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A forty years scientometric investigation of artificial intelligence for fluid-flow and heat-transfer (AIFH) during 1982 and 2022

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ABSTRACT

A scientometric approach is utilized to investigate the dynamic maps of relationships among researchers, institutes, and countries in the field of Artificial Intelligence for Fluid-flow and Heat-transfer (AIFH). The Web of Science database was searched for related publications during the last 40 years (1982 and 2022). A total of 6151 articles were discovered, which were analyzed in detail. Using a bibliometric analysis, the most relevant and most cited sources of publications were identified. The most active researchers, institutions, and countries leading AIFH were reported. Then, the worldwide dynamic collaboration maps and coupling maps of relationships were reported. The Islamic Azad University (1893 T.C.), the Chinese Academy of Sciences (1374 T.C.), and Beihang University (1266 T.C.) were the most influential institutes in AIFH. The most influential countries were China, the USA, and Iran. The dynamic map of collaborations shows a good worldwide collaboration distribution. The USA and China established the most connection with the rest of the world. ANNs are the most studied topic (19.5% of publications), followed by Machine Learning (17.9%) and Neural Networks (15.4%). Support Vector Machines lag behind at 1.4%. ANNs boast the highest total citations (17,064) and H-index (63). Most ANIF papers were published by Medical Physics (119 T.P.). Half of the articles in AIFH were published by five journals of Medical Physics, Neurocomputing, International Journal of Heat and Mass Transfer, International Journal of Radiation Oncology Biology Physics, and IEEE Access. The International Journal of Heat and Mass Transfer received the most citations in AIFH.

1. Introduction

Convective heat transfer is an essential part of many industrial production and process systems, and many researchers are seeking ways to enhance heat transfer (Ali et al., 2021; Sadeghianjahromi and Wang, 2021). Engineers use mathematical models (Hay et al., 2021) and traditional numerical approaches (Kumar and Amano, 2021; Sharma et al., 2021; Verma and Mondal, 2021) to design heat transfer systems.

Artificial Intelligence (AI) and machine learning approaches have recently found important applications in the simulation and design of heat transfer systems. For example, Ma et al. (2021) reviewed the application of Machine Learning (ML) methods, including artificial neural networks (ANNs) for heat renewable energy and exchanger. They concluded that ML methods are fundamentally beneficial for estimating the radiative-optical performance, thermo-hydrodynamic performance, and thermophysical properties of nanofluids. Alizadeh et al. utilized AI methods to predict heat transfer for nanofluids (Alizadeh et al., 2021b) and hybrid nanofluids (Alizadeh et al., 2021a) in heat transfer systems. They (Alizadeh et al., 2021a, 2021b) reported that very recently, a new generation of advanced numerical tools has been established to decrease

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computational costs and enhance the estimation of design goals. A combination of AI and traditional numerical simulations is a sample of these advancements. These authors employed AI and estimated the heat transfer characteristics successfully.

AI methodologies such as ANNs, Long Short-Term Memory (LSTM) networks, Relevance Vector Machines (RVMs), and Convolutional Neural Networks (CNNs) have shown exceptional capabilities in solving complex engineering problems. A few examples include a recent study that employed extended marine predators algorithm-based artificial neural network (ANN-EMPA) for precise streamflow prediction, showing significant improvements over other metaheuristic algorithms. The ANN-EMPA model proved superior in root mean square error and mean absolute error compared to other hybrid ANN methods (Ikram et al., 2022). In hydrology, a hybrid long short-term memory neural network and ant lion optimizer model (LSTM–ALO) have been effectively used for monthly runoff forecasting. This model demonstrated a higher accuracy compared to existing models (Yuan et al., 2018). Relevance Vector Machines tuned with Improved Manta-Ray Foraging Optimization (RVM-IMRFO) have shown very good in predicting monthly pan evaporation using limited climatic data. The RVM-IMRFO model significantly improved performance metrics like RMSE, MAE, R2, and NSE over other tuning algorithms (Adnan et al., 2023). CNNs integrated with novel optimization algorithms have been successfully applied in environmental science for predicting daily water temperatures. Specifically, the LSTM-INFO model considerably reduced the errors in root mean square and mean absolute errors (Ikram et al., 2023).

The versatility of AI is demonstrated by its successful applications across various disciplines. For instance, Accurate water runoff and streamflow predictions are critical for effective water management. Models like LSTM-ALO and ANN-EMPA have been pivotal (Ikram et al., 2022; Yuan et al., 2018). AI models like RVM-IMRFO provide a reliable method for predicting pan evaporation based on minimal climatic data, which is essential for regions with limited resources (Adnan et al., 2023). The LSTM-INFO model offers a robust technique for estimating daily water temperatures, thus playing a crucial role in environmental impact assessment and aquatic ecosystems' management (Ikram et al., 2023). These examples underscore the relevance and effectiveness of AI methodologies in scientific research, setting the stage for their potential contributions to fluid flow and heat transfer.

A scientometrics investigation aims to find the relation between literature studies of a topic and learn the scientific relationship between authors, organizations, and countries by analyzing publication data (Ghalambaz et al., 2022). Some of the recent publications utilized bibliometric analysis and investigated the mathematical modeling approaches (Verma et al., 2021), heat transfer for thermal energy storage applications(Borri et al., 2021), nanogenerators for smart cities (Alagumalai et al., 2021), heat exchangers (Sridharan, 2020), zero energy buildings (Manzoor et al., 2022), and photovoltaic thermal systems (Azad and Parvin, 2022). In (Verma et al., 2021), the co-authorship and co-occurrence of keywords, citation, co-citation analysis, and bibliographic coupling were investigated for the journal "Applied Mathematical Modelling". The findings indicate a significant growth of the journal through time and a good diversity of published documents. The outcomes of (Alagumalai et al., 2021) regarding nanogenerators for smart cities indicate notable recent (during the past five years) investments of China in the field. Chinese scholars published over 1000 papers during 2015–2020, significantly higher than the USA publications. The authors also concluded that European countries need to pay more attention to nanogenerators to compete.

Some recent publications considered the bibliometric analysis of artificial intelligence in breast cancer (Zhang et al., 2022), finance systems (Goodell et al., 2021), E-Commerce (Bawack et al., 2022), and branding (Varsha et al., 2021). In (Goodell et al., 2021), the authors utilized bibliometric-coupling and co-citation analyses and surveyed the thematic structure of AI and ML research in finance during 1986–2021. The authors identified three overarching finance scholarship groups, highlighting the research directions and trends of AI and ML in the field.

The literature review shows several bibliometric aspects of heat transfer (Alagumalai et al., 2021; Azad and Parvin, 2022; Borri et al., 2021; Manzoor et al., 2022; Sridharan, 2020; Verma et al., 2021) and AI (Bawack et al., 2022; Goodell et al., 2021; Varsha et al., 2021; Zhang et al., 2022), but no literature study addresses the bibliometric analysis of Artificial Intelligence for Fluid-flow and Heat-transfer (AIFH). Providing a comprehensive analysis of literature due to the large number of publications in the field is a time-consuming and challenging task. Thus, the purpose of this study is to address the following goals in the field of AIFH: 1- Discovering the most active researchers, institutions, and countries leading AIFH. 2- Identifying the most cited publications in the field of AIFH. 3- Identifying the most influential countries and institutes. 4- Plotting the characteristics of the AIFH's worldwide dynamic collaboration maps. 5- Plotting coupling maps of relationships among researchers, publications, institutes, and countries.

2. Material and methods

The main source of data in this investigation was the Web of Science (WoS), which is the worldwide powerhouse in scientific knowledge. Scholars can use descriptive and evaluative analysis tools with the scientific data in WoS. Many famous publications across the world are available in the WoS *Core Collection*. To obtain bibliographic information for articles related to AIFH was adopted. WoS was searched on the May 9, 2022 for the research items published between 1982 and 2022 years (Over the past forty-one years). There was a total of 6151 articles discovered. In order to analyze the data, the VOSviewer program was utilized. Bibliographic mapping and clustering are both provided by VOSviewer's mapping and clustering capabilities.

The following search algorithm was utilized in order to obtain information about the artificial intelligence fluid flow and heat transfer:

((TI=("artificial intelligen*" OR "neural network*" OR "deep neural*" OR "convolutional network" OR "deep neural network*" OR "machine learning*" OR "convolutional neural*" OR "data * driven")) OR (AK=("artificial intelligen*" OR "neural network*" OR "deep neural*" OR "convolutional network" OR "deep neural network*" OR "machine learning*" OR "convolutional neural*" OR "data * driven"))) AND ((TI=("convection*" OR "convective*" OR "radiation*" OR "heat conduction*" OR "heat transfer*" OR "temperature field*" OR "diffusion*" OR "navier * stokes" OR "fluid*" OR "turbulen*" OR "laminar*" "flow field*")) OR (AK=("convection*" OR "convective*" OR "radiation*" OR "heat conduction*" OR "heat transfer*" OR "temperature field*" OR "diffusion*" OR "navier * stokes" OR "fluid*" OR "turbulen*" OR "laminar*" "flow field*")))

Readers can see Table 1 and Fig. 1 for descriptive and graphical representations of the search string. Our findings are presented in the next sections. The far more successful and significant writers, institutions, and countries are presented first, followed by bibliometric analysis, publications, number of cited papers per year, and the number of authors, institutions, and nations through time. In the second part, we

Table 1
Search category, formula, and item.

Search Category	Search string	Search area
First Search category (C1)	"artificial intelligence*" OR "neural network*" OR "deep neural*" OR "convolutional network" OR "deep neural network*" OR "machine learning*" OR "convolutional neural*" OR "data * driven"	• Author Keywords (A. K.) • Title (T.I.)
second Search category (C2)	"convection*" OR "convective*" OR "radiation*" OR "heat conduction*" OR "heat transfer*" OR "temperature field*" OR "diffusion*" OR "navier * stokes" OR "fluid*" OR "turbulence*" OR "laminar*" "flow field*"	• Author Keywords (A. K.) • Title (T.I.)

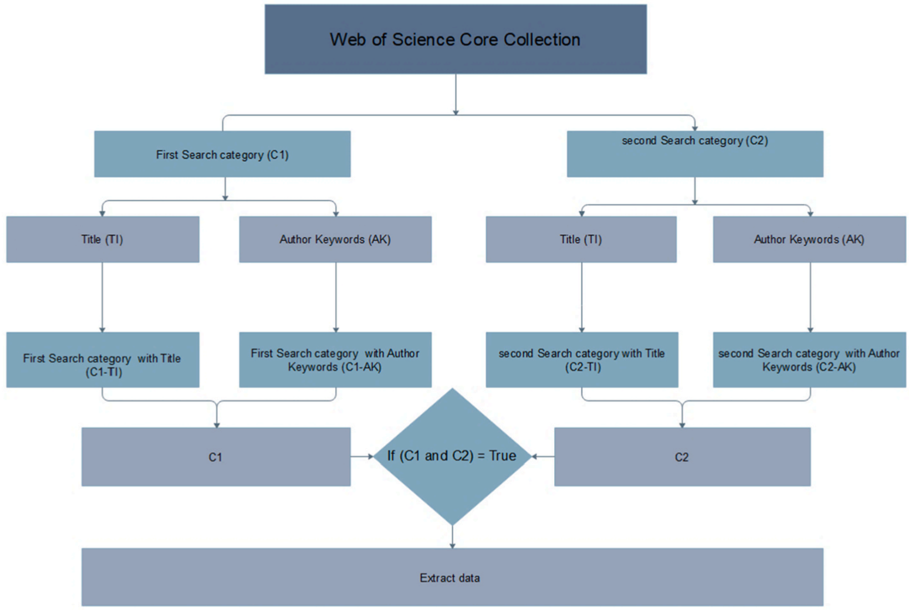

Fig. 1. Web of Science (WoS) search flowchart.

visualized the network, co-authorship, co-citation, and bibliographic linkage of writers, institutions, and nations.

3. Bibliometric evaluation

The most productive and significant writers, universities, and nations are all included in this section, along with annual publications and citations.

3.1. Yearly number of publications and citations

The very first task is to study AIFH's publication and citation record during the past forty-one years (1982–2022 years). For each publishing year, the total number of papers published (T.P.) and the total citations number (T.C.) are shown in Table 2 and Fig. 2. Additionally, the table lists the number of papers that have received more citations than a given threshold. Minimum criteria of 200, 100, 50, 25, 10, 5, and 1 citation Minimum criteria of 200 are considered here. They also (i.e., Table 2 and Fig. 2) demonstrate that since 2015, there has been a significant jump in total citations (T.C.). Since 2018, there has been a significant jump in total publications (T.P.). While in the decades of 80' and 90', the number of publications in AIFH was negligible. Nevertheless, from 2000 to 2015, T.P. and T.C. have been increasing with a very slight slope, and there has been an increasing trend in almost these 15 years.

The maximum total citation (T.C.) occurred in 2019. This means that researchers have highly regarded AIFH since 2019. Accordingly, the maximum number of total publications (T.P.) occurred in 2021. A recent fall can signify a delay between an article's release and its citation in later publications. That is because they were just released, and 2020, 2021, and 2022 publications have not yet been cited. 3887 out of 6151 papers that were published had at least one citation or more, around 63 percent.

