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Review

Applicability and Trend of the Artificial Intelligence (AI) on Bioenergy Research between 1991–2021: A Bibliometric Analysis

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Abstract: The bibliometric analysis investigated the impact of publications on trends in the literature and bioenergy research using artificial intelligence (AI) from 1991 to 2021. In this study, 1721 publications were extracted from the Web of Science, and an analysis of the countries, authorship, institutions, journals, and keywords was visualised. In the recent decades, this field has entered an outbreak phase. India was the most productive country in this area, followed by China, Iran, and the US. It also noted several notable differences between trends and subjects in developed and developing countries. The former led this field at the initial stage and later attached importance to using AI for research feedstock and impact assessment. Developing countries encouraged the advancement of this area and emphasised the feedstock usage of phase treatment and process optimisation. In addition, a co-authorship and institutes study revealed that authors and institutes in distant regions rarely collaborated. The journal analysis shows strong links between *Energy*, *Fuel*, and *Energy Conversion and Management*. Machine learning is by far the most common application of artificial intelligence (AI) technology in bioenergy research, with 53% of the articles using it. In these AI-related publications, the keyword artificial neural network (ANN) appeared most frequently in the articles.

Keywords: artificial intelligence; bioenergy; bibliometric analysis; ANN; web of science

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1. Introduction

In the recent decades, the increased fossil consumption and greenhouse gas emissions introduced and emphasised renewable energy sources, which derive from natural resources or processes to achieve zero-emission without polluting the atmosphere [1,2]. As a vital form of renewable energy, bioenergy originated from various natural sources, such as energy crops, biomass wastes or by-products, algae, seaweeds, and aquatic plants [3,4]. However, the defects and imperfections of bioenergy make it improbable to be an immediate marketable energy. Therefore, to fulfil the commercial energy demand, relevant studies encouraged new techniques and upgrades for bioenergy with considerable scope for efficiency, sustainability, and safety improvement [5].

Artificial intelligence (AI) is a computational science that imitates the human mind for decision making and problem solving by combining computer science and robust datasets [6,7]. Researchers have been applying various AI algorithms to develop specific prediction-making systems based on input data. In bioenergy research, AI modelling and prediction have been applied widely, such as in supply chain management and process prediction [8]. In supply chain management, a bioenergy production facility needs extensive logistical planning, power plant design, and resource appraisal [9]. With a multi-scaling feed database of logistical data, demand, availability, and feedstock characteristics, an AI predictive strategy can enable rapid assessment and minimise risks or disruptions throughout the supply chain [10]. Ghugare et al. [11] examined the genetic programming (GP) and multilayer perceptron models to estimate the higher heating value (HHV) of solid biomass fuels (MLP). The models provided 95% accuracy in their forecasts, which might displace the current models. Ozveren [12] predicted gross calorific value (GCV) using an artificial neural network (ANN) model. The ANN model could replace the current costly GCV-predicting method with a cheaper and more applicable model to configure and design thermal conversion systems. In particular, in bioenergy research, AI could establish prediction models with experimental results and parameter data. In previous studies, AI models optimised bioenergy production from oilseeds and accessed the estimation with more data points than current optimisation technologies [13]. Kargbo et al. [14] predicted two-stage biomass gasification for hydrogen production with the ANN model to reduce time and costs in testing and development. The model accuracy was improved by considering feedstock size, shape, and composition, which obtained optimum operating conditions for carbon conversion and hydrogen yield.

Despite the early related research encouraging the broad usage of AI in bioenergy research, consensus on the efficacy of the technologies was still absent in the fields. The bibliometric analysis is a quantitative assessment to evaluate the standard and growth of the literature on a selected subject. Large amounts of scientific data can provide an informative understanding, of which results give suggestions on work evaluation, determine the impact of institutions, and state the progress in the field [15,16]. Donthu et al. [17] split bibliometric methods into two different categories. One is about performance analysis that delves into the contributions of research constituents as it is traditional to present information, such as authors, institutions, countries, and journals. The second is called "science mapping", which focuses on identifying relationships between the research constituents by utilising citation analysis, co-citation analysis, bibliographic coupling, co-word analysis, and co-authorship analysis.

Current bibliometric studies cover various fields by applying several techniques to provide accurate data. Niu et al. [18] investigated global research on AI from 1990 to 2014 by utilising two citation databases for data analysis of the science citation index and conference proceedings citation index. Results include the location of authors, the subjects related to AI, the countries and institutes that publish the most articles, the keywords that provide the most results, and many more. The bibliometric study could find the patterns in academic collaborations and scientific output related to AI to reveal AI research trends worldwide [19,20]. Obileke et al. [21] found that 84 countries engaged in bioenergy research, and the most productive institutions were in China and Denmark. These visual results recommended that more countries collaborate and share information to promote more research in this field.

AI and its application in bioenergy research have boomed with the advancement of relevant areas and approaches. However, it has yet to be a comprehensive bibliometric analysis for such a plethora in this area. The present work carried out a bibliometric analysis of AI application in bioenergy research by accounting for the literature and publications from 1991 to 2021. A long-time span grants the critical observation of the trends and tracks information travels worldwide. The analysis reveals the characteristics of countries or areas in AI technology in bioenergy for research-trend-targeted predicting.

2. Methodology

2.1. Dataset Collection

Current literature following bibliometric indicators leads to adopting a search strategy. The existing publications for this bibliometric analysis were from the Web of Science (WoS) global citation database. The unique data source of WoS provided numerous samples for further analysis and enabled minimizing errors from data collection overlap to maintain consistency. The search years ranged from 1991 to 2021, and the subject areas were material science, engineering, chemistry, chemical engineering, energy, and environmental science. The search document type and language were Research articles and English.

For the strategy procedure, the initial search consisted of 37 words identified from literature, combining words for both AI and bioenergy. Notably, the search strategy disregards "earthquake" and "seismic" as partial liquefaction articles are about AI technology prediction or optimisation for soil liquefaction susceptibility. The initial search criteria included the words "bioelectric" and "bio-electric" as terms representing the use of biomass in electricity generation. However, these terms refer to electrical currents generated by living tissue, cells, and organisms and were, therefore, out of search strategy. The exporting formation of the publications attained from WoS was as a comma-separated values file (CSV) to Microsoft Excel for transferring a high volume of data to concentrated databases. The organisation of exported literature data was performed according to the date published and the AI methodology utilised in each article.

