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# Artificial intelligence, sustainability and environmental impact. A narrative and bibliometric study

# Inteligencia artificial, sostenibilidad e impacto ambiental. Un estudio narrativo y bibliométrico

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**ABSTRACT**

Studies on artificial intelligence (AI) have increased significantly over the past decade to the point that they have recently become essential to diverse fields. Regarding studies on sustainability, environmental care, and the application of technological advances, AI-based models have also gained particular significance. Accordingly, this study explored the relationship between AI, sustainability, and environmental impact through a mixed documentary review, which combined a narrative review and a bibliometric analysis. The narrative review examined the main ideas and stages that permeate the intersection of AI and sustainability, identifying their contributions and challenges. The bibliometric analysis provided a quantitative overview of scientific production, highlighting trends in terms of production, countries, and most influential keywords. The results reveal that AI has a crucial role in promoting sustainable practices, but it also poses risks that require careful consideration. Hence, the costs of AI must also be analyzed. The study underlined the need for a balanced approach that maximizes the benefits of AI while minimizing its negative impacts on the environment.

**Keywords:** bibliometrics, climate change, indexing languages, sustainable development.

**JEL Classification:** Q54, Q55

**RESUMEN**

Los estudios sobre inteligencia artificial (IA) han aumentado de manera ostensible en la última década, al punto de que recientemente forman una parte importante de campos disímiles. En lo concerniente a los estudios sobre sostenibilidad, cuidado medioambiental y aplicación de avances tecnológicos, los modelos basados en IA también han cobrado particular significación. En consecuencia, este estudio exploró la relación entre la IA, la sostenibilidad y el impacto ambiental mediante una revisión documental mixta, que combinó una revisión narrativa y un análisis bibliométrico. A través de la revisión narrativa, se examinaron las principales ideas y etapas que permean la intersección de la IA y la sostenibilidad, identificando tanto sus contribuciones como sus desafíos. El análisis bibliométrico proporcionó un panorama cuantitativo de la producción científica, destacando las tendencias en cuanto a producción, países y palabras clave más influyentes. Los resultados revelan que la IA tiene un papel crucial en la promoción de prácticas sostenibles, pero también plantea riesgos que requieren una consideración cuidadosa, de ahí que sus también deban analizarse. El estudio subrayó la necesidad de un enfoque equilibrado que maximice los beneficios de la IA mientras se minimizan sus impactos negativos en el medio ambiente.

**Palabras clave:** bibliometría, cambio climático, desarrollo sostenible, lenguaje de indexación.

**Clasificación JEL:** Q54, Q55

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## INTRODUCTION

Artificial intelligence (AI) has emerged as one of the most influential technologies of the 21st century, especially in the last five years and currently, with a boom that has also been reflected in popular culture and political agendas (Fosso et al., 2021; Oduro et al., 2022; Straub et al., 2023). Due to the possibilities and capabilities it offers, which are not only flexible and reinforced by continuous learning and development but also depend on the creativity and objectives of its use, AI has transformed a wide range of sectors. From healthcare to finance, with significant growth in other areas, AI has become popular as a broad set of tools.

Its evolution has been marked by significant advances in machine learning algorithms, processing large volumes of data, and improvements in computing power. Since its early conceptualization, AI has undergone several phases of development, moving from the first expert systems in the 1970s to the resurgence of deep learning in the 2010s.

Currently, its expansion into more complex applications has placed these large models at the center of a wide variety of processes, which has eased the workload of human scientists and is expected to constitute a new avenue for job creation. Even under the perception that society is not entirely ready for the full integration of AI, a wide variety of potential exists (Fosso et al., 2021).

One of the fields where AI has shown the greatest transformative potential is environmental studies (Balsalobre-Lorente et al., 2023; Nti et al., 2023; Yu et al., 2021). In response to growing concerns about climate change, climate variability, biodiversity loss, and ecosystem degradation, researchers and organizations have begun to apply AI techniques to address these global challenges (Ahmad et al., 2022; Antonopoulos et al., 2020; Zare et al., 2024).

In the last two decades, especially since 2019, there has been an exponential increase in the number of studies using AI to model environmental phenomena and optimize the use of natural resources (Casado-Aranda et al., 2021; H. Tan et al., 2021; Zhang et al., 2022). In addition to their use for diagnostic purposes, AI models have begun to gain relevance in designing mitigation and adaptation strategies to the effects of climate change.

The integration of AI into environmental studies has enabled advances in areas such as the prediction of extreme weather events, water resource management, and the conservation of endangered species, although it has also extended to urban environments and the design of smart cities (Balogun et al., 2020; Bolón-Canedo et al., 2024). AI-based predictive models have proven to be particularly useful tools for anticipating changes in climate patterns and providing critical information for sustainability policy decision-making (Bibri et al., 2024; Chakraborty et al., 2021; Nishant et al., 2020). In this sense, AI facilitates the analysis of large ecological datasets, allowing scientists to identify complex patterns and relationships within ecosystems that were previously difficult to discern or access.

As AI technology continues to evolve, its applications in the environmental field are rapidly expanding and being refined. However, the use of AI also poses ethical and practical challenges, such as the need to ensure that models are transparent, explainable, and accessible to the communities that would benefit most from them (Cabitza et al., 2021; Chiu et al., 2023; Du and Xie, 2021). In this context, a critical, historical, and topographical analysis of how AI is being used in environmental studies is essential in order to assess both its achievements and limitations.

This article explores the main historical and current trends in the evolution of AI, with a particular focus on its application in environmental and sustainability studies. Through a narrative review and bibliometric analysis, the aim is to offer a comprehensive overview of the current status and future potential of AI as a tool to address the most pressing environmental challenges of the current and foreseeable future.

## METHODOLOGY

The study was conducted using a mixed-method approach to the literature review, allowing for the combination of qualitative and quantitative data in the analysis of bibliographic sources, but also based on the stages of the research process itself. Thus, the research began with a narrative review, critical and holistic in nature, conducted based on two major themes: the stages of its conceptual evolution and the environmental impact of the use of AI. This methodological decision was driven by the need to understand and present milestones, historical trends, and the foundations of current AI studies to subsequently map the field based on its main bibliometric trends over the last decade.

### First stage

In the first stage of the study, a narrative review was conducted to explore and synthesize the evolution of AI. Key academic articles, books, and reports addressing major milestones and developments in AI from its origins to the present were collected and analyzed. Sources were selected based on relevance to the topic, and theoretical approaches and practical applications were covered. This review allowed for the construction of a solid theoretical framework that served as a basis for the subsequent stage of the study and the understanding of the findings.

