimization, blockchain, and cloud computing. Other keywords show

Fig. 6 Keyword Co-occurrence and Strong Connections

the importance of using technologies and data-driven methods for sustainability for effective and complex decision-making, real-time data-driven solutions, and higher prediction accuracy. They address trade-offs, transparent and traceable communication and transactions, and scalable, on-demand computing resources and services. These technologies and methods can be useful instruments for systems integration [197].

Analyzing the keywords' co-occurrence network indicates the relationships between various keywords. The module detection algorithm applied for the co-occurrence network shows a high modularity score of 0.58, indicating that the keywords form distinct groups closely connected within themselves and loosely connected to other groups. These groups represent different research topics and are composed of technology-related, sustainability-related, and other keywords. These keywords highlight the relation between various topics, research themes, and subjects discussed in each group's topic. For instance, Module 1 (see Table 13, Appendix) includes, amongst others, the keywords BD, IoT, I4.0, SDGs, CE, business model, and strategies. Economic sustainability, business model development, manufacturing, and the SDGs are not independent but intertwined. The modules highlight the major interconnected themes of research topics related to sustainability, AI, and data-driven methods.

The enrichment analysis using the Fisher exact test determines which of the 14 modules were significantly enriched toward social, environmental, or economic dimensions of sustainability. Eight modules were significantly enriched to at least one

Table 8 Identification of significant representation of sustainability-related terms in various modules using the Fisher test

Module (with total nodes)	Sustainability aspects	q value	Key terms reflecting sustainability aspects
1 61 nodes	Social	0.49	Smart sustainable city, ethical ai, population, gender equality, biodiversity, urban development, urban, governance
	Economic	**< 0.0001**	Industry 40, fourth industrial revolution, industry, industrial ecology, manufacturing, smart manufacturing, sustainable manufacturing, sustainable smart manufacturing, circular economy, business model, business strategy, cyber physical production system, sustainable finance, internet of things, digitalisation, digital technologies, technology, digitalization, digital twin
	Environmental	**0.02**	Environmental sustainability, urban development, urban, water quality, e waste, environment, industrial ecology, resource recovery, emission, green ai, climate change, conservation, biodiversity, earth observation
2 38 nodes	Social	**0.01**	Social sustainability, sustainable smart city, healthcare, internet of health things, ai ethics, ethics, smart agriculture, ai governance
	Economic	**0.02**	Firm performance, supplier selection, logistics, internet of health things, internet of thing, blockchain, supply chain management, supply chain, digital transformation
	Environmental	1	Environmental indicators
3 5 nodes	Social	1	
	Economic	**< 0.0001**	Digital economy
	Environmental	1	
4 28 nodes	Social	0.44	Social media, engineering education, educational data mining, education, higher education, sustainable education
	Economic	0.19	Production
	Environmental	**0.026**	Energy efficient, environmental pollution, waste, wastewater treatment, fuel cell
5 40 nodes	Social	0.49	Agricultural sector, generative design, life cycle assessment
	Economic	**< 0.0001**	Manufacturing industry, bioeconomy, economic development, cleaner production, predictive maintenance
	Environmental	**< 0.0001**	Sustainable energy, renewable energy, energy demand, environmental decision support system, environmental performance, generative design, sustainable environment, sustainable transport, global warming, co2 emissions, greenhouse gas emissions, biomass, corporate sustainability, biofuel, bioeconomy, cleaner production
6 26 nodes	Social	0.18	AI for social good, future generations, urban governance
	Economic	0.33	Additive manufacturing, digital twins, infrastructure planning
	Environmental	**< 0.0001**	Building energy, performance-based design, natural resources, land use, electric vehicles
7 44 nodes	Social	1	Smart city, sustainable cities
	Economic	1	Big data technology, data driven technologies, infrastructure
	Environmental	1	Energy planning, design, smart sustainable urbanism
8 32 nodes	Social	1	
	Economic	1	Emerging technologies, technological innovation
	Environmental	**0.01**	Environmental management, environmental factors, data driven design, sustainable design, green building, air pollution

Table 8 (continued)

Module (with total nodes)	Sustainability aspects	q value	Key terms reflecting sustainability aspects
9 28 nodes	Social	0.21	Global health, policy, agricultural supply chains, sustainable food systems
	Economic	0.38	Agricultural supply chains, food supply chain, sustainable supply chain management
	Environmental	1	Design for sustainability
10 26 nodes	Social	0.38	Social network analysis, education for sustainable development
	Economic	1	Sustainable technology
	Environmental	1	Materials science, engineered nanomaterials
11 50 nodes	Social	0.56	Urbanization, municipal solid waste
	Economic	**< 0.0001**	circular bioeconomy, blockchain technology, digital divide
	Environmental	**0.0012**	Urbanization, municipal solid waste, solid waste management, waste management, lignocellulosic biomass, circular bioeconomy
12 50 nodes	Social	0.49	Corporate social responsibility, health
	Economic	**0.02**	Economic sustainability, business sustainability, productivity, digital agriculture
	Environmental	0.10	Green energy, environmental impact, environmental monitoring, water, water resource management, water sustainability, food security, smart environments, sustainable building, corporate social responsibility, groundwater
13 34 nodes	Social	1	Social networks
	Economic	**0.0008**	Industry 50, economic growth, sustainable production, closed loop supply chain, sustainable supply chain
	Environmental	0.99	Energy efficiency, energy management, energy consumption, water demand, water supply, built environment, carbon footprint, smart grid
14 2 nodes	Social	1	
	Economic	1	
	Environmental	**0.02**	Wastewater treatment plant

Bold represents terms significantly enriched (values less than 0.05) within their respective categories, indicating a significant presence of these terms in the module related to "social," "economic," or "environmental" aspects

aspect of sustainability. Modules 1, 5, and 11 showed topics interconnected with economic and environmental aspects. Module 2 showed the interconnection of social and economic dimensions. The remaining modules were enriched with economic (three modules) and environmental (three modules) dimensions. Only Module 2 was enriched with the social dimension, specifically regarding sustainable AI implementation, regulation, governance, and protecting privacy. When gaining economic benefits from AI and data-driven models, these are important social aspects. The enrichment of the environmental dimension may be due to the selection of more environmental keywords, which could be different if more keywords related to sustainability for different aspects had been obtained. However, the current analysis overviews topics enriched with specific aspects within each module. This analysis can be useful for understanding different research topics and the extent of involvement in the three dimensions of sustainability within the specific sustainable theme, identifying all three sustainability-related concerns, and addressing all aspects equally.

Semantic analysis of key topics

To determine the optimal number of topics, we evaluated 64 models using different combinations of UMAP's number of neighbors parameter and hdbscan's minimum cluster size parameter, calculating the corresponding C_V scores. The results of these evaluations are presented in Fig. 7. The figure shows that the C_V coherence increases as the number of topics decreases, while the score decreases for higher numbers of topics. The selected input parameters for BERTopic influence the variation in C_V scores. The top three C_V scores exceeding 0.47 correspond to models with topics ranging from 1 to 3. However, these models are deemed suboptimal, as they do not exhibit sufficient variation in topics related to sustainability and AI.

In contrast, the fourth and fifth largest C_V scores, 0.476 and 0.448, are associated with models having 12 and 13 topics, respectively, displaying less variation in topic distribution. The sixth-largest C_V score, 0.446, is the selected model with 34 topics (highlighted in blue). We chose this model because its coherence is relatively close to the fourth and fifth models, capturing a larger variation in AI and sustainability topics. The selected model has 34 topics and is characterized by UMAP's number of neighbors set to 8 and hdbscan's minimum cluster size set to 10. The topic modeling with BERTopic generated 34 clusters of keywords, which are shown in Table 11 (see Appendix). The description of these clusters is shown in Table 9. Through topic modeling, key research themes emerging from multiple studies are identified. While many papers do not align with any specific theme, these papers do mention AI and sustainability.

Cluster -1 contains 643 documents that do not belong to any specific cluster. This occurrence can be attributed to two primary reasons. First, it might be due to a higher noise level in the data, causing these documents to not fit neatly into any theme or category. Second, the clusters formed may be smaller than the minimum cluster size parameter, set at ten during the implementation. Comprehensive parameter tuning may be required to address this issue and assign these unclustered documents to appropriate clusters. However, it is important to note that fine-tuning these parameters may provide more granular topics, but results remain unaffected. Figure 9 (see

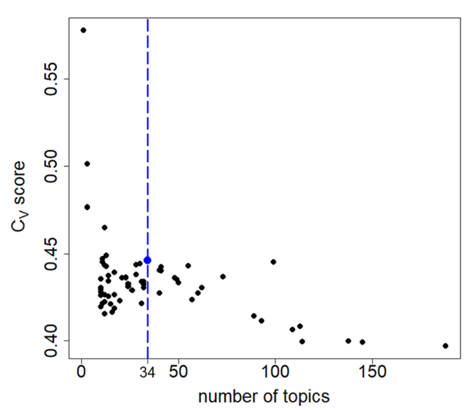

Fig. 7 Number of topics vs. C_V score obtained by varying parametes of different BERTopic models

Table 9 Different topic labels identified using BERTopic (details of topic keywords are shown in Table 11 in the Appendix)

Topic	Docu-ments	Description	Topic	Docu-ments	Description
− 1	643	Mixed topics that are not part of any clusters but broadly discuss the application of AI, and sustainability-related research and applications	16	23	Decision support systems for sustainable land use management
0	187	AI and sustainable development	17	22	Sustainable supply chain management
1	150	ML and sustainable agriculture	18	22	Sustainable Finance and ESG (Environmental, Social, Governance)
2	83	Sustainable and renewable energy	19	22	Sustainability in manufacturing
3	63	Big data, data analytics, and data driven methods for sustainable industrial manufacturing	20	20	Smart sustainable city development
4	61	Data-driven smart sustainable cities	21	19	AI and the IoT
5	59	Application of AI in healthcare	22	19	Sustainability of the palm oil industry
6	50	ML approaches in sustainable urban planning	23	17	Waste and waste management
7	47	Product sustainability assessment	24	17	Data driven smart cities and governance
8	47	Sustainable supply chains	25	17	Big data, business model, innovation for sustainable competitive advantage
9	44	Predicting properties of concrete using ML techniques	26	15	Cybersecurity and Intrusion Detection for sustainable use of AI and technology
10	41	Decision support systems for sustainable building design	27	14	Water and wastewater treatment using AI
11	37	The role of ML and AI in making a digital classroom and its sustainable impact on education during Covid-19	28	13	Pavement management for sustainable transport
12	35	Water resources management	29	12	Sustainability energy usages and AI
13	30	Sustainable development, nanomaterials, and nanotechnology	30	12	Sustainable transportation systems
14	27	Predictive modeling of water resources using ML techniques	31	11	AI for smart and sustainable cities
15	25	Biofuels, biowaste remediation, and sludge	32	10	Digital Technologies and sustainability in data journalism, communication, and information sharing

Appendix) presents a two-dimensional projection of document embeddings obtained through the UMAP approach. This visualization highlights the distribution of all the documents across different clusters resulting from the BERTopic modeling. Notably, the grey-colored points represent the documents in the -1 labeled group scattered throughout the visualization, indicating their lack of clear association with any specific cluster. Using a multivariate hypothesis test using N-statistic, we compared the clusters (topics) obtained from “hdbscan” in BERTopic using 2D UMAP projection (Figure 9, see Appendix) of document embeddings. The aim was to determine if significant differences existed between the topic distributions shown by the two main UMAP components. The results of the N-statistic are shown in Figure 10 (see Appendix). The distribution of different clusters is shown to be significantly different, showing that the identified clusters, as represented by topics, are distinct. The p-values between all pairs of clusters are < 0.00001. In the final step of the analysis, hierarchical clustering (ward) was performed on the topic-text c-TF-IDF matrix. First, cosine similarity between topics was calculated, cosine dissimilarity as a distance measure was obtained, and ward clustering was applied.

The C-index was used to optimize the number of clusters [124]. Six clusters from 33 topics were obtained (see Fig. 8). Cluster 1 (from left) contains only one member, Topic 32. The second cluster has three members: data-driven business model innovation (BMI), sustainable SC, and sustainable supply chain management (SCM). The third cluster is the biggest one, with 13 members, and the main topic is related to AI applications in different areas, highlighting the closer connection in terms of semantic similarity of the text. The remaining clusters have eight, four, and four members, respectively.

