IMPACTS OF ARTIFICIAL INTELLIGENCE: A BIBLIOMETRIC ANALYSIS

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ABSTRACT

This study investigates the environmental impact of artificial intelligence (AI) through a bibliometric analysis of 490 academic articles published between 2004 and 2024. Using Bibliometrix and VOSviewer, it identifies key trends, authors, journals, and thematic clusters, highlighting AI's dual role as both a driver of sustainable innovation and a source of environmental challenges. The analysis reveals research gaps, such as limited geographic perspectives and insufficient lifecycle assessments. Adopting a multidisciplinary approach, the study connects AI, sustainability, and service management, offering theoretical and practical insights to optimize resource use, reduce waste, and promote environmentally conscious service delivery.

KEYWORDS: Artificial intelligence, environmental impact, AI, sustainability, service management, bibliometric analysis.

Introduction

Modern technology has been transformed by artificial intelligence (AI), which is now a key component of innovation in many different sectors. However, worries about AI's effects on the environment have surfaced as its adoption picks up speed. These issues include resource use, carbon emissions, and energy use. A bibliometric examination of 490 academic papers from 2004 to 2024 that are indexed in Scopus shows that there is a growing emphasis on comprehending and resolving these issues. In addition to identifying significant trends, seminal works, and thematic gaps in the field, this study attempts to chart the development of research on AI's environmental impact.
The computing needs of AI and energy efficiency were the main topics of early study. In Joule, for example, de Vries (2023) drew attention to the increasing energy consumption of machine learning systems, especially large-scale neural networks, whose carbon emissions are comparable to those of whole nations. In the meanwhile, Demestichas and Daskalakis (2020) highlighted the function of AI in frameworks for the circular economy, demonstrating its capacity to minimize waste and maximize resource utilization. These studies highlight how AI may be both a cause of environmental problems and a means of accomplishing sustainability objectives.
The energy requirements of AI-powered devices, such data centers and training models, are important topics in the literature. In their review published in the Journal of Cleaner Production, Herva and Roca (2012) explored how incorporating multi-criteria decision-making frameworks might improve AI systems' environmental performance. In a similar vein, Rahmati *et al.* (2019) illustrated how AI may be used to simulate land subsidence, underscoring its potential to address important environmental concerns.
Notwithstanding these developments, there are still a lot of unanswered questions about the environmental effects of AI during its whole career. For instance, in their paper on biohydrometallurgy (Hydrometallurgy), Kaksonen *et al.* (2020) emphasized the necessity of sustainable methods for handling the end-of-life disposal of AI technology.
The disparity in research outputs per area presents another difficulty. While places like Africa and South America, where AI usage is expanding quickly, continue to be under-represented, a sizable percentage of research come from North America, Europe, and East Asia (Demestichas and Daskalakis, 2020). This geographical discrepancy highlights the need for more inclusive research and restricts the current findings' worldwide application.
To examine the intellectual, conceptual, and social structures found in the literature, this study makes use of bibliometric tools such as Bibliometrix and VOSviewer. VOSviewer's thematic clusters highlight certain areas of interest, like lifecycle analysis, energy efficiency, and the incorporation of AI with the concepts of the circular economy. Alves *et al.* (2022), for example, talk about AI-driven innovations in the textile sector and offer models that improve sustainability by reducing waste. These examples show how AI may support sustainable behaviors and address environmental issues at the same time.
An early road map for next multidisciplinary study is provided by this preliminary analysis. It offers a basis for investigating AI's dual function as a source of environmental concern and a facilitator of sustainability by mapping research clusters and finding gaps. In the future, thorough lifecycle analyses, international

partnerships, and regional research will be essential to coordinating AI development with sustainability objectives and reducing its environmental impact.

Literature review

Service management research emphasises how digital technology may revolutionise resource efficiency and waste reduction (Grönroos & Voima, 2013; Vargo & Lusch, 2004). The "Service-Dominant Logic" framework underpins this discourse, advocating for value co-creation through innovative service solutions. AI-powered tools, such as predictive analytics and automated decision-making systems, enhance efficiency and sustainability in service delivery. For example, smart grids and demand forecasting systems enable resource optimization, aligning with the circular economy principles (Demestichas & Daskalakis, 2020). Artificial Intelligence (AI) has emerged as a transformative technology with significant implications across multiple industries. However, its environmental impact has increasingly become a subject of concern. A growing body of research highlights the dual role of AI as both a contributor to environmental degradation and a tool for sustainability.

Energy Consumption and Emissions

AI systems, particularly those relying on deep learning and large-scale computations, are known for their energy-intensive nature. For instance, training a single large AI model can result in carbon emissions equivalent to the lifetime emissions of multiple vehicles (Strubell *et al.*, 2019). Data centers, which form the backbone of AI computations, consume an estimated 1% of global electricity, with forecasts suggesting a steady increase due to the growing demand for AI-powered services (de Vries, 2023). Despite the use of renewable energy sources in some facilities, the environmental burden remains substantial.
On the other hand, AI technologies have demonstrated potential in addressing environmental challenges. Applications range from optimizing energy grids and reducing resource waste to enhancing climate modeling and promoting circular economy practices (Kouhizadeh *et al.*, 2021). For example, machine learning algorithms are increasingly used to forecast energy demand, enabling better integration of renewable energy sources into power grids.
A key challenge in assessing AI's environmental footprint is the lack of standardized metrics and transparency in reporting energy usage. Studies often rely on approximations due to the proprietary nature of many AI algorithms and the infrastructure supporting them (Henderson *et al.*, 2020). Additionally, the geographic location of data centers and their reliance on local energy grids significantly influence their carbon footprint.
Recent literature emphasizes the importance of developing "green AI" practices, including energy-efficient model architectures and hardware optimizations (Schwartz *et al.*, 2020). Researchers also advocate for a lifecycle assessment (LCA) approach to evaluate the environmental impact of AI technologies comprehensively, from development to deployment.

