THE EVOLUTION OF RENEWABLE ENERGY FORECASTING WITH MACHINE LEARNING: A STATE-OF-THE-ART BIBLIOMETRIC ANALYSIS AND SUGGESTIONS FOR FUTURE RESEARCH

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Abstract. This study performed bibliometric analyses to evaluate the evolution of machine learning (ML) and renewable energy forecasting (REF) in terms of the article, author, source, country, and topic dimensions from 1990 to 2023, based on 1232 articles from the Web of Science, with Bibliometrics (Biblioshiny) and VOSviewer. Results revealed that article publications and citations regarding ML and REF have grown rapidly since 2012 and 2013, respectively. The articles were distributed across 53 research areas. Deo, R. C. and Trans, K. were the most productive and influential authors in terms of article publications and citations, respectively. *Energies* and *Applied Energies* were the most productive and influential sources, respectively. Geographically, China ranked first in terms of both article publications and citations. It played an important role in bridging collaborative relationships between countries from 2017 to 2023. Over time, the major themes in ML and REF evolved from “artificial neural network” into “predictive models,” and “smart grid”. Interdisciplinarity, topic diversification, and sophistication of techniques were identified as key features in the evolution of ML and REF. Applying hybrid models with various deep learning algorithms, utilizing large language models, and diversifying topics into “anaerobic digestion” are suggested for future ML and REF research.
Keywords: *bibliometric analysis, machine learning, renewable energy forecasting, Biblioshiny, VOSviewer*

Introduction

Owing to concerns about climate change (Wuebbles and Jain, 2001) and fossil fuel depletion (Höök and Tang, 2013), renewable energy has become increasingly important for sustainable growth worldwide. Various renewable energy sources, which includes solar energy (Guangul and Chala, 2019), wind energy (Kumar et al., 2016), hydro energy (Adom et al., 2018), and biomass energy (Perea-Moreno and Samerón-Manzano, 2019), can contribute to generating pollution-free energy and to replacing fossil fuels (Iqbal et al., 2014; Bull, 2001). Therefore, many scholars, experts, and policymakers have focused on this issue.

Accurate renewable energy forecasting (REF) is crucial for the effective operation and management of renewable energy sources (Golestaneh et al., 2016). However, improving REF accuracy remains challenging (Wang et al., 2019). The difficulty of REF reveals two main barriers. One salient barrier is that renewable energy sources are highly variable (McGovern et al., 2017), and their data exhibit intermittent, nonstationary, and random characteristics (Wang et al., 2019). Another barrier is that improving REF accuracy requires treating complex nonlinear relationships (Benti et al., 2023) and considering various influential factors, including weather conditions and

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forecasting time spans (Kumari and Toshniwal, 2021). Conventional approaches to improving the accuracy of REF, such as statistical and physical models (Ghalehkhondabi et al., 2017), have limited ability to overcome these two barriers (Benti et al., 2023). Meanwhile, applying machine learning (ML) to REF is a promising approach to address this limitation (Benti et al., 2023).

ML is a sort of artificial intelligence (AI) which makes it possible for machines to learn from data and increase their task performance as their learning develops (Jordan and Mitchell, 2015). It is classified into the four types as follows (Benti et al., 2023): supervised learning, which trains ML models with labeled data based on expected results (Saravanan and Sujatha, 2018); unsupervised learning, in which ML models are trained with an unlabeled dataset containing expected outcomes (Dike et al., 2018); reinforcement learning, which enables machines to learn how to perform tasks to increase cumulative rewards (Qiang and Zhongli, 2011); and deep learning, which utilizes artificial neural networks so as to train machines (Janiesch et al., 2021). ML has made a significant contribution to the evolution of REF (Benti et al., 2023; Lai et al., 2020), and researchers have applied the four different types of ML models in their studies on REF. For example, for solar energy forecasting, Bajpai and Duchon (Bajpai and Duchon, 2019) applied support vector regression and random forest, which belong to supervised learning (Benti et al., 2023). Khan et al. (2019) used principal component analysis, a branch of unsupervised learning (Benti et al., 2023), to predict wind energy. For solar and wind energy, Jeong and Kim (2021) proposed a method for error-compensable forecasting based on an actor–critic policy gradient, which is a type of reinforcement learning (Benti et al., 2023). Gangwani et al. (2020) utilized long short-term memory (LSTM) that is a subset of deep learning (Benti et al., 2023) to forecast geothermal energy. These examples are summarized in *Table 1*.

Table 1. *Four types of machine learning (ML) and application in renewable energy forecasting (REF)*

Type of ML	Example algorithm	Application area	Reference
Supervised learning	Support vector regression, random forest	Solar energy forecasting	Bajpai and Duchon (2019); Benti et al. (2023)
Unsupervised learning	Principal component analysis	Wind energy prediction	Khan et al. (2019); Benti et al. (2023)
Reinforcement learning	Actor–critic policy gradient	Solar and wind energy forecasting	Jeong and Kim (2021); Benti et al. (2023)
Deep learning	Long short-term memory (LSTM)	Geothermal energy forecasting	Gangwani et al. (2020); Benti et al. (2023)

With the increasing importance of ML in REF, the number of both publications and citations concerning review articles analyzing the evolution of ML and REF has rapidly grown (*Fig. 1*). However, relevant recent review articles on ML and REF, summarized in *Table 2*, seem to have two salient limitations. First, they cannot provide state-of-the-art analysis results about the evolution of ML and REF under a holistic view based on multiple dimensions, including the article, author, source, country, and topic dimensions. None of the relevant review articles in *Table 2* present any analysis results related to the year 2023. Second, these review articles do not illuminate the changes in the collaboration networks of countries with regard to studies on ML and REF under a dynamic view. To overcome these limitations, the current study attempts to shed light on the evolution of ML and REF from 1990 to 2023 in terms of the article, author, source, country, and topic dimensions while elucidating the changes in the collaboration network of countries with regard to ML and REF research. Accordingly, this study aims at identifying the features of the evolution of ML and REF from 1990 to 2023 and provide novel implications for future relevant research.

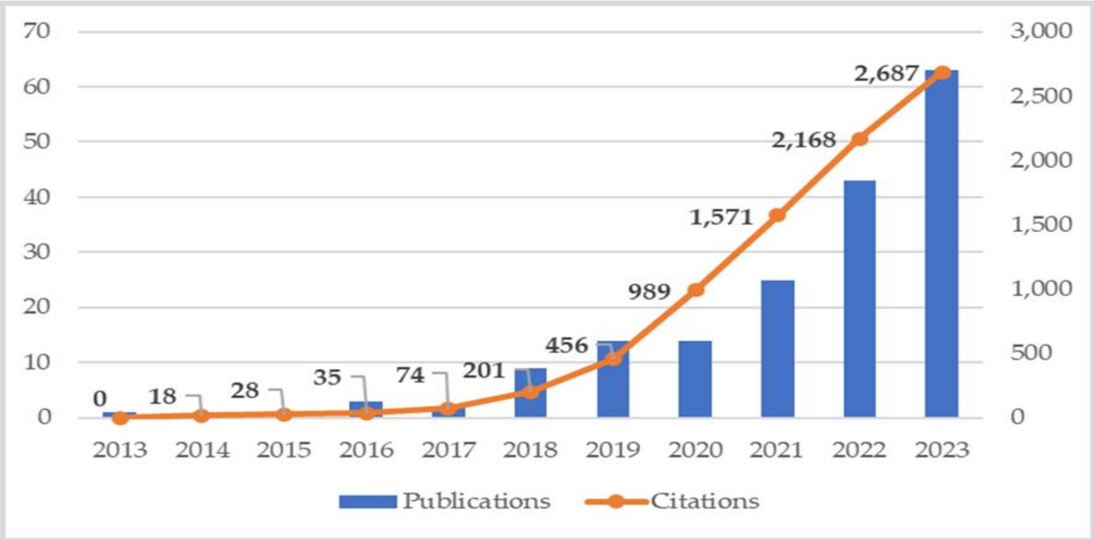

***Figure 1.** Annual publications and citations concerning review articles on machine learning (ML) and renewable energy forecasting (REF) from 2013 to 2023. (Analysis results are based on data from the Web of Science Core Collection)*

***Table 2.** Relevant recent review articles on the evolution of machine learning (ML) and renewable energy forecasting (REF)*

Author	Title	Journal	Keywords	The number of citations from publication year to 2023
Wang et al. (2019)	A review of deep learning for renewable energy forecasting	*Energy Conversion and Management*	Deep learning; Renewable energy; Deterministic forecasting; Probabilistic forecasting; Machine learning	488
Lai et al. (2020)	A survey of machine learning models in renewable energy predictions	*Applied Sciences*	Renewable energy; machine learning; prediction	60
Zwane et al. (2022)	A bibliometric analysis of solar energy forecasting studies in Africa	*Energies*	Bibliometric review; emerging topics; current trends; low-carbon economy; thematic map analysis	5
Benti et al. (2023)	Forecasting renewable energy generation with machine learning and deep learning: current advances and future prospects	*Sustainability*	Accurate predictions; deep learning; energy management; machine learning; renewable; energy forecasting	7
Ying et al. (2023)	Deep learning for renewable energy forecasting: A taxonomy, and systematic literature review	*Journal of Cleaner Production*	Deep learning; renewable energy; literature review; bibliometric analysis; forecasting	10

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To effectively illuminate the features of the evolution of ML and REF from 1990 to 2023 under a holistic view based on five dimensions (article, author, source, country, and topic) and to overcome the limitations of previous literature studies, this study poses five research questions (RQs):

RQ 1: What are the features of the evolution of the article dimension?

