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Research article

Artificial intelligence and sustainable development during the pandemic: An overview of the scientific debates

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ABSTRACT

The current work aims to analyze the main themes related to artificial intelligence (AI) and sustainable development during the pandemic period. This study provides an overview of the specialized literature related to AI and sustainability from the beginning of the pandemic through 2023. The present paper analyses scientific literature emphasizing both artificial intelligence's positive and negative impacts on sustainable development objectives (SDGs). To conduct the research, we employed bibliometric analysis and text-mining techniques to identify the major themes in the literature indexed in the Web of Science and Scopus databases. Firstly, we used descriptive measures to identify the authors' impact, the article production by country, the main keywords used, and other descriptive data. We further used data reduction methods based on co-word analysis (such as multiple correspondence analysis) on authors' keywords to show patterns in the themes explored in the literature. Bibliometric analysis was supplemented by text mining using Latent Dirichlet allocation (LDA) and structural topic modeling on abstracts to provide a comprehensive view of scientific debates on AI and sustainable development. Our research has identified various themes in the literature related to AI and sustainable development. These themes include social sustainability, health-related issues, AI technologies for energy efficiency, sustainability in industry and innovation, IoT technologies for smart and sustainable cities, urban planning, technologies for education and knowledge production, and the impact of technologies on SDGs. We also found that there is a significant positivity bias in the literature when discussing the impact of AI on sustainable development. Despite acknowledging certain risks, the literature tends to focus on the potential benefits of AI across various sectors. In addition, the analysis shows a growing emphasis on energy efficiency, which is facilitated by the use of AI technologies. Our study contributes to a better understanding of current scholarly discussion trends and emerging scientific avenues regarding AI and sustainable development. It also highlights the areas where research is needed and the implications for practitioners and policymakers.

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1. Introduction

In the past decade, there has been a significant increase in the adoption and use of artificial intelligence (AI) in various industries and private life. AI can be defined in different ways depending on context and political interpretations [1]. Artificial intelligence (AI) represents the capacity of a machine to execute certain cognitive functions specific to humans in order to solve problems and achieve specific goals [2]. These functions or abilities include perceiving and understanding external information, mimicking human thinking, behaviors (speech and vision), and emotions through machine learning algorithms, connecting with a specific environment, problem-solving, and creativity [2–4].

The scientific dialogue on artificial intelligence has recently significantly expanded to include considerations regarding sustainability. Sustainability is defined as the practice of living enclosed by limited resources – spanning physical, natural, social, and cultural dimensions in ways that enable the thriving of all life forms, extending beyond humans, into the distant future [5]. Furthermore, sustainable development seeks to foster growth and progress by introducing new physical, economic, environmental, or social facets that improve the quality of life without exhausting the current resources for the future [5].

In the literature, a nuanced distinction is made between the concepts of AI for sustainability and sustainable AI. AI for sustainability refers to the use of AI to achieve sustainable development goals, while sustainable AI primarily focuses on the durability of its technology [6]. On the other hand, sustainable AI focuses on creating principles and strategies that lead to reduced carbon emissions and more efficient energy use in technological developments of artificial intelligence development in terms of consumption [7].

Sustainable AI involves developing and operating artificial intelligence (AI) systems in a way that aligns with environmentally responsible and sustainable business practices. Many AI systems used by modern companies are known for having negative environmental impacts. However, sustainable development practices can help to mitigate these negative impacts. It is important to note that sustainable AI is not about maintaining the development of artificial intelligence. Instead, it is about developing these technologies while conserving resources for both present and future generations [8].

The increasing prevalence of debates and controversies surrounding artificial intelligence in various sectors, along with the growing importance of sustainability as a megatrend, prompted the initiation of the present research. Consequently, our study aimed to answer the following two questions.

Q1. What are the major themes regarding the impact of artificial intelligence in sustainable development?

Q2. What are the most used methods and technologies of artificial intelligence in order to achieve the goals of sustainable development?

Our research on the role of artificial intelligence (AI) in sustainable development is driven by the recognition of a wealth of information dispersed across academic literature and online resources. This knowledge is valuable; however, it provides a fragmented view of the subject. Our contribution relies on the focus of our research on collating, analyzing, and synthesizing these diverse insights from different strands of literature to provide a compressed outlook that highlights the major themes emerging at the intersection of AI and sustainable development. This contribution is particularly important at a time when the intersection of technology and sustainability is of central importance to both policy formulation and the broader societal pursuit of sustainable living.

With the increasing use of artificial intelligence (AI) in various sectors, it's important to assess their impact on achieving the Sustainable Development Goals. AI cand have positive and negative effects on sustainable development [9].

AI raises concerns regarding the environment such as an increased carbon footprint. Sustainable AI focuses on reducing energy consumption and emissions to address this drawback. These objectives can be accomplished through a new reprioritization of data quality, rebalancing the scale of the model, developing energy-efficient infrastructure, policy implementation, and raising awareness through education [10].

On the positive side, artificial intelligence can contribute to the optimization of energy consumption and reducing waste, compressing greenhouse gas emissions, expanding, and performing sustainable practices in the industry, and designing new sustainable materials to observe and anticipate environmental changes [11]. Other benefits of artificial intelligence can be found in the medical field, such using smart devices to recognize certain diseases and symptoms and identify epidemics at early stages [11,12]. In agriculture, artificial intelligence provides advice on planting, harvesting, fertilization and weather forecasting information [13,14]. Another advantage is offering more efficient storage, manufacturing, and distribution systems [15,16].

The literature emphasizes the following negative environmental impacts of AI technologies: the amount of energy needed to train and conduct AI algorithms, the potential for AI to aggravate current environmental problems, ethical connotations of using AI to handle the environment, electronic waste, raised consumption of resources like water and other materials [17,18]. Studies also emphasize the augmentation or replacement of specific jobs and tasks with artificial intelligence technologies [19,20]. At the same time, artificial intelligence technologies rely heavily on data collection, which can raise issues related to the confidentiality and security of personal information and problems related to the perpetuation of inequality and bias [21,22]. These studies highlight the negative impacts on social sustainability goals.

Despite recognizing adverse effects, studies concentrating on individual perspectives have predominantly displayed a positivity bias. Survey analyses focused on the academic field, students, and users of AI technologies [23–25]. These survey studies showed that individuals believe AI can positively influence sustainable development goals from the three pillars [23,24]. This positivity bias in evaluating the impact of AI on sustainable development was also noticed by other authors who evaluated artificial intelligence as a favorable or inhibitory factor on sustainability and concluded that 79 % of sustainable development objectives are positively affected, while 35 % are negatively affected [9]. These results may indicate a tendency of the individuals and research literature for a deterministic view of AI technologies. Our research challenges the overly optimistic portrayal of AI's impact on sustainable development by identifying gaps that need to be addressed in the literature.

A wide array of research delves into the ramifications of artificial intelligence (AI) on sustainable development, often concentrating on particular dimensions of sustainability or specific sectors (health, agriculture, manufacturing, etc.). For instance, several studies have investigated AI's influence on the social and economic aspects of sustainable development, as exemplified by the works of Mhlanga [26], Kulkov et al. [27], Thamik and Wu [28], and Di Vaio et al. [29]. Conversely, research by Goralski and Tan [30] has been pivotal in examining AI's impact on environmental sustainability. As mentioned already, in the light of the granulated literature on this topic, our research seeks to synthesize these diverse strands of inquiry and comprehensively analyze how AI intersects with and influences all three pillars of sustainable development goals. This perspective aims to provide a more integrated understanding of AI's role in advancing sustainable development.

Methodologically, researchers studying artificial intelligence's impact on sustainable development have primarily used literature analyses, surveys, case studies, and content analyses. The literature analyses have focused mainly on systematic literature reviews [27,28,31,32], bibliometric analyses for topic mapping, or a combination of both approaches [29,33]. Still, studies that use text-mining approaches with topic modeling to understand the impact of AI on sustainable development are relatively scarce [34]. Although, in recent years, several authors have started to use text-mining approaches to reveal insights regarding the impact of AI on sustainable development, the literature using these approaches is relatively scarce [34,35]. Our research enhances the traditional approach to literature analysis, which predominantly relies on either bibliometric analyses or systematic reviews, by combining bibliometric analysis and text mining methods. This text-mining approach allows for a more comprehensive understanding of the field. Specifically, we employ Latent Dirichlet Allocation to identify and categorize topics, providing a nuanced and detailed exploration of the subject matter. The application of LDA and insights from structural topic modeling enables the dynamic clustering of topics, offering insights into emerging areas of interest and shifts in research focus over time.

Sustainable development goals (SDGs) consist of represent a set of 17 interconnected objectives that aim to provide a universal framework for "peace and prosperity for people and the planet, now and into the future" [36]. The goals can be categorized into three main pillars or categories - environmental, social, and economic.

The social pillar consists of goals 1, 3, 4, 5, 11 and 16. The first goal aims to reduce extreme poverty as much as possible by 2023. However, ongoing trends regarding inequalities continue, there are predictions from experts that expect an increase in extreme poverty. One article by Scheyvens and Hughes explored if tourism could help reduce and eradicate extreme poverty in all its forms and everywhere [37]. The third goal aims to improve people's health. In the light of COVID-19 pandemic, this goal gained even more significance [38]. The fourth goal aims to improve the quality education. This goal was analyzed by Morales et al., who tried to propose a model for physical education [39]. The fifth aims to promote gender equality and empower women. On average, women still face a disadvantage compared to men due to the existing gender gap in wages. Eden and Wagstaff, advocate for the development of evidence-based policies on gender equality [40]. The eleventh goal aims to make cities and human settlements comprehensive, secure, robust, and endurable. Yamasaki and Yamada presented a framework for analyzing the local implementation of this goal [41]. The sixteenth goal aims to promote peace, access to justice for everyone, and efficient and responsible institutions, thereby reducing geopolitical conflicts. Quality education is seen as an important element in reaching the sixteenth goal from a global perspective [42].

The economic pillar of sustainable development includes four goals: 8, 9, 10, and 17. The eighth goal aims to promote inclusive and sustainable economic growth, employment, and decent work for everyone. However, the global economy is currently under threat due to various crises that have occurred over the years. Researchers have contributed to constructing new frameworks to address this issue [43], while other researchers examined sustainable business practices and financial performances of Small and Medium Enterprises (SMEs) [44]. The ninth goal aims to build a strong infrastructure, promote sustainable industrialization, and drive innovation. Studies have explored concepts such as Industry 4.0 and Society 5.0 in relation to achieving this goal [45]. The tenth goal seeks to reduce inequalities or disparities. O'Sullivan et al., highlighted the importance of digitization to ensure fairness in achieving this goal [46]. The seventeenth goal aims to revitalize the global partnership. Halkos and Gkampoura, work aims to evaluate the current state of progress towards this goal [47].

The environmental pillar comprises five goals: 2, 7, 12, 13 and 15. The second aims to achieve a world free of hunger by 2030. Viana et al. presented their perspective on supporting food security in a systematic approach [48]. The seventh is to ensure access to clean and affordable energy. Elavarasan et al., have shared their vision regarding energy sustainability in the post-pandemic period [49]. The twelfth goal aims to ensure sustainable consumption and production practices to support the means of living for current and future generations. Lenzen et al. have discussed evaluating progress towards sustainable development through the implementation of the material footprint [50]. The thirteenth goal concerns the actions environmental action such as addressing the increase in temperature. He et al. have proposed environmental policies in the energy sector to achieve this goal [51]. The fifteenth goal focuses on preserving life on land. Sun et al. have recommended excluding the practice of grazing to achieve this goal in the Tibetan Plateau [52].

2. Theory

There are several theories in the literature about how new technologies, such as artificial intelligence are adopted, accepted, and diffused. One of the most prominent ones is the Diffusion of innovations (DOI) theory, which was proposed by Rogers [53]. DOI theory focuses on the features of technologies that determine their adoption. The main key features that can increase the adoption of a particular technology or innovation are greater relative advantage, compatibility with personal experiences, needs, and values, less complexity, trialability (the degree to which the product permits experimentation), and observability [53]. Another widely discussed theory in technology adoption is the Theory of Planned Behavior (TPB) [54], which is based on the theory of reasoned action [55]. TPB suggests that behavior can be determined by three main factors: subjective norms, attitudes toward the behavior, and perceived behavioral control [54]. The more positive these three factors are evaluated, the higher the intention toward the behavior.

Technology Acceptance Model (TAM) is a popular theory used to predict how artificial intelligence technologies will be adopted in different sectors. According to Davis [56], to proponent of TAM, technology is more likely to be accepted if users find it useful and easy to use [56]. The Unified Theory of Acceptance (UTA) and Use of Technology (UTAUT) are extensions of TAM, which suggest that intentions to use the technology comes before the actual usage. These intentions are influenced by factors such as performance expectancy (the degree to which the individual believes that the technology would help to achieve his goal), effort expectancy (perceived ease of use, complexity, and actual ease of use), social influence (or social norms from other individuals), facilitating conditions (perceived control, organizational provision of technologies and guidance and compatibility) [57]. Behavioral intentions influence the actual usage of technology. Other such as socio-demographic factors (such as gender and age), work experience with technologies, and voluntariness of use also play a role in technology adoption [58]. UTAUT2 adds three more predictors to the original theory: hedonic motivation (enjoyment from using technology), habit (or automaticity in using technology), and price value (perceived advantage compared with the price).

The Technology Acceptance Model (TAM) is a well-known theory that provides valuable insights into how people accept and use new technologies. However, it doesn't fully address the broader impacts of emerging technologies on society, particularly within the context of sustainable development. To address this gap, Al-Emran introduced the Technology-Environmental, Economic, and Social Sustainability Theory (T-EESST) [24]. This innovative framework is designed to comprehensively evaluate the effects of technology across the three pillars of sustainable development: social, economic, and environmental. Rather than just focusing on technology usage or acceptance, T-EESST takes a broader view and assesses the positive and negative impacts of technology on sustainable development.