Research Methodology

This section outlines the methodology employed to achieve the objectives of this study, which aim to identify the state of the art and analyze the role of artificial intelligence in environmental impact, with a particular focus on its implications for service management. By leveraging bibliometric analysis tools, such as Bibliometrix and VOSviewer, the study systematically examines the existing body of literature to uncover key trends, thematic clusters, and research gaps. This approach ensures a comprehensive understanding of AI's dual role as both a contributor to environmental challenges and a potential enabler of sustainability solutions. This study incorporates references from service management literature to establish a robust theoretical foundation. In the realm of business research, bibliometric analysis has gained popularity recently (Donthu, Kumar, & Pattnaik, 2020b; Donthu, Kumar, Pattnaik, & Lim, 2021; Khan *et al.*, 2021). The development, accessibility, and widespread availability of bibliometric tools like Gephi, Leximancer, and VOSviewer, as well as extensive academic databases like Scopus and Web of Science, are the primary causes of this growing popularity. The second is the incorporation of bibliometric techniques from information science into business research, which promotes interdisciplinary applications. Applying quantitative methods, such bibliometric analysis (e.g., citation analysis), to bibliometric data – which comprises publications and citations – is known as bibliometric methodology (Pritchard,1969). To determine the most significant topic clusters and their interrelated networks, the study uses scientific mapping techniques such keyword co-occurrence analysis. Co-citation analysis is also used to identify the theme clusters within the study area and identify the publications that are most often cited. This method is essential to scientific mapping since it looks at the connections between papers that are often referenced

together to identify multidisciplinary themes and delineate the field's thematic structure. Different research clusters start to appear when many authors co-cite the same pairs of publications that are mentioned jointly in source articles, according to co-citation analysis (Surwase *et al.*, 2011).
These clusters of publications frequently include recurring topics that provide a thorough understanding of earlier studies. Additionally, using graph theory to examine the underlying data structure, co-citation mapping is a type of exploratory data analysis (EDA) (Fahimnia *et al.*, 2015).
Protocol SPAR-4-SRL
This study adheres to the Paul *et al.* (2021)-proposed Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) procedure to guarantee a thorough approach.

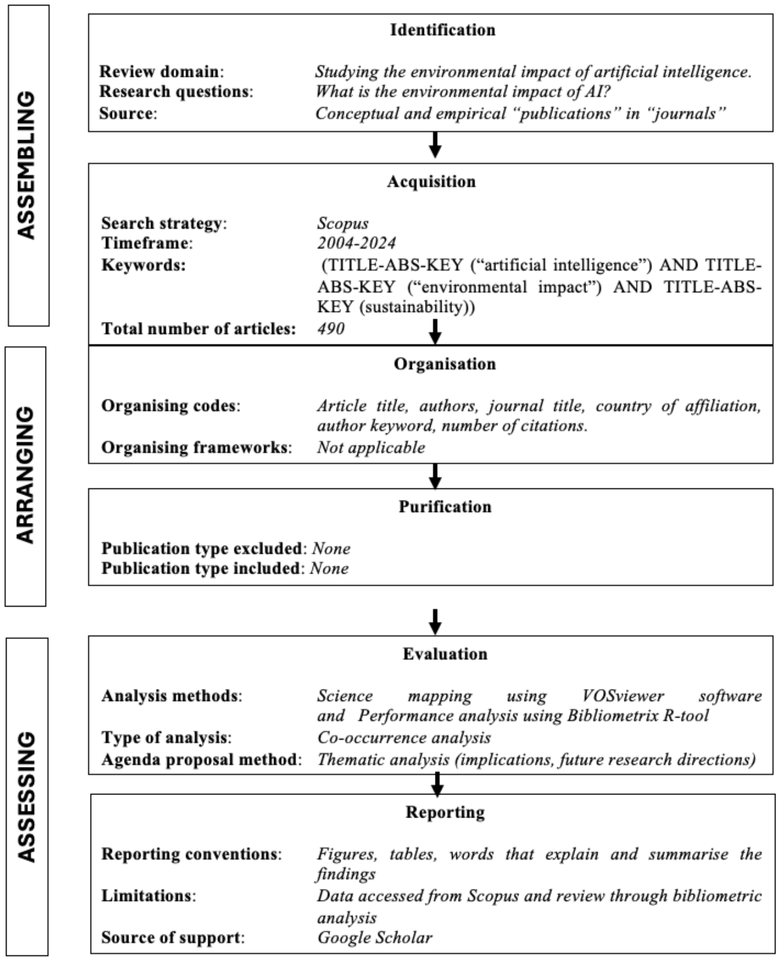

Figure 1. Research design follows the SPAR-4-SLR protocol

Results and discussion

The results of the bibliometric analysis are presented in this section, which starts with a descriptive analysis and a performance assessment of the documents that were part of the research. The findings of the co-occurrence analysis are next examined, emphasizing the discovery of significant clusters within the topic of study. After then, a detailed description of each cluster is given to shed light on the dataset's patterns and thematic structure.
Performance Analysis and Science Mapping
The "Annual Scientific Production" graph illustrates the evolution of academic interest in the environmental impact of AI. From 2004 to 2015, research activity was minimal, reflecting the early stages of interest in the topic. However, a sharp increase in publications is observed from 2016 onwards, peaking around 2023, likely driven by the growing use of energy-intensive AI systems, heightened sustainability awareness, and advancements in research methods. The peak in 2023 suggests a turning point in this field, coinciding with global sustainability goals like the UN's SDGs. A noticeable drop after 2023 may be due to data limitations or publishing cycles. Overall, the graph highlights the transition of this topic from niche research to a prominent field with significant academic focus.