RQ 2: What are the features of the evolution of the author dimension?

RQ 3: What are the features of the evolution of the source dimension?

RQ 4: What are the features of the evolution of the country dimension?

RQ 5: What are the features of the evolution of the topic dimension?

Materials and methodology

Data source and retrieval methods

This study used the Web of Science (WoS) as the data source for our bibliometric analysis. The WoS is a major database that provides comprehensive and reliable academic data for bibliometric analysis and is globally used (Zhang et al., 2022; Zhang and Liang, 2020). To perform rigorous data retrieval, this study undertook three steps: identifying, refining, and confirming relevant studies.

In step I for identifying relevant studies, this study performed an advanced search query in the titles, keywords, and abstracts of studies in the core collection of WOS by using a combination of keywords such as "((‘machine learning’) AND (((‘renewable energy’) OR (‘solar energy’) OR (‘wind energy’) OR (‘ocean energy’) OR (‘biomass energy’) OR (‘hydro energy’) OR (‘geothermal energy’)) AND ((forecast*) OR (predict*))))". These keywords were adapted from the keyword search verified in a prior study (Ying et al., 2023) in the field of ML and REF. The advanced search query was based on a time span ranging from 1990 to 2023. This step yielded 1765 relevant studies.

In step II for refining relevant studies, this study employed two processes to further screen the 1765 studies by document type and language. First, by document type, they were refined to 1243 articles not belonging to review articles which this study did not aim at. In the second phase, the 1243 articles were refined to 1238 English articles.

In step III for confirming relevant studies, the 1238 articles were closely reexamined with the criteria from the step I and II, resulting in the exclusion of 6 articles published in 2024, which was outside the time span of this study. Therefore, 1232 articles were used for the bibliometric analysis. *Figure 2* summarizes the three data retrieval steps.

Analysis methodology

This study applied bibliometric analysis, which involved performance analysis, scientific mapping (network analysis), and thematic analysis, to analyze the evolution of ML and REF in the article, author, source, country, and topic dimensions across the 1232 articles from the WOS (*Fig. 3*). Bibliometric analysis is a rigorous scientific method that is useful for quantitatively analyzing the evolution of specific fields (Donthu et al., 2021).

In this study, Bibliometrix (Biblioshiny) (Aria and Cuccurullo, 2017) and VOSviewer (Van Eck and Waltman, 2010) were adopted as bibliometric analytical tools to conduct the performance analysis and science mapping (network analysis). Bibliometrix is a package of the open-source program R (R Core Team, 2024) that specializes in comprehensive bibliometric analyses (Aria and Cuccurullo, 2017;

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www.bibliometrix.org). Biblioshiny is a web-based application that facilitates the easy use of Bibliometrix (www.bibliometrix.org). The R packages such as “bibliometrix” and “shiny” were appled for this study.

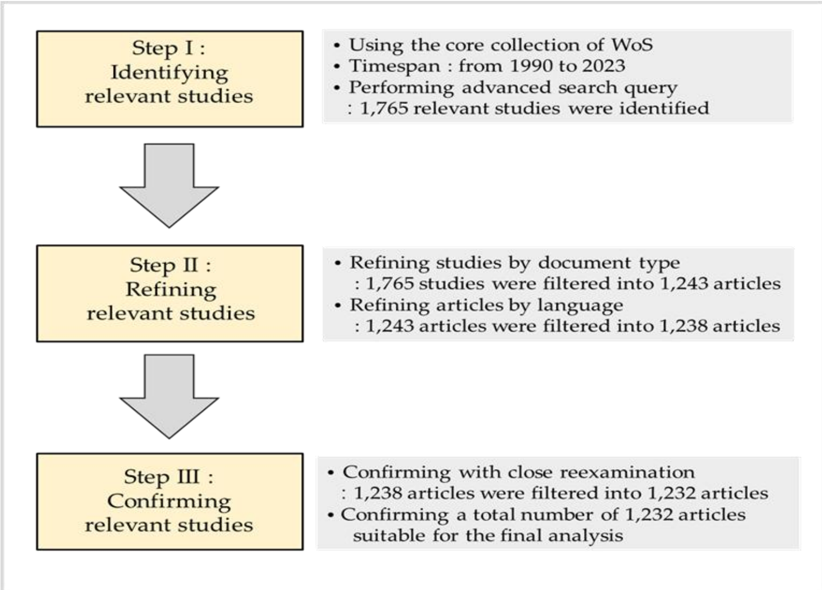

Figure 2. *Summary of the three steps in identifying, refining, and confirming relevant studies*

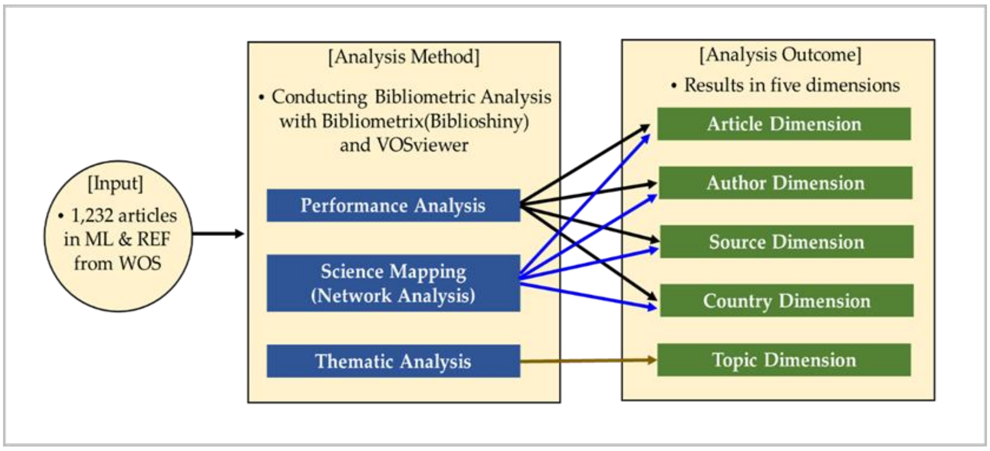

Figure 3. *Framework of analysis methodology in terms of input, analysis, and outcome*

VOSviewer specializes in visualizing bibliometric networks (www.vosviewer.com). This study adopted these bibliometric analysis methods given their effectiveness, as verified in relevant research (Sajovic et al., 2023; Barbosa et al., 2023).

Performance analysis, which is descriptive but essential for bibliometric analysis, inspects the contributions of research constituents such as articles, authors, sources, and countries to a given domain (Donthu et al., 2021). In this study, performance analysis was conducted according to the four dimensions in *Figure 3*: (i) annual article publications, article distribution by research area, annual article citations, and top 10 articles in citations in the article dimension; (ii) top 10 authors in article publications

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and top 10 authors in citations in the author dimension; (iii) top 10 sources in article publications and top 10 sources' article citations in the source dimension; and (iv) top 10 countries in article publications and top 10 countries in citations in the country dimension.

Science mapping in bibliometric analysis examines networks resulting from interactions or connections between research constituents (Donthu et al., 2021). It is useful in visualizing not only the citation network of articles or sources but also the collaboration networks of authors or countries (Donthu et al., 2021). This study conducted science mapping in the four dimensions shown in *Figure 3*: (i) the citation network of articles in the article dimension, (ii) the collaboration network of authors in the author dimension, (iii) the citation network of sources, and (iv) the collaboration network of countries.

Thematic analysis identifies basic, declining, emerging, niche, and important topics and detects the evolution in a given field (www.bibliometrix.org). This study conducted a thematic analysis of the topic dimension, as shown in *Figure 3*. The next section presents the results of the performance analysis, science mapping, and thematic analysis.

Results

Article dimension result

Article-related performance analysis result

A total of 1232 articles on ML and REF were identified in this study. The article publications began in 2012, and the titles of the first two relevant articles in 2012 are "Adaptive Local Learning Techniques for Multiple-step-ahead Wind Speed Forecasting" (Vaccaro et al., 2012) and "State Estimation for Anaerobic Digesters Using the ADM1" (Gaida et al., 2012).

As shown in *Figure 4*, the annual article publication trend grew rapidly from 2012 to 2023. Only two articles were published in 2012; however, 388 articles were published in 2023, hence the rapid growth, with the compound annual growth rate (CAGR) being 61.43%.

