SCIENCE & TECHNOLOGY LIBRARIES
https://doi.org/10.1080/0194262X.2023.2292049

A Bibliometric Analysis of Quantum Machine Learning Research

Ali Asghar Ahmadikia[a], Arman Shirzad[a], and Ali Mohammad Saghiri[b]

[a]University of Science and Culture, Tehran, Iran; [b]William Paterson University, Wayne, New Jersey, USA

ABSTRACT
Quantum Machine Learning is an interdisciplinary field that combines the principles of quantum physics, quantum computers, and machine learning to enhance computational performance. In recent years, there have been significant advancements in the field of quantum machine learning. Researchers have developed quantum algorithms for various tasks. Furthermore, quantum machine learning has been applied to various domains, such as chemistry, cryptography, and finance. Previous bibliometric surveys in this area covered the period from 2014 to 2020. However, as demonstrated in this paper, the pace of publication has increased significantly from 2018 to the present. Therefore, it has become essential to provide a new analysis of the current state of research in this field. In this paper, we deployed visualization tools to analyze co-authorships, co-occurrences, and keyword density in this research area. Our study covers and analyzes a total of 918 publications from the Web of Science database and 1171 publications from the Scopus database from 2006 to 2022. Following the analysis, we identify research questions, opportunities, and research gaps in the field of Quantum Machine Learning.

KEYWORDS
Biblometric analyses; quantum computing; quantum machine learning

Introduction

Quantum Machine Learning (QML) is an emerging interdisciplinary field that combines the principles of quantum mechanics and machine learning to develop new algorithms and techniques for solving complex computational problems Schuld and Killoran (2019). QML has garnered significant attention from researchers in recent years due to its potential to revolutionize various industries, including pharmaceuticals, finance, and cryptography.

In this bibliometric survey, we will explore the current state of research in QML, encompassing its history, related works, and their advantages. The concept of quantum computing was first introduced by Richard Feynman in 1982 when he proposed that a quantum computer could efficiently simulate the behavior of quantum systems compared to classical computers. In 1985, David Deutsch published a seminal paper Deutsch (1985) establishing the universality of quantum computers, which laid the foundation for the development of quantum algorithms and their potential applications, including machine learning.

In 1994, Peter Shor developed an algorithm for prime number factoring that was almost exponentially faster than the most efficient classical algorithms Shor (1997) Shor (1994), marking a turning point in quantum computing and demonstrating the potential of quantum algorithms in solving computationally challenging problems, including those in machine learning. In recent years, the field of QML has experienced substantial growth and garnered interest from researchers and practitioners. Seminal works have been published, including quantum algorithms for linear regression Rebentrost et al. (2016), Gaussian process regression Smolin et al. (2012), and principal component analysis Lloyd

CONTACT Ali Asghar Ahmadikia aliasghar.ahmadikia77@gmail.com University of Science and Culture, Tehran, Iran
This article has been corrected with minor changes. These changes do not impact the academic content of the article.

et al. (2014). Furthermore, quantum neural networks Altaisky (2001) and Reinforcement-learning-assisted quantum optimization Wauters et al. (2020) have been proposed.

One influential paper in the field is "Quantum Machine Learning" by Biamonte et al. (2017) Biamonte et al. (2017), which provides an overview of the state of QML and its potential applications. Another essential contribution is "Quantum Machine Learning in Feature Hilbert Spaces" by Schuld and Killoran (2019) Schuld and Killoran (2019), introducing a novel algorithm for classifying data points in high-dimensional feature Hilbert spaces. These papers, along with many others, have significantly contributed to the development of QML and its increasing popularity within the scientific community.

Other notable works in QML include "A Quantum Hopfield Neural Network" by Rebentrost et al. (2018) Rebentrost et al. (2018), proposing a quantum version of the Hopfield neural network for unsupervised learning, and "Supervised Learning with Quantum-Inspired Tensor Networks" by Stoudenmire and Schwab (2016) Stoudenmire and Schwab (2016), introducing a new class of quantum-inspired tensor network algorithms for supervised learning. Additionally, "Quantum Generative Adversarial Learning" by Lloyd and Weedbrook (2018) Lloyd and Weedbrook (2018) presents a fresh approach to quantum machine learning using generative adversarial networks.

Several review articles provide an overview of the state of the field of QML. Biamonte et al. reviewed the state of the art and provided a roadmap for future research Biamonte et al. (2017), while Schuld et al. reviewed the development of quantum algorithms for supervised Schuld et al. (2014a). Dunjko et al. reviewed quantum-enhanced reinforcement learning Dunjko et al. (2016), and Stahl et al. reviewed quantum algorithms for unsupervised and supervised learning Lloyd and Mohseni (2013).

In summary, the field of QML has experienced rapid growth in recent years, and numerous research studies have contributed to its development and potential applications. In this bibliometric survey, we aim to provide an overview of the current state of research in QML, including its history, related works, and their advantages, to offer readers a comprehensive understanding of the field. This paper presents a bibliometric survey of QML publications from Scopus and Web of Science databases spanning the past 16 years (2006–2022). Our contributions are summarized as follows:

We investigate articles from 2006 to 2022, whereas previous reviews focused only on research from 2014–2020. We show that QML's application fields have changed in recent years, with computer science now being the primary field employing QML. We demonstrate an increase in the annual number of articles published in recent years, highlighting the importance of continued research and investment in this field. We identify new research gaps in QML. To the best of our knowledge, this paper is one of the few comprehensive reviews of recent QML studies and likely the only one encompassing the current extent of QML publications over the past 16 years. The rest of the paper is organized as follows: Section 2 describes the research questions, Section 3 presents the Framing Keywords of QML, Section 4 offers a detailed analysis of QML publications from the Scopus and Web of Science databases, Section 5 discusses research gaps and future work in the field of QML, and Section 6 concludes the paper.

Related works

In the field of Quantum Machine Learning, relatively few scientometric studies have been conducted. Notable works in this domain include Dhawan et al.'s (2021) publication, "Quantum Machine Learning: A Scientometric Assessment of Global Publications during 1999–2020" Dhawan et al. (2021). In their study, they analyzed 1374 publications from the Scopus database spanning the years 1999 to 2020. The research explored the leading countries contributing to this field based on the number of citations, identified the primary research topics within Quantum Machine Learning, and examined the institutions at the forefront of this research. Additionally, Dhawan and colleagues presented a Keyword co-occurrence network analysis.

Pande and Mulay, in their 2020 work, "Bibliometric Survey of Quantum Machine Learning" Pande and Mulay (2020), delved into 276 publications from the Scopus database and 154 publications from the Web of Science database, encompassing the years 2014 to 2019. They meticulously investigated the leading countries and institutions from both the Web of Science and Scopus databases. The study also highlighted the distribution of publications across various subject areas in the Scopus database. Furthermore, the authors covered patents filed between 2014 and 2019, concluding with a comparative analysis of data from the two databases and addressing pertinent research gaps.

In 2021, Deshmukh and Mulay presented "Quantum Clustering Drives Innovations: A Bibliometric and Patentometric Analysis" Deshmukh and Mulay (2021), drawing from publications available on platforms like IEEE, Scopus, Web of Science, Google Scholar, and the Association for Computing Machinery. Their study spanned the years 2014 to 2020, focusing on quantum clustering. The authors delineated the predominant domains in quantum machine learning and employed a PRISMA flow chart to depict data sources. Additionally, they provided insights into patent trends during these years.

Ichikawa's (2022) study, "Bibliometric Analysis of Topic Structure in Quantum Computation and Quantum Algorithm Research" Ichikawa (2022), scrutinized the quantum computer field from 1985 to 2020. This analysis revealed leading countries in the field by assessing paper citations, particularly those pertaining to quantum machine learning as a subset of quantum computing.

In 2023, Sood and Monika presented "Bibliometric Analysis and Visualization of Quantum Engineering Technology" Sood and Monika (2023). Their research, based on scientific literature extracted from the Scopus database spanning 2008 to 2022, explored publication patterns, citation structures, and keyword co-occurrence networks. Their work, akin to previous studies, included an analysis of quantum machine learning publications as a subset of quantum computing.

A distinguishing feature of our paper is its extensive coverage of publications from 2006 to 2022, ensuring a more up-to-date dataset. Our findings indicate a shift in the quantum machine learning field, with physics and astronomy dominating until 2020, followed by a prominent role for computer science, taking the first place. Moreover, our approach leverages tools such as VOSviewer to conduct in-depth analyses of co-authorships, co-occurrence networks, and co-citation networks. We augment our analysis by harnessing data from both the Web of Science (WOS) and Scopus databases, enhancing the accuracy and comprehensiveness of our results. Our research addresses fundamental questions regarding the leading countries in the field, the prevalence of patents, top institutions, research gaps, opportunities, prolific authors, annual publication trends, and other pertinent aspects of this dynamic field.

Research questions

In this paper we have answered the following questions below:

(1) How many papers have been produced from 2006 to 2022 in the field of quantum machine learning?
(2) Which subject areas are most commonly using quantum machine learning according to Scopus and Web of Science databases, and how have these changed over time, and which one is the main subject now?
(3) Who are the most prolific authors in quantum machine learning in Scopus and Web of Science databases, and what are their areas of specialization within the field?
(4) Which scientific research journals have published the most papers on quantum machine learning, and how do the publication patterns in these journals reflect the evolution of the field over time?
(5) What are the top countries in Scopus and Web of Science databases producing research in quantum machine learning, and how has this changed over time?
(6) What are the leading funding sponsors in quantum machine learning research domains?
(7) What are the most highly cited articles in quantum machine learning, and how have these papers influenced the development of the field in terms of theory, methods, and applications?