The selected publications in the initial screening underwent itemised manual screening to clarify the research scope. Manual screening involves a review of the abstract and the full text when necessary. It obtained 1721 publications after duplicate removal and exclusion based on screening criteria. Meanwhile, manual operation marked each publication by subdivision areas, according to a previous study from the judgments of the title, abstract, and keywords [8].

2.2. Data Analysis and Visualization

VOSviewer software was then used for the visual analysis for facilitating bibliometric networks and trends by exporting three visualisation maps: network visualisation, overlay visualisation, and density visualisation [22].

The software statistically outputted the data analysis results of publication numbers each year; the top 10 authors, institutions, and most cited journals each decade, primary keywords every five years; and the AI method emergence frequency in the past decade. In the case of the years with few numbers, particularly at the beginning of this area, the statistical analysis merged or skipped those years for better understanding. Moreover, by tracing the surge from year statistics, the authorship connection research divided the thirty years into three stages of before 2008, 2008–2016, and after 2016 to map the networking of those authors. The first two stages selected the authors with over three publications and the last stage with a minimum of eight.

Apart from the availability of data statistics and the analysis of authorship, institutions, and the publication source, this work also manually sorted the studies into four groups based on the purpose of AI applications, according to reference [8]:

Category 1: biomass properties for feedstock screening and species selection.

Category 2: process-based performance indicators of biomass conversion for technology optimization and design.

Category 3: biofuel properties and facilities performance for the optimal utilization of bioenergy.

Category 4: supply chain design and planning towards technical and sustainability perspectives.

3. Results and Discussion

3.1. Worldwide Publication Analysis

The results of the bibliometric analysis for AI on bioenergy research in this section ranged from 1991 to 2021. A total of 1721 papers provided bibliometric results by focusing on the relationship between the trend, country, and relevant policy. Figure 1 shows the variation in publications released yearly since 1991. A surge point first emerged in 2014. The publications in the rest of the seven years accounted for 90% of all publications in the total of three decades. Hence, AI in bioenergy research is still a new concept with rapid growth.

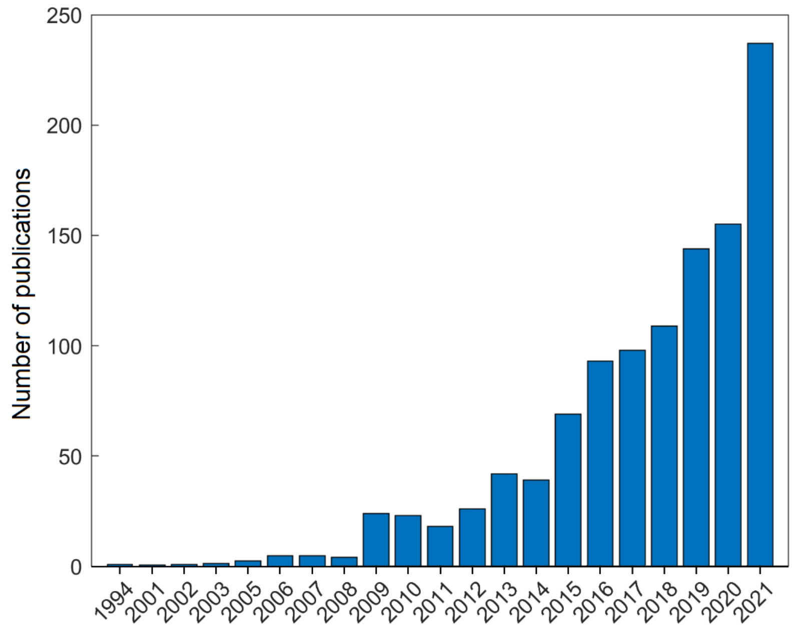

Figure 1. The overall trend for the number of publications in AI on bioenergy research.

Figure 2 highlights the progressive output of AI in bioenergy publications based on the top 10 most productive countries since 1991. The diagram also shows an ascending trend in released publications. Most of these countries have a large uprise from 2014 onwards, which occupies the dominant share of the global increase. Throughout the entire research period, the remaining countries provide minimal output, and some of those nations only have one publication. The diagram displays the productivity of Canada and Germany before 2005 as the leading countries in this field. However, after 2005, these countries seemed to have fallen behind their counterparts, with the US, Iran, China, and India emerging as crucial contributors to AI in bioenergy research.

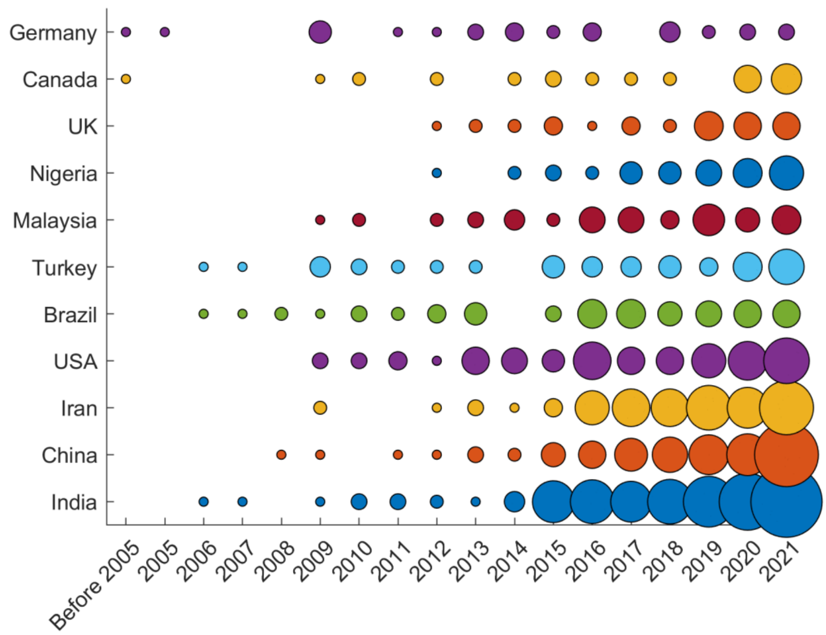

Figure 2. Graphical representation of the most productive countries in AI in bioenergy research from 1991–2021.