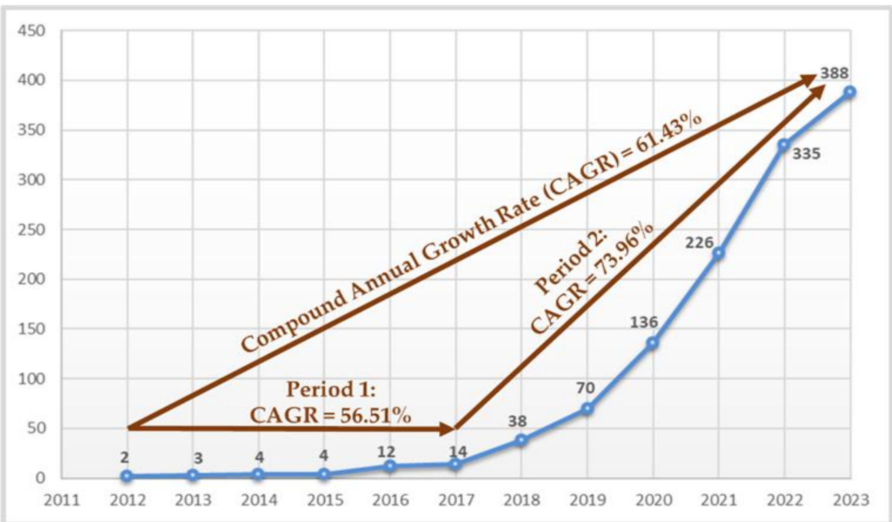

Figure 4. *Annual publication trend in the articles on ML and REF from 2011 to 2023*

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Two salient periods were observed in the annual article publication trends. Period 1 showed relatively slow growth from 2012 to 2016, during which 25 articles were published with a CAGR of 56.51%. Period 2 showed a relatively drastic growth from 2017 to 2023, in which 1207 articles were published with a CAGR of 73.96%.

Table 3 shows the top 10 research area for the 1232 articles. An article can be classified into more than one research area in the WoS database. In this study, the 1232 articles on ML and REF were sorted into 53 research areas. Energy Fuels was ranked first with 563 articles, accounting for 45.7% of all articles, followed by Engineering with 433 articles (35.1%), Science Technology Other Topics with 220 articles (17.9%), Computer Science with 169 articles (13.7%), and Environmental Sciences Ecology with 143 articles (11.6%).

Table 3. *Distribution of the articles on ML and REF by research area from 2011 to 2023*

Research area	Number of articles	Ratio (%)
Energy fuels	563	45.7
Engineering	433	35.1
Science technology other topics	220	17.9
Computer science	169	13.7
Environmental sciences ecology	143	11.6
Thermodynamics	81	6.6
Chemistry	75	6.1
Materials science	75	6.1
Physics	63	5.1
Telecommunications	63	5.1

Figure 5 shows the annual article citation trends for ML and REF. The first two article citations appeared in 2013. Subsequently, the article citations grew drastically. The number of articles cited in 2013 increased to 397 in 2018 and 6932 in 2023. This drastic growth was reflected in the CAGR of 125.93% from 2013 to 2023. This result confirmed the increasing number of researchers paying special attention to ML and REF and the significant impact of articles on the field of ML and REF.

Figure 6 shows the L-shaped distribution of article citations. The mean, which is average citation per article, is 15.86. The maximum, and minimum values are 435, and 0, respectively. The total number of citations of the top 10 articles exceeded 178. The title of the top-ranked article is "Active Learning Across Intermetallics to Guide Discovery of Electrocatalysts for CO_2 Reduction and H_2 Evolution" (Tran and Ulissi, 2018). Ranked second is the article titled, "Comparison of Support Vector Machine and Extreme Gradient Boosting for Predicting Daily Global Solar Radiation Using Temperature and Precipitation in Humid Subtropical Climates: A Case Study in China" (Fan et al., 2018). The third-ranked article is "Predictive Modelling for Solar Thermal Energy Systems: A Comparison of Support Vector Regression, Random Forest, Extra Trees and Regression Trees" (Ahmad et al., 2018). *Table 4* presents the top 10 articles in total citations and average citations per year, along with their major findings.

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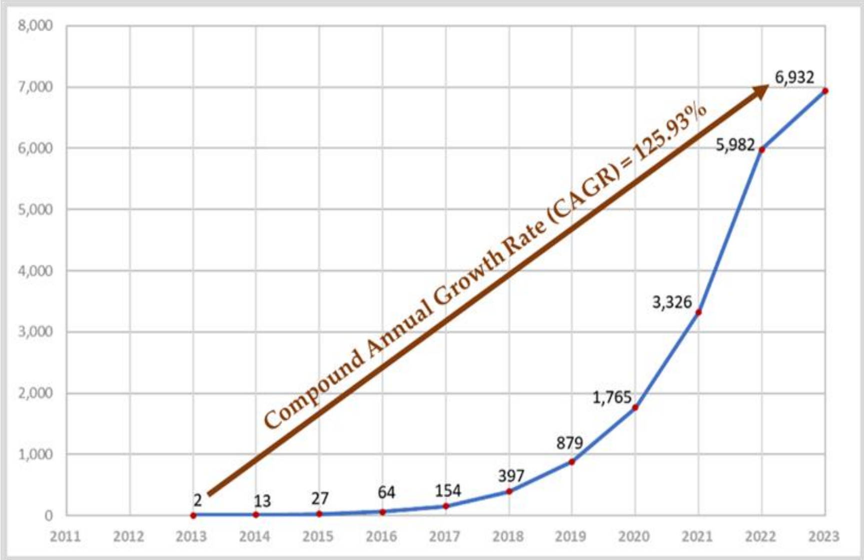

Figure 5. *Annual citation trend in the articles on ML and REF from 2011 to 2023*

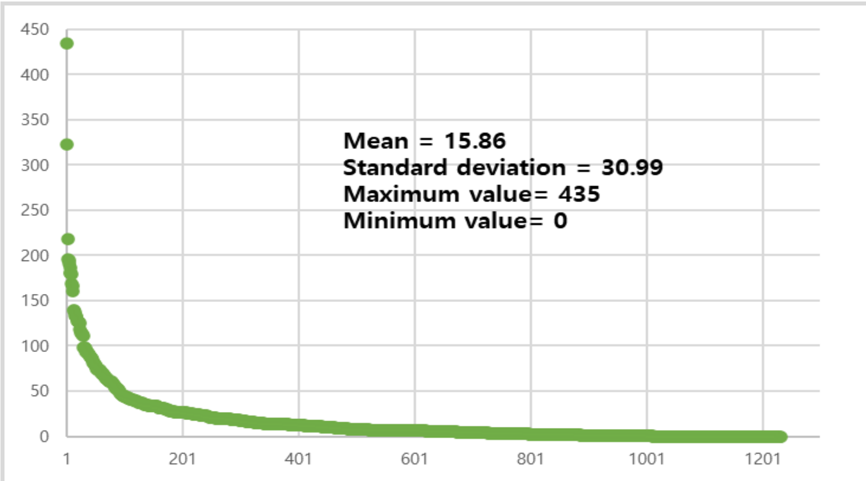

Figure 6. *Distribution of total citations of the articles on ML and REF from 2011 to 2023. The green dots indicate ML and REF articles. The X-axis indicates each article arranged by the order in its total citations while the Y-axis represents the total citation of each article*

Article-related science mapping

Figure 7 shows the entire citation network of the 1232 articles on ML and REF resulting from science mapping using VOSviewer. The entire citation network comprised 502 clusters and 1412 links. In terms of citations, the top-ranked article with 435 citations was that of Tran (Tran and Ulissi, 2018), titled “Active Learning across Intermetallics to Guide Discovery of Electrocatalysts for CO_2 Reduction and H_2 Evolution,” as shown in *Table 4* and the largest node in *Figure 8*. Regarding citation links, the work of Demolli, titled “Wind Power Forecasting based on Daily Wind Speed Data using Machine Learning Algorithms” was the top article with 37 links (Demolli et al., 2019). *Figure 8* shows the largest citation network of articles comprising 724 articles with 46 clusters and 1361 links.

Table 4. *Top 10 articles on ML and REF from 2011 to 2023 in terms of total citations*

Author	Title	Total citations	Major finding	Average citations per year
Tran and Ulissi (2018)	Active learning across intermetallics to guide discovery of electrocatalysts for CO_2 reduction and H_2 evolution	435	An automated screening method, integrating machine learning with optimization, to forecast electrocatalyst performance	72.5
Fan et al. (2018)	Comparison of support vector machine and extreme gradient boosting for predicting daily global solar radiation using temperature and precipitation in humid subtropical climates: a case study in China	323	Comparable prediction accuracy in Support Vector Machine and Extreme Gradient Boosting for predicting daily global solar radiation	53.83
Ahmad et al. (2018)	Predictive modelling for solar thermal energy systems: A comparison of support vector regression, random forest, extra trees and regression trees	218	Comparing decision trees, tree-based ensemble machine learning models, and support vector regression to forecast a solar thermal energy	36.67
Persson et al. (2017)	Multi-site solar power forecasting using gradient boosted regression trees	196	Gradient boosted regression trees for forecasting solar power generation	28
Ma et al. (2018)	Data-driven proton exchange membrane fuel cell degradation predication through deep learning method	195	Forecasting method for fuel cell degradation with grid long short-term memory and recurrent neutral network	32.5
McGovern et al. (2017)	Using artificial intelligence to improve real-time decision-making for high-impact weather	191	Applying AI techniques to improve the forecasting of various kinds of high-impact weather	27.29
Magazzino et al. (2021)	A machine learning approach on the relationship among solar and wind energy production, coal consumption, GDP, and CO_2 emissions	186	Causal relationship among wind and solar energy production, economic growth, coal consumption, and CO_2 emissions for China, India, and the USA	62
Golestaneh et al. (2016)	Very short-term nonparametric probabilistic forecasting of renewable energy generation—with application to solar energy	181	A nonparametric approach for very short-term predictive densities based on extreme learning machine	22.63
Jang et al. (2016)	Solar power prediction based on satellite images and support vector machine	180	A solar power prediction model with support vector machine and satellite images	25.71
Demoli et al. (2019)	Wind power forecasting based on daily wind speed data using machine learning algorithms	179	Long-term wind power forecasting based on five machine learning algorithms	35.8