3.2. The most prolific and significant authors

Table 3 lists the leading authors connected to publications published in AIFH. W. Zhang (46 T.P.) is the most prolific contributor to AIFH publications, equally followed by J. Kim (33 T.P.), Muhammad Asif Zahoor Raja (33 T.P.), and then followed by Yan-li Huang (29 T.P.), and Jin-Liang Wang (29 T.P.). At least ten publications from each of the top forty authors have appeared in AIFH. Earning the most citations is C. Voyant (1443 T.C.), followed by P. Paoli (1303 T.C.), M.L. Nivet (1293 T.C.), J.L. Wang (1250 T.C.), Huai-Ning Wu (1099 T.C.), and T. Huang (1076 T.C.). Of the top forty authors, these six authors have received over a thousand citations. Remarkably, the three authors who received the most citations, i.e., Cyril Voyant, P. Paoli, and M. L. Nivet, just published a few papers, i.e., T.P. $\leq$ 13. This specifies that these three authors have produced high-quality articles. Earning the highest h-index values is J. L. wang (16 H.I.), which is equally followed by M. A. Zahoor Raja (14 HI), J. Cao (14 H.I.), and T. Huang (14 H.I.). There are fifteen authors in AIFH who have an h-index (H.I.) above ten. This suggests that Each of these fifteen authors has published ten papers that earned at least ten citations each.

Authors are plotted in Fig. 3 according to total publications and citations. There are two criteria that divide academics into four categories, according to [21].: *productivity* and *citations*. Authors who are prolific are distinguished by great productivity and many citations. Authors with large productivity but few citations are known as mass producers. Those with a high number of citations but low production are perfectionists. However, both the productivity and the number of citations of silent authors are low. Seven authors are in the prolific zone. W. Zhang is the most productive author and is located on the border of mass producers and the Prolific zone. C. Voyant, C. Paoli, and M. L. Nivet are in the Perfectionists zone. These three authors also received the most citations in AIFH, respectively. Most of the authors are clustered in the silent zone. Only six authors have received more than a thousand citations in AIFH, three of them are in the Perfectionists zone, and the rest are in the Prolific zone.

3.3. The most productive and significant universities

According to the total number of publications, Table 4 lists the top 40 university affiliations of writers who have published. Seventeen universities in China and twelve universities in the United States are among the top forty universities in the world.

- Top five universities base T.P. index:
  1. Chinese Academy of Sciences
  2. Islamic Azad University
  3. Stanford University

Table 2
Total papers and total citations by year.

Year	T.P.	T.C.	>200	>100	>50	>25	>10	>5	>1	DECADES	T.P.	T.C.
1982	1	7	0	0	0	0	0	1e	1	80’	2	22
1983	0	0	0	0	0	0	0	0	0			
1984	0	0	0	0	0	0	0	0	0			
1985	0	0	0	0	0	0	0	0	0			
1986	0	0	0	0	0	0	0	0	0			
1987	0	0	0	0	0	0	0	0	0			
1988	1	15	0	0	0	0	1	1	1			
1989	0	0	0	0	0	0	0	0	0			
1990	2	0	0	0	0	0	0	0	0	90’	183	3013
1991	5	134	0	0	1	1	2	4	4			
1992	6	22	0	0	0	0	0	2	3			
1993	10	103	0	0	0	2	3	5	7			
1994	23	271	0	0	2	3	7	9	14			
1995	14	130	0	0	0	1	4	5	10			
1996	31	413	0	1	2	4	9	15	21			
1997	37	600	0	1	1	6	15	24	31			
1998	26	767	1	2	3	8	13	17	20			
1999	29	573	0	1	3	9	14	16	18			
2000	37	763	1	2	4	8	13	16	25	00’	736	15539
2001	43	803	0	0	5	9	20	25	34			
2002	55	1005	0	4	4	8	23	33	42			
2003	43	1052	0	2	6	13	21	26	33			
2004	47	812	0	2	4	9	18	25	32			
2005	70	1830	1	4	13	20	35	41	51			
2006	97	2210	2	3	11	25	43	56	72			
2007	90	1860	0	2	12	24	46	57	70			
2008	117	2391	2	4	14	28	47	55	76			
2009	137	2813	0	5	13	36	58	80	102			
2010	113	2566	1	4	15	32	55	65	82	10’	2551	46516
2011	137	3096	1	5	18	39	72	87	110			
2012	164	3234	0	4	19	34	76	106	136			
2013	142	3227	2	4	14	30	62	86	107			
2014	181	3555	1	6	19	33	78	98	129			
2015	191	3619	0	7	20	39	78	109	145			
2016	251	5791	1	14	31	64	121	151	192			
2017	319	6571	2	8	31	79	142	182	249			
2018	390	6165	0	8	25	72	173	237	302			
2019	663	8692	2	7	29	89	230	339	501			
2020	937	7507	1	1	10	52	209	391	690	20’	2679	11070
2021	1202	3310	0	0	0	12	65	177	532			
2022	538	253	0	0	0	1	2	5	45			
Total	6151	76160	18	101	329	790	1755	2546	3887			
%	100	–	0.29	1.64	5.35	12.85	28.54	41.41	63.18			

Nomenclature: T.P. = total number of papers, T.C. = total number of citations >200, >100, >50, >25, >10, >5, >1 = publications having at least 200, 100, 50, 25, 10, 5, and 1 citations.

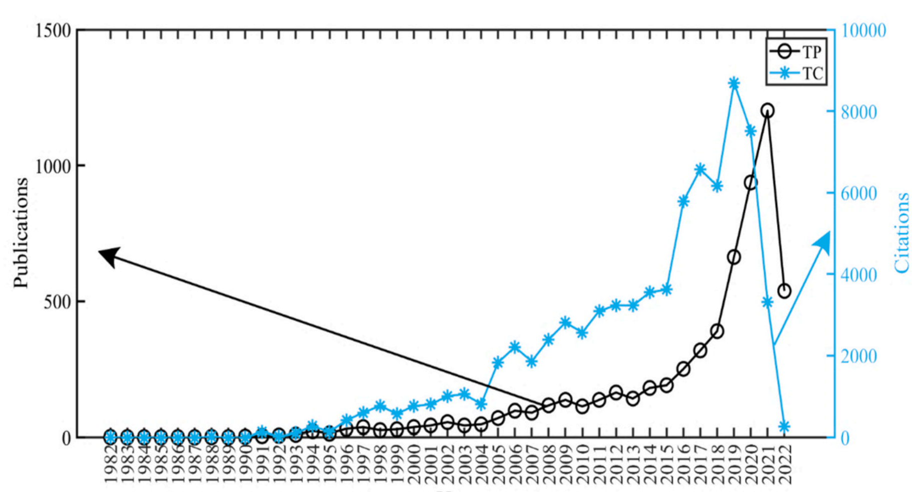

Fig. 2. T.P. = Total papers; T.C. = Total citations.

Table 3
Forty leading authors in AIFH.

R	Author name	Affiliation	Country	T.P.	T.C.	HI	T.C./T.P.
1	Zhang, Wei	Northwestern Polytech Univ.	China	46	445	11	9.7
2	Kim, J	Yonsei Univ	South Korea	33	382	8	11.6
3	Raja, Muhammad Asif Zahoor	Natl Yunlin Univ Sci & Technol	Taiwan	33	587	14	17.8
4	Huang, Yan-Li	Tiangong Univ, Sch Comp Sci & Technol	China	29	321	11	11.1
5	Wang, Jin-Liang	Tianjin Polytech Univ	China	29	1250	16	43.1
6	Ren, Shun-Yan	Tianjin Polytech Univ	China	28	746	13	26.6
7	Cao, Jinde	Southeast Univ	China	27	995	14	36.9
8	Huang, Tingwen	Texas A&M Univ	USA	24	1076	14	44.8
9	Shoaib, Muhammad	Comsats Univ Islamabad	Pakistan	21	199	7	9.5
10	Jiang, Haijun	Xinjiang Univ	China	19	544	9	28.6
11	Song, Xiaona	Henan Univ Sci & Technol	China	19	164	9	8.6
12	Wang, Zhen	Shandong Univ Sci & Technol	China	18	217	7	12.1
13	Wu, Huai-Ning	Beihang Univ	China	18	1099	11	61.1
14	Xu, Rui	Hijiazhuang Mech Engn Coll	China	18	173	7	9.6
15	Lee, C	Yonsei Univ	South Korea	17	298	6	17.5
16	Gan, Qintao	Shijiazhuang Mech Engn Coll	China	16	344	11	21.5
17	Wang, Linshan	Ocean Univ China	China	16	264	9	16.5
18	Xiao, Heng	Virginia Tech	USA	16	869	13	54.3
19	Zeng, Zhigang	Huazhong Univ Sci & Technol	China	16	408	12	25.5
20	Zhong, Shouming	Univ Elect Sci & Technol China	China	16	252	9	15.8
21	Wang, Jianchun	Southern Univ Sci & Technol	China	15	155	8	10.3
22	Balaji, C.	Indian Inst Technol Madras	India	13	230	9	17.7
23	Hu, Cheng	Xinjiang Univ	China	13	391	8	30.1
24	Voyant, Cyril	Univ Corsica	France	13	1443	12	111.0
25	Wang, Yangfan	Ocean Univ China	China	13	251	8	19.3
26	Li, Wei	Zhejiang Univ	China	12	216	4	18.0
27	Paoli, Christophe	Univ Corsica	France	12	1303	10	108.6
28	Park, Ju H.	Yeungnam Univ	South Korea	12	164	5	13.7
29	Song, Qiankun	Chongqing Jiaotong Univ	China	12	470	8	39.2
30	Wu, Q. Jackie	Duke Univ	USA	12	151	5	12.6
31	Zhang, Hao	Huazhong Univ Sci & Technol	China	12	222	7	18.5
32	Bahiraei, Mehdi	Kermanshah Univ Technol	Iran	11	200	8	18.2
33	Elkatatny, Salaheldin	King Fahd Univ Petr & Minerals	Saudi Arabia	11	219	7	19.9
34	Ge, Yaorong	Univ North Carolina Charlotte	USA	11	150	5	13.6
35	Nivet, Marie-Laure	Univ Corsica	France	11	1293	10	117.5
36	Noack, Bernd R.	Harbin Inst Technol Shenzhen	China	11	464	4	42.2
37	Valdes, Gilmer	Univ Calif San Francisco	USA	11	306	8	27.8
38	Xie, Chenyue	Southern Univ Sci	China	11	155	8	14.1
39	Fukagata, Koji	Keio Univ	Japan	10	325	8	32.5
40	Fukami, Kai	Keio Univ	Japan	10	325	8	32.5

Nomenclature: T.P. = total papers; T.C. = total citations; h = h-index (TF&SC only); C/P = citations/paper (i.e., T.C./T.P.).

4. Shanghai Jiao Tong University
5. Zhejiang University

- Base T.C. index:
  1. Islamic Azad University with (1893) has the highest number of citations,
  2. Chinese Academy of Sciences (1374),
  3. Beihang University (1266),
  4. University of Michigan (1203) and
  5. Tianjin Polytechnic University (1085) is in the next rank on the table
- Base H.I.:
  1. Azad University
  2. Tianjin Polytechnic University
  3. Chinese Academy of Sciences
  4. Beihang University
  5. Stanford University is among the top five University based H.I. in AIFH.
- Top five university base T.C./T.P. index:
  1. Virginia Tech
  2. Beihang University
  3. Sandia National Laboratories
  4. University of Michigan
  5. National Institute of Technology

These universities are among the top five universities in AIFH in terms of at least three different metrics: Islamic Azad University, Chinese Academy of Sciences (T.P., T.C., HI) and Beihang University (T.C., HI, T.C./T.P.). Among the top five universities in AIFH in terms of at least two different metrics are Stanford University (T.P. and H.I.), University of Michigan (T.P. and T.P./T.C.), and Tianjin Polytechnic University (T.C. and H.I.).

The institutions are shown in Fig. 4, mapped by total articles and total citations. There are six universities with more than forty publications in the prolific zone. These universities are: Stanford Univ, Johns Hopkins University, University of California, Los Angeles from the United States and Tianjin Polytechnic University, Chinese Academy of Sciences from China, and Islamic Azad University from Iran, which are in the prolific zone. There are two universities with more than forty publications in the mass producer zone: These universities are Zhejiang University and Shanghai Jiao Tong University; many of the universities are in the silent zone.

3.4. The most productive and influential nations

According to population size, Table 5 shows summarized information on the top 40 nations. In terms of total publications (T.P.), China is in the first place, followed by the United States of America, India, Iran, and England; in terms of total citations (T.C.) and h-index, China, USA, Iran, India, and France are in the top five countries in AIFH. In terms of the average number of citations per publication (T.C./T.P.), Qatar, Algeria, France, Turkey, and Iran are in the top five countries in AIFH. Iran is one of the top five countries in terms of four different metrics (T.P., T.C., H.I., and T.C./T.P.) in AIFH. China leads the ranking in terms of three different metrics (T.P., T.C., and H.I. (, followed by the United States. After the United States, there is a big gap in the number of T.P., T.

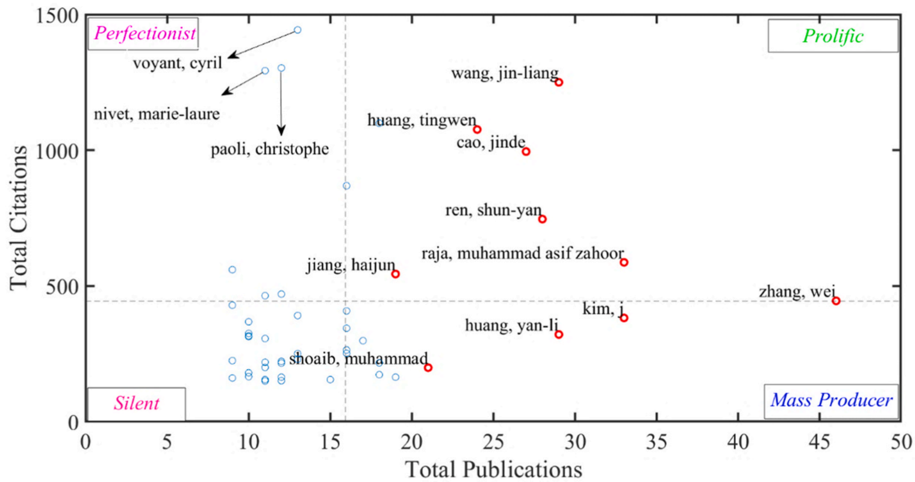

Fig. 3. Authors' total publications and citations are plotted (fifty top authors).

