mathematics

IMPACT FACTOR 2.3

CITESCORE 4.0

Review

Exploring the Role of Material Science in Advancing Quantum Machine Learning: A Scientometric Study

Manish Tomar, Sunil Prajapat, Dheeraj Kumar, Pankaj Kumar, Rajesh Kumar and Athanasios V. Vasilakos

Special Issue
Mathematical Perspectives on Quantum Computing and Communication

Edited by
Dr. Artur Czerwinski and Dr. Xiangji Cai

MDPI

https://doi.org/10.3390/math13060958

mathematics

MDPI

Review

Exploring the Role of Material Science in Advancing Quantum Machine Learning: A Scientometric Study

Manish Tomar [1], Sunil Prajapat [2], Dheeraj Kumar [3], Pankaj Kumar [2,*], Rajesh Kumar [1] and Athanasios V. Vasilakos [4,5,*]

1 Department of Physics and Astronomical Sciences, Central University of Himachal Pradesh, Dharamshala 176215, India; manishmt777@gmail.com (M.T.); rajeshkumarf11@hpcu.ac.in (R.K.)
2 Srinivasa Ramanujan Department of Mathematics, Central University of Himachal Pradesh, Dharamsala 176206, India; cuhp21rdmath13@hpcu.ac.in
3 Department of Computer Science, Hansraj College, University of Delhi, New Delhi 110007, India; dheeraj@hrc.du.ac.in
4 Department of Networks and Communications, College of Computer Science and Information Technology, Imam Abdulrahman Bin Faisal University (IAU), P.O. Box 1982, Dammam 31441, Saudi Arabia
5 Center for AI Research (CAIR), University of Agder (UiA), 4879 Grimstad, Norway
* Correspondence: pkumar240183@hpcu.ac.in (P.K.); thanos.vasilakos@uia.no or th.vasilakos@gmail.com (A.V.V.)

Abstract: Quantum Machine Learning (QML) opens up exciting possibilities for tackling problems that are incredibly complex and consume a lot of time. The drive to make QML a reality has sparked significant progress in material science, inspiring a growing number of research publications in the field. In this study, we extracted articles from the Scopus database to understand the contribution of material science in the advancement of QML. This scientometric analysis accumulated 1926 extracted publications published over 11 years spanning from 2014 to 2024. A total of 55 countries contributed to this domain of QML, among which the top 10 countries contributed 65.7% out of the total number of publications; the USA is on top, with 19.47% of the publications globally. A total of 57 authors contributed to this research area from 55 different countries. From 2014 to 2024, publications had an average citation impact of 32.12 citations per paper; the year 2015 received 16.7% of the total citations, which is the highest in the 11 years, and the year 2014 had the highest number of citations per paper, which is 61.4% of the total. The study also identifies the most significant document in the year 2017, with the source title *Journal of Physics Condensed Matter*, having a citation count of 2649 and a normalized citation impact index (NCII) of 91.34.

Keywords: quantum computing; machine learning; scientometric; material science; Scopus database

MSC: 81P45

Academic Editor: Raymond Lee

Received: 17 January 2025
Revised: 3 March 2025
Accepted: 12 March 2025
Published: 14 March 2025

Citation: Tomar, M.; Prajapat, S.; Kumar, D.; Kumar, P.; Kumar, R.; Vasilakos, A.V. Exploring the Role of Material Science in Advancing Quantum Machine Learning: A Scientometric Study. *Mathematics* **2025**, *13*, 958. https://doi.org/10.3390/math13060958

1. Introduction

QML is a multi-disciplinary field that merges quantum computing principles with machine learning techniques [1]. It uses features of quantum mechanics such as entanglement, superposition, and parallelism, which can provide an exponential speedup for specific machine learning tasks like data processing, the factoring of large numbers, and searching for an unsorted database. [2]. Quantum computation relies on quantum bits (qubits). Qubits exploit the principles of linear algebra, whereas classical bits are based on the principles of Boolean algebra [3]. In quantum mechanics, some state $|\psi\rangle$ is known; this state enables us to obtain the superimposed state, $|\psi\rangle = |0\rangle + |1\rangle$. The vectors $|0\rangle$ and $|1\rangle$ are the orthonormal basis of 2D Hilbert space; in quantum computing, these vectors are known as the computational basis. Classical computers require classical gates to change the states of the classical bits. Similarly, quantum computers use quantum gates to change the state of the qubits [4]. Typically, we present all the gates as unitary matrices. Quantum computing consists of several quantum gates; some commonly used quantum gates are the RX gate, RY gate, and RZ gate (these all are called the rotation gates), as well as the Hadamard gate (H). All of these are single-qubit gates, while the Controlled Not gate (CX) and Controlled Z gate (CZ) are two-qubit gates [5]. By adding quantum gates and quantum entanglement to machine learning methods, a lot of powerful tools have been created that help with image classification and image recognition tasks and show impressive results on a number of benchmark datasets [6].

Exploiting material science (MatSci) at the quantum level can generate various models, and hence, QML can be applied to solve real-world problems. MatSci creates qubits with a high coherence time (qubits that maintain states for a very long time) [7,8]. Materials like aluminum and niobium are used to make superconducting qubits because they are superconducting at very low temperatures, which means they can conduct electricity with no resistance at low temperatures [9,10]. Josephson junction (J.J.) allows quantum mechanical effects to control the superposition of states. Superposition is created and maintained using microwaves that alter the phase difference across the junction [11]. Microwave pulses are electromagnetic pulses that carry specific frequencies and energies. Carefully tuning the frequency, amplitude, and direction of these pulses influences the quantum states of the qubits. When applied to a superconducting qubit, a microwave pulse can introduce a transition between its energy levels, thereby altering the phase difference across the J.J. (Krasnok, 2024) [12]. On the Bloch Sphere, the pulse rotates the qubit states, letting them move between $|0\rangle$ and $|1\rangle$ or any point in between $\frac{1}{\sqrt{2}}|0\rangle| + |1\rangle$ and $\frac{1}{\sqrt{2}}|0\rangle - |1\rangle$ [13].