To gain insight into the details of the research themes, the topic modeling approach using BERTopic identified 33 different sustainability-related topics (see Table 9 and Table 11, Appendix). These categories include sustainable development, renewable energy, manufacturing, health care, urban planning, product sustainability, sustainable SC, education, and other topics. The identified topic outlines the research and efforts and major emerging research themes of sustainability.

One of the results is related to the sustainable development of nanomaterials and nanotechnology. Nanomaterials and nanotechnology have widespread applications

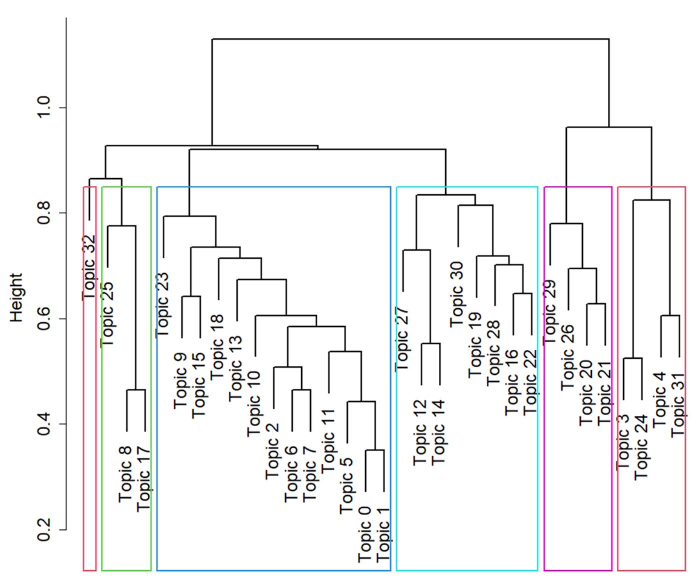

Fig. 8 Topic clustering based on topic-terms c-TF-IDF matrix with cosine dissimilarity (C-Index optimized clusters)

and are promising technologies offering disruptive transitions in the use of resources, environmental sustainability, transportation, energy usage, health, and other areas [257]. AI and nanotechnology can offer promising results [103, 270], highlighting the increasing importance of sustainable practices and innovations in nanoscience and nanotechnology, emphasizing sustainability's growing intersection and cutting-edge technological advancements.

Additionally, by conducting further clustering of the topic-term matrix (c-TF-IDF matrix) to find the clusters of topics, five distinct groups from the initial 33 topics could be distinguished. These clusters of topics share interconnected themes within a broader context. For instance, the second cluster from the left (colored green) comprises three topics: Topic 25 (focused on BD and BMI), Topic 8 (centered around sustainable SC), and Topic 17 (on sustainable SCM). These topics are closely related, particularly regarding their underlying theme of adopting data-driven approaches for sustainable BMI.

Discussion

The data analysis provides insights into current trends in AI and sustainability, covering three aspects: sustainability trends, the emphasis on AI and sustainability research by country, and keyword analysis highlighting key research themes using AI and data-driven methods. Additionally, topic modeling is utilized to identify key topics within sustainability research. The following sections will discuss the various methods applied to sustainability and AI. The analysis of topics, keywords, key application areas of AI, and the intersection of technology and AI in the context of sustainability emphasizes four key aspects that impact the role of AI in achieving sustainable outcomes and shaping the future of sustainable AI practices. The first aspect is various data-driven and AI methodologies applied for different levels of sustainability-related problems. It is important to understand the scope and application of these methods, as well as the integration of these methods, which is essential for informed and effective decision-making for multi-dimensional and multi-level sustainability problems. The second aspect revolves around the scope and challenges associated with data-related characteristics, BD, and BD technologies, particularly its sustainable utilization. The third aspect centers on adopting sustainable AI practices, highlighting the importance of integrating sustainability principles into AI development and deployment. Lastly, the fourth aspect emphasizes facilitating sustainable human-AI ecosystems, where the widespread use of AI and the active interactions of humans and AI systems lead to the emergence of different unknown social, environmental, and economic phenomena. These four aspects collectively define the trajectory of AI's contributions to sustainability and illustrate the path towards the future of sustainable AI practices. These aspects will be briefly discussed in the next sub-chapters.

AI, ML, and data-driven methods

The AI and data-driven methods for sustainability applications are divided into nine categories: DL and neural network models; Other supervised and unsupervised ML models; forecasting methods; optimization methods; fuzzy methods; multi-criteria decision-making; complex network-based analysis, ontology-based models; statistical, stochastic, Bayesian methods. These method classes are based on the surveyed literature and keyword analysis. The different categories of the methods and relevant publications are shown in Table 10 (additional details in Table 12, Appendix), and the corresponding plausible sustainability dimensions they address.

The recent publications published within the last eight years were selected. The different categories of sustainability dimensions are based on their relevance, as mentioned in the abstract and keywords. Some publications can belong to more than one category regarding methods and sustainability criteria. However, it was assigned to only one category based on the importance of the subject given in the article. These models are applied across a wide range of sustainability domains. However, the studies might not directly relate to the 17 SDGs but rather focus on the general idea of sustainability within their problem space and practical implementation, although it relates to sustainability's social, environmental, and economic dimensions. This can help understand sustainability issues internally or for a more expansive understanding and application of methods for sustainability-related problems.

DL and neural network models are major methods for addressing sustainability-related problems among these categories. This is evident from the keyword analysis, where DL is shown among the top keywords. DL models are specifically for prediction, forecasting, optimization, and classification. The data for these methods are IoT data, BD, production and manufacturing data, text data, structured data, temporal data, image data, and geological and satellite data. The methods are beneficial for where data is in large amounts and well managed. The social dimension of DL applications includes challenges related to sustainable urbanization, education, health, and healthcare automation. The other major application is the environmental dimension for smart and sustainable agriculture, soil management, waste management, sustainable energy usage, wetland and ecosystem management, crop yield, and plant disease prediction. The economic dimension applies to resource optimization, smart and sustainable manufacturing, inventory control, financial crisis prediction, efficient scheduling, resource allocation, predictive maintenance, condition monitoring, and energy-efficient production. The DL and neural network models include ensemble models, convolutional neural networks, deep transfer learning models, Gaussian and Bayesian neural networks, recursive neural networks, recursive support vector neural networks, deep reinforcement learning models for classification, regression, forecasting, and unsupervised learning models with deep encoder-decoder architectures.

It is important to distinguish DL models from ML models because they are data- and resource-intensive; other than that, the lack of explainability of models cannot fit them into certain applications, particularly those related to critical health decision-making or policy formulation where transparency is crucial. TinyML is an emerging trend as edge computing provides ML-as-a-Service (MLaaS) to IoT devices. The resources are limited for edge computing, and using deep models cannot be useful for response time and accuracy. However, the other ML models can be useful for tinyML [361]—other than that, the other methods are more useful where the data is sparse and requires fewer resources.

The **other supervised ML methods** are widely used for various sustainability-related questions. It is shown that they cover a wide range of sustainability applications for pattern recognition, prediction, and classification. The most applied approaches for

Table 10 Different ML and data-driven methods applied to different sustainability problems

DL, artificial neural network models	
Social	Li et al. [190], Alqahtani et al. [18], Dolawattha et al. [77], Nosratabadi et al. [235], Shafiq et al. [288], Ali and Shirazi [15]
Environmental	Wongchai et al. [351], Dairi et al. [65], Rangel-Martinez et al. [263], Sohani et al. [301], Nañez Alonso et al. [227], Park and Yang [245], Himeur et al. [119], Yang et al. [355], Jendoubi and Bouffard [137], Pham et al. [252], Selukar et al. [287], Padmapriya and Sasilatha [242], Rastogi et al. [265], Tariq et al. [315], Jin et al. [140], Ashwitha and Latha [28], Ferdous et al. [93], Karka et al. [153], Zhang et al. [366], Abbas et al. [2], Papagiannis et al. [244]
Economic	Sachithra and Subhashini [271], Grant [106], Latif [184], Jamwal et al. [131], Lazaroiu et al. [186], Jan [133], Cavus et al. [50], Wang et al. [348], Verma et al. [338], Elhoseny et al. [87], Danishvar et al. [67], Demir [71], Walk et al. [343], Corceiro et al. [61], Fisher et al. [94], Latif and Ahmed [185], Gómez et al. [104], Liu et al. [201]
ML/Supervised ML	
Social	Mrówczyńska et al. [223], Pham et al. [250], Mishra et al. [215], Novak et al. [236], Mashaba-Munghemezulu et al. [211], Naseer et al. [228], Kim and Kim [162], Rathore et al. [266], Almalki et al. [17], Dash et al. [68], Molina-Gómez et al. [218], Piscitelli and D'Uggento [256], Abbas et al. [1], Wang et al. [347], Arango-Uribe et al. [26], Ijadi Maghsoodi et al. [126], Yigitcanlar and Cugurullo [357], Garg et al. [100]
Environmental	Taghizadeh-Mehrjardi et al. [312], Niu and Feng [233], Pal et al. [243], Sugiawan et al. [307], Elavarasan and Vincent [86], Iddianozie and Palmes [125], Shahbeik et al. [289], Badreldin et al. [31], Xiaonuo Li et al. [192], Javed et al. [135], Singh et al. [299], Liu et al. [199], Gültepe [108], Carrera et al. [49], Li et al. [190], Al Duhayyim [12], Mao et al. [210], Agrawal et al. [4], Shrimali et al. [292]
Economic	Kumar Mohapatra et al. [180], Akbari et al. [8], Ullah et al. [333], Wu et al. [352], Onyelowe et al. [238], Thanh et al. [319], Sankaranarayanan et al. [278], Ghanizadeh et al. [101], Dai and Zhang [64], Khoh et al. [161], Erçen et al. [89], Pham et al. [251], Momenitabar et al. [220], Jamil et al. [130], Wang et al. [344]
Unsupervised learning	
Social	Nilashi et al. [231], Kumar et al. [179], Mukherjee [224], Zhang et al. [365, 367], Tsaples et al. [326], Mumtaz and Whiteford [225], Suha and Sanam [308], Qi and Li [260]
Economical	Tayal et al. [317], Schöggl et al. [284], Zhou et al. [368], Tirth et al. [321]
Environmental	Kosir et al. [173], Aqel et al. [25], Viet and Jang [340]; Priyanka et al. [259], Heo et al. [117]
Time series and forecasting	
Social	Kumari and Tanwar [181], Lee and Jung [189], Molina-Gómez et al. [217], Kahwash et al. [149], Suchetana et al. [306]
Environmental	Kazancoglu et al. [158], Sugiawan et al. [307], Rani Hemamalini et al. [264], Alsaidan et al. [19], Li et al. [191]
Economic	Abidi et al. [3], Choi et al. [55], Amin et al. [22], Ilie et al. [128], Uppal et al. [335], Mohammed et al. [216], Cadenas et al. [48], Saxena et al. [283], Couto and Rangel [63]; Dutta et al. [81], Kayakus et al. [156], Sapitang et al. [281].
Bayesian/statistical/probabilistic methods	
Social	Holloway and Mengersen [120], Akhtar et al. [10], Kontokosta and Jain [170], Tao et al. [314], Kong [169], Aly et al. [20]
Environmental	Chakraborty et al. [51], Zeynoddin et al. [363], Akbarian et al. [9], Ijlil et al. [127], Li et al. [191]
Economic	Yunpeng Li et al. [195], Jun [146], González-Cancelas et al. [105], Jong et al. [143], Hao Wang [345], Jun [145]

Table 10 (continued)