(8) How does the number of patents in quantum machine learning compare to the number of research papers, and what can this tell us about the commercial viability of the field?
(9) What are the major research gaps and opportunities in quantum machine learning, and how are these reflected in the literature?

Research methodology and framing of the keywords

After experimenting with various combinations of keywords related to Quantum Machine Learning, we ultimately settled on the following set of core keywords for our paper titled "Bibliometric Survey of Quantum Machine Learning:" "Quantum Machine Learning," "Classical-Quantum Hybrid Algorithms," "Quantum PCA," "Quantum SVM," "Variational Circuits," "Quantum Annealers," "Quantum Enhanced Kernel Methods," "Quantum Deep Learning," and "Quantum Matrix Inversion." Our selection was guided by several observations:

(1) During our earlier attempts, we encountered overlapping meanings of some keywords, which could cause confusion in the research results.
(2) Some of the keywords we initially considered had multiple definitions across other fields of research unrelated to our focus, as discovered through database searches.
(3) It was crucial to include non-overlapping keywords to achieve comprehensive coverage of Quantum Machine Learning research in different aspects.
(4) Each of the selected keywords represents a distinct set of algorithms or related physical and mathematical foundations underlying the algorithms.

We have carefully considered these observations in selecting our set of keywords.

Results

In the previous section, we discussed the challenges we faced while selecting the keywords. In this section, we present our findings, which are divided into two main sections. The first section consists of an analysis conducted using the Scopus database, while the second section presents an analysis performed using the Web of Science database. We selected these databases for their reliability and global coverage.

Bibliometric analysis from 2006 to 2022 with the scopus database

In this section, we provide a detailed bibliometric analysis of the field of Quantum Machine Learning using the Scopus database. As a new and evolving field, we aim to examine it from various angles. We will begin by presenting the number of papers published between 2006 and 2022, followed by a discussion of the diverse range of subjects explored in this field. We will then analyze the top ten authors and countries that have contributed significantly to this area of research. Additionally, we will present the top sponsors who have funded research in this field. Next, we will discuss the most frequently cited papers in this area, and conclude by presenting the annual number of patents filed in this field.

Number of papers from 2006 to 2022

Figure 1 presents the number of documents that have been published every year. We can see from this figure that the valuable research started only in 2014 and from 2019 till now their number has grown faster. But now we restrict our analysis to the period 2006–2022. Because we wanted to have a Comprehensive analysis of this area of research. We have found 1171 documents from the Scopus database.

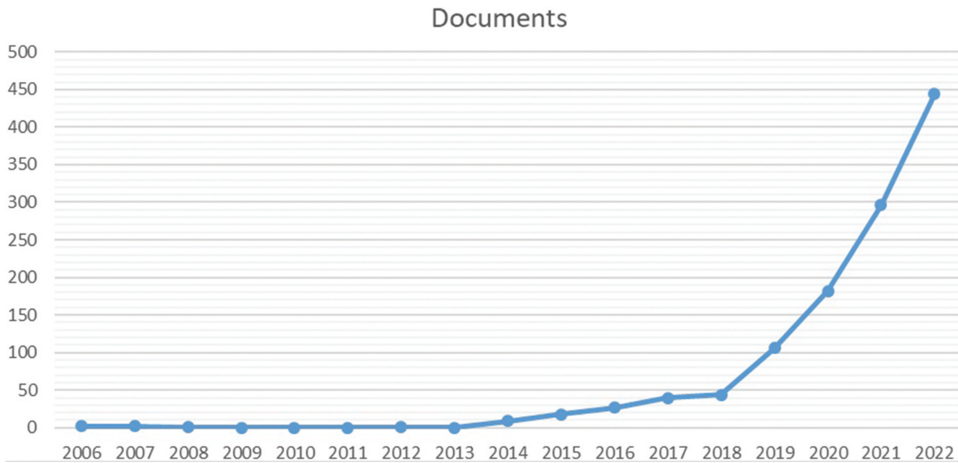

Figure 1. Another sample figure.

Table 1. Number of documents per year.

Year	Documents
2006	2
2007	2
2008	1
2009	0
2010	0
2011	0
2012	0
2013	0
2014	9
2015	18
2016	27
2017	40
2018	44
2019	106
2020	182
2021	296
2022	444

In Table 1 we show the annual breakup of research publications from (2006–2022) has been shown in a table. There is a meaningful increase in the number of publications.

Variety of the subjects in QML and the main subject by most percentage

Figures 2, and Table 2, show the variety of the subjects or research areas which have largely contributed to the research. As we can see from Figure 3 part a, Computer Science, Physics and Astronomy, Engineering, and Mathematics have contributed to about 79In terms of the number of publications, from Figure 3 part b, Computer Science has 706, Physics and Astronomy have 522, Engineering has 363 and Mathematics has 344 publications.

Top 10 most prolific authors in quantum machine learning in scopus

In Figure 3, the number of publications of the top 10 most prolific researchers is given as a bar chart. Lamata, L, leads the pack with 18 publications in the period that we have considered (2006–2022).

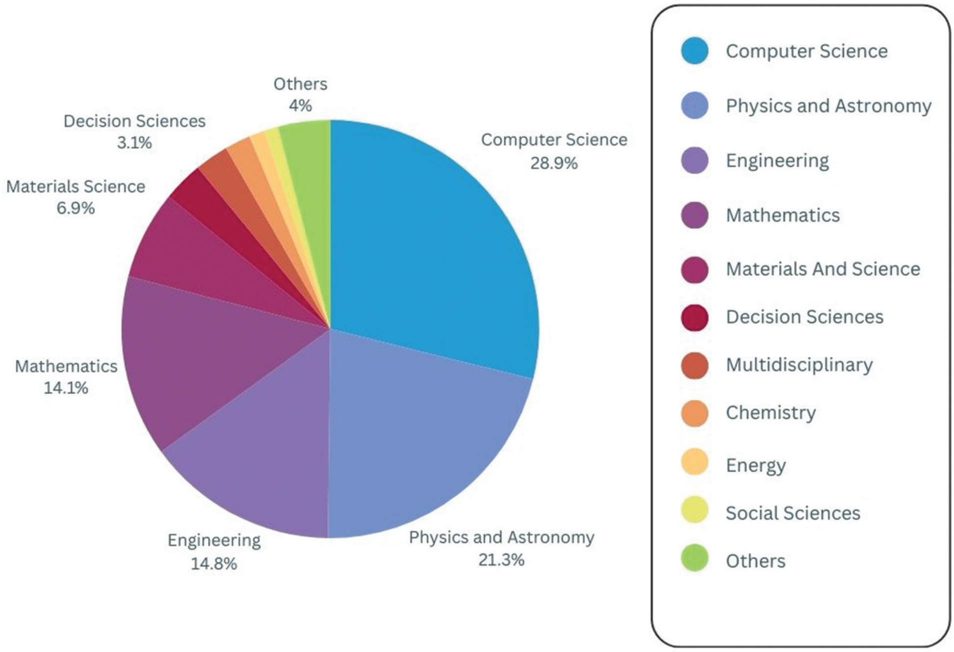

Figure 2. Subject area-wise percentage spread of the publications, from. Scopus database.

Table 2. Top 10 subject area wise number spread of the publications, as given by Scopus.

Subject	Documents
Computer Science	706
Physics and Astronomy	522
Engineering	363
Mathematics	344
Materials Science	168
Decision Sciences	76
Multidisciplinary	64
Chemistry	49
Energy	30
Social Sciences	26
Earth and Planetary Sciences	24
Biochemistry, Genetics and Molecular Biology	20
Medicine	18
Chemical Engineering	11
Neuroscience	11
Business, Management and Accounting	6
Arts and Humanities	3
Environmental Science	3
Agricultural and Biological Sciences	1

Analyzing co-authorship patterns using scopus: understanding the dynamics of author relationships

The utilization of co-authorship analysis is instrumental in exploring the interconnections among authors, institutions, or countries within scholarly publications. When applied to authors, co-authorship analysis unveils the intricate social relationships existing among them. In our investigation, we employed VOSviewer to visualize the co-citation network. Additionally, we implemented network clustering, utilizing community detection techniques, to highlight authors who predominantly collaborate on similar subjects within each community.

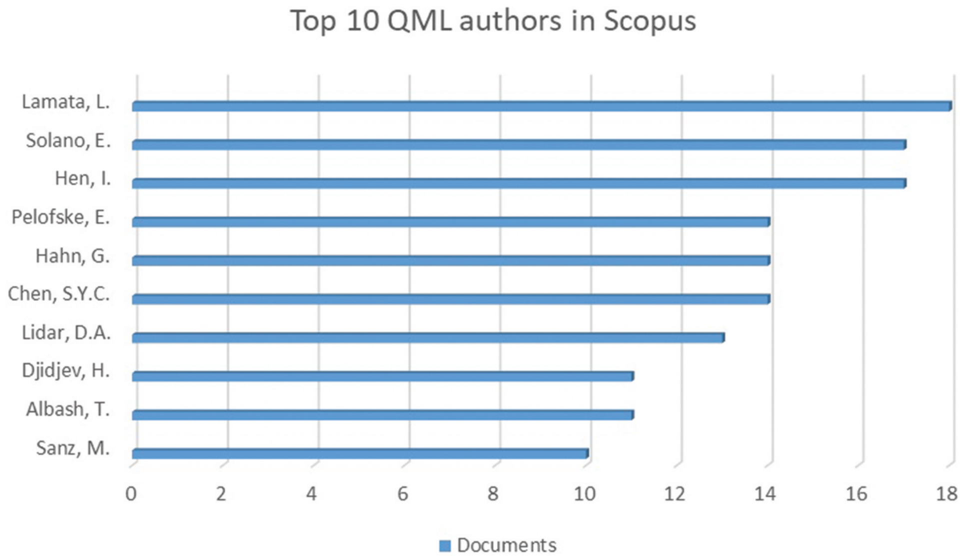

Figure 3. Top 10 authors who have published and contributed their expertise in scopus database.