One of the primary challenges is qubit stability. The performance of QML systems heavily relies on the ability of qubits to maintain coherence over extended periods. However, qubits are highly susceptible to decoherence due to environmental interactions, temperature fluctuations, and electromagnetic noise. Developing robust quantum materials, such as high-quality superconductors, is crucial to mitigating these effects. Another major hurdle is material robustness and scalability. Many quantum materials, including topological insulators and 2D materials like graphene, exhibit promising quantum properties but often face fabrication difficulties, reproducibility issues, and instability under operational conditions. Ensuring that these materials can be synthesized consistently and integrated into scalable QML architectures remains a significant challenge. Integration with classical computing devices is another critical issue. While QML promises superior performance in certain tasks, it must often work alongside classical machine learning and computing systems. The development of hybrid architectures that efficiently transfer data between quantum and classical processors without introducing excessive latency or error remains an ongoing research challenge. In addition, material compatibility with existing quantum hardware is a limiting factor. Many quantum computing platforms, such as superconducting circuits and trapped-ion systems, require highly specialized materials with strict purity and processing conditions. Identifying materials that enhance qubit performance while maintaining compatibility with fabrication techniques is essential for the advancement of QML.

1.1. Objectives

MatSci has played a crucial role in building specific physical systems and devices, which were further used to power the QML. In this research, the goal is to look for the contribution of MatSci in the advancement of QML through the help of scientometric analysis. By analyzing the literature of QML in the context of MatSci, the goal is to understand the foundation of this interdisciplinary field better. Additionally, this study aims also to uncover how research is growing in this area and the collaborations of various nations in developing the QML by exploiting MatSci. Ultimately, this analysis will shed light on promising opportunities for future exploration, offering valuable guidance to technology leaders and R&D organizations as they invest in cutting-edge innovations.

1.2. Motivation and Contributions

Our study investigates the critical role of MatSci in accelerating advancements in QML. QML has immense potential to revolutionize data processing exponentially by relying on quantum mechanics principles to accomplish supreme computational speed and efficiency. However, the practical execution of QML depends on the evolution of MatSci to create quantum modules such as memory units, quantum detectors, and processors. Understanding the interplay of QML and MatSci is crucial to speeding up the successful application of QML to real-world challenges. This research employs a scientometric approach to analyze the landscape of QML-related material innovations, identifying key research trends, influential works, and emerging technologies that are shaping the field. We utilize document co-citation analysis, burst detection, and link walk-through analysis to map the intellectual structure of QML-oriented material science research. Our study aims to highlight the most promising quantum materials, such as superconducting materials, topological insulators, and defect-engineered diamond systems, which play a pivotal role in advancing QML hardware. By systematically exploring the evolution of research collaborations, funding patterns, and technological breakthroughs, this scientometric study provides valuable insights into the synergy between QML and material science. The findings serve as a roadmap for future research directions and interdisciplinary collaborations that are essential for the rapid development of quantum-enhanced computational frameworks. The main key contributions of our study are as follows:

- This study systematically examines the contributions of MatSci in the advancement of QML, a pivotal area in quantum computing. Additionally, it provides a comprehensive exploration of machine learning from a classical to quantum perspective, ensuring the article's relevance and accessibility to a broad audience.
- By thoroughly analyzing the publication trends, this study recognizes the leading nations' contributions to QML development through advancements in MatSci. Moreover, it shows the most impactful research papers through the citation analysis and provides critical insights into the state of the field.
- The collaborative network provides a detailed view of how nations are collaborating on QML research. This analysis uncovers the global research ecosystem and the interconnected efforts in this evolving domain.
- Through overlay network analysis and keyword co-occurrence, the study highlights the cutting-edge research areas and the latest technological trends in QML.

2. Literature Survey

Scientometrics is a quantitative research methodology that focuses on analyzing and measuring scientific literature and research outputs. It includes ways of measuring the quality and impact of research . It helps in evaluating the influence of specific papers, institutions, authors, or even entire research fields [14,15]. Scientometrics uses empirical data to analyze scientific activities such as publication trends, influential authors, citation patterns, and their global distribution. To identify new and emerging trends in science and technology, researchers have created advanced methods that analyze large collections of published studies. These approaches analyze extensive databases of published research using advanced computational tools. These techniques help uncover the latest technological developments and breakthroughs. Leydesdorff (2007) [16] demonstrated the use of journal maps to reveal citation structure among selected groups of journals that met specific citation thresholds. Savov et al. [17] proposed a citation-based method to identify groundbreaking papers driving progress in their respective fields. Klavans et al. [18] highlighted the importance of evaluating relationships between bibliometric elements, like keywords and journals, to better understand the structure and evolution of scientific disciplines. These findings have practical applications, particularly in shaping research and development (R&D) strategies and fostering innovation, which can help organizations maintain a competitive edge in rapidly changing markets [19,20].

Scientometric analysis has been widely applied to explore a variety of research domains. In this study, however, we focus specifically on areas closely associated with QML that have been subjected to scientometric examination. If we look at the data, then, there is very little research carried out on topics such as 'QML', 'quantum technology (QT)', and 'ML'. In the year 2021, Dhawan, Gupta, and Mamdapur [21] examined 1374 publications on QML during the period from 1999 to 2020 using the Scopus database. The research identified the contribution of the top 15 most productive countries, the top 25 global organizations and authors, and 43 highly cited papers. In the area of QML, Sood and Agrewal (2023) [22] analyzed the scientific literature spanning the years 2003 to 2023 using the Web of Science (WOS) database. Their analysis reveals that in this time span, QSVM, QNN and Q-learning are among the most widely used algorithms in this field. Ahmadikia, Shirzad, and Saghiri (2024) [23] examined 918 publications on QML using the WOS database and 1171 publications from the 'Scopus' database spanning the years 2006 to 2022.

However, it falls short of detailing the specific contributions of materials science or other fields to QML. R Walke [24] addressed a scientometric analysis, examining the growth and publication trends in MatSci from 1993 to 2001. Schuhmacher (2022) [25] takes quantum computing further by integrating materials science and leveraging machine learning properties. The scientometric approach in the current research presents the distribution of publication globally, growth analysis, the most significant documents, and the collaboration analysis of authors and countries. To the best of the authors' knowledge, no research has yet explored the full extent of MatSci's contribution to QML. This article aims to bridge that gap.

3. Preliminaries

3.1. Machine Learning and Its Brief History

Machine learning combines the fields of mathematics, statistics, and computer science. It enables computers to make decisions and generate predictions based on datasets [26]. ML originated as the data-centric aspect of AI; ML aims to build machines with human-like abilities [27] such as understanding language, recognizing images, and making decisions. Teaching machines to do the same remains a complex challenge. This problem was solved by enabling the computer to uncover patterns within the data [28]. Historically, ML has made a big transition from simple statistical methods to advanced approaches like artificial neural networks, becoming crucial in fields like image recognition, natural language processing, and predictive analytics [29].

The evolving journey of ML has taken several decades; it started with theoretical foundations in statistics and mathematics and evolved into a highly impactful technology.