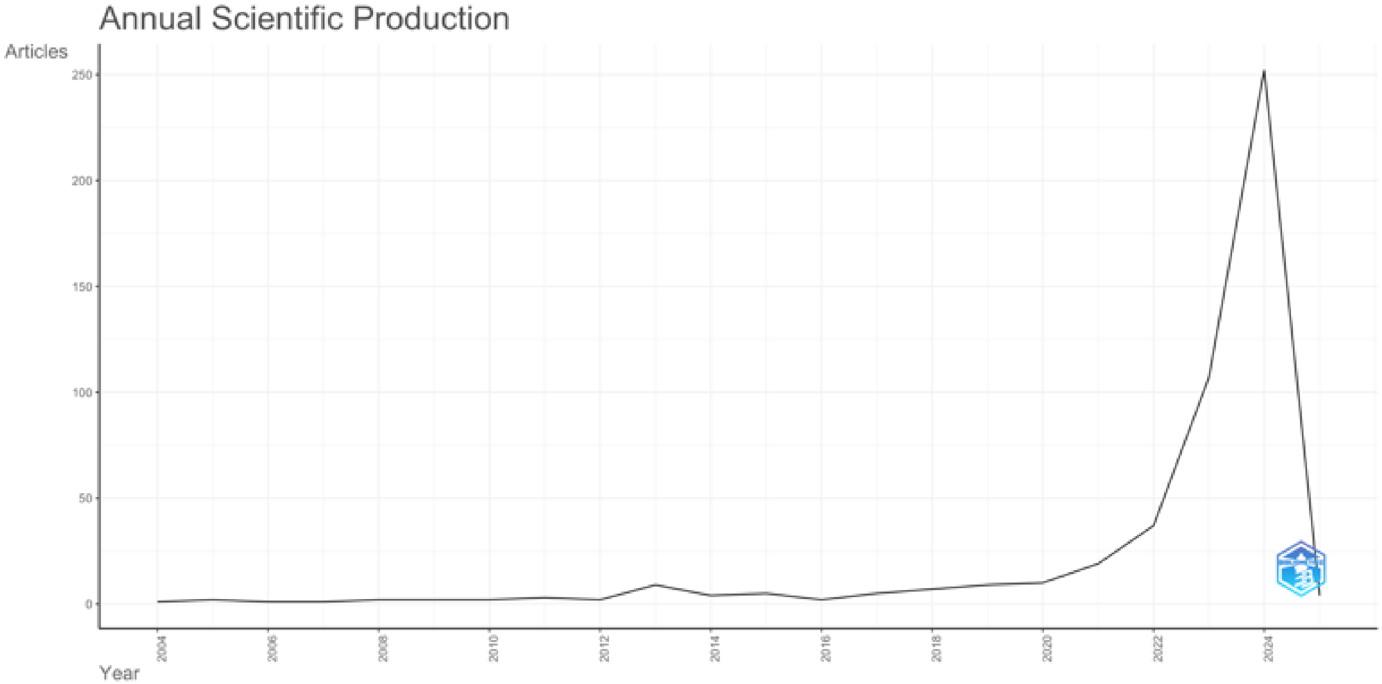

Figure 2. Annual scientific production (Biblioshiny)

The graph shows the average annual number of citations for the study's included documents. Over time, the trajectory shows a varying pattern, with reductions occurring after times of increased citation effect. Interestingly, maxima are seen in some years, such 2006 and 2022, suggesting that some papers from these years attracted a lot of scholarly attention. The fluctuation in citation averages might reflect the topic's changing significance and the impact of seminal research. Since it frequently takes longer for publications written in recent years to receive many citations, the recent fall in 2024 may be explained by the shorter time frame for citations to collect. This pattern emphasizes how crucial it is to place citation data in the context of research activities and publication dates.