**Bibliometric analysis**

In the second stage, a bibliometric analysis was conducted to examine research trends at the intersection of AI, environment, and sustainable development during the period 2014–2024. For this purpose, the Scopus database was used, selected for its broad scope and recognition in the academic community. Specific keywords related to AI, ecology, and sustainable development were defined to retrieve relevant documents. The search was divided into two concurrent fields, allowing for a better visualization of the transition from studies on sustainable development to the use of AI in addressing the environmental impact of the phenomena discussed in the introduction.

**Table 1**.
*Search strategy*

| AI AND sustainable development | AI AND environmental impact |
|---|---|
| ( TITLE-ABS-KEY ( artificial AND intelligence ) AND TITLE-ABS-KEY ( sustainable AND development ) ) AND PUBYEAR > 2013 | ( TITLE-ABS-KEY ( artificial AND intelligence ) AND TITLE-ABS-KEY ( environmental AND impact ) ) AND PUBYEAR > 2013 |

**Source:** own elaboration

**Methodological procedure**

*Inclusion criteria*

The time range was used, so only articles published between 2014 and 2024 were included. No other filters were used, such as language, region, or publication type.

*Data extraction*

Data were extracted according to indicators related to the number of annual publications, citations received, countries of origin of the publications, types of publications, and areas of knowledge. The file was downloaded in .CVS format and exported to VOSviewer software.

*Analysis*

VOSviewer, a specialized bibliometric analysis software, was used to run various analyses aimed primarily at understanding the categorical structure of the field through the keyword co-occurrence dimension. In addition, collaboration networks by country were visualized, and the units of analysis were compared within the studied dimension.

**Interpretation of results**

The findings from both stages were integrated to provide a comprehensive overview of the current state and future trends in research on the intersection of artificial intelligence, ecology, and sustainable development. This methodological approach not only allowed for a holistic exploration of the historical evolution of AI but also facilitated the identification of how its models and capabilities are applied in contexts related to sustainability and ecology. Furthermore, this data integration approach provided the basis for a comprehensive and concurrent triangulation for comparison with relevant findings and proposals found in the specialized literature.

## RESULTS AND DISCUSSION

**Narrative review**

*History of ideas about AI*

The most significant developments in artificial intelligence (AI) systems occurred in the 20th century. However, it should be noted that as early as 1842, mathematician and computer scientist Ada Lovelace programmed the first algorithm to be processed by a machine (Abeliuk & Gutiérrez, 2021). In Lovelace's view, the machine could compose complex musical pieces and scientific works and act solely on the basis of numbers. This vision of AI has resulted in a particular line of conceptualization, which uses terms such as the "Lovelace effect" and the "Lovelace objection," which allow for the approach to cultural rather than purely cognitive issues, such as creativity (Gonçalves, 2024; Natale & Henrickson, 2024).

One of the authors who has worked to detail the history of AI is Luis Eduardo Múnera (2010), who, in addressing the topic, uses a revealing metaphor to assert that AI reached its peak in a very remote era. In this author's opinion, its study must date back to, or be interested in, the very evolution of humanity, which he supports with a comparison between human characteristics, their projection, and the automatisms they generate. In fact, Múnera asserts that the first examples of automatisms and incipient ideas related to what is now called AI date back to Archimedes' Greece.

Furthermore, this author highlights that the first literary work to discuss AI, the Iliad, was published in Greece. One of its episodes narrates the scene in which Hephaestus's forge is mentioned, where countless automatisms are found that the king used to navigate. On the other hand, the author explores the history of AI up to the 20th century since it was in this century that a new science, namely cybernetics, was developed.

The first studies were conducted at MIT in Boston under the scientific direction of Norbert Wiener. Wiener is credited with fundamental ideas such as the vision of complementarity, the possibility of integration between humans and systems, and the need to develop models with a multidisciplinary approach (Godoy, 2024). Today, Wiener is considered the father of cybernetics and an important precursor to integrated systems and complex models (Bittanti, 2022; Groupos, 2024).

In addition to Wiener, McCulloch and Pitts also conducted studies in the field of cybernetics. Specifically, the latter are credited with creating a Boolean approach to the study of neural connections and their impact on information storage and processing. Today, the study of neural networks and the philosophical and worldview implications of these authors' work can be considered a field in itself, with multiple applications and issues addressed (An et al., 2022; Lobo et al., 2020).

Another important milestone was the Dartmouth Conference, during which the first definition of AI was established (Kubassova et al., 2021; Xin et al., 2021). Samuels also participated in this conference, presenting a checkers game that was capable of learning, something that generated confusion since this perception was conditioned by a lack of understanding of the qualities attributed by Samuels's design. Additionally, this conference was significant for highlighting AI as a legitimate and diverse field of study with multiple future applications (Chang & Limon, 2024; Krauss, 2024).

In short, the Dartmouth conference was the turning point for AI science. It established its three epochs, which are detailed below:

*1956-1970*

According to the sources consulted, the primary techniques of AI, such as algorithms and problem-solving strategies, were developed during this period. Thanks to the research work of Newell and Simon, the term "production systems" was coined, which the two used to solve problems. Today, these conceptual rudiments continue to be used, developed, and reviewed under the lens of new technological advances.

However, during this period, the potential of these production systems was overestimated, as they did not yet have the characteristics that would allow them to become "General Problem Solvers." Specifically, the systems were weakened by the size and speed of their memories, as well as by the limited fluidity of the first programming languages and operating systems.

Although very little advanced, these systems managed to solve problems that, until then, only very intelligent people had solved. Therefore, in the first stage of AI, their potential was celebrated. In fact, Simon was convinced that AI would soon be able to defeat the world chess champion, a feat that would only be reached in 1997 when IBM's Deep Blue defeated Garry Kasparov (Múnera, 2010). These ideas have now been developed, and AI-based chess programs are powerful analytical engines, support training applications, and can play at the highest level (Krakowski et al., 2023).

From 1956 to 1970, work on natural language also began, and to a certain extent, the concept that would later become known as "machine translation" was outlined. Researchers at the time argued that translation tasks would be simplified through mega-dictionaries and the programming of grammatical rules. Today, these ideas have revolutionized language translation and transformed text generation, so human-AI partnerships remain necessary, especially for effective and ethical use (Doo et al., 2023; Lim & Zhang, 2022; Lund et al., 2023).

In reality, this project was a massive failure. In fact, the system the researchers managed to devise failed to consider aspects such as the complexity of language and its cultural and biological aspects. As an example, a translation obtained by the machine translation system used in the early stages of AI is presented. Specifically, the system had been asked to translate a recovered passage from the Bible, which read, “The spirit is strong, but the flesh is weak.” The system eventually translated this passage as “Vodka is very good, but the flesh is rotten” (Múnera, 2010).

*The 60s*

The second stage in the history of AI can be classified as the prototype era, beginning in the 1960s. During this period, the projects carried out until then were examined, and an attempt was made to discover why they had failed. These projects failed because they failed to take into account the heuristic component of the human problem-solving process. Heuristic knowledge consists of incorporating experience and knowledge into the decision-making process.