The moments of transition in the overall growth trend can be seen in the periods of 2014–15 and 2018–2019. There was a rise in machine learning activity in the period of 2014–2015, and the first global bioenergy statistics report was also released during this time. Because of their superior problem-solving abilities, technical firms have begun to focus more on machine learning techniques, for example, Google shelling out USD 600 million for the machine learning software DeepMind [23,24]. Another milestone in this area was the World Bioenergy Association (WBA) publishing its "Global Bioenergy statistics 2014 report" to address the dearth of consistent and credible bioenergy statistics at the time. The report states that many countries have not yet accessed data to meet the "potential, the production, conversion, and utilisation of biomass for energy" [25]. The development of AI in the bioenergy sector may be traced back to these historical events.

In 2018, this area witnessed a second explosion, as shown in Figure 2. Since this year, explosive growth has occurred in the UK, Nigeria, Malaysia, the US, Iran, China, and India. From 2015 to 2018, most countries showed either levelling off or decreasing trends, except for some developing countries: Malaysia, Brazil, and Iran. AlphaGo match in 2016 might be one reason for the boom in this area [26,27]. A program with a deep neural network defeated a human champion in the Go-game. This competition confirmed the potential and feasibility of AI in complex systems. Another reason for the boom was that many countries and regions issued plans and laws for carbon neutral and net zero emissions during this period [28–30]. Energy supply is a multi-scale complex system with technologies, management, and policy. The complexity of the object and the capacity for problem solving made AI an ideal solution for the complex system of bioenergy research.

Despite the global prosperity in this area, the developed and developing countries still perform some discrepancies in increasing trends. The United States maintains its position as the global leader in artificial intelligence (AI) because to its top-tier research institutes and industry-defining AI companies [31]. AI research covered 149 subject areas, of which computer science and engineering are the priority, while energy is ranked 10th; however, the top-ranked AI-related firms in the US primarily work on robotics research, and bioenergy is not their priority [31]. Therefore, although it is not the primary contributor to publishing numbers, as seen in Figure 2, the United States is still the most significant output country. Compared to other developed nations, the UK, Canada, and Germany maintained a constant output speed to keep up with the world rate in this area in previous decades. The probable reason for this issue was that these countries have multi-energy supply structures and advanced energy technology. Bioenergy is not the only way to handle sustainability and renewable energy sources [32].

The developing countries of India, China, and Iran are the top three publication contributors. Following the US, another four developing countries rank from 5 to 8. These countries share the characteristics of rapid economic growth, abundant bio-resources, and large populations. China and India, as emerging AI power countries, underwent rapid growth in AI innovation and mass employment in the AI sector [33]. Regarding research in AI, the Chinese global share of research papers has skyrocketed from 4.26% in 1997 to 27.68% in 2017, surpassing every other country worldwide [34]. The Chinese government issued the New Generation Artificial Intelligence Plan in 2017, which proposed the development of AI technology and applications until 2030 [35]. Moreover, China and India, the world's two most populated countries, account for more than a third of the entire world's people. During the global energy shift, multiplex energy was developed in response to the skyrocketing demand for power [36]. In particular, these countries' vast bio-resources pushed them to advance their respective sectors. Most of these countries reached agricultural self-sufficiency [37]. In addition, Brazil is the world leader in sugarcane production, and Malaysia is a major exporter of vegetable oil [38,39]. The need to supply a hungry populace resulted in a tremendous amount of waste in the farming and forest industries. When it comes to energy transition and resource utilisation, these developing countries have more pragmatic needs. Thus, developing countries were encouraged by digital progress and the energy shift to increase their use of artificial intelligence applications in renewable energy study.

3.2. Output of Publications

The bioenergy system is a complex network that involves crop cultivation, harvest, feedstock pre-treatment, energy conversion, transportation, and industrial or household usage [40]. Hence, bioenergy-related research comprises several aspects, such as feedstock production, process optimisation, use phase and post-treatment, and supply chain with impact assessment [8]. According to these subdivisions, the present work classified the searched publications into four categories for further analysis.

Figure 3 states the category ratios of using AI in bioenergy research for the top 5 countries worldwide. About 70% of publications in China, Iran, and Brazil focused on the post-treatment, usage phase, and conversion technologies. India reached as high as 80% in these categories. In contrast, the US gave only 20% in these areas, and their major contributions were feedstock production, supply chain, and relevant impact assessments. This observation revealed that there is still a significant gap between developing and developed nations. Their divergent views on energy demands and the international states probably explained this difference.

