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Artificial Intelligence and Sustainability: A Bibliometric Analysis and Future Research Directions

Natalia Bracarense[1,*], Ransome Epie Bawack[2], Samuel Fosso Wamba[3], Kevin Daniel André Carillo[4]

[1,*]North Central College, USA, nbracarense@noctrl.edu
[2]ICN Business School, CEREFIGE – University of Lorraine, France, ransome.bawack@icn-artem.com
[3]TBS Business School, France, s.fosso-wamba@tbs-education.fr
[4]TBS Business School, France, k.carillo@tbs-education.fr

Abstract

Background: *The proliferation of research on artificial intelligence (AI) and sustainability has increased the lack of perspective on how future research can contribute to the big picture of sustainable development. This paper aims to synthesize and analyze academic research on AI and sustainability to reveal the main trends and propose a robust agenda to tackle future research on the theme. It answers four main research questions: (i) what is the current state of research on AI and sustainability? (ii) which are the most productive countries and journal outlets in this research area? (iii) how has the research in the area evolved? (iv) what are the research lacunae and, thus, the opportunity for future exploration?*

Method: *To answer the research questions, we performed a bibliometric analysis of 3887 documents extracted from the Web of Science core collection of databases.*

Results: *The primary finding of this research is that the motor themes pushing the research in AI for sustainability are related to energy efficiency, smart grid, and renewable energy. Yet the field suffers from eight main shortcomings: overreliance on ML; lack of study on human responses to climate crisis mitigation strategies; lack of performance measurement; lack of research about how cybersecurity risks may impact sustainable development efforts; lack of research about the adverse impact of AI development on the environment; lack of research on the impact of economics on AI for sustainability efforts; lack of discussion about policymaking and policy recommendation; and excessive focus on renewable energy.*

Conclusion: *This paper contributes to scholarly conversations on the direction research on AI for sustainability should take by highlighting its shortcomings and proposing a robust research agenda to address them.*

Keywords: Artificial Intelligence, Sustainability, Bibliometric Analysis, Energy, Smart Grid.

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Introduction

Artificial intelligence (AI) is unquestionably transforming society in general, including human interactions (Acemoglu & Restrepo, 2018; Wang W. & Siau, 2019), urban organization (Guo et al., 2018), policymaking (Sun & Medaglia, 2019), business practices and industries (Hilb, 2020), to name a few. The extent of AI's reach, nonetheless, has the potential of addressing major societal problems, including sustainability. Degradation of the natural environment and the climate crisis are exceedingly complex phenomena requiring the most advanced and innovative solutions. As discussed in the present paper, the application of AI for environmental sustainability already supports organizational processes, forest and species management, and individual practices to reduce the impact on natural resources and energy use for human activities. According to Nishant et al. (2020), however, the actual value of AI goes beyond its support for the social reduction of energy, water, and land use; it instead may, at a higher level, facilitate and foster environmental governance. Environmental governance is defined as the formal and informal rules governing human behavior in decision-making processes. The decisions themselves dictate how society determines and acts on goals and priorities for managing natural resources (Linkov et al., 2018).

Although environmental sustainability is a long-term complex issue that involves many factors at different levels of social organization, the solutions provided are frequently short-term and simplistic, relying on game-theory models, which treat such issues as rational choice trade-offs between competing desired outcomes (Shogren & Taylor, 2008; Van den Bergh, 2011). AI, alternatively, is capable of offering and executing holistic solutions to environmental degradation and the climate crisis, free from reductionism and the self-interest of individuals and small collectives (United Nations, 2019). Even though humans create the originating architecture of AI applications, as the machine consumes and learns from vast amounts of data, the resulting decisions (informed by objective data and free of cognition biases and emotions) will differ from those taken by humans. AI, thus, can bridge the divide between scientific findings and environmental policymaking by overcoming information asymmetry and human emotion's biases (Cullen-Knox et al., 2017).

More than 12000 researchers have explored the theme of AI and environmental sustainability. Knowing what has been done in the field to design a robust research agenda to tackle future research on the topic is an important research objective. The present paper contributes to the debate on AI and sustainability through a bibliometric analysis to achieve this goal. More specifically, the current study aims to address the following research questions:

- What is the current state of the art of research on AI and sustainability?
- Which are the most productive countries and journal outlets in AI for sustainability?
- How has the research on AI for sustainability evolved?
- What are the research lacunae and, thus, opportunities for future research on AI and sustainability?

The paper draws on a bibliometric analysis of data on AI for sustainability extracted from the Web of Science (WoS) database to address these research questions. It evaluates how it corroborates and contrasts with some findings from recent literature reviews on the theme (e.g. Nishant et al., 2020). The following section presents the research methodology. After that, we present the results and discussion. The next section discusses the findings and proposes a research agenda, followed by a concluding paragraph.

Materials and Methods

This paper is based on data downloaded from the Web of Science (WoS) database to evaluate the current state of research regarding the application of AI to sustainability and indicate possible topics for future research. This choice was made due to WoS's highly reliable sub-databases of publications selected based on highly objective criteria (Merigó & Yang, 2017). However, the main limitations of this approach are that WoS does not list books and most conference proceedings (Wang C. et al., 2020). It also does not distinguish 'journals' or 'publications' quality. Thus, interested parties need to rank the bibliographies in their areas of interest based on their individual/institutional rankings systems before choosing which papers may be of greater interest.

A Google scholar search for literature reviews on AI for sustainability was conducted to decide which terms to use for the search strings in WoS's search tool. That search delivered the paper by Nishant et al. (2020), which served as a foundation for creating two strings input in the search tool of the WoS database to capture existent research on the topic of AI for sustainability. The first search string contained the terms "artificial intelligence" OR "machine learning" OR "deep learning" OR "natural language processing" OR "robotics" OR "computer vision", and the second string was composed of the words "sustainability" OR "renewable energy" OR "energy conservation" OR "climate change" OR "environmental sustainability". The search included title, keywords, and abstract and returned 3887 results on May 14, 2021, including articles (2515), proceedings papers (838), reviews (334), and editorial material (46).

Results were analyzed using bibliometric techniques—a statistical approach used to examine bibliographic data (Wang C. et al., 2020). The present paper relies on the bibliometrix® package for the R software (Aria & Cuccurullo, 2017). Its biblioshiny interface is a software tool that reports co-authorship, keyword co-occurrences, citation, co-citation, and bibliographic coupling maps based on bibliographic data. This quantitative approach has proven effective in evaluating the dynamics of a given research domain and presenting the results in a graphically explicit manner (Aria & Cuccurullo, 2017). This method has been used recently in several renowned journals to consider the state of research in several domains like green supply chain management (SCM) (Fahimnia et al., 2015), big data (Mishra et al., 2018), humanitarian supply chain (Fosso Wamba, 2020) and corporate social responsibility (Feng et al., 2017).

Bibliometric Analysis and Results

Basic Bibliometric Overview

This section discusses the results of the bibliometric analysis based on WoS and conducted using bibliometrix®. The bibliometric analysis shows that, between 1991 and 2021, the interplay of AI and sustainability resulted in 3887 published academic manuscripts, 64.7% of which comprise scholarly articles. Each document was cited 12.5 times on average. The field presents an annual publication growth rate of 23.26% (Figure 1). However, the rapid growth picked up in 2014 and is expected to continue as 430 new documents have already been published as of May of 2021. Three-forth of the 3887 publications date from 2017 onward. This research area counts 12600 authors, with publications predominantly consisting of multiple-authored manuscripts (12358) rather than single-authored ones (242), averaging 3.24 authors per document and yielding a collaboration index of 3.41.