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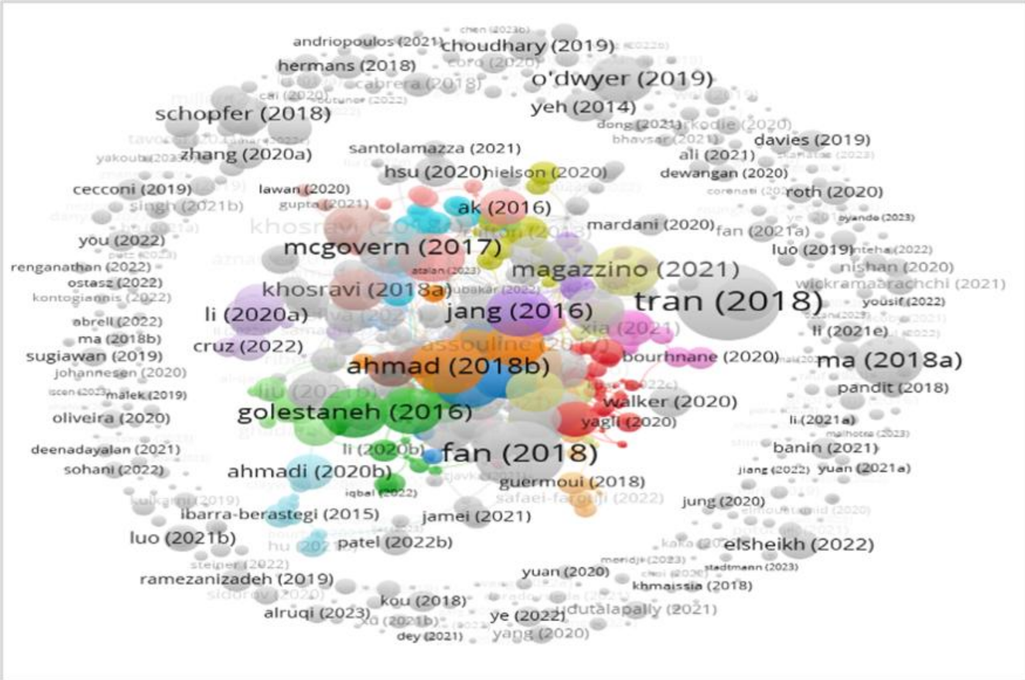

Figure 7. *Whole citation network of the articles on ML and REF from 2011 to 2023*

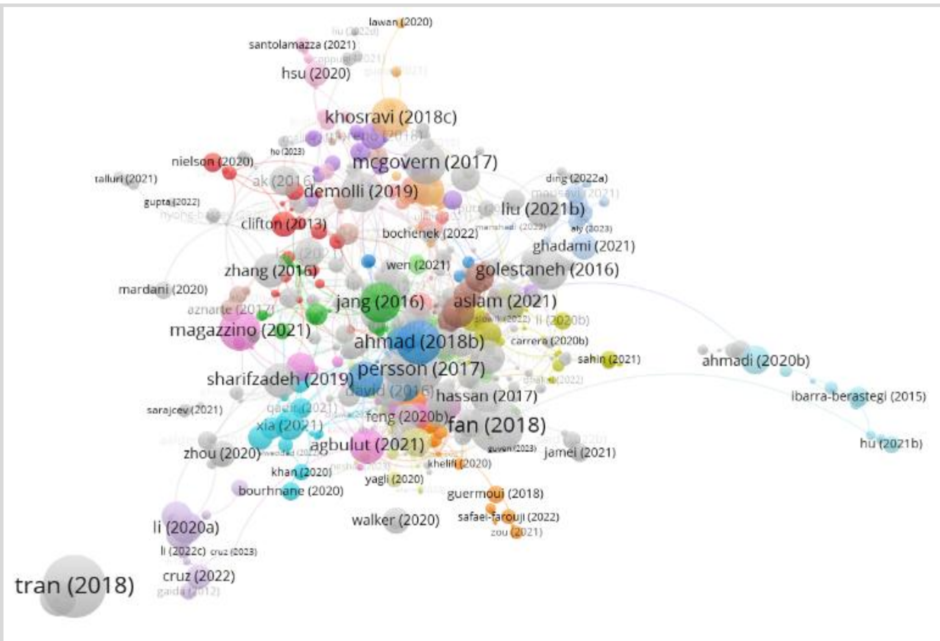

Figure 8. *Largest citation network of the articles on ML and REF from 2011 to 2023*

Author dimension analysis result

Author-related performance analysis result

Figure 9 shows the L-shaped distribution of articles by author, which is based on multiple authorship calculation in which one article is evaluated to belong to its respective coauthors. The total number of authors for the articles on ML and REF was

4791. The mean and standard deviation of their article publications were 1.14 and 0.49, respectively. The maximum and minimum values were 9 and 1, respectively. Of the 4791 authors, 475 (9.91%) authors published 2 or more articles.

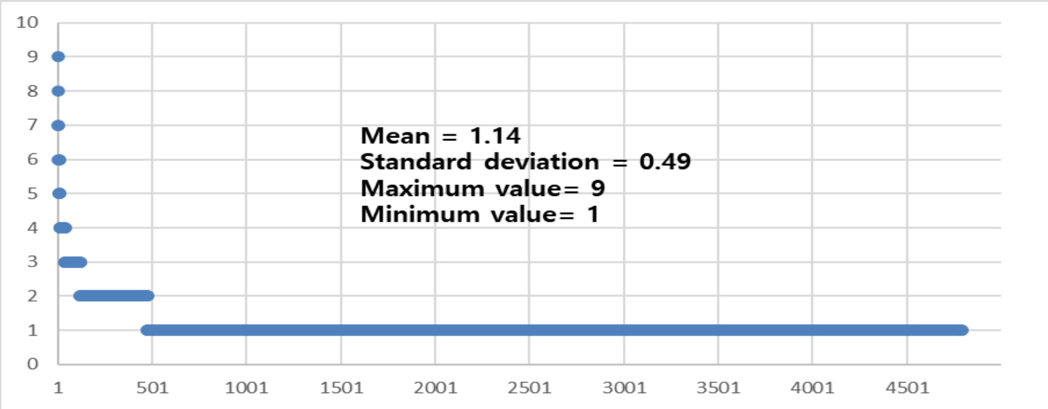

Figure 9. *Distribution of publication of the articles on ML and REF by author from 2011 to 2023. The blue dots and lines indicate the number of articles on ML and REF. The X-axis indicates each author arranged by the order in the number of article publication while the Y-axis represents the number of article publications of each author*

The top 10 authors published more than 4 articles (*Table 5*). Deo, R. C. was the top-ranked and most productive author with 9 publications, followed by Mosavi, A with 8 articles and by Salcedo-sanz, S. and Sharma, P. with 7 articles.

Table 5. *Top 10 authors of the articles on ML and REF from 2011 to 2023 in terms of article publications*

Rank	Author	Institution	Article publications	Article citations
1	Deo, R. C.	University of Southern Queensland	9	418
2	Mosavi, A.	Technische Universität Dresden	8	272
3	Salcedo-sanz, S.	Universidad de Alcalá	7	225
3	Sharma, P.	Delhi Skill and Entrepreneurship University	7	132
5	Ghimire, S.	University of Southern Queensland	6	308
5	Wang, X.	Tsinghua University	6	300
5	Li, J.	Chinese Academy of Sciences	6	299
8	Yaseen, Z.	King Fahd University of Petroleum & Minerals	5	172
8	Zhou, Y.	The Hong Kong University of Science and Technology	5	121
8	El-kenawy, E.	Delta Higher Institute of Engineering and Technology	5	46
8	Kumar, N.	Bharati Vidyapeeth's College of Engineering	5	18

Table 6 lists the top 10 authors in terms of total citations. Tran, K. is the top-ranked and most influential author with 574 citations, followed by Khosravi, A. with 477 citations. Machado, L. and Ulissi, Z. W. are tied for third place, each with 435 citations.

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Table 6. *Top 10 authors of the articles on ML and REF from 2011 to 2023 in terms of citations*

Rank	Author	Total citations	The number of publications
1	Tran, K.	574	2
2	Khosravi, A.	477	4
3	Machado, L.	435	3
4	Ulissi, Z. W.	435	1
5	Deo, R. C.	418	9
6	Fan, J.	410	2
6	Wang, X.	410	2
6	Wu, L.	410	2
6	Zhang, F.	410	2
10	Rezgui, Y.	372	3

Author-related science mapping

Figure 10 shows the largest collaboration network of the authors, comprising 196 authors and 16 clusters, as identified by the different colors in *Figure 10*. The largest cluster comprised 18 authors. The smallest cluster comprised 6 authors. This study examined the importance of 4791 authors in terms of total link strength. It indicates the intensity of collaborative article publications through co-authorship (Van Eck and Waltman, 2013). Li. J was the top author with the strongest total link of 39, which indicated an important role in collaboration with co-authorship. Deo. R. C. was ranked second with total link intensity of 37 and was followed by Mosavi. A with a total link intensity of 35. *Table 7* summarizes the top 10 authors with regard to total link strength.