The utilization of T-EESST, TAM, and related theories for studying the effects of artificial intelligence (AI) technologies on sustainable development outcomes is still in its early stages. Most investigations conducted so far have only focused on specific technologies or sustainability dimensions. Therefore, there is a critical need for research that employs these theoretical frameworks to comprehensively understand the complex relationship between AI and sustainable development [24,59,60]. As a response to this identified limitation, the present study aims to enrich the existing body of literature by incorporating T-EESST with TAM and related theories, thereby offering a nuanced investigation of AI technologies' impacts on sustainable development. Our research seeks to reveal both the positive aspects—such as perceived uses, advantages, and applications—and the negative impacts, including challenges and barriers of AI technologies within the context of sustainable development. Our research takes a holistic approach to examine how AI can facilitate or impede sustainable development objectives. We aim to provide a nuanced understanding of AI's capabilities and limitations, and to critically assess its impact on sustainability efforts. By exploring this complex relationship between AI and sustainability, we hope to contribute to the discourse and offer insights for academic research, policymaking, and strategic

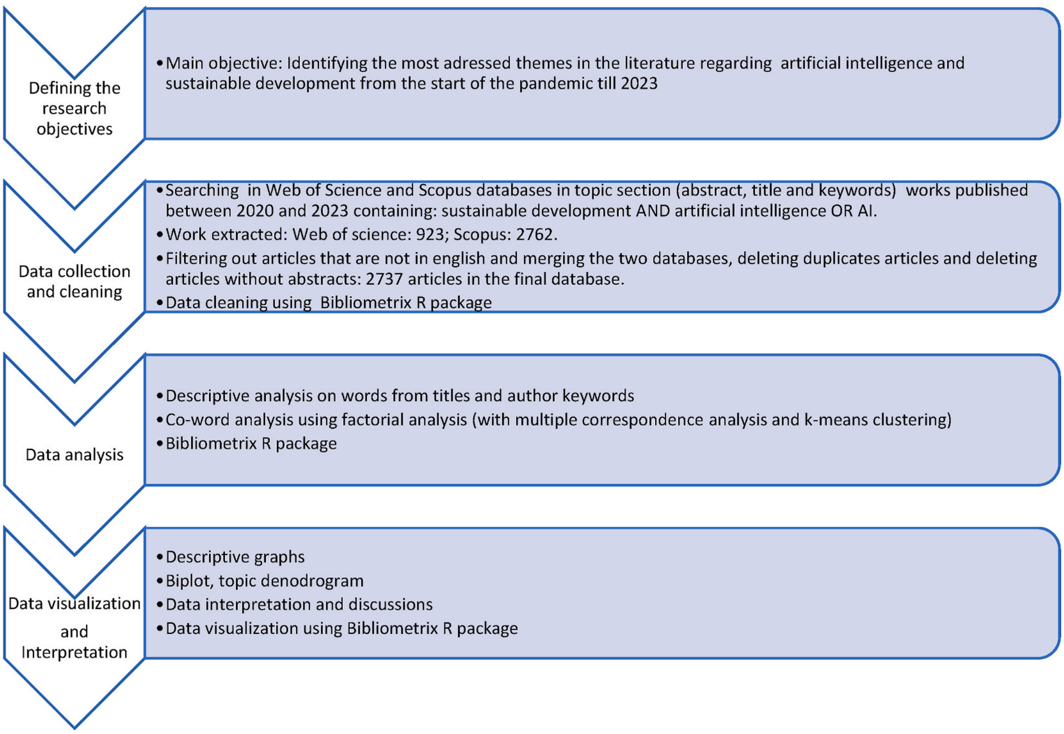

Fig. 1. Bibliometric analysis workflow.

deployment of technology.

In recent times, discussions around the relationship between artificial intelligence and sustainability have gained more attention. As a result, there has been an increase in the number of articles written on these topics. Given this growing interest, this article aims to contribute to the emerging field of artificial intelligence and sustainable development by providing new insights into the connection between these two aspects in the current scientific debate.

3. Materials and methods

In the present work, we used two primary methods to analyze the scientific discourse on sustainable development and artificial intelligence during the pandemic. The first method was bibliometric analysis based on bibliometric analysis, and the second method was text mining using topic modeling with Latent Dirichlet allocation, supplemented by a structural topic model approach. The bibliometric analysis focused on general information, author keywords, and title words, while the text mining approach used information provided in the articles' abstracts. Our main specific objective of the paper was to uncover the impact of Artificial Intelligence technologies on sustainable development. Additionally, we aimed to identify the primary AI technologies, methods, and techniques used in sustainable development research.

3.1. Bibliometric analysis

The bibliometric analysis approach consists of four stages, illustrated in Fig. 1, inspired by insights from Zupic and Čater and Aria and Cuccurullo [61,62]. Bibliometrix R package and Biblioshiny interface were used for data cleaning, analysis, and visualization phases [62]. The bibliometric analysis proved to be a valuable tool to measure the scientific performance and impact of the actors involved in scientific production. It also helped to map the scientific structure, assess the cognitive thematic structure of a field of research, and identify co-citation patterns [63]. Bibliometric analysis as a performance analysis tool quantitatively measures the publications' production and received citations to assess the research performance of individual researchers, institutions, or countries [64]. Science mapping, also known as bibliometric mapping, is used to highlight collaborative, conceptual, and intellectual aspects of the scientific field [65]. Bibliometric analysis has been used in business and economics research [66,67], sociology [68], psychology [69], education [70], public health [71], and many others. In sustainability research bibliometric analysis has been used to reveal insights about climate change [72], waste management [73], corporate social responsibility [74], sustainable tourism [75], and other environmental issues.

The present research uses a combination of the two approaches, with a greater emphasis on the science mapping approach. Firstly, it focuses on descriptive measures to reveal the most influential actors writing on the association between artificial intelligence and sustainable development (such as the main authors, countries, or sources). Secondly, centering on science mapping of the literature, it aims to uncover the conceptual and thematic patterns in the literature using descriptive word analysis and data reduction methods (such as multiple correspondence analysis and k-mean clustering) in order to uncover the patterns in the keywords used in articles metadata sections.

During the initial stage of bibliometric analysis, we outlined the research goals. The general research objective was to identify the predominant themes in the literature on artificial intelligence and sustainable development. Additionally, we aimed to investigate the most commonly used AI techniques and methods, as well as associated technologies in the scientific literature on sustainable development.

During the second phase of the bibliometric analysis, we focused on data collection and cleaning. Initially, we considered using "sustainability" and "artificial intelligence" (AI) as search terms, but the results were too broad, with around 19,000 entries. We decided to use a more precise term closely aligned with sustainable development to narrow our scope and ensure a more targeted examination. Using Boolean operators, we searched in Web of Science (specifically Web of Science Core Collection) and the Scopus database in articles' abstracts, titles, and keywords, the following search query: "sustainable development" AND ("artificial intelligence" OR "AI"). We covered articles from four years (2020–2023). We extracted 923 articles from the Web of Science database and 2762 from the Scopus database. After the extraction, we deleted the articles in languages other than English. Following these procedures, we were left with 903 articles from WOS and 2697 from Scopus. We merged the databases and deleted the duplicates, which left us with 2835 publications. We further deleted retracted papers, articles without abstracts, and articles without authors (such as collective publications as conference books proceedings). The final sample comprised 2737 articles.

We created our article database by extracting metadata from Scopus and Web of Science databases. While these two databases are the most popular and comprehensive scientific databases, articles from journals not indexed in Scopus and WOS are not covered in the present analysis. Using articles only from these two databases might pose bias in selecting articles from specific disciplines and regions. For example, by selecting these databases, our research is leaving out a large body of articles from newer journals yet to be indexed in these databases: non-western journals, non-English literature, and research from arts, humanities, and social sciences [76]. Moreover, conference papers included in proceedings not indexed in these two databases are excluded, as well as grey literature, including reports from international organizations (OECD, European Commission, United Nations, etc.), policy papers or legislative documents from governments, interviews with relevant stakeholders, white papers, NGOs reports, or private companies reports. Limitations are also influenced by data selection and cleaning practices. For example, certain publications such as books or chapters (which often do not include an abstract section) are excluded. Moreover, some proceedings books without authors (or with collective authors) are also excluded from the analysis. These practices impact research results generalizations. Therefore, the generalization of the findings from this study to the broader research landscape should be interpreted with an awareness of the outlined limitations.

The third stage of bibliometric analysis involved data analysis. In the first phase, descriptive analyses were employed to observe the general characteristics of the publications and characteristics regarding the actors' scientific performance (i.e., authors' documents, countries, and sources frequencies). The second phase of this stage was to descriptively analyze authors' keywords and words from titles, followed by co-word analysis using a factorial approach, which included multiple correspondence analysis (MCA) and k-means clustering on author keywords.

Co-word analysis is a method used in bibliometric studies to determine the themes present in scientific publications within a specific field. Co-word analysis is a methodological approach that uncovers word co-occurrence patterns within textual sections of papers (such as abstracts, titles, and author-provided keywords). In other words, it is a technique for identifying the topics in literature and their relationships with one another [62,77]. The factorial approach uses a combination of multiple correspondence analysis and k-means clustering. Multiple correspondence analysis (MCA) is a data reduction method equivalent to principal components analysis (PCA) but for nominal categorical variables [78]. MCA reduces dimensionality in big textual data in order to find patterns in a dataset while representing them visually in a biplot graphic (simultaneously representing both rows – cases and columns – characteristics or attributes). The MCA is an extension of the correspondence analysis and applies its algorithm to a Burt table with the variables included in the analysis [79]. The data results in a lower dimensional space in which the characteristics regarding the relationships between words are preserved. These lower-dimensional coordinates (for each document) are then used as numeric continuous variables for k-mean clustering. The k-mean algorithm is used in the factorial approach to group the words in clusters with similar themes and concepts. The number of clusters was chosen based on interpretability after attempting with different numbers of clusters.

The fourth stage included data visualization and interpretation of the results. The visualizations comprised descriptive graphs (bar charts), a trend topic graph, an MCA biplot map, and a topic dendrogram. This stage also included data interpretation and discussions based on the outputs in relation to the existing literature findings.

3.2. Topic modelling

We used a text-mining approach, specifically topic modeling, to gain a more profound understanding of the themes explored in scientific literature. Text mining approaches have significantly increased in utilization within scientific methodologies in social sciences [80,81]. To conduct this analysis, we used Blei, Ng, and Jordan's Latent Dirichlet Allocation (LDA) on the articles' abstracts [82]. Topic modeling using LDA is a popular unsupervised text mining technique for exploring thematic patterns in large unstructured textual data [83]. Moreover, it is a probabilistic technique that operates on two fundamental assumptions: first, that the documents under examination are composed of a mixture of topics, and second, that each topic is an amalgamation of words [81].

A topic model using Latent Dirichlet allocation was conducted on publications abstracts. While keywords and titles are core aspects of the articles, these elements convey little textual information compared to abstracts. In addition, the abstract is seen as the central element of an article because it usually contains a summary of the article in terms of method, research objectives, findings, as well as possible limitations and contributions to the scientific literature [82,84]. Because of abundant textual information, we chose abstract fields for LDA topic modeling. The sample of abstracts used for LDA topic modeling was the one that resulted after the bibliometric analysis selection and cleaning, which comprised 3737 articles with abstracts.

The inputs needed for LDA analysis are the number of topics to be generated and a document term matrix (DTM) with the word frequencies for each document. We used a combination of three main criteria to determine the number of topics to be generated. Firstly, we examined the measures Deveaud2014 [85] and CaoJuan2009 [16] using the ldatuning R package [86]. The first measure [85] is based on the maximization of the distances between the topics, and the second measure [16] is based on the minimization of the distances between the topics. Usually, an optimal number of topics is selected when the first measure has a higher score and when the second measure has a lower score. The second criterion considered for choosing the number of topics was the number of clusters of keywords identified in the factorial approach using multiple correspondence analysis. The third criterion was based on the interpretability of the topics produced by the LDA analysis. Nevertheless, before selecting the number of topics and running the LDA algorithm, the database of articles' abstracts required processing, cleaning, and several procedures to transform the original database into a document term matrix (DTM).

The document term matrix (DTM) was obtained after several procedures on the original data. The first step was to import the data into a data frame and convert it to corpora (a collection of natural language text documents). The next phase data preprocessing, which included converting words to lowercase and removing punctuation and numbers. This phase also involved removing stop words, such as commonly used words in the corpus of the abstracts (such as prepositions and connectors words), and also high occurrence words (such as artificial intelligence, sustainable, sustainability, technologies, research, study, paper, etc.). Another procedure at this stage was grouping the plurals of the words in the singular form of the words, reducing words to their base form, and grouping some words with similar meanings. After the text processing, we used word cloud graphs to see the most used words in the abstracts. Further, we transformed the cleaned corpus to a document term matrix, a format in which each document is a row, the word/term is a column, and each cell is the frequency of that word/term. We used the DTM and the number of topics desired (based on measures discussed earlier and interpretability) and ran the LDA algorithm. The final results generated by the algorithm comprised nine topics. Our findings are based on β probabilities (beta) distributions, which represent the words' probability of pertaining to a specific topic. We used bar graph visualizations for each topic to picture the most representative words of these topics. Finally, to conduct the LDA topic modeling, we used the topicmodels R package [87].

We used the Structural Topic Modeling Approach, in addition to the conventional LDA model, to provide a temporal view of the topics related to the COVID-19 pandemic. Our analysis considered factors such as the type of document, year of publication, and citations, and we examined the changes in topics over time. Although we used the LDA algorithm, we employed the stm R package for our analysis [88].

