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Review article

A bibliometric analysis of machine learning techniques in photovoltaic cells and solar energy (2014–2022)

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ABSTRACT

Solar energy presents a promising solution to replace fossil-based energy sources, mitigating global warming and climate change. However, solar energy faces socio-economic, environmental, and technical challenges. Computational tools like machine learning offer solutions to these technical challenges. Despite numerous studies, there's a lack of comprehensive research on ML applications in Photovoltaics and Solar Energy. This study conducts a critical analysis of ML applications in Photovoltaics and Solar Energy research using publication trends and bibliometric analysis, employing the PRISMA approach on Scopus database. Results reveal a high publication output, citations, and international collaboration. Notable researchers include G. E. Georghiou and Haibo Ma, with the Ministry of Education (China) being a prolific affiliation. China emerges as the most active nation due to funding programs like the National Natural Science Foundation and the National Key Research and Development Program. This research contributes in terms of providing an analysis of publication patterns from 2014 to 2022, including topic categories and important metrics, at the levels of country, institution, and funding organisation. Analysing author-keyword data to aggregate publishing themes and identify the most influential journals. Enhancing comprehension of hotspots and focal points in machine learning applications in Photovoltaics and Solar Energy research. This research also aims to discuss the role of Cognitive Computing in cancer/tumor and oncological research, emphasising the potential for significant advancements and the obstacles that need to be overcome in order to fully utilise its advantages. Future studies on the topic could include extensive research into the cybersecurity of Photovoltaics and solar energy systems particularly in the wake of numerous malware, phishing, and other intrusion attacks on the energy and grid infrastructure worldwide.

1. Introduction

The convergence of technology and environmental responsibility is becoming increasingly important at a time when there is a growing urgency to curb or mitigate climate change and global warming (Rai, 2013). According to analysts, the paradigm shift from environmentally polluting and rapidly depleting sources of fossil-based energy to sustainable energy sources has become imperative (Johari, 2015). One such example is the sun's radiant energy otherwise termed solar energy. It is an abundant, clean, and sustainable source of energy (Hosseini and Wahid, 2020), which has the potential to significantly alter the global energy mix (Pfeifer, 2019). As a result, solar energy has become a glimmer of hope, particularly against the backdrop of issues associated with global warming and climate change intensifying worldwide (Masson, 2014). The unending supply of solar energy combined with technological advancements has sparked a global energy revolution. At the centre of this transition are solar panels, which are made up of photovoltaic cells and convert sunlight into electricity with ever-increasing efficiency (Toothman and Aldous, 2000).

However promising, solar energy still faces numerous technical, socio-economic, and environmental challenges before widespread adoption. For example, it has technical problems such as intermittency, variability, and energy storage requirements, as well as socioeconomic challenges such as high initial expenses, conflicts with land use, restrictions on efficiency, aesthetic issues, shortage of materials, and complexity of grid integration (Mlilo et al., 2021; Chanchangi, 2023). In addition, its adoption is also impacted by political, legal, and public awareness concerns (Sovacool and Ratan, 2012; Gullberg and Hovi, 2016). Hence, the widespread use of solar energy as a sustainable, clean, and renewable power source requires the resolution of these issues. To overcome these challenges and accelerate the global adoption of solar energy, ongoing research and innovation are important in this regard.

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One approach is the use of computational tools such as machine learning (ML). Many analysts posit that ML could be an essential partner in not only addressing fossil to clean energy transition but also addressing the technical challenges of solar energy. Machine learning is a branch of artificial intelligence (AI) (Stafford, 2020), which is growing at a rate never seen before. It is becoming acknowledged as a tool that can change many fields including energy, energy economics, and renewables (Entezari, 2023; Ghoddusi et al., 2019). The use of ML techniques has become a potent accelerator for innovation and optimization in the field of solar energy research (Jebli, 2021). ML can identify patterns in large datasets and generate predictions based on data (Zhou, 2017). It presents a seductive possibility of refining and improving processes (Liu, 2017). In photovoltaics, ML has opened up new possibilities from forecasting solar irradiance to optimizing solar panel layout (Li, 2016).

Over the years, numerous studies have been published on the application of machine learning in photovoltaics and solar energy systems (MLPVSE) worldwide. However, there is currently no comprehensive study that examines the landscape of this research field. The various academic, industrial, and policymaking stakeholders interested in MLPVSE may lack clarity regarding the status of development at the moment, particularly about the notable studies, researchers, affiliations, nations, publishers, and funding organisations. Therefore, this paper provides a deep dive into the critical intersection of ML and photovoltaic cells in the context of solar energy research, covering eight years of research and development from 2014 to 2022. Our exploration of this terrain reveals a bibliometric study that measures clarifies and breaks down the patterns and influence of these transdisciplinary domains. Bibliometrics is a popular instrument used to statistically evaluate the research output and trends on any given topic (Donthu, 2021). In this instance, we examine the extensive body of literature, collaborative networks, and information dissemination in the field of machine learning as it relates to solar energy and photovoltaic cell development. Given the recent advancements in photovoltaic cells and solar energy, several articles have emerged, making it imperative to provide a concise overview of the present research. Bibliometric analysis is a method that examines the relevant literature to track the development of a subject or journal across time. This work seeks to conduct a comprehensive bibliometric analysis of MLPVSE publications from 2014 to 2022 in order to gain a deeper understanding of the evolution of MLPVSE research and to visually represent the research themes and trends. An analysis is conducted on the attributes of publications, with a focus on identifying hotspots, research trends, and future research directions. The primary focus of this study encompasses the following facets:

(1) This analysis examines the essential features of publications, such as the distribution of publication types, popular study topics, annual publishing and citation rates, prolific countries/regions, and the most highly referenced articles.
(2) The analysis of institution distribution is conducted by examining citations and collaborative networks to identify the most influential and cooperative institutions.
(3) Authors' distribution is examined by creating citation and collaboration networks.
(4) Co-occurrence analysis is conducted to examine the relationship between network visualisation and overlay visualisation of keywords in order to gain insights into the hotspots and research trends in the MLPVSE research field. Additionally, an analysis is undertaken to identify the funding bodies involved in this research area.

2. Literature review

The review of literature on MLPVSE was based on the keywords deduced during cluster analysis. Hence, it can be resolved that MLPVSE research is characterised by three hotspots or thematic areas of research namely;

(i) Solar Innovation Integration,
(ii) Predictive Solar Analytics,
(iii) Solar Tech Synergy.