In the early 1950s, concepts like regression analysis and statistical decision theory were employed in the development of ML [30]. In 1950, Alan Turing presented the idea of the Turing Test, which states that machines could simulate human intelligence [31]. This laid the foundation for artificial intelligence (AI) and ML [31]. In 1958, Frank Rosenblatt introduced the computation model of a perceptron [32], a neural network algorithm that could perform simple pattern recognition tasks [33]. It is one of the first true machine learning algorithms. Then backpropagation was introduced by Geoffrey Hinton, David Rumelhart, and Ronald Williams in their 1986 paper [34,35]. In the 1990s, Support Vector Machines (SVMs), a supervised learning model, were developed, which introduced better techniques for classification and regression problems [36]. Now, in the 2010s, a subset of machine learning, deep learning, has become dominant [37,38], and it is based on deep neural networks. Deep neural networks play a significant role in fields like computer vision and recognition tasks. Further, the development of convolutional neural networks (CNNs) makes the recognition of images and classification of image tasks possible [39].

3.2. QML and Its Evolution

QML is a relatively recent and fast-growing field that merges machine learning techniques with quantum computing [1,40]. The idea of combining these two disciplines was first proposed in the early days of quantum computing back in the 1980s [41,42]. In 1985, Berthiaume, and Feynman exploited the concept of a universal quantum computer [43], which laid the foundation for quantum computing [42]. In 1995, some quantum models such as neural networks were proposed [44,45]; in 1994, Shor developed an algorithm [46] that could factor large numbers exponentially faster than any classical algorithm and proved that quantum computers could surpass classical ones for certain tasks. Then, in 1996, Grover's algorithm was developed, according to which unsorted databases can be searched quadratically faster than classical algorithms [47]. In the early 2000s, researchers focused on understanding how these quantum algorithms could boost machine learning techniques, such as pattern recognition and optimization [48]. In the 2000s, the topic of applying statistical theory to a quantum framework was discussed but received modest attention at that time. Many workshops on quantum computation and learning were organized; in the third event of the proceeding, Bonner and Freivals observed that quantum learning is an emerging theory [49], and its scientific production is rather fragmented. The QBoost algorithm was given by Schuld, and Petruccione and co-workers in 2009 [45], which was performed on the first commercial quantum annealer, 'the D-Wave device'. The intersection of quantum computing and machine learning was initiated in 2010 [45,50]. Now, researchers have started developing QML algorithms that can exploit the potential of quantum computing for tasks like clustering, classification, and regression [48]. The QML term came into use around 2013. Mohseni, Lloyd, and Rebentrost [51] mentioned the term in their 2013 manuscript. In 2014, Peter Wittek [52] published a monograph with the title 'QML—What quantum computing means to data mining'; it contains a summary of some previous papers. In the same year, the idea of integrating quantum with machine learning techniques like Support Vector Machines (SVMs) [53] and quantum neural networks (QNNs) [54] was proposed. The aim of these models was to harness quantum entanglement and superposition to represent that in a way that classical neural networks cannot represent. Quantum principal component analysis (QPCA) [55] is a machine learning technique that expresses the potential of quantum algorithms to perform tasks like linear algebra faster than classical algorithms. The present generation of quantum computers are used to perform specific tasks like linear algebra, feature selection, and optimization [56]. The current trend in QML is to focus on the development of 'hybrid quantum-classical algorithms' [6,57] so that the systems can combine the quantum and classical tactics. Firms like Google, IBM, and Rigetti are achieving noticeable performance in the development of the quantum processors [58] that support much more complex QML algorithms.

3.3. Material Science's Contributions to Quantum Machine Learning

Material science enhances the performance, scalability, and reliability of quantum computing hardware, which is essential for QML. The efficiency of quantum processors heavily depends on advances in material science, influencing error correction, coherence time, and computational accuracy.

1. **Superconducting Qubits**
   - Superconducting materials like niobium (Nb) and aluminum (Al) exhibit zero electrical resistance at cryogenic temperatures, allowing for efficient quantum state preservation.
   - These materials facilitate the creation of high-quality Josephson junctions (J.J.'s), which are critical for stabilizing quantum superposition and entanglement, and they also provide key benefits such as:
     (a) Minimal energy dissipation, reducing quantum errors.
     (b) Enhanced qubit performance, leading to improved computational efficiency.
     (c) Increased coherence time, enabling longer and more stable quantum computations.
2. **Topological Qubits**
   - **Topological insulators and superconductors** contribute to the development of topological qubits, which are highly resistant to errors.
   - Quantum information in topological qubits is stored in a non-local state, meaning it is distributed across multiple locations.
   - This property makes them highly resistant to local noise and decoherence, leading to improved fault tolerance.
3. **Two-dimensional Materials for Quantum Hardware**
   - **Graphene and other 2D materials** improve qubit connectivity and quantum gate operations by enabling better electron mobility and minimizing decoherence.
   - These materials assist in creating low-loss transmission lines, enhancing quantum circuit performance.
4. **Quantum Memory and Storage**
   - Rare-earth-doped crystals serve as excellent quantum memory materials, improving quantum state storage and retrieval efficiency.
   - These materials help in maintaining quantum coherence for longer periods, supporting error correction in QML algorithms.
5. **Quantum Sensors for QML Applications**
   - Advanced materials used in superconducting quantum circuits significantly improve QML applications by enabling higher precision, faster data acquisition, and enhanced sensitivity.
   - These circuits enhance large-scale optimization in QML by boosting computational speed and reducing errors in learning algorithms.

By integrating these advancements in material science, QML systems become more robust and capable of handling complex data-driven problems with greater efficiency.

3.4. Material Science Has Advanced Quantum Machine Learning

Research in materials science has directly enabled key advancements in QML, improving speed, accuracy, and scalability. Materials science is shaping the future of real-world quantum applications.

1. Superconducting Materials for Faster Quantum Computing: Google's Sycamore quantum processor uses superconducting qubits (made from niobium and aluminum) to achieve 'quantum supremacy', solving a complex problem faster than the best classical supercomputers. These superconducting circuits enable high-speed computations for QML models in fields like drug discovery, optimization, and cryptography.
2. Topological Materials for Error-Resistant Quantum Systems: By cutting down on errors, topological materials make machine learning models much more dependable. This increased reliability makes Quantum Machine Learning more feasible for everyday tasks, like predicting financial risks and optimizing logistics with AI.
3. Quantum Sensors in Biomedicine: Diamonds with nitrogen-vacancy (NV) centers are being used to create highly sensitive quantum sensors that can map brain activity down to the cellular level. These sensors capture incredibly precise biological data, which are then used in Quantum Machine Learning (QML) algorithms to help with early disease detection, drug discovery, and personalized treatments. This could lead to faster diagnoses, more effective medications, and tailored healthcare solutions for individuals.
4. Cryogenic Materials: NASA and Google rely on liquid-helium-based cryogenic systems to keep quantum computers stable, allowing them to run complex simulations. This technology helps improve aerospace engineering designs and optimize satellite trajectories, making space missions more precise and efficient.