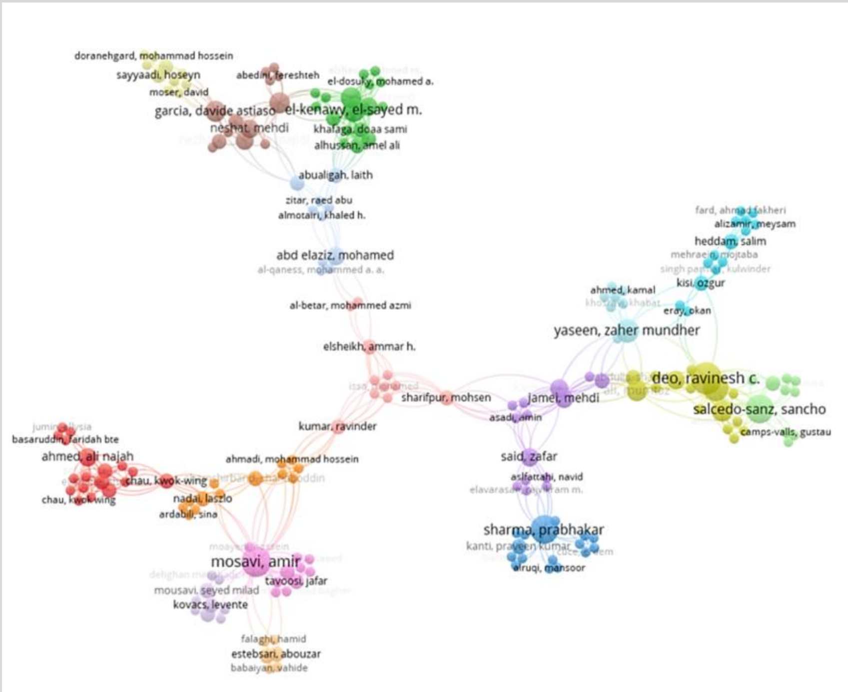

Figure 10. *Largest collaboration network of authors of the articles on ML and REF from 2011 to 2023*

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Table 7. *Top 10 authors in terms of total link strength in the collaboration network of authors of the articles on ML and REF from 2011 to 2023*

Rank	Author	Total link strength
1	Li, J.	39
2	Deo, R. C.	37
3	Mosavi, A.	35
4	Wang, X.	32
4	Haupt, S. E.	32
4	Das, A.	32
4	Goyal, S.	32
4	Heras-Domingo, J.	32
4	Shuaibi, M.	32
4	Sriram, A.	32
4	Ulissi, Z.	32

Source dimension analysis result

Source-related performance analysis result

Figure 11 shows the L-shaped distribution of articles by source. The total number of sources for the 1232 articles on ML and REF was 371. The mean and standard deviation were 3.32 and 9.47, respectively. The maximum and minimum values were 145 and 1, respectively. Of the 371 sources, 142 (38.54%) sources published 2 or more articles.

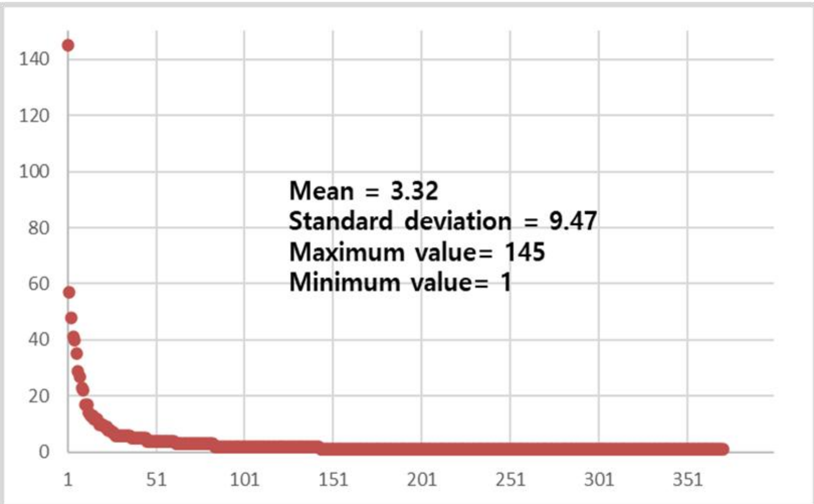

Figure 11. *Distribution of article publications by source of the articles on ML and REF from 2011 to 2023. The red dots and lines indicate articles on ML and REF. The X-axis indicates each source arranged by the order in the number of article publication while the Y-axis represents the number of article publications of each source*

In the top 10 sources, more than 21 articles were published (*Table 8*). *Energies* was the top-ranked source with 145 articles, followed by *Applied Energy* with 57 articles and *Renewable Energy* with 48 articles.

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Table 8. *Top 10 sources of the articles on ML and REF from 2011 to 2023 in terms of article publications*

Rank	Source	Article publications	H-index*
1	*Energies*	145	22
2	*Applied Energy*	57	24
3	*Renewable Energy*	48	17
4	*IEEE Access*	41	14
5	*Sustainability*	40	11
6	*Energy*	35	17
7	*Energy Conversion and Management*	29	17
8	*Applied Sciences-Basel*	27	10
9	*Energy Reports*	23	8
10	*Journal of Cleaner Production*	22	14

*The h-index combines productivity and citation impact, showing that a journal has *h* articles with at least *h* citations each (Donthu et al., 2021)

Figure 12 shows the top 10 sources of article publications over time. Notably, the quantity of articles published in *Energies* increased rapidly in 2019. In 2018, *Applied Energy* was ranked as the top source with five articles while *Energies* was ranked third with two publications. However, since 2019, *Energies* has been ranked first. In 2019, eight articles were published in *Energies*. This number increased to 46 in 2023, with the CAGR being 54.85%.

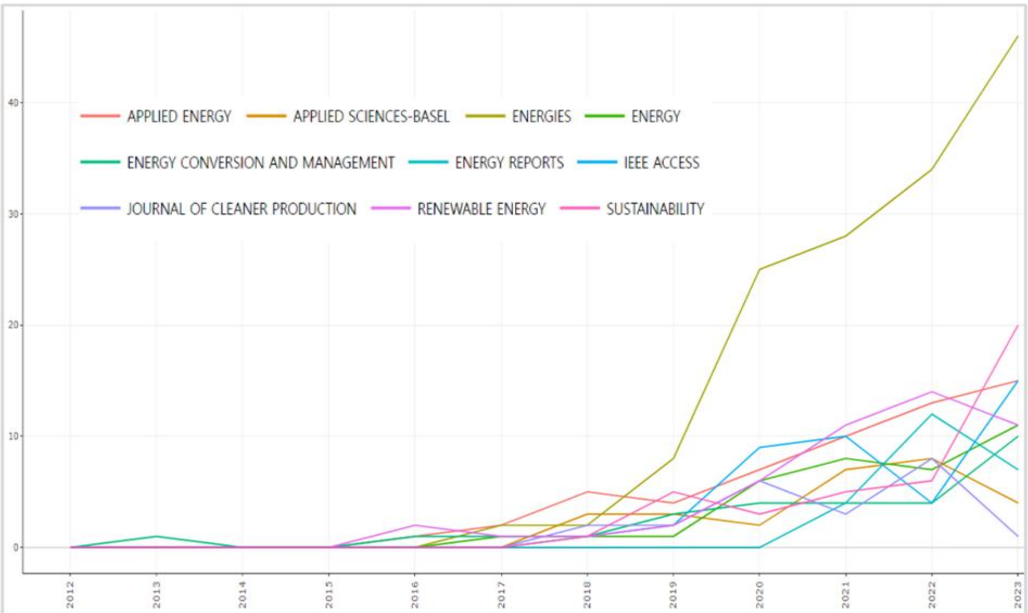

Figure 12. *Annual article publication trend in top 10 sources of the articles on ML and REF from 2011 to 2023*

Table 9 lists the top 10 sources of citations. *Applied Energy* was the top-ranked source with 1974 citations, followed by *Energies* with 1496 citations and *Energy Conversion and Management* with 1215 citations.

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Table 9. *Top 10 sources of the articles on ML and REF from 2011 to 2023 in terms of total citations*

Rank	Source	Total citations	H-index*
1	*Applied Energy*	1974	24
2	*Energies*	1496	22
3	*Energy Conversion and Management*	1215	17
4	*Energy*	1183	17
5	*Journal of Cleaner Production*	1005	14
6	*Renewable Energy*	968	17
7	*Renewable & Sustainable Energy Reviews*	857	12
8	*IEEE access*	751	14
9	*Solar Energy*	642	8
10	*Nature Catalysis*	435	1

*The h-index combines productivity and citation impact, showing that a journal has *h* articles with at least *h* citations each (Donthu et al., 2021)

Source-related science mapping

Figure 13 illustrates the entire citation network of the 371 sources of the 1232 articles on ML and REF. It comprised 152 clusters and 792 links. *Figure 14* shows the largest citation network of the sources comprising 248 sources with 38 clusters and 791 links. *Energies*, *Applied Energies*, *Sustainability*, and *IEEE Access* were important nodes in the largest citation network of sources.