(i) **Solar Innovation Integration (SII)**

Cluster 1 consists of the keywords photovoltaics, machine learning, solar cells, organic solar cells, perovskite, and power conversion technologies which denote the Solar Innovation Integration or SII. The concept connotes the application of cutting-edge techniques and sustainable technologies to the solar energy industry. It proposes the use of cutting-edge methods like ML learning algorithms in the design, operation, and optimization of solar cell and photovoltaic systems (Ajibade, 2021; Chweya et al., 2023). The goal is to increase the competitiveness and accessibility of solar energy, while also improving its efficiency, dependability, and performance. It also highlights how ML, cutting-edge methods and solar technology may work together to improve the efficiency and sustainability of solar energy systems. The ideas of SII have gained traction over the years with numerous studies carried out to examine the use of ML in PVSE. Other studies have sought to draw attention to the wide range of uses of machine learning in the solar and photovoltaic industries. For example, ML has been used to forecast the characteristics of photovoltaic materials and improve solar cell efficiency (Weston and Stampfl, 2018). ML has been successfully used to categorize city-scale roof forms for solar energy applications (Mohajeri, 2018). It has also been critical to improving the effectiveness of organic photovoltaic materials (Sun, 2019; Kranthiraja and Saeki, 2021), and hastening the discovery of high-performance solar cell components (Wu, 2020). Furthermore, ML has been utilised to enhance the stability and bandgap predictions of lead-free perovskites (Stanley et al., 2020; Im, 2019; Ajibade et al., 2019). These publications demonstrate the increasing interest in using ML to drive efficiency and innovation in the field of solar energy, as well as the versatility of this technology in improving renewable energy research, from materials discovery to system integration.

(ii) **Predictive Solar Analytics (PSA)**

Cluster 2 comprises the keywords forecasting, machine learning models, photovoltaic power, solar energy, solar power generation, and mean square error which is described as "Predictive Solar Analytics" or PSA. This concept describes how different aspects of solar energy output and performance are forecasted and predicted using data analytics, which frequently includes machine learning and statistical modelling. Predictions about solar irradiance, energy production, system efficiency, and other topics can fall under this cluster. PSA can help optimize the operation of photovoltaic systems and solar power generation by evaluating historical data and real-time information. This allows for the provision of forecasts and insights. The reliability and economic viability of solar energy solutions will eventually be improved by this technology's improvements to energy output, grid integration, and maintenance scheduling. Over the years, the research landscape has seen extensive studies on the use of ML to forecast and or predict solar energy and photovoltaic performance using data analytics. These investigations cover diverse aspects, showcasing the wide-ranging influence of machine learning on this field. ML techniques have been applied to promote the forecasting of solar irradiance, which is critical to optimizing photovoltaic systems operations (Li, 2016; Li, 2016). These studies showed that ML techniques not only improve forecasting energy generation but also assist efficient integration of solar power into the grid systems (Su et al., 2019; Markovics and Mayer, 2022). Another prominent application of ML is the design of experiments and optimization of materials and devices, such as organic photovoltaics (Cao, 2018; Li, 2019), which also improves performance and efficiency. Other researchers have made efforts to utilise ML and enhanced descriptors to accurately predict the organic solar cells' efficiency (Sahu, 2018; Zhao, 2020), which helps in the selection of materials and making design decisions. ML has also been used in the synthesis of efficient solar cells such as Mn^{2+}-doped kesterite and Cu^2(Mn, Zn)Sn (S, Se)$_4$ cells, which are achieved through ML-aided processes (Li, 2018). The prediction of the power output of photovoltaic systems can be estimated using ML (Ağbulut, 2020; Zazoum, 2022). According to the studies, ML models can be applied to enhance energy planning and system design (Theocharides, 2018). Beyond these applications, ML helps operators and utility companies detect faults in photovoltaic systems, which could greatly help in improving reliability and maintenance (Fazai, 2019; Kurukuru, 2019; Hajji, 2021). Furthermore, it reveals correlations between molecular properties and device parameters in organic solar cells, aiding material design (Sahu, 2019). The findings also emphasize the value of ML in power forecasting, capacitor planning and radiation estimation, which could enhance overall system performance and energy management.

(iii) **Solar Tech Synergy (STS)**

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Cluster 3 consists of the keywords photovoltaic systems, photovoltaic cells, support vector machines, learning systems, and learning algorithms, which describe the concept of Solar Tech Synergy (STS). The concept of STS captures the idea of combining several elements such as learning systems, learning algorithms, support vector machines (SVM), and photovoltaic cells for application in the field of solar technology. The long-term goal is to integrate, improve, and foster cooperation between state-of-the-art technologies to improve efficiency and effectiveness in forecasting, system optimization, and the production of solar energy. Furthermore, the concept of STS aims to demonstrate the many ways that ML models, SVM, and learning systems are being used to advance solar energy and photovoltaics. Over the years, several studies have been conducted to demonstrate and highlight the use of such learning systems in energy production and prediction. For example, the study by Li, Mahbobur Rahman (Li, 2016), (Rabbi, 2022) demonstrated that hierarchical models can be developed along with other training approaches to enhance the dependability of predictions. Other studies have explored the synergy between ML and other fields such as materials science for optimizing concentrating on solar cell materials (Dolara, 2018; Dadhich, 2023). Likewise, Li, Pradhan (Li, 2019), (Vaidya, 2023) showed that ML has the potential to enhance the design and development of high-performing perovskite solar cells, whilst also discovering hopeful molecules for organic-based solar cells. As a result, the development of highly efficient solar cell materials that can reform the renewable energy landscape can be accelerated (Sahu, 2019; Choudhary, 2019). Furthermore, the use of ML for measuring and charting daily solar radiation and photovoltaic electricity across the world has been explored by Feng, Hao (Feng, 2020), (Jayeola, 2022). The findings showed that such models could potentially improve photovoltaic power generation worldwide and enhance comprehension of the dispersion of solar energy. The synergies between ML and nanotechnology have also been examined in the literature. Cao, Kamrani (Cao, 2022), (Ajibade and Zaidi, 2023) developed and demonstrated the potential for utilising an ML-based evolutionary algorithm for cooling nanofluids with the view to optimizing the electrical efficiency of photovoltaic/thermal collectors. The findings revealed that simulation and optimization using evolutionary algorithms help create energy systems that are more sustainable and efficient. All things considered, the studies on STS highlight the revolutionary potential of ML in the solar energy and photovoltaics industry (Ajibade et al., 2020). ML is an essential tool for optimizing materials, enhancing efficiency, mapping radiation, predicting, and other areas to advance and improve renewable energy systems (Ojeniyi, 2022).

2.1. Some existing technical challenges in the field of solar energy and possible solutions

Even though there have been great strides in solar energy, there are still a number of technological obstacles. All of these things make it harder for solar power to be used efficiently and by more people. We should investigate these problems and discuss groundbreaking remedies to fix them. Firstly, solar energy generation exhibits intrinsic intermittency and variability because of the daily and monthly fluctuations in the availability of sunshine. The irregularity of solar power can put pressure on the stability and dependability of the electrical grid, especially when solar power makes up a substantial percentage of the energy combination (Modu, 2023). An effective approach to tackle the issue of intermittency involves the use of sophisticated energy forecasting models. These models employ weather data, historical patterns, and predictive analytics to effectively predict solar irradiation. system operators can enhance their management of solar energy integration into the system and minimise the effects of intermittency by accurately predicting changes in solar power generation (Notton, 2018).