Table 4
Most frequent university affiliations of authors published in AIFH.

Rank	Name	Country	T.P.	T.C.	H.I.	T.C./T.P.
1	Chinese Acad Sci	China	91	1374	16	15.1
2	Islamic Azad Univ	Iran	86	1893	25	22.0
3	Stanford Univ	USA	57	983	15	17.2
4	Shanghai Jiao Tong Univ	China	54	488	12	9.0
5	Zhejiang Univ	China	49	370	11	7.6
6	Univ Calif Los Angeles	USA	47	643	14	13.7
7	Univ Maryland	USA	46	553	12	12.0
8	Harbin Inst Technol	China	45	528	12	11.7
9	Johns Hopkins Univ	USA	44	639	12	14.5
10	Tianjin Polytech Univ	China	41	1085	17	26.5
11	Huazhong Univ Sci & Technol	China	40	838	15	21.0
12	Indian Inst Technol	India	40	792	13	19.8
13	Univ Michigan	USA	39	1203	11	30.8
14	Southeast Univ	Bangladesh	38	909	12	23.9
15	Univ Calif San Francisco	USA	38	298	11	7.8
16	Yonsei Univ	South Korea	38	546	13	14.4
17	Tsinghua Univ	China	38	381	11	10.0
18	Imperial Coll London	England	37	293	11	7.9
19	Beihang Univ	China	36	1266	15	35.2
20	Univ Tehran	Iran	36	470	12	13.1
21	Univ Penn	USA	36	774	13	21.5
22	Univ Chinese Acad Sci	China	34	281	10	8.3
23	Univ Washington	USA	33	271	9	8.2
24	Univ Toronto	Canada	33	391	10	11.8
25	Univ Elect Sci & Technol China	China	33	182	8	5.5
26	Duke Univ	USA	33	418	9	12.7
27	Univ Melbourne	Australia	33	723	11	21.9
28	Xidian Univ	China	33	155	7	4.7
29	Xi An Jiao Tong Univ	China	31	309	8	10.0
30	King Abdulaziz Univ	Saudi Arabia	31	466	10	15.0
31	Comsats Univ Islamabad	Pakistan	31	161	7	5.2
32	Natl Yunlin Univ Sci & Technol	Taiwan	31	629	12	20.3
33	Natl Inst Technol	South Korea	30	363	11	12.1
34	Nanjing Univ Sci & Technol	China	30	397	12	13.2
35	Mem Sloan Kettering Canc Ctr	USA	30	812	10	27.1
36	Wuhan Univ	China	29	538	12	18.6
37	Ocean Univ China	China	29	188	9	6.5
38	Univ Illinois	USA	29	326	10	11.2
39	Seoul Natl Univ	South Korea	29	642	11	22.1
40	Sandia Natl Labs	USA	28	213	8	7.6

C., and H.I. For example, the United States is more than four times larger than India (third rank in T.P. and fourth rank in T.C.) in terms of T.P. and T.C.

In the field of AIFH, China and the United States are closely vying for supremacy across four key metrics, including T.P., T.C., H.I., and T.C./T.P. Taiwan leads in generating the most publications about its R&D investment, evidenced by a T.P./R&D ratio of 24.1. In terms of publications per capita, represented by T.P./POP, China, Italy, Turkey, and Spain are at the forefront. When it comes to impact, as measured by T.C./POP, Canada, India, Germany, and China emerge as the leaders.

Fig. 5 shows that many of the countries are in the silent zone. There are seven countries with more than 250 publications in the prolific zone (China, USA, India, Iran, England, and Germany). China and the United States appear to be the most prolific countries. There are two universities with more than forty publications in the mass producer zone: Zhejiang University and Shanghai Jiao Tong University. Many countries are in the silent zone. No country is in the perfectionist zone. Of the top 50 countries, only two are in the mass producer zone.

3.5. *Authors, institutions, and country distribution across time*

Fig. 6 and Table 6 depict an increasing trend in the number of institutions, authors, countries, and total publications that can be seen over time. However, this trend is not uniform from the early years until 2015. From 2015 onwards, there has been a steady upward trend. No definite opinion can be expressed about 2022 because this year is not over yet, and its articles have not been fully published at the time of writing. Because some authors shared institutions and countries, in comparison to the number of writers, institutions and nations underperformed.

Table 7 presents AIFH contributions by country. The first is the period of AIFH's publication (D1: 1982–2000). The USA was the most productive nation., followed by Spain, England, and Canada. The second is the period of AIFH's publication (D2: 2001–2005). The USA was the most productive nation., producing around 21 percent of publications of AIFH. China (19 percent), Spain (6 percent), and Japan (6 percent) are the next places. In the third period of AIFH's publication (D3: 2006–2010), The USA was the most productive nation., producing around 28 percent of publications of AIFH. China (14 percent), Spain (6 percent), and Japan (6 percent) are in the next places. Finally, the fourth period of AIFH's publication (D4: 2011–2015). The USA was the most productive nation., producing around 23 percent of publications of AIFH. China (11 percent), Japan (10 percent), and Spain (7 percent) are the following places. From 1982 to 2015 (D1-D4), the United States was the leader, and China was second from 2016 to 2021. In a recent shift,

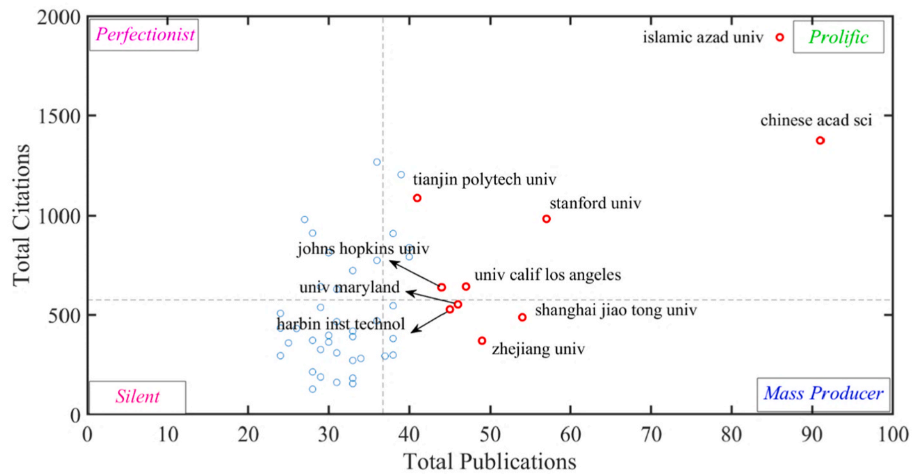

Fig. 4. Maps of institutions based on total publications and citations (fifty top institutions).

Table 5
Most productive and influential countries in AIFH.

R	Country	T.P.	T.C.	H.I.	T.C./T.P.	Pop	T.P./Pop	T.C./Pop	R&D	T.P./R&D	T.C./R&D (K)
1	China	1608	19490	63	12.1	1410.9	1.1	13.8	2.1	751.2	9105.0
2	USA	1458	19174	62	13.2	329.5	4.4	58.2	2.8	514.7	6768.5
3	India	386	4530	33	11.7	1380.0	0.3	3.3	0.7	591.3	6939.1
4	Iran	369	7028	45	19.0	84.0	4.4	83.7	0.8	444.4	8464.7
5	England	273	4036	30	14.8	67.2	4.1	60.0	1.7	160.3	2370.3
6	Germany	261	3812	28	14.6	83.2	3.1	45.8	3.1	83.3	1216.9
7	Canada	229	2541	26	11.1	38.0	6.0	66.9	1.5	148.4	1647.2
8	South Korea	219	1865	25	8.5	51.8	4.2	36.0	4.5	48.4	411.9
9	France	206	4470	33	21.7	67.4	3.1	66.3	2.2	93.9	2038.4
10	Italy	202	2449	27	12.1	59.6	3.4	41.1	1.4	145.1	1759.6
11	Spain	177	2402	27	13.6	47.4	3.7	50.7	1.2	142.4	1932.1
12	Turkey	176	3777	31	21.5	84.3	2.1	44.8	1.0	183.4	3935.3
13	Japan	173	1616	21	9.3	125.8	1.4	12.8	3.3	52.8	493.4
14	Australia	159	2142	25	13.5	25.7	6.2	83.4	1.9	84.8	1142.6
15	Saudi Arabia	122	1939	22	15.9	34.8	3.5	55.7	0.8	149.7	2378.7
16	Taiwan	109	800	15	7.3	23.6	4.6	33.9	–	–	–
17	Brazil	108	1075	18	10.0	212.6	0.5	5.1	1.2	93.1	926.4
18	Netherlands	102	1053	18	10.3	17.4	5.8	60.4	2.2	47.1	486.7
19	Poland	82	715	16	8.7	38.0	2.2	18.8	1.2	67.8	591.1
20	Switzerland	81	1485	19	18.3	8.6	9.4	171.9	3.4	24.1	440.9
21	Pakistan	77	1022	18	13.3	220.9	0.3	4.6	0.2	325.9	4325.6
22	Russia	76	289	11	3.8	144.1	0.5	2.0	1.0	77.3	294.1
23	Malaysia	69	1004	14	14.6	32.4	2.1	31.0	1.0	66.3	964.6
24	Greece	60	1011	15	16.9	10.7	5.6	94.3	1.2	51.0	858.7
25	Egypt	57	504	10	8.8	102.3	0.6	4.9	0.7	78.7	696.2
26	Sweden	52	724	12	13.9	10.4	5.0	69.9	3.3	15.7	218.5
27	Scotland	49	626	15	12.8	5.5	8.9	113.8	–	–	–
28	Singapore	49	730	13	14.9	5.7	8.6	128.4	1.9	25.5	379.3
29	Uae	48	437	12	9.1	9.9	4.9	44.2	1.3	37.5	341.8
30	Algeria	47	1325	16	28.2	43.9	1.1	30.2	0.5	86.6	2440.3
31	Vietnam	46	529	13	11.5	97.3	0.5	5.4	0.5	87.3	1004.3
32	Finland	45	357	13	7.9	5.5	8.1	64.5	2.8	16.3	129.5
33	Belgium	44	665	13	15.1	11.6	3.8	57.5	2.8	15.9	240.4
34	Portugal	43	326	12	7.6	10.3	4.2	31.6	1.3	31.9	241.9
35	Norway	42	573	12	13.6	5.4	7.8	106.5	2.1	20.3	276.5
36	Thailand	40	446	13	11.2	69.8	0.6	6.4	1.0	39.9	445.2
37	Austria	39	353	11	9.1	8.9	4.4	39.6	3.2	12.1	110.0
38	Serbia	38	335	11	8.8	6.9	5.5	48.5	0.9	41.3	364.2
39	Kuwait	35	519	10	14.8	4.3	8.2	121.5	0.1	561.1	8320.0
40	Qatar	34	1145	15	33.7	2.9	11.8	397.4	0.5	66.8	2249.5

China has now taken the lead in AIFH, relegating the United States to the second position across key metrics like T.P., T.C., H.I., and T.C./T.P. Moreover, the trend of publishing in AIFH has been on the rise for most countries, particularly between 2016 and 2021.

4. Network visualization

Network visualization is demonstrated in this section.: co-authorships, co-citations, and bibliographic couplings between writers, institutions, and nations.

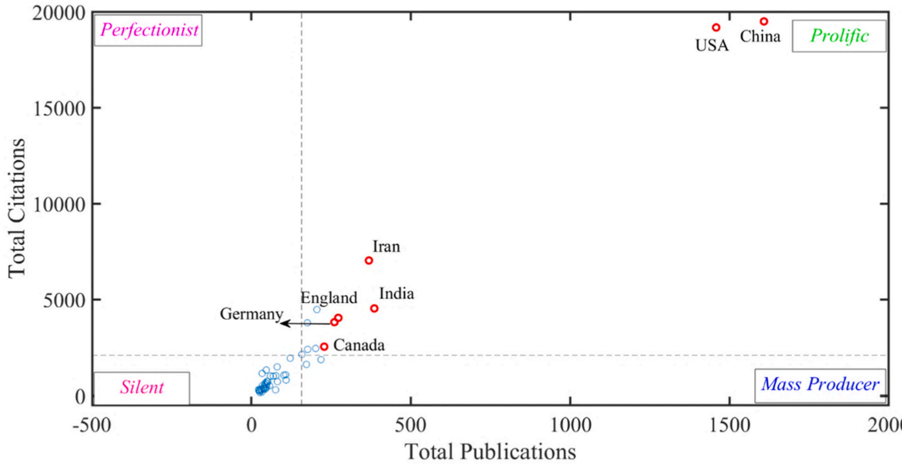

Fig. 5. Countries mapped by total citations and publications (fifty top countries).

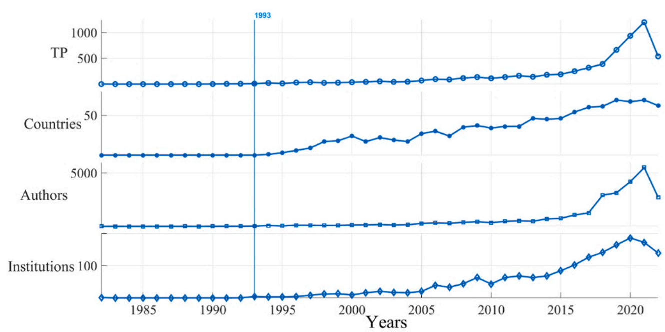

Fig. 6. Authors, organizations, nations, and total publications (T.P.) numbers across time.