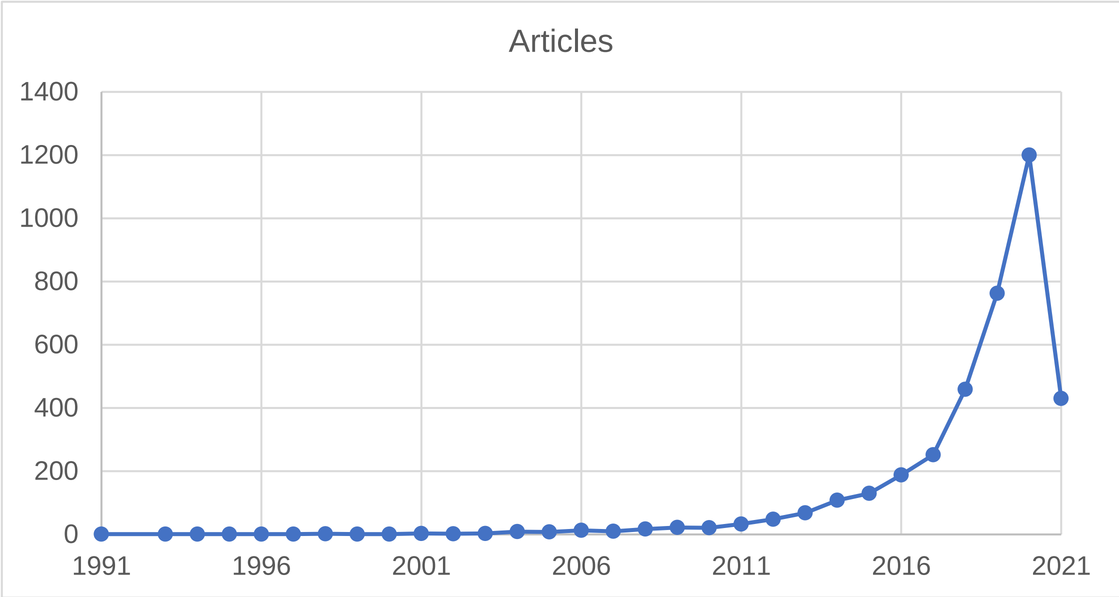

Figure 1 - Annual Research Production on AI and Sustainability from 1991 to May 2021

Collaborative Relationships Existing within the Authors, Journals, Institutions, and Countries

Regarding collaboration, the bibliometric analysis allows for assessment at different levels: countries, institutions, research teams, and individuals. Institutionally, it is possible to note that there are four main clusters in AI for sustainability, three of which orbit around one of the four most prominent contributing universities in the research area (Figure 2). The first cluster is organized around the Vietnamese institution Ton Duc Thang University, responsible for 109 publications. University of Chinese Academy of Science leads the second cluster with 62 publications. The third cluster is formed by the University of California-Berkeley, with 48 publications. Finally, the fourth cluster is centered on the University of Oxford, with 48 publications. Among the 4204 institutions that have contributed to the field, 112 have published at least 20 articles on AI for sustainability.

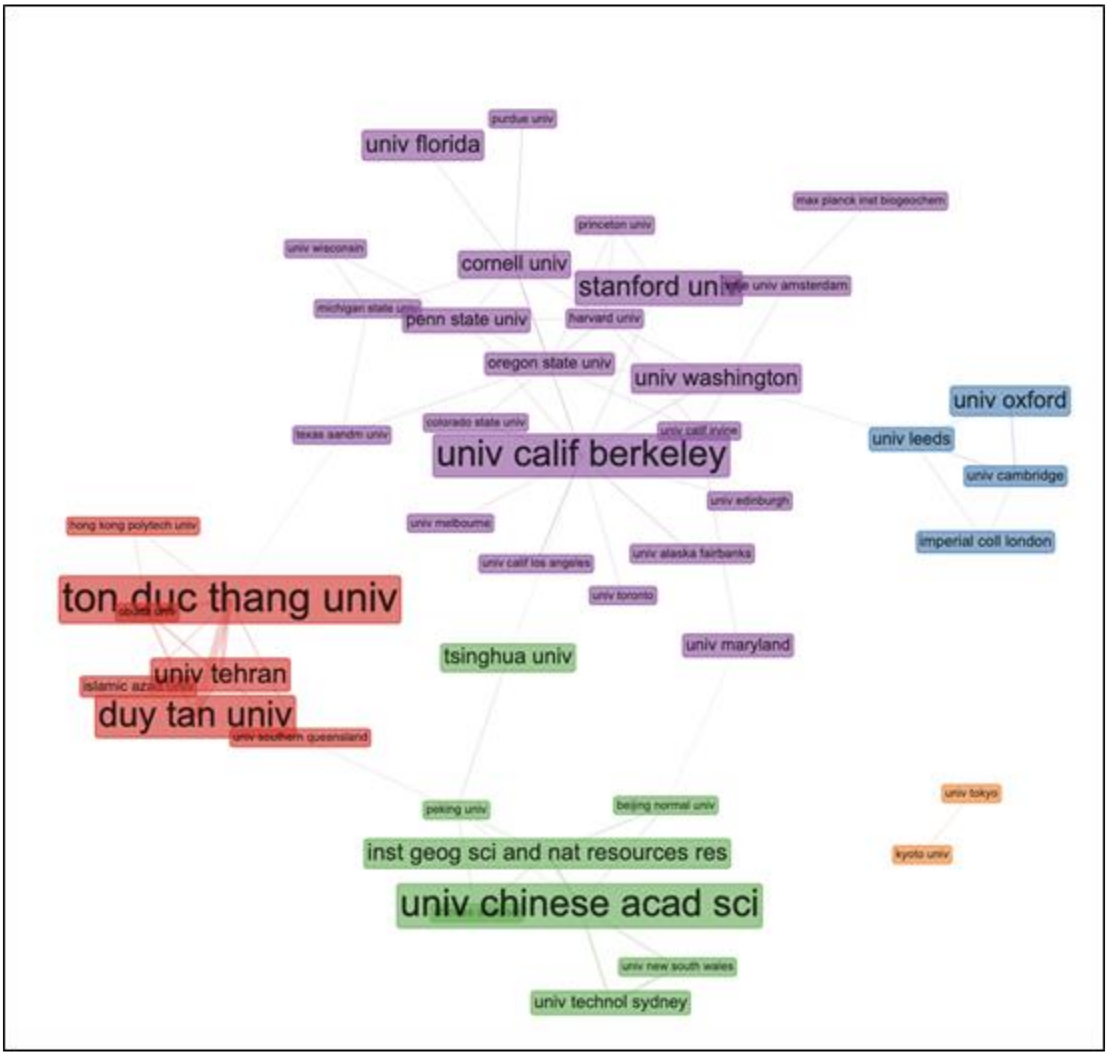

Figure 2 - Institutional Collaboration Network on AI and Sustainability

Research on AI for sustainability is widely spread worldwide, being conducted in 112 countries, among which 60 have contributed with 20 papers or more. The five countries leading this research area are the USA (2940 documents, 10755 citations), China (2428 documents, 5522 citations), India (752 documents, 1761), England (751 documents, 1774 citations), and Germany (686 documents, 2687 citations). It is important to add that although Australia is not among the top 5 producers of documents, it is placed second in terms of citation, with its 600 documents being referenced 7206 times. Production from China has been increasing most speedily in the past decade, coherent with the countries' focus on the production and exportation of green energy started in 2013. To illustrate this point, it suffices to notice that in 2010, the number of scientific documents produced by the USA equaled 128, six-fold that of China (with 21 documents), respectively first and second-biggest research-based country for AI and suitability. Still, in 2017, US-based researchers were responsible for 681 documents while their Chinese counterparts had 258 publications in the field, which, when compared to recent publications, shows the fast pace through which the field is advancing in China. Currently, the field contains three main country-based research clusters one revolving around the United States, China, and Australia, a second one centered on the United Kingdom, which counts mostly with other European countries, and a third cluster slightly concentrated around India, formed mostly by countries in the Middle East and North Africa (MENA) region (Figure 3).