QML is revolutionizing industries by harnessing breakthroughs in materials science to boost computing power and accuracy. In healthcare and pharmaceuticals, cutting-edge quantum sensors made from advanced materials help detect biomolecules, paving the way for new drug discoveries and a better understanding of protein structures. The finance sector benefits from superconducting materials, which make quantum computing faster and more efficient, helping banks and analysts with fraud detection, risk assessment, and smarter investment strategies. In aerospace and defense, cryogenic materials keep quantum systems stable, ensuring secure communication and precise satellite navigation. Meanwhile, in energy and environmental science, nanomaterials improve quantum simulations, accelerating the development of better batteries and more accurate climate models. These breakthroughs show how materials science is playing a key role in making QML a real-world game-changer across multiple fields.

4. Research Methodology

The science mapping method is implemented [59] in this research to examine and envision the contributions of MatSci in advancing QML. Science mapping is about creating visual representations and analyzing how scientific knowledge is structured, how ideas and disciplines are connected, and how they evolve over time. It often uses tools and methods like scientometrics and bibliometrics to explore these relationships [60]. Bibliometrics performs literature analysis, while scientometrics helps in evaluating the influence of specific papers, authors, institutions, or even entire research fields. It enables the exploration of research areas in a way that is not attainable through other methodologies [59]. The framework for this research is defined in Figure 1, which is divided into four steps. Step 1 is to define the research objectives. Step 2 contains a selection of suitable databases for this research followed by identifying relevant keywords, conducting query searches, and finally manually reviewing the retrieved data. Step 3 is the scientometric analysis, which includes publication and citation analysis, collaboration networks at a country level and organization level, and keyword analysis. Step 4 is the visualization of the data using selected visualization tools. And lastly is the interpretation of the results, which goes with the discussion of the analysis and ends with future directions or recommendations.

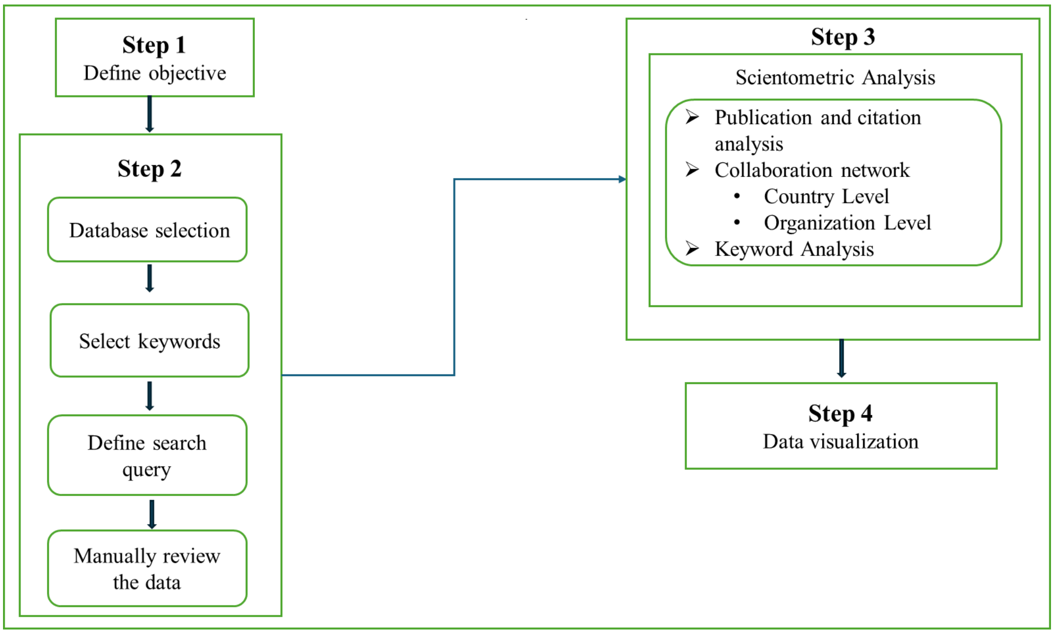

Figure 1. Framework for the methodology of scientometric study.

5. Database Selection and Data Search

Scopus, maintained by Elsevier, is a widely used multidisciplinary database that indexes journals, conference proceedings, and patents across diverse fields such as science, technology, and medicine. It provides citation metrics, including h-index tracking and author impact analysis, which are crucial for evaluating research's influence. The Web of Science (WoS), managed by Clarivate Analytics, is another authoritative database that focuses on high-impact journals and conference proceedings, offering advanced citation tracking and impact factor analysis. In contrast, arXiv, hosted by Cornell University, is an open-access preprint repository that primarily serves disciplines like physics, mathematics, and computer science, allowing researchers to share early-stage findings before formal peer review.

Each database has distinct strengths and limitations that can influence scientometric analysis. The WoS follows a stringent selection process, indexing only high-impact journals, which ensures quality but may limit dataset size. arXiv, as an open-access repository, provides early access to emerging research but lacks formal peer review, which may impact data reliability. Scopus, on the other hand, is known for its broad coverage and frequent updates, making it an effective tool for capturing emerging trends across multiple disciplines [61–63].

In this study, Scopus was selected as the primary database for bibliographic analysis due to its extensive multidisciplinary coverage and frequent updates, ensuring access to the latest research. Scopus also offers a user-friendly search interface, facilitating efficient data retrieval and analysis. Many scientometric studies have relied on Scopus as their primary data source, reinforcing its credibility in bibliometric research [64,65]. Using Scopus, we extracted bibliographic data on the 'Contribution of QML in MatSci', resulting in 1926 publications from 2014 to 2024 after applying specific filters on subject area, document type, and keywords.

6. Selection of Visualization Tools

To conduct our scientometric analysis, we utilized a systematic approach to bibliometric data collection, processing, and visualization. Researchers have access to a range of data visualization tools, including VOSviewer [66], SciMAT [67], CiteSpace [68], Gephi [69], and UCInet- 6.421, each offering distinct capabilities. In this study, we selected VOSviewer to construct, analyze, and visualize bibliometric networks due to its advanced functionalities in clustering, co-authorship analysis, and citation mapping.