4.1. Co-citation of authors

When a third document cites two other papers, this is referred to as a co-citation [22]. The premise behind co-citation analysis is that two works referenced together have a close relationship [23]. Hence, it ought to be concentrated in a visualization map's cluster solution. Following the examination of author co-citations in the AIFH, network visualization is shown in Fig. 7. This study was based on authors with at least 100 citations on AIFH. Finally, of 93614 authors, only 120 authors meet the threshold. The linkages between the nodes show the association between authors (i.e., via co-citations), while each circle or node represents one author. The approximate distance between the two authors on the map reveals their relative co-citation relatedness [24].

In Fig. 7, the focus is on author co-citation mapping. Each node symbolizes an author, with the node's weight influenced by both the prominence of the author's name and the circle's diameter. A more substantial node suggests greater weight within the overall mapping. This node weight is also shaped by the sum strength of all connecting linkages to it. From a pool of 93,701 authors surveyed, 89 authors met or exceeded the minimum citation benchmark of 100, making them the exclusive subjects of this visualization.

This figure illustrates four numbered clusters. The first cluster (Red) with 44 authors is anchored by author L. Ling with a total link strength of 2776. The second cluster (green) with 31 authors is anchored by authors J. L. Wang and Q. K. Song, with total link strength of 5971 and 4278, respectively.

J. L. Wang has the highest total link strength among all authors. Eighty percent of the top ten authors with the most total link strength belong to the second cluster in AIFH. The third cluster (blue) with 12 authors is anchored by authors S. Haykin, with total link strength of 1212 and A. Mellit, with total link strength of 1094. The fourth cluster (yellow) with two authors is anchored by author M.A.Z. Raja with total link strength of 656. According to Fig. 7, most communication between the second and third clusters is established by S. Haykin, while J. Wang connects the first and second clusters.

4.2. Co-authorships

One of the most prominent types of scientific cooperation is co-authorship. A co-authorship network is a type of social network where members have been connected to one another by involvement in one or more publications. A network representation of the mapping of co-authorship among various authors was presented using the *VOSviewer* program in Fig. 8. Utilizing information from authors with at least ten articles on AIFH and 100 citations, this mapping employed the fractional counting approach. Consequently, just 52 authors out of 20518 authors match the requirement. The size, thickness, color, and font of the connecting lines all convey information about the degree of the writers' relationships. The identical color indicates related writers, who are frequently listed together. The linkages between two nodes indicate co-authorship between the authors; every node represents one author. Fig. 8 illustrates the Co-authorship of the author. Each author had at least ten publications and 100 citations to be included in the analysis.

Fig. 8 provides a visual representation of co-authorship among authors in the form of a network diagram. In this illustration, every node stands for an individual author. The connecting lines between these nodes, varying in size, thickness, color, and font, offer nuanced information about the quality and degree of relationships between these authors. Lines of the same color signify authors who are commonly co-cited, indicating a strong working relationship or similar research interests. These linkages specifically represent instances of co-authorship. To be included in this analysis and visual representation, each author had to meet specific criteria: a minimum of ten publications and at least 100 citations. This ensures that the diagram focuses on authors with a significant impact and a substantial body of work.

Of 20195 authors, only 44 authors meet the threshold. It consists of twenty-one clusters. Most clusters contain only one author. The red and green clusters are among the largest clusters in Fig. 8, with six and five authors, respectively. Wang, Jin-Liang, with total link strength (49), and Ren, Shun-Yan, with total link strength (46) from cluster two (green) have the highest total link strength among all authors. Cluster eight and cluster twelve are connected to cluster two (green) by Huang, Tingwen. Cluster three is connected to cluster one (red) by Park, Ju H.

Table 6
Over time, the number of authors, institutions, and nations per paper.

Year	T.P.	Authors	Institutions	Countries	T.P./Authors	T.P./Institutions	T.P./Countries
1982–1990	4	8	1	1	0.5	4	4
1991	5	10	1	1	0.5	5	5
1992	6	13	1	1	0.5	6	6
1993	10	34	4	1	0.3	2.5	10
1994	23	70	3	1	0.3	7.7	23.0
1995	14	43	3	3	0.3	4.7	4.7
1996	31	100	4	6	0.3	7.8	5.2
1997	37	92	8	9	0.4	4.6	4.1
1998	26	75	12	17	0.3	2.2	1.5
1999	29	83	13	18	0.3	2.2	1.6
2000	37	115	9	24	0.3	4.1	1.5
2001	43	131	16	17	0.3	2.7	2.5
2002	55	166	20	22	0.3	2.8	2.5
2003	43	118	17	19	0.4	2.5	2.3
2004	47	149	16	17	0.3	2.9	2.8
2005	70	275	20	27	0.3	3.5	2.6
2006	97	318	39	30	0.3	2.5	3.2
2007	90	286	33	24	0.3	2.7	3.8
2008	117	373	44	35	0.3	2.7	3.3
2009	137	431	63	37	0.3	2.2	3.7
2010	113	346	43	34	0.3	2.6	3.3
2011	137	462	63	36	0.3	2.2	3.8
2012	164	519	68	36	0.3	2.4	4.6
2013	142	478	63	46	0.3	2.3	3.1
2014	181	700	68	45	0.3	2.7	4.0
2015	191	751	84	46	0.3	2.3	4.2
2016	251	1060	102	54	0.2	2.5	4.6
2017	319	1263	126	60	0.3	2.5	5.3
2018	390	2914	141	61	0.1	2.8	6.4
2019	663	3147	164	69	0.2	4.0	9.6
2020	937	4190	186	67	0.2	5.0	14.0
2021	1202	5511	172	69	0.2	7.0	17.4
2022	540	2730	139	62	0.2	3.9	8.7

4.3. Bibliographic coupling of authors, institutions, and countries

When two documents cite the exact same third document, this is known as bibliographic coupling. As described by Martyn (1964), "Two papers that share one reference contain one unit of coupling, and the value of a relationship between two papers having one or more references in common is stated as being of strength one, two, etc., depending on the number of shared references". Citations are used in bibliographic coupling to describe the similarities between two texts, authors, institutions, or nations. This method is predicated on the notion that two papers that cite the third paper are highly connected and must be grouped in the visualization map's cluster solution. The overall quantity of references to or citations from other third-party papers that they have in common determines how strong the bibliographic coupling is.

Fig. 9 provides an illustration of the authors' bibliographic coupling. To be considered in the study, each author must have at least ten articles and 100 citations. 52 of the 20518 authors satisfied the requirements. The network's node-to-node distance is correlated with how closely linked their respective subjects are. The strength of the bibliographic connection between network nodes is represented by the thickness of the connecting lines. Fig. 9 shows five clusters. The first cluster (red) consists of eighteen authors, the second cluster (green) consists of twelve authors, the third cluster (blue) consist of seven authors, the fourth cluster (yellow) consists of four authors, and the fifth cluster (purple) consist of three authors. Wang, Jin-Liang, and Ren, Shun-Yanfrom, both from the third cluster, received the highest link total strength (22657) and (21250), respectively. According to Fig. 9, it can be seen that the whole system is heterogeneous. This heterogeneity has led each cluster to establish a strong bibliographic pair with itself. The fifth cluster (purple) has a strong relationship with the first cluster (red) and a weak connection with the third cluster (blue), and this cluster has no connection with other clusters. Fig. 9 also shows that Zhang Hao has established a connection between the third and fifth clusters. When works from two different institutions cite works from a third, shared institution, this is known as bibliographic coupling.

A complicated chain of institutional linkage between those represented by AIFH is shown in Fig. 10. Each institution had at least ten publications and 300 citations to be included in the analysis. Apart from 4802 Institutions, only 84 institutions meet the thresholds. There are four clusters: red consists of 39 institutions (first cluster), green consists of 25 institutions (second cluster), blue consists of 18 institutions (third cluster), and yellow consists of 2 institutions (fourth cluster). The first cluster (red) is anchored by the Chinese Academy of Sciences. The second cluster (green) is anchored by Islamic Azad University. The third cluster (blue) is anchored by Tianjin Polytechnic University, and the fourth cluster (yellow) is anchored by Wuhan University.

Table 8 revealed the Documents, Citations, and Total link strength of the top ten institutions. Chinese Academy of Sciences from China received the highest link strength (20232), followed by Tianjin Polytechnic University from China (18060), Huazhong University of Science and Technology from China (16139), Beihang University from China (14835), and the University of California, Los Angeles from the United States has received 13375 Total link strength. There are four universities located in China that are ranked among the top five linked institutions. This means that 80% of the top five linked Institutions belong to China in AIFH. Also, among the top ten linked institutions, there are five Institutions from China, and half of the top ten Institutions in AIFH are from China.

The bibliographic coupling of the countries covered by AIFH is seen in Fig. 11. If publications of two nations cite works from a third, this is known as a bibliographic coupling of countries. A complicated web of linkage between the nations represented in AIFH is seen in Fig. 11. Each country had at least ten publications and 300 citations to be included in the analysis. Apart from 105 countries, only 44 countries meet the thresholds. There are five clusters: red consists of 19 countries (first cluster), green consists of 19 countries (second cluster), blue consist of 4

Table 7
AIFH publications by country over time.

R	Country	Total	D1	D2	D3	D4	2016	2017	2018	2019	2020	2021	2022
1	China	1608	5	52	172	216	47	70	101	195	260	322	168
2	USA	1456	18	58	83	104	57	81	110	206	285	353	101
3	India	386	0	10	36	66	12	25	33	30	57	64	53
4	Iran	369	2	4	36	94	27	28	28	36	52	44	18
5	England	273	9	4	18	34	8	9	14	30	48	69	30
6	Germany	261	6	12	21	19	9	15	18	29	47	59	26
7	Canada	229	7	7	23	18	9	18	18	23	34	50	22
8	South Korea	219	2	6	4	15	3	8	14	16	40	69	42
9	France	206	6	6	13	32	11	20	14	21	33	37	13
10	Italy	202	7	12	18	20	12	11	17	13	31	45	16
11	Spain	177	10	16	20	30	2	8	12	16	25	30	8
12	Turkey	176	1	8	28	41	10	8	4	13	16	32	15
13	Japan	173	7	16	11	15	5	8	9	20	32	35	15
14	Australia	159	5	2	5	14	8	8	9	24	31	38	15
15	Saudi Arabia	122	2	0	3	17	1	7	4	9	14	41	24
16	Taiwan	109	0	8	16	4	3	3	3	8	11	37	16
17	Brazil	108	4	6	7	12	6	9	6	8	20	17	13
18	Netherlands	102	1	1	4	5	6	7	13	15	24	14	12
19	Poland	82	1	2	8	20	4	3	6	8	14	12	4
20	Switzerland	81	2	1	3	4	4	2	6	11	19	20	9
21	Pakistan	77	0	1	0	3	4	2	3	7	8	33	16
22	Russia	76	2	6	3	5	6	7	7	7	9	17	7
23	Malaysia	69	1	0	7	12	6	6	4	8	8	11	6
24	Greece	60	2	5	7	9	6	1	4	2	4	12	8
25	Egypt	57	0	1	6	5	2	3	6	6	8	12	8
26	Sweden	52	0	3	2	1	1	5	3	8	9	14	6
27	Scotland	49	1	0	1	6	1	1	4	7	14	10	4
28	Singapore	49	1	2	2	2	2	2	5	6	8	15	4
29	United Arab Emirates	48	0	0	3	13	3	3	5	5	7	6	3
30	Algeria	47	0	2	2	11	5	5	2	3	8	6	3
31	Vietnam	46	0	0	2	0	1	3	2	6	12	14	6
32	Finland	45	0	1	7	5	2	0	5	6	10	6	3
33	Belgium	44	2	0	3	6	1	3	1	3	8	11	6
34	Portugal	43	0	1	5	7	3	4	2	2	4	8	7
35	Norway	42	1	1	0	1	3	2	7	4	10	12	1
36	Thailand	40	1	3	3	9	0	0	4	2	4	9	5
37	Austria	39	0	3	0	4	0	2	2	5	4	12	7
38	Serbia	38	1	0	2	8	1	3	2	4	8	8	1
39	Kuwait	35	2	4	3	3	2	6	2	4	1	5	3
40	Qatar	34	0	0	1	5	3	3	4	4	9	2	3

Abbreviations: D: decade; D1: 1982–2000; D2: 2001–2005; D3: 2006–2010; D4: 2011–2015.

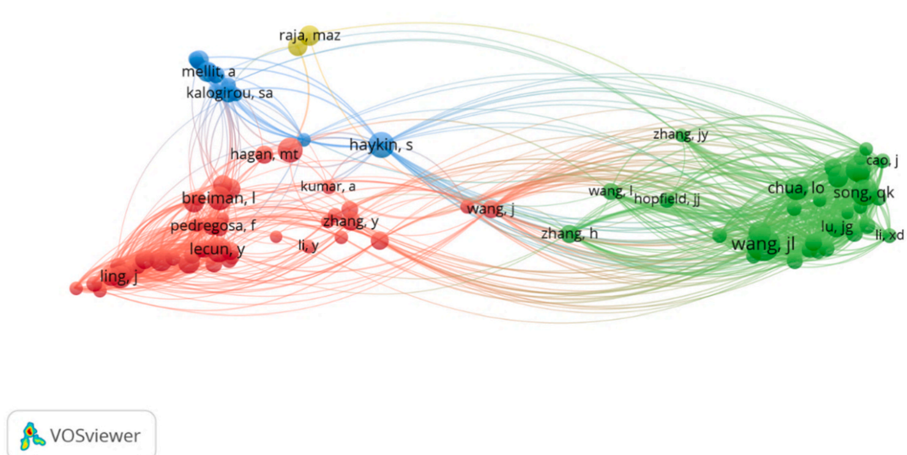

Fig. 7. Author co-citation mapping in the AIFH.

countries (third cluster), yellow consists of one country (fourth cluster), and purple consists of one country (fifth cluster). 38 out of 44 countries belong to the first and second clusters.