While LDA is a popular technique for identifying patterns in large textual data, it has several limitations. The first drawback is that the order of words is not accounted for. The algorithm regards documents as a "bag of words," meaning that the contextual nuances are missing and potentially affecting the interpretations. Other approaches can be used to address this limitation, such as Word2Vec or BERT, which account for word order. These methods will be explored in future research. Another limitation of LDA stems from the fact that it treats topics as static and not influenced by other covariates, such as specific document characteristics. Hence, the methods do not account for changes over time or for document metadata such as length, document type, authors, author keywords, etc. These disadvantages can also be overcome in future research using BERT approaches or dynamic topic modeling. Furthermore, LDA assumes that topics are independent, but themes are often correlated in texts. Approaches such as correlated topic modeling can be used to address this limitation. Future research will consider these approaches to improve the accuracy of topic modeling.

4. Results

4.1. Descriptive analysis

Table 1 displays the characteristics of the database of articles that have been analyzed in the papers downloaded from the Web of Science and Scopus databases. In the present paper, we analyzed the articles from the beginning of the pandemic (2020) until now (2023). The analyzed documents were extracted from 1246 sources (journals, books, conferences, etc.), were written by 8416 authors, and had over 12000 keywords plus words and 7704 author keywords. The average number of citations per document was 7.6. This number may be inflated by articles with higher citations (pictured in Fig. 5). Only 320 authors were authors of single-authored papers. Regarding the collaboration between authors on artificial intelligence and sustainability, the analysis indicates an average number of authors per paper of 4 and a low international collaboration. Therefore, most papers result from collaborative work between authors from the same country. Moreover, most analyzed documents were journal articles or conference proceedings papers.

The number of articles increased by approximately 21 % from one year to another (Table 1). Therefore, as can be seen from Fig. 2, from the beginning of the analyzed period, the number of articles has steadily increased yearly, reaching a maximum of 839 in 2022. However, we expect the number of documents for the year to grow by the end of the year. The analyzed documents are those published until September 2023.

Table 2 highlights the top countries contributing to scientific debates on artificial intelligence and sustainable development. China, India, and the USA are the leading contributors based on the total number of articles published. Regarding influence, China is the most cited country, followed by the USA, Italy, Sweden, and India, each with over 1000 citations.

Regarding the sources involved in the production of papers on Artificial Intelligence and sustainable development, Figs. 3 and 4 indicate that the most relevant journal in the scientific debate is "Sustainability", both by the number of published articles and by the influence in the field through the high number of citations. It was expected that Sustainability and similar journals, such as the Journal of Cleaner Production, would be the most influential because of the thematic approaches of these journals on sustainability issues.

The most relevant sources by the number of articles comprise mainly book series based on conference proceeding papers in computer science and engineering fields related to artificial intelligence (Advances in Intelligent Systems and Computing, E3S Web of Conferences, Lecture Notes in Computer Science, ACM International Conference Proceeding Series, IFIP Advances in Information and Communication Technology, Communications in Computer and Information Science). On the other hand, the relevance of sources by the number of citations reveals that journals are more influential than book series. Therefore, besides the journals discussed above, other sources with a strong influence on the construction of the academic debate regarding sustainability and artificial intelligence are

Table 1
Main information on publications.

Main information about data		Results
General information	Timespan	2020:2023
	Sources (Journals, Books, etc.)	1246
	Documents	2737
	Annual Growth Rate %	20.47
	Average citations per doc	7.617
Keywords	Keywords Plus (ID)	14144
	Author's Keywords (DE)	7704
Authors	Authors	8416
	Authors of single-authored docs	320
Authors collaboration	Co-Authors per Doc	3.94
	International co-authorships %	2.59
Document type	Article	1207
	Book chapter	220
	Book	46
	Conference paper	945
	Review	291
	Other	28

Data source: Web of Science and Scopus databases. Authors' calculations.

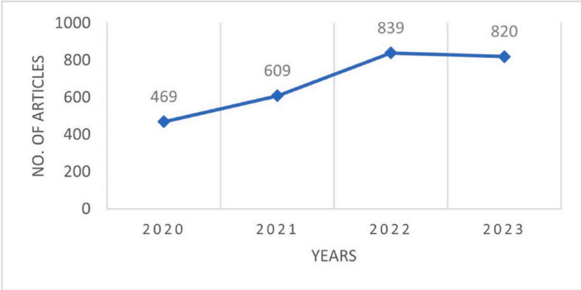

Fig. 2. Annual scientific production. Source: Web of Science and Scopus databases. Authors' calculations.

Table 2
Top countries by article production and top countries by citations.

Country	Number Of Articles	Country	Number Of Total Citations
China	565	China	2793
India	348	USA	1367
USA	227	Italy	1252
Italy	144	Sweden	1099
United Kingdom	133	India	1059
Germany	102	Australia	993
Spain	92	United Kingdom	991
Australia	76	Spain	805
France	74	Germany	529
Poland	65	South Africa	473
Ukraine	63	Canada	434
Canada	56	Portugal	418
Saudi Arabia	55	Finland	396
Brazil	51	Malaysia	396
Sweden	51	France	391
Portugal	47	Turkey	309
South Africa	47	Saudi Arabia	293
Turkey	44	Korea	291
Norway	43	Pakistan	283
Malaysia	41	Iran	243
Iran	40	Egypt	231
Singapore	39	Poland	223
South Korea	39	Japan	207
Netherlands	38	Brazil	185
Finland	37	Singapore	185

Source: Web of Science and Scopus databases. Authors' calculations.

other journals on sustainability (such as Sustainable Cities and Societies, Nature Communications, Science of the Total Environment, etc.), journals from technical fields such as engineering and computer science (such as Technological Forecasting and Social Change, IEEE Access, Energies, Sensors, etc.) and business and economics journals (such as Journal of Business Research, International Journal of Information Management, Business Strategy and the Environment, etc.). The analysis of the most impactful and influential sources confirms findings by previous research on the relationship between AI and sustainable development [89].

A look at the most influential authors by the most cited documents indicates the paper published by Vinuesa et al. as the most cited document in our sample (see Fig. 5). Their work stands out as a seminal paper in the field that studied the impact of artificial intelligence on sustainable development goals. Broadly stated here, their paper used expert elicitation and found that artificial intelligence can lead to implementing 134 targets but can impede another 59 targets in sustainable development goals [9]. A similar research endeavor was conducted by Del Río Castro, González Fernández, and Uruburu Colsa, which emphasized the present research gaps in the literature and current rising anticipation and expectations regarding the impact of AI on sustainable development goals [90].

Another important article in this field is Di Vaio, Palladino Hassan, and Escobar's article on the role of artificial intelligence technologies on sustainable business practices and models based on a systematic review of the literature. Their work pointed out the presence of a cultural turn or change in organizations to use emerging types of technologies (such as AI) in business processes to improve productivity and competitiveness while simultaneously preventing negative impacts on the environment [29]. Their article also emphasizes that AI technologies can improve and help achieve goals related to resilience, education, and health systems but have a scarce influence on sustainable development targets related to consumption and production practices. Other works, such as Mondejar et al., stressed the importance of digital technologies, such as the Internet of Things and artificial intelligence, in constructing sustainable societies in terms of energy production, water management, food practices, and manufacturing practices [91]. On the other hand, Nishant, Kennedy, and Corbett's paper pointed out that AI will be advantageous for environmental governance rather than

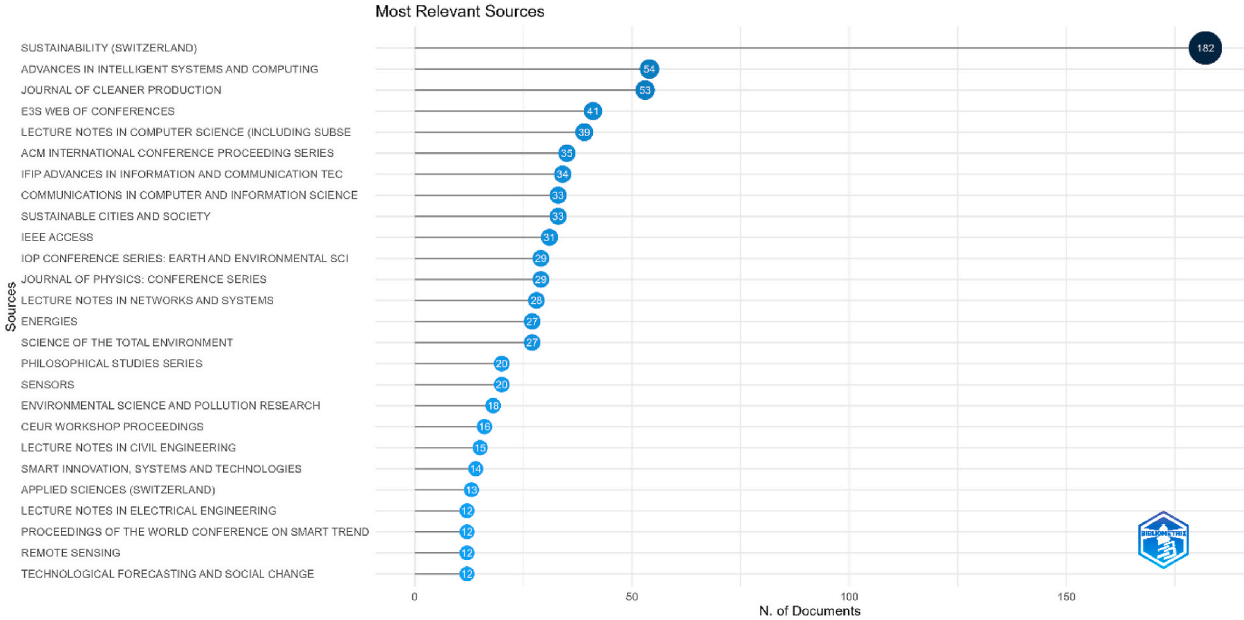

Fig. 3. Most relevant sources by the number of articles. Source: Web of Science and Scopus databases. Authors' calculations.

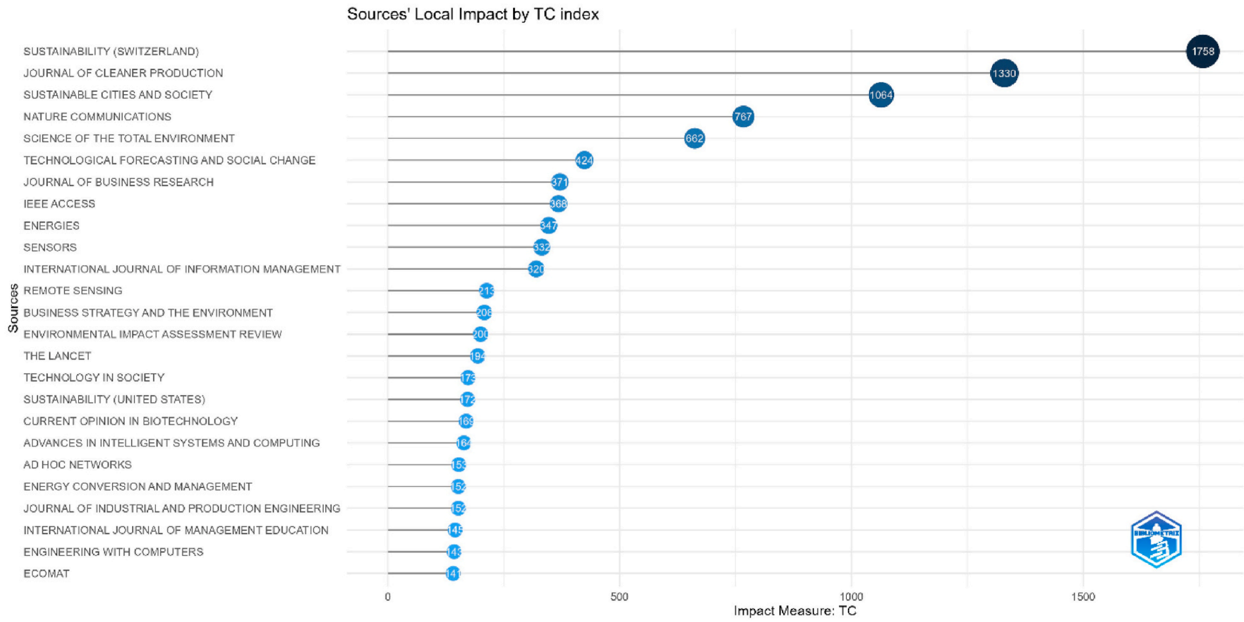

Fig. 4. Most relevant sources by the number of total citations (TC). Source: Web of Science and Scopus databases. Authors' calculations.

giving tangible solutions to ongoing environmental issues [2].

Other significant literature contributions focused on specific matters related to sustainability or specific economic sectors. For example, Ahad, Paiva, Tripathi, and Feroz and, Yigitcanlar, Desouza, Butler, and Roozkhosh discuss the importance of artificial intelligence technologies in creating sustainable and smart cities [92,93]. Similarly, Xiang, Li, Khan, and Khalaf discussed AI models that can improve urban water resources management for a sustainable environment [94]. Other academics were concerned with health-related issues [95], agriculture, and farming [96].