Secondly, conventional silicon-based solar cells have a low energy conversion efficiency, as they typically convert just 15–20% of sunlight into electricity. The limited efficiency of solar panels hampers their energy production and necessitates larger installation areas, resulting in increased prices (Ajibade et al., 2021). To tackle this, tandem solar cells present an innovative approach to augment energy conversion efficiency. These cells integrate various semiconductor materials with complimentary absorption spectra to efficiently capture a wider spectrum of sunshine wavelengths. Perovskite-silicon tandem solar cells have exhibited efficiency more than 25%, beyond the limitations of conventional silicon cells. Researchers want to get greater efficiency and reduced costs by utilising tandem cell topologies and sophisticated materials (Ajibade, 2023). Thirdly, SE has intrinsic intermittency, producing electricity solely during periods of sunlight. In the absence of efficient energy storage systems, surplus energy generated during peak sunshine hours is frequently squandered, and the provision of dependable electricity during periods of minimal or no sunlight is hampered (Boito and Grena, 2023). A promising solution for overcoming the intermittent nature of solar energy include next-generation energy storage technologies including flow batteries, solid-state batteries, and improved pumped hydro storage. These technologies provide a high level of energy density, quick response times, and extended cycle lifetimes, allowing for efficient storage and retrieval of electricity supplied by solar power (Poulose et al., 2022). In addition, the incorporation of energy storage devices into solar installations can improve the stability of the power grid, facilitate the reduction of peak energy demand, and enable the use of solar power in locations that are not connected to the main electricity grid.

Furthermore, the integration of solar energy into established electrical grids poses issues pertaining to voltage regulation, frequency management, and grid stability. The volatility in solar generation can result in voltage variations and grid imbalances, which can affect the dependability of the power supply (Shafiullah et al., 2022). An innovative solution is utilizing advanced power electronics and grid management technologies which are essential for addressing grid integration difficulties. Incorporating grid-support features like voltage regulation and reactive power control, intelligent inverters facilitate the smooth integration of solar energy into the power system. In addition, virtual power plant (VPP) systems combine distributed solar installations and energy storage assets to offer grid functions including frequency management and demand response. By utilising these technologies, grid operators can improve grid stability and optimise the utilisation of solar resources (Ahmed, 2020).

The availability and sustainability of materials play a crucial role in the extensive implementation of solar energy technologies, as they depend on the presence of essential elements like silicon, cadmium, and tellurium. The limited availability of solar electricity, along with worries about its environmental impact and vulnerabilities in the supply chain, presents hurdles to its scalability and sustainability (Yu and He, 2020). To tackle this, thin-film solar technologies provide a more environmentally friendly option compared to traditional silicon-based solar cells. Thin-film technologies employ semiconductor layers that are thinner than conventional methods, and they also utilise alternative materials such as cadmium telluride (CdTe), copper indium gallium selenide (CIGS), and perovskites. These materials necessitate a reduced amount of resources, possess decreased manufacturing expenses, and provide enhanced adaptability in deployment. Moreover, progress in recycling and circular economy strategies can reduce material waste and optimise resource efficiency across the whole life cycle of solar energy (Adetokun and Muriithi, 2021).

By effectively tackling these technical obstacles through inventive remedies, the solar energy sector may expedite its shift towards a more environmentally friendly and robust energy future. Effective cooperation between academics, industry stakeholders, and policymakers is crucial to stimulate technological advancement, overcome obstacles to implementation, and fully use the capabilities of solar power.

3. Data source and bibliometric methodology

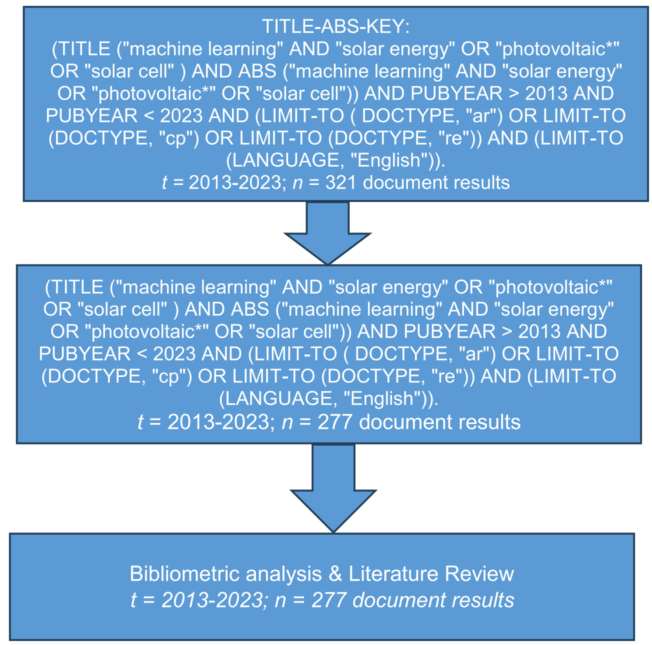


Fig. 1. PRISMA flowchart methodology for analysing MLPVSE research landscape.

Web of Science (WoS) and Scopus are the most extensive integrated academic information resources worldwide, offering comprehensive scholarly information across a wide range of fields (Zhang et al., 2023; Ajibade, 2023). However, in the paper the data source is Scopus. We chose the Scopus database for the following reasons (Singh, 2021): Scopus offers a more extensive selection of indicators for assessing the impact of research compared to the Web of Science. Scopus offers a greater range of collaboration capabilities compared to Web of Science, including author profiles and a collaboration network. Scopus contains a greater amount of open-access material compared to Web of Science (Ajibade, 2022).

Bibliometric analysis is effective for evaluating the merits of a given discipline (Yu, 2021; Ajibade and Ojeniyi, 2022). Hence, In this paper, the research landscape on the application of machine learning algorithms in photovoltaic cells and solar energy research was mapped using bibliometric analysis and a methodical review of the literature. To accomplish these objectives, the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach was selected as shown in Fig. 1. The technique is widely used to detect, choose, and analyse published documents on various topics in the literature (Armenise, 2021; Zaidi, 2023). This study aims to identify, select, and evaluate all the related publications on the application of machine learning algorithms in photovoltaic cells and solar energy (hereafter abbreviated as MLPVSE) research currently deposited in the Elsevier Scopus database between 2014 and 2022. The time range selected for enabling repetition spans from 2014 to 2022. In addition, the crucial aspect of scientometric analysis is the quality of literature data (Yu and Hong, 2022). Therefore, this study necessitates the filtration of documents(Ajibade, 2023).

The methodology adopted for mapping the research landscape on MLPVSE research is a three-stage process outlined as follows. The first stage involved identifying related publications on MLPVSE research in the Scopus database. To this end, a suitable search string comprising the major keywords related to the topic was developed and executed in the Scopus database on the 25th of October 2023. The executed search string was as follows: (TITLE ("machine learning" AND "solar energy" OR "photovoltaic*" OR "solar cell") AND ABS ("machine learning" AND "solar energy" OR "photovoltaic*" OR "solar cell")) AND PUBYEAR > 2013 AND PUBYEAR < 2023 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "re")) AND (LIMIT-TO (LANGUAGE, "English")). The search recovered a total of 321 documents comprising various document types, source types, and languages published and indexed in the Scopus database from 2013 to 2023.