Optimization	
Social	Kolak et al. [168], Huang et al. [123], Oyebode et al. [240], Shifa Ma et al. [206], Mousavi et al. [222],Yue Li et al. [194], García-Esparza et al. [99], Arslan et al. [27], Bliek [43]
Environmental	Santos et al. [279], Manos et al. [209], Nowakowski et al. [237], Lytras and Chui [205], Liu et al. [198],Chen et al. [53], Tavakoli and Barkdoll [316]
Economic	Quariguasi Frota Neto et al. [261], Shuaiyin Ma et al. [207], Jiao et al. [139], Xu et al. [354], Anvari and Turkay [24], Lotfi et al. [204], Hombach et al. [121], Simeoni et al. [295], Honghui Wang et al. [346], Peng et al. [247], Doliente and Samsatli [78], Sharma et al. [290], Nayeri et al. [230], Momenitabar et al. [220], Choi [56], Jayarathna et al. [136], Yue Li et al. [194]
Simulation models	
Social	Bibri [41], Saeid Atabaki et al. [273], Verma et al. [339], Hart et al. [114], Torres et al. [323], Islam and Tareque [129]
Environmental	Singh et al. [296], del Caño et al. [69], Medvedev et al. [212], Dlugosch et al. [75], La Torre et al. [183], Strand et al. [304], Ghasemi and Yazdani [102], Eckhoff et al. [83], Mirshafiee et al. [214]
Economic	Rackes et al. [262], Jung in Kim et al. [165], Ekici et al. [85], Elnour et al. [88], Hatim et al. [115], Relich [267], Pirola et al. [254]
Fuzzy methods	
Social	Alimohammadlou and Khoshsepehr [16], Sarkar et al. [282]
Environmental	Krishankumar et al. [176], Song et al. [302], Bui and Tseng [46], Tayebi et al. [318], Kadham et al. [148], Alzain et al. [21]
Economic	Kannan [151],Tseng, Tran, et al. [329]; Orji and Wei [239], A. Kumar et al. [178], Bui et al. [45], Kokkinos et al. [167], Tsai et al. [325], Balaman et al. [33], Khalili-Damghani and Sadi-Nezhad [160], Tirkolaee and Aydin [320], Tseng et al. [327], Fallahpour et al. [91], Pereira et al. [249], Jeong and Ramírez-Gómez [138], Tseng, Bui, et al. [328], Choy et al. [57], Kazancoglu et al. [157], Su et al. [305], Alassery and Alhazmi [13]
MCDM	
Social	Zhang et al. [364]
Environmental	Dogra and Adil [76], Alghassab [14]
Economic	Lo [202], Bhatia et al. [40], Ozkan-Ozen et al. [241], Singh et al. [297], Li et al. [196], Tseng et al. [330]
Complex networks/Knowledge graphs/ontology	
Social	Juhwan Kim et al. [164], Lorimer et al. [203], Konys [171], Silva et al. [293], Draschner et al. [79], Zovko et al. [370], Bellantuono et al. [36], Jing and Wang [141]
Environmental	Ahmed et al. [7], Tran and Draeger [324], Sebestyén et al. [286]
Economic	Muñoz et al. [226], Aydin et al. [29], Yang and Yu [356], Kim [163], Perdana et al. [248], Zhou et al. [368]

sustainability tasks are tree-based models, including decision trees, random forest, and gradient boosting. The other methods are Support Vector Machine (SVM), regression models (linear, polynomial, beta, Bayesian, and support vector regression), and ensemble models. Other than predicting various social, environmental, and economic questions and feature selection shown in Table 10, various studies utilize these methods to evaluate different sustainability tasks, socio-economic factors, and environmental challenges. For example, Molina-Gómez et al. [218] use different sustainability indicators to collect data to predict different levels of sustainable development of the urban ecosystem. This approach can be useful for identifying the quality of life in urban ecosystems and policy-making decisions for disadvantaged societies. The other application is sustainability performance assessment with SVM for large-scale decision-making for inclusive decisions with incomplete data [126]. Yigitcanlar and Cugurullo [357] discuss key aspects of the sustainable adoption of AI that require significant improvement for sustainable urbanism. Similar aspects are needed to design for sustainable adoption.

The unsupervised models are applied for data exploration, formulation of hypotheses, dimensionality reduction, latent variable modeling, anomaly detection, and clustering. The unsupervised methods are independently applied or in conjunction with other data-driven and machine-learning approaches. Some examples where it is integrated with other methods: Nilashi et al. [231] use clustering and supervised learning methods to predict the overall sustainability performance of different countries. Tayal et al. [317] discuss a staged approach, including data envelopment analysis, meta-heuristic approach, and k-means clustering to optimize sustainable facility layout design (shop floor, manufacturing unit), maximizing performance and minimizing operating costs.

The other methods are **forecasting and time series-based models**, which require estimating predictions based on historical temporal data and are useful for anticipating future events to reduce uncertainty, analyzing trends, optimizing resources, and taking proactive actions. The various applications are forecasting energy and other resources usage, load management, and forecasting values or patterns of various social, climate-related, and economic variables. These forecasting models can be applied for short and long-range forecasting. Clark et al. [59] discuss the need for iterative near-term ecological forecasting that maximizes ecological relevance to society,similar situations can be realized in various other social and economic cases, where the availability of BD can make iterative forecasting approaches possible for effective and adaptive decision making which can critically evaluate and update models based on new understanding. BD for forecasting is categorized into three categories: user-generated, device, and log data. Successful utilization of BD in forecasting demands a systematic approach: expertise in method development/selection (including statistical, ML, and hybrid methods), data processing, and domain knowledge [313].

ML model applications include transportation, food security, urbanization, agriculture, governance and public services, poverty, education, water, sustainable goal evaluation and SC applications, energy optimization, manufacturing, sustainable material properties, sustainable power supply, and green technology adoption. The designing of efficient AI algorithms is a challenge due to the open-ended complexity of problems related to sustainability. As more and more data are available in different domains, a wide range of applications of AI-based methods for sustainability problems become visible. From the implementation point of view, data quality, dimensionality, online effect, interpretability, accuracy, generalization, hyperparameter tuning, model updating, cost, and resources involved in developing models are key factors for appropriate ML model selection for ML methods. To ensure the robustness and sustainability of AI, it is imperative to examine how AI can adapt to external changes for long-term sustainability and identify the model development requirements that consider temporal effects, data characteristics, hyperparameter selection, continuous model updating, interpretation, and explainability.

One of the important cases is the multi-dimensional consideration of the problems in all three directions of sustainability. For instance, if an organization solely targets reducing expenditure and maximizing profit by minimizing energy usage and carbon footprint within its operations, it may inadvertently overlook other conflicting objectives across different dimensions of sustainability. This limited approach might yield immediate results by promoting the adoption of alternative energy sources. However, such alternatives could introduce challenges. Transitioning to these sources might necessitate utilizing resources with a substantial carbon footprint and additional maintenance requirements, potentially compromising long-term sustainability. Moreover, the cumulative effects could trigger broader ecological repercussions if multiple organizations embrace similar energy solutions. A widespread shift towards specific energy storage or generation methods could escalate the demand for particular materials, resulting in unforeseen environmental consequences. Therefore, the long-term effect must be understood by data-driven methods in maintaining sustainability.

Several multi-objective optimization methods can be applied to various social, environmental, and economic factors. The **optimization** methods are largely applied to complex problems to search for the best feasible solution, maximizing sustainability objectives considering problem constraints [272]. Metaheuristic, Pareto, scalarization, dominated, non-dominated, stochastic, and simulation methods can be applied to sustainability problems [82, 109, 136].

Multi-criteria decision-making is another area of methods applied as a decision support system for complex technological, social, and economic systems. Policymakers, managers, investors, and academicians can use these decision-making methods to identify and prioritize key indicators. Multi-criteria decision-making methods with fuzzy approach and simulations are applied to address various aspects of sustainability in multiple sectors. These include building and urban design, SCM, production, transportation, air pollution and waste management, and sustainable project selection. These methodologies assist in addressing complex decision-making strategies encompassing multiple conflicting criteria underneath uncertainty. This highlights the key role of these methods for optimization and decision-support tools for identifying sustainable solutions in diverse fields. The data sources for these studies include surveys, expert groups, observational studies, databases, or experimental design, depending on the specific context and requirements of the decision problem by identifying influential, dependent, and conflicting variables.

Sustainable big data and analytics

With the recent advancement in ICT and its widespread application, data can easily be gathered from various sources, including governmental, industrial, transactional, and urban data. “Datafication” has become an important factor in many sectors. It describes the current trend of defining phenomena, processes, and operations by turning them into digitized data to analyze and extract information [41]. The extracted information offers a huge potential to reinforce social, environmental, and economic sustainability. The prospect of leveraging BD resources to improve sustainability is a topic of research in many domains, including but not limited to sustainable agricultural SCs, sustainable health care, sustainable organization performance, innovation, sustainable urban planning, and smart cities.

Multiple studies discuss using BD approaches for sustainability applications and their potential to improve sustainability. Kamble et al. [150] highlight the potential of data analytics to augment the sustainability of the agri-food SC. For instance, the author discussed how descriptive analytics, namely the life cycle assessment tool, is widely used to address environmental concerns, analyze the misuse of resources leading to food waste, and design short SCs that increase the involvement of farmers and contribute to sustainable community development. Suvarna et al. [311] examine how "industrial data" can be leveraged by manufacturing companies for multiple purposes, including real-time process monitoring, data-driven process control and optimization, and decentralized manufacturing. This falls in line with the improvement of sustainability. From an economic perspective, improving the efficiency of manufacturing processes through control and optimization improves the company's financial profitability and ensures its economic sustainability. The improved process efficiency also significantly impacts energy consumption and resulting emissions, strongly contributing to environmental sustainability. Moreover, by allowing decentralized manufacturing, the exploitation of industrial data can contribute to a more even geographical distribution of job opportunities and hence empower social sustainability.

Similarly, BD plays a key role in health care. The literature suggests several BD tools that could be implemented in a digital healthcare system and allow for the exploration of hidden patterns, early detection of diseases, and reduction of the required time and cost of analysis [360]. "Open Data" platforms are another tool that strongly contributes to sustainability goals. "Open data" platforms, where data can be shared between multiple parties, can lead to highly granular information content and allow all involved parties to benefit from it. For instance, the development of open-data healthcare platforms where citizens can share their medical data can contribute to better knowledge, diagnosis, and treatment of diseases. Moreover, locally or globally, sharing information from different population sections can help researchers better understand inequities, highlight them, and address them with dedicated healthcare interventions [174]. However, even though BD can offer lucrative opportunities in many fields and help reinforce sustainability, implementation comes with critical challenges. The challenges range from data collection to storage, processing, governance, privacy, and accessibility and pose questions about how sustainable BD approaches are from all social, environmental, and economic aspects [337].

H. Zhang et al. [364] highlight the difficulties service design teams face in fully understanding and exploiting BD due to a lack of big data analytic capabilities (BDAC). In line with that, excessive investment in BD resources alone without parallel investment in BDAC can hinder sales growth and negatively affect companies' sustainable growth [113]. Apart from the negative implications of the financial sustainability of companies, the perspective of the knowledge gap hypothesis, which posits that significant investments in BD resources and analytics are required, can also be detrimental to social sustainability. In line with the knowledge gap hypothesis, when there is a rise in the introduction of mass media information into social systems, communities or countries with a higher socio-economic status typically acquire this information more quickly than their counterparts with lower socio-economic status. This results in an amplification of the gap between them rather than a reduction [234]. Applying this hypothesis to BD, economically advanced regions will likely have the capacity to swiftly make substantial investments in harnessing BD and developing essential skills, outpacing the progress of underdeveloped regions. Such a scenario could reinforce a monopoly on BD technologies, ultimately affecting social or economic aspects of sustainability.

In addition, the potential offered by open data platforms is opposed by serious privacy concerns, which in turn raise questions about the lack of "Data Governance" standards to regulate the way data is collected and processed, as well as define who is accountable for the decision making resulting from data usage [258]. This lack of governance can lead to data usage that contradicts social and environmental sustainability goals, namely climate protection and reducing inequalities. Within the social context, some researchers discussed the thriving data broker industry in which data is used for purposes it was never intended for, including "to predictively profile, socially sort, behaviorally nudge, and regulate, control and govern individuals and the various systems and infrastructures with which they interact" [166]. This trend is alarming in terms of its implications for individual privacy. Regarding the environmental aspect, the amount of data generated from various sources requires energy-intensive computational resources to collect, store, and conduct analytics. This could potentially negate the positive effect of BD and its analytics on sustainability. These powerful computational resources require mining rare materials for their manufacturing, consuming high energy levels for processing and cooling, and generating waste when discarded, raising questions about their sustainability.