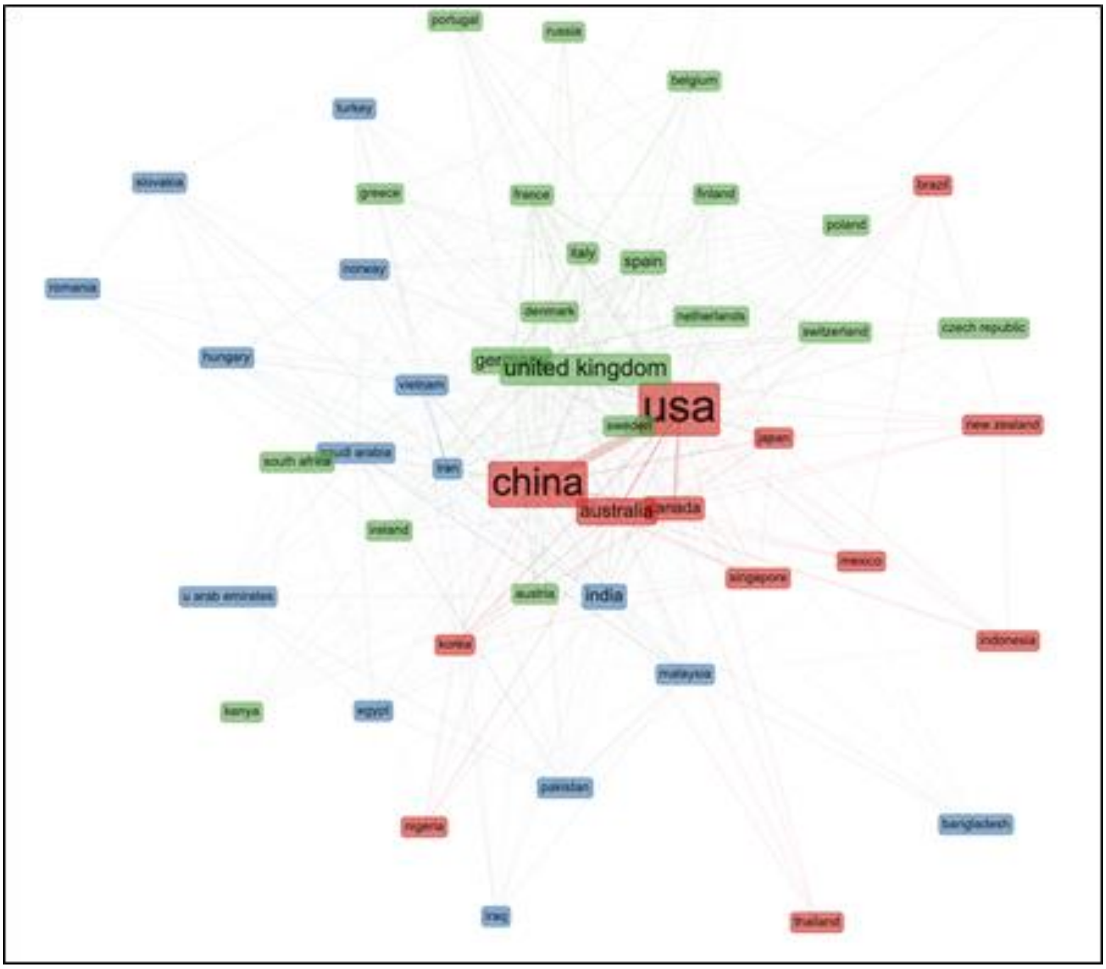

Figure 3 - Country-wide Network Collaboration Clusters

Publication, Journal, Reference and Author Citation and Co-Citation Analysis

From the 3887 publications about the intersection between AI and sustainability, 779 have been in environmental sciences, 637 in electrical and electronic engineering, 550 in energy fuels, 433 in green sustainable science technology, 227 in remote sensing, 249 in environmental studies, 150 in meteorology and atmospheric sciences, and 144 in ecology. This finding corroborates Nishant et al.'s (2020) assessment that "biodiversity, water, energy, and transportation are rich areas of investigation for AI" (p.2). All 20 most influential sources – responsible for more than one-fourth of the total publications in AI and sustainability – are composed of journals in energy production and distribution, energy conservation, sustainability, and environmental preservation. However, as developed in more detail throughout the paper, the fastest-growing subfield is electrical and electronic engineering, whose growth rate was greater than 200% in the past year. Meanwhile, in the same period, publications in ecology increased by around 25%.

Table 1 lists all these sources and their contribution to the field. While 1815 sources have published on this topic, only 39 journals have ten or more articles on AI for sustainability. The concentration of publications in just a few areas of research and journals could indicate that the discussions in the field have not yet reached the wider academic community and are still restricted to very specific circles. Most research in this area focuses on technical issues, not yet consistently encompassing areas related to economics, political science, and sociology. This point will become more evident in the next section, introducing thematic trends.

Table 1 - Most Relevant Sources in AI and Sustainability	
Sources	**Articles**
Sustainability	166
Remote Sensing	99
IEEE Access	91
Energies	90
Journal of Cleaner Production	59
Science of the Total Environment	49
Applied Energy	46
Renewable & Sustainable Energy Reviews	46
Applied Sciences-Basel	42
Environmental Research Letters	38
Sensors	38
Water	31

Finally, among the 10 most relevant sources, nine have presented an exponential increase in the number of publications on AI and sustainability starting in 2014, indicating the prospect of an increasingly higher growth rate in the number of documents in this area in the next few years (Table 2). The sole exception is *Renewable and Sustainability Energy Reviews*, which is an early starter in terms of publications on AI for sustainability; its first contribution appeared in 2000, totaling four contributions in 2013, when Science of the Total Environment, chronologically the second journal to focus on the area of study, published its first paper on AI for sustainability. Table 2 shows that the most productive journals in AI for sustainability currently focus on two main topics: energy production and conservation and environmental management. As discussed in more detail in the subsection, this point is essential because it shows that the field has undergone a thematic shift in the mid-2010s. Before this date, most publications about AI for sustainability dealt with forest and species conservation and monitoring. But from 2013 onward, the emphasis has been placed on the production of clean and sustainable energy.

Table 2 - Source Dynamics							
Year	**Sustain-ability**	**Energies**	**Renewable & Sustainability Energy Reviews**	**Remote Sensing**	**Science of the Total Environment**	**Applied Energy**	**Journal of Cleaner Production**
2013	0	0	1	0	1	0	0
2014	0	0	2	1	0	0	1
2015	0	0	4	0	0	0	0
2016	2	2	4	1	1	1	0
2017	5	3	8	4	3	3	2
2018	26	7	9	8	7	7	9
2019	28	20	7	20	11	12	7
2020	81	49	3	49	18	14	27
2021	24	9	5	26	8	9	13

Another evidence of the importance of Renewable and Sustainability Energy Reviews to research on AI for sustainability is that the journal is the only source that appears in the top 5 journals in both the list of most relevant sources, with 46 publications, and the list of the most cited source due to its publications yielding a total of 2873 citations.

The journals that most favor research in AI for sustainability are not necessarily the most impactful sources in the field. There is more diversity in the most impactful source list, including journals on ecology, such as Ecography, whose seven papers on AI for sustainability were cited 5101 times and Ecological Modelling, with 17 papers and 1183 citations. The journals in natural sciences like Nature (5 publications and 1190 citations) and IEEE Journal of Oceanic

Geography (2 publications and 897 citations) were also among the most influential sources. Renewable Energy comes next with 16 articles and 934 citations. Finally, the ISPRS Journal of Photogrammetric and Remote Sensing, whose focus is on technological development, also had two publications on AI for sustainability cited 999 times. However, it is evident between the two lists (most relevant and most cited sources) that AI for sustainability is mainly limited to discussing technical issues. Such a characteristic is also evident in most cited documents (Table 3).