The second stage involved analysis of the 277 publications resulting from the identification stage followed by analysis of the publication trends and bibliometric analysis. This analysis provides insights into the growth patterns of the published documents on the topic based on the total publications, source titles, highly cited publications, source titles, and thematic or subject areas. Bibliometric analysis is a quantitative and statistical technique typically employed to assess and examine many facets of scientific literature such as academic publications (Donthu, 2021; Ajibade, 2023). The goal of BA is to gain further insights into the research trends, academic impact, and collaborative networks among academics, scientists, and other stakeholders in the research landscape (Otitolaiye, 2022). BA was used in this study to map the collaboration networks among researchers and nations to examine the effects on research productivity, scientific growth, and technological development of MLPVSE. Lastly, it was used to identify the current research hotspots and thematic focus areas currently explored by researchers in the field.

The third and final stage involved the methodical review of literature, as well as the identification of research gaps, and future research areas on the topic based on the keywords occurrence analysis. Science mapping is a crucial method in the field of bibliometrics. The objective is to demonstrate the structure and development of the scientific research field (Cobo, 2011; Yu, 2018). Currently, there are numerous software programmes available for conducting science mapping analysis (Yu et al., 2018). The primary tool utilised in this work is VosViewer, which proves to be highly efficient in the field of information visualisation. The bibliometric software VOSviewer (version 1.6.18) widely used for mapping and visualising research landscapes was used for bibliometric analysis in this study due to its user-friendly interface, robust clustering abilities, dynamic visualizations, open access, data source integration, co-authoring network analysis, keyword mapping, customization choices, and frequent updates.

4. Results & discussion

4.1. General publication trends

Fig. 2 shows the growth trend for publications on MLPVSE research from 2014 to 2022. As observed, the number of total publications (TP) on the topic shows an incremental trend from 2 to 111, which indicates a 5450% increase over the period examined. Likewise, the number of total citations (TC) ranged from 3 to 1474 showing a 49,033.33% increase over the same timeframe.

Overall, the publications analysis shows that a total of 277 documents have been published on the topic garnering over 5926 citations, which have resulted in an *h*-index of 41. The outlined metrics indicate that the research landscape on MLPVSE is characterized by high rates of publication and citation. This observation indicates that MLPVSE research is highly impactful with the potential for even higher output in the near future. This findings is related and supported by the work of (Mishra & Singh) (Mishra and Singh, 2023) and Hassan et al. (Hassan, 2024), in which they also observed high publication growth in the machine learning and solar energy research.

4.2. Document types and subject areas

The analysis of the document types for MLPVSE research was carried out to examine the preferred medium of knowledge dissemination among the researchers in the field. The document types indicate the medium the researchers in the topic prefer to publish their findings and can determine the rate of growth and development of the field of research. Fig. 3 shows the sectoral distribution of document types in MLPVSE research. As observed, researchers have published articles, conference papers, and reviews that account for 183, 82, and 12 publications out of the 277 total publications on the topic, respectively.

The data indicates that researchers prefer articles to conferences and reviews for dissemination of their findings on MLPVSE. The reason for this observation may be due to numerous factors. In general, articles shall provide an enhanced peer review process which not only guarantees the quality of research but also increases the chances of receiving more citations which are readily available for long periods (Stremersch et al., 2007). Furthermore, journals facilitate interdisciplinary research, cater for wider audiences, and provide flexible publication schedules (Porter et al., 2008). In addition, the advancement of academic careers is positively affected by prestigious journals (Paulus, 2015). The publication of journals may also be a priority for funding agencies (Schmidt). However, selected professional disciplines such as mathematics, physics,

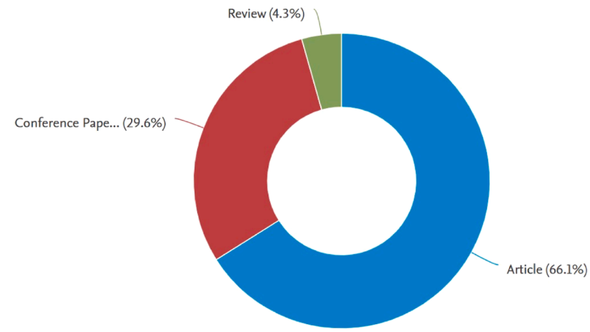


Fig. 3. Distribution of document types on MLPVSE research.

and electrical engineering value conference papers (Zdravkovic et al., 2016), which indicates preferences may also vary according to the field of research or study.

On the other hand, the analysis of subject areas provides insights into the interdisciplinary nature of any topic or field of research (Ajibade, 2023). Fig. 4 shows the distribution of subject areas for publications on MLPVSE research. The interdisciplinarity of any research area is critical to effectively addressing interconnected challenges, and fostering innovation (Wong, 2020; Wong, 2022). It also helps to improve research quality and facilitate problem resolution by integrating ideas from

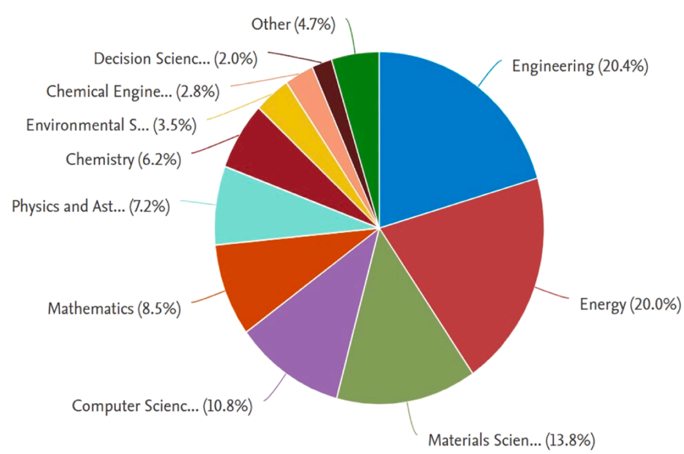
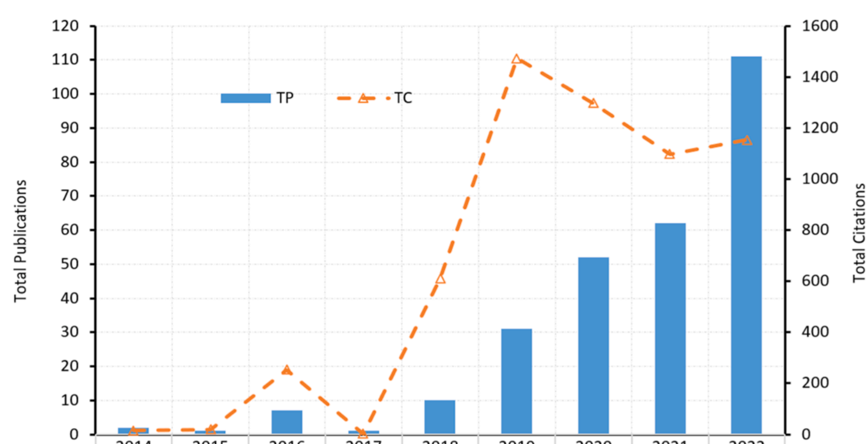


Fig. 4. Distribution of subject areas on MLPVSE research.