Simon’s studies were fundamental to the development of heuristic models for problem-solving and later for decision-making (Navaneethakrishnan, 2021). Specifically, these contributions conceptually transformed computer science and paved the way for what is known as decision science, where AI also plays a central role. The greatest achievement of this stage was the production of the first expert system, which has now become one of the main avenues for task automation and application in different fields (Radaideh et al., 2020; L. Tan & Yi, 2024).

*1981 – present*

The third and final stage in the history of AI began in 1981, following the results obtained in the preceding era when the aforementioned prototypes became widespread in universities and laboratories. This era was characterized by widespread interest in entrepreneurship, and applied research declined before the surge in the last decade, which occurred in a wide variety of disciplines (Di Vaio et al., 2022; Jimma, 2023; Riahi et al., 2021).

Specifically, the sources consider that work is still needed in the fields of knowledge representation and inference; furthermore, lines of research on informed use and ethical responsibility have increased. An important element noted is that, when developing and perfecting AI systems, social issues such as job losses, fraud, or potential failures without human supervision must be considered.

Furthermore, the field of study seems increasingly aware of the benefits of AI development; for example, decision-making to safeguard the planet, facing one of the greatest dilemmas of our time, namely mitigating the effects of climate change (Goralski & Tan, 2020; Kaack et al., 2022; Palomares et al., 2021).

**Environmental impact of AI**

The analysis of the topic took as its starting point a study conducted by Kaack et al. (2022), which analyzes the effects of machine learning on the regulation of greenhouse gas emissions. These authors highlight the need to develop a holistic understanding of all the positive and negative impacts of using machine learning on climate change.

Specifically, they begin their analysis by explaining that in their work, they study the computing impacts from a dual perspective: bottom-up and top-down. The first evaluates the energy use of individual machine learning models, focusing not only on their use but also on their development and design. The second, in contrast, estimates the total global greenhouse gas emissions associated with machine learning workloads, analyzing the energy consumption used in computing as well as the emissions resulting from the extraction and production of the material. Similarly, these authors state that creating and running a machine learning model consumes computing energy as well as electricity, although it is clear that the amount varies greatly between different algorithms and different stages of the machine learning model lifecycle.

On the other hand, studies show that Deep Learning models continue to increase in size, leading to an increase in the computational resources required for their execution (Yuan et al., 2020). In this regard, there are differences in power consumption between machine learning models. The first of the constituent phases describes how the model is used in the world; for example, the machine is able to identify whether an image is of a dog or a cat based on what it has learned. This is the phase that consumes the least energy, but it is also the one used most often.

The objective of the training phase is to learn the functions by analyzing a database from which the machine extracts the parameters useful to define the functions mentioned above. Kaack et al. (2022) state that training a machine learning model consumes much more energy than using it, but it is a less frequent operation. The final phase involves the researcher choosing the model that provides the best results in the research field.

In another case, Dhar (2020) observed something very interesting. In fact, this author states that AI plays a dual role. On the one hand, it can help reduce the impact of climate change while being a major pollutant in itself. This idea is crucial, as it implies the need to recognize and address the sustainability of AI-based systems, their environmental impact, and the costs of reducing this impact (Van Wynsberghe, 2021).

In light of this, Tamburrini (2022) asserts that what the European Commission is requesting is important for understanding the magnitude of AI's carbon footprint and underlines the harmful contributions of many AI fields, ranging from research to industry. He also highlights the need for effective policies to reduce the carbon footprint of the AI sector and mitigate its impact on global warming. Regarding sustainability, van Wynsberghe (2021) asserts that various authors have studied the environmental benefits offered by AI but have dismissed the environmental impacts of these technologies. Therefore, he proposes to define sustainable AI and asserts that it is a recent line of research that studies the technology behind AI and its applications in combating climate change, including sustainable development.

Furthermore, the author adds that this line of research should also focus on the entire life cycle, primarily addressing aspects ranging from design, training, development, validation, and tuning to the implementation and use of AI. In this regard, she explains that a distinction should be made between two concepts that fall within the same line of research: "AI for sustainability" and "AI sustainability." The first concept addresses how AI can support humanity in achieving environmental sustainability, while the second focuses on assessing AI sustainability. The author concludes by stating that the previously discussed line of research encompasses both concepts, as it is impossible to develop AI systems that aim to reduce the impact of climate change if the environmental aspects underlying the development of AI systems are not also considered (van Wynsberghe, 2021).

As for exact pollution figures, a study conducted by MIT researchers (Strubell et al., 2020) estimates that training a large model using a GPU produces approximately 625 155 pounds of carbon dioxide, equivalent to approximately 316 round-trip flights from New York to San Francisco. An even more disturbing example is the comparison between the carbon dioxide emissions generated by training an AI model and the emissions generated by a human in one year of their life. In this case, training consumes as much as 57 years of a human's life.

A similar position was also observed in Truhn et al. (2023), who in their work state that a citizen of the EU Member States emits about 6.8 tons of carbon dioxide. Furthermore, they present a figure very similar to that offered by Strubell et al. (2020), analyzing that a flight between Munich and New York emits about 2.1 tons of carbon dioxide per person.

These authors then focus on emissions caused by medical equipment, stating that an MRI scanner emits approximately 58.3 tons of carbon dioxide per year, based on the work of Woolen et al. (2023). As a solution, Truhn et al. (2023) argue that optimized equipment could be purchased for use in neural network inference, which would further reduce the amount of energy required. They also emphasize the importance of using renewable sources to reduce polluting emissions and add that this leads to cost savings, as solar or wind energy costs less than energy produced from fossil fuels.

In addition to the studies already mentioned in this analysis, Lacoste et al. (2019) also attempt to shed light on how the emissions of AI systems could be estimated. In their study, the authors explain the factors that have the greatest impact on the amount of carbon they emit. These factors include the server location, the type of electrical grid used, the duration of the training, and the hardware used to train the model.

Similarly, the study's authors created a machine learning-generated emissions calculator. Lacoste et al. (2019) state that it is difficult to provide precise guidelines, as many factors that influence the results or modify the conditions under which the study is conducted must be considered. However, they create a list of best practices to follow to reduce the emissions generated by the machine learning phase; specifically, they urge researchers to use their calculator in addition to reflecting on the factors mentioned above. In particular, they explain that in recent years, cloud computing companies have begun to implement measures to reduce their environmental footprint.