4.2. Thematic areas from author keywords and titles

Fig. 6 shows the graph that includes the author's most relevant keywords according to the number of occurrences. The most

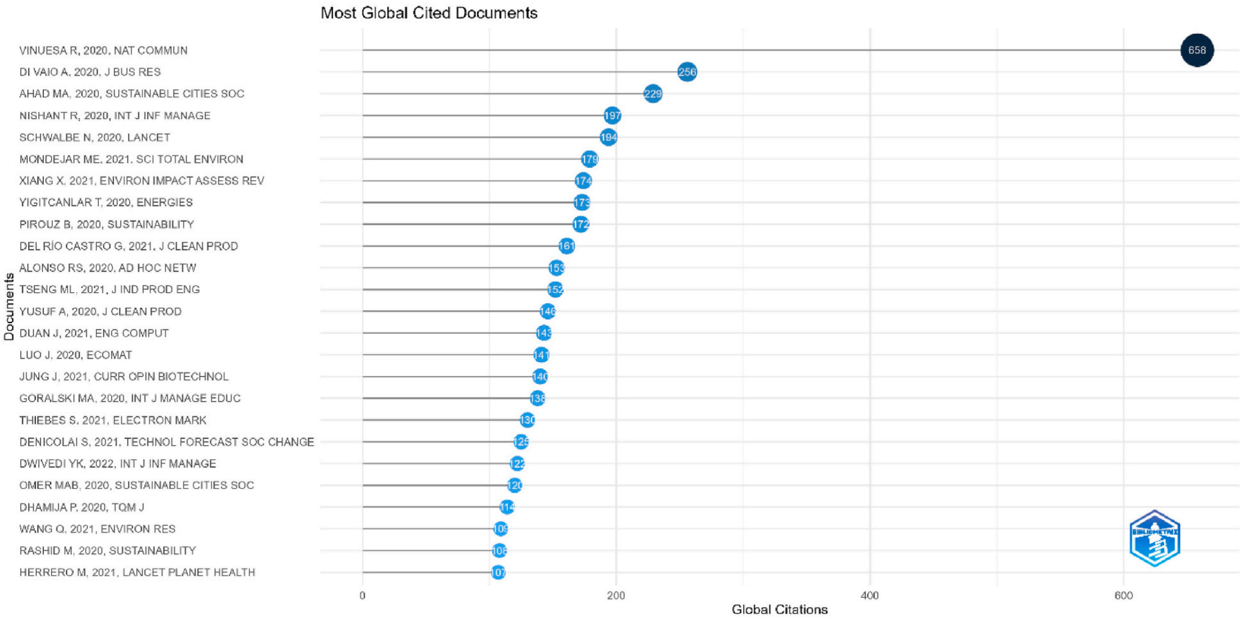

Fig. 5. Most relevant authors' documents by the total number of citations. Source: Web of Science and Scopus databases. Authors' calculations.

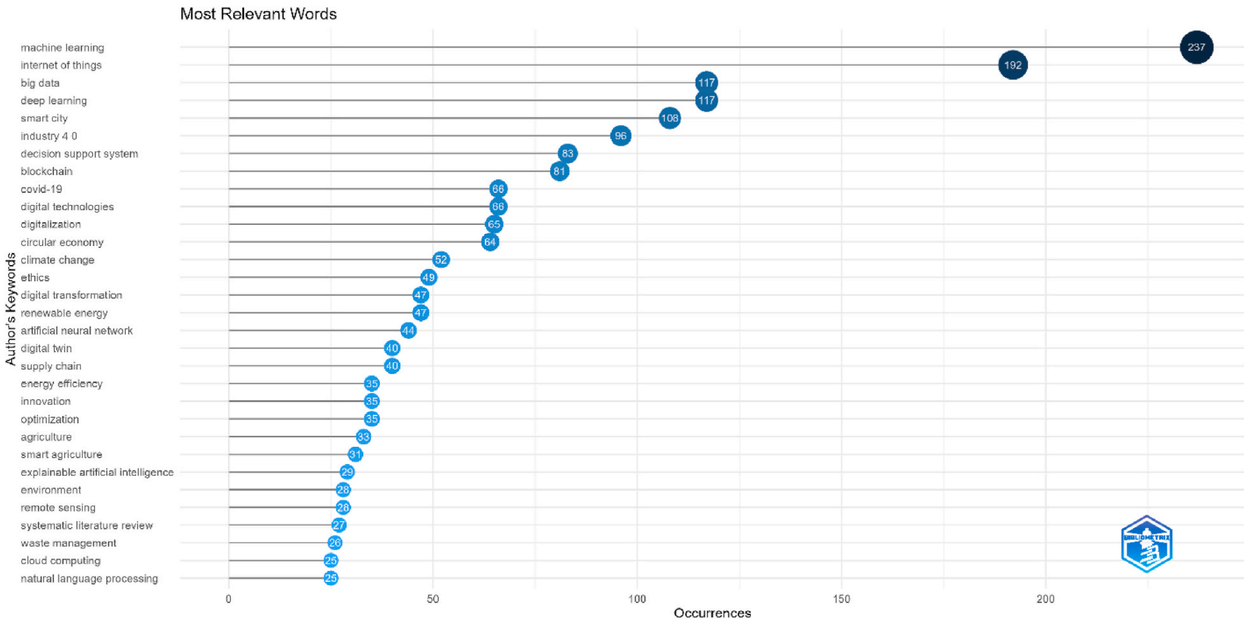

Fig. 6. Most relevant author keywords by the number of occurrences. Source: Web of Science and Scopus databases. Authors' calculations.

frequently encountered keyword in the analyzed database is “machine learning”, followed by “Internet of things” (IoT), “big data”, and “deep learning”. Most of the highly mentioned keywords focus on technologies, methods, and techniques (for example, “machine learning”, “deep learning”, “artificial neural network”, “natural language processing”, “remote sensing”, “cloud computing”, “digital twin”, “blockchain”). Therefore, the literature emphasizes an important focus on technical and computational intricacies. Moreover, it was expected to find IoT technologies (and other related technologies) among the most used keywords, as these technologies complement artificial intelligence technologies to create smart machines to simulate smart behavior. These technologies are also used to support decision-making with little or no human intervention [97]. The following two keywords have the same number of occurrences: “big data” and “deep learning”. Both artificial intelligence and deep learning algorithms use big data, hence the dependency between them. Other keywords are related to the industry or industry-technology symbiosis and perceived economic benefits from the introduction of technologies in business processes (such as “industry 4.0″, “innovation”, “decision support system”, “supply chain”, "digitalization"), perceived sustainability benefits or outcomes regarding sustainable economy ("circular economy"), smart and sustainable planning and agriculture and current environmental disadvantageous outcomes and solutions ("climate change", "environment", "energy efficiency", "renewable energy").

Among the used keywords in 2020 (until 2022), pictured in Fig. 7, are words related to technical intricacies of models and tools used in artificial intelligence and statistical modelling (such as "modelling", "forecasting", "neural network", and "network analysis", "Python"). Words used highly in 2020 are pertaining to social-economic sustainability (such as "poverty" reduction and "corporate social responsibility") and smart agriculture.

Regarding the year 2021, the trends in keywords used consisted of various areas. The terms "ICT" and "AI technology" started with the mentioned year. Rising concerns in literature are also related to health and biodiversity. Moreover, around this period, discussions regarding automation and robotics in the labor market for a digital economy using various ICTs also increased. The year 2022 brought a series of new challenges. Many of these changes and developments occurred due to the emergence of "COVID-19″ and an increasing interest in virtual currencies. The most frequent keywords were "machine learning", "internet of things", and "deep learning". Digital technology has been perfected due to developments in "machine learning", "deep learning" and "big data". Less observed in the previous literature but quite prominent from the analysis of the keywords in the present research is the attention to blockchain technologies when discussing artificial intelligence technologies. Blockchain represents the technology behind cryptocurrencies like Bitcoin. There is a growing acceptance of virtual currencies and related technologies, but also an increasing hype from investors. As previously mentioned, the scientific discourse in 2022 also emphasized an interest in smart urban planning and a digitalized industry ("Industry 4.0″).

The words from 2023 draw attention to the measures that should be taken to fulfill sustainable development goals. For this reason, the trends in terms of keywords find terms such as "carbon footprints" and "carbon emissions". Sustainable development goals want to achieve "food security", "smart manufacturing", "energy management", and develop a "reliability bioenergy" and "innovation". The literature from this year also revealed scientific interest in the concept of "metaverse" which experienced a high inflation in public debate and big corporations' interests.

Fig. 8 below refers to the most used combinations of two words in publications' titles (bigrams). Similar to the keyword analysis among the most used combination of two words, we have methods and technologies and computational methods ("machine learning", "deep learning, "neural networks", "blockchain technologies"), words related to sustainable development goals ("energy consumption", "achieving sustainable", "energy efficiency", "sustainable cities", "climate change", "renewable energy") and words related to sustainability and digitalization in the industry "digital economy", "circular economy"). As other researchers pointed out, besides general discussions regarding the technological impact on sustainable development, the literature emphasizes the relevance of sustainable technological practices in economic sustainability, as seen in current business practices and processes [29].

Fig. 9 (multiple correspondence analysis on author keywords) and Fig. 10 (dendrogram based on multiple correspondence analysis on author keywords) reveal the results of the factorial approach on the keywords and can be interpreted simultaneously. Based on the analysis of multiple correspondences, we can distinguish seven different clusters of literature that were apparent in the descriptive analysis of keywords. The brown-colored cluster reveals the literature regarding "Technologies for biodiversity and energy consumption reduction" because it includes keywords related to techniques and technologies (such as convolutional neural network,

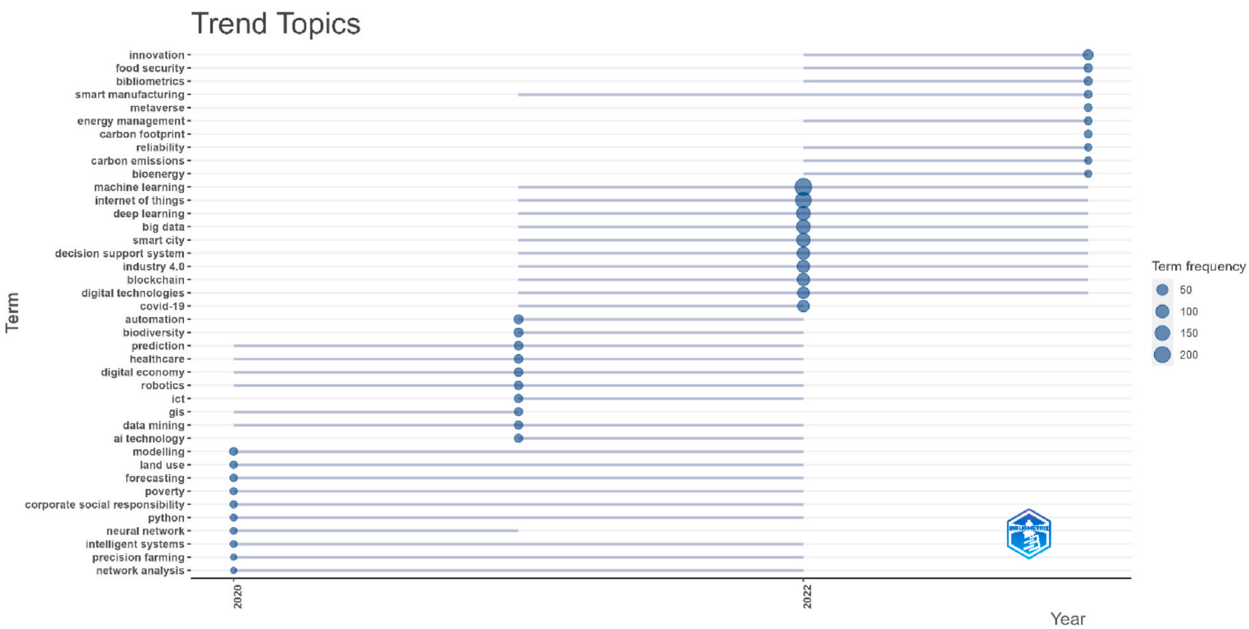

Fig. 7. Topic trends of author keywords. Source: Web of Science and Scopus databases. Authors' calculations.

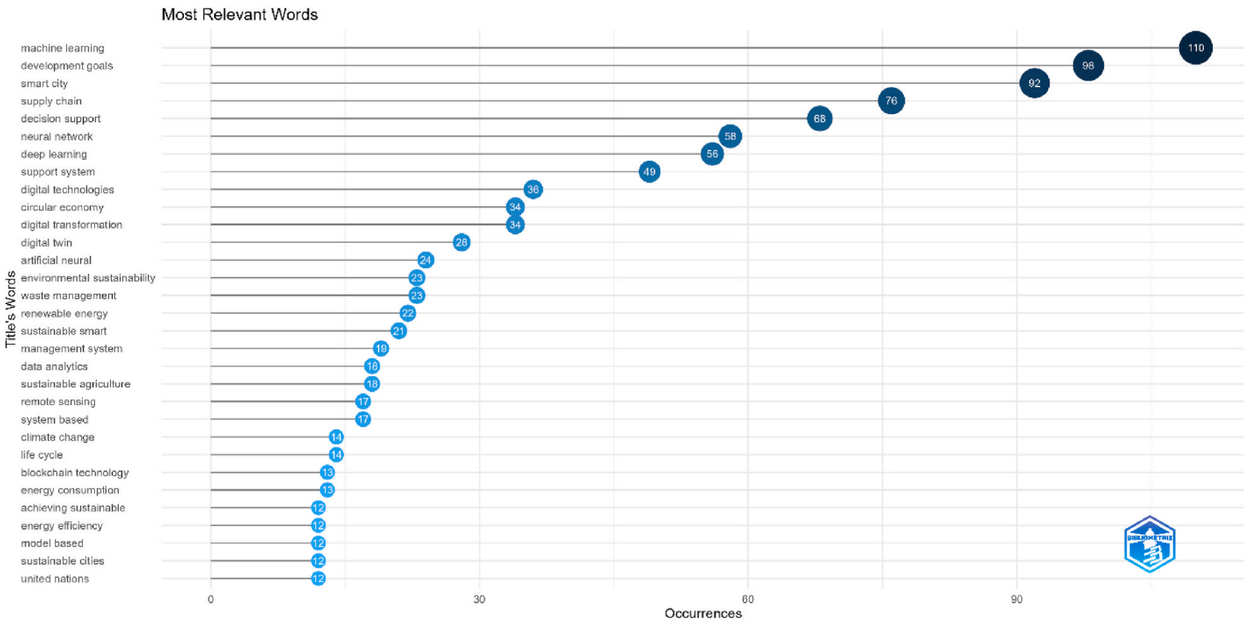

Fig. 8. The most used combinations of two words publications' titles (bigrams). Source: Web of Science and Scopus databases. Authors' calculations.