	2014	2015	2016	2017	2018	2019	2020	2021	2022
TP	2	1	7	1	10	31	52	62	111
TC	15	20	254	3	613	1474	1297	1097	1153

Fig. 2. Publications growth trend for MLPVSE research (2014–2022).

multiple experts from various fields, which results in holistic solutions and breakthroughs (Abramo et al., 2018; Adams, 2005).

In the MLPVSE research landscape, the top three subject areas (and total publications) are *Engineering* (144), *Energy* (141) and *Materials Science* (97). Collective the top 3 areas account for 54.18% of the TP on the topic, which according to Bradford's Law of Scattering (Nash--Stewart et al., 2012) indexed are the core journals on the topic in the literature. The three subject areas *Engineering, Energy,* and *Materials Science* (E^2MS) are critical to the field of MLPVSE research in several ways. First off, E^2MS are critical to progressing the technology, efficiency, and sustainability of MLPVSE. Ultimately, these ensure the research progress, scientific growth, and technological development of the MLPVSE landscape. For instance, mechanical and electrical engineers create renewable energy and energy-efficient technologies.

On the other hand, materials science engineers develop novel materials for use in building and solar energy applications. This shows how the complementary nature of the disciplines encourages creativity and interdisciplinary collaboration. MLPVSE research helps in reducing negative effects on the environment thereby advancing sustainability and promoting economic growth in the global green technology industry. Lastly, it has a significant impact on education, presenting professionals with the know-how to tackle energy and sustainability issues and paving the way for a more technologically advanced and sustainable future. This findings is also evident in the work of (Dada & Popoola, 2023) (Dada and Popoola, 2023), which shows and supports that Engineering, Energy and Material Science are very vital subject areas in MLPVSE research.

4.3. Source titles and highly cited publications

The most influential source titles and most highly cited publications on MLPVSE research were also examined in this paper. Table 1 presents the list of the top 10 source titles with the most publications on MLPVSE Research. The data reveals that the top 10 source titles on the topic have cumulatively published 65 documents which account for 23.47% of TP. The top source title is the open-access journal *Energies* with 13 publications or 4.69% of TP. Tied in second place are the *Journal of Materials Chemistry A*and *Solar Energy* each with 7 publications (or 2.53% TP). Other notable source titles include *IEEE Access, Advanced Energy Materials,* and *Renewable Energy*.

Further analysis of the list of top 10 journals indicates that their scopes fall within the subject areas of *Energy, Engineering,* and *Material Sciences*, which as earlier surmised are the top 3 focus areas of MLPVSE research. Therefore, it is likely that the researcher's preference for the journals listed above stems in significant part from the scope of their research. Another important consideration may be due to the prestige, high-impact factors and nature of the journals. For example, the top 3 journals *Energies, Journal of Materials Chemistry A,* and *Solar Energy* have impact factors ranging from 3.2 to 11.9 (year 2022). Overall, it can be seen that the high impact factors, nature, and scope of the top 10 journals have strongly influenced their productivity. This findings is also supported and evident in work done by Pandey, A. K., et al. (Pandey, 2018).

Table 1
Top source titles on MLPVSE Research.

Source Titles	Total Publications (TP)	Percentage Total Publications (%TP)
Energies	13	4.69
Journal of Materials Chemistry A	7	2.53
Solar Energy	7	2.53
IEEE Photovoltaic Specialists Conference	6	2.17
Energy Technology	6	2.17
IEEE Access	6	2.17
Advanced Energy Materials	5	1.81
Applied Sciences Switzerland	5	1.81
International Journal of Photoenergy	5	1.81
Renewable Energy	5	1.81

4.4. Highly cited publications

The analysis of the most cited publications in any research landscape helps to identify and provide critical insights into the seminal works, track trends, and research priorities (Donthu, 2021; Nyakuma, 2021). It also helps in finding gaps in the literature, evaluating the effects of multidisciplinary research, and disseminating knowledge (Bortoluzzi et al., 2021; Donthu et al., 2020). Table 2 shows the list of the top 10 most highly cited publications on MLPVSE research over the years.

Data analysis indicates that these publications have gained between 112 and 246 citations (or 152.5 on average per publication) to date. As observed in Table 2, the most highly cited publication on the topic is the review paper "Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques" by Akhter, Mekhilef (Akhter, 2019) Published in the *IET Renewable Power Generation*, the paper has been cited 246 times in the literature. In second place is another review "How to optimize materials and devices via design of experiments and machine learning: Demonstration using organic photovoltaics" published in the *ACS Nano* journal by Cao, Adutwum (Cao, 2018). The most highly cited article is "Dye-sensitized Solar cells under ambient light powering machine learning: Towards autonomous smart sensors for the Internet of Things" published in *Chemical Science* with 164 citations.

In general, the top 10 cited publications indicate a strong emphasis on using data-driven methods and machine learning in solar energy and photovoltaics. The review of the literature shows the studies have explored several topics including the estimation of PV-based power generation using ML and metaheuristic methods, materials and devices optimization through experimental design and ML, as well as the development of smart sensors for the IoT powered by dye-sensitized solar cells below ambient light (Michaels, 2020). Others have examined the use of ML for molecular design and efficiency prediction in organic photovoltaic materials, predicting the efficiency of organic solar cells, and design of non-fullerene small molecule acceptors for organic solar cells (Mahmood et al., 2022). Furthermore, some papers have used ML to identify and examine lead-free perovskite solar cells, forecast solar irradiance, and integrate electronic and structural features, as well as predict organic solar cell characteristics (Padula et al., 2019). Overall, the topmost highly cited publications on MLPVSE research have cumulatively highlighted the rising importance of ML in advancing solar energy and PV research and applications. In (Mohammad and Mahjabeen, 2023), the significance of ML in enhancing photovoltaic cells and solar energy is highlighted by the high citations counts which they observed in their studies and this also supports the findings of our study.

4.5. Authors

Fig. 5 shows the plot of the most prolific researchers on MLPVSE research. The analysis of the most prolific authors in any research landscape is necessary to identify the most important contributors to the field promote cooperation and comprehend publishing trends (Nyakuma, 2023). Likewise, the analysis helps to facilitate networking, and quality assessment, and stimulate early career researchers in the field (Ajibade, 2023). In this study, the position of the topmost prolific researcher is tied between *G. E. Georghiou* based at the University of Cyprus (Cyprus) and *Haibo Ma*, resident at Nanjing University (China). Both researchers have produced 5 publications each on MLPVSE research, which have been cited a total of 522 times in Scopus. The most notable publication of *G. E. Georghiou* and co-workers is "Day-ahead photovoltaic power production forecasting methodology based on

Table 2
Top 10 most highly cited publications on MLPVSE research.