Country dimension analysis result

Country-related performance analysis result

China was the top-ranked and most productive country with 207 article publications, as calculated based on the corresponding author's country. The USA ranked second with 131 articles while India ranked third with 111 articles. *Table 10* presents the top 10 countries with regard to article publications.

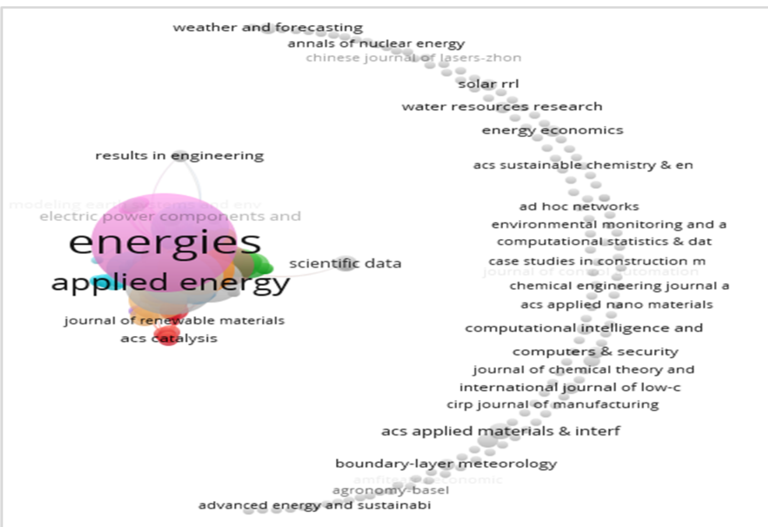

Figure 13. *Whole citation network of sources of the articles on ML and REF from 2011 to 2023*

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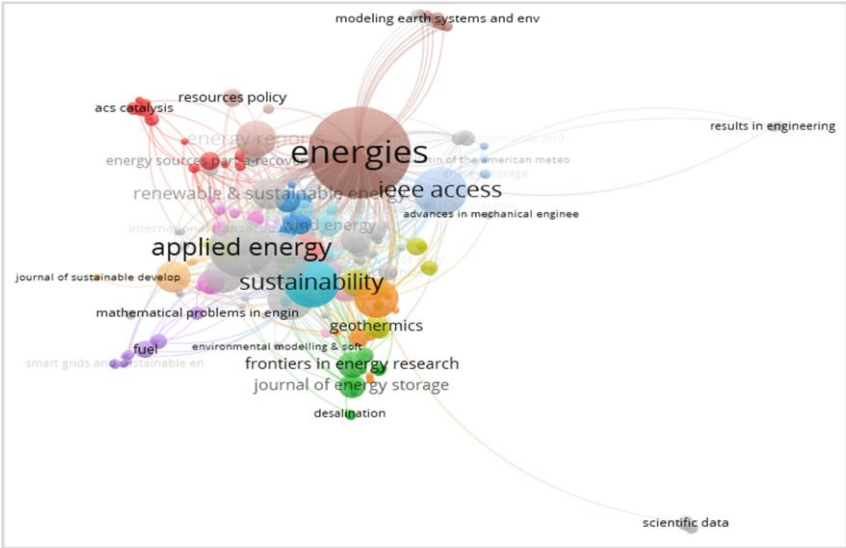

Figure 14. *Largest citation network of sources of the articles on ML and REF from 2011 to 2023*

Table 10. *Top 10 countries in terms of article publications in ML and REF from 2011 to 2023**

Rank	Country	Article publications
1	China	207
2	USA	131
3	India	111
4	Korea	55
5	Spain	50
6	Saudi Arabia	42
7	Italy	40
8	United Kingdom	37
9	Iran	33
10	Turkey	31

*Article publications counted based on the corresponding author's country

Table 11 lists the top 10 countries in terms of total citations. China was the top-ranked and most influential country with 3488 citations, followed by the USA with 2489 citations and the United Kingdom with 1129 citations.

Country-related science mapping

This study examined two collaboration networks of countries in ML and REF according to the two salient periods identified in the annual article publication trends shown in *Figure 4*. The first is the collaboration networks of countries in period 1, which was characterized by a relatively slow growth in article publications from 2012 to 2016. The other one is the collaboration networks of countries in period 2, which showed a relatively drastic growth in article publications from 2017 to 2023.

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Table 11. *Top 10 countries in terms of total citations of the articles on ML and REF from 2011 to 2023*

Rank	Country	Total citations
1	China	3488
2	USA	2489
3	United Kingdom	1129
4	India	973
5	Brazil	862
6	Korea	852
7	Turkey	790
8	Italy	758
8	Spain	758
10	Australia	673

Figure 15 shows the collaboration networks of countries in period 1, comprising 16 countries and 5 clusters, as shown in *Table 12*. Of the clusters, only two (red and green) were connected to each other, and the other three (purple, blue, and orange) had no connection with the other clusters.

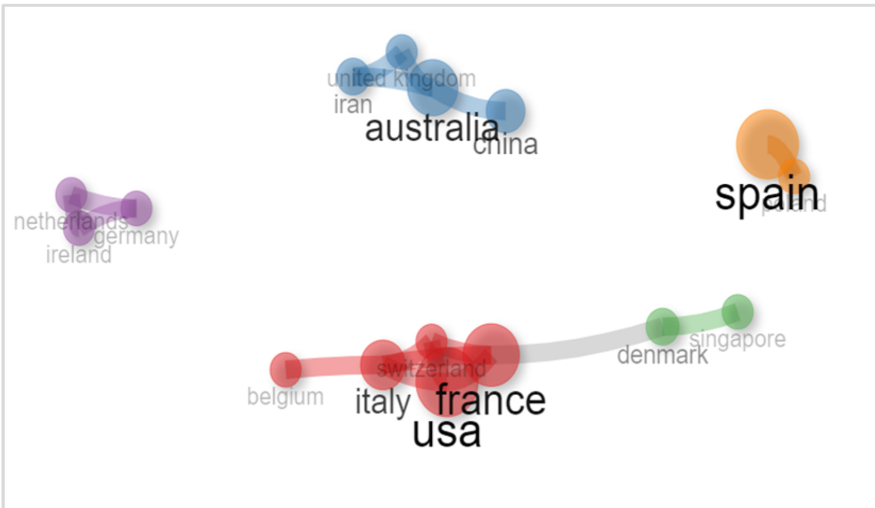

Figure 15. *Collaboration network of countries in the articles on ML and REF from 2012 to 2016*

Assessing betweenness centrality revealed that France played the most important role in bridging the collaborative relationships within the networks of countries in the 2012–2016 period. France was the top-ranked country with a betweenness centrality of 8. Italy and Denmark ranked second with a betweenness centrality of 5. *Table 12* lists the countries and their betweenness centrality in the collaboration network of countries for 2012–2016.

Figure 16 shows the collaboration networks of countries in 2017–2023, comprising 50 countries and 5 clusters. All clusters were connected to at least one other cluster. The largest cluster consisted of 28 countries while the smallest one comprised 1 country.

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China played the most important role in bridging the collaboration network of countries in 2017–2023. China was the top-ranked country with a betweenness centrality of 191.74, followed by the USA and Saudi Arabia with betweenness centrality of 175.1 and 90.2, respectively. *Table 13* reports the top 10 countries in regard to betweenness centrality in the collaboration network of countries in 2017–2023.

***Table 12.** Countries in the collaboration network in the articles on ML and REF from 2012 to 2016*

Country	Cluster	Betweenness centrality
France	Red	8
Italy	Red	5
Denmark	Green	5
Australia	Blue	2
USA	Red	0
Belgium	Red	0
Switzerland	Red	0
China	Blue	0
Iran	Blue	0
United Kingdom	Blue	0
Singapore	Green	0
Germany	Purple	0
Ireland	Purple	0
Netherlands	Purple	0
Spain	Orange	0
Poland	Orange	0

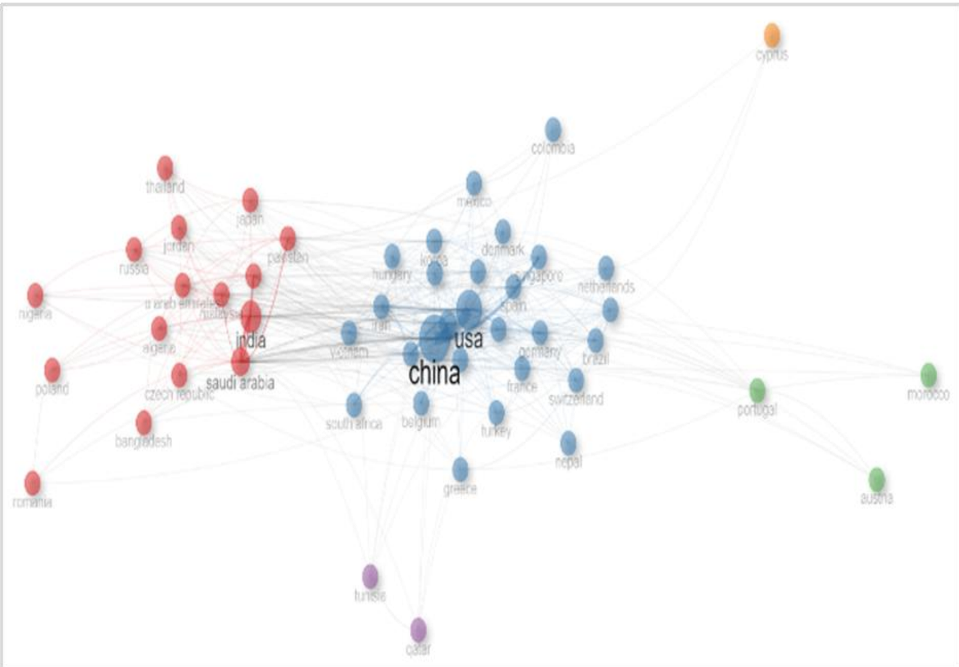

***Figure 16.** Collaboration network of countries in the articles on ML and REF from 2017 to 2023*

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Table 13. *Top 10 countries in terms of betweenness centrality in the collaboration network of countries in the articles on ML and REF from 2017 to 2023*