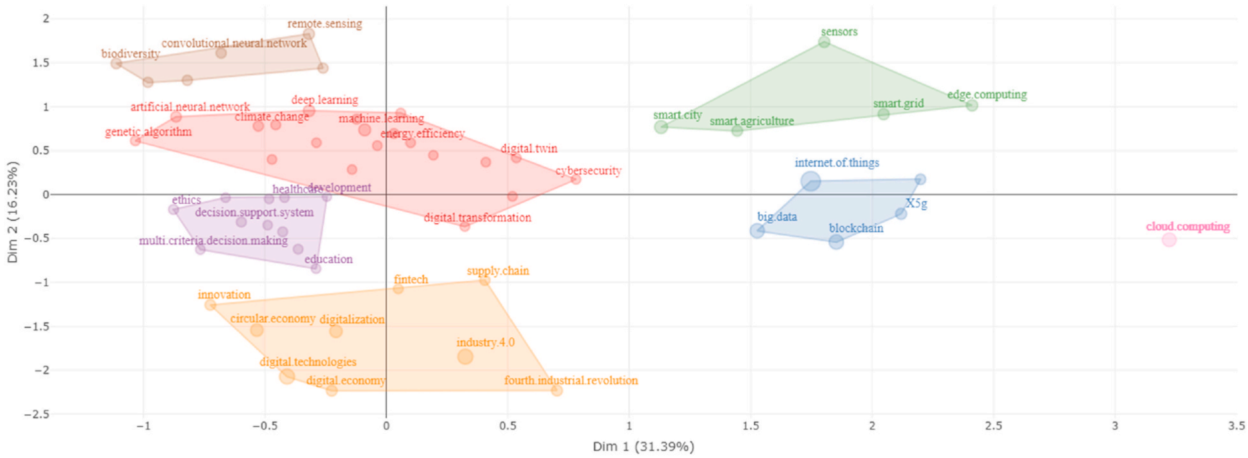

Fig. 9. Multiple correspondence analysis on author keywords. Source: Web of Science and Scopus databases. Authors' calculations.

remote sensing, green AI) for a more efficient "energy consumption" and protection of biodiversity. This cluster of literature emphasizes the potential benefits of AI and related technologies in reaching sustainable development outcomes related to sustainable energy consumption and climate outcomes [34]. The second cluster, the red-colored one, can be named "Techniques and methods of AI for sustainable development goals related to energy" and includes keywords related to AI models and techniques and words related to energy efficiency and the potential environmental impact. Consistent with the findings from previous literature this cluster has a twofold significance related to AI's impact on sustainable development. It implies possible benefits in energy efficiency and environment protection, but also the polemical nature of AI in aggravating climate change outcomes [34,49,51].

The third cluster, the purple-colored one, is related to "Social sustainability" issues and consists of terms related to healthcare (including COVID-19), ethical decision-making, and education. This cluster raises concerns regarding negative impacts on the social sustainability pillar. Negative ethical implications regarding Artificial Intelligence decision support systems are discussed regarding privacy and manipulation practices, security, and well-being of individuals [28,98]. However, at the same time, insights regarding AI technologies in education are arising as possible facilitators in personalized learning, collaborative teaching, immersive learning, and efficient assessment of students [99]. The fourth cluster, the orange one, was named "Industry, Innovation and Sustainability" as it comprises terms such as: "innovation", "digital economy", "industry 4.0″, and "circular economy". AI technologies have proved useful for companies in creating sustainable growth, improving competitiveness, and supporting decision-making [91]. In Fig. 9's biplot,

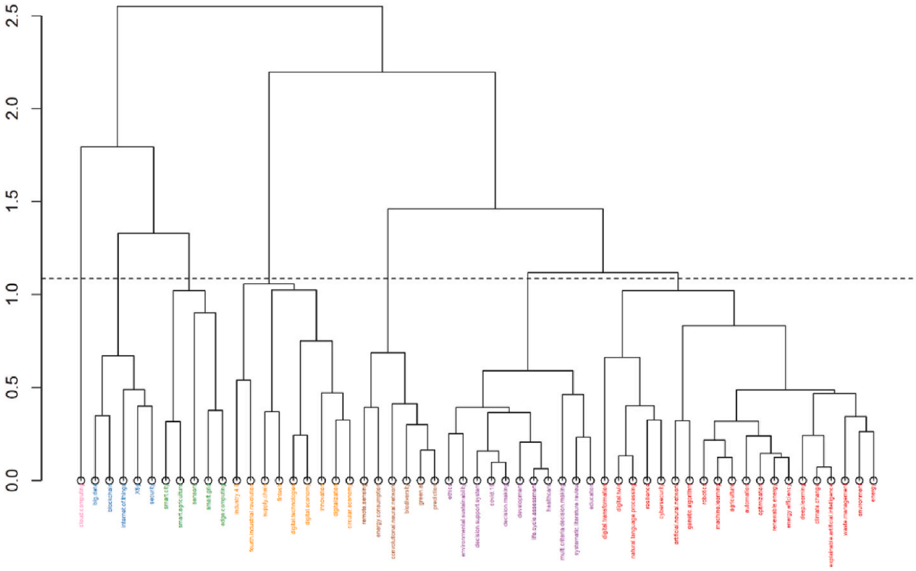

Fig. 10. Dendrogram based on multiple correspondence analysis on authors keywords. Source: Web of Science and Scopus databases. Authors' calculations.

Fig. 11. Wordcloud with the most frequent words in the abstracts. Source: Web of Science and Scopus databases. Authors' calculations.

these four clusters are closely related, indicating interdisciplinary relations among these literature's themes.

The fifth cluster, the green one, incorporates keywords related to "Smart infrastructure" like: "smart cities", "sensors", "edge computing", "smart grid", and "smart agriculture". This cluster emphasizes the importance of AI and related technologies (sensors in edge computing and smart grids) in sustainable and efficient urban and agriculture management practices. Some of the activities in which AI can play an important role in sustainability are transportation management, precision farming, soil, water, nutrients management and livestock farming management). Hence, the cluster mainly focuses on AI applications in these domains. The sixth cluster, the blue one, can be named "Internet of Things" as it includes terms related to IoT-related aspects such as: "5G", "big data", "IoT", "blockchain", and "security". This cluster contains literature that mainly discusses aspects related to artificial intelligence technologies, 5G communications and IoT-based technologies in urban settlements to improve residents' quality of life [97]. The last cluster, the pink one, is comprised of a single term that also gives the name of the cluster. This cluster is distinct because cloud computing technology has existed since before the recent developments in artificial intelligence. The distinctiveness can also be noted by the distance of this cluster in relation to other clusters of literature.

4.3. Topic modelling

Fig. 11 shows the words with the highest frequency in the documents' abstracts. In the abstracts of the texts, the most mentioned words are "data", "environment", "model" and "energy". The wordcloud provides us with various thematic areas that can give us a better understanding of the relationship between artificial intelligence and sustainability in literature. Thus, terms that pertain to the technical field that describe artificial intelligence models, methods, and techniques (model, machine learning, neural networks, algorithm, big data, cloud, internet of things, deep learning, etc.) are present here. On the other hand, some words are related to industrial economic sectors, including "agriculture", "construction", "manufacturing", "industry", and "sector". Similarly, there are words related to business processes and their transition to sustainable practices and green transitions connections with innovation and economic growth. Some of the words describing this thematic avenue are "economics", "innovation", "production", "business", "enterprise", "growth", "management" and "production". On the other hand, words pertaining to the literature regarding the transition to a green economy and the reduction of environmental impacts are also pervasive in abstracts. Words related to the transition to a green economy that emphasizes environmental impacts are "energy", "efficiency", "carbon", "emission", "water", "food", "land", "waste", "ecology", "climate", "change". Lastly, abstracts focus on words related to social sustainability about possible business impacts on humans. Accordingly, words related to health impacts, educational disparities, rights, and ethical implications emerge from the abstracts ("social", "healthcare", "covid", "pandemic", "ethics" and "education").

As stated in the methodology, the most important criterion for selecting the number of topics in the LDA model was the number of clusters revealed by keywords analysis and the interpretability of topics according to the words' assignment in topics. Besides these two criteria, we used Deveaud2014 [85] and CaoJuan2009 [16] measures. The two measures combined are not entirely consistent, but the results indicates that an optimal number of topics is between 3 and 11 (see Fig. 12). For interpretability reasons, we chose nine topics that are consistent with the results from the factorial approach based on MCA.

Our LDA model produced nine topics. The words with higher probabilities of appearing in each topic are pictured in the following figures (Figs. 12–20). The words are ranked in descending order according to their β probability, describing which terms are more likely to represent each topic. The nine thematic topics describe different areas in the literature on sustainability and artificial intelligence technologies. Among all topics, the topic most likely to appear was "IoT Technologies for Smart Cities".

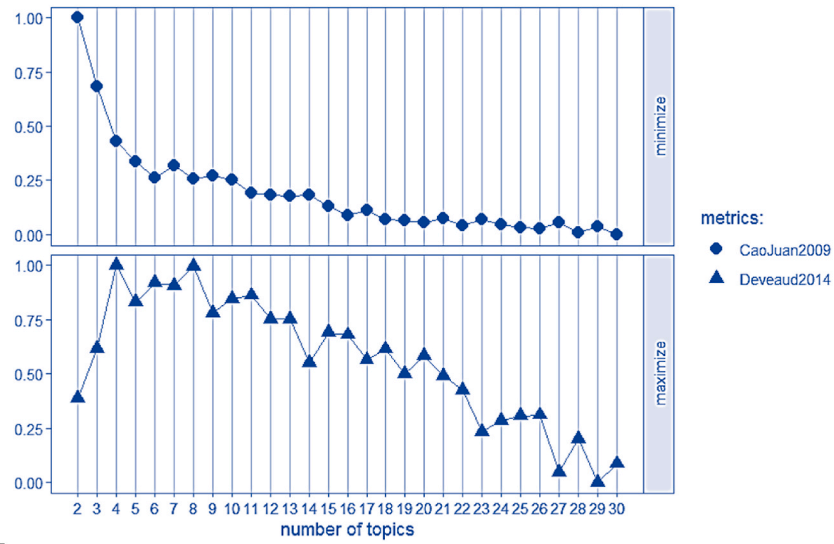

Fig. 12. Measures for selecting the optimal number of topics. Authors' calculations.

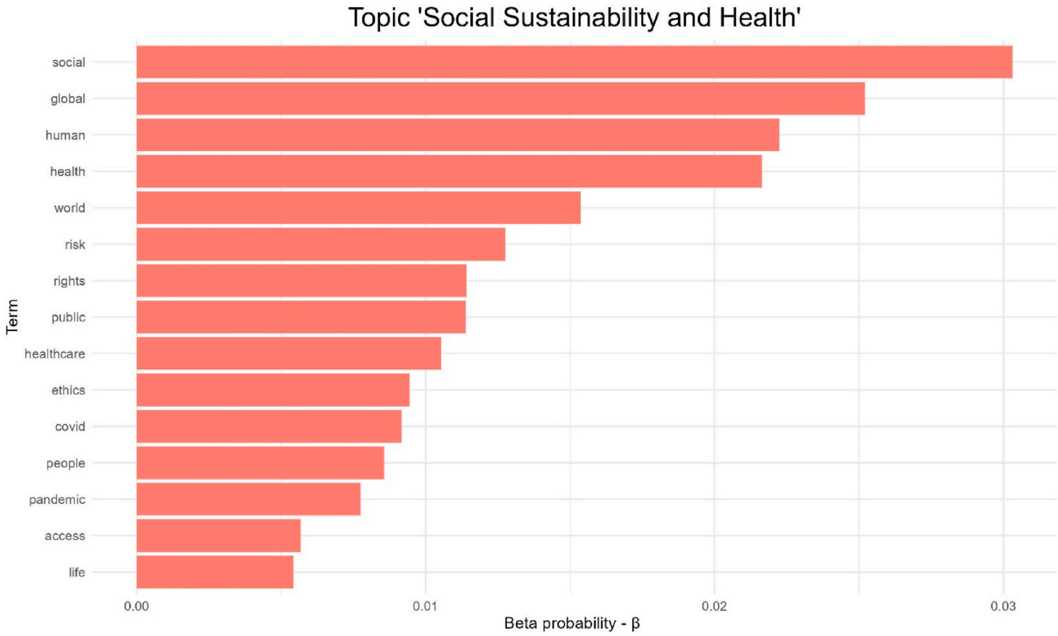

Fig. 13. Top 15 words for the topic Social Sustainability and Health. Source: Web of Science and Scopus databases. Authors' calculations.