References	Title	Source Title	Cited by	Document Type
Akhter, Mekhilef (Akhter, 2019)	Review on forecasting of photovoltaic power generation based on machine learning and metaheuristic techniques	IET Renewable Power Generation	246	Review
Cao, Adutwum (Cao, 2018)	How to optimize materials and devices via design of experiments and machine learning: Demonstration using organic photovoltaics	ACS Nano	197	Review
Michaels, Rinderle (Michaels, 2020)	Dye-sensitized solar cells under ambient light powering machine learning: Towards autonomous smart sensors for the Internet of Things (IoT)	Chemical Science	164	Article
Sun, Zheng (Sun, 2019)	Machine learning–assisted molecular design and efficiency prediction for high-performance organic photovoltaic materials	Science Advances	164	Article
Mahmood and Wang (Mahmood and Wang, 2021)	Machine Learning for high performance organic solar cells: Current scenario and future prospects	Energy and Environmental Science	159	Review
Sahu, Rao (Sahu, 2018)	Toward Predicting Efficiency of Organic Solar Cells via Machine Learning and Improved Descriptors	Advanced Energy Materials	132	Article
Mahmood, Irfan (Mahmood et al., 2022)	A time and resource-efficient machine learning-assisted design of non-fullerene small molecule acceptors for P3HT-based organic solar cells and green solvent selection	Journal of Materials Chemistry A	121	Article
Im, Lee (Im, 2019)	Identifying Pb-free perovskites for solar cells by machine learning	npj Computational Materials	116	Article
Li, Ward (Li, 2016)	Machine learning for solar irradiance forecasting of photovoltaic system	Renewable Energy	114	Article
Padula, Simpson (Padula et al., 2019)	Combining electronic and structural features in machine learning models to predict organic solar cells properties	Materials Horizons	112	Article

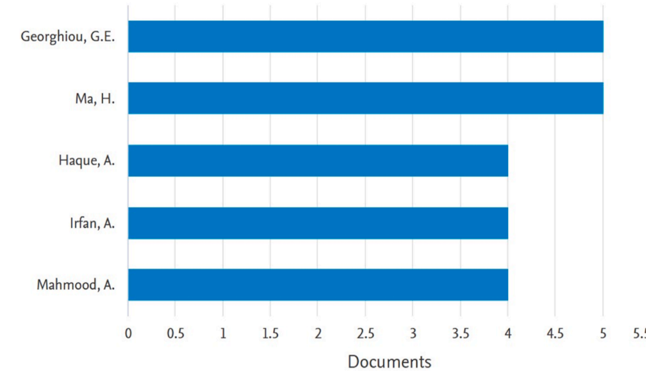


Fig. 5. Most prolific researchers on MLPVSE Research.

machine learning and statistical post-processing" published in the journal *Applied Energy* with 99 citations. The most important publication by *Haibo Ma* is "Toward Predicting Efficiency of Organic Solar Cells via Machine Learning and Improved Descriptors" published in Advanced Energy Materials with 135 citations.

Other notable researchers in the landscape include Haque, A., Irfan, A., and Mahmood, A. who have each published 4 documents on the topic. Further analysis shows that there are numerous co-authored publications between the top authors such as *George Makrides* and *G. E. Georghiou* based at the University of Cyprus (Cyprus) as well as *Asif Mahmood* and *Jinliang Wang* based at the Beijing Institute of Technology, Beijing, China. This finding indicates that collaborations may play an important role in the research productivity of researchers in the MLPVSE landscape. To further examine this, the degree of co-authorships between the top researchers in the field was examined using VOSviewer software. Fig. 6 depicts the overlay visualisation map of co-authorships among researchers in the MLPVSE research landscape.

The overlay visualisation maps show that although 48 researchers have published 3 or more publications on the topic only 19 are co-authored publications. As a result, it can be surmised that only 39.58% of publications are due to co-authorships which indicates that collaboration does not play a significant role in the productivity of researchers in the MLPVSE landscape. Hence, the productivity may be due to other factors such as institutional focus, national research policies access to research funding and or other forms of financial support.

4.6. Affiliations

The affiliation of researchers and their productivity in the MLPVSE research landscape was examined in this study. Research institutions provide not only a base for researchers but also influence their research focus. Fig. 7 presents the plot of the top 5 most productive research

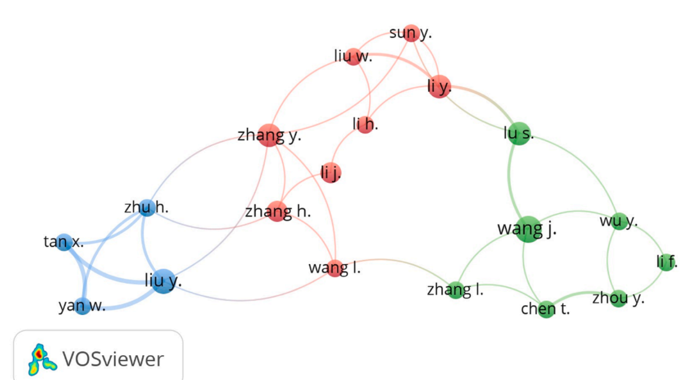


Fig. 6. Overlay visualisation of co-authorships in MLPVSE research landscape (Min docs = 3 per author).

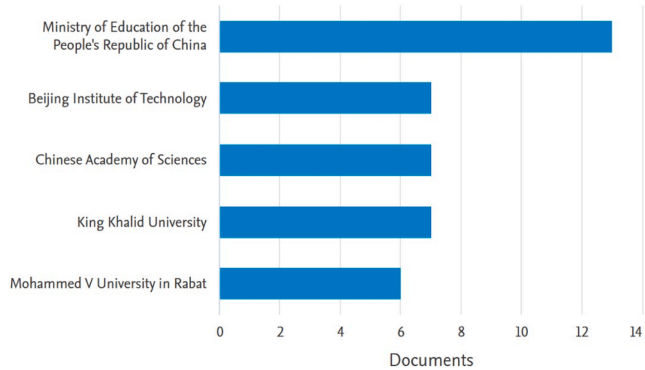


Fig. 7. Most productive research institutions on MLPVSE research.

institutions on MLPVSE research.

Based on the data in Scopus, the most prolific affiliation is the *Ministry of Education* with 13 publications (citations). In second place is the Beijing Institute of Technology, while in third place goes to the Chinese Academy of Sciences each with 7 publications. The findings indicate that the top 3 spots belong to institutions based in China, whereas the 4th and 5th places are taken up by King Khalid University (Saudi Arabia) and Mohammed V University (Morocco). Based on the foregoing, it can be practically presumed that China has taken a leading role in the MLPVSE research landscape. To further examine its role and dominance in the field, the analysis of national contributions was examined as detailed in section VII of the study.

4.7. Countries

Similar to affiliations, countries provide a base of operation for researchers to grow and thrive in their research landscapes. Fig. 8 shows the most prolific countries actively working on MLPVSE research topics worldwide. As observed, the list consists of countries such as China, India, the United States, Saudi Arabia, and Spain.

Based on TP, the most prolific nation engaged in MLPVSE research is China with 68 publications that have gained 1971 citations to date. The productivity of China can be largely ascribed to the efforts of various researchers such as Haibo Ma, Asif Mahmood, and Asif Wang, as well as institutions such as Beijing Institute of Technology, Chinese Academy of Sciences, and Nanjing University among others within the country. The second most prolific country is India with 40 publications that have been cited 446 times large due to efforts of notable researchers such as Ahteshamul Haque, Mohammed Ali Khan, and K.V.S. Bharath based at institutions such as Jamia Millia Islamia, Karunya Institute of Technology and Sciences, and Pandit Deendayal Energy University. Other notable nations (publication counts) involved in MLPVSE research are the United States (40), Saudi Arabia (19), and Spain (19). Overall, the data shows high productivity among the nations engaged in the research landscape. High productivity is often ascribed to numerous factors, one of which is collaboration. To further shed light on this submission, the degree of co-authorship among nations was examined using VOSviewer software. Fig. 9 shows an overlay visualisation map of the co-authorships among nations involved in the MLPVSE research landscape.