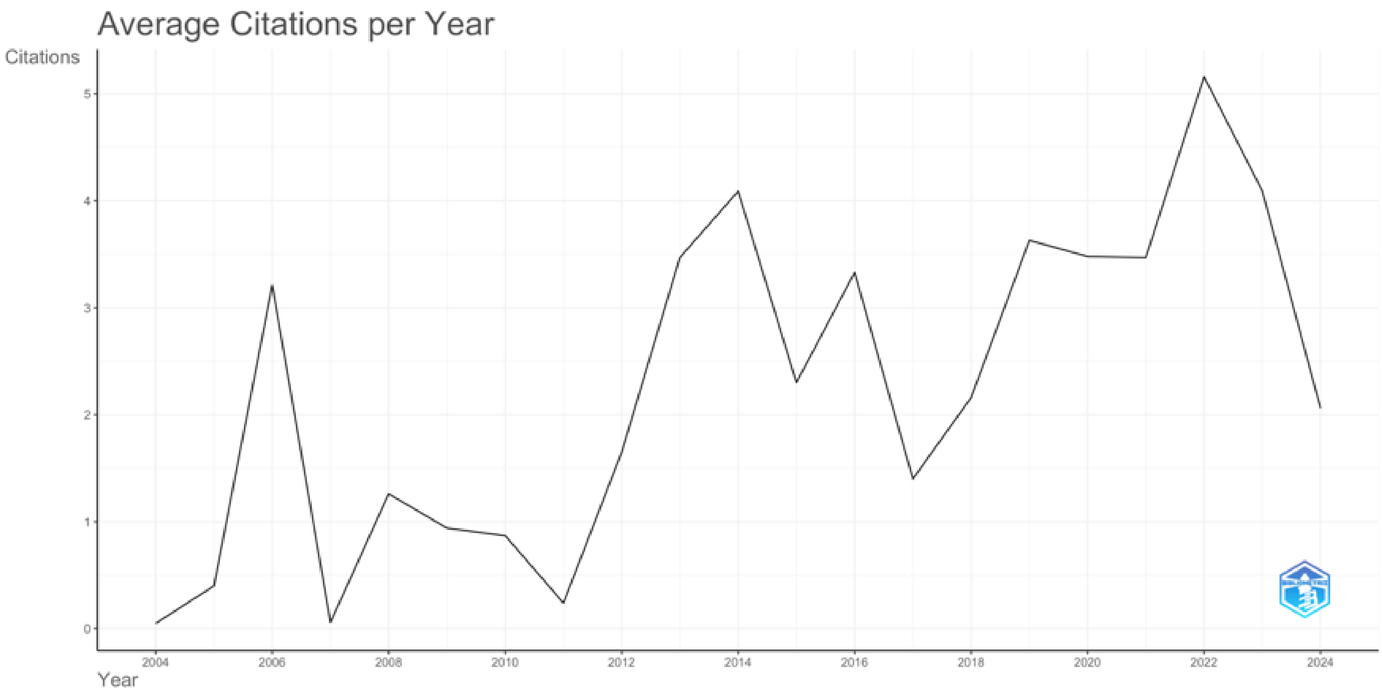

Figure 3*. Average citations per year (Biblioshiny)*

The graphic highlights the most cited papers in the dataset, focusing on those with over 70 citations. Herva and Roca's (2013) work in Journal of Cleaner Production leads with 161 citations, serving as a foundational study on sustainability and environmental evaluation. Rahmati *et al.*'s (2019) paper in Science of the Total Environment follows with 119 citations, reflecting its influence on AI-driven environmental research. Other notable works include Wilkinson *et al.* (2020) in Grass and Forage Science (82 citations), Kurniawan *et al.* (2023) in Journal of Environmental Management (75 citations), and Hassoun *et al.* (2024) in Critical Reviews in Food Science and Nutrition (73 citations). These highly cited studies have shaped the discourse on AI's environmental impact, emphasizing the importance of foundational and interdisciplinary research.

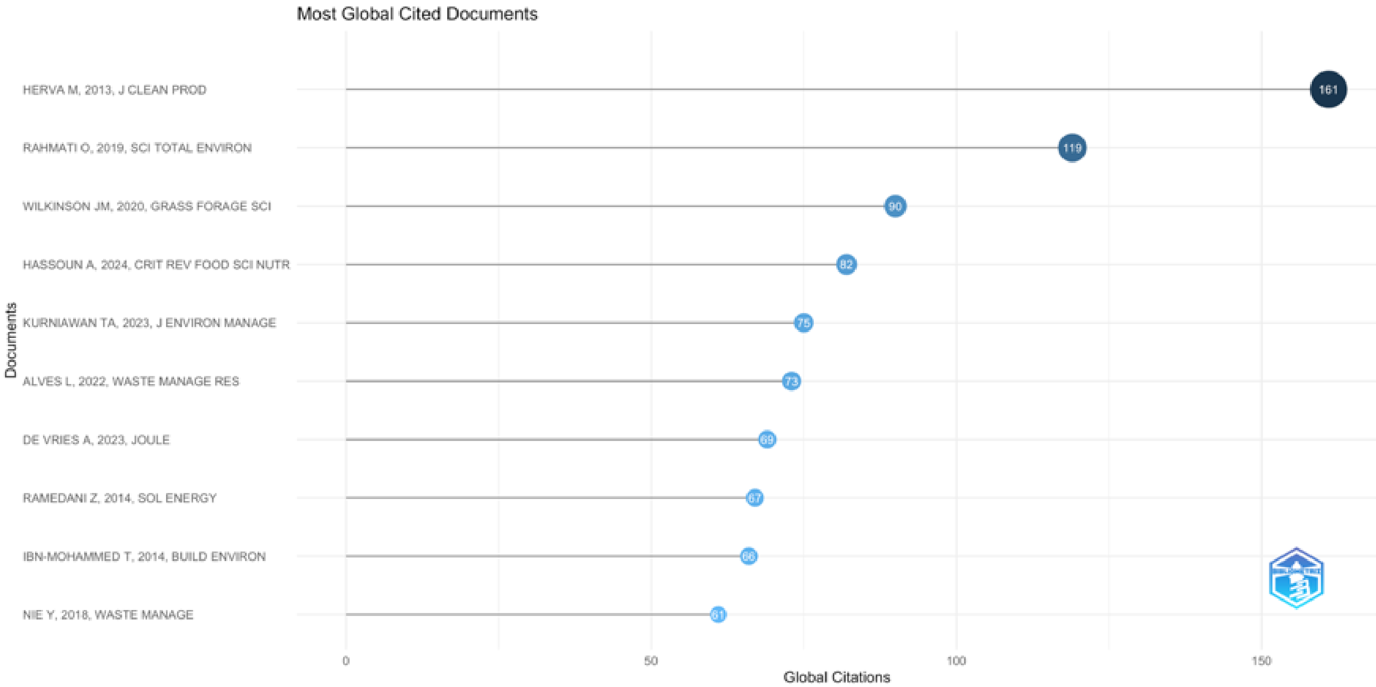

Figure 4. *Most cited articles (Biblioshiny)*

The graphic highlights the key journals contributing to the study topic. Sustainability (Switzerland) leads with 24 publications, reflecting its focus on multidisciplinary research addressing sustainability issues, making it ideal for studies on AI's environmental effects. Science of the Total Environment follows with 14 publications, emphasizing its role in exploring the ecological impacts of technological advancements. The Journal of Cleaner Production contributes nine studies, aligning with its focus on sustainable development and innovative environmental solutions. Together, these journals underscore the interdisciplinary nature of research on AI's environmental impact, bridging sustainability, environmental science, and technology innovation.