6.1. Selection of Keywords and Data Processing

The selection of keywords plays a crucial role in ensuring the accuracy and relevance of the retrieved literature. Our methodology for keyword selection follows these steps:

1. Defining the Research Scope:
    - We identified key concepts at the intersection of QML and MatSci based on a preliminary literature review and expert consultations.
    - The primary search terms included 'Quantum Machine Learning', 'Materials for Quantum Computing', 'Quantum Materials', 'Quantum Computing in Material Science', and their variations.
2. Database Selection and Query Formulation:
    - We sourced bibliographic data from the Web of Science (WoS) and Scopus, as these databases provide comprehensive and structured metadata on scientific publications.
    - Boolean operators and wildcard searches were employed to refine results, ensuring the inclusion of relevant studies while minimizing noise.
3. Data Collection and Cleaning:
    - Retrieved data were exported in RIS, CSV, and BibTeX formats for compatibility with VOSviewer.
    - Duplicate records were removed, and irrelevant entries were manually filtered based on title, abstract, and keyword relevance.

6.2. Co-Authorship Analysis and Network Construction

To analyze the collaborative relationships among individual researchers, we conducted a co-authorship analysis based on joint publications:

1. Setting the Author Threshold:
    - A total of 8299 authors contributed to the field, but to ensure meaningful visualization, only 57 authors meeting a predefined threshold (a minimum of five publications) were included in the network.
    - The Total Link Strength (TLS) metric was used to quantify the strength of collaborations, representing the frequency and intensity of co-authorship connections.
2. Network Visualization Using VOSviewer:
    - VOSviewer was employed to generate a co-authorship network map, where nodes represent individual researchers, and edges denote collaborative links.
    - The size of the nodes reflects the number of publications by each author, while the thickness of the edges represents the strength of co-authorship ties.
    - Clustering algorithms within VOSviewer were used to detect research communities, identifying dominant collaboration groups.

6.3. Justification for Using VOSviewer

VOSviewer was chosen over other bibliometric tools due to its advanced text-mining capabilities, which facilitate the identification of noun phrase combinations for mapping tasks. Unlike other tools, which primarily rely on similarity matrices and textual unit processing, VOSviewer incorporates merged clustering techniques to analyze co-citation and co-occurrence data. Additionally, its interactive visualization features allow users to navigate networks dynamically, enhancing the interpretability of relationships between researchers, keywords, and cited references. The visualizations generated by VOSviewer streamline information processing, assess the performance of bibliographic data, and predict publishing trends. By revealing empirical patterns in citation networks, it contributes to a deeper theoretical understanding of the evolving landscape in quantum machine learning and material science.

7. Analysis and Results

7.1. Publication and Citation Analysis

This scientometric study in QML for the subject category of MatSci accumulated 1926 extracted publications from 2014 to 2024, an average of 175.09 publications per year. In 2014, there were just two publications, and it grew to 73 in 2019. In 2024, there were a total of 653 publications, and in just 4 years, there was a 794.52% increase in the research output in the field of QML. This shows that there is a rapid growth in research activity in the domain of the 'contribution of QML in MatSci' during the study period from 2019 to 2024. Within the years 2014 to 2024, QML research received an average citation impact of 32.12 citations per paper (CPP), and it was the highest in 2014, with 4636 citations. From 2014 to 2019, the average number of citations was 271, and it slipped to 11.09 CPP from 2020 to 2024. Data are given in Table 1. Of the results, 83.12% of the publications appeared as articles, 14.67% as review papers and 2.17% as conference papers. More than 50% of the publications resulted from research funded by more than 100 national and international funding agencies.

Table 1. Publication and citation data (2014–2024).

Publication Period	Total Publications	Citation per Paper	Total Citation
2014	2	4100	8201
2015	7	1477	10,339
2016	12	494.5	5394
2017	21	288.143	6051
2018	41	144.32	5917
2019	73	79.92	5834
2020	134	47.44	6358
2021	240	26.66	6400
2022	297	13.12	3915
2023	446	5.405	2411
2024	653	0.77	505

7.2. Global Distribution of Publications

To obtain the most intense insights into contributions, we further look for the publications by per nation in QML within the subject category of MatSci. A total of 55 countries participated in the global research. In all 55 countries, the top 16 most productive nations account for over 100.0% of the global share of both citations and publications. The analysis, as illustrated in Figure 2, demonstrates that in the field of productivity, USA has dominated, with 29.64% of total publications, followed by the China (15.85%), Germany (7.2%), UK (5.15%), India (3.78%), France (3.1%), Japan (2.97%), Canada (2.7%), Switzerland (2.5%), South Korea, Italy, Australia, etc. during the period from 2014 to 2024 (Table 2). Furthermore, examining the global distribution of publications offers valuable insights into a nation's industrial progress in a particular research area. For instance, the United States' leading role in material science productivity suggests that American companies may have a competitive edge in accessing cutting-edge research and talent for implementing QML.

Table 2. Distribution of documents globally.

Country	Documents
USA	608
China	495
Germany	225
U.K.	161
India	118
France	97
Japan	93
Canada	87
Switzerland	80

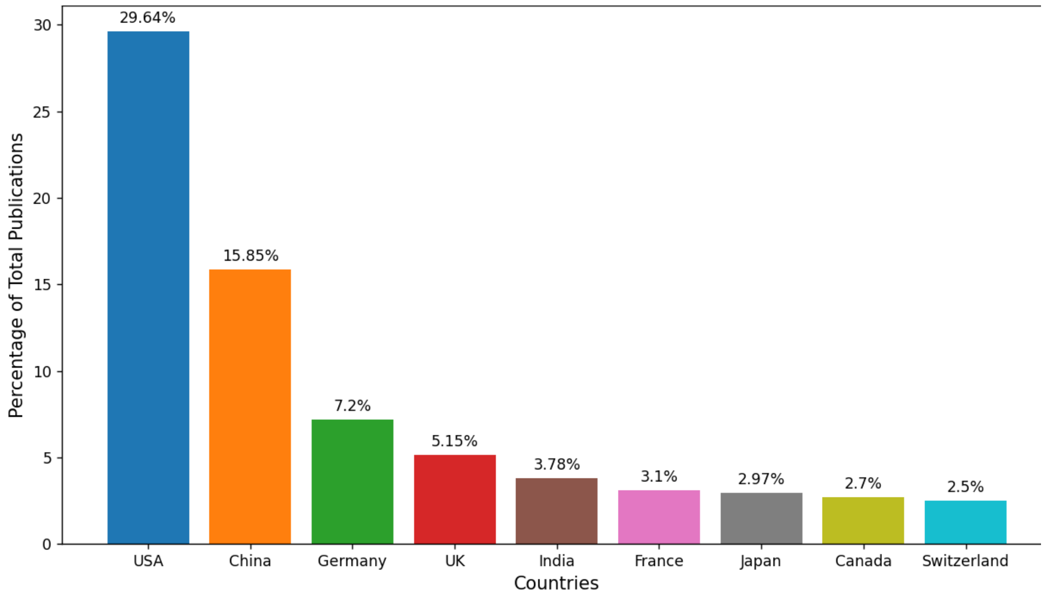

Figure 2. Countries contributing to MatSci research in the advancement of QML.