Moreover, the ease and low cost of data collection and its potential financial benefits have encouraged organizations to focus on accumulating vast amounts of data in their databases to commercialize it. In the absence of governance to regulate how data is collected, this can lead to "data obesity," in which case redundant data might be collected from multiple sources, thus increasing the size of datasets without contributing to their information content [213]. To counteract the effect of data redundancy, allowing for more energy-sustainable data sharing and computing, the scientific community is reverting to "data aggregation and fusion" techniques, which aim to reduce data size without affecting its information. Data aggregation and fusion encompass a variety of methods, including redundant data elimination, data compression, in-network processing, and data sampling and prediction [52]. The challenge remains, however, in minimizing the data quality loss when reducing its size, which is a prominent area of research. For instance, Pielli et al. [253] propose an RL technique to choose the compression rate that maximizes data quality and adheres to the energy constraint.

Even though research seeks to optimize techniques that reduce data size without affecting its quality, a correlation between data size and quality still exists in certain cases. This conflict arises between the financial rewards of data approaches and their environmental impact. Commercial institutions face the challenge of deciding between financial gain and environmental sustainability due to the absence of proper data governance or a framework defining responsibilities. The literature shows that exploiting BD to enhance sustainability and analytics still faces significant challenges. While the potentials presented are promising, the different social, environmental, and economic aspects are interconnected and, at times, can be inversely proportional. Therefore, implementing such approaches can have differing impacts on each aspect of sustainability. The field of BD is an active research topic with ongoing efforts by scholars to refine the analytic methods and develop frameworks that can mitigate the potential negative implications of BD approaches.

Sustainable AI characteristics and challenges

The IoT and AI have the potential to support prevailing sustainability measures like the circular or sharing economy. Fraga-Lamas et al. [95] explicitly mentioned that IoT could pave the way for more sustainability in various sectors in operations, maintenance, and processes and areas addressed in the UN's SDGs, like water distribution. Bachmann et al. [30] delivered a comprehensive work about the contribution of data-driven technologies (including IoT) to achieving the SDGs. Sætra [274] emphasizes the different levels AI might influence in the context of the SDGs. As an example, it is pointed out that positive effects for a country (meso level) might create negative effects on other countries (macro level) and raise tensions within the country (micro level). Therefore, Sætra [274] describes AI not as a single technology but as something connected to various other technologies that may simultaneously trigger positive and negative effects.

On the one hand, IoT and AI can serve as facilitators for sustainability, but paradoxically, the IoT sector itself has a high carbon footprint [95]. Also, Schwartz et al. [285] claim that ML-based text and image generators have improved in quality over the last few years. However, this AI research has become increasingly "Red AI," meaning it seeks to improve accuracy by using massive computational power, which is costly, environmentally unfriendly, and exclusive. Furthermore, Schwartz et al. [285] propose that a "Green AI" should treat efficiency as a primary evaluation criterion alongside accuracy, and they suggest reporting the number of Floating-Point Operations (FPO) required to generate a result as an indicator of how green an AI-based result is. An approach to optimize the energy consumption of Deep Neural Networks (DNN) is presented by Liu et al. [198–200] through a combination of deep and spiking neural networks, which lead to a six times lower energy consumption. Another approach, the optimization framework called "Zeus," is presented by You et al. [359]. This framework proposes to decouple the optimization of batch size and Graphics Processing Unit (GPU) power limit. It uses an online exploration–exploitation approach based on multi-armed bandit and just-in-time energy profiling to navigate the trade-off between energy consumption and performance optimization. The work by S. Choi et al. [54] focuses on energy saving when using multi-GPUs for DNN training with their proposed framework "EnvPipe." This framework should save energy by using multiple GPUs with pipeline parallelism while providing high accuracy and performance. However, this highlights that the challenges are multifaceted, encompassing identifying appropriate application fields for AI and IoT to enhance a business's sustainability and determining the optimal level of AI and IoT utilization.

Besides the intensity of IoT use, Dunn et al. [80] are especially addressing the vulnerability of IoT systems. They claim that ML technology, often the basis for IoT systems, could suffer from data poisoning or cyber-attacks, which create false assumptions, results, or outcomes and may harm the application field. In smart cities, for example, AI can support efficiencies in decision-making, infrastructure assessment, post-disaster reconnaissance, connected urban mobility, or service agent chatbots, to name a few [358]. However, its use is reluctant due to the technocratic use of AI and its not being implemented sustainably. The main focus has been on increasing efficiency, but a sustainable implementation also needs a social and environmental equitable point of view [358]. The challenge of sustainability in the product service system is addressed by Xinyu Li et al. [193]. Their article emphasizes integrating sustainability considerations into Product-Service Systems (PSS) design and development, particularly in a cyber-physical environment. It underscores the lack of existing studies that see cyber-physical resources as a whole regarding sustainability rather than just physical materials and components. As cyber-physical systems often use AI or IoT technology, Xinyu Li et al. [193] propose a data-driven reversible framework that extends the traditional scope of resource management to create Sustainable Smart PSS. This framework incorporates a four-step context-aware process that involves requirement elicitation, solution recommendation, solution evaluation, and knowledge evolution to support decision-making and optimization throughout the product lifecycle.

Apart from the technological point of view, a challenge of AI is presented by How et al. [122]. The authors emphasize the critical role that AI can play in understanding and promoting sustainable development. It specifically focuses on how AI can be made more accessible and user-friendly to people who do not have a computer science background. How et al. [122] introduce a novel, human-centric probabilistic reasoning approach that democratizes AI by allowing non-computer scientists to use AI to analyze socio-environmental data. Wilson and van der Velden [349] focus on the public sector and claim that ethics, explainability, responsibility, and accountability are important aspects of analyzing the societal impacts of AI. These concepts alone do not support regulating and implementing AI in the public sector. Wilson and van der Velden [349] explored the concept of "sustainable AI" in their work to address this gap by aligning the research on sustainable development with that on public sector AI. A conceptual model identifying five boundary conditions, diversity, learning capacity, self-organization, common meaning, and trust, can assist in public sector decision-making about AI governance [349]. There are still challenges when using AI in smart cities, production, or the public sector. Scholars work to make AI more sustainable,they review current approaches, derive new possible pathways, and propose frameworks, models, and concepts to make AI more sustainable.

Sustainable human AI ecosystems

The different data-driven and AI methods for sustainable applications are applied at different levels of decision-making where the outcome of these methods is involved for subsequent levels considering several factors, including social, environmental, and economic aspects and the local, regional, and global constraints. Different methods can be useful for problems at different levels, from large data-intensive AI models to tiny or small data-related decision-making models, ML, and analytics. It is, therefore, useful to know the effectiveness and power of different methods at different levels of decision-making given the various method-related, data-related, and other application-related constraints, explainability, and impact on decisions.

A systematic framework and a hybrid approach to decision-making are critical and show better performance, context awareness, and improved accuracy [282]. The hybrid approach involves humans and different AI and data-driven methods, and its aim should be to maximize the impact of decision-making towards sustainability goals. The framework must ensure who will make the final decisions, and the allocation of responsibility for decision-making is an important consideration. While AI can significantly assist decision-making, there should always be a mechanism to ensure that human judgment and values can supersede AI-generated decisions when necessary.

The other challenge is the implications that can originate from large-scale interactions between "AI" and "humans." The future of AI will be about AI not working in isolation but evolving as multi-agent systems, and AI (or multi-agent)-human ecosystem where humans and AI systems continually interact and learn from each other lead to an extensive shift in decision-making processes. This effect would generate a social impact and affect the decision-making compass of companies, policy-making bodies, and other decision-making entities, subsequently influencing sustainability-related aspects. Key considerations include the consequences of bias in these decisions [310] or error propagation initiated either by humans or AI [72]. These errors have the potential to propagate through the system and compound due to repeated interactions. The other interesting part is that AI and human interactions as a Social and Technological System (STS) lead to unknown emergent behavior from the aggregated outcomes that can lead to conformism and potential unanticipated and undesirable consequences [246]. Pedreschi et al. [246] emphasize the design of next-generation AIs with the "complexity-informed perspective" abided by the sustainability goals where individual and collective concerns are addressed effectively.

Conclusion and future research

The study has conducted four main analyses, which include an overview of publications, an analysis of research articles across multiple countries that showcase collaborative research actions in the context of sustainability tasks and data-driven methods, keywords and co-occurrence analyses, and topic modeling. Collaborative research highlights the substantial lack of collaboration in underdeveloped regions and is to be emphasized further for global sustainability goals. The frequency of emerging concepts, application areas, and key technologies has been highlighted by analyzing keywords, particularly concerning AI and data-driven approaches that are gaining prominence. The modules with keywords in the co-occurrence network reveal common interconnected concepts and their social, environmental, and economic dimensions, highlighting the relevance of the complexity of different data-driven applications. The topic analysis has also highlighted the major research area related to sustainability and data-driven applications. These findings from the literature have further driven us to explore the different AI and data-driven methods applied to different types of applications. We have found that nine categories of methods are applied for different cases and applications for different levels of decision-making and their importance. It is important to understand that a single method cannot show its importance in decision-making. However, different methods have their utility and shortcomings for various sustainability-related problems, covering different aspects of sustainability and the scope of applications in engineering, basic research, health and medicine, business and policy-making, and governance. Therefore, their scope and power in multi-level and multi-dimensional decision-making must be understood before using different methods for decision-making, given the data and methods-related constraints and their ability to provide meaningful and reasonable explanations.

It is important to remember that different decision-making processes are not single, isolated decisions but multi-level and multi-dimensional processes requiring different methodologies. Therefore, it is crucial to systematically integrate these methods to maximize their ability to provide accurate and long-term insights into sustainability. Additionally, BD and AI will play a significant role in decision-making. With the expansion of IoT and other technologies, BD and AI will be widespread, posing several sustainability-related challenges. AI continues to evolve as a multi-agent system and a human-AI ecosystem where new challenges will arise. We must be aware of them to apply AI to address sustainability challenges effectively and adopt sustainable AI characteristics in both development and decision-making processes. Additionally, it is imperative to remain informed about the personal and collective responsibilities associated with its use, its future implications, and potential challenges.

Limitations and future research

Our analysis may have limitations, such as relying on a single database for selecting research papers, which may overlook certain published papers and lead to incomplete results and understanding of some topics. Additionally, selecting keywords that define social, environmental, and economic dimensions may lack in-depth understanding as the research area is multidisciplinary and can only be based on limited keywords. Additionally, including a more detailed list of AI and technology-related keywords in the search criteria can enhance the results' quality and relevance. Furthermore, topic analysis based on only the abstract, title text, and keywords may limit understanding of the subject matter. In contrast, a more comprehensive approach would involve an in-depth analysis of the entire text. Fine-tuning approaches, including different embeddings, dimension reduction methods, and clustering methods, and aggregating different types of analysis could further improve results. Employing multiple semantic analysis methods and incorporating domain understanding for topic selection, interpretation, and identifying key representative documents is advisable to enhance result stability.

Future research could focus on data-driven methods for sustainable BMI, sustainable SC analysis, and developing a framework that systematically integrates different methods for different levels of decision-making in BMI for robust outcomes and complementing all aspects of sustainability.

Appendix

See Tables 11, 12 13 and Figs. 9, 10.