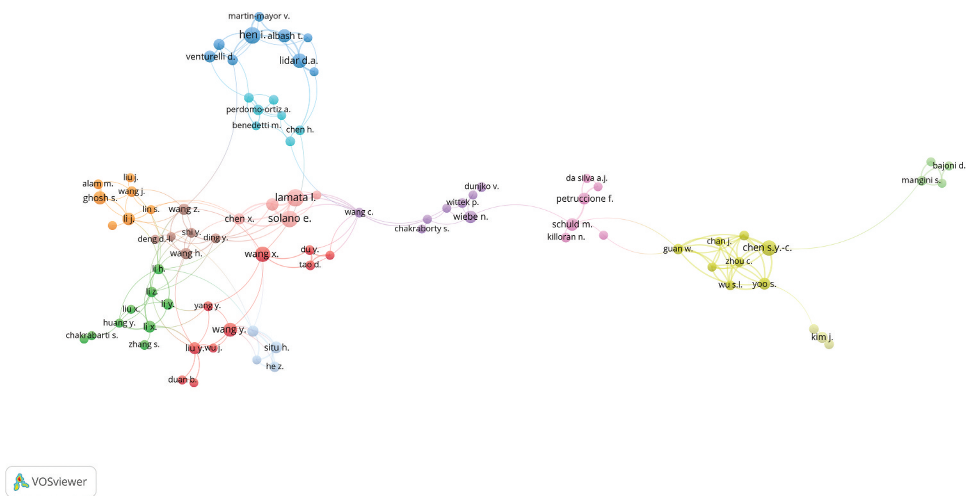

Figure 4. Co-authorship network with its 13 communities (clusters).

The resulting co-authorship network, derived from a subset of authors with a minimum of 5 articles, is depicted in Figure 4. This research domain comprises 13 distinct clusters. Node size within the network is proportionate to the number of articles published by each author, while the community structures are discernible through both node color and position. Furthermore, in Figure 5, the co-authorship network with its 13 community structures is overlaid with colors corresponding to the publication year, covering the period from 2014 to 2022. Node size in this representation remains relative to the number of articles published by each author, while the color of each node signifies the number of publications per year by the respective author.

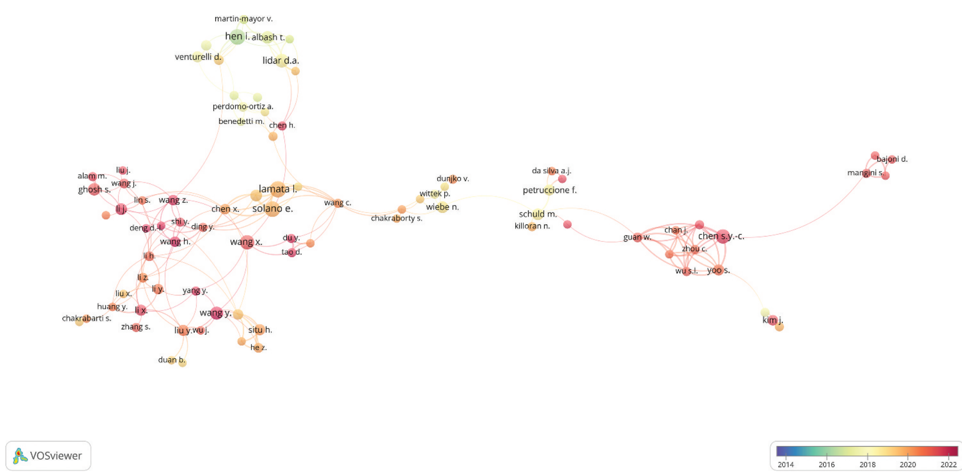

Figure 5. Co-authorship network as overlay visualization during 2014–2022.

List of top best scientific journals where research work in quantum machine learning has been published from scopus

The top leading sources where these works have been published are given in Table 3. This table presents the number of research documents that have been published from 2006 to 2022. In this part, we have tried to present sources that have published more than 10 papers about this area of research. And also in Figure 6, we can see a citation network of key journals for the research related to the topic of "Quantum machine learning." As we can see the Physical Review A is at the center by the biggest node and we can see the Quantum Information Processing at the top of the map by a big node but smaller than the Physical Review A.

Table 3. List of top best scientific journals where research work in quantum machine learning has been published, unveiled from scopus database.

Name of journal	Number of documents
Physical Review A	67
Quantum Information Processing	39
Lecture Notes In Computer Science Including Subseries Lecture Notes In Artificial Intelligence And Lecture Notes In Bioinformatics	36
Scientific Reports	36
Quantum Machine Intelligence	35
Quantum Science And Technology	29
IEEE Access	20
Machine Learning Science And Technology	19
Physical Review Applied	19
Proceedings Of SPIE The International Society For Optical Engineering	18
Quantum	18
New Journal Of Physics	17
Physical Review Letters	14
Physical Review Research	14
Advanced Quantum Technologies	12
International Geoscience And Remote Sensing Symposium IGARSS	12
International Journal Of Quantum Information	11
Journal Of Physics Conference Series	10
Npj Quantum Information	10
Proceedings Of The International Joint Conference On Neural Networks	10
Quantum Information And Computation	10

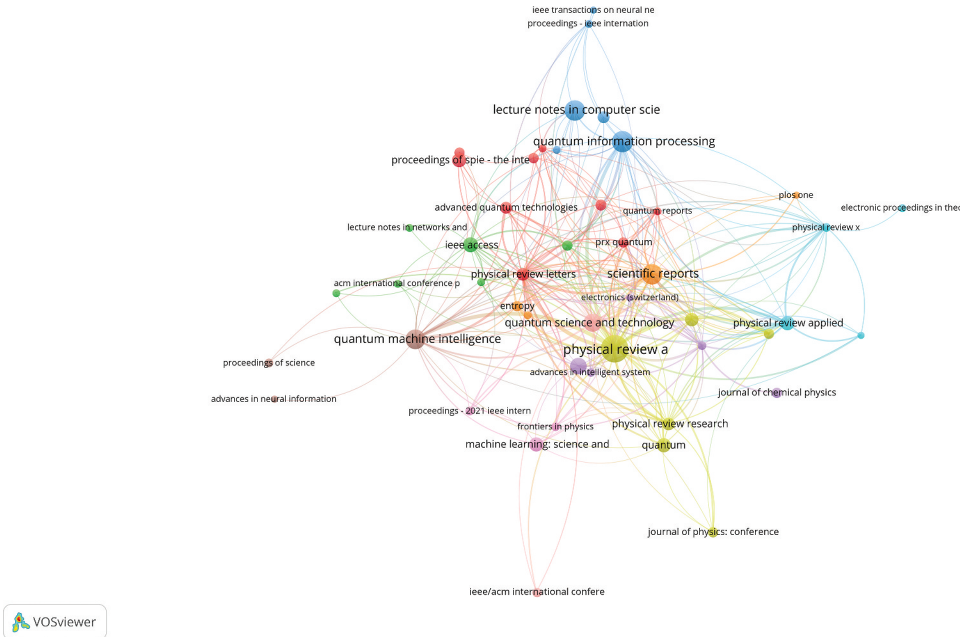

Figure 6. Citation network of key journals for the research related to topic of "Quantum machine learning".

Top 10 nations that publish the most scientific articles in QML

It might be interesting to see that 33.3% of the research publications come from the USA. USA share had been about 50% till 2020. This decline in percentage shows that other countries have specific interest in this field and the followers of the USA can be new leaders in this field in the future. It means that out of 1171 publications, USA has contributed to 391 of them. China is following the USA by 187 publications. After that, we can see the United Kingdom in 103 publications. This is presented in Figure 7.

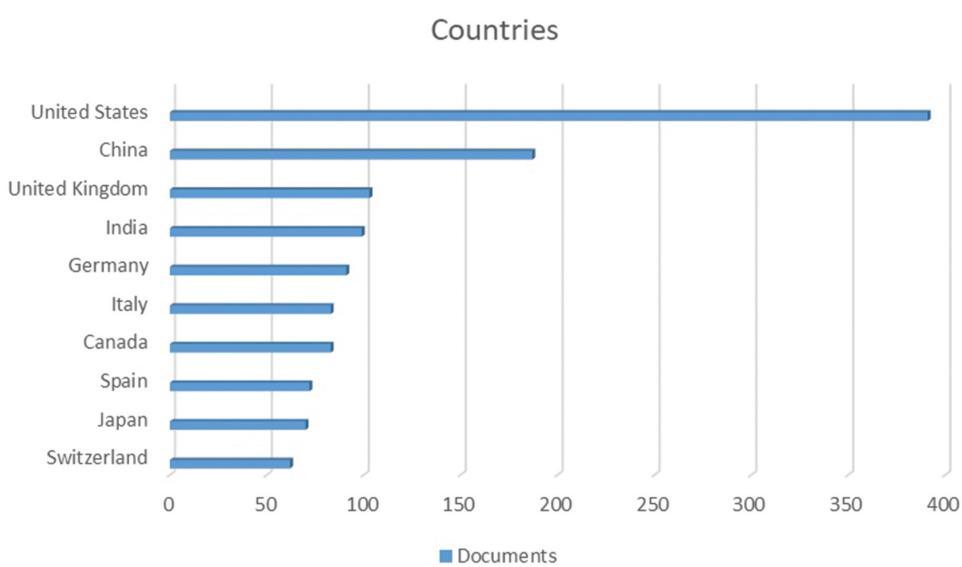

Figure 7. Data were retrieved from Scopus about the top publishing nations for scientific journals in QML.