One of the key factors contributing to the increase in publication trends is technological advancements in quantum computing and material science. Over the past decade, significant breakthroughs-such as the development of high-coherence superconducting qubits, advances in topological materials, and improvements in quantum algorithms-have fueled research interest in applying material science to QML. The emergence of quantum hardware prototypes and cloud-accessible quantum processors has also encouraged more interdisciplinary research, leading to a surge in publications. Another crucial driver is government and private-sector research funding. Countries with a high number of QML-related MatSci publications, such as the United States and China, have heavily invested in national quantum initiatives. Programs like the U.S.'s National Quantum Initiative and China's Quantum Science and Technology Plan have led to a significant increase in research output. Similarly, the European Union's Quantum Flagship program has encouraged collaboration across multiple nations, further boosting publication numbers.

Industrial engagement and commercialization efforts have also played a role. Leading technology companies, including IBM, Google, and Microsoft, are investing in QML research, often in collaboration with academic institutions. This has resulted in an increase in high-impact publications focusing on material innovations for quantum computing applications. On the other hand, fluctuations in publication growth can be attributed to several challenges. One factor is the complexity and cost of quantum research. Unlike classical AI and ML, which can be developed with accessible computing resources, QML requires specialized quantum hardware and materials, making it more challenging for many research institutions to contribute consistently. Additionally, shifting research priorities due to funding policies and economic conditions can lead to variations in publication trends. For example, some countries may redirect resources to alternative AI advancements, leading to temporary declines in QML research output.

7.3. Collaboration Analysis of Nations

The top 16 most productive nations involved in QML within the subject category of material science exhibited a range of one-to-many collaborative connections, varying from 83 to 568, and one-to-one connections, ranging from 1 to 81. Among these partnerships, the United States and China led the way at the country level, recording the highest number of collaborative connections (81), followed closely by the USA and Germany (53), the USA and the UK (50), and the UK and Germany (53), among others. Notable collaborations also included partnerships like the USA and France (37), China and Hong Kong (23), the USA and South Korea (22), the USA and Japan (22), and India and the USA (19). A collaborative network chart showcasing the top 15 countries can be found in Figure 3. Countries within the same color form a single cluster, with China leading the way with six clusters, followed by Germany, Japan, and the USA each with five clusters and the UK with four. The thickness of the lines and the distance between the nodes indicate the strength of research collaboration. A larger network node diameter and font size suggest greater significance in research collaboration. The USA remains the dominant force in collaborative research, followed by China, Germany, the UK, India, and others. We have structured the visualization as follows:

- Clusters and Colors: Countries with the same color form a distinct research cluster, highlighting regional and strategic collaborations.
- Node Representation: The diameter of each node and its font size correspond to the significance of a country's involvement in research collaborations.
- Connection Strength: The thickness of the connecting lines and the proximity of the nodes reflect the intensity of research collaboration between countries.

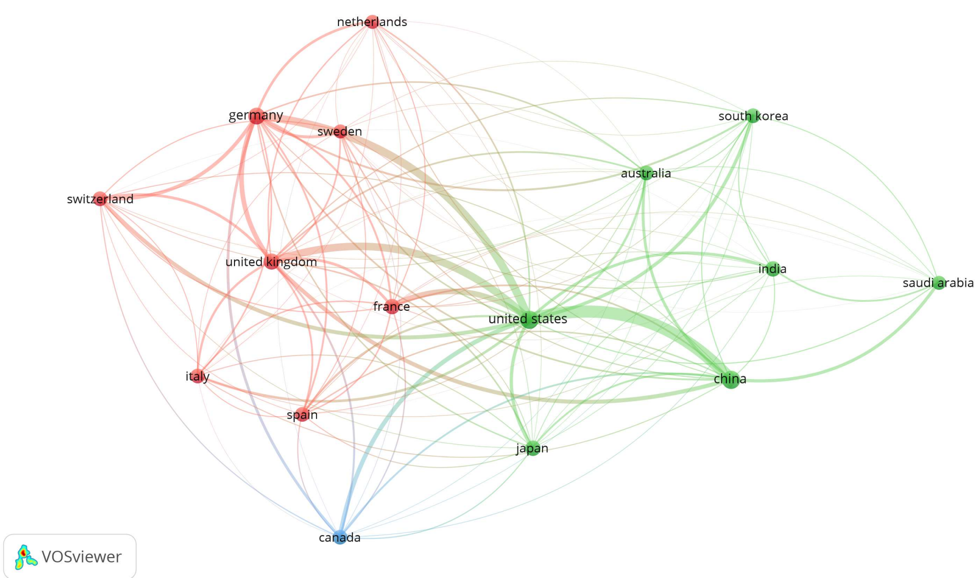

Figure 3. International collaboration in the domain of contribution of material science in Quantum Machine Learning.

7.4. Most Significant Documents

By looking at the top influential documents, both learners and new arrivals can quickly grasp the essential elements of the area, including its current state, historical context, and future possibilities. This approach helps us to grasp major advancements and notable innovations without having to go through all the literature in the domain. In this section, we explore the contributions of the most cited documents (see Table 3) in MatSci related to QML. The documents are ranked according to their citation count and the Normalized Citation Impact Index (NCII) [70], which reflects the average number of citations each document acquires annually.

$$\text{NCII} = \frac{\text{Total citation received per document}}{\text{longetivity of document}} \tag{1}$$

Table 3. Most significant documents.