Table 3 - Most Globally Cited Documents in Research on AI and Sustainability

Article Title	Reference	# of Citations	Journal
Novel methods improve prediction of species' distributions from occurrence data	(Elith et al., 2006)	4903	Ecography
Recent decline in the global land evapotranspiration trend due to limited moisture supply	(Jung et al., 2010)	1110	Nature
An assessment of the effectiveness of a random forest classifier for land-cover classification	(Rodriguez-Galiano et al., 2012)	966	ISPRS—Journal of Photogrammetry and Remote Sensing
Stable adaptive teleoperation	(Niemeyer & Slotine, 1991)	882	IEEE Journal of Oceanic Engineering
Evaluating predictive models of species' distributions: criteria for selecting optimal models	(Anderson et al., 2003)	730	Ecological Modelling
Evaluation of consensus methods in predictive species distribution modelling	(Marmion et al., 2009)	678	Diversity & Distribution
Artificial neural networks in renewable energy systems applications: a review	(Kalogirou, 2000)	622	Renewable and Sustainable Energy Reviews
Solar forecasting methods for renewable energy integration	(Inman et al., 2013)	482	Progress in Energy and Combustion Science
Machine learning methods for solar radiation forecasting: a review	(Voyant et al., 2017)	391	Renewable Energy
State of the art in building modelling and energy performance: a review	(Foucquier et al., 2013)	319	Renewable and Sustainable Energy Reviews

Only one of the 10 most cited works on AI for sustainability was published before the 2000s. On the top of the list with 4903 citations is the work by Elith et al. (2006) in ecology. The influential piece runs 16 different models, some applying machine learning, to predict species distribution in six world regions based on electronic information in museums' and herbarias' records. According to the authors, such prediction models are prone to application in ecology, species evolution, and conservation science. While the second most cited paper comes from the same field, the focus is different. It uses data analysis and machine learning to estimate the intensity of evapotranspiration over 26 years and create an algorithm to evaluate its changes over time (Jung et al., 2010). Next is the paper by Rodriguez-Galiano et al. (2012), which assesses 14 different land categories in Spain to assess the level of accuracy of a random forest algorithm as a land-cover classifier. The authors found that the algorithm presented a 92% level of accuracy. Fourth on the list is the paper by Niemeyer and Slotine (1991), who analyze how transmission time delays affect the application of advanced robots in operations such as microsurgeries and safety. The fifth paper studies the possibility of creating an optimal modal for identifying species' distribution without resorting to a test data set (Anderson et al., 2003). According to the authors, their model resulted in a much more reasonable estimation of species' potential distribution. The following paper also deals with species distribution, testing several commonly used AI models (i.e. random forest and decision trees) and consensus methods to evaluate which technique renders the most accurate model (Marmion et al., 2009). It concludes that "consensus methods based on average function algorithms may significantly increase the accuracy of species distribution forecasts, and thus they show considerable promise for different conservation biological and biogeographical applications" (p.59).

While all these six papers belong to areas of ecology, biology and biodiversity, the next set of papers relates to renewable energy. As evident by the title, Kalogirou (2000) discusses the application of artificial neural networks to renewable energy by analyzing the existing literature. Inman et al. (2013) also demonstrate the current treatment of AI models for solar forecasting to suggest how to improve the market for solar energy. Building a model to better forecast and improve solar energy production and usage is also the main objective of Voyant et al. (2017). Finally, Foucquier et al. (2013) review existing literature on the use of machine learning to model and make energy performance predictions. The paper compares physics models with machine learning models and suggests the development of hybrid models to tackle the problem of energy performance. In sum, the most globally cited papers in the field of AI for sustainability focus on technical issues such as the creation and assessment of algorithms for the fields of ecology and energy conservation.

The areas of studies comprised of the most cited references are also diverse but technical (Table 4). The global analysis of these numbers, together with the source dynamics, due to the recent increased number of publications since 2009, indicates an expected growing share of the articles on energy production and distribution and energy conservation when it comes to the intersection between AI and sustainability. A tendency boosted by the larger participation of Chinese researchers in the field, most likely due to the country's economic plans to boost green energy both domestically and internationally in 2013 (Breiman et al., 2017).

Table 4 - Most Cited References by Researchers in AI and Sustainability

Article	Reference	# of Citations	Type of Publication
Random forests	(Breiman, 2001)	479	Article
Classification and regression by randomForest	(Liaw & Wiener, 2002)	165	Article
Deep learning	(LeCun et al., 2015)	157	Review Article
Long short-term memory	(Schmidhuber & Hochreiter, 1997)	130	Article
Scikit-learn: Machine Learning in Python	(Pedregosa et al., 2011)	126	Article
Greedy function approximation: a gradient boosting machine	(Friedman, 2001)	96	Article
Support-vector network	(Cortes & Vapnik, 1995)	93	Article
Random forest for classification in ecology	(Cutler et al., 2007)	88	Article
A working guide to boosted regression trees	(Elith et al., 2008)	85	Article
Classification and regression trees	(Breiman et al., 2017)	66	Book

Interestingly, the fields of study of the most cited references are composed of contributions of precursors of the field, counting primarily on papers published before research in AI for sustainability started gaining more attention in 2009. Their areas of concentration are machine learning, ecology, and forest management. Leo Breiman is one of the most important forerunners in the field: his book on forest classification (Breiman, 2001), whose statistical model became the foundation of a set of Radomforests software, appears as the leading research influencing the field of AI and sustainability. Additionally, his more recent article is the most cited reference amongst the studies in question (Breiman et al., 2017). The crossing between AI and sustainability, thus, seems to have a strong initial footing in forest management and then branched out to biology, ecology, and species distribution models, to then, more recently, reach research in energy production and distribution, energy conservation, environmental preservation, and sustainability.

Table 5 analyzes the most cited authors by researchers in AI for sustainability. All the authors on the list below have collaborated in producing the paper "Novel methods improve prediction of species' distribution from occurrence data", published in Ecography and cited 4903 times by researchers in AI and sustainability.

Table 5 - Most Locally Cited Authors by Researchers in AI and Sustainability from 1991 to 2021

Reference	# of Citations	# of Publications	Research Area
Robert P. Anderson	5680	3	Biology
Townsend A. Peterson	5633	2	Biodiversity
Falk Huettmann	5043	14	Biology
Li Jin	5001	17	Mechanical Engineering
Lucia G. Lohmann	4963	2	Biogeography
Robert J. Hijmans	4921	2	Environmental Science
Stephen E. Williams	4911	2	Biology
Miroslav Dudik	4903	1	Machine Learning
Jane Elith	4903	1	Ecology
Simon Ferrier	4903	1	Biodiversity

Publications from 2017 to 2021 raise the question of a possible evolution of the research in AI for sustainability. The research areas of the main contributors pertinent to AI for sustainability moved away from biology towards renewable energy, machine learning (ML) and smart manufacturing (Table 6). All except the first author in this list collaborated on the paper "Machine learning methods for solar radiation forecasting: a review", published at Renewable Energy. The article presents a model to forecast the output power of solar systems to optimize the operation of power grids. According to Nishant et al. (2020), most recently, AI for sustainability research strongly focuses on ML models and algorithms to show how machines can analyze and learn from data. ML learning techniques include reinforcement, transduction, multitasking, supervised, unsupervised, and semi-supervised learning. While technical research predominates in the field, an evolution is taking place away from natural science research toward engineering-oriented research. The thematic analysis presented in the next section illustrates this evolution in more detail.

Table 6 - Most Locally Cited Authors by Researchers in AI and Sustainability from 2017 to 2021

Authors	# of Citations	# of Publications	Research Area
Yingfeng Zhang	557	34	Sustainable production and smart manufacturing
Christophe Paoli	413	4	Renewable energy
Alexis Fouilloy	405	2	Solar energy and data science
Fabrice Motte	405	2	Solar energy
Marie-Laure Nivet	405	2	Neural networks
Gilles Notton	405	2	Renewable energy and artificial neural networks
Cyril Voyant	405	2	Biophysics and Energy

Thematic Trends on AI and sustainability

Authors have selected around 11500 keywords, among which the most used are machine learning, artificial intelligence, deep learning, climate change, and sustainability. Table 7 displays all keywords that were used 70 times or more. It is possible to note that the most used keywords revolve around four main themes related to artificial intelligence, energy conservation, prediction models, and forest management. Additionally, researchers in AI for sustainability have also applied machine learning (ML) models to environmental, economic, and, to a lesser degree, social inquiry, particularly regarding climate change and smart cities, which are fertile areas for future inquiries (Nishant et al., 2020).