Primary affiliation analysis

The graphical representation of the top ten institutions with a significant volume of published articles is depicted in Figure 8, highlighting Los Alamos National Laboratory as the leading institution with 52 articles, followed closely by researchers from the University of Southern California with 36 articles. To delve deeper into each affiliation, the corresponding country of each institution was extracted for further examination, as illustrated in Figure 7.

As evidenced in Figure 7, institutions in the USA (391 articles), China (187 articles), and the UK (103 articles) emerge as the primary contributors to the field. This observation underscores the global appeal of quantum machine learning, attracting researchers from diverse geographical locations.

The co-authorship network among institutions of contributing authors is visualized in Figure 9, where the size of each node is proportionate to the number of citations received by articles published by authors affiliated with these institutions. Similarly, Figure 10 presents the co-authorship network among countries of authors' institutions, with each node size reflecting the number of articles published by authors affiliated with institutions in the respective countries.

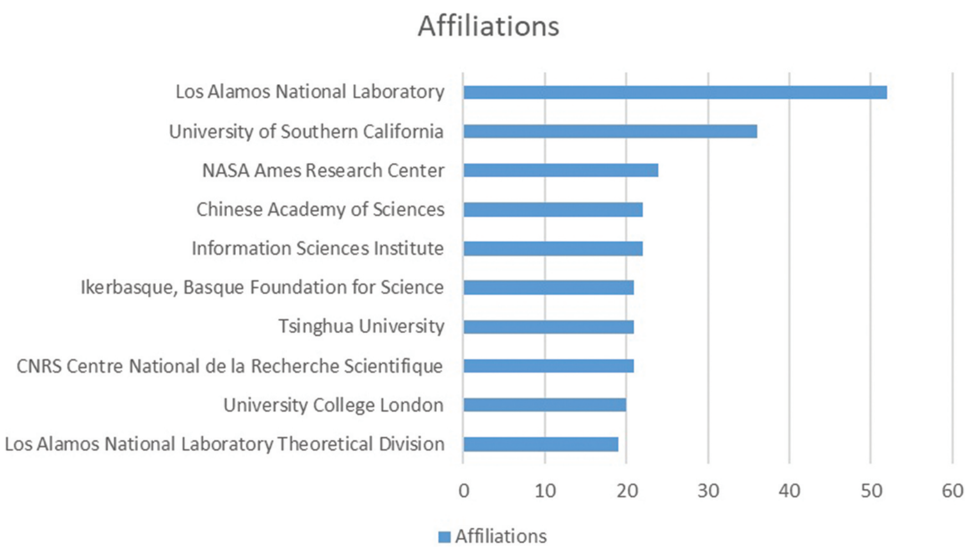

Figure 8. The top ten institutions for research on "quantum machine learning" with widely published articles.

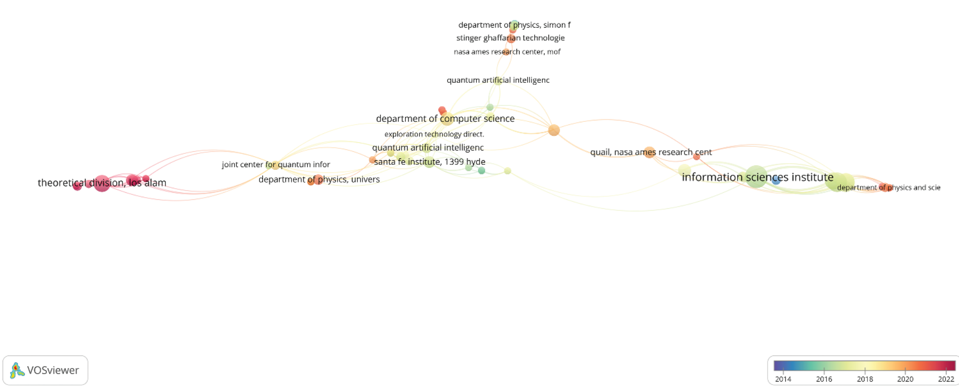

Figure 9. Institutions' co-authorship network for research on the subject of "quantum machine learning".

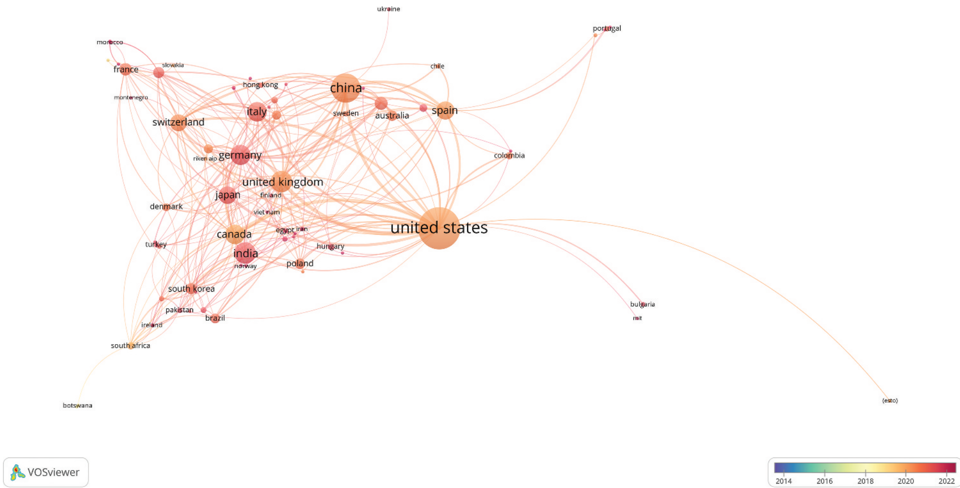

Figure 10. Co-authorship network for countries.

Top funding sources in the fields of quantum machine learning research

As we show in Figure 7, it is not surprising that most of the research funding sponsorship comes from the USA as we can see in Table 4. One of the surprising things is out of 187 publications that China provides, 96 of them are sponsored by the National Nature Science Foundation of china. And they are in first place in research funding sponsorship. And this number has grown over the years (2006–2022). which means that china shows a focus on this research area.While till a few months ago the National science foundation was in first place for years.

Highly cited works from 2006 to 2022

Table 5 provides an overview of the most cited publications and books within the field. Given the nascent nature of this research area, we opted to delve into the details of influential papers rather than relying solely on statistical figures. The table focuses on papers and books that have garnered more than 150 citations during the period 2014–2022.

Remarkably, the list includes a notable book authored by Peter Wittek, securing the 11th position, consistently gaining citations annually. The publication with the highest citation count, reaching 1136, belongs to the second paper by Biamonte et al. This work has achieved the maximum citations within a relatively brief duration, spanning slightly over two years since its publication in September 2017 until 2020. Notably, it continues to receive citations annually and stands as the most cited paper in quantum machine learning research from 2020 to the present. This paper serves as a comprehensive summary of diverse quantum machine learning algorithms. The citation network for articles visualized in Figure 11. Each node shows an author and his/her relations to other authours in his/her works.

Table 4. Top funding sources in the fields of quantum machine learning research, as shown by the scopus database.

Name of sponsor institutions	Number of documents
National Natural Science Foundation of China	96
National Science Foundation	89
U.S. Department of Energy	80
Office of Science	49
Los Alamos National Laboratory	39
Engineering and Physical Sciences Research Council	34
Horizon 2020 Framework Programme	33
Army Research Office	31
Laboratory Directed Research and Development	31
National Key Research and Development Program of China	26

Table 5. Highly cited works from the scopus database between 2006 and 2022.

No	Authors	Title	Year	Source Title	Cited by
1	Biamonte, J., Wittek, P., Pancotti, N., Rebentrost, P., Wiebe, N., Lloyd, S.	Quantum machine learning	2017	Nature	1136
2	Boixo, S., Rønnow, T.F., Isakov, S.V., Wang, Z., Wecker, D., Lidar, D.A., Martinis, J.M., Troyer, M.	Evidence for quantum annealing with more than one hundred qubits	2014	Nature Physics	452
3	Schuld, M., Sinayskiy, I., Petruccione, F.	An introduction to quantum machine learning	2015	Contemporary Physics	351
4	Mitarai, K., Negoro, M., Kitagawa, M., Fujii, K.	Quantum circuit learning	2018	Physical Review A	309
5	Schuld, M., Killoran, N.	Quantum Machine Learning in Feature Hilbert Spaces	2019	Physical Review Letters	301
6	Denchev, V.S., Boixo, S., Isakov, S.V., Ding, N., Babbush, R., Smelyanskiy, V., Martinis, J., Neven, H.	What is the computational value of finite-range tunneling?	2016	Physical Review X	240
7	Nawaz, S.J., Sharma, S.K., Wyne, S., Patwary, M.N., Asaduzzaman, M.	Quantum Machine Learning for 6G Communication Networks: State-of-the-Art and Vision for the Future	2019	IEEE Access	204
8	Faber, F.A., Christensen, A.S., Huang, B., Von Lilienfeld, O.A.	Alchemical and structural distribution based representation for universal quantum machine learning	2018	Journal of Chemical Physics	204
9	Dunjko, V., Taylor, J.M., Briegel, H.J.	Quantum-Enhanced Machine Learning	2016	Physical Review Letters	176
10	Benedetti, M., Lloyd, E., Sack, S., Fiorentini, M.	Parameterized quantum circuits as machine learning models	2019	Quantum Science and Technology	175
11	Wittek, P.	Quantum Machine Learning: What Quantum Computing Means to Data Mining	2014	Quantum Machine Learning: What Quantum Computing Means to Data Mining	175
12	Sheng, Y.-B., Zhou, L.	Distributed secure quantum machine learning	2017	Science Bulletin	169

Patent breakdown by year in quantum machine learning

An intriguing aspect worth noting is the patent activity within the specified period of interest (2014–2022). The data reveals a total of 424 patents, with a noteworthy observation that, in the last three years, the annual patent count has consistently exceeded 50.