Year	Source Title	Cited by	NCII
2020	Information Fusion	4636	79.93
2021	Journal of Big Data	3565	74.27
2017	Journal of Physics Condensed Matter	2649	91.34
2020	Journal of Chemical Physics	1769	11.63
2020	Mechanical Systems and Signal Processing	1755	12.71
2018	Physical Review Letters	1425	11.87
2020	Chemical Reviews	1185	9.87
2017	Journal of Materiomics	893	68.69
2021	Journal of Chemical Physics	663	4.27
2019	Optica	608	38.00

7.5. Co-Authorship Analysis of Authors

To perform a co-authorship analysis of authors, we analyzed the collaborative relationships among individual researchers based on their joint publications. In the field of QML within the scope of material science, a total of 8299 authors contributed, out of which only 57 meet the threshold for co-authorship analysis. For some leading authors, the total strength (TLS) of the co-authorship links with other researchers is summarized in Table 4. Figure 4 visually represents the global contributions of different authors, highlighting key collaboration networks. The size of the nodes corresponds to the number of publications, while the thickness of the connecting lines represents the strength of co-authorship links. Larger nodes indicate authors with more publications, and thicker lines represent stronger collaborative relationships.

Table 4. Collaboration analysis of different authors.

S. No	Author	Documents	Citations	TLS
1	Green, William H.	14	948	14
2	Kulik, Heather J.	12	464	16
3	Csanyi, Gabor	12	1088	6
4	Dornheim, Tobais	11	202	17
5	Darwish, Ahmad S.	10	236	33
6	Vorberger, Jan	10	184	17
7	Margraf, Johannes T.	10	187	12
8	Reuter, Karsten	10	185	12
9	Coley, Connor W.	10	1113	7
10	Lemaoui, Tarek	9	215	33

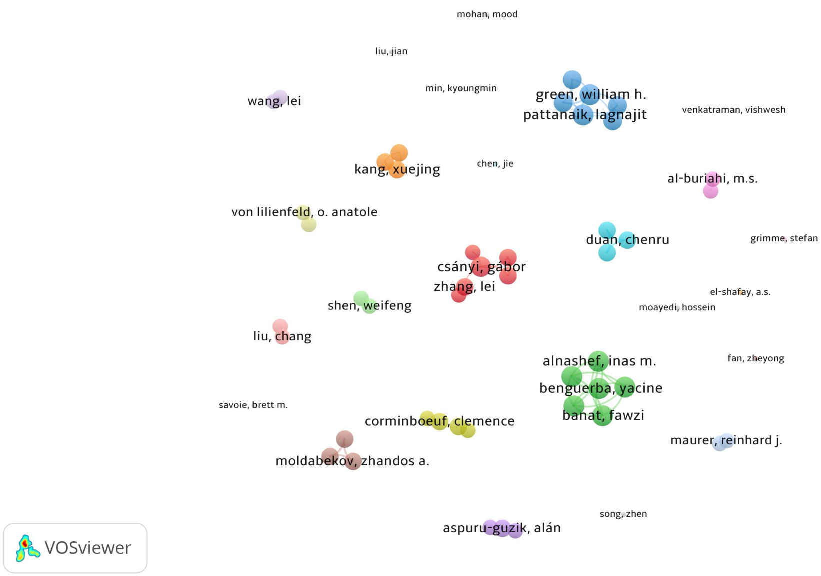

Figure 4. Contributions of different authors globally.

7.6. Keyword Analysis

Analyzing the significance and frequency of keywords helps uncover key themes and trends in various approaches and techniques within a research area over the span of time [71]. Keywords were used to highlight the main subjects and focus areas of scientific studies. Here, we used VOSviewer, setting a minimum threshold of 20 occurrences for each keyword. As a result, we obtained the result that only 258 keywords fulfilled the criteria out of 1587 keywords. Before constructing the network, keywords must go through an initial screening procedure, where similar and duplicate terms were combined into one, increasing their frequency count. Among all of the keywords, 65 were assumed to be significant. The frequency of occurrence of keyword in QML literature for the SC of MatSci 2014–2024 was the maximum (1173) for machine learning, followed by article (752), controlled study (314), density functional theory (308) and forecasting (308), molecular dynamics (286), human (216), quantum chemistry (211), learning systems (187), molecules (179), quantum computing (137), QML models (178), simulation (158), quantum theory (146), quantum theory (146), chemistry (142), artificial intelligence (138), deep learning (137), learning algorithm (118), neural network (117), etc. The top 65 keywords co-occurrence relationship chart is shown in Figure 5, where each node is linked to a keyword and its size corresponds to the number of documents where the keyword arises. Machine learning has the largest node in diameter, and its font size in the keyword co-occurrence network. The nodes with the same color belong to a single cluster. Article and controlled study are the second- and third-ranked keywords, but both have the same color in the cluster. The top 65 keywords were further divided into four clusters. Cluster 1 with red color has 22 keywords, followed by cluster 2, with a green color, which has 16 keywords; cluster 3, with a blue color, which has 16 keywords; and the fourth cluster, with a yellow color, which has 11 keywords.

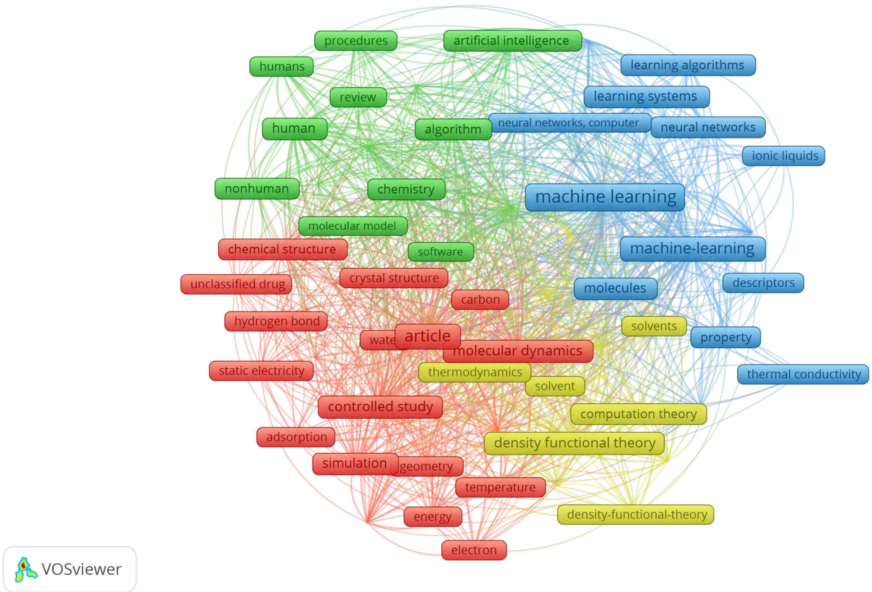

Figure 5. Keyword co-occurrence network visualization.

7.6.1. Cluster 1

Every article consists of multiple keywords, where some of them signify a broader research area and some focus on specific elements of the work. For the first cluster, represented in red, most of the keywords highlight the specific elements used in MatSci such as carbon, catalyst, chemical structure, crystal structure, hydrogen, hydrogen bond molecular dynamics, and water. Very few of the keywords in this cluster do ot directly relate to the MatSci field (keywords are given in Table 5).