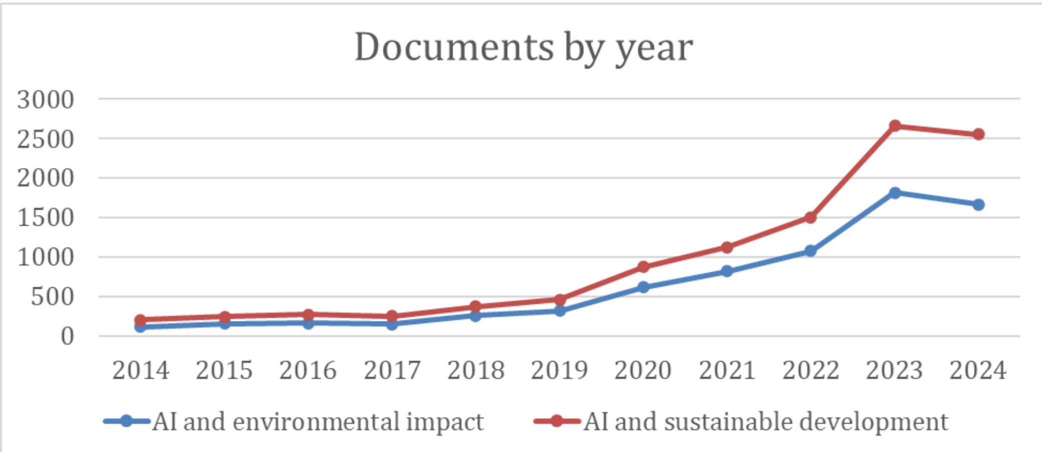
As a result, a better understanding of the disciplines and lines of research that have delved into the uses of AI-based systems for climate change mitigation and the promotion of sustainable development is needed. These findings will facilitate the exploration of the environmental impact generated by AI, which will, in turn, contribute to the responsible design of systems, as well as to policies and regulations that guide the governance of these technologies. Consequently, the main findings of the bibliometric study are presented below.

**Bibliometric study**

The first indicator analyzed was the number of publications per year during the period (see figure 1). As can be seen, at the beginning of the period, interest in the relationship between AI and sustainable development was relatively low, with a stable, slightly growing trend and even registering a slight decline in 2017 (n=154). However, since 2019, the trend has been toward accelerated growth, with a peak of 1814 in 2023 and the possibility of surpassing this number in 2024, when 1664 were registered by mid-year.

Regarding studies addressing the relationship between AI and environmental impact, these represented a smaller field but showed similar trends, including the decline seen in 2017. However, in 2024, 37 more studies were registered than in 2023, which also suggests moderate growth in concern about environmental impact and the role of AI, although further study focus is needed.

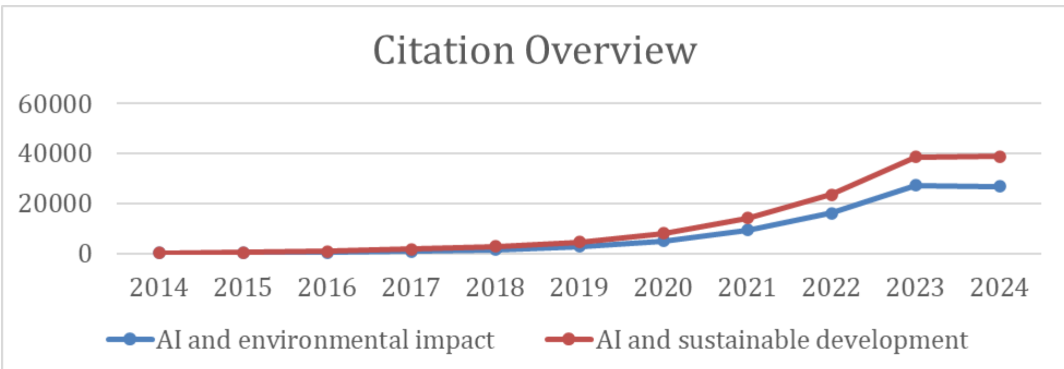
**Figure 1**.
*Documents by year. Comparative chart*




**Source:** own elaboration based on data provided by Scopus

Another impact indicator was the citation ratio for both fields (figure 2). In the first case, the total number of publications was 7162, of which 4683 were cited, for a total of 89 894 citations and an h-index of 123. Similar to the findings in the first analysis, the citation peak occurred in 2023 (27 144), but this is expected to be surpassed in 2024 (26 697).

**Figure 2.**
*Citation Summary. Comparative chart*

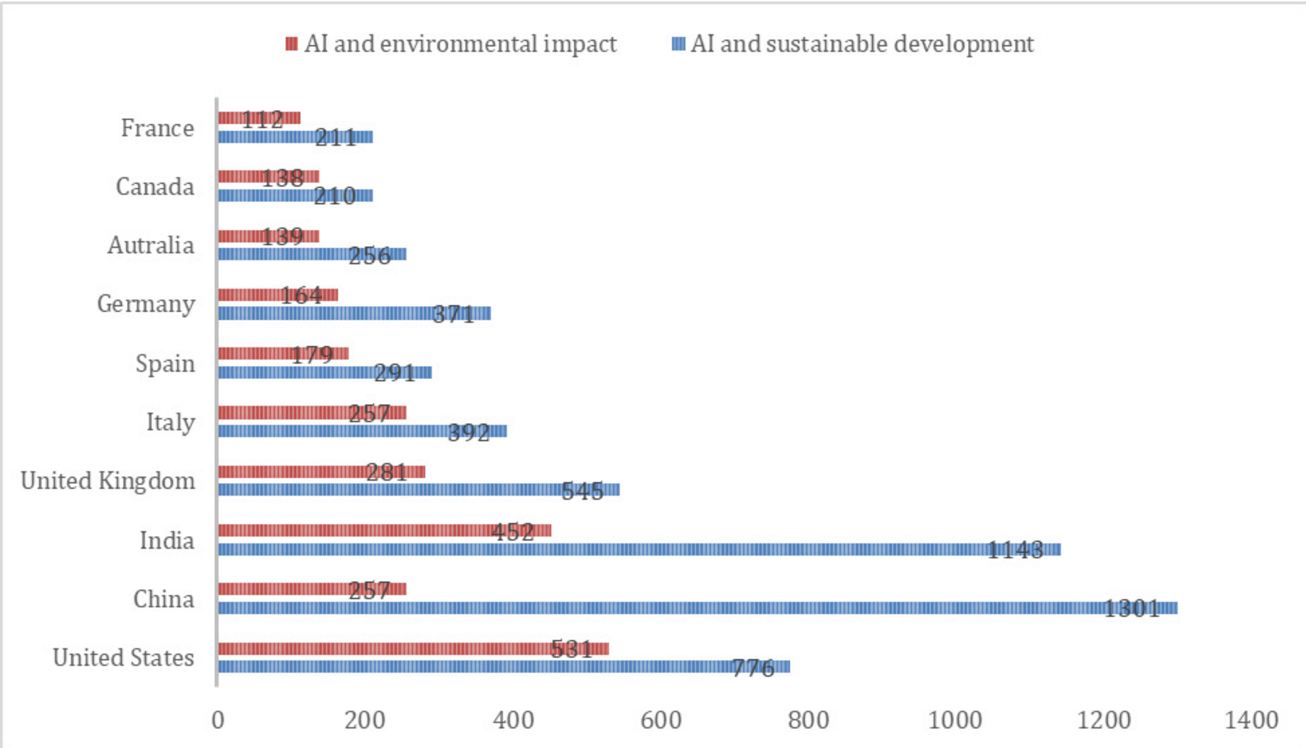



**Source:** Own elaboration based on data provided by Scopus

Similarly, the field of AI and environmental impact studies showed an upward trend and the potential for exponential citation growth. In this case, the total number of documents was 2221, with 43 336 citations and an h-index of 89. While lower than the macro-field of sustainability studies, it demonstrates the growing importance of exploring the environmental impact of human processes and the use of AI-based systems for this purpose. These results confirm that the use of AI models in sustainable development studies is a line of research of particular relevance, impact, and visibility.