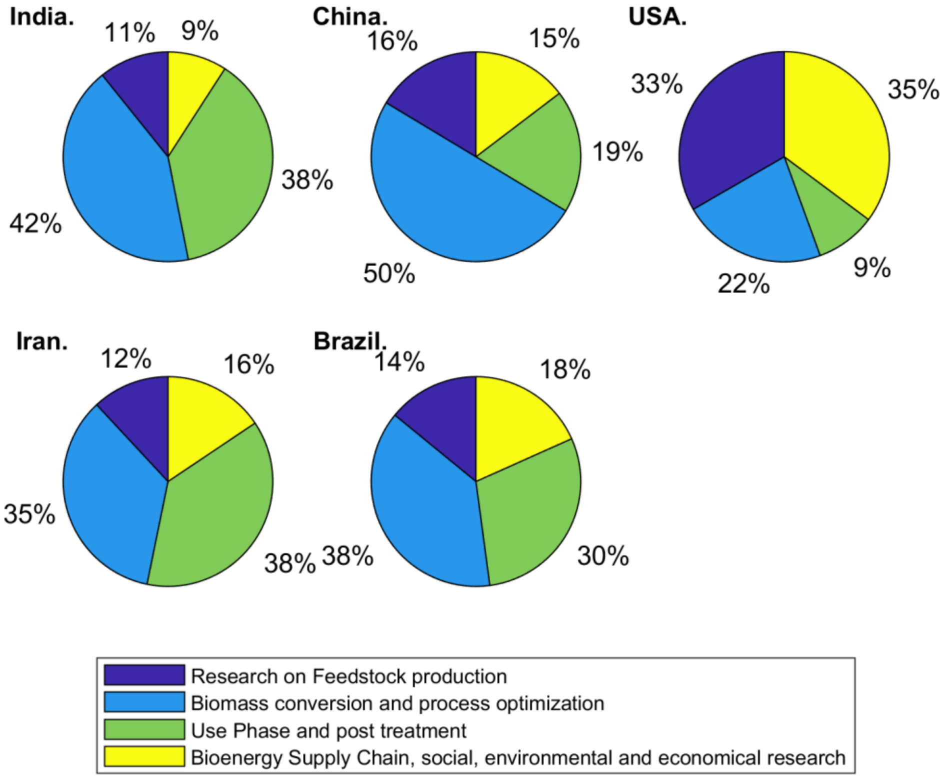

Figure 3. The category ratios of using AI in bioenergy research for the top 5 countries worldwide.

Because of their large populations and increasing concern for environmental stability, developing countries are working quickly to address pressing domestic problems [41,42]. Bioenergy products originate from various bio-resources, including woody biomass, agricultural residues, aquatic biomass, animal biomass, industrial biomass, and mixtures. However, the ash content, moisture content, chemical compositions, heating value, density, and particle size of each species varied widely and were neither stable nor predictable [43]. Therefore, developing domestic technology pathways using local crops or resources is essential for developing countries. With the help of AI, local biomass data could be a valuable resource for screening potential energy conversion technologies in a shorter amount of time [8].

International status is another factor that sets developed countries apart from developing ones. The United States and European countries, among other developed nations, play pivotal roles in driving global economic and scientific progress. As a result, they started thinking more broadly about technology viability and economic feasibility. So, 35% of all bioenergy supply chain, social, environmental, and economic research publications came from the United States. Research on feedstock production also received 33% of its funding from the United States. This demonstrates that, instead of focusing on solving local problems, they would instead focus on growing more efficient energy crops.

3.3. Authors and Institutional Analysis

3.3.1. Co-Authorship Analysis

Figure 4 shows the top 10 most successful authors in AI in bioenergy research for each decade since 1991. All researchers in the figure appear only once within the 30 years, except E. Betiku from Nigeria. E. Betiku has published the most, with 15 publications within the last 30 years, despite Nigeria not being in the top few productive countries in this area. Google Scholar shows that he has had 105 publications since 2005, and that number is growing. His research interests include biofuel development, bioprocessing, catalysis process modelling and optimisation, and process intensification. Another active researcher is M. Tabatabaei from Malaysia with 15 publications, who has been the most productive researcher since 2016. Google Scholar shows he has 371 publications in biofuels, biomass, climate change, sustainability, and food security. The total citations of his research are 18,966 and 16,922 since 2017. An Iranian author, M. Aghbashlo, with 244 articles in the fields of drying technology, biofuels, renewable energy, and energy analysis, is the second most active author. His total citations reached 12,128.

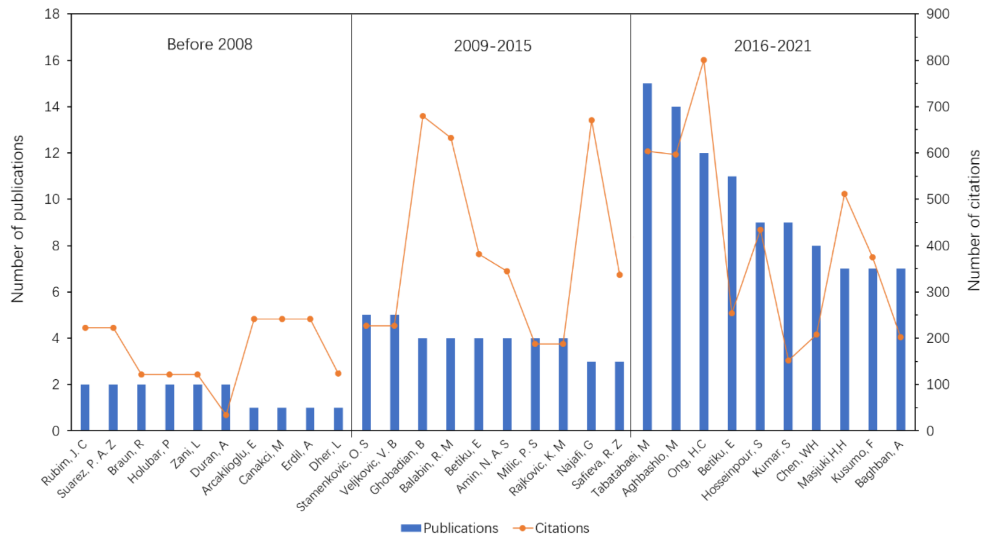

Figure 4. The most accomplished authors in relation to number of publications and citations in AI in bioenergy research between the years of 1991–2021.

Figure 5 details the co-authorship analysis of those who have published at least three publications before 2008, three publications in the period of 2009–2015, and eight publications in the period of 2016–2021, respectively. Each circle represents a different author, with the size denoting the number of publications and the colour referring to the cluster to which it belonged. The lines between these circles represent links, where thick lines mean a strong linkage between the two authors, and the distance between each circular node shows their relatedness. The authors from different places who have over eight publications, as shown in Figure 5, contributed the most to this field. However, these authors rarely collaborate with other authors from different regions, except those from Australia, Iran, and Malaysia. Figure 5c displays that those authors in the same regions are more likely to cooperate and work together. With easily accessed publications and information worldwide, it is unsurprising that there are minimal links between authors. The most prominent yellow circular node of Tabatabaei in Malaysia has 15 published papers. Despite having the most publications, Tabatabaei likes to collaborate with regional partners.