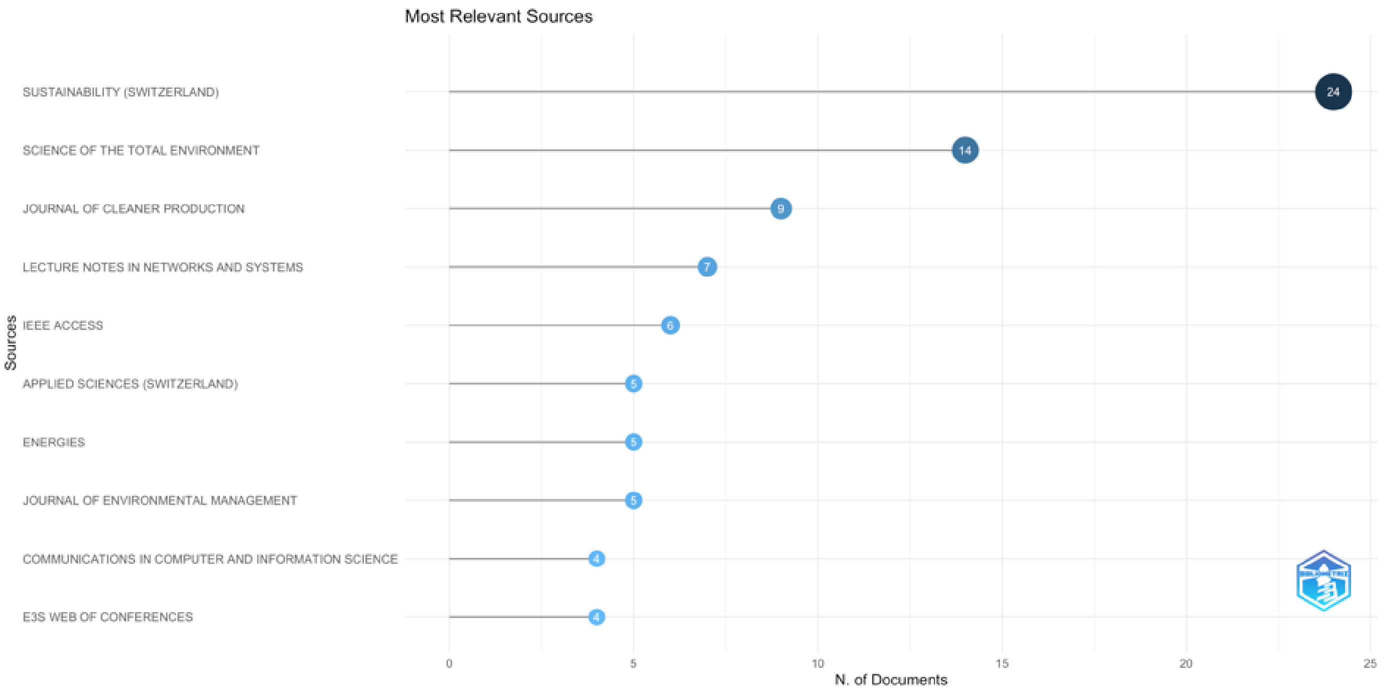

Figure 5. Most Relevant Source (Biblioshiny)

The graphic highlights the nations with the most-cited papers in the dataset. The UK leads with 420 citations, reflecting its prominent role in AI-environmental research, supported by strong universities and funding. Spain (334 citations) and China (293 citations) follow, with Spain focusing on sustainability and China investing in AI for energy and resource management. Italy, the USA, and France also contribute significantly (164–169 citations), with the USA showing leadership in AI development. The international distribution underscores the global nature of this research while highlighting under-representation from regions like South America and Africa, emphasizing the need for broader collaboration to address AI's environmental challenges.

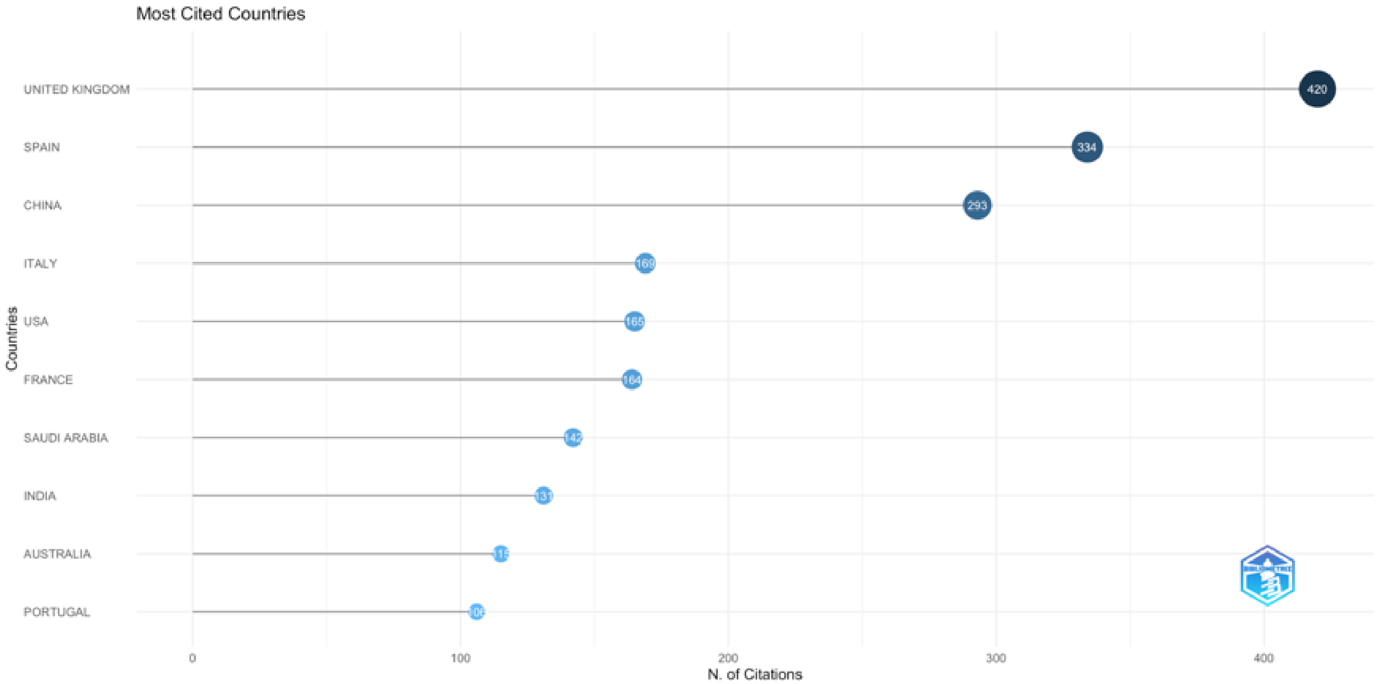

Figure 6. Most Cited Countries

De La Salle University leads the graph with eleven publications, followed by Islamic Azad University, King Fahd University, and Lovely Professional University, each with seven, and Saveetha School of Engineering, with nine. This demonstrates how international and multidisciplinary the study is, with notable contributions from organizations in many different countries, including Asia and the Middle East.