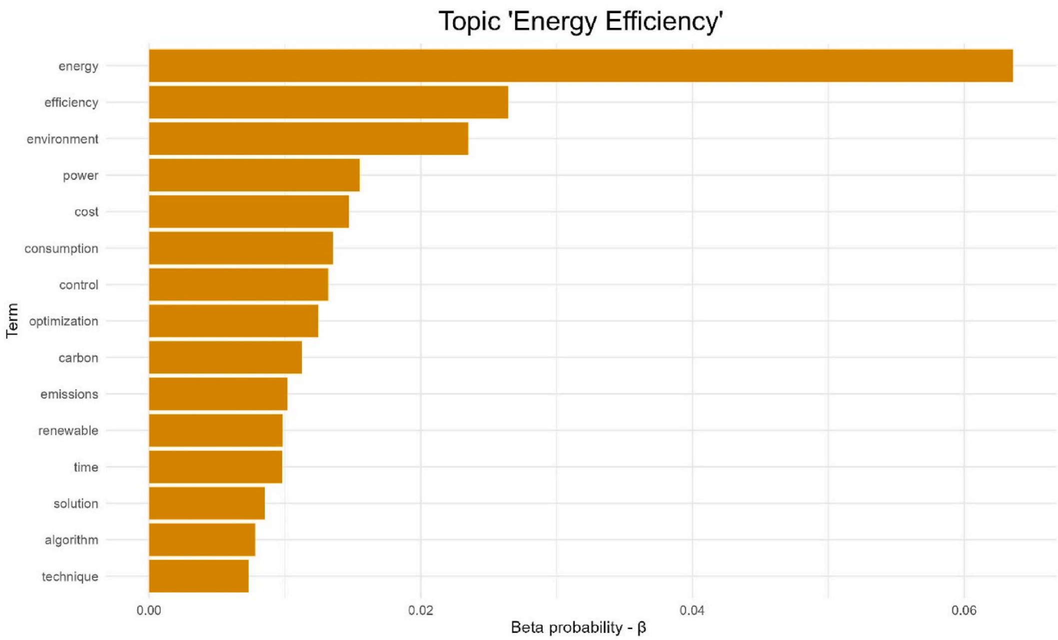

Fig. 14. Top 15 words for the topic Energy Efficiency. Source: Web of Science and Scopus databases. Authors' calculations.

The first topic (Fig. 13) is connected to social sustainability, one of the three pillars of sustainability. We named it "Social Sustainability and Health", as it covers social aspects, especially health-related ones. The central focus is on the individuals and communities and the possible repercussions of companies' decisions on their well-being, quality of life, and equity and provision of these aspects. Our literature analysis of the abstracts revealed that providing access to healthcare is one of the most critical aspects of social sustainability during the pandemic. The outbreak of COVID-19 has created challenges for healthcare systems worldwide, and the literature emphasizes these challenges. From the words belonging to this topic, the social aspects related to human rights and their provision can be derived, particularly in the face of the growing emergence of artificial intelligence technologies and the increasing digitalization of all aspects of life. Moreover, "ethics" is connected to human rights, as social sustainability goals can be achieved using

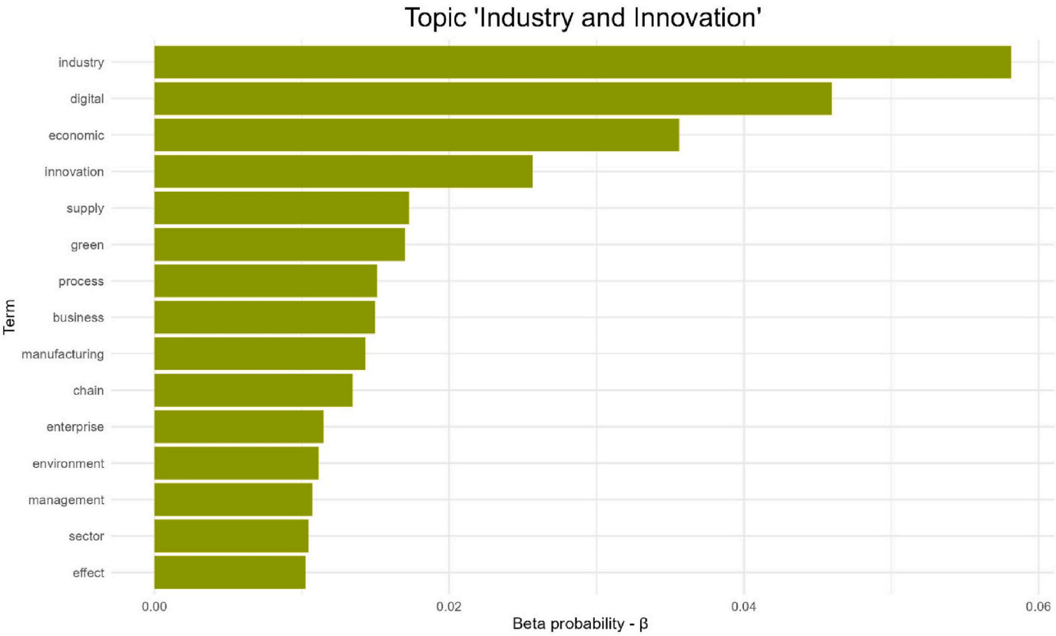

Fig. 15. Top 15 words for the topic Industry and Innovation. Source: Web of Science and Scopus databases. Authors' calculations.

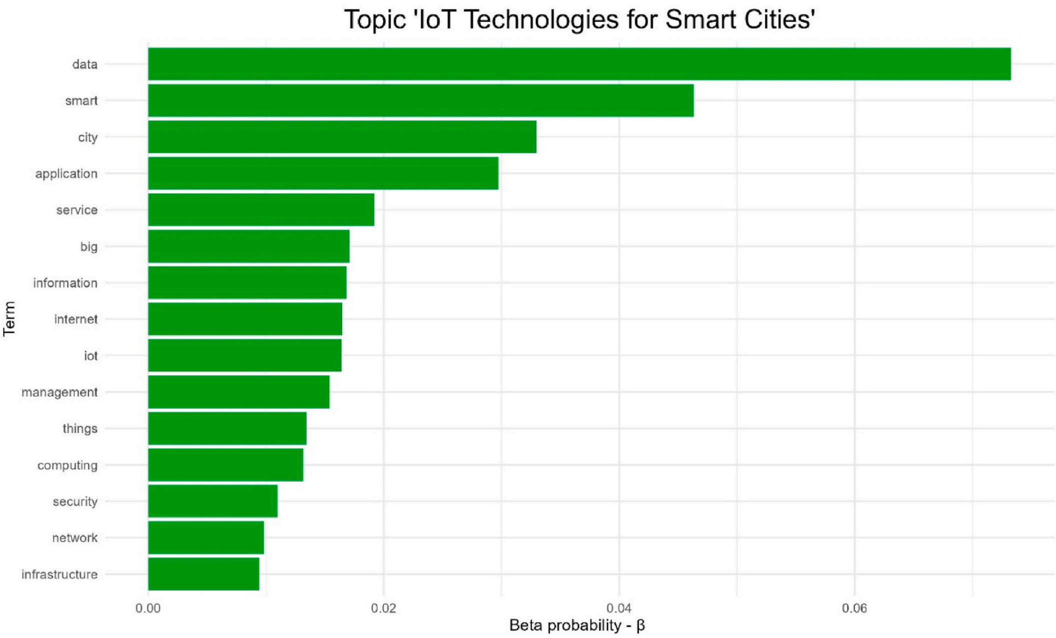

Fig. 16. Top 15 words for the topic IoT Technologies for Smart Cities. Source: Web of Science and Scopus databases. Authors' calculations.

ethical principles. The topic below encloses the literature analyzing AI technologies and the sustainable development objectives related to good health/well-being (SDG 3), sanitation and clean water (SDG 6), decent employment and economic growth (SDG 8), reducing inequality (SDG 10), peace, justice and strong institutions (SDG 16) but also partnerships for the goals (SDG 17). Various studies have pointed out artificial intelligence's positive and negative impacts on the medical sector. Researchers have identified several benefits of using AI, such as chatbots that can converse with patients, robots that provide fast and accurate diagnoses, and precise surgical operations [100]. However, there are also potential negative impacts, including ethical concerns regarding access to healthcare, incorrect diagnoses, and issues with technical and organizational infrastructure [101,102].

The second topic pertains to environmental sustainability and describes the literature regarding energetical efficiency (Fig. 14).

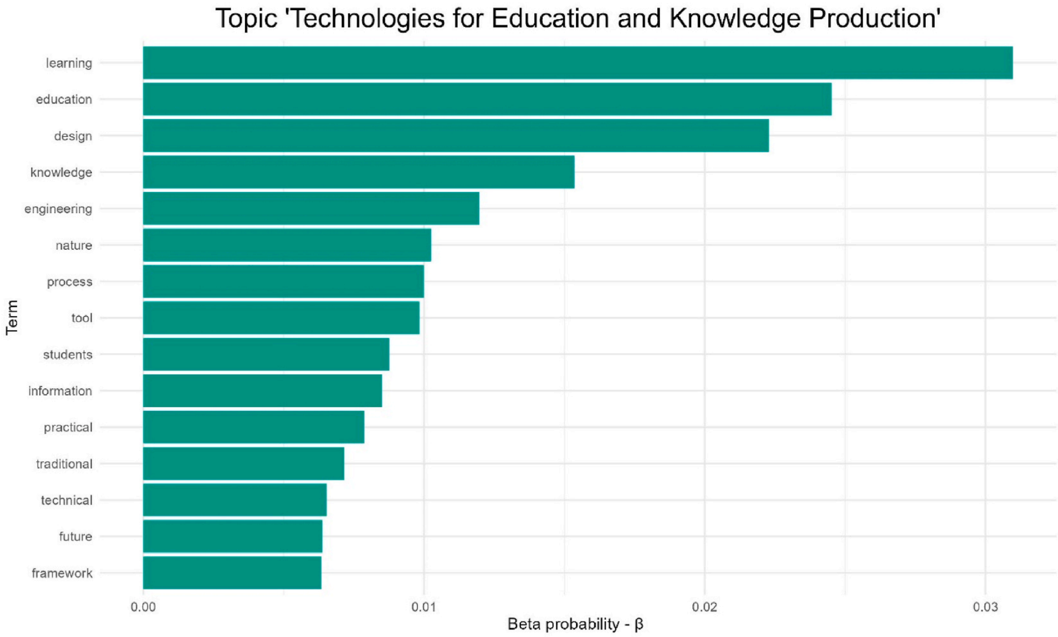

Fig. 17. Top 15 words for the topic Technologies for Education and Knowledge Production. Source: Web of Science and Scopus databases. Authors' calculations.

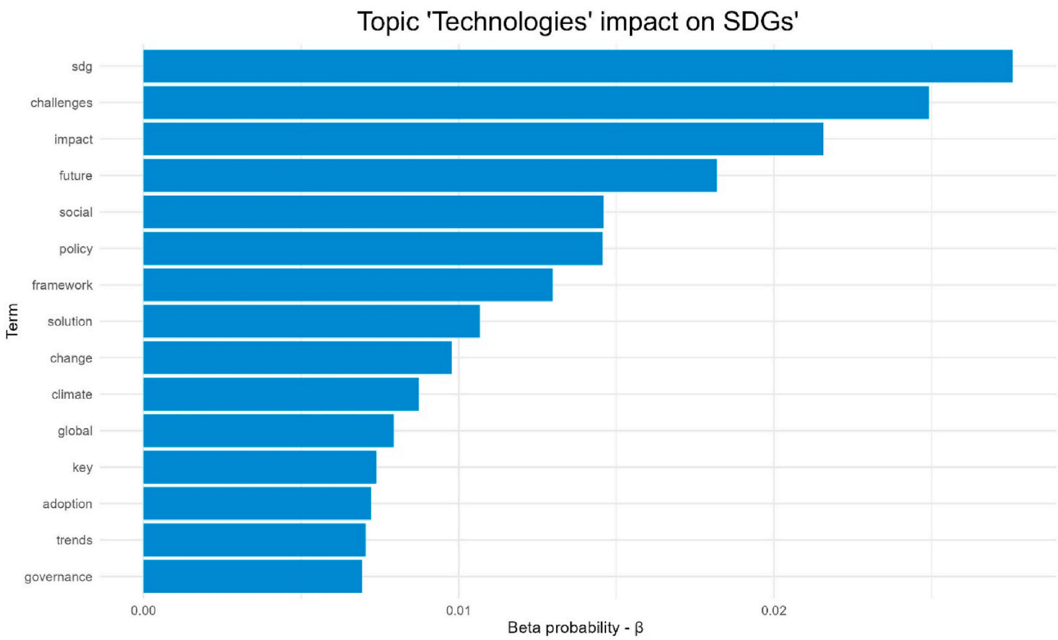

Fig. 18. Top 15 words for the topic Technologies' impact on SDGs. Source: Web of Science and Scopus databases. Authors' calculations.

Energy efficiency is one of the most important objectives of environmental sustainability. By energetic efficiency, we can understand from the results the reduction of carbon (CO2) emissions from the air, a reduction of energy by reducing the consumption of conventional energy sources, and a transition to new sustainable energy sources such as solar and wind energy. The most used words in this topic also suggest the use of artificial intelligence solutions, algorithms, and techniques to achieve energy efficiency, which involves monitoring and optimizing energy usage. Affordable and clean energy (SDG 7) fits to this topic. Studies related to the impact of artificial intelligence in the energy field have demonstrated that it can improve energy efficiency and increase energy use from renewable sources [103]. Some examples are evident from our analysis but also pointed out by other previous works of AI uses for

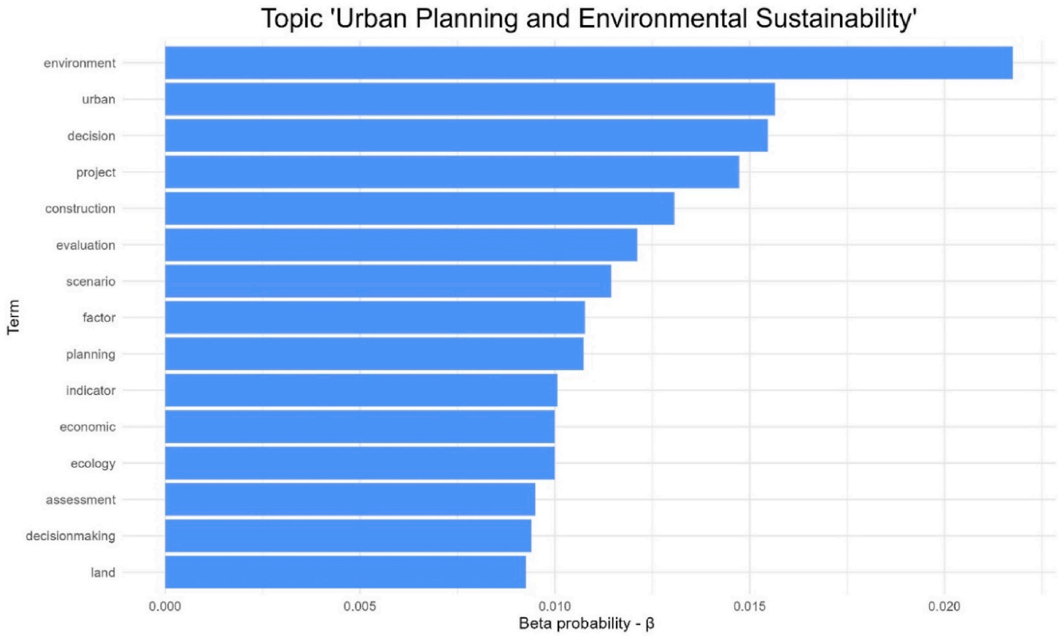

Fig. 19. Top 15 words for the topic Urban Planning and Environmental Sustainability. Source: Web of Science and Scopus databases. Authors' calculations.