Regarding the most productive countries in terms of studies, an analysis was conducted of those that overlapped in both fields, as well as their collaboration networks for the case of "AI AND environmental impact." The results showed a predominance of developed countries, particularly China, the United Kingdom, the United States, and India (see figure 3). In both cases, Spain ranked among the 15 most productive countries worldwide, which highlights the importance given by Spanish academia not only to environmental issues but also to the potential impact of using AI-based systems in their study and generation.

**Figure 3.**
*Documents by country. Comparative chart*



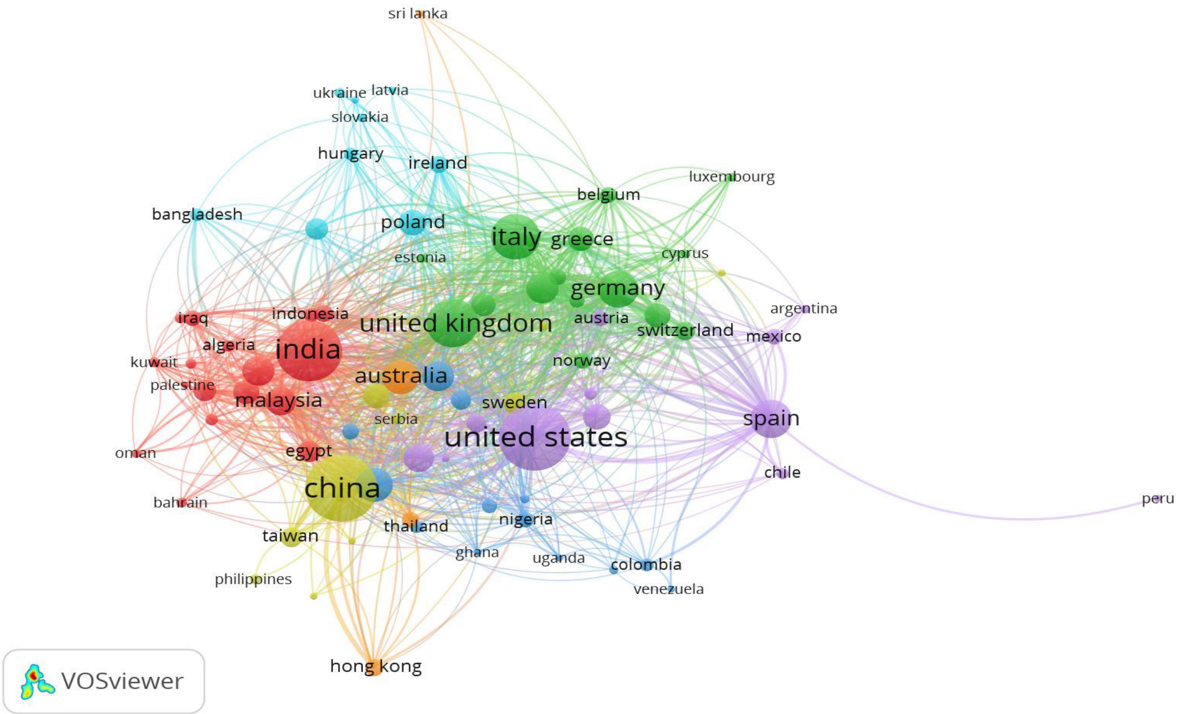

**Source:** own elaboration based on data provided by Scopus

In the specific field of studies on the relationship between AI and environmental impact, the analysis of co-authorship networks by country revealed the formation of six large clusters and two small, barely distinguishable ones. Among the large clusters, the one led by the United States stands out, where Spain occupies an important position by serving as a connecting node with Latin American countries such as Mexico, Chile, Peru, and Argentina. This demonstrates the vitality of building bridges and generating collaborative projects to strengthen the mitigation of environmental problems in the global south (figure 4).

Another interesting result of this analysis is that Spain is excluded from the cluster formed by European Union countries (the United Kingdom is included due to the pre-Brexit period), although it exhibits collaborative relationships. The remaining clusters are organized according to geopolitical and geographic factors, making them easily distinguishable regarding location or strategic alliances.

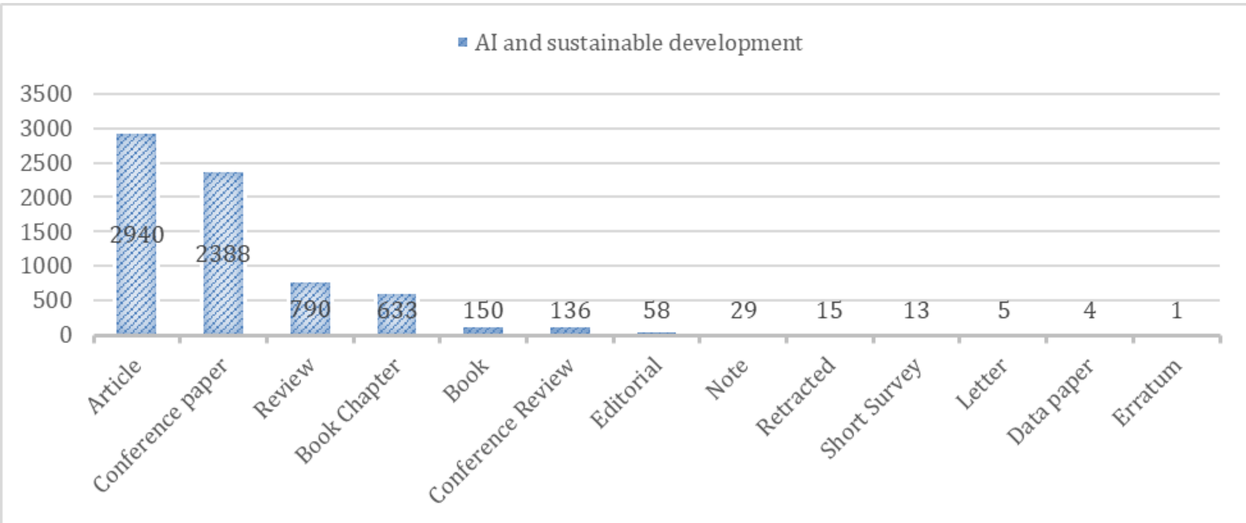
Regarding the types of publications, the analysis revealed a dynamic field in which applied research is produced, knowledge is transferred, and results are disseminated in diverse ways (figures 5 and 6). In both cases, original articles and conference papers predominated, results that underscored the previous statement.