The country map in the field of AIFH presents a homogeneous landscape, segmented into three main clusters, each anchored by a key player. The first cluster, represented in red, is centered around the United States. The second, depicted in green, has Iran as its focal point. The third and final cluster, illustrated in blue, is notably anchored by China. Although this third cluster comprises only four countries, it includes China, which is one of the most influential nations in AIFH. Interestingly, the two countries with the highest total link strength in this field—China and the United States—are found in the third and first

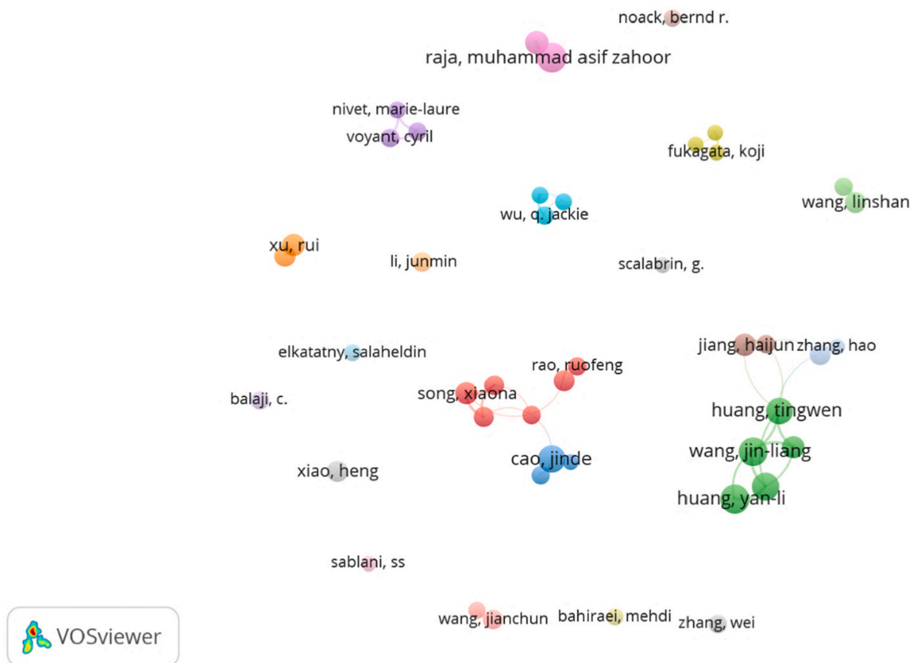

Fig. 8. Co-authorship of an author's AIFH publication. The threshold is set to a minimum of 100 citations and ten documents published.

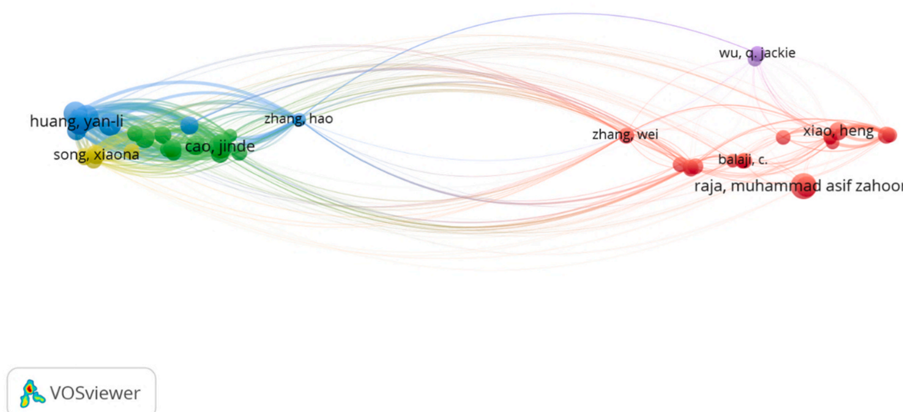

Fig. 9. Bibliographic coupling of authors publishing in AIFH: The threshold is set to a minimum of 100 citations and ten documents published.

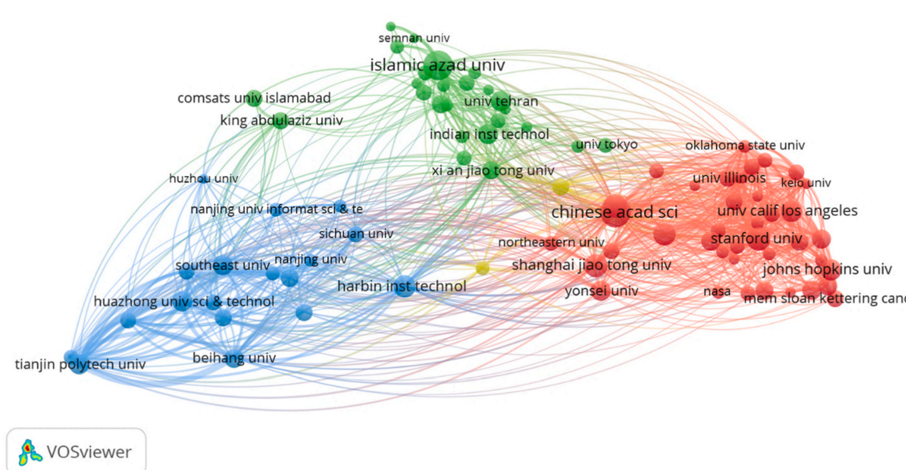

Fig. 10. Bibliographic coupling of institutions publishing in AIFH: The threshold is set to a minimum of 300 citations and ten documents published.

Table 8
Top-10 most linked Institution base Total link strength.

R	Organization	Documents	Citations	Total link strength
1	Chinese Acad Sci, China	97	1433	20232
2	Tianjin Polytech Univ, China	41	1085	18060
3	Huazhong Univ Sci & Technol, China	42	843	16139
4	Beihang Univ, China	36	1266	14835
5	Univ Calif Los Angeles, USA	48	807	13375
6	Southeast Univ, Bangladesh	44	1286	12482
7	Texas A&M Univ Qatar, Qatar	23	908	12317
8	Harbin Inst Technol, China	49	546	12270
9	Stanford Univ, USA	57	983	11989
10	Islamic Azad Univ, Iran	87	1920	11866

clusters, respectively. This highlights the significant roles these two countries play in shaping the global landscape of AIFH.

Table 9 revealed the Documents, Citations, and Total link strength of the top ten countries. The United States received the highest total link strength (387880), followed by China (359197), France (99858), England (96938), and Iran (94800). China (second rank) is about 3.5 times larger than France (third rank) in terms of total link strength. There is a huge difference between China and France in terms of total link strength, but between France (third rank) and Canada (tenth rank), these differences decrease almost linearly.

5. Source publishers and most influential documents

Fig. 12 offers a comprehensive overview of the twenty most impactful journals in AIFH. In this figure, the horizontal axis quantifies the number of articles, while the vertical axis lists the journal titles. Significantly, the journal "Medical Physics" leads the pack with a total of 119 articles published in the AIFH domain.

In an intriguing revelation, half of all the articles in the AIFH field are concentrated in just the top five journals, underscoring their authoritative role in disseminating critical research in this area. These leading journals include "Medical Physics," "Neurocomputing," "International Journal of Heat and Mass Transfer," "International Journal of Radiation Oncology Biology Physics," and "IEEE Access."

Furthermore, it is noteworthy that "Medical Physics" has an exceptionally high publication count, outperforming the second-ranked journal, "Neurocomputing," by nearly one and a half times. This indicates not only the central role of "Medical Physics" in AIFH research but also suggests that this journal could be an essential avenue for researchers looking to publish significant work in this field.

The top 20 ranked journals based on the number of citations in AIFH are shown in Fig. 13. International Journal of Heat and Mass Transfer has received the most citations in AIFH. The top journals that were cited more than 2000 times were the International Journal of Heat and Mass Transfer (cited 3080 times), followed by the Journal of Fluid Mechanics (2675), Solar Energy (2350), Neurocomputing (2329), and NeuroImage (2069).

The top articles that have the most citations published in AIFH are shown in Table 10. A brief description of these publications is presented in the followings. A summary of solar irradiation forecasting techniques employing machine learning techniques was provided by Voyant et al. (2017). Their findings demonstrate that several experts suggested using hybrid models or an ensemble forecast strategy to enhance prediction performance. Zhu et al. (2013) detailed the creation, assessment, and example case study demonstrating the use of 30-year data sets of LAI and FPAR. Following that, the equivalent LAI3g and FPAR3g data sets with particular properties were produced using the trained neural network technique. The findings showed that satellite-based estimations of leaf area were consistently overestimated by the models. Furthermore, the satellite result disagrees with how the models simulate the seasonal cycle in the northern latitudes. Deep neural networks were used by Ling

Table 9
Top-10 most linked Country base Total link strength.

Rank	Country	Documents	Citations	Total link strength
1	USA	1473	19523	387880
2	Peoples R China	1609	19490	359197
3	France	208	4472	99858
4	England	277	4064	96938
5	Iran	369	7028	94800
6	Germany	261	3812	91146
7	India	388	4564	88463
8	South Korea	222	1870	73385
9	Turkey	177	3783	68171
10	Canada	231	2546	66947

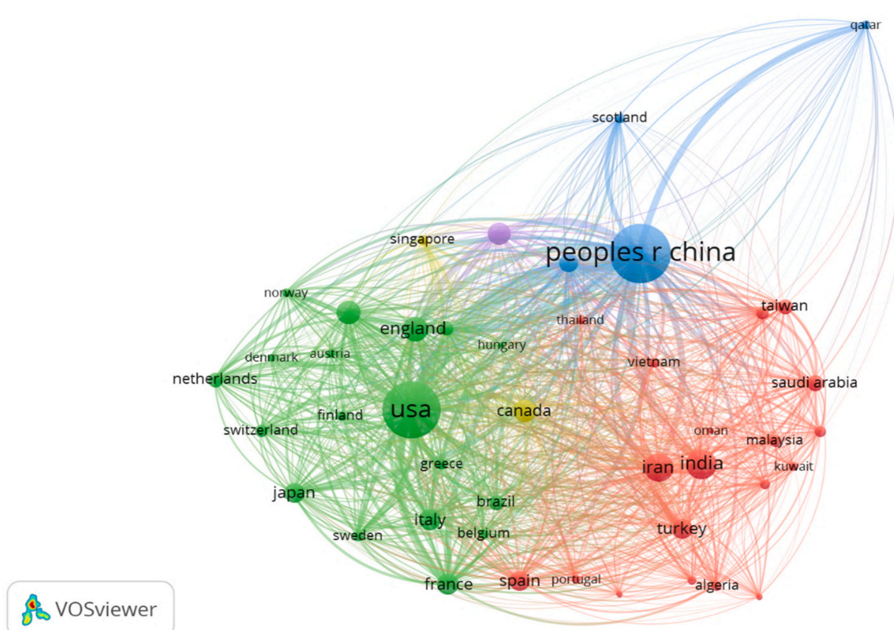

Fig. 11. Bibliographic coupling of countries publishing in AIFH: The threshold is set to a minimum of 300 citations and ten documents published.

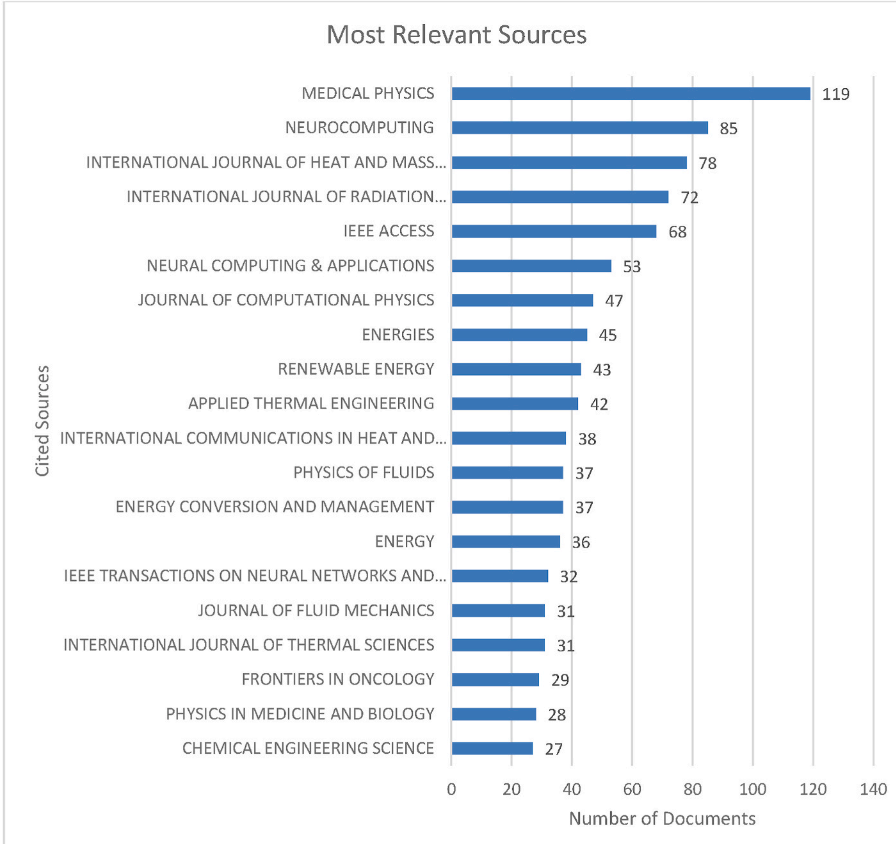

Fig. 12. Most relevant sources of articles published in different journals in AIFH.