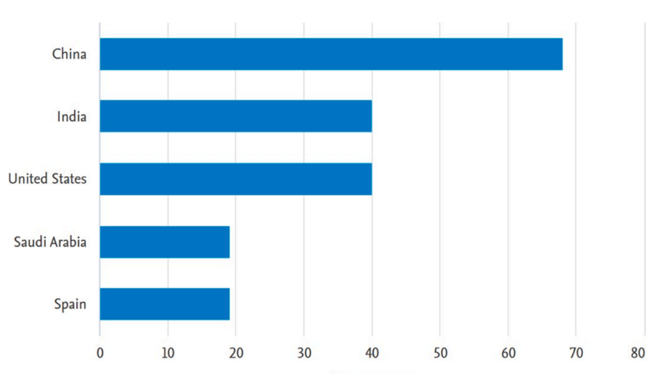


Fig. 8. Most prolific countries working on MLPVSE research.

The OV map shows that 32 out of the 33 that have published 3 or more publications on MLPVSE are strongly linked, which suggests active collaborations exist within the research landscape. As a result, a total of 7 clusters comprising 3–6 countries exist in the MLPVSE research landscape. The largest (red) cluster comprises Canada, Germany, and Turkey among others, whereas the smallest (orange) cluster consists of Egypt, Pakistan, and Saudi Arabia. However, the highest total link strength (TLS) was observed for Saudi Arabia (31), followed by China (27), and then the United States (26). Owing to its high TLS, Saudi Arabia has the largest and strongest collaborations despite the higher productivity of China, India, and the US on the topic. It can be surmised that Saudi Arabia has a very active and influential presence in the global research community on MLPVSE. Ultimately, this dynamic has the potential to enhance its global research, academic reputation, and impact. As the largest producer and exporter of fossil fuels, Saudi Arabia wants to diversify its energy sources and reduce its reliance on fossil fuels by utilising its enormous solar resources. The potential benefits from this paradigm shift include improved energy security, environmental sustainability, and economic versatility. ML could be used to optimize energy production, enhance forecasting, and boost PV system performance, making it a strategic choice in Saudi Arabia. Hence, the nation's commitment to international agreements and a sustainable energy future further drives its interest in this research, which could position the nation to lead in the renewable energy sector and ensure long-term sustainability. To this end, the nation and others in the research landscape have invested significant funds into research and development through various grants, research, and developmental funding schemes. Section VIII will highlight the various existing funding bodies charged with financing the applications of ML in PVSE research around the globe.

4.8. Funding bodies

It is widely reported that funding is key to scientific growth and technological development (Kwon, 2011). Hence, it is pertinent to examine its impact on the research landscape on MLPVSE over the years. Fig. 10 presents the top 5 funding bodies or agencies that have supported MLPVSE research across the globe.

As can be observed in Fig. 10, the most active funder of MLPVSE research is the National Natural Science Foundation of China (NSFC) with 42 publications that have been cited 1616 times. The NSFC is mandated by the government of the People's Republic of China to financially support basic and applied scientific research in the country. As part of its mandate, the agency supports research across fields and disciplines such as natural sciences, engineering, and social sciences. Over the years, the agency has supported research such as ML and its application in PVSE sectors particularly works by researchers such as *Haibo Ma, Asif Mahmood,* and *JinLiang Wang* among others based at institutions such as the Chinese Academy of Sciences, Nanjing University, and Beijing Institute of Technology among others in the country.

The second most active funder of MLPVSE research is another China-based organisation called the National Key Research and Development Program of China. The program was established in 2016 to fund, develop, and promote research projects in key areas of science and technology. To date, the program has successfully funded 12 publications by *Bo Che, Jinlian Chen,* and *Tao Chen*, as well as notably researchers such as *Asif Mahmood,* and *JinLiang Wang* among others based at various institutions such as Nanjing Tech University, University of Chinese Academy of Sciences, and Guangdong Academy of Sciences. Other notable funders (publication count) of MLPVSE research are the

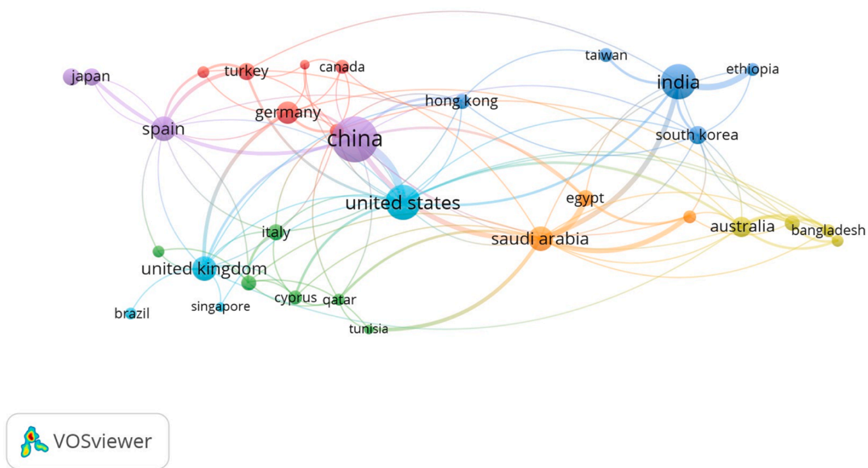


Fig. 9. Overlay visualisation map for country-based co-authorships on MLPVSE research.

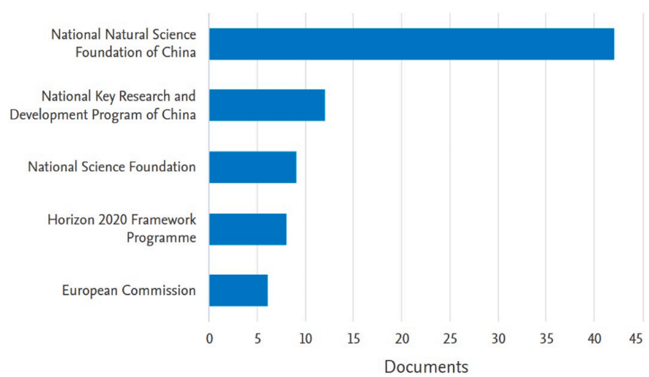


Fig. 10. Largest research funding bodies for MLPVSE research.

United States National Science Foundation (9), the Horizon 2020 Framework Programme (8), and the European Commission (6). Overall, the data shows that the top five funders are based in China, the United States, and the European Union.