**Figure 4**.
*Analysis of collaborative networks based on co-authorship in the field of "IA AND environmental impact"*




**Source:** own elaboration based on data provided by Scopus

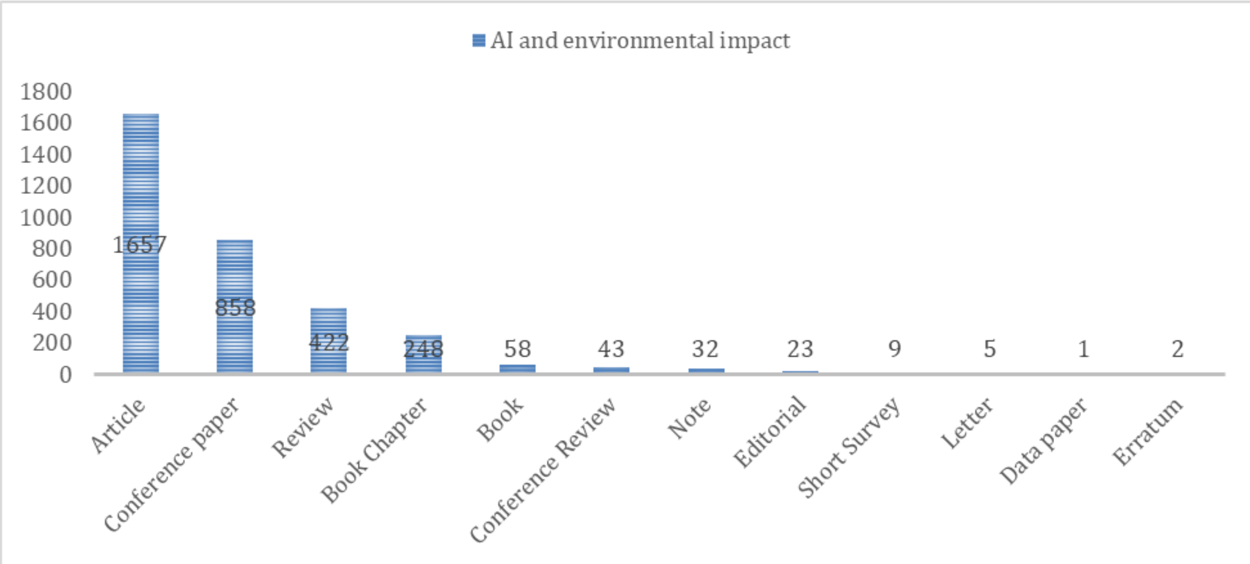
**Figure 5**.
*Document type for the field "AI and sustainable development"*




**Source:** own elaboration based on data provided by Scopus

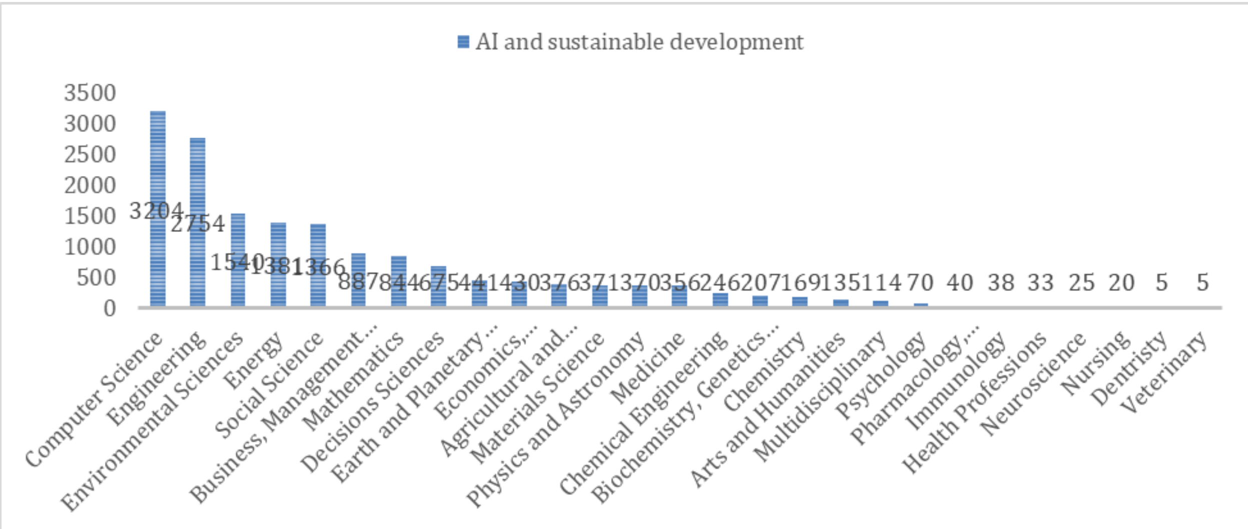
Another important finding emerged from the examination of the areas of knowledge where – although Computer Science and Engineering stood out, as expected – the diversity of disciplines reaffirms the notions mentioned in the narrative review about multidisciplinarity and the importance of the study of cultural and social factors (figures 7 and 8). In the case of studies on sustainable development, the Scopus database recorded 27 disciplines with at least 5 publications, while in the case of studies on environmental impact, 27 were also recorded, but with the mention that in the field of dentistry, 2 appeared and one remaining publication was not defined (Undefined field).