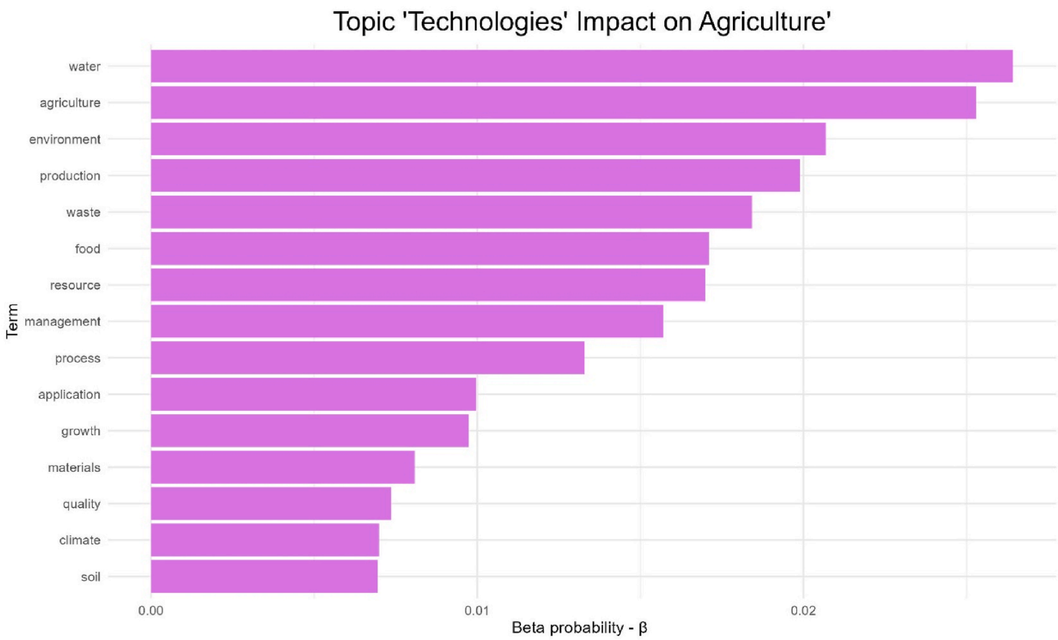

Fig. 20. Top 15 words for the topic Technologies' impact on agriculture. Source: Web of Science and Scopus databases. Authors' calculations.

energy efficiency which are energy optimizations and evaluation of consumption practices and renewable energy sources (solar, water, and wind) [34].

The next topic (Fig. 15) encompasses literature focused on economic sustainability regarding industry and innovation. This theme involves innovation in business processes using digital technologies while also transitioning to a green economy and creating sustainable economic growth. Some sustainable practices in companies include corporate social responsibility (CSR) and green supply chain management that reduce the environmental impact. According to the words in the topic, one of the most examined sectors when considering the promotion of sustainable practices such as CSR is manufacturing. The literature related to industry, innovation and infrastructure (SDG 9) goal pertains to this topic. The advantages analyzed by the studies showed that the digital economy could meet customers' needs, monitor key performance indicators, explore complex economic models, and identify links between invisible variables at first glance [104]. Opposing studies have noted disadvantages like containing errors in the data, privacy or security issues, and anti-money laundering [104]. Regarding supply chain management, most of the implications of artificial intelligence are positive, such as quality control, superior customer experience, demand forecasting, warehouse automation, and route optimization [105]. The adverse effects of AI technologies on economic sustainability glimpsed by other studies are the security and confidentiality of the data used, job loss, and relatively high implementation costs [106]. Our study reveals a relatively optimistic picture of the advantages and solutions for transitioning towards a sustainable digital economy despite the perils and challenges mentioned in the previous literature.

The next topic incorporates literature regarding the use of Internet of Things technologies in designing smart cities. As illustrated in Fig. 16, various ICTs and IoT network technologies are used to create sustainable smart cities (such as smart grids and edge computing). These technologies, including artificial intelligence technologies, aim to improve cities' infrastructures and increase individuals' quality of life and services offered (healthcare, transportation, education, community services, etc.) while also providing security for the residents. These implemented technologies are based on and, at the same time, generate huge amounts of data used for big data analytics to improve the application of technologies in cities. These vast amounts of information and data also open new challenges regarding data protection and cyberattack vulnerability. This theme relates to the goal of sustainable cities and communities (SDG 11). Studies discussing smart cities pointed out the favorable use of artificial intelligence, such as automating processes, improving the inhabitants' quality of life, optimizing the infrastructure, and efficiently using smart networks for energy [107]. The favorable aspects of artificial intelligence on the Internet of Things discovered in diverse themes are related to saving money and reducing human effort. The unfavorable aspects include security and ethical issues [108].

The fifth topic (see Fig. 17) encompasses academic research concerning education and knowledge in light of the new technological developments. During the pandemic, along with lockdowns, the education systems experienced a forced digitization to allow virtual learning. The words describing this topic also point out the literature regarding the role of technological tools in educational design in promoting sustainability and in creating sustainable educational systems that meet the needs of current and future generations. Education that promotes sustainability may include lessons regarding sustainable consumption practices, climate change actions, poverty alleviation practices, disaster risk reduction, and promoting biodiversity [109]. The literature regarding SDGS goals related to no poverty (SDG 1), quality education (SDG 4), reduced inequality (SDG 10), and peace, justice, and strong institutions (SDG 16) are included in this topic. The findings obtained by other researchers suggest that Artificial Intelligence has a beneficial place in education because it facilitates the personalization of learning, provides instant feedback, optimizes the evaluation process, and monitors students' progress [99,110]. Likewise, virtual reality encourages collaboration and teamwork and uses virtual assistants for various types of interactions [110]. As drawbacks of AI technologies for social sustainability, the literature indicates disparities regarding access to information and technology, ethics, confidentiality, data security, and various types of discrimination [110].

Another topic produced by our LDA model was related to the impact of technologies on sustainable development goals (Fig. 18). While other topics were more specific on the three pillars of sustainability, this topic is more general. It incorporates the social, environmental, and economic implications of sustainability. Sustainable development goals are interlinked with sustainability governance as these sustainability goals often serve as a baseline framework for formulating environmental policies and strategies, including energy reduction regulation for climate change alleviation. In this context, AI technologies and, more generally, digital technologies can be used to track and report indicators related to SDGs [2]. Based on the words used in the given topic, we can infer that it covers several goals, such as gender equality (SDG 5), decent work and economic growth (SDG 8), responsible consumption and production (SDG 12), climate action (SDG 13), life below water and on land (SDG 14 and SDG 15). The growing concerns of researchers related to climate change indicated that artificial intelligence is more of an exchange in the sense that, if we want an effective response regarding this, we must be aware of the sacrifices that will exist, such as ethical risks and the carbon footprint raised [111]. Digitization and technological change have generally sparked debate in scientific communities, regarding both positive and negative influences on sustainable development [20]. For example, some researchers argue that manual and routine jobs requiring minimal knowledge are at risk in the labor market due to strong automation and digitization [112]. In contrast, others foresee adverse effects even for highly skilled labor [20].

Another topic from our analysis encompasses urban planning and environmental sustainability literature (see Fig. 19). This topic is similar to the topic related to the use of Internet of Things technologies in designing smart cities. While the topic of smart cities is more centered on the technical aspects of designing cities using technology, this topic is more focused on urban planning as a holistic process that involves evaluation and assessment of the indicators, possible impacts, risks, and scenarios (including economic impacts), policies and decision-making deliberations regarding environment, land-use and transportation systems [113]. In this topic, we included the following SDG goals: economic growth and decent employment (SDG 8), responsible consumption and production (SDG 12), and life below water and on land (SDG 14 and SDG 15). Studies examined the impact of artificial intelligence on the conservation of wildlife, the oceans, and the earth. These studies found many positive aspects of AI, such as using drones and self-driving cars to monitor illegal catches and reduce waste and using micro-robots to break down plastics and identify the causes of forest loss [114]. In urban planning, artificial intelligence is seen as an enabler with the following functionalities: high speed for data and information processing and procedural justice to help make decisions related to marginalized communities [115].

Another topic is focused on AI technologies used in the agricultural and farming sectors. It encompasses the literature regarding impact of technologies, such as precision agriculture systems, on creating sustainable agriculture systems. As pictured in Fig. 20, sustainable agriculture implies some aspects. Sustainable agriculture is committed to conserving and using natural resources efficiently while protecting soil and reducing water consumption. On the other hand, sustainable agriculture seeks to improve food production sensitive to climate change challenges while also creating population awareness regarding sustainable consumption practices and waste reduction. In this topic, even other objectives can be brought up again, such as zero hunger (SDG 2), sanitation and clean water (SDG 6), responsible consumption and production (SDG 12), climate change action (SDG 13), life below water (SDG 14) and life on land (SDG 15). In agriculture, various subjects mentioned drones, which are used for watering the land, self-driving tractors, which allow farmers to have other activities during this time, and image recognition, which helps them know if the fields are healthy [116].

The last topic characterizes the literature regarding artificial intelligence models and techniques for sustainability. As observed in previous topics, specific models, algorithms, and techniques are used to achieve and monitor indicators regarding sustainability in areas such as urban planning, agriculture, education, economics, energy efficiency, and sustainable corporate governance. Some of these models and techniques are portrayed in Fig. 21. These techniques include machine learning, deep learning (including neural networks), predictive analysis and forecasts, and classification techniques. This topic answers one of the questions of the article, which is related to the artificial intelligence techniques and methods used in sustainable development objectives. This topic is distinct from other topics focusing on the technical intricacies of the domain of artificial intelligence in sustainable development.

We used a structural topic model with the publication type, citations, and year of publication as covariates to analyze the impact of AI on SDGs. After experimenting with different numbers of topics, we arrived at eight topics that closely align with the themes from the previous analysis (see Fig. 22). The first topic concerns AI's impact on SDGs, while the second focuses on AI models and techniques. The third topic combines the previous topics on education and knowledge with other aspects of health. The fourth topic is about urban planning, and the fifth is about agriculture and AI technologies. The sixth topic covers industry and innovation, while the seventh concerns energy efficiency. Finally, the eighth topic looks at smart cities and IoT technologies.

Upon reviewing trends over time (in Figs. 23 and 24), AI's impact on SDGs (Topic 1) appears to have remained stable. However, there is a slight upward trend in the literature on AI methods and techniques (Topic 2) and urban planning (Topic 4). Conversely, there is a slight downward trend in the social sustainability literature regarding education, knowledge, and health (Topic 3). Furthermore, a stronger trend indicates increasing interest in energy efficiency (Topic 7) and a slight increase in agriculture (Topic 5). Simultaneously, there is a slight decrease in interest during this period in topics concerning industry and innovation (Topic 6) and smart cities and IoT technologies (Topic 8).

5. Discussion and conclusions

The main aim of the present paper was to identify the impact of Artificial Intelligence on sustainable development while mapping the major themes in the domain from the beginning of the COVID-19 pandemic. To achieve this objective, we employed bibliometric analysis and a text-mining technique based on topic modeling using Latent Dirichlet Allocation (LDA). The results and findings have shed light on the main themes approached in the literature regarding Artificial Intelligence and sustainable development during the pandemic. The bibliometric analysis and LDA topic modeling revealed similar thematic areas.

The first theme in the literature concerns social sustainability and health-related issues. Generally, this topic uncovered discussions in the literature regarding negative aspects of corporate practices on individuals' well-being, quality of life, and equity. The topic strongly underlined the healthcare sector, as the literature covering the pandemic period and issues related to health and quality of life

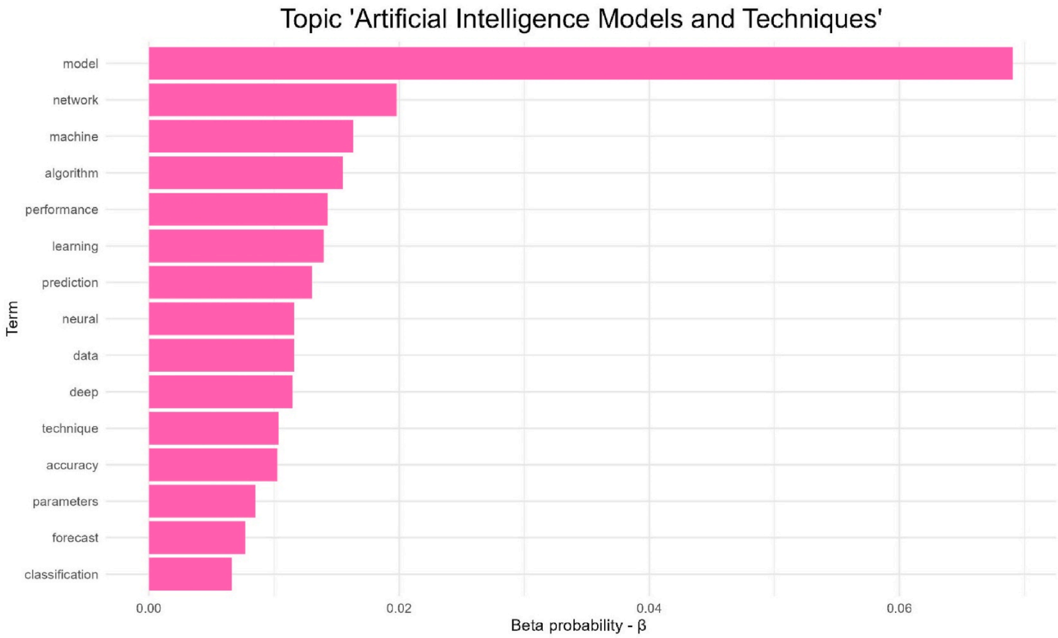

Fig. 21. Top 15 words for the topic Artificial Intelligence Models and Techniques. Source: Web of Science and Scopus databases. Authors' calculations.