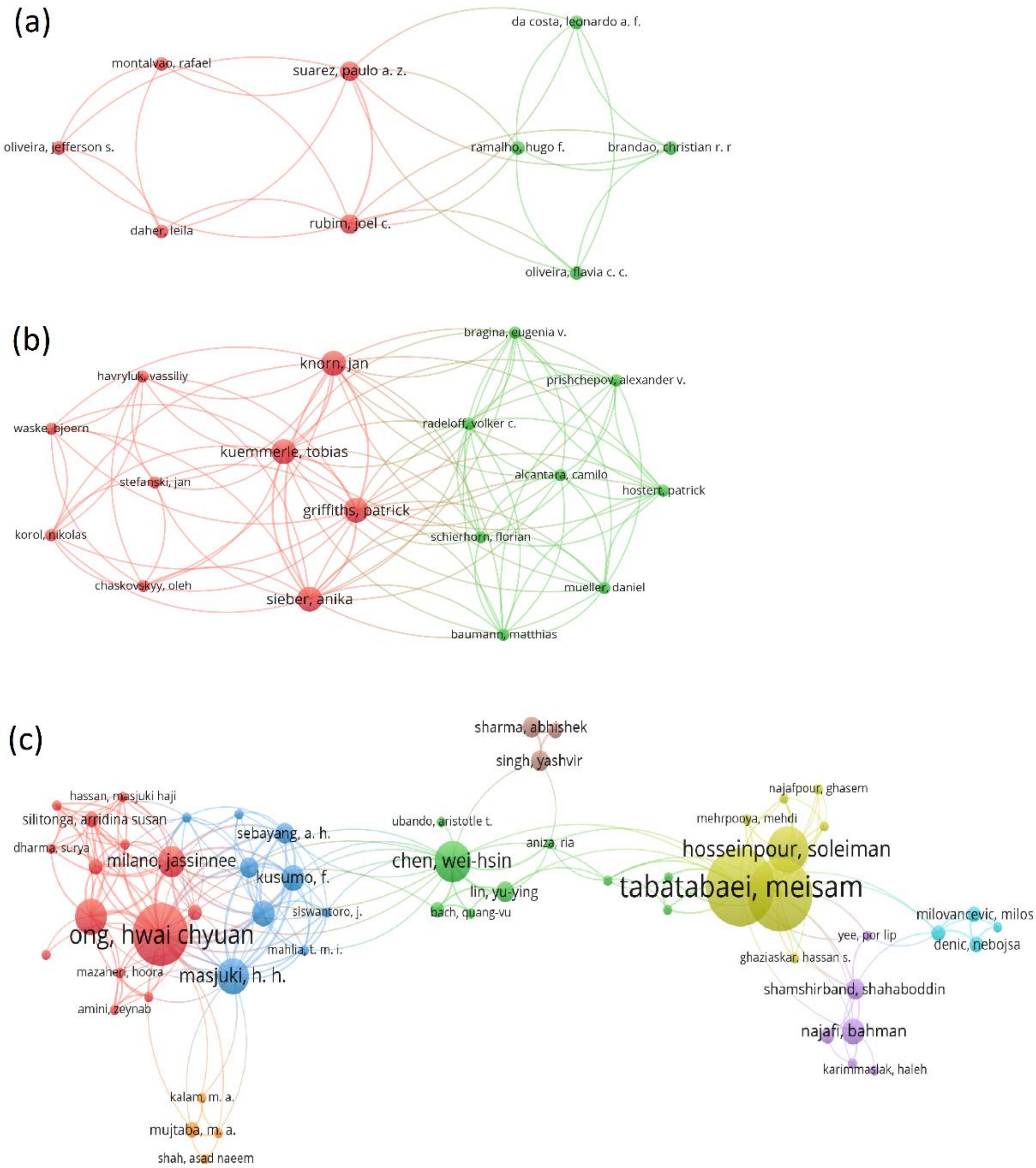

Figure 5. Co-authorship map of authors highlighting their contribution to AI in bioenergy research between the years before 2008 (**a**), 2009–2015 (**b**), and 2016–2021 (**c**). The maps in (**a**,**b**) had a minimum of 3 publications, and (**c**) had a minimum of 8 publications.

3.3.2. Institutional Analysis

Figure 6 presents the institutions with the most publications and citations for each decade since 1991. The first authors of the publications were used to identify the institutes in this analysis. In the first two decades, European and American institutions dominated this field. In the last ten years, however, western institutes have been replaced by Asian ones. Nine of the top ten institutes are from Asia. Among the top ten institutes since 2011, two institutes are from Iran, four are from China, and the rest are from India, Singapore, Malaysia, and Nigeria. The top two institutes are Iranian Universities, which are Islamic Azad University and the University of Tehran. Despite being a fossil-rich country with 9% of the world's oil reserves, the Iran government encourages using renewable resources, such as biomass from municipal waste, fruits, and other agricultural products [44]. In the late 2000s and early 2010s, the Iranian government put in place fuel diversification policies and development programme goals to reduce the amount of oil used [45]. Figure 6 evidenced that the University of Tehran is very influential in the AI in bioenergy by contributing to 1496 citations, over 500 more than the next most influential institute. Another notable observation is that India contributed the second most publications in this field, but only one institute is within the top 10. It implies that various institutions in India carried out relevant research rather than a few institutions carrying out a lot of research.