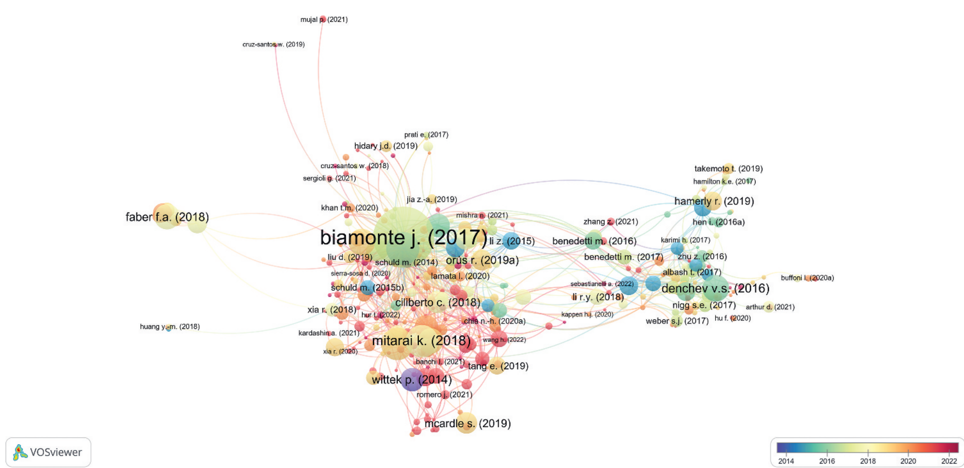

Figure 11. Citation network for articles.

Table 6 provides a detailed breakdown, emphasizing that a substantial portion, specifically 324 patents, has been filed in the most recent three years (2020–2022). This surge in patent filings underscores the potential of the field to translate scientific concepts into practical solutions for industry challenges.

Primary keywords examination

This section unveils the outcomes of the keyword analysis, offering insights into the intellectual core and identity formation within the discipline by scrutinizing keywords employed in research articles. The methodology involved a similar approach used to identify prevalent words in article titles.

Table 7 presents the top 10 frequently used words in article titles pertaining to the subject of "Quantum machine learning." The co-occurrence network of words extracted from titles and abstracts is visualized in Figure 12, where each node size corresponds to the frequency of occurrences in the entire text of titles and abstracts of articles. Notably, the central community in the network plot encompasses key words related to machine learning and quantum machine learning.

Figure 13 provides a density visualization of co-occurring keywords based on the total number of occurrences in articles. The central positioning of primary keywords related to machine learning and quantum computing is evident from the results.

Bibliometric analysis from 2006 to 2022 with the web of science database

In this section, we present a detailed bibliometric analysis of the data provided by the Web of Science database. We used the same set of keywords that we used in the Scopus database. Our search for publications from 2006 to 2022 resulted in a total of 918 papers. Therefore, it is clear from the data that

Table 6. Patent breakdown by year in quantum machine learning from scopus database.

Year	Number of Patents
2022	140
2021	99
2020	85
2019	50
2018	27
2017	18
2016	3
2015	1
2014	1

Table 7. Primary keywords examination of articles related to quantum machine learning.

Keyword	Frequency
Machine Learning	444
Quantum Machine Learning	442
Quantum Machines	402
Quantum Computing	352
Quantum Computers	326
Quantum Theory	324
Qubits	226
Machine-learning	225
Learning Algorithms	208
Quantum Optics	207

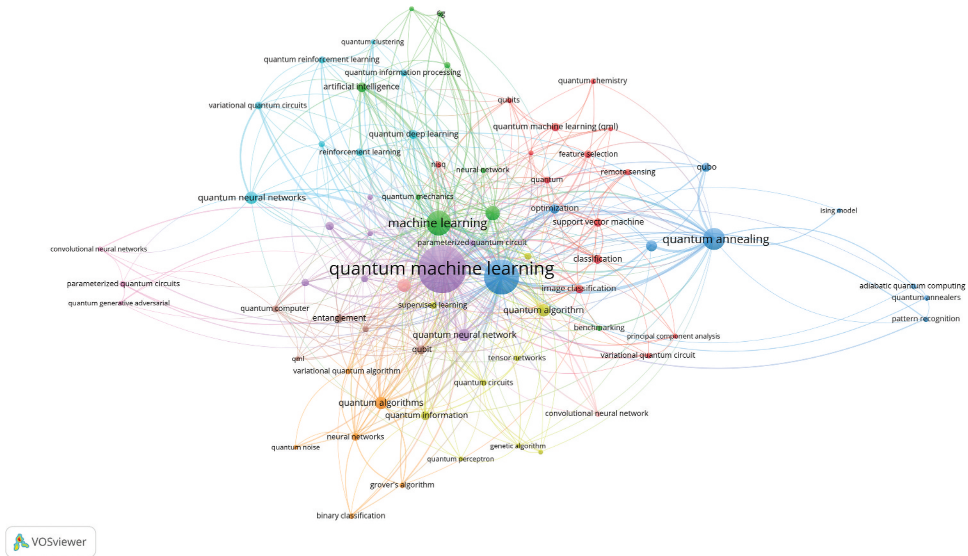

Figure 12. Co-occurrence network of terms found in the abstracts and titles.

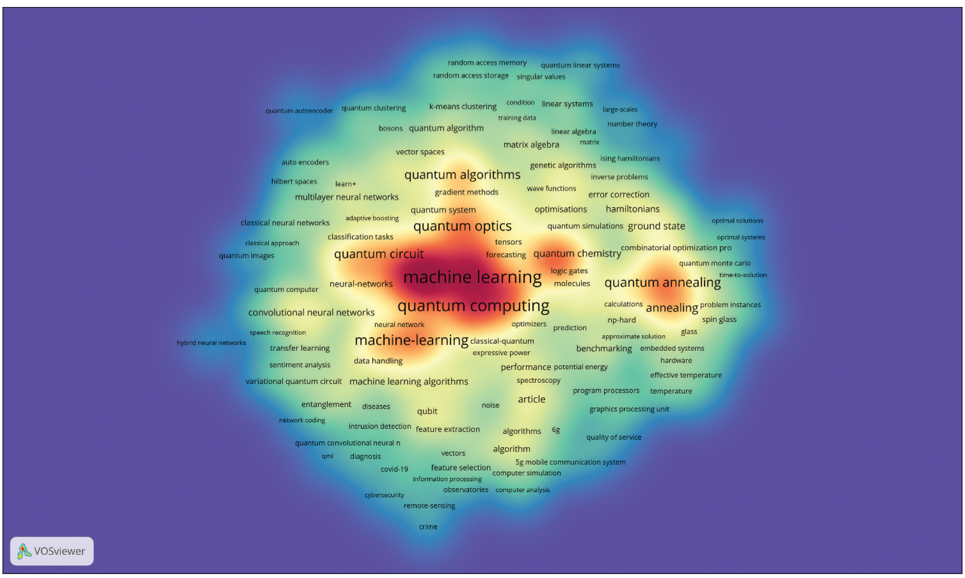

Figure 13. Density representation of the keyword co-occurrence network.

research interest and publication in the field of Quantum Machine Learning started only about 8 years ago, and its growth rate accelerated from 2018 onwards

Annual breakdown of publications in quantum machine learning, over the past 16 years, retrieved from the web of science database

In Table 8, we show the number of papers each year published in the Web of Science database. As we can see in the years 2006 and 2007 we just had 2 papers and from 2008 till 2013, we don't have any publications in this database. It shows that in those years, this field of research was not popular and researchers didn't show interest in this field. And in continuation we can see from 2014 to 2019, the number of publications are less than 100 each year. But suddenly from 2020 till now they grow up sharp and the number of papers has crossed from 100 annual. as we can see in 2022, we have 321 papers.

Tree map of articles published between 2014 and 2022 across different subject categories

Figure 14 shows the Treemap given by the Web of Science database showing us the top 10 categories in QML between 2006 and 2022. It proves that Quantum science technology is the subject area with the maximum publication. In previous research between 2014 and 2019, Physics Multidisciplinary was the highest in the table of the top 10 categories. This presents that Quantum science technology is significantly grown up from 2019 to 2022. So it shows us that recently researchers had a specific concentration in this category.

Author comparison between the WoS and scopus databases

Table 8 presented the yearly publication across all the subject categories. As we can see the number of publications grows up yearly and also its speed grows every year. This also is true

Figure 14. WoS database treemap of articles published in different subject groups between 2014 and 2022.

Table 8. Annual breakdown of publications in quantum machine learning, over the past 16 years, retrieved from the web of science database.