Table 11 Representative keywords from c-TF-IDF matrix for different topic segments from BERTopic modelling

Topic	Count	Key representation	Description
− 1	643	Sustainability, sustainable development, sustainable, AI, artificial intelligence, machine learning, environmental, economic, industry, development, intelligence, technologies, datadriven, analysis, technology, energy, management, models, artificial, manufacturing, learning, machine, data, research, smart, urban, proposed, model, approach, framework, performance, process, systems, design, social, city, method, network, supply, chain, study, it, information, decision, results	Mixed topics that are not part of any clusters but broadly discuss the application of AI, and sustainability related research and application
0	187	Sustainable AI, AI, sustainability, intelligence ai, sustainable development, artificial intelligence, sustainable, artificial intelligence ai, sustainable development goals, artificial intelligence, intelligence, environmental, technologies, innovation, technology, economic, ethical, artificial, ethics, economy, development, future, policy, management, business, systems, research, global, goals, data, social, framework, development of, challenges, analysis, potential, human, digital, change, paper, impact, legal	AI and sustainable development
1	150	sustainable agriculture, agricultural, farming, crops, sustainable food, ai, deep learning, farmers, irrigation, crop, artificial intelligence, machine learning, iot, food, soil, technologies, classification, sustainability, technology, sustainable, data, monitoring, machine, learning, models, smart, artificial, algorithms, environmental, model, development, productivity, production, deep, digital, water, management, systems, system, precision, analysis, research, results	ML for sustainable agriculture
2	83	Renewable energy, sustainable energy, smart grid, of renewable energy, energy consumption, energy systems, renewable, machine learning, energy, ai, artificial intelligence, forecasting, energy and, solar, electricity, of energy, the energy, prediction, smart, learning, machine, power, sustainable, optimization, algorithms, efficiency, grid, intelligence, algorithm, consumption, demand, models, neural, generation, artificial, heat, data, building, ml, model, cooling, load, have, thermal, control, performance, wind	Sustainable energy and renewable energy
3	63	Sustainable smart manufacturing, smart manufacturing, sustainable smart, sustainable industrial, internet of things, big data, industrial value creation, manufacturing systems, industrial, industrial value, big datadriven, automation, manufacturing, analytics, industry, industries, industry 40, decisionmaking, artificial intelligence, cyberphysical, technologies, data collected, sustainability, sustainable, made estimates, made estimates regarding, analyses and made, and replicating data, datadriven, data collected from, smart, data, internet, and made estimates, production, intelligence, in sustainable, value creation, data from, process, realtime, estimates regarding, internet of, estimates, structural equation modeling, creation, management, artificial, analyses, made	Big data, data analytics and data driven methods for sustainable industrial manufacturing

Table 11 (continued)

Topic	Count	Key representation	Description
4	61	Smart sustainable urbanism, smart sustainable cities, sustainable urbanism, sustainable cities, smart sustainable, smart urbanism, smart cities, smart city, big data, sustainable, urban, urbanism, datadriven smart, sustainability, urbanism, data technologies, cities, of urban, city, cities and, ecocities, analytics, cities as, planning, technologies, smart, the future, technology, of smart, future, big, science, development, of the future, approaches, research, futures	Data-driven smart sustainable cities
5	59	Healthcare, healthcare system, ai, health care, intelligence ai, global health, health, artificial intelligence ai, artificial intelligence, medical, ethical, intelligence, sustainability, sustainable, in health, artificial, sustainable development, sustainable development goals, technology, for sustainable, technologies, oral health, machine, research, patients, care, disease, machine learning, the pandemic, development, pandemic, data, digital, future, global, immunization, model, learning, human, covid19 pandemic, analysis, applications, management	Application of AI in health care
6	50	Machine learning methods, of machine learning, machine learning, urban planning, urban, air pollution, classification, urban sprawl, learning methods, the urban, prediction, pollution, cities, data, sustainable development, air quality, environmental, models, sustainable, remote sensing, learning, planning, housing, sustainable development goals, sustainability, earth, algorithms, building, land, spatial, model, automl, future, development, sensing, ml, machine, area, parking, development goals, tools, satellite, co2, air, analysis, results, this study, methods, economic, food	ML approaches in sustainable urban planning
7	47	Product sustainability, sustainable design, of sustainable, sustainable, sustainability, machine learning, product reviews, classification, environmental impact, environmental, products, design, models, product, reviews, design space, prediction, software, machine, manufacturing, model, learning, of machine, performance, industry, customers, using machine, proposed, analysis, methods, customer, framework, decision, research, process, identify, approach, value, requirements, data, impact	Sustainable Product design and manufacturing
8	47	Sustainable supply chain, sustainable supply chains, supply chain management, supply chain, sustainable supplier, sustainable supply, supply chains, chain management, supplier selection, sustainability, logistics, decision support system, sustainable, decision support, suppliers, strategic, supplier, criteria, chains, chain, management, industry, datadriven, supply, knowledge base, closedloop supply, indicators, environmental, support system, fuzzy, data, economic, transportation, risks, analysis, decision, knowledge, resilience, design, programming, evaluation, based, optimization, risk, approach, systems, based on, robust, performance, multiobjective	Sustainable supply chains

Table 11 (continued)

Topic	Count	Key representation	Description
9	44	Sustainable concrete, concrete, machine learning, of concrete, neural network, prediction of, compressive strength, cement, artificial neural, of cement, prediction, predicting, compressive strength of, the compressive strength, predict, regression, compressive, to predict, predict the, support vector, neural, the compressive, soil, learning, tensile strength, optimization, models, mechanical properties, materials, ml, strength, strength of, waste, construction, material, machine, recycled, optimized, model, programming, tensile, algorithm, artificial, accuracy, mechanical, sustainable, ash, vector, formula, of sustainable	Predicting properties of concrete using ML techniques
10	41	Sustainable building design, sustainable construction, building design, sustainable building, construction management, construction projects, building, construction industry, project selection, buildings, decision support system, decisionmaking, construction, civil engineering, of design, engineering, of sustainable, sustainability, decision support, sustainable, design, criteria, projects, artificial intelligence, development, environmental, materials, the construction, structural, project, decision, ai, project, fuzzy, knowledge, artificial, intelligence, support system, model, selection, methods, management, analysis, making, framework, based, bim	Decision support systems for sustainable building design
11	37	Sustainable education, of artificial intelligence, educational, education, in education, artificial intelligence, ai, curriculum, learning, ai and, higher education, student, students, the students, teaching, intelligence, courseware, study, technology, training, machine learning, sustainable development, sustainable, schools, academic, teachers, development, sustainability, research, data, software, skills, for sustainable, of artificial, software engineering, artificial, engineering, prediction, machine, algorithms, model, coding, elearning, ability, pandemic, systems, performance, online, the proposed, techniques	The role of ML and AI for making a digital classroom and its sustainable impact on education during Covid-19
12	35	Water resources management, sustainable water, water management, groundwater resources, water resources, decision support system, water demand, water supply, groundwater, sustainable development, sustainable management, river basin, sustainability, decision support, sustainable, for sustainable, resources management, water use, wastewater, support system for, basin, of water, support systems, indicators, support system dss, environmental, support system, river, the water, management of, water, system for, system dss, systems, development, climate, assessment, decision, management, framework, system, integrated, and water, analysis, planning, dss, project, supply, management in, based	Water resources management

Table 11 (continued)

Topic	Count	Key representation	Description
13	30	Sustainable chemistry, sustainable chemistry and, nanotechnology, chemical industry, engineered nanomaterials, engineered, chemical, sustainable, sustainability, materials science, chemistry, chemicals, nanomaterials, sustainable development, chemistry and, nanoparticles, the chemical, synthesis, technologies, nanoparticle, carbon, ai, artificial, environmental, and sustainable, synthesis of, artificial intelligence, compounds, organic, energy, machine, solvents, machine learning, industrial, science, research and development, materials, co2, industry, and materials, development, enms, co2 capture, intelligence, and development, design, cobalt complex, green, retrosynthesis, reaction	Sustainable development, nanomaterials, and nanotechnology
14	27	Water quality, support vector machine, machine learning, groundwater, groundwater potentiality, hydrological, of groundwater, vector machine, groundwater level, classification, svm, water resources, water level, pollution, prediction, models, regression, support vector, water, of water, basin, predict, modeling, reservoir, flood retention, model, algorithms, algorithm, ensemble, learning, sustainable, accuracy, flood, for sustainable, ml, in water, monitoring, data, parameters, intelligence, vector, methods, multilabel, decision, based on, urban, processes, machine, based, potential	Predictive modeling of water resources using ML techniques
15	25	Biofuels, biofuel, biomass, biorefinery, bioethanol supply, biorefineries, pyrolysis, fuels, machine learning, bioethanol, biowaste, biowaste remediation, biowaste remediation and, sludge, hydrothermal, fuel, sustainable, energy, sustainability, macroalgae, feedstock, life cycle assessment, optimization, biooil, gasification, waste, regression, production, models, life cycle, machine, yield, processes, hydrochar, learning, model, cycle assessment, process, microwave, ml, valorization, methods, syngas, applications, analysis, method, lignocellulosic, parameters, cycle, nitrile	Biofuels, biowaste remediation, and sludge
16	23	Spatial decision support, geographic information, spatial decision, decision support system, land use, land resources, gis, sustainable development, of sustainability, multicriteria, geospatial, sustainability, information system, decision support, spatial, ecological, criteria, sustainable, environmental, land, support system for, agricultural, maps, planning, areas, region, integrated, regional, development, support system, assessment, and environmental, conservation, area, rural, systems, development and, urban, system for, scenarios, evaluation, coastal, housings, framework, development of, resource, resources, management, decision, analysis	Decision support systems for sustainable land use management

Table 11 (continued)

Topic	Count	Key representation	Description
17	22	AI supply chain, sustainable supply chain, sustainable supply chains, supply chain management, supply chain, supply chain finance, the supply chain, supply chains, ai supply, sustainable supply, chain management, chain finance, ecommerce, sustainability, suppliers, sustainability and resilience, ai, of supply, outsourcing, firms, business, sustainable, companies, outsourcing relationships, cloud, artificial intelligence, supply, chain, the supply, chains, finance, their supply, management, efficiency, development, environment, intelligence, datadriven and adaptive, financial, datadriven, framework, global, cultural intelligence, resilience, contract governance, and adaptive leadership, adaptive leadership, artificial, and adaptive, and resilience	Sustainable supply chain management
18	22	Sustainable finance research, sustainable finance, of sustainable finance, sustainability, sustainable development, finance research, sustainable, of sustainable, governance esg, finance, financial statement, and governance esg, investing, financial, firms, investors, esg ratings, corporate, using big data, machine learning, big data, credit risk, governance, companies, sovereign credit risk, social and governance, financing, and governance, banking, sovereign credit, stock, ratings, macroeconomic, risk, reporting, research, learning, esg, development, prediction, credit, artificial intelligence, risks, data, intelligence, impact, using big, social, sovereign	Sustainable Finance and ESG (Environmental, Social, Governance)
19	22	Sustainable manufacturing, production scheduling, production planning, sustainability and productivity, process manufacturing, scheduling, energy consumption, energy consumption and, machining system, operation plans, sustainability, sustainable, optimization, machining, efficiency, manufacturing, of manufacturing, productivity, product lifecycle, production, process and operation, and operation plans, the manufacturing, energy, programming, and productivity, planning, process, consumption, algorithm, the production, decision support, environmental, discrete event simulation, models, lifecycle, model, plans, multiobjective, event simulation, performance, tool, operation, equipment, cost, design, service, shop, products, simulation	Sustainability in manufacturing
20	20	Intelligence blockchain, ai and blockchain, blockchain, blockchain technology, of blockchain technology, blockchainbased, blockchain and, of blockchain, and blockchain, smart city, iot, smart cities, sustainable smart, things iot, iot applications, of things iot, internet of things, cloud, energy trading, ai, smart, ai and, artificial intelligence, privacy, computing, secure, farming environment, security, network, farming, data, internet, energy, intelligence, technology, identity, proposed, the internet, technologies, sustainable, artificial, city, internet of, the proposed, cities, for sustainable, consensus, trading, agricultural, devices	Smart sustainable city development

Table 11 (continued)