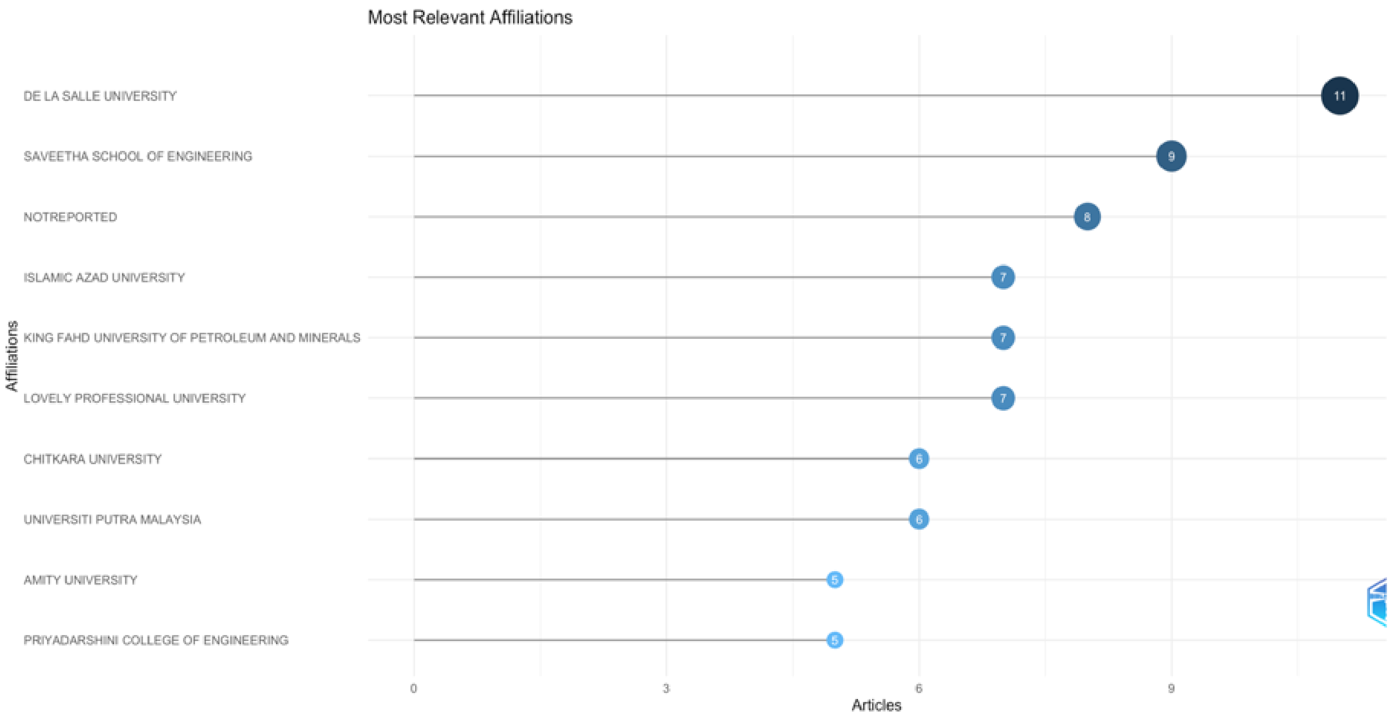

Figure 7. Most Relevant Affiliation

Co-occurrence analysis

The findings of the co-occurrence analysis carried out with VOSviewer are shown in this section. Through the identification of keyword links within the information, this analysis reveals themes and patterns within the subject of study. Several clusters reflecting different subject areas were found by mapping the co-occurrence of terms. By highlighting both known subjects and new areas of interest in the study of AI's environmental effect, these clusters offer insightful information on the composition and emphasis of the body of existing research. The characteristics of these clusters and their consequences for the field will be covered in detail in the sections that follow.
The network visualization produced by VOSviewer, which displays the co-occurrence of terms in the data-set, is shown in Figure 8. Larger nodes indicate greater frequencies, while linkages between nodes show how strongly co-occurrence associations exist. Each node represents a term. The network is separated into clusters, each of which is represented by a different color and highlights a particular theme within the topic of study.
As a reflection of their fundamental function in this field of study, important nodes including "artificial intelligence," "sustainable development," and "environmental sustainability" predominate. The red cluster highlights the technical uses of AI while concentrating on energy efficiency, sustainable practices, and machine learning. The green cluster connects AI to circular economy projects by addressing waste management, recycling, and decision support systems. While the purple cluster emphasizes developments in precision agriculture, automation, and digitization, the blue cluster investigates climate change, greenhouse gas emissions, and environmental monitoring. By highlighting the major topics and connections influencing the subject, this graphic illustrates how research on AI's effects on the environment is interrelated and diverse.