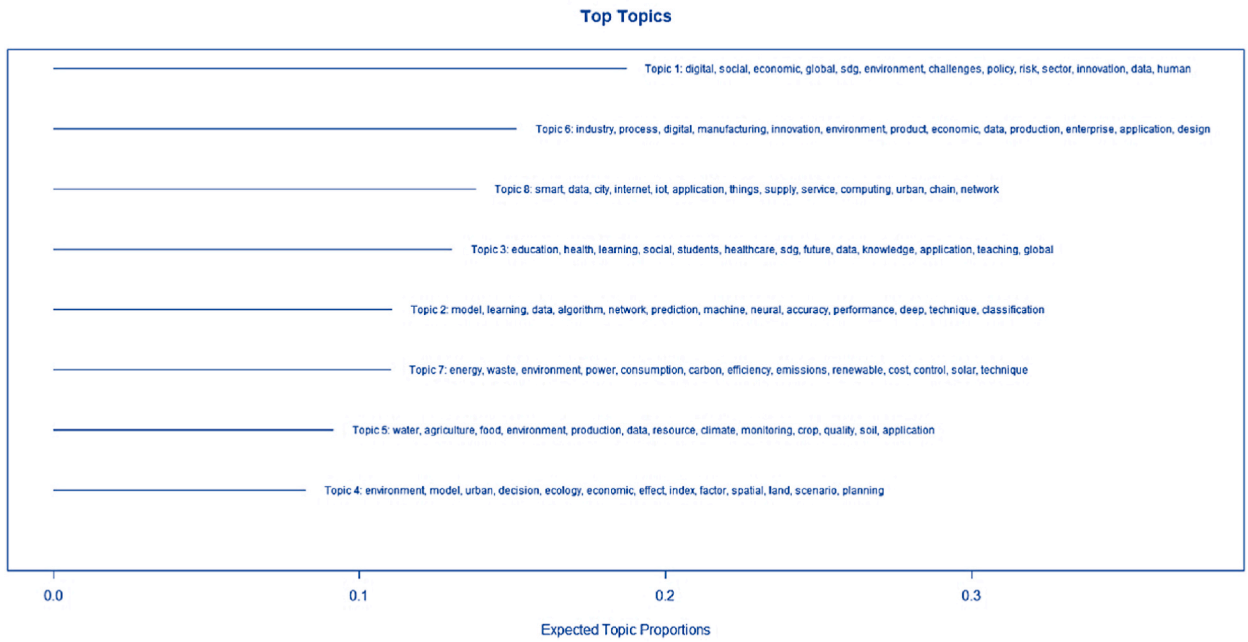

Fig. 22. Top terms in each topic using Structural Topic Modeling. Authors' calculations.

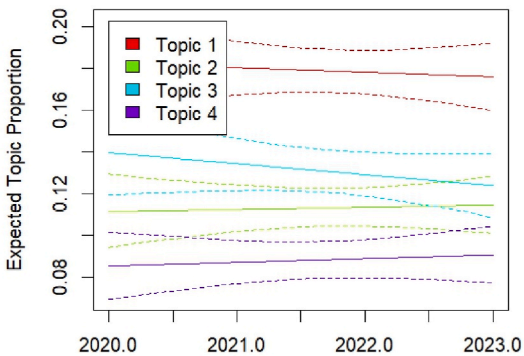

Fig. 23. Expected topic proportions by publication time for topics 1–4. Source: Web of Science and Scopus databases. Authors' calculations.

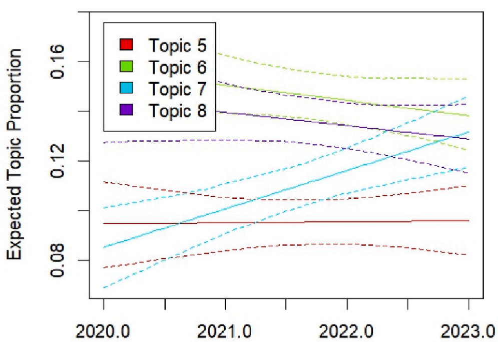

Fig. 24. Expected topic proportions by publication time for topics 5–8. Source: Web of Science and Scopus databases Authors' calculations.

were intensely debated in the literature. While previous literature shows both the positive and negative impact of AI on the social pillar of sustainable development, this topic in our research emphasizes the negative impact of AI, such as harm to human rights and ethical dilemmas regarding access to healthcare. Generally, the acceptance of artificial intelligence and the use of technology in addressing social sustainability issues reveals a skeptical view paved with risks and concerns. This topic can aid policymakers and governments in informing policies and legislation for more equitable access to health and human rights provisions, especially during health crises such as epidemics and pandemics. Implications for healthcare organizations can also be derived from this topic for more resilience during crises, such as corporate social responsibility practices, prepared and protected workforce, and efficient operations and supply chains. Research on subjective individual repercussions of AI technologies, such as subjective well-being (especially psychological/mental well-being), is relatively scarce, as seen from this topic regarding social sustainability and health. There is a need for more research on the impact of artificial intelligence on psychological/mental well-being. Moreover, the diminishing focus on social sustainability (as seen from the structural topic model analysis), including aspects related to education, health, and knowledge emphasize the importance of revisiting and revitalizing themes in literature within the sustainability discourse.

The second topic emphasized the aid of AI technologies for energy efficiency. The topic comprises literature discussing AI technologies for energy reduction from conventional sources and potential solutions for using alternative energy sources. This topic on energy efficiency shows AI's positive impact as a solution to current issues regarding sustainable energy. The acceptance of AI technologies in the energy field is strongly associated with constructing these as a solution to current problems. As per the temporal analysis, there has been a notable increase in interest towards this literature strand, especially in the context of global energetic crisis. This topic shows the importance of AI technologies in addressing climate change and environmental issues. It can be valuable for policymakers in designing policies and regulations that promote technological innovations in energy. Moreover, this topic can also be relevant for industry stakeholders using AI technologies for competitive advantage and cost reductions. The results for this topic can also be relevant for researchers in the energy field in creating technological innovations for reaching sustainability outcomes.

The third topic about sustainability in industry and innovation encompasses using Artificial Intelligence technologies for innovative solutions in business processes, focusing simultaneously on a just transition to a green economy while creating sustainable economic growth. Hence, AI positively impacts innovations, economic growth, manufacturing, and improved supply chains. Despite the risks and challenges mentioned in the previous literature, this topic reveals a positive outlook on the benefits of AI in transitioning towards a sustainable digital economy. From the start of the pandemic this topic has slightly decreased. Moreover, there is a lack of attention to the negative impact of AI technology practices on workers. For example, issues that are relatively poorly addressed in our sample relate to data privacy, surveillance practices, and algorithmic surveillance or algorithmic hiring. Consequently, more future research focusing on algorithmic human resources practices in the workplace and their impact on employees is needed. Nonetheless, the results can inform the need for data protection regulation that protects employees and users of AI technologies, and policies that support green innovations. The research can be informative for practitioners, regarding the importance of responsible business practices and potentially valuable AI benefits for competitive advantages.

The fourth and fifth topics are related to Artificial Intelligence and Internet of Things technologies used to create smart and sustainable cities and urban planning. These two clusters focused on AI and related technologies (such as IoT) for sustainable urban planning. The former topic is focused on technical particularities and reveals AI technologies as a solution for technologically enabled smart cities. The latter is centered on urban planning as a holistic process and constructs AI technologies as a solution in evaluating indicators, impacts, and supporting decision-making. Therefore, topics in our research reveal an optimistic view of the impact of artificial intelligence and related technologies on urban planning. As in the case with other topics in our study, research focusing on possible impacts, especially social impacts at the individual level, is insufficient. Future research must focus on possible risks and impacts of AI on the subjective and objective quality-of-life indicators and possible repercussions regarding surveillance practices in city design. These insights can be relevant for policymakers as they prioritize citizens' quality of life over technical complexities.

Another topic in our research tackled Artificial Intelligence technology as a solution for education and knowledge production. This theme highlights the benefits of Artificial Intelligence technologies in offering personalized learning solutions and evaluation tools. However, it mainly concentrates on the positive effects of AI and does not sufficiently cover the potential negative consequences of these technologies. One such drawback is the digital skills gap or other inequalities that can arise from the use of AI-based tools between students, teachers, educational institutions, and even educational systems from different countries. Future research is needed to tackle issues regarding skill gaps and inequalities regarding access to emergent technologies such as AI across different regions. Moreover, research regarding skill demand for high-skilled individuals to the disadvantage of low-skilled individuals in the present labor market is also needed [117]. Nevertheless, this topic can inform policymakers, education institutions, and practitioners about the general benefits of using AI technologies as a base for resource allocation, curriculum changes, and teachers' skills development programs.

Another theme revealed by our analysis was a general topic regarding technology's impact on sustainable development goals. This topic shows the use of AI technologies to monitor, track, and report indicators for sustainable development goals. AI's potential in contributing to SDGs has consistently been recognized, as highlighted by the temporal analysis. Another topic disclosed the use of artificial intelligence as a tool in agriculture for natural resources management, natural resource protection, and food production and consumption improvements. As with previous topics, this topic accentuates a positive representation of AI in agriculture, possibly undermining other issues such as workforce displacement and possible digital divides between small farming businesses and large corporations regarding access to specific technological resources. Although the analysis reveals a slight uptick in research regarding AI in agriculture, more research is needed to address these issues in the agriculture industry.

The last topic highlighted aspects of artificial intelligence or related techniques and methods used to achieve sustainable development goals, such as the Internet of Things (IoT), machine learning, big data, blockchain, deep learning, cloud computing, natural language processing (NLP), neural networks, remote sensing, and digital twins.

In conclusion, themes highlighted by our research are shaping the positive influence of artificial intelligence technologies on sustainable development. Negative aspects, particularly social-related ones, are undermined by the benefits of artificial intelligence in literature. Moreover, the thematic areas in the literature are strongly interconnected with the objectives regarding sustainable development (social, economic, environmental). The analysis reveals general themes (sustainable development goals), but also emphasizes specific areas such as AI methods, urban planning, energy, and agriculture.

Our research adds to the existing body of knowledge on the influence of emerging technologies, such as artificial intelligence, on sustainable development. It highlights the thematic areas of interest in scientific debates from the beginning of the COVID-19 pandemic. Also, the current study contributes to the emerging scientific literature that employs the technology acceptance model (TAM) and similar theories to understand the importance of the perceived benefits of using these technologies for sustainable development, showing an overall positivity bias in the themes addressed in the literature [118]. Moreover, themes revealed by our research contribute to recent debates regarding the impact of AI on sustainable development acting as a basis for legislative initiatives such as the European AI Act.

5.1. Limitations and future research

Theoretically, our research presents some limitations. We use some insights from Technology Acceptance Theory in interpreting our results. Technology Acceptance Theory might be oversimplistic in explaining artificial intelligence adoption for sustainable development as it relies upon perceived usefulness and ease of use. Discussing technology adoption not at an individual level, such as company and country level, may undermine the role of decision-making aspects and processes in technology acceptance. To address this limitation, our future research plans to use insights from theories such as the Technology–Organization–Environment (TOE) framework for organizational adoption and Social Construction of Technology (SCOT) for better understanding the social construction of technology at different levels [119,120].

The study also presents some limitations regarding the body of literature analyzed. For example, due to the period analyzed, and the words searched in the scientific databases, it does not exhaustively comprise all the articles on sustainable development and artificial intelligence. Scopus and Web of Science articles indexed in these databases are not exhaustive and often biased, not covering much of non-English and non-western literature or grey literature. We plan to include more papers on these issues by capturing more keywords, additional databases, grey literature, and a more extended period. Concerning the methods used, our study presents some limitations. Bibliometric analysis, which we employed, tends to overemphasize the quantitative aspects of themes in literature and overlooks qualitative aspects related to themes, such as specific variables used in methodologies. In order to address this limitation, we plan to use other approaches, such as systematic literature review and meta-analysis, in conjunction with bibliometric analysis in our future research. We also used Latent Dirichlet Allocation for topic modeling in our study, which has some limitations. It misses contextual nuances of word order, does not account for changes in time or the influences of other variables, and treats topics as independent of each other. Therefore, in our future research, we will address these limitations by using different approaches such as BERT and correlated topic modeling simultaneously.

Data availability statement

Data included referenced in article.

CRediT authorship contribution statement

Anamaria Năstasă: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Teodora-Cătălina Dumitra:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Adriana Grigorescu:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Nastasa Anamaria reports financial support was provided by Ministry of Research, Innovation and Digitalization. Teodora-Catalina Dumitra reports financial support was provided by Ministry of Research, Innovation and Digitalization. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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