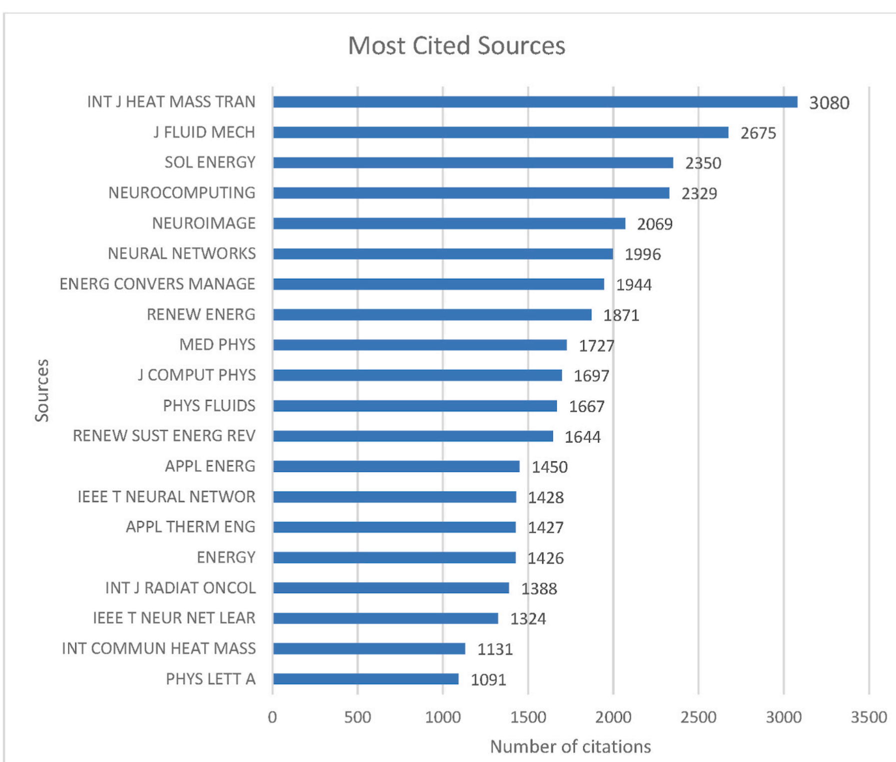

Fig. 13. The most cited journals in AIFH.

Table 10
Top publications that have received more than 200 citations.

R	Ref.	Type	[a]C.A.	Year	T. C.	Title	Web of Science Category
1	Voyant et al. (2017)	review	Voyant, C	2017	592	"Machine learning methods for solar radiation forecasting: a review"	Green & Sustainable Science & Technology; Energy & Fuels
2	Zhu et al. (2013)	Article	Zhu, Z	2013	547	"Global data sets of vegetation leaf area index (lai)3g and fraction of photosynthetically active radiation (fpar)3g derived from global inventory modeling and mapping studies (gimms) normalized difference vegetation index (ndvi3g) for the period 1981 to 2011"	Environmental Sciences; Geosciences, Multidisciplinary; Remote Sensing; Imaging Science & Photographic Technology
3	Ling et al. (2016)	Article	Ling, J	2016	444	"Reynolds averaged turbulence modelling using deep neural networks with embedded invariance"	Mechanics; Physics, Fluids & Plasmas
4	Brunton et al. (2020)	Review	Brunton, S et al.	2020	387	"Machine learning for fluid mechanics	–
5	Lafon and Lee (2006)	Article	Lafon, S	2006	367	diffusion maps and coarse-graining: a unified framework for dimensionality reduction, graph partitioning, and data set parameterization"	Computer Science, Artificial Intelligence; Engineering, Electrical & Electronic
6	Yadav and Chandel (2014)	Review	Chandel, S.S.	2014	328	"Solar radiation prediction using artificial neural network techniques: a review"	Green & Sustainable Science & Technology; Energy & Fuels
7	Han (2017)	Article	Han, X	2017	326	"MR-based synthetic C.T. generation using a deep convolutional neural network method"	Radiology, Nuclear Medicine & Medical Imaging
8	Duraisamy et al. (2019)	Review; Book Chapter	Duraisamy, K	2019	301	"Turbulence modeling in the age of data"	Mechanics; Physics, Fluids & Plasmas
9	Yang et al. (2013)	Article	Cao, J	2013	261	"Synchronization of coupled reaction-diffusion neural networks with time-varying delays via pinning-impulsive controller"	Mathematics, Applied; Mathematics, Interdisciplinary Applications; Mechanics; Physics, Fluids & Plasmas; Physics, Mathematical
10	Sahiner et al. (2019)	Review	Sahiner, B	2019	255	"Deep learning in medical imaging and radiation therapy"	Radiology, Nuclear Medicine & Medical Imaging
11	Mohandes et al. (1998)	Article	Mohandes, M	1998	239	"Estimation of global solar radiation using artificial neural networks"	Green & Sustainable Science & Technology; Energy & Fuels
12	Sfetsos and Coonick (2000)	Article	Sfetsos, A	2000	232	"Univariate and multivariate forecasting of hourly solar radiation with artificial intelligence techniques"	Energy & Fuels
13	Paoli et al. (2010)	Article	Muselli, M	2010	221	"Forecasting of preprocessed daily solar radiation time series using neural networks"	Energy & Fuels
14	Lu (2008)	Article	Lu, J.G	2008	214	"Global exponential stability and periodicity of reaction-diffusion delayed recurrent neural networks with Dirichlet boundary conditions"	Mathematics, Interdisciplinary Applications; Physics, Multidisciplinary; Physics, Mathematical
15	Lafon et al. (2006)	Article	Lafon, S	2006	208	"Data fusion and multicore data matching by diffusion maps"	Computer Science, Artificial Intelligence; Engineering, Electrical & Electronic
16	Tymvios et al. (2005)	Article	Tymvios, F	2005	205	"Comparative study of angstrom's and artificial neural networks' methodologies in estimating global solar radiation"	Energy & Fuels
17	Rehman and Mohandes (2008)	Article	Rehman, S	2008	203	"Artificial neural network estimation of global solar radiation using air temperature and relative humidity"	Economics; Energy & Fuels; Environmental Sciences; Environmental Studies

[a] CA: Corresponding author.

et al. (2016) to provide a technique for learning a Reynolds stress anisotropy tensor model from high-fidelity simulation data. In comparison to a generic neural network architecture that does not include this invariance trait, it has been shown that this neural network architecture offers better prediction accuracy.

An overview of the background, existing state, and future prospects of machine learning (ML) for fluid mechanics was provided by Brunton et al. (2020). They described the foundational ML techniques and argued about how to utilize them to comprehend, model, improve, and manage fluid flows. Based on their findings, it can be concluded that fluid modeling, optimization, and control all include the use of machine learning (ML), which includes potent information-processing techniques. Additionally, a lot of fluid mechanics issues, such as reduced-order modeling, form optimization, and feedback control, may be framed as optimization and regression problems. Lafon and Lee (2006) gave proof that the nonlinear dimensionality reduction, clustering, and data set parameterization problems may all be handled using the same methodology. They demonstrated how compressing operators is the same as clustering in embedding spaces.

Yadav and Chandel (2014) investigated ANN-based techniques to find appropriate approaches offered in the literature for solar radiation prediction and to pinpoint research needs. It was discovered that the architectural configurations, input parameter combinations, and training procedures all affect how well ANN models predict outcomes.

Han (2017) introduced a unique deep convolutional neural network (DCNN) approach for producing sCTs and assessed the effectiveness of the system using a set of patient pictures with brain tumors. Despite the fact that training a DCNN model might be laborious, it only has to be done once. For each fresh patient M.R. image, using a trained model to build a whole sCTs volume only took 9 s, which is substantially quicker than the atlas-based method. The use of statistical inference to define model coefficients and quantify discrepancy, as well as the use of machine learning to enhance turbulence models, are new discoveries that Duraisamy et al. (2019) reviewed. One of the main viewpoints promoted in their study is that data-driven techniques can provide valuable prediction models by utilizing fundamental knowledge in turbulence modeling and physical restrictions. Yang et al. (2013) used an impulsive controller to a small subset of nodes to study the global exponential synchronization stability in a collection of linearly diffusively linked reaction-diffusion neural networks with time-varying delays. Their findings show that as long as a traditional state feedback pinning controller or an adaptive pinning controller can meet the synchronization objective by managing the same nodes, we can always construct a suitable pinning-impulsive controller to do so. Deep learning (DL) and convolutional neural networks were presented by Sahiner et al. (2019) in order to evaluate five important areas of DL application in medical imaging and radiation treatment, find recurring patterns, and explain techniques for dataset enlargement. According to their findings, there are still many computational and statistical issues that "traditional" medical image analysis and DL-based approaches must overcome.

Mohandes et al. (1998) proposed a neural networks approach to simulate the regional fluctuation of solar radiation on a global scale. Ten sites were used for testing, and 31 locations were used to split the available data from the 41 data gathering stations. The findings for these ten locations showed that the observed and anticipated values generally accord with one another. A novel method for predicting the mean hourly global solar radiation received by a horizontal surface utilizing artificial intelligence-based methodologies was developed by Sfetsos and Coonick (2000). According to their findings, creating artificial intelligence models are more successful at forecasting solar radiation time series than conventional methods based on the clearness index. An application of ANNs in the field of renewable energy was reported by Paoli et al. (2010). They focused especially on the Multi-Layer Perceptron (MLP) network, which has been the most popular ANN design in both the time series forecasting and renewable energy fields. They discovered that when compared to more traditional prediction techniques like Markov chains or Bayesian inference, the suggested data pre-processing methodology may dramatically reduce forecasting errors by roughly 6%.

By creating appropriate Lyapunov functionals and applying various inequality techniques, Lu (2008) addressed the global exponential stability and periodicity for a class of reaction-diffusion delayed recurrent neural networks with Dirichlet boundary conditions. With Dirichlet boundary conditions, they demonstrated the periodicity of reaction-diffusion delayed recurrent neural networks. The recently developed diffusion framework was used by Lafon et al. (2006) to handle high-dimensional data processing. They acquired great accuracy with little preprocessing when their method was effectively applied to lipreading. They also showed how high-dimensional visual data might be aligned.

The development of several models for assessing solar radiation on a horizontal surface was compared by Tymvios et al. (2005) in their article. They used both ANNs and the well-known Ångström's linear method. Their findings point to the viability of using ANN models to estimate solar radiation in locations without reliable data on sunlight duration. In the work of Rehman and Mohandes (2008), observed air temperature and relative humidity values between 1998 and 2002 for the Saudi Arabian city of Abha were utilized to estimate global solar radiation (GSR) in the future time domain using an artificial neural network algorithm. Using temperature and relative humidity as inputs, they acquired findings that demonstrated how effectively neural networks can estimate GSR.

6. Trending and keyword analysis

Table 11 presented the total number of publications, percentage of total publications, total citations, and H.I. for the top twenty keywords in AIFH. The greatest number for T.P. is 1059, which corresponds to the term "Artificial Neural Network" and represents 19.5% of total publications (T.P.%). This suggests that artificial neural networks are the subject of the most study in AIFH. The next two most popular subjects in terms of T.P. are "Machine Learning" (972, 17.9%) and "Neural Network" (837, 15.4%), highlighting the great emphasis on neural networks and machine learning approaches in the field.

The keyword "Support Vector Machine," which accounts for 1.4% of all articles, has the lowest T.P. value, which is 75. This shows that, despite the ongoing study, support vector machines are less popular than other machine learning techniques in AIFH.

Table 11
Top twenty keyword AIFH.

Keyword Root	T.P.	T.P. (%)	T.C.	H.I.
Artifici Neural Network	1059	19.5	17064	63
Machin Learn	972	17.9	7991	36
Neural Network	837	15.4	10864	49
Comput Fluid Dynam	267	4.9	2242	24
Deep Learn	261	4.8	2409	22
Convolut Neural Network	234	4.3	2101	20
Artifici Intellig	233	4.3	1738	19
Reaction Diffus	177	3.3	4238	39
Solar Radiat	167	3.1	3871	35
Heat Transfer	163	3	2415	27
Genet Algorithm	132	2.4	2014	25
Diffus Tensor Imag	116	2.1	1604	20
Model	109	2	2247	27
Predict	91	1.7	1991	27
Diffus	86	1.6	1216	19
Optim	84	1.5	919	16
Synchron	83	1.5	2496	25
Deep Neural Network	80	1.5	620	12
Nanofluid	76	1.4	1749	23
Support vector machin	75	1.4	1088	19

The maximum number of total citations for the keyword "Artificial Neural Network" is 17064. This indicates the enormous impact that artificial neural networks have had on the AIFH sector, as they have been cited the most among the top 20 keywords. Some prominent keywords in terms of total citations are "Neural Network" (10864) and "Machine Learning" (7991), which further demonstrates the importance of these subjects in the field.

The minimal number of citations connected with the keyword "Deep Neural Network" is 620. Deep neural networks are regarded as a crucial development in machine learning; however, they have not yet received as many citations as other AIFH topics.

The H-index assesses the effect and productivity of published work. The keyword "Artificial Neural Network" has the highest H.I. value in the table, which is 63. This highlights the significance and influence of artificial neural networks in AIFH. The minimal H.I. value linked with the term "Deep Neural Network" is 12. This lower H-index number indicates that while deep neural networks have contributed to the area, they have not yet attained the same level of influence as other terms.