Table 7 - Most Frequently used Keywords

Keywords	# of Occurrences
Machine Learning	925
Artificial Intelligence	335
Deep Learning	302
Climate Change	244
Sustainability	237
Renewable Energy	189
Artificial Neural Networks	134
Forecasting	109
Random Forest	102
Big Data	90
Remote Sensing	87
Smart Grid	73

The h-index is applied to analyze the relationship between the most impactful authors and themes used in the field. This index is an author-level metric that measures both the productivity and citation impact of the publications of a scientist or scholar. We can see that all authors in Table 8 below used the term machine learning, and about half of the scholars in the list deal with the topic of renewable energy. More than 80% of the papers were published after the 2010s, reinforcing the points that machine learning has become the primary method used in the field and that interest has been directed towards renewable energy. Scholars whose emphasis is not on the latter topic still focus on themes concerning climate change, classification, and natural disasters; that is, topics more closely related to ecology – the original concentration of scholars in the field.

Table 8 - Main Themes Listed by Most Influential Authors

Author	h_index	# of Citations	# of Publications	Year 1 of publication	Themes
Wang, Y.	11	552	31	2013	Machine learning, climate change, deep learning, renewable energy
Zhang, Z.	10	171	22	2008	Machine learning, remote sensing, deep learning, forecasting, classification
Liu, Y.	9	335	32	2015	Machine learning, prediction, random forest, renewable energy, artificial intelligence
Zhou, Y.	9	340	20	2016	Machine learning, deep learning, renewable energy, optimization
Yang, Y.	9	306	18	2016	Machine learning, climate change

Table 8 - Main Themes Listed by Most Influential Authors

Dieu Tien Bui, D. T. B.	9	204	9	2018	Modelling, machine learning, artificial intelligence, climate change, natural disaster
Zhang, Y.	8	682	38	2013	Machine learning, deep learning, artificial intelligence, renewable energy, smart grid
Chen, Y.	8	261	21	2016	Machine learning, prediction, big data, renewable energy, artificial neural networks
Liu, X.	8	185	17	2012	Machine learning, remote sensing, random forest, climate change, sustainability, deep learning
Deo, R.C.	8	291	13	2018	Prediction, modelling, machine learning, renewable energy, sustainability
Li, X.	7	248	29	2013	Machine learning, prediction, random forest, energy, climate change, artificial intelligence
Zhang, J.	7	286	29	2015	Deep learning, machine learning, random forest, big data, renewable energy, sustainability
Wang, C.	7	239	20	2014	Machine learning, climate change, renewable energy, forecast, smart grid, optimization
Zhang, X.	6	261	25	2013	Machine learning, renewable energy, big data, remote sensing, prediction, sustainability
Wang, J.	6	284	19	2013	Deep learning, machine learning, climate change, remote sensing, artificial neural networks
Wang, L.	6	133	15	2016	Machine learning, climate change, remote sensing, big data, deep learning, sustainability
Huettmann, F.	6	5043	14	2006	Machine learning, random forest, climate change, data mining
Wang, B.	6	148	14	2018	Machine learning, climate change, random forest, remote sensing
Chen, X.	6	140	13	2003	Machine learning, deep learning, smart grid, renewable energy, climate change
Yang, X.	6	133	13	2017	Internet of things, machine learning, climate change, sustainability, remote sensing

Two breaking points were chosen for the thematic evolution analysis (Figure 4): 2007 and 2017. The first indicates when publications in the field started becoming more frequent. The second represents the beginning of a faster acceleration in the number of publications in AI for sustainability. The thematic evolution figure below corroborates the argument that since the mid-2000s, most of the research combining AI and sustainability moved away from ecology and environmental science to consider topics related to machine learning, energy efficiency, and renewable energy. However, the research has been heavily concentrated on machine learning, deep learning, artificial intelligence, and forecasting in the past four years.

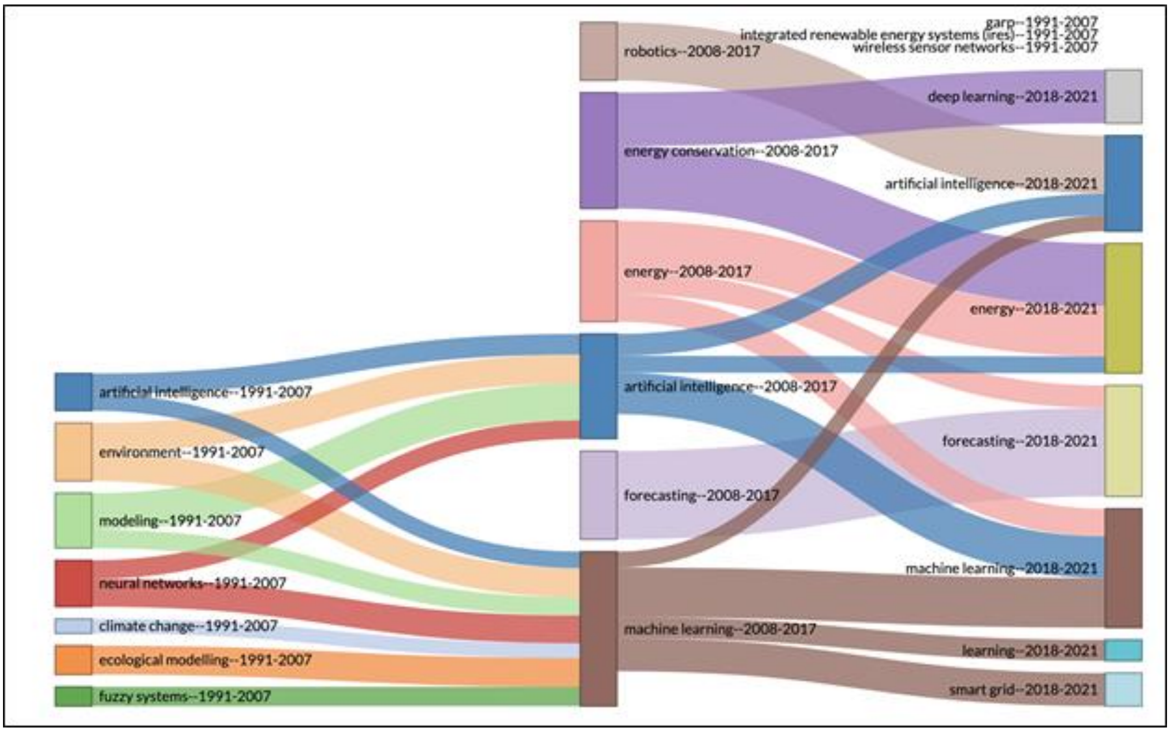

Figure 4 - Thematic Evolution in AI and Sustainability

Table 9 and Figure 5 present the main themes in AI for sustainability research based on author-provided keywords. The thematic clusters make it clear that the main focus of the intersectional research between AI and sustainability relies on the emergence of machine learning as a tool to support prediction models, energy distribution and production, renewable energies, smart cities, and forest management. Renewable energy, AI, and machine learning are the motor themes in AI and sustainability research. Meanwhile, the emerging themes are deep learning, AI neural networks, and machine and deep learning.