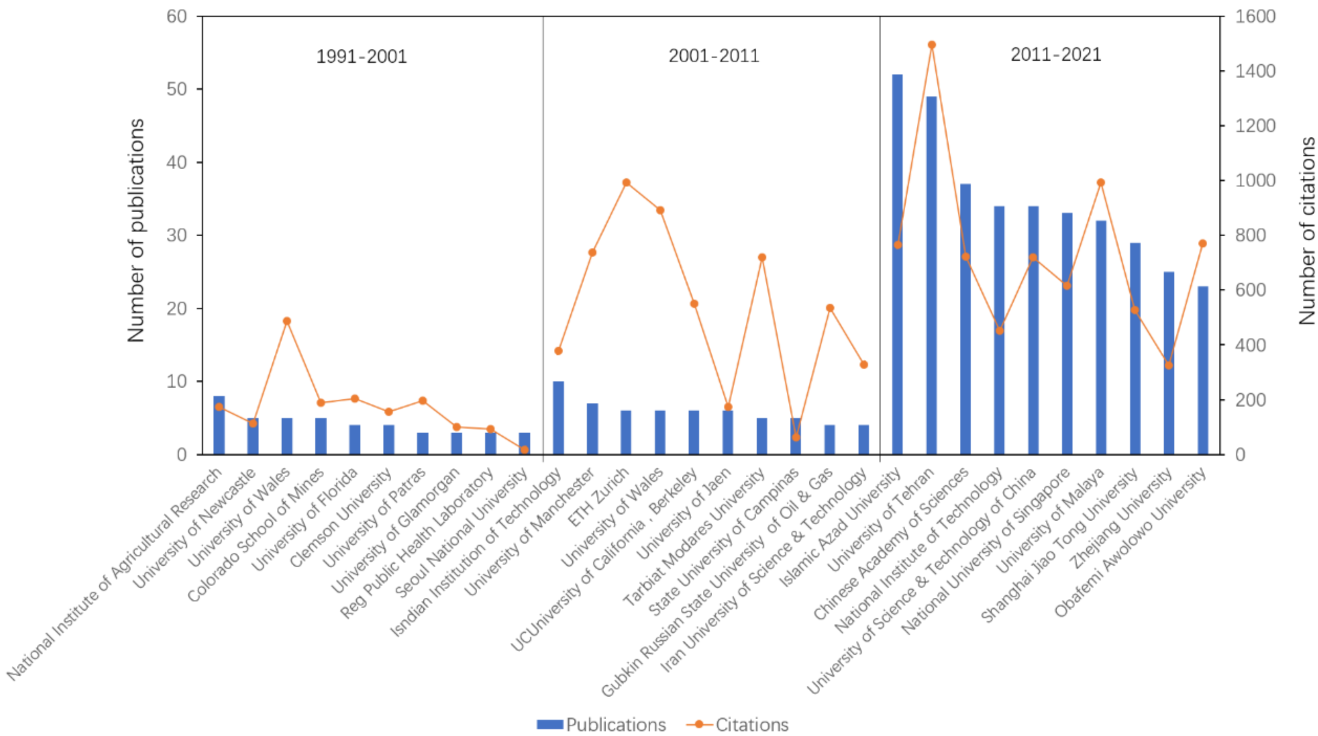

Figure 6. The most accomplished institutions in relation to the number of publications and citations in AI in bioenergy research between the years of 1991–2021.

Figure 7 displays a citation analysis for the institutes with a minimum of 20 citations to overcome the interference of low-citation publications. Each link is a connection between two institutes where one institute cites the other. Here, it has no distinction between a citation from one institute to another and the opposite direction. The mutual citations of the institutes achieve the sharing of information between each other. The most cited institutions of the Islamic Azad University and the University of Tehran show the most links, which might be because they published the most content. The strength of each link refers to the number of citations from one institute to another. Once again, the most notable links are between institutes within the same regions.

3.4. Journal Analysis

Figure 8 shows the top 10 journals with the most publications for each decade since 1991, with each journal displaying the number of publications published and citations. The ranking of the journals came from several factors: citation numbers, publication outputs, h-index, and impact factor. In the present work, the impact factor (IF) and the number of citations per publication determined the ranking/impact of a journal. Of the highest ranked journals, the maximum publication output occurred in the latest decade, with

701 publications, a 1360% increase from the middle decade. IF of a journal shows the importance by measuring the frequency of a journal citation in a particular time frame. Journals with more published articles will get higher IFs than journals with few publications. The high IF journals reflect the ability of the journals and editors to attract the best papers [46].

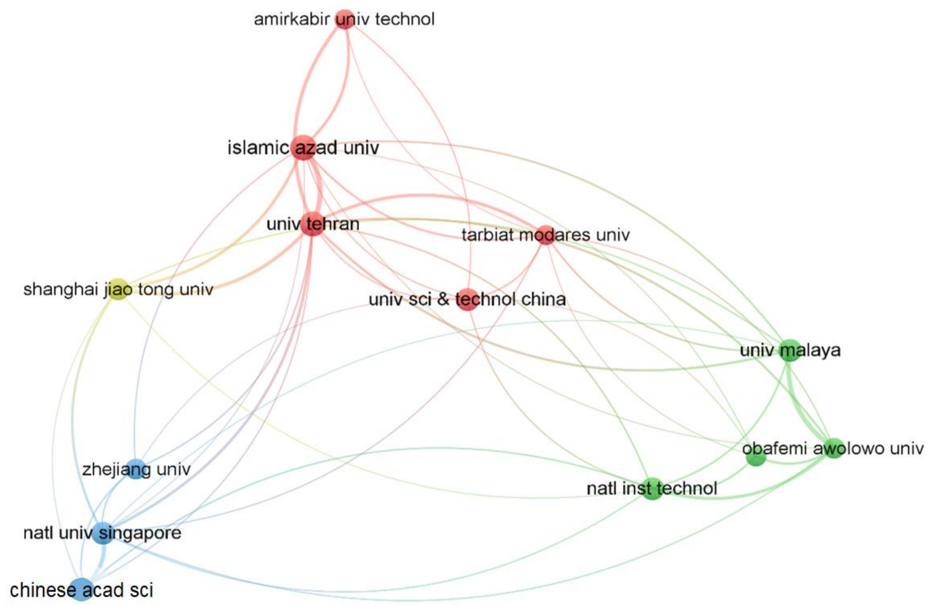

Figure 7. A citation map analysis based on the highest contributing institutions in AI in bioenergy research. Lines in between each institution represent an institution citing from another. The size of each node represents an institution's contribution to the research. The colours of the nodes represent the location of the institutions.