Year	Documents	Percentages
2022	321	34.967%
2021	223	24.292%
2020	145	15.795%
2019	89	9.695%
2018	48	5.229%
2017	39	4.248%
2016	27	2.941%
2015	16	1.743%
2014	8	171%
2013	0	0%
2012	0	0%
2011	0	0%
2010	0	0%
2009	0	0%
2008	0	0%
2007	1	0.109%
2006	1	0.109%

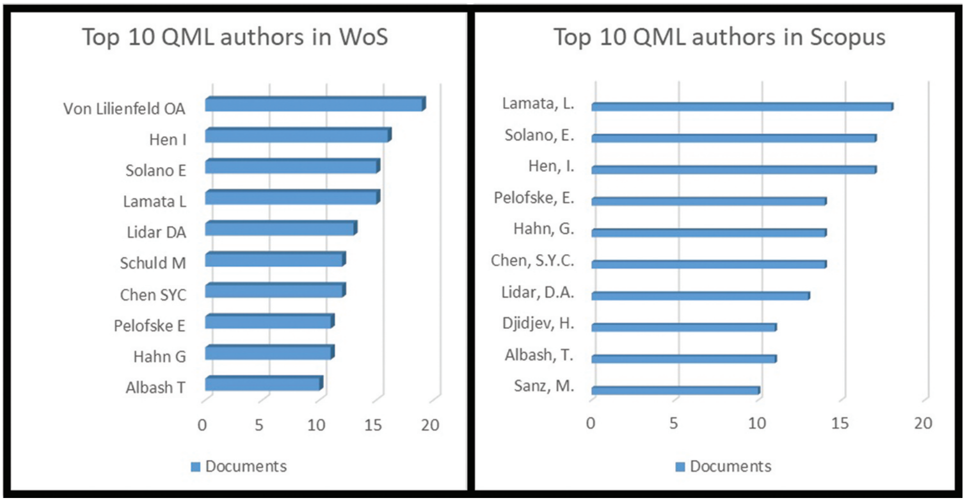

Figure 15. Comparison of writers who have published in the databases WoS (left figure) and Scopus (right figure).

about corresponding data from the Scopus database. In Figure 15, we have done a comparison between the top 10 authors who have published in Scopus and Web of Science databases. The first author with 18 publications from the Scopus database is Lamata, L. He was the first in both databases till 3 years ago but now in the Web of Science database Von Lilienfeld, O. Anatole is the first by 19 publications. Till 2019 the first three leading authors were the same in both databases but now as we can see names of the first three leading authors are different in both databases. At the left you can see the top 10 authors from the Web of Science database and at the right is the top 10 authors from the Scopus database. And also in Figure 16 we present co-authorship from the web of science as we can see and for comparison co-authorships in the Scopus database were more crowded and meaningful. In Figure 17, we present the co-authorships during the years 2014–2022. As we can see all of them are yellow which means they were around 2018.

A comparison of the top subjects and research fields published in papers between the databases WoS and scopus

In Table 9 we have compared the top research areas (which in the Scopus table it is called Subject areas) in both databases Web of Science and Scopus. While not all subject (or research) areas are the same, largely the research areas are the same. For example, In both charts, we can see Computer science, Engineering, and Physics are the first three leading subjects but their places are different in each table.

Key affiliation in web of science database

We have analyzed the top 10 institutes with highly published articles in this area of research in the Web of Science database as we have mentioned in Figure 18, like what we have done for the Scopus database before. According to the Figure 18, most article are published by the UNITED STATES DEPARTMENT OF ENERGY with 82 articles and is followed by the LOS ALAMOS NATIONAL LABORATORY and the UNIVERSITY OF SOUTHERN CALIFORNIA by 45 papers and 35 papers respectively. In Figure 19 we have demonstrated the Co-authorship network for institutions for the research related to the topic of "Quantum machine learning" from the Web of Science database which is the minimum documentation of an organization is 2. As we can see the Los Alamos National Laboratory has the biggest ball because it has 5 documents in co-authorships and 3 links. And many of them were around 2020 as we can see from its color in Figure 19 In

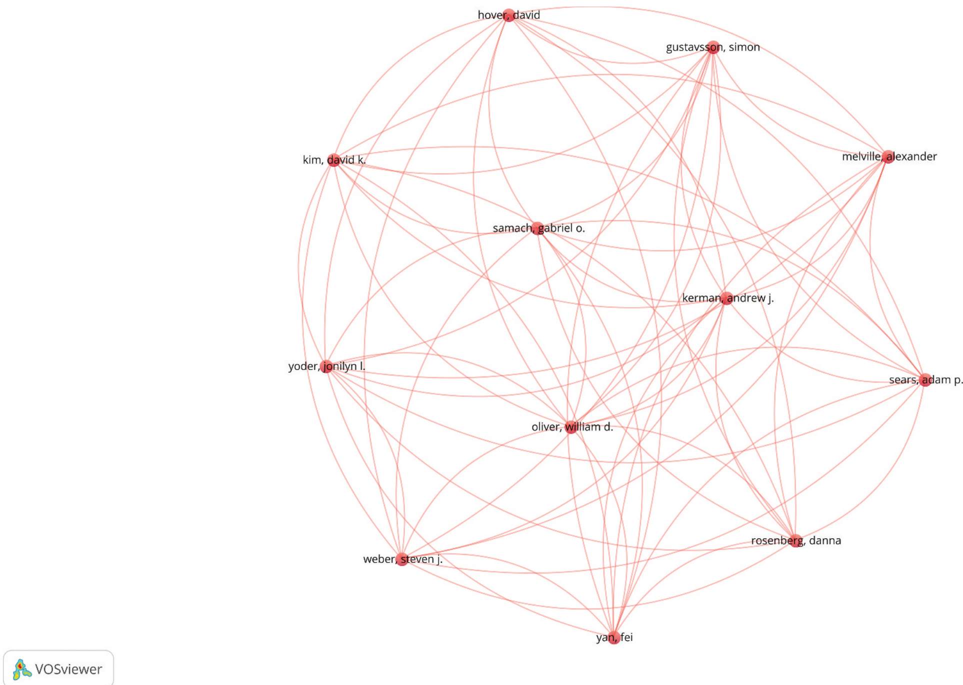

Figure 16. Network of co-authors from the web of science database.

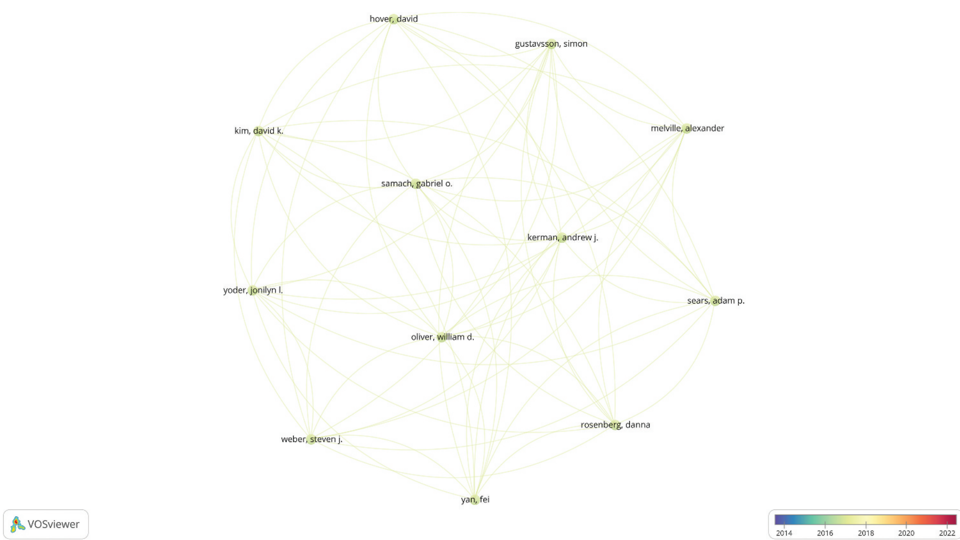

Figure 17. Co-authorship network as an overlay visualization from the Web of Science database, spanning the years 2006–2022.

Figure 20 we have presented the Co-authorship network for countries from the Web of Science database which is the minimum documentation of a country is 2. According to Figure 20 the USA has the biggest ball with 26 documents in co-authorship and 7 links. And many of them were around 2018 as we can see from its color in Figure 20.

Table 9. A comparative analysis of the top research topics and subjects published in papers. Table from WoS on the right, and table from Scopus on the left.

Subject	Documents	Subject	Documents
Computer Science	706	Physics	491
Physics and Astronomy	522	Computer Science	377
Engineering	363	Engineering	141
Mathematics	344	Optics	107
Materials Science	168	Science Technology Other Topics	98
Decision Sciences	76	Telecommunications	41
Multidisciplinary	64	Chemistry	36
Chemistry	49	Mathematics	21
Energy	30	Materials Science	17
Social Sciences	26	Operations Research Management Science	15
Earth and Planetary Sciences	24	Automation Control Systems	14
Biochemistry, Genetics and Molecular Biology	20	Imaging Science Photographic Technology	14
Medicine	18	Remote Sensing	12
Chemical Engineering	11	Acoustics	6
Neuroscience	11	Energy Fuels	6
Business, Management and Accounting	6	Environmental Sciences Ecology	6
Arts and Humanities	3	Neurosciences Neurology	6
Environmental Science	3	Biochemistry Molecular Biology	5
Agricultural and Biological Sciences	1	Mathematical Computational Biology	5

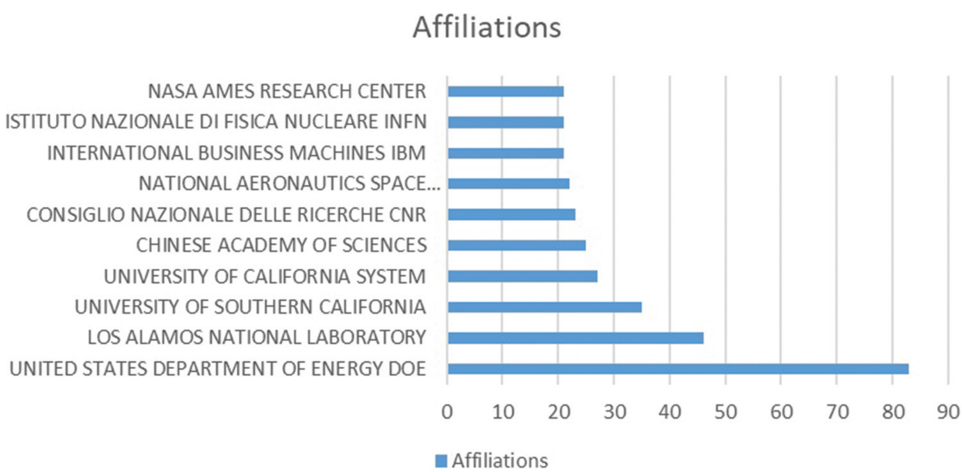

Figure 18. Top 10 institutions with highly published articles for the research related to the topic of "quantum machine learning" from the web of science database.