Table 8 - Cluster of Research Themes and Keywords

Clusters #	Theme	Keywords and Themes
Cluster # 1 (32 items)	Machine learning and Forest management	Machine learning, climate change, random forests, deep learning, remote sensing
Cluster #2 (13 items)	Artificial Intelligence and Sustainability	Artificial intelligence, sustainable development, smart grids, smart cities
Cluster #3 (11 items)	Machine learning and Renewable energy	Renewable energy, wind and solar energy, energy consumption, time series, energy conservation
Cluster #4 (9 items)	Artificial intelligence and Energy efficiency	Energy management, artificial intelligence, energy conservation, smart energy storage
Cluster #5 (6 items)	Smart grid	Smart grid, internet of things, networks

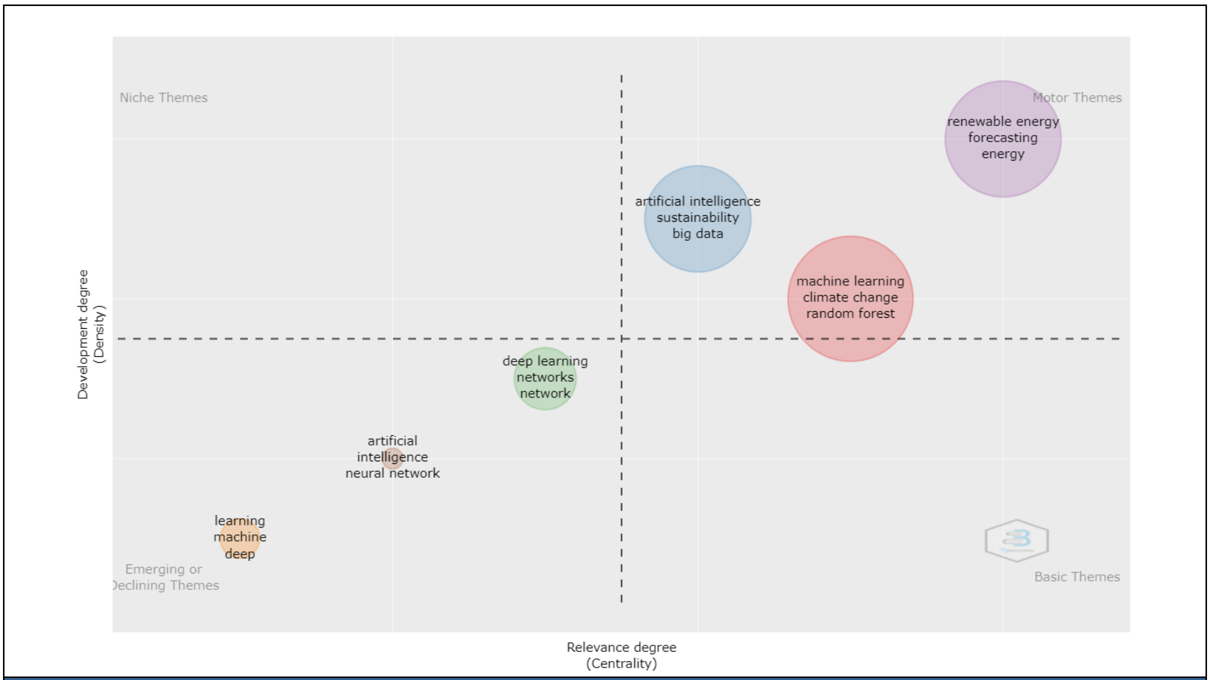

Figure 5 - Key Themes of AI and Sustainability Research

Additionally, the thematic network (Figure 6) supports these findings as well as the assertion that most of the research in AI for sustainability consists of technical fields related primarily to modelling methods (i.e. machine learning, artificial neural networks, remote sensing, data mining) and energy conservation (energy efficiency, renewable energy, solar energy, smart grid). However, implementing these findings into actual practices needs to pass through society, political decisions, and the economy. These fields involve the public perception of climate change and the application of AI to support sustainable development. Consequently, there is a demand for further research that engages with a multidimensional analysis of the problem, including broader social, political, and economic factors. In other words, the research area would gain from additional studies on environmental governance.

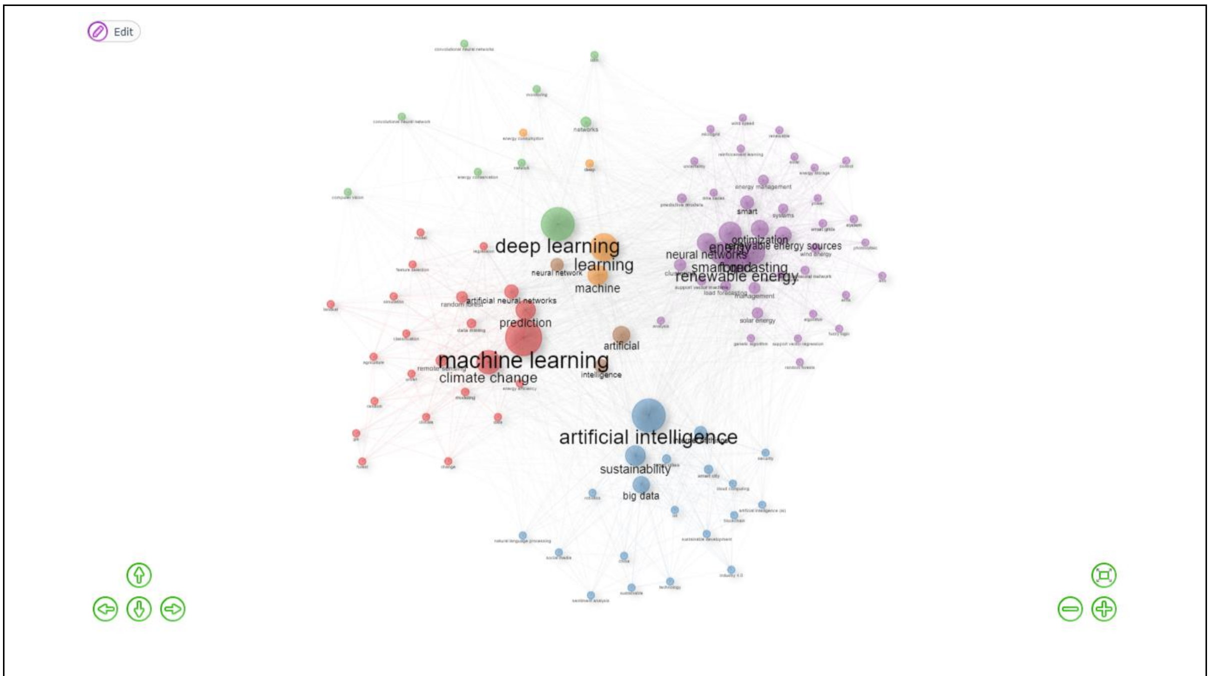

Figure 6 - Thematic Network on AI and Sustainability Research

Discussion and Research Agenda

The objective of the present paper is to discuss four main points proposed through our research questions. With regards to the first point (i.e., the state of the art of AI for sustainability), the bibliometric study puts in evidence the rapid rate of growth of research in the field (23.26% per year) since 1991, but with increased acceleration, reaching an average annual growth rate of 70% since 2017; a likely indicator of the increasing importance that the field will gain shortly. The observation of such progression is made clear due to the extended temporal scope of the bibliometric analysis. Additionally, the long term perspective of the present study makes it clear that although most of the publications are still in technical fields, a shift from natural sciences such as ecology, biology and forest preservation towards new modelling methods (machine learning, random forest, forecasting) and engineering, pertaining primarily to energy production and conservation and smart grid took place since 2017. However, a new tendency towards more socially-oriented fields such as management is still incipient.

This bibliometric study on AI for sustainability supports the conclusions from the literature review done by Nishant et al. (2020) concerning researchers' overemphasis on technical issues. However, the study shows that this research area has already gone through a few transformations despite being still primarily technical. Namely, it has moved from a focus on ecology and biology toward energy engineering and management fields. It indicates a recent shift towards production-related issues that may naturally lead to discussions about more socially-oriented studies like management, energy consumption, public policy, network security, and economics. In other words, the bibliometric study corroborates the literature review (Nishant et al., 2020). Still, due to its longer temporal scope – the former observes the field's evolution since 1991, while the latter only focuses on publications between 2017 and 2019, which can shed light on this tendency.