4.9. Hotspot analysis

Hotspots or thematic area analysis presents critical insights into the current trending topics in any field of science or research endeavour. In this study, the keywords co-occurrence analysis feature of VOSviewer was used to examine the focus areas on MLPVSE currently examined by various researchers across the globe. Fig. 11 presents the (a) Network Visualisation (NV) and (b) Overlay Visualisation (OV) of the Keywords occurrences in MLPVSE research. The NV and OV maps present the keywords with 25 occurrences in the VOSviewer search and analyses. As a result, a total of 23 keywords out of 2297 fulfilled the search conditions, thereby resulting in 3 clusters including 7–8 keywords, 232 Links, and a TLS of 2850. The highest occurring keywords are machine learning (231), Solar Power Generation (84), and Forecasting (83), whereas the highest TLS were observed for machine learning (858), Solar Power Generation (421), and Forecasting (420).

Based on the KCO analysis, it would appear that ML has robust links to the two other major keywords forecasting and solar energy. Studies have shown that ML is used to optimize the operation and efficiency of solar energy systems (Cao, 2018; Cao, 2022; Al-Saban and Abdellatif, 2021). As with renewable energy systems, solar power generation is intermittent due to the strong influence of various factors such as solar radiation, weather conditions, and solar PV efficiency (Markovics and Mayer, 2022; Liu, 2022; Martin, 2016). In addition, ML can be used to leverage data from weather stations, solar sensors, and satellite imagery to enhance the power generation process (Michaels, 2020; Yin and Zhou, 2022). The data could then be used to forecast solar power generation by analyzing previous historical solar generation and meteorological data to predict future energy output (Khalyasmaa et al., 2020). This process can enable energy planners and grid operators to successfully integrate and manage solar power into the grid. Ultimately, this approach will not only reduce the need for backup power sources and ensure a stable energy supply. Likewise, ML models can improve solar panels efficiencies by predicting prime times for the production and maintenance of generated energy. This assists in maximizing energy output while extending the lifetime of solar infrastructure. Ultimately, ML application in solar power not only advances low-carbon initiatives but also influences cost reduction, making solar energy more friendly and profitable for a greener and more sustainable future.

5. Conclusions

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology was utilised in this investigation for the purpose of identifying, screening, and analysing articles that were associated with the utilisation of machine learning in photovoltaic and solar energy systems. The high publication output, citation rates, and worldwide collaboration that characterise the MLPVSE research landscape are the characteristics that are reflected in the publication patterns and bibliographic analyses of the landscape. Consequently, it is possible to draw the logical conclusion that the research landscape is extremely influential, particularly due to the fact that it has the ability to improve the design, development, and optimisation of materials for photovoltaic and solar energy. With the financial assistance of the several funding organisations that are already involved in the research environment, it is anticipated that the number of publications, citations, and collaborations, particularly between countries, will continue to rise in the years to come. Future works would focus on extracting data from other databases such as Web of Science, PubMed, Google Scholar. We also predict that future studies on the topic could include extensive research into the cybersecurity of such MLPVSE systems particularly in the wake of numerous malware, phishing, and other intrusion attacks on the energy and grid infrastructure worldwide.

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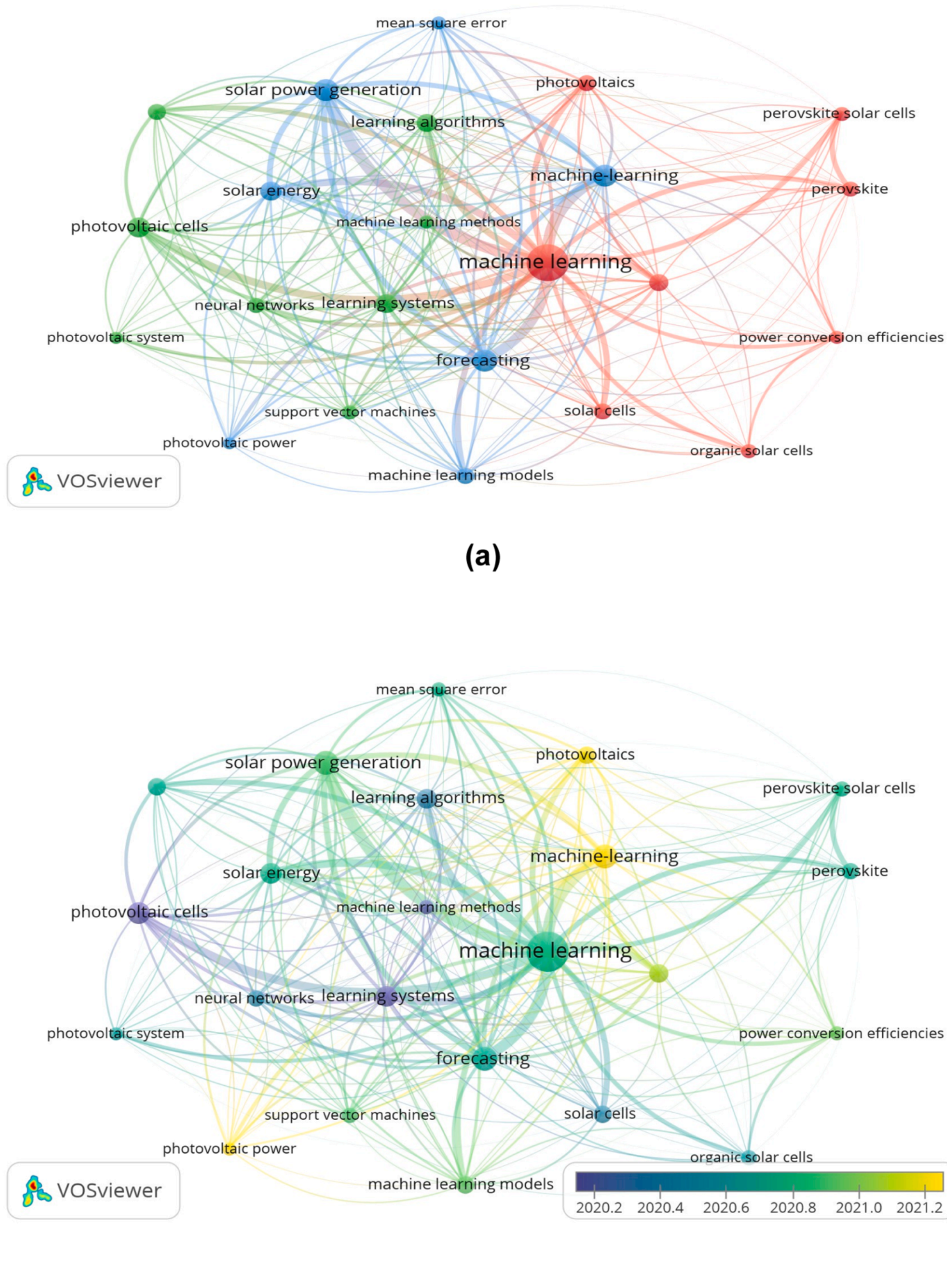

(a)

(b)

Fig. 11. Keywords occurrence analysis of MLPVSE Research Landscape (a) Network visualisation (b) Overlay Visualisation.

CRediT authorship contribution statement

Abdelhamid Zaidi: Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

No data was used for the research described in the article.

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