Fig. 14 shows the top hundred words cloud in the field of AIFH. This figure highlights the most important and frequently occurring keywords and allows viewers to quickly grasp the major themes or topics within the field. Each keyword is displayed with varying font sizes and colors. The size of a keyword typically indicates its importance and frequency. Larger and bolder keywords represent the most significant or frequently occurring terms, while smaller keywords are less frequent or less relevant. In the AIFH keyword cloud map, the three red-colored keywords—Artificial Neural Network, Machine Learning, and Neural Network—are the field's most significant and frequently occurring terms. The large size of keywords indicates that they are the primary topics in AIFH, and they likely represent the main focus areas for researchers and professionals in the field.

The top eight nations with the most involved keywords in the subject of AIFH are present in Fig. 15. The figure illustrates the scope of each nation's research efforts and contributions to AIFH by emphasizing the number of keywords used in relevant papers. China leads the list with 3667 involved keywords, indicating that it has the most extensive research output in AIFH among the top eight countries. This reflects China's significant interest and investment in the sector, which may be motivated by the country's quickly expanding economy, emphasis on technological developments, and growing demand for effective energy management.

The United States ranks second with 3314 involved keywords, showing the country's major contributions to AIFH's study. This is due

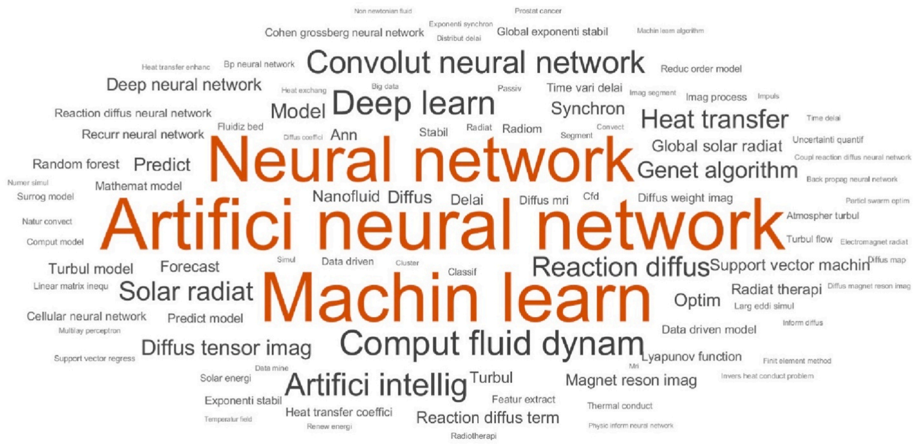

Fig. 14. Keyword root cloud map for the top 100 keywords.

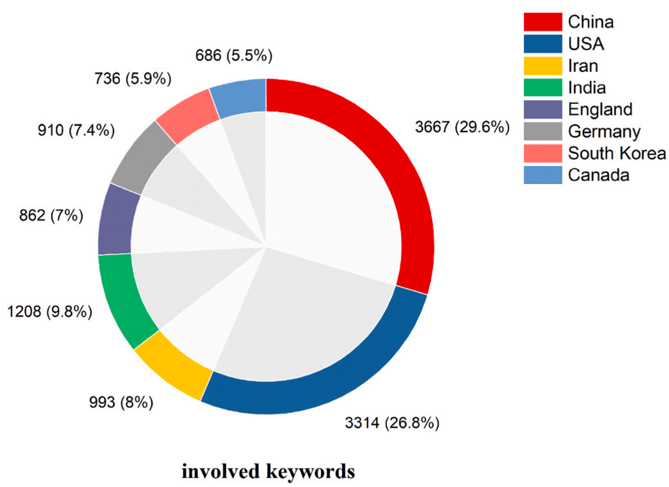

Fig. 15. Top eight Countries with involved keywords (DE) in AIFH.

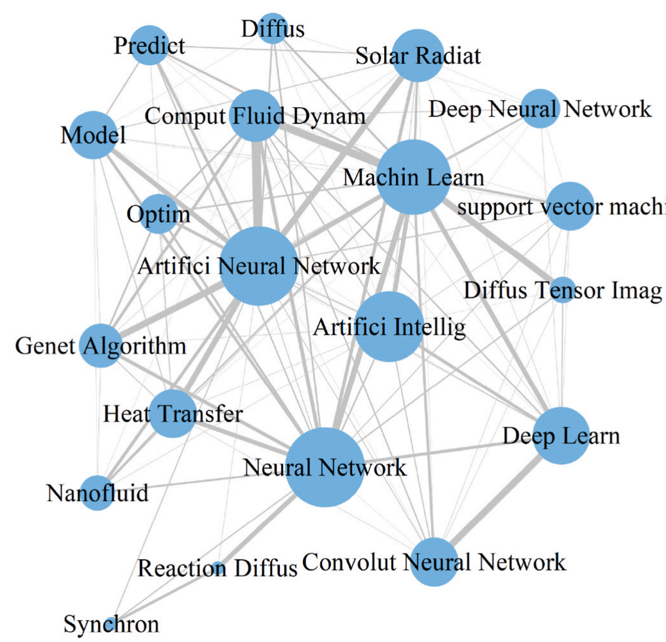

Fig. 16. Connectivity network of a top twenty Keyword in AIFH.

to the United States' well-established research institutes, advanced technology, and lengthy history of innovation in numerous scientific disciplines, such as artificial intelligence and fluid dynamics.

Iran and India are rated third and fourth, respectively, with 993 and 1208 involved terms. Due to their booming industrial sectors and the necessity to address efficiency and energy management concerns in various engineering applications, both nations have been focusing more and more on AIFH. Also among the top eight countries are England, Germany, South Korea, and Canada, with keywords ranging from 686 to 862. Several nations have made significant research contributions to AIFH.

Fig. 16 highlights the keywords with connections to other keywords in AIFH. This figure shows that Artificial Neural Network is a central technique in the AIFH field, with strong ties to Machine Learning, Neural Network, Computational Fluid Dynamics, Deep Learning, and Convolutional Neural Network. Additionally, it has established strong connections with Genetic Algorithm and Solar Radiation, emphasizing its significance in various aspects of AIFH.

Machine Learning has strong connections to Artificial Neural Network, Neural Network, Computational Fluid Dynamics, Deep Learning, and Convolutional Neural Network. Furthermore, it shares a strong connection with Diffusion Tensor Imaging, demonstrating its importance in developing and enhancing algorithms and models for a wide range of AIFH applications. Neural Network form the basis of machine learning and deep learning algorithms and have strong connections with Artificial Neural Network, Machine Learning, Computational Fluid Dynamics, Deep Learning, and Convolutional Neural Network. These connections showcase the relevance of Neural Network in the AIFH field, particularly in modeling, prediction, and optimization.

Genetic Algorithm (GA) shares a strong connection with Artificial Neural Network, suggesting combining GAs with Artificial Neural Network to optimize and improve AIFH models. Solar Radiation has a strong connection with Artificial Neural Network, emphasizing the role of Artificial Neural Network in predicting and analyzing solar radiation data for fluid-flow and heat-transfer applications.

Computational Fluid Dynamics is essential in the simulation and analysis of fluid-flow and heat-transfer problems. It shares strong connections with Artificial Neural Network, Machine Learning, Neural Network, Deep Learning, and Convolutional Neural Network, indicating its significant role in the context of AI-driven techniques. Deep Learning is a crucial component of advanced AI algorithms and models for AIFH applications. It has strong connections with Artificial Neural Network, Machine Learning, Neural Network, Computational Fluid Dynamics, and Convolutional Neural Network. The strong connection with Convolutional Neural Network emphasizes the importance of Deep Learning in image-based fluid flow and heat-transfer problems. Convolutional Neural Network are a type of deep learning algorithm that is particularly relevant in image-based AIFH applications. They share strong connections with Artificial Neural Network, Machine Learning, Neural Network, Computational Fluid Dynamics, and Deep Learning. Diffusion Tensor Imaging has a strong connection with Machine Learning, indicating the potential for Machine Learning techniques to analyze and interpret Diffusion Tensor Imaging data in fluid-flow and heat-transfer applications.

Fig. 17 illustrates the particular keywords that the top eight productive countries in AIFH focus on. China has a diverse range of research interests, with a focus on Artificial Neural Networks, Machine Learning (ML), Neural Networks, and Reaction Diffusion. The Chinese research community seems to emphasize AI and machine learning techniques, particularly in the context of neural networks. Additionally, the focus on Reaction Diffusion indicates an interest in related fields such as physics, chemistry, and biology.

The USA, England, and Germany mainly concentrate on Machine Learning. This shared interest in ML research suggests a strong drive for AI and data-driven solutions within these countries. Machine Learning techniques have widespread applications in various industries, including healthcare, finance, and transportation. This common research focus might indicate similar goals in technological advancements and innovation across these three countries.

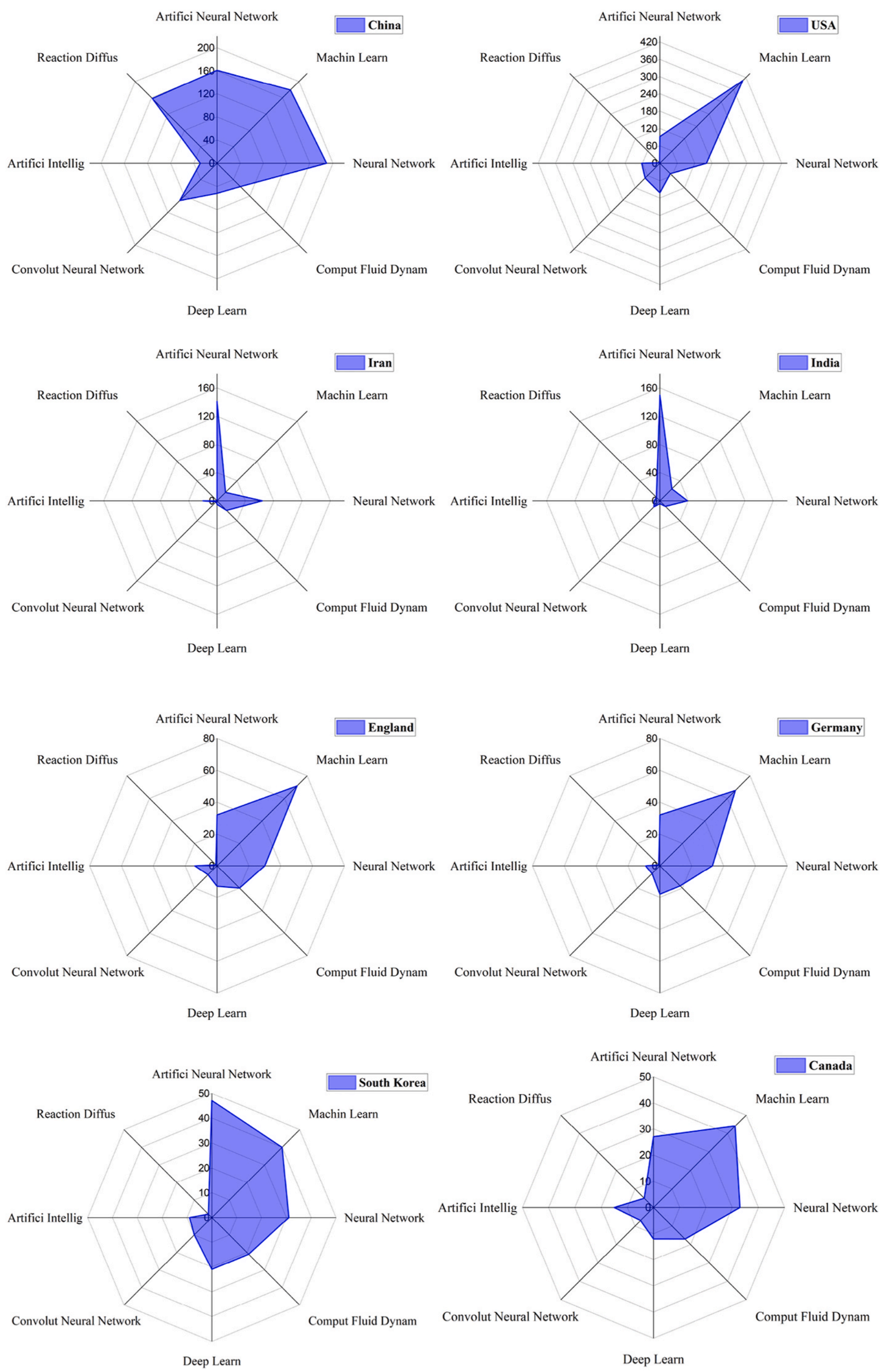

Fig. 17. Radar maps of keywords for the top eight productive countries in AIFH.

India and Iran primarily focus on Artificial Neural Networks. Their research interests are more specialized and less diverse compared to other countries. Artificial Neural Networks, a subset of ML, are inspired by biological neural networks and have applications in image and speech recognition, natural language processing, and game playing, among other areas. The similarity in research interests between India and Iran suggests that they might share specific scientific goals or challenges. South Korea has a diverse research focus, with interests in Artificial Neural Networks, Machine Learning, Neural Networks, Computational Fluid Dynamics, and Deep Learning. This broad range of research topics indicates that South Korea is investing in various AI and ML techniques and their applications in fields such as fluid dynamics.

Canada also has a diverse research interest, focusing on Artificial Neural Networks, Machine Learning, Neural Networks, and Computational Fluid Dynamics. Similar to South Korea, Canada's research interests cover various AI and ML techniques and their applications in other scientific fields. India and Iran: As both countries primarily focus on Artificial Neural Networks, their research interests are more specialized and less diverse compared to other countries.

USA, England, and Germany: These countries share a common interest in Machine Learning research, which could signify shared scientific goals or similarities in their technological advancements. South Korea and Canada: Both countries have a more diverse research focus, covering Artificial Neural Networks, Machine Learning, Neural Networks, and Computational Fluid Dynamics. Additionally, South Korea also has a focus on Deep Learning.