Another contribution of the bibliometric studies is the inclusion of a regional analysis of the research in AI for sustainability, which relates to the second discussion question raised at the beginning of the paper. The most productive researchers have been in Chinese institutions in the past three years, while the most-cited authors are housed in the United States. However, collaboration, rather than competition, between scholars of these two countries is made clear by the nation-based cluster analysis. US and China, together with Australia, form the most significant cluster in terms of inter-nations collaboration. Countries in the European Union form a second cluster. A more thorough discussion of the conclusions derived from the composition of these clusters will be developed in the last point, which deals with the field's shortcomings.

Thirdly, the observation of the thematic evolution of the field over time entails that the most explored themes are motivated by energy conservation concerns and rely primarily on ML, a point supported by the production rate of the currently most prominent journals in the field. An inquiry on the thematic evolution showed that most recently, the motor themes pushing the research in AI for sustainability are related to energy efficiency, smart grid, and renewable energy. Nishant et al. (2020) showed concerns regarding such technical bias, calling scholars from economics, sociology, and political science to engage in the debate.

Based on their literature review, the authors suggest that the themes surrounding AI for sustainability suffer from five main shortcomings: overreliance on ML; lack of study on human responses to climate crisis mitigation strategies, lack of performance measurement; lack of research about how cybersecurity risks may impact sustainable development efforts; and lack of research about the adverse impact of AI development on the environment. The bibliometric study captured these lacunae and identified three additional ones: lack of research on the impact of economics on AI for sustainability efforts; lack of discussion about policymaking and policy recommendation; and excessive focus on renewable energy. These points pertain to the fourth and last research question proposed by the present paper. They are summarized in Table 10 and will be discussed in detail below.

Table 9 - Gaps in the Field of AI for Sustainability and Future Research Agenda

Gaps	Opportunities	Challenges
1. Overreliance on machine learning	New methods such as deep learning, remote sensing, artificial neural networks.	Motivating interaction between machines and experts
2. Human responses to the climate crisis	New data collected	Treating data and choosing new information to be collected
3. Economic impact and reaction	Studies in energy management	Other aspects of how profits and growth may impact the environment
4. Lack of public policy analysis and recommendation	Studies in energy management	Analysis of different policies impact
5. Excessive focus on renewable energy	Open opportunity to collaborate with other fields	Neglect of other aspects of ecological crisis
6. Performance measurements	New studies have focused on environmental performance	Other indexes need to be incorporated Defining and targeting sustainable development
7. Cyber security impact on sustainable development	New studies are already analyzing the issue	Lack of understanding of how cyberattacks may be produced in this area. Need to discuss future regulation
8. Adverse impact of artificial intelligence	Discussions among AI scholars	Complexity of measurement

Regarding the first lacuna and the future of research on AI for sustainability, it is possible to see that while ML is prevalent in the most recent research, other artificial intelligence techniques, such as artificial neural networks and remote sensing, are gaining space in the field. The development of studies on human response to the climate crisis is missing and presents an interesting point for future analysis. Secondly, the recent focus on energy production and conservation and interest in renewable energy presents both opportunities and challenges. Related to the former, topics of human response could be more easily initiated because of the data collection inherent in these studies. In terms of a shift to socially-oriented fields, the bibliometric analysis suggests that studies could easily evolve into discussions related to economics and policymaking. Investment in infrastructure (such as energy grids) relies heavily on government subsidies and licensing, and the assessment of their feasibility calls for economic considerations. However, an obstacle to such development could be the lack of training for scholars in economics and politics to understand the management and effects of technological change concretely. A quick bibliometric analysis in May 2021 of the overlap of economics and artificial intelligence elucidates a gap in this study area, resulting in only 1542 articles.

On the one hand, the impact of government planning and policy-making on the research on AI for sustainability is already evident by the predominance of Chinese scholars and institutions, whose increased academic production coincides with both the Chinese government's plan to move toward production, implementation, and exportation of green energy since 2013 and with the emergence of renewable-and-sustainable-energy related themes (Kong & Gallagher, 2017). The regional analysis of the research field supports that point as scholars from China, and the United States have collaborated in 139 publications, forming together the biggest international research cluster. Given the tight economic connection between the two countries in the past 20 years, the two biggest world economies have become increasingly dependent on one another productively (Observatory of Economic Complexity, 2021) and monetarily (Schwartz, 2019), so collaboration is expected.

The unfolding of this relationship – as China emerges geopolitically (Dirlik, 2011; Ramo, 2004) and discourses of the Chinese threat become more frequent in the United States (Politi & Fedor, 2020) and its impact on both the production of machinery for energy production and on research in AI for sustainability is a rich field of future inquiry. Unsurprisingly, countries in the European Union form another cluster. Promoting renewable energy is part of their obligation to comply with the Renewable Energy Directive 2009/28/EC, an EU directive and subsequently part of the EU 2020 Energy Strategy. This directive mandates that 20% of the bloc's final energy consumption be produced from renewable energy sources by 2020 (Kong & Gallagher, 2020). In other words, despite the limited political science research in the current field of AI for sustainability, an evolution in that direction is bound to occur as governments in different regions promote the implementation of renewable energy.

However, the focus on renewable energy also imposes challenges. The current environmental crisis cannot be simplified or resolved by implementing a new energetic matrix that reduces the greenhouse effect. Ecological challenges, such as flora and fauna preservation, still need to be addressed. Studies in the management of natural disasters and new energy consumption patterns in agriculture, manufacturing, service sectors, and households need to be further pursued. Table 11 proposed a few discussion questions on the first five gaps proposed.

Table 10 - Discussion Questions for Future Research on Topics 1 through 5

Topics	Discussion questions
Gap 1. Machine learning and experts	What kind of training do data scientists, economists, political scientists, ecologists need to treat collected data ethically?
	What are the data points that should be collected and analyzed?
	What is the role of experts to improve the performance of AI for sustainability?
Gap 2. Natural and man-made disasters	How can AI help reduce uncertainty in decision-making during disaster management?
	How can AI be used with other new technologies such as drones, driverless cars, and nanosatellites to enhance disaster response?
	How can AI analyze social media to detect, monitor, and manage disasters?
	How can AI be used to assess disaster damage and optimize aid delivery?
	How can AI support social resilience during natural disasters?
Gap 3. Economic empowerment in agriculture	What is the economic value of integrating AI solutions into farming processes (e.g., real-time monitoring of livestock and crops)?
	How can farmers use AI to improve waste management and regenerative agriculture practices?
	How can AI systems help improve water management and water usage in farms?
	How can AI systems assist farmers in introducing sustainable and organic practices?
	How can AI systems sustain primary commodities fair trade practices?
Gap 3. Financial inclusion	How can AI promote financial inclusion by using smart devices?
	How can AI help develop AI-based micro-credit services in developing countries, supporting family farmers and traditional communities?
	How can AI help empower vulnerable people in developing countries?

Table 10 - Discussion Questions for Future Research on Topics 1 through 5	
Topics	**Discussion questions**
Gap 3. Initiatives for sustainable economic development	How can AI help monitor and prevent manufacturing waste?
	How should AI systems assist manufacturing and services sector waste management?
	How can AI solutions reduce and optimize consumption at the individual, group, city, state levels?
	How can AI be used to combat food waste?
	How can AI be used to optimize surplus food distribution to needy populations?
	How can AI contribute to reducing hunger?
	Can AI systems help predict food crises based on past and current weather and harvest data?
	How can AI help optimize the labor market and reduce unemployment?
	How can AI be used to identify labor abuse and exploitation?
	How can AI support a circular economy in water distribution and waste management?
	How can AI applications enhance social diversity and inclusion?
Gap 4. Effective management of the public sector	How can AI applications improve the protection of endangered species or exhausted populations?
	What skills are required to use AI productively in public sector management?
	To what extent can AI optimize the management of public finances toward sustainable development?
	How can AI support intergovernmental collaboration toward sustainability goals?
Gap 5. Energy efficiency and sustainability	How can AI optimize energy distribution and pricing to patterns of energy consumption?
	How can AI techniques be used to optimize energy consumption on smart grids?
	How should an AI tool be designed to help cities optimize energy supply and demand?
	How can AI applications contribute to sustainable production?
	What is the contribution of AI to sustainable resource management?
Gap 5. Land, air, and water conservation	How can AI applications contribute to minimizing air pollution?
	How can IoT, analytics, and AI help maintain good air quality in large cities?
	How can AI help anticipate air pollution?
Gap 5. Climate change and adaptation	How can AI help discover unanticipated climate change events?
	Will AI improve the societal indicators for the environment in emerging economies?
	How can AI help develop a response, contingency, and continuation planning before a climate change event?
	How can IoT and AI systems be used to monitor and control global warming more precisely?
	To what extent can companies use IoT and AI systems to evaluate and monitor their carbon imprint precisely?
	How can AI applications contribute to combating climate change?