Topic	Count	Key representation	Description
21	19	Iot, things iot, internet of things, in iot, iot devices, of things iot, sensor networks, sensor network, wireless sensor networks, wireless sensor network, wireless sensor, cloud, energy consumption, energyefficient, sensor, protocol, wireless, energy efficiency, energy, network, sensors, networks, machine learning, internet of, internet, iwsn, computing, sustainable communication, smart, cluster, the internet, nodes, data, edge, devices, routing, transmission, intelligence, wsn, wsns, ioht, aieawcswcs, edge fog, machine, learning, green, communication,, architecture, the aieawcswcs	AI and the IoT
22	19	Sustainability performance, sustainability index, oil mill sustainability, sustainability, sustainable, the sustainability, mill sustainability, sustainable solid waste, waste management, solid waste management, decision support system, criteria, sustainable solid, decisionmaking, environmental, fuzzy cognitive, hierarchy process, decision support, analytic hierarchy, palm oil mill, oil mill, fuzzy, management, bioenergy, assessment, hierarchy, oil, chinese cement industry, cement industry, solid waste, prioritization, palm oil, evaluation, economic, the palm oil, process, technologies, support system, development, analysis, decision, industry, support system dss, method, approach, based, energy, policy, of chinese cement, lowcarbon	Sustainability of the palm oil industry
23	17	Sustainable waste management, solid waste management, waste management, municipal solid waste, sustainable waste, waste generation, waste recycling, solid waste, electronic waste, solid waste msw, waste, of waste, waste collection, recycling, in waste, disposal, the waste, landfill, waste msw, sustainable, sustainability, municipal solid, ai, municipal, management, economic, economy, leachate, technologies, ewaste management, policy, energy, industry, equipment, model, unit pricing, materials, system, metals, digitalization, digitalization in, solid, analysis, city, analysis of, per, weee, msw, generation, swm	Waste and waste management
24	17	Datadriven smart cities, smart cities, smart sustainable, smart city, sustainable urban, urban governance, structural equation modeling, sustainable, citizendriven internet of, the citizendriven internet, citizendriven internet, datadriven smart, urban, using structural equation, internet of things, structural equation, governance, governance and, governance networks, cities, on data, the citizendriven, data, using structural, and replicating data, of things smart, things smart, citizendriven, research model, city, datadriven, smart, analyses and made, on data collected, made estimates regarding, internet, data collected, made estimates, analyses, and the citizendriven, analyses and, equation modeling, structural, estimates regarding, data from, data collected from, modeling, replicating data, internet of, and made estimates	Data driven smart cities and governance

Table 11 (continued)

Topic	Count	Key representation	Description
25	17	Innovation capability, sustainable innovation capability, dynamic capabilities, technology capability, business model innovation, capabilities, dynamic capability, of big data, sustainable innovation, business model, model innovation, big data, innovation, capability, information technology, strategic, competitive advantage, customer relationship management, organizational, firms, customer relationship, business, industry, businesses, relationship management, strategic intent, technology, sustainability, data analytics, manufacturing, family businesses, management, firm, sustainable, smes, research, b2b, advantage, datadriven culture, datadriven, resourcebased, economy, performance, relationship, theory, data, flexibility, competitive, significant, big	Big data, business model, innovation for sustainable competitive advantage
26	15	Attack detection, intrusion detection, internet of things, deep learning, iot, intrusion detection systems, ddos attacks, intrusion detection system, iot devices, machine learning, classification, data poisoning attacks, ddos, security, attacks, random forest, intrusion, data traffic, denial of service, attack, detection, cloud, distributed denial of, detection systems, distributed denial, malware, detection system, the cloud, scada, traffic analysis, data poisoning, learning, cloud computing, network, malicious, trained, poisoning attacks, internet of, the internet of, ids, internet, service, algorithms, deep, traffic, devices, data, smart, the internet, machine	Cybersecurity and Intrusion Detection for sustainable use of AI and technology
27	14	Wastewater treatment, wastewater treatment plants, wastewater, municipal wastewater, of wastewater, sludge, water quality, membrane processes, membranes, membrane, fertilizer, treatment plants, ai, microbial, sustainable, processes, artificial, water, artificial intelligence, environmental, process, pollutants, river, electrodeionization, nanocomposite, chemical, egypt, oxygen, intelligence, struvite, technologies, in egypt, of river, isopropanol, effluent, applications, plants, management, fuzzy, fouling, models, operation, the effluent, mosc strategy, wwtps, hardness, recovery, strategy, treatment, mgl	Water and wastewater treatment using AI
28	13	Sustainable pavement, pavement life cycle, pavement management, sustainable road, pavement life, sustainability, of pavement, pavement, road infrastructure, the sustainability of, sustainable, the sustainability, multicriteria decision, multicriteria decision analysis, life cycle costs, decision support system, decision support, decision analysis, multicriteria, decision makers, environmental, cycle costs, road, criteria, maintenance and rehabilitation, environmental and, cycle assessment, emissions, assessment, maintenance, maintenance and, infrastructure, indicators, appraisal, life cycle, highway, impacts, the appraisal, costs, transport, decision, costbenefit, support system, economic, comprehensive and, the decision, reducing, comprehensive, reducing devices, multiobjective	Pavement management for sustainable transport

Table 11 (continued)

Topic	Count	Key representation	Description
29	12	Workload prediction, energy consumption, energy efficiency, the energy consumption, cloud, power consumption, cloud data center, cloud data, building energy, deep learning, carbon footprint, of machine learning, the cloud, workload, energy, edge computing, machine learning models, data center, efficiency, computing, ml algorithms, machine learning, efficient, the energy, ai, data science, common data science, cloudfog, machine, prediction, learning models, carbon emission, algorithms, prediction is, carbon, power, hardware, of machine, consumption, resources, sustainable, models, footprint, learning, implementations, data, tasks, sustainability, neural, distributed	Sustainability energy usages and AI
30	12	Sustainable transportation, transportation utility method, sustainable urban mobility, transportation utility, the transportation utility, urban mobility, winter traffic models, public transport, transportation systems, traffic models, transportation, sustainable urban, road tolling, winter traffic, the transportation, traffic, mobility, transport, utility methods, traditional utility methods, road segments, utility method, bus, transit, road, sustainable, travel time, utility, motorway, vehicles, travel, vehicle, commuter, emissions, tolling, traditional utility, spatial transferability, urban, planning, route, evaluation methods, transferability, planning and, by car, car, technologies, application, models, hub, evaluation	Sustainable transportation systems
31	11	Smart cities, artificial intelligence, urban artificial intelligences, smart citiesartificial, citiesartificial intelligence, intelligence in sustainable, smart cities, sustainable urban, sustainable urban development, urban artificial, in sustainable urban, smart and sustainable, urban planning, sustainable cities, urban development, urban planning in, intelligence ai, ai implementation, ai, ai applications, ai is, ai and, of artificial intelligence, for urban planning, and sustainable cities, artificial intelligence, citiesartificial, artificial intelligences, artificial intelligence in, of ai, urban, sustainable development, sustainable, intelligence, intelligence in, sustainability, for urban, in sustainable, in smart, cities, planning, city, technologies, smart, of artificial, artificial, of smart, and sustainable, smart and, data, development	AI for smart and sustainable cities

Table 11 (continued)

Topic	Count	Key representation	Description
32	10	Data journalism, ict, sustainable growth of, sustainability, of ict, sustainable growth, of digital technologies, data journalism will, the sustainable growth, sustainable development, digital technologies, digitalisation, information cultures, sustainable, information systems, datadriven narratives, technologies, of digital, of information and, growth of economies, growth, of information, digital, data, quality management, information and, case studies, of economies, economies, journalism, development, information, research, media, narratives, economies across the, business, and communication technologies, journalism will, panel data, economies across, growth of, narrative, lowincome economies, analysis, panel data from, studies, communications, corporate, communication	Digital Technologies and sustainability in data journalism, communication, and information sharing

Table 12 Different ML and data-driven methods applied to different sustainability problems

Deep learning, neural network models	
Social	Li [190, 191]; Alqahtani [18]; Dolawattha [77]; Nosratabadi [235]; Shafiq [288]; Ali [15] (e-waste policy evaluation, BERT, NLP)
Environmental	Wongchai et al. [348]; Dairi [65]; Rangel-Martinez [263]; Sohani [301]; Nañez Alonso [227]; Park [245]; Himeur [119]; Yang [355]; Jendoubi [137]; Pham, [250, 251]; Selukar [287]; Padmapriya [242]; Rastogi [265]; Tariq [315]; Jin [140]; Ashwitha [28]; Ferdous [93] (sustainable removal of crop residues, deep ensemble learning); Karka [153] (LCA analysis of bio-based process); Zhang [366] (waste water management); Abbas [2] (deep extreme learning machines, sustainable energy); Papagiannis [244]
Economic	Sachithra and Subhashini [271]; Grant [106]; Latif [184]; Jamwal [131]; Lazaroiu [186]; Jan [133]; Cavus [50]; Wang [344, 348]; Verma [339]; Elhoseny [87]; Danishvar [67]; Demir [71]; Walk [343]; Corceiro [61]; Fisher [94]; Latif [185] (sustainable water supply); Gómez [104] (anomaly detection in resource consumption, deep learning framework); Liu [201] (crop harvesting prediction model, lstm)
ML/Supervised ML	
Social	Mrówczyńska [223] (svm); Pham [250, 251]; Mishra [215] (random forest); Novak [236] (predictive models for transportation review); Mashaba [211] (svm, gradient boosting for food security); Naseer [228] (boosting, ensemble for technical education) Kim [162] (text analysis for patent data for sustainable cities); Rathore [266] (multiple ML models for sustainable medical services for low income countries); Almalki [17] (impact of food access on health issues); Dash [68] (socio-economic factor analysis for sustainable agriculture with ensemble learning); Molina-Gómez [218] (classifying sustainability levels of urban ecosystem); Piscitelli [256] (sustainable behavior, random forest); Abbas et al. [1] (governance and public services random forest); Wang [347] (poverty monitoring and analysis using geographical data, regression model); Arango-Uribe [26] (impact of online education for sustainable education, beta regression structural equation modelling); Maghsoodi [126] (sustainability performance assessment with svm); Shrimali [292] (performance of desalination based atmospheric water extraction system under various climate situations using Gaussian regression and BoA); Yigitcanlar [357] (sustainable adoption of AI for smart cities); Garg [100] (sustainability goals; ML comparisons); Wong et al. [350] (cloud-based blockchain and ML integration, sustainable supply chain)

Table 12 (continued)

Environmental	Taghizadeh-Mehrjardi [312] (random forest, svm); Niu [233] (regression, neural network); Pal [243] (ensemble); Sugiawan [307] (decision tree); Elavarasan [86] (extreme gradient boosting); Iddianozie [125] (classification); Shahbeik [289] (random forest); Badreldin [31] (random forest); Li [192, 194, 201] (decision tree); Javed et al. [135] (ground water management, ensemble model); Singh [299] (arsenic mitigation techniques from water analysis, ensemble learning); Liu [198–200] (green synthesis of nanoparticles, svm); Gültepe [108] (sustainable fisheries, svm); Carrera [49] (plastic classification using near-infrared spectroscopy data and ML); Li [190, 191] (optimizing energy w.r.t. seasonal factors, extreme learning machine, and partial swarm optimization); Al Duhayyim [12] (recognize different categories of solid wastes and enable smart waste management with particle swarm optimization and ML); Mao [210] (ML based evaluation of green innovation); Agrawal [4] (AI for sustainable manufacturing)
Economic	Sapitang [281] (Bayesian regression, regression decision tree, nn), Kumar Mohapatra et al. [180] (random forest), Akbari [8] (classification); Ullah [333] (ensemble learning); Wu [352] (fuzzy ensemble); Jun [145] (Bayesian regression), Onyelowe [238] (polynomial regression, soil and agriculture); Thanh et al. [319] (natural gas storage); Sankaranarayanan et al. [278] (random forest for green machining); Ghanizadeh [101] (evaluating sustainable material properties, regression and CART); Dai [64] (green technology adoption analysis, gbm), Khoh [161] (churn prediction, business sustainability using ensemble learning); Erçen [89] (macroeconomic sustainability using fuzzy logic and svr); Pham [250, 251] (sustainable concrete, svr); Momenitabar [220] (sustainable supply-chain, ML); Jamil [130] (peer to peer trading for sustainable electrical power supply grid, ML and predictive models, blockchain)
Unsupervised learning	
Social	Nilashi [231] (Evaluating sustainability performance of different countries, clustering); Kumar [179] (privacy-preserving secured framework for sustainable smart cities, PCA, XGBOOST); Ahmed [6, 7] (intelligent transportation, knowledge graph similarity); Mukherjee [224]; (sustainability indicators selection, k-means); Zhang [365, 367] (sustainable urban transport development, autoencoder, clustering); Tsaples [326] (sustainability composite indices, DEA); Mumtaz [225] (household identification that need urgent welfare, k-means clustering); Suha [308] (key indicators for sustainable AI-based healthcare decision-making system, clustering); Qi [260] (tourism sustainable development path, latent variable analysis)
Economical	Tayal [317] (optimizing energy efficient facility layout, DEA, k-means); Schöggl [284] (insights into the CE research, multiple correspondence analysis); Zhou et al. [368] (predicting topics on sustainability in ultra precision machining, clustering and network analysis); Tirth [321] (sustainable energy management, clustering)
Environmental	Kosir [173] (sustainable fuel, PCA, nn); Aqel [25] (plant disease classification, k-means); Viet [340] (waste water treatment, PCA); Priyanka [259] (energy efficient IoT network for sustainable agriculture); Heo [117] (sustainable waste water treatment, c-means clustering)
Time series and forecasting	
Social	Kumari [181] (load forecasting, sustainable city); Lee [189] (analyze the concept and scope of social sustainability; time series data, change detection, network analysis); Kazancoglu [158] (forecasting e-waste, grey model); Molina-Gómez [217] (analyzing studies focusing on forecasting sustainable development and air quality); Kahwash [149] (sustainable electric supply in health care, forecasting, multi-objective optimization); Suchetana [306] (sustainable water usage and monitoring using time series data, policy decisions)
Environmental	Sugiawan [307] (analysis of impact of CO_2 emission reduction on sustainable well-being and forecasting future growth); Rani Hemamalini et al. [264] (air quality monitoring and forecasting, deep learning); Alsaidan [19] (solar energy forecasting for smart energy management)