**Figure 6**.
*Document type for the field "IA and environmental impact"*




**Source:** own elaboration based on data provided by Scopus

**Figure 7.**
*Areas of knowledge for the field "AI and sustainable development"*

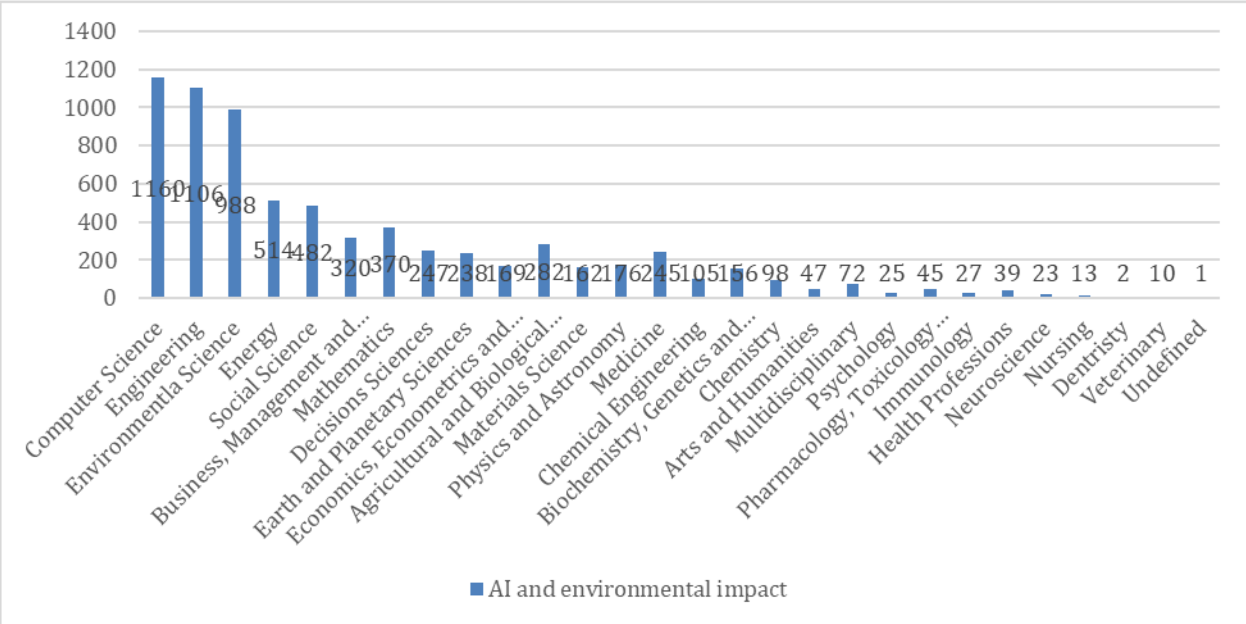



**Source:** own elaboration based on data provided by Scopus

Finally, it is necessary to address the results of the keyword co-occurrence analysis dimension, with a minimum value of 5. In this regard, we started with an analysis of the "AI and sustainable development" field, emphasizing the units determined by indexers (index keywords) and sources (all keywords). In the case of the "all keywords co-occurrence" unit, the analysis showed four large clusters in which AI occupied a particularly central position, and no clear criterion was identified for delimitation and grouping. In this network, the presence of terms that indicated processes, technologies, key actors, policies, fields of study, and social and environmental issues, among others, was observed.

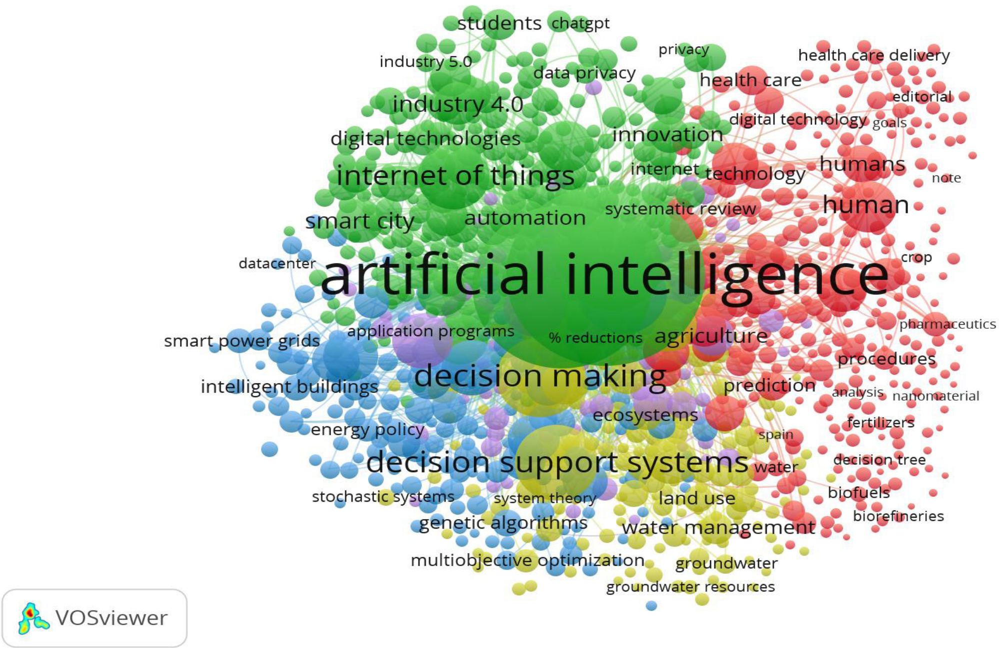
In contrast, in the analysis of the keywords used by the indexer, sustainable development took center stage, which was somewhat predictable, given the search strategy (figure 10). Although this analysis revealed five clusters, it did not reveal any new themes compared to the previous unit of analysis.

**Figure 8**.
*Areas of knowledge for the field "AI and environmental impact"*




**Source:** own elaboration based on data provided by Scopus

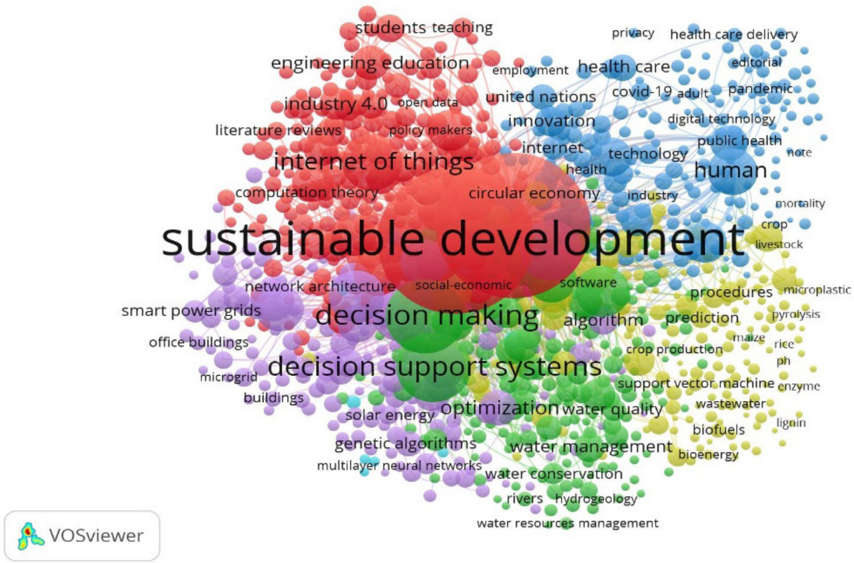
**Figure 9**.
*Analysis of all keywords for the field "AI and sustainable development"*