7. Conclusions

The WoS database was used to extract the publication data in the field of AIFH during the past forty years (1982–2022). Then, the publication records and citation data were used to perform a scientometric analysis on the field. The most productive and cited scientists, institutes, and countries were identified. The investigations of publication sources also discovered the most influential publication sources. The dynamic maps of the relationship between authors, institutes, and countries were also produced and plotted.

The results showed that the leading author with the highest number of AIFH publications was W. Zhang (46 T.P.) equally, followed by J. Kim (33 T.P.) and M.A. Zahoor Raja (33 T.P.). C. Voyant (1443 T.C.) received the most citations in AIFH and produced only 13 publications in AIFH. Thus, the author was concluded as a perfectionist in the T.C.-T.P. chart.

The Chinese Academy of Sciences, Islamic Azad University, and Stanford University were the institutes with the greatest number of publications. The most cited institutes were the Islamic Azad University (1893 T.C.), the Chinese Academy of Sciences (1374 T.C.), and Beihang University (1266 T.C.).

Considering T.P., China leads the ranking, followed by the USA and India. In terms of total citations (T.C.) and h-index, China, the USA, and Iran, respectively, were the leading countries. China, the USA, and India were placed in the prolific zone of the T.C.-T.P. chart.

A general increasing inclination in the number of total publications, total countries, total authors, and countries can be seen after 2015.

Dynamic maps for the authors' co-citation show four clusters. The first and second clusters contained 44 and 31 authors, respectively. The third and fourth clusters contain only 12 and 2 authors, respectively. Only a few authors act as a communication link between clusters. The co-authorships map also indicated 21 clusters containing only a few authors. Dynamic maps of the bibliographic coupling showed a heterogeneous behavior. Thus, it was concluded that each cluster established a strong bibliographic pair with itself. This means there is a weak bibliographic coupling of the author's clusters. Four clusters were found for coupling between institutions. The Chinese Academy of Sciences, Islamic Azad University, Tianjin Polytechnic University, and Wuhan University led the clusters. The coupling between countries showed five clusters, and the map showed a homogeneous behavior indicating a fair collaboration distribution between group countries (clusters). The United States, followed by China, showed the highest worldwide collaboration.

Medical Physics (119 T.P.) published most of the papers on AIFH. Five journals of Medical Physics, Neurocomputing, International Journal of Heat and Mass Transfer, International Journal of Radiation Oncology Biology Physics, and IEEE Access published half of the articles in the field. Moreover, the International Journal of Heat and Mass Transfer has received the most citations in AIFH.

ANNs are the most studied subject in AIFH, accounting for 19.5% of total publications, followed by Machine Learning (17.9%) and Neural Network (15.4%). Support Vector Machines are less popular, with only 1.4% of total publications. ANNs have the highest total citations (17,064) and H-index (63) among the top 20 keywords.

China has the most extensive research output in AIFH among the top eight countries, followed by the United States, Iran, and India. ANN, Machine Learning, and Neural Network are the most significant and frequently occurring terms in the AIFH keyword cloud map. Computational Fluid Dynamics, Deep Learning, and Convolutional Neural Network are strongly connected to ANN, Machine Learning, and Neural Network in AIFH. The top eight productive countries in AIFH have diverse research interests, with a focus on ANN, Machine Learning, and Neural Networks.

The bibliometric approach focused mainly on the number of publications and citations, which may not fully capture the qualitative impact of the research in the AIFH field. Geographic bias is also evident, as the study highlights contributions predominantly from China and the United States, potentially overshadowing other impactful work. Moreover, the dynamic maps, while insightful, may not capture the complexities of interdisciplinary collaborations and may show weak bibliographic coupling between author clusters.

Incorporating qualitative measures, such as peer reviews or industrial impact, could offer a more holistic understanding of an author or institute's influence in the AIFH domain. Given the current geographic concentration, efforts could be made to include more diverse contributions from underrepresented countries or institutions.

CRediT authorship contribution statement

Sepideh Ghalambaz: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Supervision. **Mohammad Abbaszadeh:** Visualization, Writing – original draft, Investigation, Formal analysis, Data curation. **Ideen Sadrehaghighi:** Methodology, Software, Formal analysis, Data curation. **Obai Younis:** Investigation, Formal analysis, Writing – review & editing. **Mehdi Ghalambaz:** Conceptualization, Formal analysis, Investigation, Writing – review & editing. **Mohammad Ghalambaz:** Investigation, Writing – review & editing, Supervision.

Declaration of competing interest

The authors clarify that there is no conflict of interest for report.

Data availability

Data will be made available on request.

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References

Adnan, R.M., Mostafa, R.R., Dai, H.-L., Heddam, S., Kuriqi, A., Kisi, O., 2023. Pan evaporation estimation by relevance vector machine tuned with new metaheuristic

algorithms using limited climatic data. Engineering Applications of Computational Fluid Mechanics 17, 2192258.
Alagumalai, A., Mahian, O., Aghbashlo, M., Tabatabaei, M., Wongwises, S., Wang, Z.L., 2021. Towards smart cities powered by nanogenerators: bibliometric and machine learning–based analysis. Nano Energy 83, 105844.
Ali, N., Bahman, A.M., Aljuwayhel, N.F., Ebrahim, S.A., Mukherjee, S., Alsayegh, A., 2021. Carbon-based nanofluids and their advances towards heat transfer applications—a review. Nanomaterials 11, 1628.
Alizadeh, R., Abad, J.M.N., Ameri, A., Mohebbi, M.R., Mehdizadeh, A., Zhao, D., Karimi, N., 2021a. A machine learning approach to the prediction of transport and thermodynamic processes in multiphysics systems-heat transfer in a hybrid nanofluid flow in porous media. J. Taiwan Inst. Chem. Eng. 124, 290–306.
Alizadeh, R., Mesgarpour, M., Ameri, A., Abad, J.M.N., Wongwises, S., 2021b. Artificial intelligence prediction of natural convection of heat in an oscillating cavity filled by CuO nanofluid. J. Taiwan Inst. Chem. Eng. 124, 75–90.
Azad, A., Parvin, S., 2022. Bibliometric analysis of photovoltaic thermal (PV/T) system: from citation mapping to research agenda. Energy Rep. 8, 2699–2711.
Bawack, R.E., Wamba, S.F., Carillo, K.D.A., Akter, S., 2022. Artificial intelligence in E-Commerce: a bibliometric study and literature review. Electron. Mark. 1–42.
Borri, E., Zsembinszki, G., Cabeza, L.F., 2021. Recent developments of thermal energy storage applications in the built environment: a bibliometric analysis and systematic review. Appl. Therm. Eng. 189, 116666.
Brunton, S.L., Noack, B.R., Koumoutsakos, P., 2020. Machine learning for fluid mechanics. Annu. Rev. Fluid Mech. 52, 477–508.
Duraisamy, K., Iaccarino, G., Xiao, H., 2019. Turbulence modeling in the age of data. Annu. Rev. Fluid Mech. 51, 357–377.
Ghalambaz, S., Hajjar, A., Younis, O., Alsabery, A., Ghalambaz, M., 2022. A scientometrics investigation of magnetic nanofluids. J. Magn. Magn Mater. 561, 169685.
Goodell, J.W., Kumar, S., Lim, W.M., Pattnaik, D., 2021. Artificial intelligence and machine learning in finance: Identifying foundations, themes, and research clusters from bibliometric analysis. Journal of Behavioral and Experimental Finance 32, 100577.
Han, X., 2017. MR-based synthetic CT generation using a deep convolutional neural network method. Med. Phys. 44, 1408–1419.
Hay, T., Visuri, V.-V., Aula, M., Echterhof, T., 2021. A review of mathematical process models for the electric arc furnace process. Steel Res. Int. 92, 2000395.
Ikram, R.M.A., Ewees, A.A., Parmar, K.S., Yaseen, Z.M., Shahid, S., Kisi, O., 2022. The viability of extended marine predators algorithm-based artificial neural networks for streamflow prediction. Appl. Soft Comput. 131, 109739.
Ikram, R.M.A., Mostafa, R.R., Chen, Z., Parmar, K.S., Kisi, O., Zounemat-Kermani, M., 2023. Water temperature prediction using improved deep learning methods through reptile search algorithm and weighted mean of vectors optimizer. J. Mar. Sci. Eng. 11, 259.
Kumar, S., Amano, R.S., 2021. An investigation in the numerical approach to solve the heat transfer phenomenon in gas turbine. J. Energy Resour. Technol. 143.
Lafon, S., Keller, Y., Coifman, R.R., 2006. Data fusion and multicue data matching by diffusion maps. IEEE Trans. Pattern Anal. Mach. Intell. 28, 1784–1797.
Lafon, S., Lee, A.B., 2006. Diffusion maps and coarse-graining: a unified framework for dimensionality reduction, graph partitioning, and data set parameterization. IEEE Trans. Pattern Anal. Mach. Intell. 28, 1393–1403.
Ling, J., Kurzawski, A., Templeton, J., 2016. Reynolds averaged turbulence modelling using deep neural networks with embedded invariance. J. Fluid Mech. 807, 155–166.
Lu, J.G., 2008. Global exponential stability and periodicity of reaction–diffusion delayed recurrent neural networks with Dirichlet boundary conditions. Chaos, Solit. Fractals 35, 116–125.
Ma, T., Guo, Z., Lin, M., Wang, Q., 2021. Recent trends on nanofluid heat transfer machine learning research applied to renewable energy. Renew. Sustain. Energy Rev. 138, 110494.
Manzoor, B., Othman, I., Sadowska, B., Sarosiek, W., 2022. Zero-energy buildings and energy efficiency towards sustainability: a bibliometric review and a case study. Appl. Sci. 12, 2136.
Martyn, J., 1964. Bibliographic coupling. J. Doc. 20 (4) https://doi.org/10.1108/eb026352, 236-236.
Mohandes, M., Rehman, S., Halawani, T., 1998. Estimation of global solar radiation using artificial neural networks. Renew. Energy 14, 179–184.
Paoli, C., Voyant, C., Muselli, M., Nivet, M.-L., 2010. Forecasting of preprocessed daily solar radiation time series using neural networks. Sol. Energy 84, 2146–2160.
Rehman, S., Mohandes, M., 2008. Artificial neural network estimation of global solar radiation using air temperature and relative humidity. Energy Pol. 36, 571–576.
Sadeghianjahromi, A., Wang, C.-C., 2021. Heat transfer enhancement in fin-and-tube heat exchangers–A review on different mechanisms. Renew. Sustain. Energy Rev. 137, 110470.
Sahiner, B., Pezeshk, A., Hadjiiski, L.M., Wang, X., Drukker, K., Cha, K.H., Summers, R. M., Giger, M.L., 2019. Deep learning in medical imaging and radiation therapy. Med. Phys. 46, e1–e36.
Sfetsos, A., Coonick, A., 2000. Univariate and multivariate forecasting of hourly solar radiation with artificial intelligence techniques. Sol. Energy 68, 169–178.
Sharma, M., Kumari, D.E., Meena, D.P., 2021. CFD Analysis in Solar Air Heater for Heat Transfer Enhancement: a Review.
Sridharan, M., 2020. Applications of Artificial Intelligence Techniques in Heat Exchanger Systems, Advanced Analytic and Control Techniques for Thermal Systems with Heat Exchangers. Elsevier, pp. 325–334.
Tymvios, F., Jacovides, C., Michaelides, S., Scouteli, C., 2005. Comparative study of Ångström's and artificial neural networks' methodologies in estimating global solar radiation. Sol. Energy 78, 752–762.
Varsha, P., Akter, S., Kumar, A., Gochhait, S., Patagundi, B., 2021. The impact of artificial intelligence on branding: a bibliometric analysis (1982-2019). J. Global Inf. Manag. 29, 221–246.
Verma, R., Lobos-Ossandón, V., Merigó, J.M., Cancino, C., Sienz, J., 2021. Forty years of applied mathematical modelling: a bibliometric study. Appl. Math. Model. 89, 1177–1197.
Verma, V.K., Mondal, S., 2021. A brief review of numerical methods for heat and mass transfer of Casson fluids. Partial Differential Equations in Applied Mathematics 3, 100034.
Voyant, C., Notton, G., Kalogirou, S., Nivet, M.-L., Paoli, C., Motte, F., Fouilloy, A., 2017. Machine learning methods for solar radiation forecasting: a review. Renew. Energy 105, 569–582.
Yadav, A.K., Chandel, S., 2014. Solar radiation prediction using Artificial Neural Network techniques: a review. Renew. Sustain. Energy Rev. 33, 772–781.
Yang, X., Cao, J., Yang, Z., 2013. Synchronization of coupled reaction-diffusion neural networks with time-varying delays via pinning-impulsive controller. SIAM J. Control Optim. 51, 3486–3510.
Yuan, X., Chen, C., Lei, X., Yuan, Y., Muhammad Adnan, R., 2018. Monthly runoff forecasting based on LSTM–ALO model. Stoch. Environ. Res. Risk Assess. 32, 2199–2212.
Zhang, Y., Yu, C., Zhao, F., Xu, H., Zhu, C., Li, Y., 2022. Landscape of artificial intelligence in breast cancer (2000–2021): a bibliometric analysis. Frontiers in Bioscience-Landmark 27, 224.
Zhu, Z., Bi, J., Pan, Y., Ganguly, S., Anav, A., Xu, L., Samanta, A., Piao, S., Nemani, R.R., Myneni, R.B., 2013. Global data sets of vegetation leaf area index (LAI) 3g and fraction of photosynthetically active radiation (FPAR) 3g derived from global inventory modeling and mapping studies (GIMMS) normalized difference vegetation index (NDVI3g) for the period 1981 to 2011. Rem. Sens. 5, 927–948.