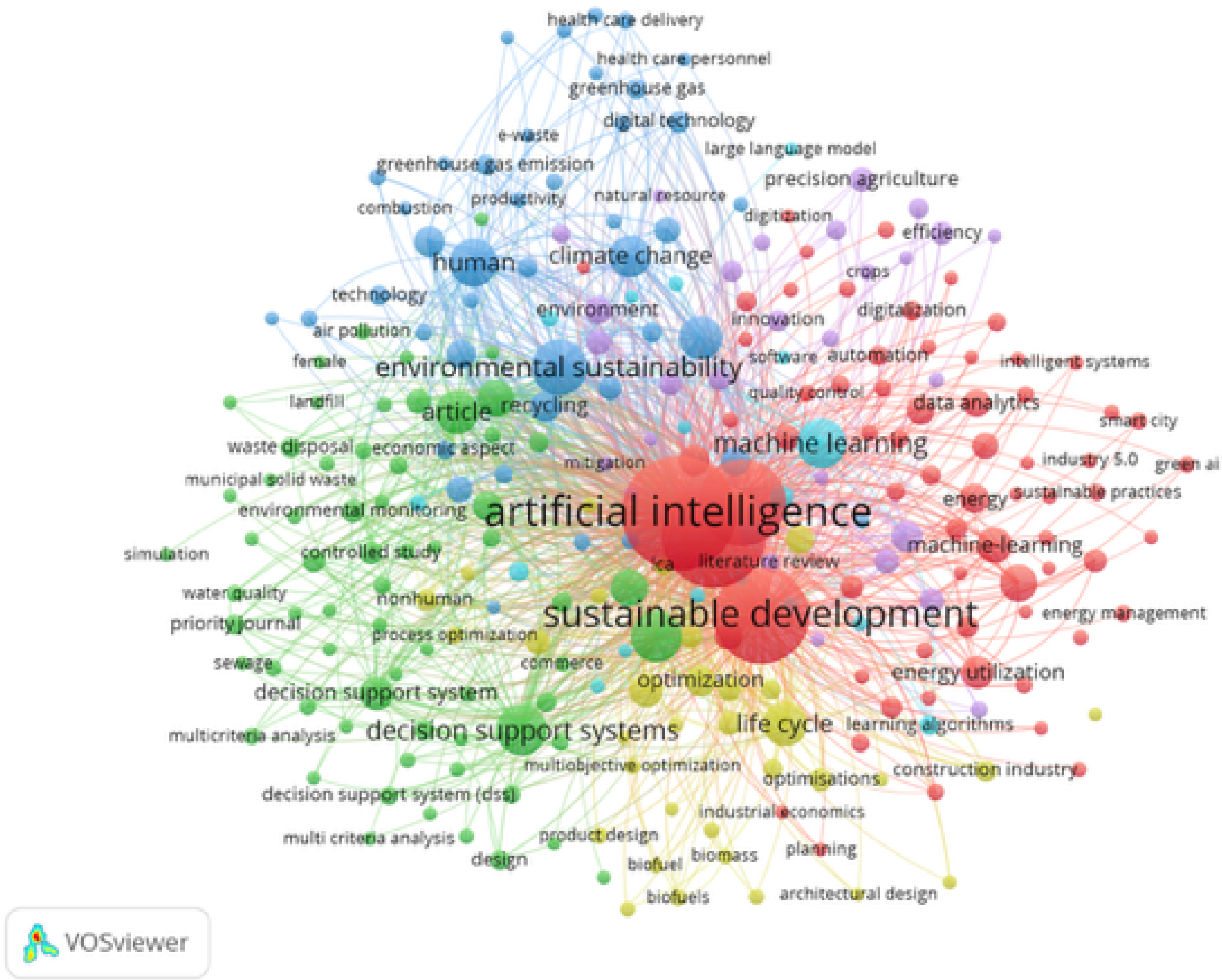

Figure 8. Network Visualization co-occurrence (VOSviewer)

The temporal history of keywords is displayed in Figure 9, which was produced using VOSviewer. The colors represent the average publishing year (2019–2024). Bigger nodes stand for often used terms, whereas blue indicates more traditional subjects like "environmental monitoring" and yellow emphasizes more recent developments like "precision agriculture" and "data analytics." The transition from fundamental research to cutting-edge AI and sustainability applications is depicted in this graphic.