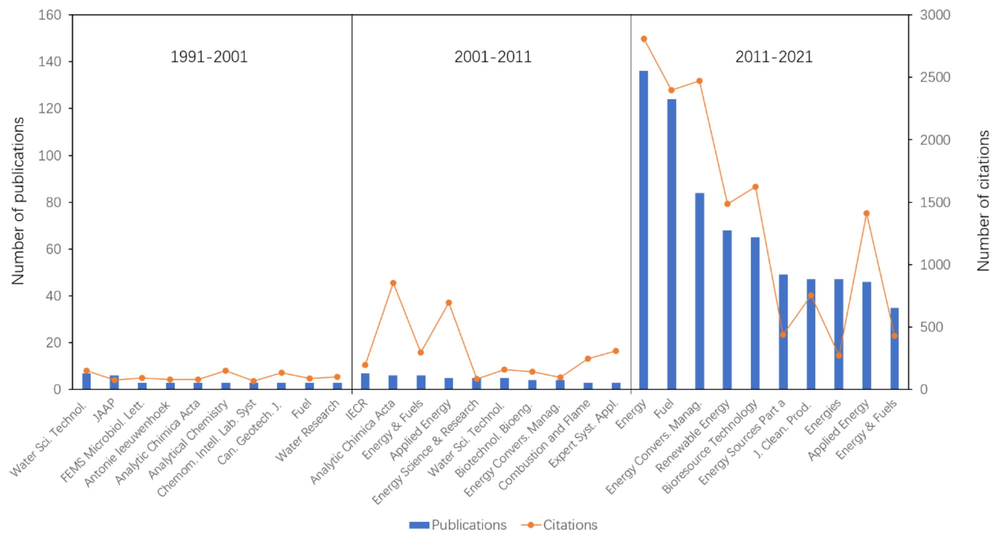

Figure 8. Journals with the most publications and citations in AI in bioenergy research for the last three decades.

As of now, the highest IF and citations are from energy-related journals: *Applied Energy* (9.746 and 30.7), *Bioresource Technology* (9.642 and 25), and *Energy Conversion and Management* (9.709 and 29.4). In contrast to the journals from the first decade, none of the highest-ranking journals were energy related. This observation shows the shift toward research in bioenergy over the last two decades and highlights the importance of research in sustainable energy. Another probable explanation for the rise is the global action to tackle climate change in the late 1990s. In 1997, the Kyoto protocol came to fruition, committing state parties to reducing the emissions of greenhouse gases below 5% in 41 countries [47]. Miyamoto investigated the effects of the Kyoto protocol on renewable energy technologies applications. He found that it led to increased patent applications in developed and developing economies [48]. Therefore, the promulgation of the policy should promote the vigorous development of relevant publishing media.

In Figure 9, the citation analysis of these journals is shown. Each of the journals shown has at least 17 publications. As the figure shows, every journal has a link with every other journal, whether the link is strong or weak. It probably states those authors are inattentive to the cited journals or publications but focus on the information inside. The figure shows that *Energy*, *Fuel*, and *Energy Conversion and Management* are all closely related. Energy is the most productive journal because it has the most visible node, which means it has published the most articles.

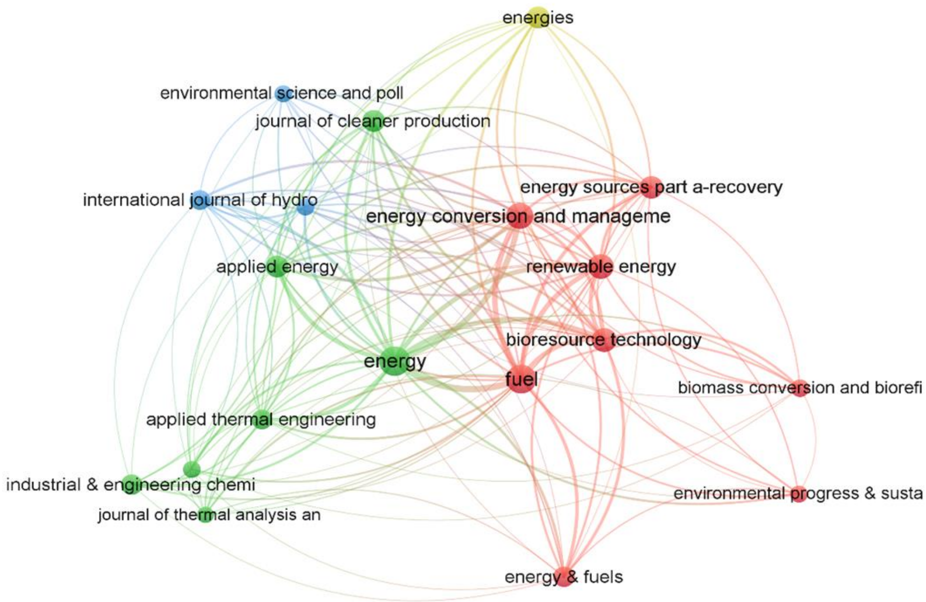

Figure 9. Citation map analysis displaying the collaboration between journals publishing AI in bioenergy research. The size of each node represents the number of publications published. The lines in between each node represent one journal citing from another.

3.5. Keyword Analysis

Figure 10 shows how the keywords used in AI research on bioenergy have changed over the last 30 years. Unlike the institution and journal, the keywords underwent an enormous revolution during the publication eruption. Figure 10, therefore, separated each decade into two sets of five years to clearly show the tendency of keywords. In the statistics, the top keyword for the artificial neural network (ANN) has stayed the same, while the other keywords change places at the top. Most research on AI applications in the bioenergy sector is based on predictions. This includes the properties of biomass, the properties of biofuel, and the performance of the process of converting biomass. AI and statistical techniques also use the terms expert system, pattern recognition, genetic algorithm (GA), and response surface methodology (RSM). Additionally, the number of AI keywords has changed a lot from the first decade to the second, with only ANN and modelling still in high demand. The total number of people in the sample is 42.7 times higher than in the first five years, and the number of people in the sample for the last five years is much bigger. It is most likely that researchers still use terms from the 1990s, though maybe not as often as they did 20 years ago. As bioenergy research grew, many researchers concentrated on improving traditional models of biomass conversion and overcoming usual computing techniques for supply chain and optimisation. AI systems, such as GA and RSM, took over expert systems and pattern recognition. GA is a type of search-based heuristic model that can solve difficult optimisation problems. Like ANN, RSM is a high-accuracy AI model for making predictions [49].