Table 12 (continued)

Economic	Abidi [3] (predictive maintenance forecasting, Jaya-based sea lion optimization); Choi [55] (EMAP-an ML-based engineering integrated analysis system, change order forecast, predictive maintenance); Amin [22] (agriculture waste based sustainable concrete strength forecast, multigene expression programming-based forecasting); Ilie [128] (forecasting European economic sentiment); Uppal [335] (load forecasting for sustainable use of energy); Mohammed [216] (time series prediction for optimal water and energy use for sustainable farming); Cadenas [48] (utilizing time series data from IoT ecosystem for DSS for smart and sustainable agriculture); Saxena [283] (grey ML for forecasting energy consumption); Couto [63] (predicting sustainability class form temporal data of sustainability indicators, multi criteria decision making); Dutta [81] (load forecasting for sustainable energy usage, multi criteria decision making); Kayakus [156] (ROA, ROE forecasting for sustainable profit)
Bayesian/statistical/probabilistic methods	
Social	Holloway [120] (statistical ML for sustainable goals); Akhtar [10] (structural equation modelling for sustainable, data-driven adaptive leadership); Kontokosta [170] (determinant analysis for water use, urban sustainability); Tao [314] (sustainable transport system, pedestrian safety, Bayesian network); Kong [169] (structural equation modelling, online triage model, sustainable health and city); Aly [20] (modelling relationship between SDGs, resilience and sustainability at national, regional, and global levels, Bayesian network)
Environmental	Chakraborty [51] (probability estimation predicting long term future weather variables, sustainable buildings); Zeynoddin, [363] (linear Stochastic model, soil temperature, sustainable agriculture); Akbarian [9] (soil bioremediation, statistical optimization); Ijlil [127] (water security, bivariate statistic test, SDGs)
Economic	Li [195] (sustainability assessment, manufacturing, life cycle analysis, Bayesian network); Jun [146] (sustainable technology analysis and management, Bayesian structural time series and regression); González-Cancelas [105] (sustainable ports, Bayesian network of transport, trade, economy, finance, population, energy, social condition and political); Jong [143] (Bayesian inference, sustainable construction); Wang [345] (evaluation of ai embedded supply chain efficiency on the social sustainable development, descriptive statistic)
Optimization	
Social	Kolak [168] (traffic network design, Bi-level optimization); Huang [123] (sustainable development in rural areas, mixed integer linear programming); Oyebode [240] (water demand modelling, evolutionary computation); Ma [206] (land-use assignment model, spatial optimization); Mousavi, [222] (interactive Nautilus-based algorithm for three stage multi-objective optimization problems for complex sustainability problems); García-Esparza [99] (ML potential for enhancing text analysis in the context of sustainable indicators, optimization of sustainability indicators); Arslan [27] (food sustainability); Bliek [43] (surrogate-based optimization, ML)
Environmental	Santos [229] (sustainable pavement management, multi-objective optimization); Manos [209] (DSS for optimizing the production plan of an agricultural region); Nowakowski [237] (root optimization, harmony search algorithm); Lytras [205] (smart and sustainable energy systems, multi-objective optimization); Liu [198–200] (recycled concrete, multi-objective optimization); Chen [53] (network pavement maintenance and rehabilitation management, multi-objective optimization); Tavakoli and Barkdoll [316] (sustainability-based optimization algorithm, life-cycle assessment)

Table 12 (continued)

Economic	Quariguasi Frota Neto et al. [261] (sustainable supply chain, DEA); Ma [207] (CE for energy intensive industry, particle swarm optimization); Jiao [139] (closed loop sustainable supply chain, distributed robust optimization model (DRO) and an adaptive robust model (ARO)); Xu [354] (joint model for energy consumption and production efficiency, enhanced Pareto-based bees algorithm); Anvari [24] (DSS for facility location, multi objective optimization); Lotfi [204] (sustainable health care supply chain, fuzzy, and data-driven optimization); Hombach [121] (sustainable supply chain performance, multi-objective optimization, pareto); Simeoni [295] (smart multi energy system, multi-objective optimization); Wang [346] (energy-efficient machining, ant colony optimization); Doliente, [78] (spatio-temporal multi-objective MILP optimization); Peng et al. [247] (job-shop scheduling problem in green sustainable manufacturing, optimizations); Sharma, [290] (cost optimization, preventive and predictive maintenances in mining equipment); Nayeri [230] (sustainable and resilient supplier selection, supply chain resilience, fuzzy robust stochastic optimization); Momenitabar et al. [219] (sustainable supply chain, bioethanol, metaheuristic); Choi [56] (application of blockchain technology for risk analysis and optimization, in operation research); Jayarathna [136] (multi-objective optimization, sustainable supply chain)
Simulation models	
Social	Bibri [41] (sustainable cities, simulation and optimization); Saeid Atabaki et al. [273] (sustainability assessment model for electricity generation system, simulation and optimization, MCDM); Verma [339] (future energy consumption, decision making, building simulation); Kurkovsky [182] (sustainable education, simulation); Hart [114] (sustainable energy systems in developing countries, DSS, simulation); Torres [323] (sustainable nutritional security and agriculture, simulation framework, DSS); Islam [129] (sustainable policy making, dynamic autoregressive distributed lag simulation)
Environmental	Singh [296] (molecular docking, molecular dynamics simulation for predictive biodegradation); del Caño [69] (uncertainty analysis for sustainable concrete structures, Monte Carlo simulation, MCDM); Medvedev [212] (sustainable agriculture, dynamic crop simulation); Dlugosch [75] (sustainable transportation, traffic simulation); de la Torre [183] (sustainable transportation, simulation); Strand [304] (sustainable waste management, simulation and optimization); Beyer et al. [38] (sustainable energy usage, dynamic multi-agent-system simulation); Ghasemi [102] (sustainable built environment, polymer design, molecular simulation); Eckhoff [83] (DSS, open-access energy system simulation, renewable energy); Mirshafiee [214] (green energy generation, flow-3D simulation)
Economic	Rackes [262] (energy and airflow simulations for smart and energy efficient buildings); Kim [165] (building information modelling for large scale development); Ekici [85] (sustainable design for high-rise metropolis, simulation); Elnour [88] (sustainable buildings, dynamic simulation); Hatim et al. [115] (sustainable and productivity of machine cell, simulation, DSS); Relich [267] (sustainable product development, simulation-based on constraint programming); Pirola [254] (sustainable production, DES)
Fuzzy methods	
Social	Alimohammadlou [16] (studying indicators of social, environmental, and economic relevance using spherical fuzzy AHP, DEMATEL, and TISM); Sarkar [282] (sustainable transportation, q-rung orthopair fuzzy set, MCDM (group))
Environmental	Krishankumar [176] (sustainable urban mobility, prioritizing measures for zero emission, double hierarchy hesitant fuzzy linguistic); Song [302] (sustainable road infrastructure performance indicators, fuzzy spatial MCDM); Bui [46] (sustainable solid waste management barriers, fuzzy DEMATEL); Tayebi [318] (fuzzy MCDM analysis for prioritizing sustainable air pollution control technologies); Kadham [148] (fuzzy integral N-transform for sustainable groundwater management); Alzain et al. [21] (sustainable solar energy, multi-layer perceptron, adaptive network fuzzy inference system)

Table 12 (continued)

Economic	Kannan [151] (sustainable supplier selection, fuzzy Delphi, MCDM); Tseng [328, 329] (sustainable industrial and operation engineering indicators, fuzzy Delphi); Orji [239] (sustainable supplier selection, fuzzy logic, topics); Kumar [178] (big data-driven framework for condition monitoring in manufacturing; fuzzy reasoning for prediction); Bui [45] (indicators for sustainable supply chain, fuzzy Delphi, DEMATEL); Kokkinos [167] (circular-bio economy, energy transition, fuzzy cognitive modelling for DSS); Tsai [325] (sustainable supply chain key indicators, fuzzy Delphi, DEMATEL); Balaman [33] (decision support system for multi-objective optimization integrating multi-technology bio-product supply chains and co modal transportation networks, fuzzy ε-constraint); Khalili-Damghani [160] (DSS for sustainable project selection, fuzzy relations and inference system, MCDM); Tirkolaee [320] (fuzzy bi-level decision support system for sustainable supply chain and transportation network); Tseng [327] (sustainable supply chain management indicators analysis, fuzzy Delphi method); Fallahpour [91] (selection of sustainable construction projects, fuzzy DSS); Pereira [249] (energy change impact on sustainability, DSS, Fuzzy cognitive mapping and cause-effect relationship); Jeong [138] (sustainable planning in construction, fuzzy DEMATEL); Tseng [328, 329] (sustainable supply chain finance indicators, fuzzy Delphi, DEMATEL); Choy [57] (sustainable product development in chemical production, fuzzy recursive operation strategy); Kazancoglu [157] (application of emerging technologies for improving the sustainability and resilience of supply chain, fuzzy DEMATEL); Su [305] (challenges in blockchain technology for sustainable manufacturing, fuzzy-entropy-rank sum-combined compromise solution); Alassery [13] (fuzzy attention deep learning, sustainable manufacturing, fault diagnosis)
MCDM	
Social	Zhang [364] (sustainable drinking water source evaluation, MCGDM)
Environmental	Dogra and Adil [76] (indicators for sustainable agriculture, ISM); Alghassab [14] (sustainable renewable energy source assessment. FAHP, FTOPSIS)
Economic	Dogra and Adil [76] (sustainable supplier evaluation, MCDM); Bhatia et al. [40] (sustainable machining, MCDM); Ozkan-Ozen [241] (risk of data-driven technologies in sustainable supply chain, MCDM); Singh et al. [297] (sustainable quality management in manufacturing, ISM); Li [196] (sustainable production capability evaluation, AHP); Tseng [330] (identify the driving and dependence factors of data-driven sustainable supply chain management performance, factor analysis, DEMATEL)
Complex networks/knowledge graphs/ontology	
Social	Kim [164] (sustainable technology analysis, social network analysis); Lorimer [203] (collaborative verification of smart user, mobile social network); Konys [171] (digital sustainability, ontology), Silva [293] (sustainability recommendation system based on social network approach); Draschner [79] (KG for ML applications for ethics and sustainability); Zovko [269] (IoT ontologies for sustainable healthcare); Bellantuono [36] (complex network framework for SDGs); Jing [141] (sustainable development evaluation, network-based approach)
Environmental	Ahmed [6, 7] (graph-based trajectory outlier detection for sustainable transportation, network similarity); Tran [324] (sustainable transportation, complex network model); Sebestyén [286] (network model for key targets, goals, and strategic environmental assessment)
Economic	Muñoz [226] (ontological framework for enterprise sustainability); Aydin [29] (DSS, network visualization, sustainable water distribution); Yang [356] (patent risk prevention, multi-level network, SD); Kim [163] (product knowledge graph, semantic relationships), Perdana et al. [248] (sustainable enterprise ontology-based on information technology-based concepts); Zhou [368] (topic discovery, network model, text analysis, sustainable ultra-precision machining)