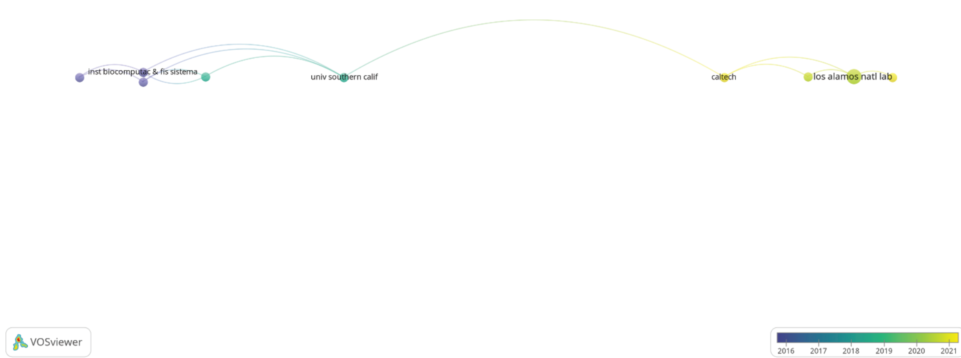

Figure 19. Co-authorship network for institutions for the research related to topic of "quantum machine learning" from web of science database.

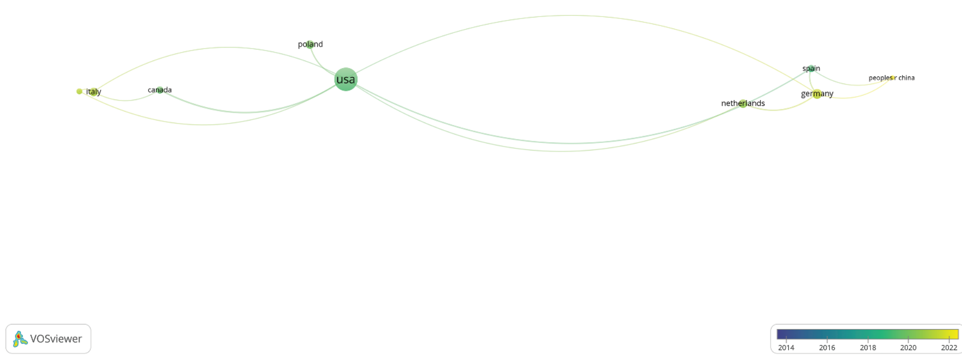

Figure 20. Co-authorship network for countries from web of science database.

Research gaps and opportunities to work in quantum machine learning field

Quantum machine learning is a rapidly growing field that holds great potential for advancing artificial intelligence. Despite the exciting progress that has been made, there are still significant research gaps and opportunities that need to be explored.

Research gaps

(1) Scalability: Currently, quantum algorithms struggle with scalability and efficiency when applied to large data sets. Improving scalability and efficiency is crucial for the practical implementation of quantum machine learning algorithms de Haan et al. (2021); Benedetti et al. (2019).
(2) Hybrid classical-quantum algorithms: A combination of classical and quantum algorithms could offer the best of both worlds. Further research is needed to develop hybrid algorithms that can take advantage of the strengths of both classical and quantum computing Shukla and Vedula (2023); Kim et al. (2020).
(3) Real-world applications: Although quantum machine learning has shown promise in various laboratory settings, there are still limited real-world applications. Research is needed to develop practical quantum machine learning solutions that can be deployed in the real world Nath et al. (2021); Rebentrost et al. (2018).
(4) Understanding quantum algorithms: Despite the rapid progress in the field, there is still much to be learned about the underlying principles of quantum algorithms. Further research is needed to gain a deeper understanding of how quantum algorithms work and how they can be optimized Montanaro (2016); Aaronson and Chen (2016).
(5) Handling noisy quantum hardware: One of the major challenges in quantum computing is the presence of noise, which can severely impact the accuracy of quantum algorithms. Research is needed to develop robust quantum machine learning algorithms that can handle noise in quantum hardware Preskill (2018); Temme et al. (2017).
(6) Integration with classical machine learning: Although quantum machine learning has the potential to improve the accuracy of machine learning models, it is still challenging to integrate quantum algorithms with classical machine learning algorithms. Research is needed to develop a seamless Schuld et al. (2017); Lloyd and Weedbrook (2018).
(7) Quantum data representation: A key aspect of quantum machine learning is the representation of data in a quantum form that can be processed by quantum algorithms. Research is needed to develop efficient quantum data representations that can be used in a variety of quantum machine learning algorithms Havlíček et al. (2019); Schuld and Killoran (2019).

Opportunities

(1) Improved accuracy: Quantum machine learning algorithms have the potential to improve the accuracy of machine learning models, especially for complex data sets Schuld et al. (2015).
(2) New applications: The unique capabilities of quantum computing open up new avenues for machine learning research and the development of new applications Schuld et al. (2014b).
(3) Interdisciplinary collaboration: The development of quantum machine learning requires interdisciplinary collaboration between computer scientists, physicists, mathematicians, and engineers Sarma et al. (2019).
(4) Solving intractable problems: Quantum machine learning has the potential to solve problems that are intractable for classical algorithms. This could lead to breakthroughs in fields such as drug discovery, financial forecasting, and materials design Benedetti et al. (2016).
(5) Improving quantum algorithms: As researchers gain a deeper understanding of quantum algorithms, they will be able to develop new and improved quantum algorithms that can be used for a variety of applications Gilyén (2019).
(6) Advancing quantum computing: The development of quantum machine learning algorithms will contribute to the advancement of quantum computing as a whole. This will have far-reaching implications for a wide range of fields, from cryptography to simulations of complex physical systems Najafi et al. (2022).
(7) Improving interpretability and transparency of quantum models: One challenge in QML is the interpretability and transparency of quantum models, which can limit their adoption in certain applications. Research is needed to develop techniques that can make quantum models more interpretable and explainable to stakeholders Meinsma et al. (2023).
(8) Combining quantum and classical techniques: Another opportunity in QML is to explore ways to combine classical and quantum techniques to create hybrid models that can harness the strengths of both. This could lead to significant improvements in the accuracy and efficiency of machine learning algorithms Abohashima et al. (2020).
(9) Applications in time-series data analysis: QML has potential applications in time-series data analysis, such as financial forecasting, but more research is needed to fully realize this potential. Research is needed to develop quantum algorithms that can effectively handle time-series data and provide new insights into this type of data Emmanoulopoulos and Dimoska (2022).
(10) Scalability and performance of quantum algorithms: Scalability and performance are critical issues in QML, as the size of data sets and the complexity of models continue to grow. Research is needed to develop quantum algorithms that can handle large-scale data sets efficiently and effectively, while maintaining high accuracy Farhi et al. (2014).
(11) Addressing security and privacy issues: Another important aspect of QML is ensuring the security and privacy of sensitive data, particularly when quantum algorithms are used to analyze data that is subject to privacy regulations. Research is needed to address these security and privacy issues and develop techniques that can protect sensitive data during the analysis process Rebentrost and Mohseni (2021).

What we have mentioned above were just some of the important research gaps and opportunities and there are more than what we had mentioned in this paper.

Conclusions and prospects for future research

Our bibliometric analysis, utilizing the Scopus database, unveils a consistent growth trend in publications over the past four years. Four key research domains – Computer Science, Physics and Astronomy, Engineering, and Mathematics – contribute significantly, accounting for approximately 79% of the publications. The United States emerges as the leading contributor among the top ten countries, representing around 33.44% of the total research publications. However, there is a notable decline in the USA's share since 2020, when it accounted for approximately 50% of publications in this research field Pande and Mulay (2020).

Furthermore, the Scopus database indicates a total of 616 published patents, with 433 of them emerging in the last three years (2019–2022). Corroborating this trend, the Web of Science database reports 757 publications during the same period, reinforcing consistency across metrics.

Looking ahead, there is a compelling opportunity to explore the impact of quantum machine learning across diverse research fields and delve into its potential for practical applications.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Aaronson, S., and L. Chen. 2016. "Complexity-Theoretic Foundations of Quantum Supremacy Experiments." *arXiv:1612.05903*. https://doi.org/10.48550/arXiv.1612.05903

Abohashima, Z., M. Elhosen, E. H. Houssein, and W. M. Mohamed. 2020. "Classification with Quantum Machine Learning: A Survey." *arXiv Preprint arXiv: 2006.12270*.