**Source:** own elaboration based on data provided by Scopus

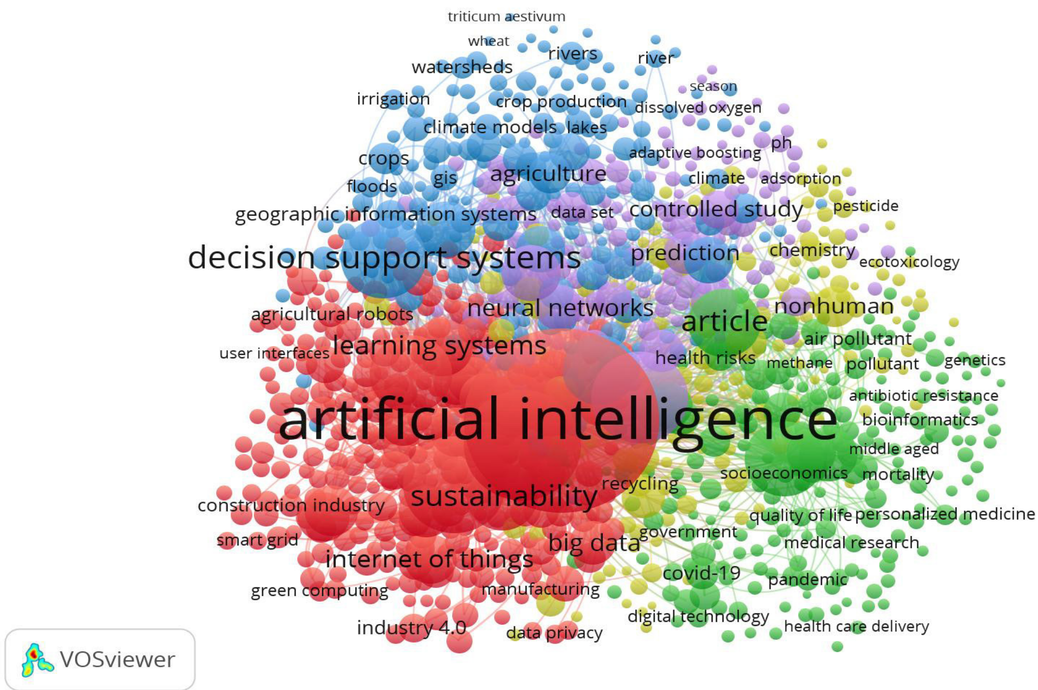
When these analyses were replicated in the Excel database created for the search "AI and environmental impact," the results were very similar, showing that, within the larger field, studies on the relationship between AI and environmental impact constitute a recurring theme and their associated issues occupy a significant niche of concepts and categories (figures 11 and 12). The main difference was that in both units analyzed, AI occupied the center of the main cluster, while the term "environmental impact" was not clearly represented; rather, the same pattern was observed, consisting of processes, technologies, key actors, policies, fields of study, and social and environmental issues.

**Figure 10**.
*Keyword analysis according to the indexer for the field "AI and sustainable development"*




**Source:** own elaboration based on data provided by Scopus

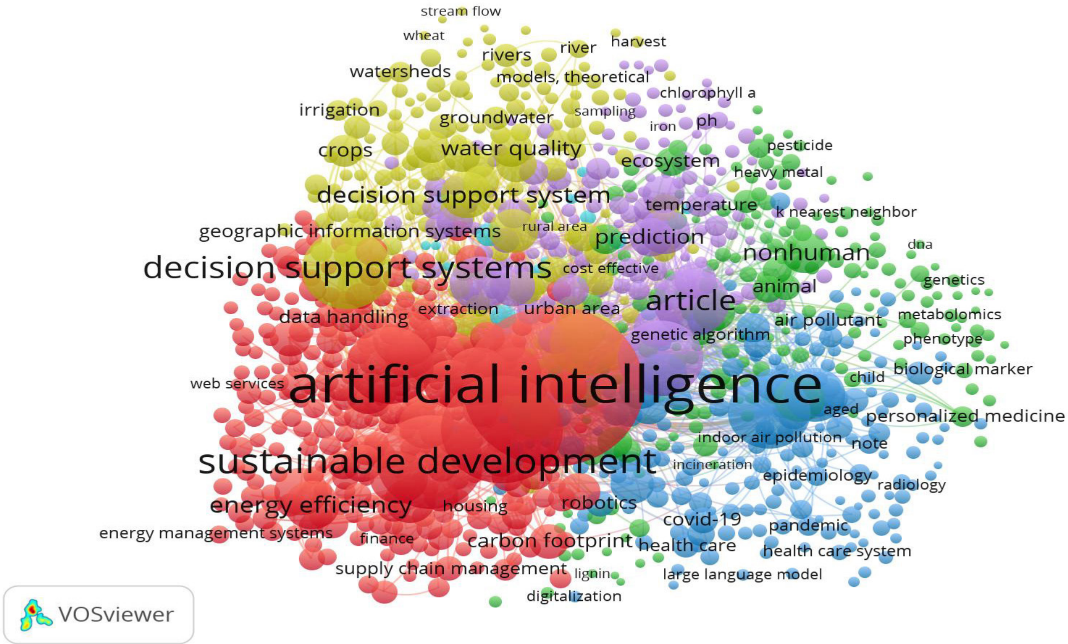
**Figure 11**.
*Analysis of all keywords for the field "AI and environmental impact"*




**Source:** own elaboration based on data provided by Scopus

Mapping these terms is expected to facilitate the identification of relevant studies, issues, and relationships, as well as serve to delve deeper into the environmental impact generated by the use of these systems. Therefore, the integration of both studies suggests the need to incorporate this approach rather than occupying new terms or smaller fields.

**Figure 12**.
*Keyword analysis according to the indexer for the field "AI and environmental impact"*




**Source:** own elaboration based on data provided by Scopus

## CONCLUSIONS

As a fundamental conclusion, this article has provided a holistic view of AI's evolution and impact throughout recent history, highlighting both its achievements and its challenges. As seen, AI has evolved from a system of primarily theoretical ideas to an applied science with profound implications in diverse fields.

From Ada Lovelace's early algorithms to today's complex machine learning systems, AI has shown remarkable progress in solving problems and simulating human cognitive processes. Furthermore, and as a main consequence of the spread of AI, the environmental challenges it poses have emerged. It is noteworthy that as AI models become larger and more complex, resource consumption and the generation of carbon emissions increase considerably.

Therefore, research on sustainable AI is emerging as a crucial line of research, focusing on AI applications to combat climate change and on the sustainability of the systems' development and operation. Developers and public policies must focus on minimizing the negative impacts of AI, promoting sustainable practices, and considering the full lifecycle of their systems. Meanwhile, the study is expected to contribute significantly to this goal by offering a comparison between the larger field of sustainable development studies and the smaller one concerning environmental impact, where the duality addressed in this research arises.

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The authors declare that there is no conflict of interest.

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