Table 13 Keywords in different modules in co-occurrence network

Module	Keywords ordered based on degree in the network (total 428 keywords, modularity: 0.58)
1	Big data, sustainable development goals, internet of things, industry 4.0, digitalization, sensor, data, iot, manufacturing, sdg 11, deep learning, environment, remote sensing, governance, circular economy, climate change, sustainable manufacturing, smart manufacturing, urban development, data analytics, urban, technology, lca, digital technologies, environmental sustainability, business model, earth observation, green ai, ethical ai, biodiversity, automation, resource recovery, sustainable finance, gender equality, smart sustainable city, digital twin, algorithm, water quality, population, cognitive automation, cyber physical system, cyber physical production system, ecosystem services, e waste, responsible ai, industrial ecology, conservation, agenda 2030, fourth industrial revolution, emission, business strategy
2	Blockchain, resilience, security, explainable ai, smart agriculture, sustainable ai, privacy, digital transformation, internet of health things, cloud computing, wireless sensor network, supply chain, safety, social sustainability, artificial intelligence techniques, supply chain management, sustainable computing, ai governance, supplier selection, fuzzy logic, ethics, logistics, ai ethics, data privacy, fog computing, edge computing, healthcare, sustainable competitive advantage, sustainable smart city, internet of thing, cybersecurity, prediction model, predictive analytics, firm performance, environmental indicators
3	Iot device, hanumayamma, edge, cow necklace, digital economy
4	E-learning, software engineering, waste, sustainable education, environmental pollutions, educational data mining, machine learning techniques, reinforcement learning, covid 19, wastewater treatment, software sustainability, pandemic, social media, production, text mining, construction, concrete, predictive model, software development, triple bottom line, crowdsourcing, higher education, engineering education, energy efficient, fuel cell
5	Life cycle assessment, renewable energy, sustainable energy, energy, sustainable environment, support vector regression, multi objective optimization, multi objective optimisation, genetic algorithms, manufacturing industry, co2 emission, bioeconomy, environmental decision support system, multi criteria decision analysis, biomass, biofuel, greenhouse gas emissions, forecasting, cleaner production, energy demand, principal component analysis, data driven decision making, genetic algorithm, global warming, corporate sustainability, biofuels, stakeholder, environmental performance, agricultural sector, sustainable transport, swarm intelligence, generative design, predictive maintenance, economic development
6	Data driven model, optimization, infrastructure planning, building simulation, cyber physical systems, data driven modelling, decisions makings, intelligent systems, performance based design, electric vehicles, data driven modeling, land use, building energy, additive manufacturing, bayesian networks, natural resources, network analysis, neural networks, ai for social good, future generations, fuzzy sets, urban governance, data driven models, classification and regression trees
7	Data driven smart sustainable cities, smart city, sustainable cities, big data analytics, compact cities, sustainable urbanism, eco cities, urban science, futures studies, big data technology, smart sustainable cities, data driven smart city, planning, data science, backcasting, urban sustainability, data driven smart sustainable urbanism, smart urbanism, simulation models, big data technologies, strategic planning, big data computing, data driven technologies, wicked problems, urban planning, data intensive science, data driven cities, infrastructure, urbanism, smart sustainable urbanism, datafication, sustainable smart city, urban intelligence functions, methodology, sustainable urban development, energy planning, design, urban analytics, data visualization, indicators, gis, machine learning methods
8	Sdgs, united nations, standard, machine learning approaches, machine learning model, innovation, sustainable design, patents, development, emerging technologies, sentiment analysis, standardization, pattern recognition, interoperability, framework, data driven design, green building, online reviews, environmental factors, bim, expert system, covid 19 pandemic, environmental management, open data, air pollution, technological innovation, visualization, strategy, long short term memory, agent based model, big data analysis
9	Sustainable supply chain management, fuzzy delphi method, design for sustainability, entropy weight method, fuzzy decision making trial and evaluation laboratory, sustainability indicators, data driven approach, sustainability reporting, developing countries, systems thinking, traceability, ai technology, food supply chain, agricultural supply chains, artificial intelligence technologies, sustainable mobility, sustainable food systems, global health, facility location, policy, information and communication technologies, supervised machine learning
10	Data mining, sustainable performance, decision making process, risk management, literature review, sustainable tourism, social network analysis, sensing, seizing, active learning, key performance indicator, sustainable technology, transfer learning, supervised learning, intelligent tutoring system, construction projects, analytic hierarchy process, education for sustainable development, deep neural network, sustainable operations, uncertainty, patent analysis, engineered nanomaterials, materials science
11	Municipal solid waste, waste management, urbanization, risk assessment, solid waste management, circular bioeconomy, convolutional neural network, smart home, artificial intelligent, ict, digital divide, lignocellulosic biomass, ann, blockchain technology

Table 13 (continued)

Module	Keywords ordered based on degree in the network (total 428 keywords, modularity: 0.58)
12	Neural network, agriculture, support vector machine, precision agriculture, sustainable agriculture, classification, sustainable concrete, random forest, extreme learning machine, food security, computer vision, feature extraction, water sustainability, smart farming, environmental impact, data driven methods, compressive strength, prediction, water, gene expression programming, groundwater, clustering, feature selection, multivariate analysis, data analysis, digital agriculture, robotics, smart environments, water resource management, simulation, sensitivity analysis, ensemble learning, green energy, gaussian process regression, productivity, soft computing, anomaly detection, decision tree, economic sustainability, africa, analytics, sustainable building, lstm, design science research, health, corporate social responsibility, sustainability index, business sustainability, data driven decision, environmental monitoring
13	Decision support system, energy efficiency, sustainability assessment, energy consumption, multi criteria decision making, decision support, sustainable development, sustainable supply chain, system dynamics, built environment, mcdm, smart grid, modelling, computational intelligence, sustainable production, closed loop supply chain, process optimization, carbon footprint, energy management, water supply, spatial decision support system, social networks, economic growth, sensor network, recommender systems, optimisation, gamification, case based reasoning, decision makers, robust optimization, data envelopment analysis, industry 50, machine learning algorithms, water demand
14	Waste water treatment plant, management

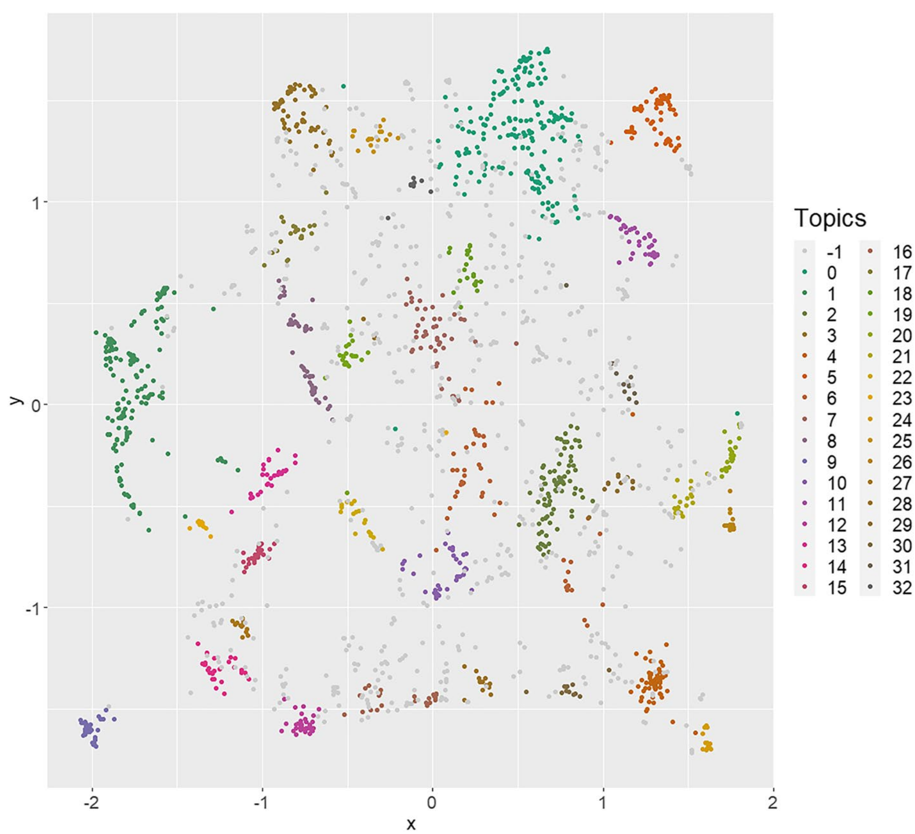

Fig. 9 UMAP-based 2-dimensional projection of document embeddings and BERTopic-identified topics (color-coded)

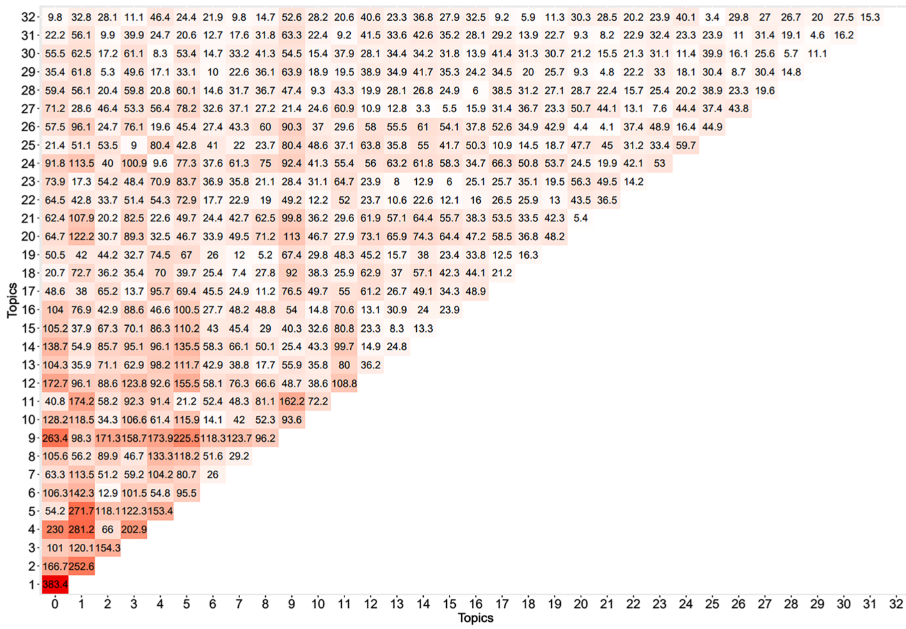

Fig. 10 N-Statistic values comparing differences between topic distributions based on the 2D UMAP projection of document embeddings and the clusters (topics) obtained from 'hdbscan' in BERTopic

Abbreviations

AI	Artificial intelligence
BD	Big data
BDAC	Big data analytic capabilities
BDAC	Business model innovationx
CE	Circular economy
C_V	Coherence
DL	Deep learning
DNN	Deep neural networks
EU	European union
FDR	False discovery rate
FPO	Floating-point operations
GPU	Graphics processing unit
GDP	Gross domestic product
I4.0	Industry 4.0
ICT	Information and communication technology
IT	Internet of things
ML	Machine learning
MLaaS	ML-as-a-Service
PSS	Product-service systems
PPP	Purchasing power parity
STS	Social and technological system
SC	Supply chain
SCM	Supply chain management
SDGs	Sustainable development goals
SVM	Support vector machine
UMAP	Uniform manifold approximation and projection
UN	United Nations

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Author contributions
S.T. conceptualized the study, designed the methodology, conducted formal analysis, interpreted the data, and authored the original draft. N.B. contributed to the critical review of the work and played a substantial role in writing, revising, editing, and finalizing the manuscript. M.B. significantly contributed to content analysis and various aspects of the writing process. Z.R. contributed to both content analysis and manuscript writing. H.J. critically reviewed the work for important intellectual content and gave final approval for the version to be published.

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Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare that they have no competing interests.

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