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Table 12 presents a few questions about the three remaining subjects. Several of these questions are inspired by a bibliometric article on AI for a good society (Fosso Wamba et al., 2021). On the other hand, much development is needed for discussions on performance measurement. Discussions about performance are usually associated with economics. Cost-benefit analysis is mainly based on traditional economic ideas of rational-choice trade-offs to maximize profits and minimize costs. However, a problem as important and complex as sustainability cannot rely on such simplistic models. Performance measurements based solely on productivity and growth may contradict sustainable development. Consequently, performance measurements relying on other factors must be developed, and artificial intelligence may be a large part of this process. Several scholars have proposed ways of moving in this direction both empirically (Bracarense & Bracarense Costa, 2022; Marks, 2006) and theoretically (Folbre, 2001; Forstater, 2013). On a different type of measurement, regarding new fields of inquiry to model, for instance, the impact of human action on reducing the speed of climate change, as new data is created and collected lately, new areas of study and forecasting models may be incorporated to scientific work to analyze new questions.

Table 11 - Discussion Questions for Future Research on Topics 6 through 8

Topics	Discussion questions
Gap 6. Performance measurements	What data needs to be collected, and what can we measure with said data?
	What new indexes need to be created to measure sustainability performance?
	How do we define targets to be measured and evaluated?
Gap 7. Cyber security and sustainable development	What are the threats that cyber insecurity presents to sustainability?
	How can AI help develop protection from cyber-attacks?
	What types of regulations can be established to avoid threats?
Gap 8. Adverse impacts of AI on sustainability	How can AI threaten sustainability?
	What can be done to reduce the negative impacts of AI on sustainability?
	How can we measure the impact of AI on sustainability?

While the theme of network security has appeared among the 50 most used keywords by the authors in the field of AI for sustainability, as concerns about cyber security seem more pressing, its application to environmental issues is still incipient, presenting a promising field for future research. In contrast, an analysis of the negative impact of AI needs to gain further attention. Discussions in academic circles have been emerging about the amount of energy consumed for the broad application of AI in daily activities. However, measurements need to be created to clarify whether its use is more beneficial than prejudicial for sustainable social development.

Finally, regarding the Nishant et al. (2020) research roadmap, which includes a multilevel view for AI, environmental psychology and sociology perspective, economic perspective, system dynamic perspective, and design thinking approach, the present paper identifies the first three points in the roadmap are interrelated. As a result, the inclusion of social scientists in the debate requires widely interdisciplinary research, an outcome that traditional, environmental, and behavioral economics cannot achieve on their own. Xu et al. (2019) have shown that interdisciplinary studies are critical for theoretical innovation. More often than not, disciplinary boundaries hinder communication between scholars and result in redundancy and lack of awareness that curbs the creative academic process. Such a point calls for the invitation of ecological economists, international political economists, gender studies scholars, among other researchers in highly interdisciplinary studies, to participate in and enrich the debate.

Conclusions

This study presents a bibliometric overview of research on AI for sustainability from 1991 to 2021. The bibliometric analysis of 3887 publications allows for some key conclusions, including the fast growth rate of publications in this line of research (23.26%), with an even higher yearly average growth rate since 2017 (70.0%). This study offers insights regarding the contributions of scientific research to advancing AI research for sustainability. It provides key information needed for researchers to better orient their resources and efforts to investigate the field of AI and sustainability further. Nevertheless, this research has some limitations inherent to bibliometric analyses. First, there is a natural bias in favor of older publications, given that they could tend to have more citations than more recent ones that may be more relevant to the line of research. Secondly, this study solely relies on keyword co-occurrences to identify themes and trends, which may suffer from an indexer effect (Fahimnia et al., 2015). Thirdly, we used full counting methods in co-authorship networks, which may lead to slightly different results if fractional counting was used instead. However, this has a limited effect on the overall findings and conclusions (Fahimnia et al., 2015). Fourthly, there may be other publications on AI for sustainability that were not have considered in this analysis because they are not indexed in the WoS database (Albort-Morant & Ribeiro-Soriano, 2016; Wang C. et al., 2020).

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About the Authors

Dr. Natalia Bracarense is an Associate Professor of economics at North Central College in the United States and a consultant in data analytics and artificial intelligence. She holds a PhD in Economics from the University of Missouri-Kansas City, a master's degree in economics from the University Federal of Uberlandia in collaboration with Unicamp (Brazil), and a master's degree in Big Data, Marketing and Management at Toulouse Business School. Her research relates to institutional economics, particularly digital, productive and economic transformation analyses. In previous years, Dr Bracarense analyzed the US foreign relations with China, while more recently, she concentrated on the impact of artificial intelligence on workers, firms, governments, and society.

Dr. Ransome Bawack holds a PhD in Information Systems from Toulouse Capitole University, France. He is currently an Assistant Professor at ICN Business School, France, and a member of Lorraine University's European Research Centre for Financial Economics and Business Management (CEREFIGE). His research currently focuses on the business value of artificial intelligence, data science, and analytics, especially in e-commerce contexts. He has published in leading academic journals like *Technological Forecasting and Social Change, Production Planning & Control, Information Technology & People, International Journal of Information Management, Business Process Management Journal,* and *Electronic Markets*.

Dr. Samuel Fosso Wamba is a Full Professor, Director of Research, and Head of the Artificial Intelligence & Business Analytics Cluster at TBS Business School. He earned his PhD in industrial engineering at the Polytechnic School of Montreal, Canada. His current research focuses on the business value of IT, inter-organizational systems adoption and use, supply chain management, electronic commerce, blockchain, artificial intelligence in business, social media, business analytics, big data and open data. He has published papers in top journals, including *Academy of Management Journal, European Journal of Information Systems, Journal of Cleaner Production, Information Systems Frontiers, International Journal of Production Economics, International Journal of Information Management, International Journal of Logistics Management, International Journal of Production Research, Journal of Business Research, Technology Forecasting and Social Change, Production Planning & Control, and Business Process Management Journal.* Prof Fosso Wamba is organizing special issues on IT-related topics for leading international journals. He won the best paper award from the *Academy of Management Journal* in 2017 and the papers of the year 2017 of The *Electronic Markets*: *The International Journal on Networked Business*. He is an Associate Editor of the *International Journal of Logistics Management information* and *Electronic Markets: The International Journal on Networked Business*. He serves on the editorial board of five international journals. Prof Fosso Wamba is a CompTIA RFID+ Certified Professional and co-founder of RFID Academia.

Dr. Kevin Carillo is an Associate Professor in Data Science & Information Systems at Toulouse Business School. His research interests include artificial intelligence, big data and data-driven business, free/open-source software communities, online communities, and peer production. Kevin holds a PhD degree in Information Systems from the School of Information Management of Victoria University of Wellington, New Zealand, a Master's Degree in software engineering and applied mathematics (ENSEEIHT, Toulouse, France) and a Master of Science in Business Administration, option Management Information Systems (John Molson School of Business, Concordia University, Montreal, Canada).