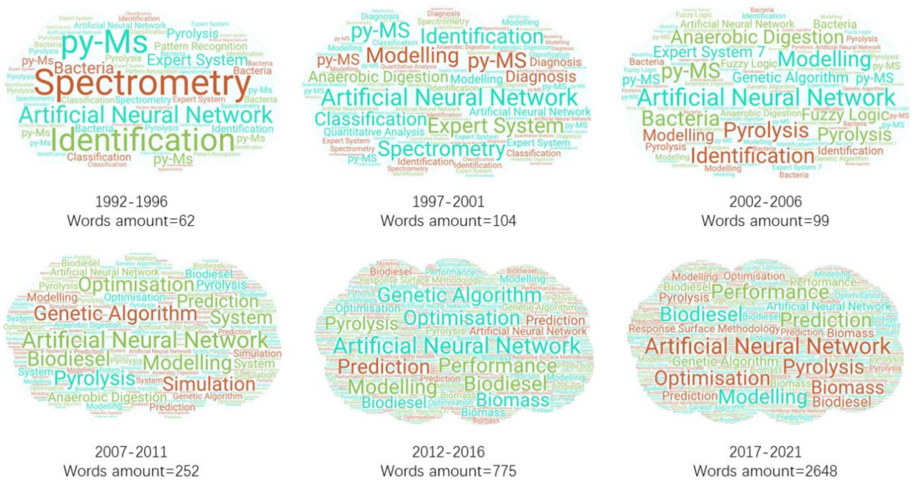

Figure 10. The occurrence frequency of the most used keywords in AI in bioenergy research from 1992 to 2021 for every five years.

Figure 11 displays an AI keyword analysis, showing varying occurrences in bioenergy papers between 2012 and 2021. The size of the circle represents the number of times the word has occurred. As seen in the figure, ANN is the most frequently occurring keyword of AI technology. The rest of the AI technologies have all had varying mentions, but there has been an increase in their involvement in bioenergy research publications. According to the AI categories sorting method from the previous study [8], 53% of the presently searched articles in the 30 years used machine learning methods, with heuristics placing second with 24%. Symbolic AI methods covered 8% of the total research. However, the ratio of adopting symbolic AI was over 50% from 1991 to 2001. The rest of the 15% of the publications are hybrid and others. These observations imply the shift towards machine learning methods over the last 30 years. It could reach 75% if moving at the same rate in the next 20 years.

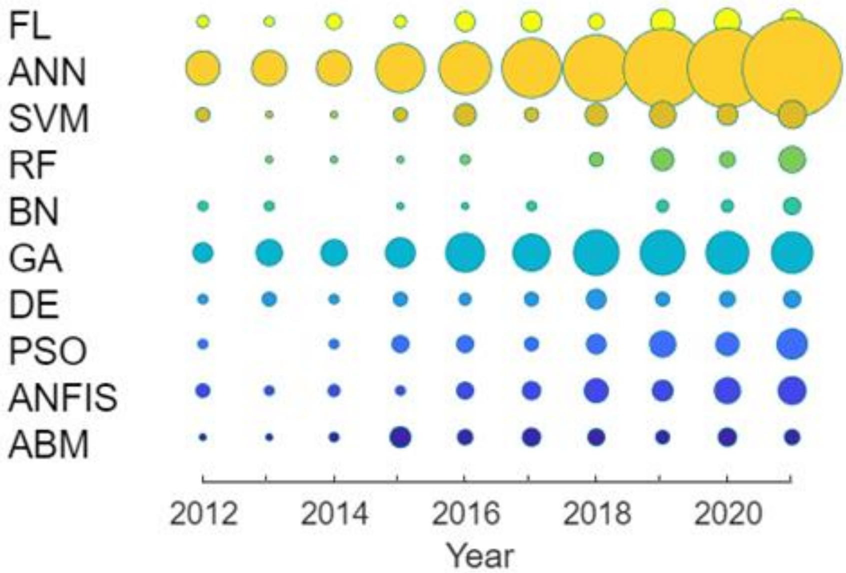

Figure 11. A graph showing the varying use of AI keywords in bioenergy research from 2012 to 2021. FL: fuzzy logic; ANN: artificial neural network, SVM: support vector machine, RF: random forest, BN: Bayesian network, GA: genetic algorithm, DE: differential evolution, PSO: particle swarm optimisation, ANFIS: adaptive neuro-fuzzy inference system and ABM: agent-based model.

4. Conclusions

The present study investigated the AI technologies in bioenergy literature across 30 years through bibliometric analysis by concentrating on the research trends and the development of AI technologies. This work reveals the constant growth of this area in the upcoming years and concludes the following.

1. AI technologies in bioenergy research experienced an outbreak over the past ten years. India was the most productive country in this field, followed by China, Iran, and the US. AI technological breakthroughs and relevant policies promoted related research.

2. The research topic shows several distinctions between developed and developing countries. Developed countries initially dominated the field, and developing countries have begun to advance in the field. The former favour research on feedstock production, the supply chain, and impact evaluation, whereas the latter prefer phase treatment and process optimisation.

3. Co-authorship and institutes analysis showed minimal collaboration between authors and institutes in distant locations in this area. The two Iranian institutes contributed the most towards AI in bioenergy research by co-publishing. Meanwhile, the journal analysis shows strong links between *Energy*, *Fuel*, and *Energy Conversion and Management*. Authors concern more about the information inside than the cited journals or publications carriers.

4. Keywords analysis reflected the explosive growth of AI in bioenergy research. Machine learning dominates as the most used AI technology in bioenergy research, with 53% of papers adopting it, and ANN was the most frequent keyword in the publications.

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Conflicts of Interest: The authors declare no conflict of interest.

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