Country	Cluster	Betweenness centrality
China	Blue	191.74
USA	Blue	175.10
Saudi Arabia	Red	90.20
United Kingdom	Blue	43.05
India	Red	40.95
Pakistan	Red	37.05
Iran	Blue	32.37
France	Blue	25.43
Australia	Blue	20.20
Spain	Blue	17.08

Topic dimension analysis result

Thematic analysis result

Figure 17 shows the thematic map analysis results for 2012–2023. The thematic map presents four themes (basic, motor, niche, and emerging or declining themes) based on the degree of development related to density and the relevance in terms of centrality (https://www. bibliometrix.org). Motor themes were the major themes, as shown in *Figure 17*.

Figure 17. *Thematic map of the articles on ML and REF from 2012 to 2023*

As shown in *Figure 17*, eight themes were identified using the thematic map analysis. “Predictive models,” “big data,” and “machine learning” belonged to the motor themes. “Anaerobic digestion” and “forecasting” were identified as niche and

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basic themes, respectively. “Energy consumption,” “supervised learning,” and “Internet of things” belonged to the emerging or declining themes. *Table 14* reports the centrality and density of the themes on the thematic map from 2012 to 2023.

Table 14. *Centrality and density of themes in the thematic map of the articles on ML and REF from 2012 to 2023*

Theme	Callon centrality	Callon density	Rank centrality	Rank density
Big data	0.27	15.37	5	7
Forecasting	2.04	12.73	8	3
Machine learning	1.41	13.79	7	5
Energy consumption	0.09	13.76	4	4
Supervised learning	0.06	12.50	3	2
Predictive models	0.97	16.29	6	8
Anaerobic digestion	0.02	14.29	1	6
Internet of things	0.05	10.00	2	1

Thematic evolution analysis result

Figure 18 shows the thematic map analysis results for 2012–2016, which is period 1 characterized by a relatively slow growth in annual article publications (*Fig. 4*). For this period, four themes were identified: “artificial neural networks,” “forecasting,” “wind power,” and “wind energy.” Artificial neural network and forecasting belonged to the motor and basic themes, respectively. Wind power and wind energy were identified at the border between the niche themes and the emerging or declining themes. *Table 15* reports the centrality and density of the themes on the thematic map from 2012 to 2016.

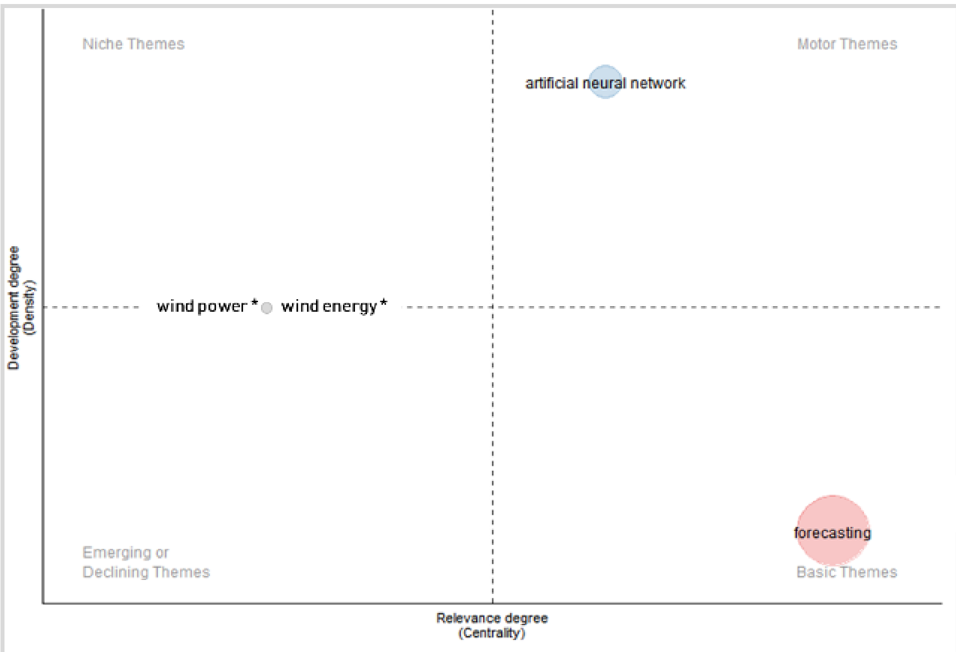

Figure 18. *Thematic map of the articles on ML and REF from 2012 to 2016. The themes such as “wind power” and “wind energy” have the same development and relevance degree, and they are marked with the same circle in the map*

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Table 15. *Centrality and density of themes in the thematic map of the articles on ML and REF from 2012 to 2016*

Theme	Callon centrality	Callon density	Rank centrality	Rank density
Forecasting	0.42	39.81	4	1
Artificial neural network	0.25	62.5	3	4
Wind power	0	50	1.5	2.5
Wind energy	0	50	1.5	2.5

Figure 19 shows the thematic map analysis results for 2017–2023, which is period 2 characterized by a relatively drastic growth in annual article publications (*Fig. 4*). Eight themes were identified. “Predictive models” and “smart grid” belonged to the motor themes. “Multi-objective optimization” and “anaerobic digestion” were identified as niche themes. “Machine learning” and “energy consumption” were the basic themes. “Supervised learning” and “Internet of things” were the emerging or declining themes. *Table 16* reports the centrality and density of the themes on the thematic map from 2017 to 2023.

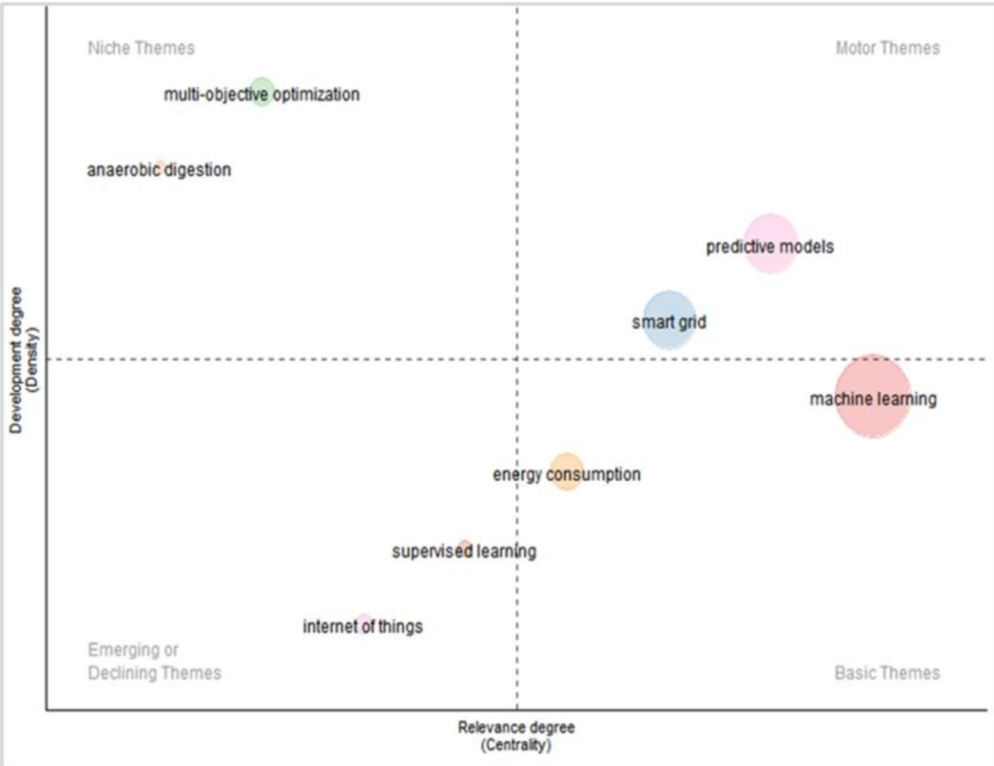

Figure 19. *Thematic map of the articles on ML and REF from 2017 to 2023*

Discussion and suggestions for future research

Summary of main findings

This study examined the features of the evolution of ML and REF articles from 1990 to 2023. Previous literature studies on ML and REF have neither included state-of-the-art findings in their analyses nor investigated the changes in the collaboration networks

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among countries. To achieve a comprehensive understanding of the evolution of research in ML and REF, this study performed a multidimensional analysis. The main findings from the analysis, which involved articles, authors, sources, countries, and topics, can be summarized as follows.