Altaisky, M. V. 2001. "Quantum neural network." *arXiv*. https://doi.org/10.48550/ARXIV.QUANT-PH/0107012.

Benedetti, M., D. Garcia-Pintos, O. Perdomo, V. Leyton-Ortega, Y. Nam, and A. Perdomo-Ortiz. 2019. "A Generative Modeling Approach for Benchmarking and Training Shallow Quantum Circuits." *Npj Quantum Information* 5 (1). https://doi.org/10.1038/s41534-019-0157-8.

Benedetti, M., J. Realpe-Gómez, R. Biswas, and A. Perdomo-Ortiz. 2016. "Quantum-Assisted Learning of Graphical Models with Arbitrary Pairwise Connectivity." *arXiv Preprint arXiv: 1609.02542* 980.

Biamonte, J., P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd. 2017. "Quantum machine learning." *Nature* 549 (7671): 195–202. https://doi.org/10.1038/nature23474.

de Haan, P., C. Rainone, M. C. Cheng, and R. Bondesan. 2021. "Scaling Up Machine Learning for Quantum Field Theory with Equivariant Continuous Flows." *arXiv Preprint arXiv: 2110.02673*.

Deshmukh, S., and P. Mulay. January 2021. "Quantum Clustering Drives Innovations: A Bibliometric and Patentometric Analysis."

Deutsch, D. 1985. "Quantum Theory, the Church-Turing Principle and the Universal Quantum Computer." *Proceedings of the Royal Society of London A* 400: 97–117. https://doi.org/10.1098/rspa.1985.0070.

Dhawan, S. M., B. M. Gupta, and G. M. N. Mamdapur. 2021. "Quantum machine learning: A scientometric assessment of global publications during 1999–2020." *International Journal of Knowledge Content Development & Technology* 11 (3): 29–44. https://doi.org/10.5865/IJKCT.2021.11.3.029.

Dunjko, V., J. F. Fitzsimons, and H. J. Briegel. 2016. "Quantum-enhanced reinforcement learning." *Physical Review X* 6 (2): 021001. https://doi.org/10.1103/PhysRevX.6.021011.

Emmanoulopoulos, D., and S. Dimoska. 2022. "Quantum Machine Learning in Finance: Time Series Forecasting." *arXiv Preprint arXiv: 2202.00599*.

Farhi, E., J. Goldstone, and S. Gutmann. 2014. "A Quantum Approximate Optimization Algorithm." *arXiv Preprint arXiv: 1411.4028*.

Gilyén, A. 2019. "*Quantum Singular Value Transformation & Its Algorithmic Applications*." PhD thesis., University of Amsterdam.

Havlíček, V., A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta. 2019. "Supervised Learning With Quantum-Enhanced Feature Spaces." *Nature* 567 (7747): 209–212. https://doi.org/10.1038/s41586-019-0980-2.

Ichikawa, T. 2022. "Bibliometric Analysis of Topic Structure in Quantum Computation and Quantum Algorithm Research." Accessed October 22, 2023. http://arxiv.org/abs/2201.01911.

Kim, M., D. Venturelli, and K. Jamieson. November, 2020. "Towards Hybrid Classical-Quantum Computation Structures in Wirelessly-Networked Systems." In *Proceedings of the 19th ACM Workshop on Hot Topics in Networks*, 110–116. New York, NY: Association for Computing Machinery. https://dl.acm.org/doi/10.1145/3422604.3425924.

Lloyd, M., and P. R. Mohseni. 2013. "Quantum Algorithms for Supervised and Unsupervised Machine Learning." *arXiv*. https://doi.org/10.48550/ARXIV.1307.0411.

Lloyd, S., M. Mohseni, and P. Rebentrost. 2014. "Quantum Principal Component Analysis." *Nature Physics* 10 (9): 631–633. https://doi.org/10.1038/nphys3029.

Lloyd, S., and C. Weedbrook. 2018. "Quantum Generative Adversarial Learning." *Physical Review Letters* 121 (4): 040502. https://doi.org/10.1103/PhysRevLett.121.040502.
Meinsma, A. L., S. W. Kristensen, W. G. Reijnierse, I. Smeets, and J. Cramer. 2023. "Is Everything Quantum 'Spooky and weird'? An Exploration of Popular Communication About Quantum Science and Technology in Tedx Talks." *Quantum Science and Technology* 8 (3): 035004. https://doi.org/10.1088/2058-9565/acc968.
Montanaro, A. 2016. "Quantum Algorithms: An Overview." *Quantum Information* 2 (1): 15023. https://doi.org/10.1038/npjqi.2015.23.
Najafi, K., S. F. Yelin, and X. Gao. The Development of Quantum Machine Learning. *Harvard Data Science Review* 4 (1). January 27. 2022. https://doi.org/10.1162/99608f92.5a9fd72c.
Nath, R. K., H. Thapliyal, and T. S. Humble. 2021. "A Review of Machine Learning Classification Using Quantum Annealing for Real-World Applications." *SN Computer Science* 2 (5): 1–11. https://link.springer.com/article/10.1007/s42979-021-00751-0.
Pande, M., and P. Mulay. 2020. "Bibliometric Survey of Quantum Machine Learning." *Science & Technology Libraries* 39 (3): 329–348. https://doi.org/10.1080/0194262X.2020.1776193.
Preskill, J. 2018. "Quantum computing in the nisq era and beyond." *Quantum* 2:79. https://doi.org/10.22331/q-2018-08-06-79.
Rebentrost, P., P. Gupt, and F. Wilhelm. 2016. "Quantum computational finance: Quantum algorithm for portfolio optimization." *Physical Review A* 98 (2): 022321. https://doi.org/10.48550/arXiv.1811.03975.
Rebentrost, P., and M. Mohseni. 2021. "Quantum Machine Learning and Privacy: Challenges and Opportunities." *ArXiv Preprint*.
Rebentrost, P., M. Mohseni, and S. Lloyd. 2018. "Quantum Computational Finance: Monte Carlo Pricing of Financial Derivatives." *Physical Review Letters* 121 (9): 090503. https://doi.org/10.1103/PhysRevLett.121.090503.
Rebentrost, P., T. R. Bromley, C. Weedbrook, and S. Lloyd. 2018. "A Quantum Hopfield Neural Network." *Physical Review A* 98 (4). https://doi.org/10.1103/PhysRevA.98.042308 .
Sarma, S. D., D. L. Deng, and L. M. Duan. 2019. "Machine Learning Meets Quantum Physics." *arXiv Preprint arXiv: 1903.03516*. https://doi.org/10.1063/pt.3.4164.
Schuld, M., M. Fingerhuth, and F. Petruccione. 2017. "Implementing A Distance-Based Classifier with A Quantum Interference Circuit." *Europhysics Letters* 119 (6): 60002. https://doi.org/10.1209/0295-5075/119/60002.
Schuld, M., and N. Killoran. 2019. "Quantum Machine Learning in Feature Hilbert Spaces." *Physical Review Letters* 122 (4). https://doi.org/10.1103/physrevlett.122.040504.
Schuld, M., I. Sinayskiy, and F. Petruccione. 2014a. "The Quest for a Quantum Neural Network." *Quantum Information Processing* 13 (11): 2567–2586. https://doi.org/10.1038/s41586-019-0988-2.
Schuld, M., I. Sinayskiy, and F. Petruccione. 2014b. "Supervised Learning with Quantum Computers." *arXiv Preprint arXiv: 1412.3489*.
Schuld, M., I. Sinayskiy, and F. Petruccione. 2015. "An Introduction to Quantum Machine Learning." *Contemporary Physics* 56 (2): 172–185. https://doi.org/10.1080/00107514.2014.964942.
Shor, P. W. 1994. "Algorithms for Quantum Computation: Discrete Logarithms and Factoring." *IEEE Conference Publication*. https://doi.org/10.1109/SFCS.1994.365700.
Shor, P. W. 1997. "Polynomial-Time Algorithms for Prime Factorization and Discrete Logarithms on a Quantum Computer." *SIAM Journal on Computing* 26 (5): 1484–1509. https://doi.org/10.1137/S0097539795293172.
Shukla, A., and P. Vedula. 2023. "A Hybrid Classical-Quantum Algorithm for Solution of Nonlinear Ordinary Differential Equations." *Applied Mathematics and Computation* 442:127708. https://doi.org/10.1016/j.amc.2022.127708.
Smolin, J. A., J. M. Gambetta, and G. Smith. 2012. "Efficient Method for Computing the Maximum-Likelihood Quantum State from Measurements with Additive Gaussian Noise." *Physical Review Letters* 108 (7). https://doi.org/10.1103/physrevlett.108.070502.
S. K. Sood and Monika. 2023. "Bibliometric Analysis and Visualization of Quantum Engineering Technology." *IEEE Transactions on Engineering Management*, 1–15. https://doi.org/10.1109/TEM.2023.3313984.
Stoudenmire, E. M., and D. J. Schwab. 2016. "Supervised Learning with Quantum-Inspired Tensor Networks." *Advances in Neural Information Processing Systems* 29:4799–4807. https://doi.org/10.48550/arXiv.1605.05775.
Temme, K., S. Bravyi, and J. M. Gambetta. 2017. "Error Mitigation for Short-Depth Quantum Circuits." *Physical Review Letters* 119 (18): 180509. https://doi.org/10.1103/PhysRevLett.119.180509.
Wauters, M. M., E. Panizon, G. B. Mbeng, and G. E. Santoro. 2020. "Reinforcement-Learning-Assisted Quantum Optimization." *Physical Review Research* 2 (3). https://doi.org/10.1103/PhysRevResearch.2.033446.