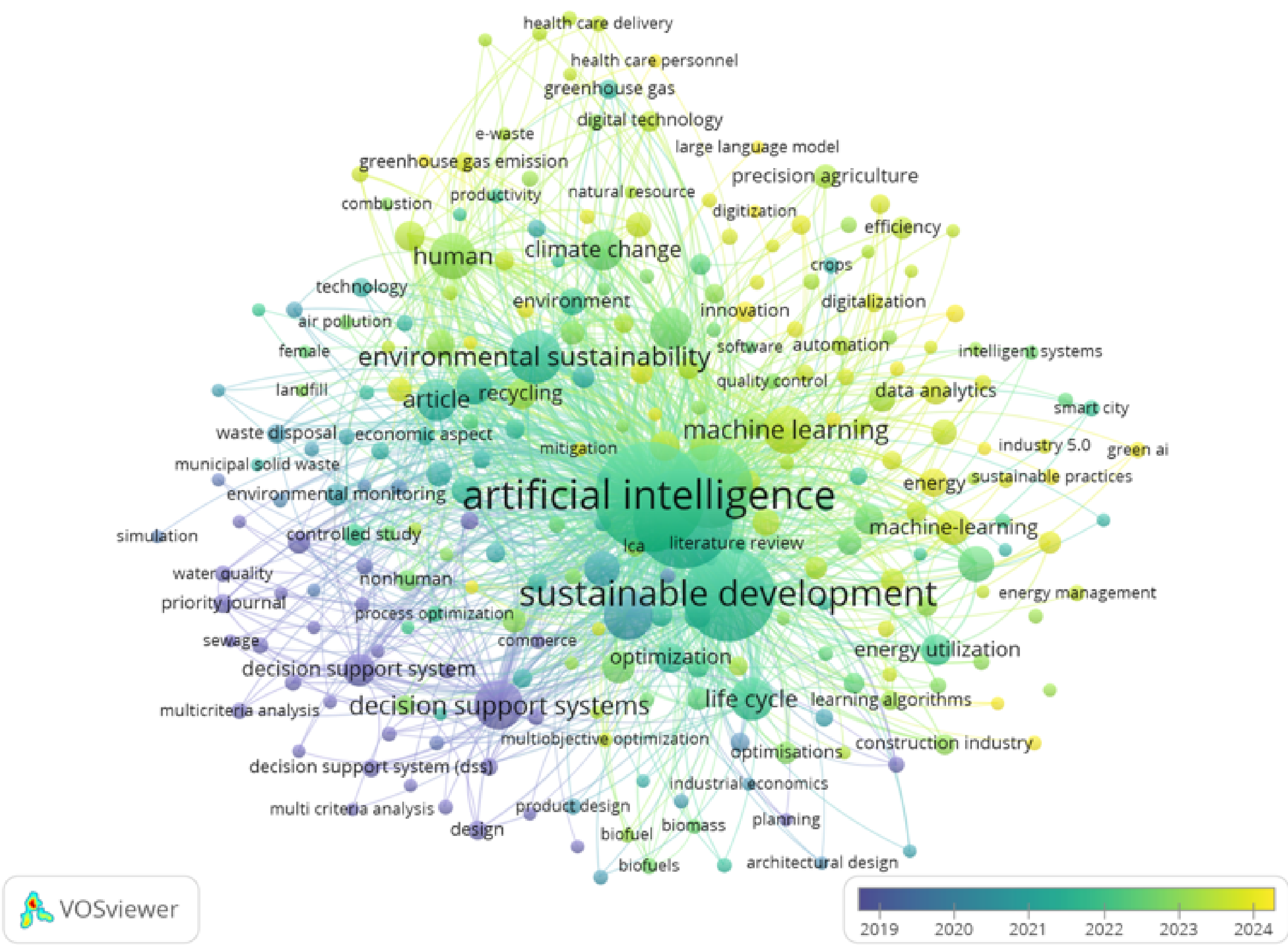

Figure 9. Overlay Visualization co-occurrence (VOSviewer)

Based on occurrences, link strength, and average citation levels for all keywords, are presentented six distinct clusters. This clustering highlights the most frequently occurring and impactful keywords that summarize the main themes of the research field. Among the most notable terms, “artificial intelligence” appears 320 times, “sustainable development” 220 times, and “environmental impact” 261 times, showcasing their central role in the discourse.

Each cluster reflects a specific thematic area, combining keywords that are strongly interconnected. The six clusters include themes such as AI and technological innovation, sustainability, energy efficiency, environmental impact, circular economy, and data analytics. These clusters not only reveal the core focus areas but also help to understand the relationships between key concepts. In the following sections, each cluster will be described in detail, along with the keywords that define its scope and significance.

Cluster 1 – AI and Technology

The keyword with the highest frequency is “artificial intelligence”, with a weight occurrence of 320. It is followed by “machine learning” with 31, “automation” with 11, “internet of things” with 19, and “smart cities” with 6. It explores the role of AI and digital technologies in driving innovation and technological development. It highlights practical applications of AI in advanced sectors like automation, urban optimization, and IoT, showcasing how these technologies are transforming industries and society.

Cluster 2- Sustainability

In the second cluster, the most frequently used keywords are “sustainability”, with a weight occurrence of 181, and “sustainable development”, with a weight occurrence of 220.It examines how AI innovations can support sustainable practices, reduce waste, and improve resource management across various sectors.

Cluster 3- Energy

In the third cluster, the keywords with the highest average citation scores are “energy efficiency”, with a score of 57,429, “renewable energy”, with a score of 138,333, and “energy utilization”, with a score of 101,154.

It explores AI’s contribution to optimizing energy systems, managing energy resources, and integrating renewable energy sources. It emphasizes how AI can reduce energy consumption and associated emissions.

Cluster 4- Environmental Impact

In the fourth cluster, the keywords with significant weight occurrences are "environmental impact", with 11, "carbon emissions", with 9, and "greenhouse gas emissions", with 7.
It focuses on the environmental effects of AI technologies and industrial processes, highlighting their influence on greenhouse gas emissions, ecological footprints, and overall environmental sustainability.
Cluster 5- Circular Economy
Cluster number 5 focuses on the keyword "circular economy", which has a weight occurrence of 23 and an average citation score of 126,087.
This cluster investigates how AI can facilitate the transition to circular economic models. It highlights the role of technology in promoting reuse, recycling, and efficient resource management, reducing waste, and supporting a more sustainable economy.
Cluster 6- Data and Analytics
This cluster includes terms such as data analytics and digitalization with weight occurrences of 19 and 11, emphasizing the importance of data analysis and digital transformation in improving processes and decision-making. It highlights how data-driven technologies are driving innovations in key sectors, enhancing efficiency and sustainability in business practices.

Conclusion

This study presents a bibliometric analysis of AI's environmental impact, highlighting trends, topic clusters, and research gaps. The findings reveal a growing interest in AI's dual role as a contributor to environmental challenges and a driver of sustainable solutions. Key terms like "artificial intelligence," "sustainable development," and "environmental impact" dominate the discourse.
Six topic clusters were identified: data and analytics, environmental impact, energy, sustainability, AI and technology, and the circular economy. The Environmental Impact cluster focuses on issues like greenhouse gas emissions, while the Energy cluster highlights AI's role in energy efficiency and renewable integration. Emerging terms like "digitalization" and "circular economy" reflect AI's incorporation into sustainability strategies.
This work lays the groundwork for future research by addressing gaps such as spatial inequalities and lifecycle assessments. Co-citation analysis will further explore the field's intellectual structure. By fostering collaboration and bridging gaps, this research promotes a balance between technological innovation and environmental sustainability, aligning AI's growth with global sustainability goals. This study contributes to the understanding of AI's environmental impact by integrating insights from service management. Future research should focus on:
Expanding geographic diversity in AI-related studies.
Conducting lifecycle assessments of AI technologies in service applications.
Bridging gaps between technological advancements and sustainable service frameworks.
By aligning AI's growth with global sustainability goals, this research provides a roadmap for integrating sustainable practices into service management.

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