Table 16. *Centrality and density of themes in the thematic map of the articles on ML and REF from 2017 to 2023*

Theme	Callon centrality	Callon density	Rank centrality	Rank density
Machine learning	1.94	13.94	8	4
Smart grid	1.05	14.24	6	5
Multi-objective optimization	0.02	17.35	2	8
Energy consumption	0.07	13.76	5	3
Supervised learning	0.06	12.5	4	2
Predictive models	1.2	16.09	7	6
Anaerobic digestion	0	16.67	1	7
Internet of things	0.05	10	3	1

First, the article dimension exhibited a distinct feature and was divided into two periods based on the quantity of publications and citations. Of the 1232 articles, 98% (1207 articles) were published after 2017. Accordingly, articles in ML and REF can be categorized into period 1 (2012–2016) and period 2 (2017–2023). With the increase in the quantity of articles published in Period 2, the quantity of annual article citations also increased significantly. The distribution of the total citations of articles was L-shaped, as shown in *Figure 6*, indicating that the citations were concentrated in a few articles.

Second, in the author dimension, the graph of the distribution of article publications by author also exhibits an L-shaped pattern, with many studies being conducted by a few key authors. The author with the greatest amount of publications was Deo, R. C., who was ranked fifth in terms of citations (*Tables 5* and *6*).

Third, in the source dimension, the distribution followed an L-shaped pattern (*Figure 11*), indicating that studies on ML to REF were overwhelmingly concentrated in a single journal. This trend was particularly noticeable in period 2; however, journals spanning diverse fields, such as chemistry, environment, and engineering (e.g., *IEEE Access* and *Nature Catalysis*), also appeared. In terms of citations, studies published in various journals, including traditional energy journals, are being increasingly referenced.

Fourth, for the country dimension, this study examined the evolutionary features based on the corresponding author's country. The article publications were highly concentrated in China, the USA, and India. In terms of citations, China ranked first, followed by the USA, the United Kingdom, and India. Regarding the collaboration network, in period 1, France held the highest betweenness centrality, connecting to 16 countries across 5 clusters. By period 2, the network had expanded to 50 countries within five clusters, with China taking the top position in terms of betweenness centrality.

Fifth, concerning the topic dimension, we observed a diversification of themes by comparing the thematic map from Period 1 (2012 to 2016) (*Fig. 18*) with that of Period 2 (2017 to 2023) (*Fig. 19*). In Period 1, there were only four themes: "wind power,"

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"wind energy," "artificial neural network," and "forecasting." However, in Period 2, the themes have diversified into eight topics, including "anaerobic digestion," "multi-objective optimization," "predictive models," "smart grid," "machine learning," "energy consumption," "supervised learning," and the "internet of things." Furthermore, we examined the evolution of these themes by categorizing them into four groups on the thematic map: basic, motor, niche, and emerging or declining themes. In Period 1, "forecasting" was categorized as a basic theme, while "artificial neural networks" were identified as a motor theme. "Wind power" and "wind energy" were found to be between niche and emerging or declining themes. In Period 2, "machine learning" and "energy consumption" were categorized as basic themes, whereas "predictive models" and "smart grids" were classified as motor themes. Additionally, themes such as "anaerobic digestion" and "multi-objective optimization" emerged as niche themes and "supervised learning" and "Internet of things" were identified as emerging or declining themes.

Discussion of main findings

In this study, we divide the evolution of articles on ML and REF into two periods. The year 2017, which marks the division between periods 1 and 2, represents the time when ML began to be applied across various industries, including REF. Machine learning has attracted widespread public attention with the emergence of AlphaGo, and it has been widely adopted across various industries since 2017, driven by advances in computer systems and the explosive growth of big data with the Internet of things. Reflecting this trend, ML and REF research has rapidly increased since 2017.

Our analysis results identify three key features of the evolution of articles on ML and REF from period 1 to period 2. The first key feature is interdisciplinarity. Research on ML and REF is evolving into a field that synthesizes multiple disciplines rather than being confined to a single discipline. As shown in the top sources of article publications in *Table 8*, journals that comprehensively cover diverse fields of study, such as engineering and natural sciences (e.g., *IEEE Access*, *Sustainability*, and *Applied Sciences-Basel*), are emerging alongside traditional energy-focused journals. This trend reflects the expansion of journals for the research on ML and REF, driven by the application of ML to REF. Furthermore, active collaboration is evident in various authors' collaboration network, as shown in *Figure 10*. With the application of ML to REF, experts from various fields are collaborating more frequently, and international collaborations are increasing. As illustrated in *Figures 15* and *16*, while research was primarily conducted independently during period 1, active international collaboration became a salient feature in period 2. This finding emphasizes the necessity of collaboration in ML and REF research and highlights the importance of international partnerships between domain experts and technology specialists.

The second key feature is topic diversification. Articles with the greatest amount of citations exert a significant influence on other studies. We examine the type of energy predicted based on the top 10 articles ranked by total citations, as shown in *Table 4*. During period 1, research primarily focused on solar power generation. However, in period 2, it expanded to include various renewable energy sources like wind power (Demolli et al., 2019), fuel cells (Ma et al., 2018), and high-impact weather (McGovern et al., 2017), in addition to solar energy. This finding indicates that the renewable energy types applied in ML and REF research are becoming increasingly diverse.

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The diversification of topics is also evident in the thematic analysis. Themes such as “anaerobic digestion” and “multi-objective optimization,” which emerged in period 2, were identified within the niche theme. Anaerobic digestion refers to process in which energy is generated through the decomposition of biodegradable organic matter by microorganisms (Adekunle and Okolie, 2015), and it is gaining increasingly growing attention as a renewable energy source. Unlike solar and wind energies, which are commonly used in ML and REF re-search and are heavily influenced by weather conditions with intermittent generation, anaerobic digestion occurs widely in ecosystems, such as natural environments and animals’ internal systems, and has the advantage of continuous availability regardless of weather. Machine learning can be applied to predict the amount of energy generated through anaerobic digestion. However, because carbon emissions are produced during combustion, multi-objective optimization is essential. This characterization emphasizes the importance of utilizing ML in anaerobic digestion not only to predict energy generation but also to simultaneously minimize carbon emissions. Meanwhile, smart grid, which falls within the motor theme, refers to an intelligent power grid system that incorporates information and communication technology into the traditional power grid to optimize the management of power generation, transmission, and consumption (Shafiullah et al., 2013). This development has been facilitated by the advancement of technologies, such as machine learning and the Internet of things.

The final feature is the key sophistication of techniques. The analysis of the techniques employed in the top 10 articles ranked by total citations during period 1 revealed that prediction models primarily relied on time series analysis and statistical methods, with artificial neural networks representing an initial application of machine learning. By contrast, during period 2, a broader range of machine learning algorithms was used in various studies (e.g., McGovern et al., 2017; Tran and Ulissi, 2018; Fan et al., 2018; Ahmad and Reynolds, 2018), including gradient boosted regression trees, random forests, decision trees, and support vector regression. Furthermore, deep learning approaches (Ma et al., 2018) such as LSTM and recurrent neural networks (RNN) have been introduced to enhance predictive performance. Period 2 represents the phase in which more sophisticated machine learning techniques were actively applied, demonstrating the diversification of prediction techniques aimed at improving predictive performance. In addition, the application of deep learning methodologies further highlights the evolution and sophistication of techniques during this period.

Suggestions for future research

Based on our main findings, we offer valuable suggestions for future research. First, applying various deep learning techniques by hybridizing two or more techniques rather than relying on a single model can enhance predictive performance. The top 10 articles identified in this study utilized various single models to compare prediction performance or applied deep learning techniques, such as LSTM and RNN. To further improve predictive performance, advanced deep learning techniques like convolutional neural networks (CNN) and deep neural networks (DNN) can be more effective, and hybrid models combining multiple methods can achieve better predictive performance. For instance, Al-Ghamdi et al. (2023) proposed a hybrid model which integrates DNN and LSTM to predict energy consumption and demonstrated improved performance.

Second, deep learning-based prediction models are often regarded as black-box models, making it difficult to understand the reasoning behind their results. To enhance

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the trustworthiness of these models, their accuracy must be improved, and their outputs must be explained clearly. Consequently, future research should prioritize the integration of explainable AI techniques into these prediction models.

Third, large language models (LLMs) that make predictions using text data are increasingly being applied to forecasting tasks. LLMs are deep learning algorithms designed to perform various natural language processing tasks by leveraging knowledge acquired from vast amounts of data (Brown et al., 2020), and have attracted significant attention in recent years. However, in ML and REF, prediction models are primarily built based on quantitative data. Meanwhile, text data are useful for providing insights into factors that quantitative data cannot capture, such as events or social issues related to renewable energy forecasting. Therefore, utilizing qualitative data in prediction models has the potential to significantly enhance predictive performance.

Fourth, the ML and REF research primarily focuses on traditional solar and wind energy generation. However, as highlighted in the niche themes of the thematic analysis in this study, “anaerobic digestion” represents an area that requires further exploration. Hence, the various applications of ML and deep learning to anaerobic digestion must be investigated further to advance this area.

Fifth, it will be useful for enriching the understanding of the evolution of research in ML and REF to make an examination of cross-references in the articles on ML and REF.

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