Table 5. Keywords in cluster 1.

S. No	Keywords	Occurence
1	ab initio calculation	79
2	Adsorption	57
3	Article	752
4	Calculation	91
5	Carbon	52
6	Catalyst	41
7	Catalysis	64
8	Chemical Structure	95
9	Controlled Study	314
10	Crystal Structure	64
11	Electron	68
12	Energy	89
13	Geometry	69
14	Hydrogen	56
15	Hydrogen Bond	57
16	Molecular Dynamics	286
17	Quantum Mechanics	44
18	Simulation	158
19	Statical Electricity	57
20	Temperature	78
21	Unclassified Drug	55
22	Water	70

7.6.2. Cluster 2

Cluster 2 is indicated with a green color, and it comprises 16 keywords (as shown in Table 6). This cluster has keywords with a variety of perspectives; from a material perspective, the keywords are drug development, molecular model, and quantitative structure. And from a computational perspective, the keywords are algorithm, artificial intelligence, computer model, software, Support Vector Machine, etc.

Table 6. Keywords in cluster 2.

S. No	Keyword	Occurence
1	Algorithm	122
2	Artificial Intelligence	138
3	Cheminformatics	52
4	Chemistry	142
5	Computer Model	49
6	Drug Development	64
7	Human	216
8	Humans	74
9	Molecular Model	49
10	Non Human	105
11	Prediction	201
12	Procedure	66
13	Quantitative Structure Activity Relation	53
14	Review	73
15	Software	48
16	Support Vector Machine	44

7.6.3. Cluster 3

Cluster 3 is blue in color and comprises 16 keywords (shown in Table 7; most of the words in this cluster are directly related to ML techniques). Keywords such as artificial neural networks, deep learning, learning algorithms, machine learning, and neural network computers have a direct link with machine learning techniques.

Table 7. Keywords in cluster 3.

S. No	Keyword	Occurence
1	Machine Learning	1173
2	Artificial Neural Network	94
3	Atoms	87
4	Deep Learning	137
5	Descriptions	78
6	Forecasting	430
7	Iconic Liquid	73
8	Learning Algorithm	118
9	Learning Systems	187
10	Machine-Learning	627
11	Machine Learning Models	178
12	Molecules	179
13	Neural Networks	117
14	Neural Networks, Computer	47
15	Property	109
16	Thermal Conductivity	74

7.6.4. Cluster 4

This cluster, yellow in color, comprises 11 keywords (shown in Table 8, which addresses the theoretical perspective of the cluster). Therefore, the keywords are computational theory, density functional theory, and density-functional theory. Interestingly, this cluster is also concerned with materials; keywords like electronic structure, free energy, quantum chemistry, solvent, solvents, and thermodynamics are contained in this cluster.

Table 8. Keywords in cluster 4.

S. No	Keyword	Occurence
1	Computational Theory	102
2	Computational Chemistry	87
3	Density Functional Theory	85
4	Density-Functional-Theory	308
5	Electronic Structure	93
6	Free Energy	67
7	Quantum Chemistry	11
8	Quantum Theory	146
9	Solvent	57
10	Solvents	55
11	Thermodynamics	91

Figure 6 illustrates the progression of various techniques in QML over time, as determined by the average number of publications in the year. In this visualization, the research area highlighted in yellow depicts the emerging research area. Light green indicates earlier topics. This analysis also reveals that areas such as semiconductor, heavy metal, solid, and pharmacokinetics have an average publication year centered around 2024. Sampling, drug metabolism, priority journal, and flash point have an average publication around the year 2020.

Figure 6. Visual network based on average publication year of each keyword.

8. Conclusions

This paper explores the contribution of material science in the advancement of QML using 'Scopus' as a database. This research shows the qualitative and quantitative analysis of QML research nationwide. The contribution of material science in QML research comprises 1926 articles over 11 years from 2014 to 2024; among these 1926 publications, there are 83.12% articles, 14.7% review papers, and 2.18% conference papers. From 2014 to 2018, there were only 4.3% publication generated out of the total number of publications, but between 2021 and 2024, there was a significant increase in publications; these four years received 84.9% publications out of the total number of publications. The year 2015 garnered the highest total citations, with 10,339 citations, while 2014 recorded the highest number of citations per paper (CPP), with a CPP of 4100. In 2024, there were 653 publications, marking the highest number of publications in a single year. The top 10 countries that dominate the QML area are the USA, China, Germany, the UK, India, France, Japan, Canada, Switzerland, and South Korea with 86% of the worldwide publications. A total of 57 authors contributed to this research area from different institutions and from 55 countries in 11 years, giving only 1926 publications. The growth rate in publications seems to be quite slow, which could be due to many factors like limited engagement of the authors in this research area and small contributions from different countries. Among the top 10 countries, the USA single-handedly contributes 29.64% documents of the total publications, followed by significant contributions from China and Germany. India has only contributed 3.78% documents in this research area globally, which is relatively small in comparison. The keyword analysis carried out in this study identifies the most extensive research topics studied in the material science field. From the perspective of MatSci, significant work is performed in the field of making materials that contribute to advancing QML, like semiconductors qubits, optical fibers, quantum dots, and also the Josephson junction effect, which allows one to control the superposition of the qubits. However, there is still a long way to go before QML can effectively address real-world problems. Scientometric analysis offers a cost-efficient way to highlight these advancements and showcase the potential of QML, helping to raise awareness about its value and future applications.

Funding: This research received no external funding.

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

References

1. Nielsen, M.A.; Chuang, I.L. *Quantum Computation and Quantum Information*; Cambridge University Press: Cambridge, UK, 2010.
2. Chen, L.; Li, T.; Chen, Y.; Chen, X.; Wozniak, M.; Xiong, N.; Liang, W. Design and analysis of Quantum Machine Learning: A survey. *Connect. Sci.* **2024**, *36*, 2312121. [CrossRef]
3. Vedral, V.; Plenio, M.B. Basics of quantum computation. *Prog. Quantum Electron.* **1998**, *22*, 1–39. [CrossRef]
4. Berman, G.P. *Introduction to Quantum Computers*; World Scientific: Singapore, 1998.
5. Crooks, G.E. *Gates, States, and Circuits*; Berkeley Institute for Theoretical Sciences (BITS): Berkeley, CA, USA, 2020.
6. Senokosov, A.; Sedykh, A.; Sagingalieva, A.; Kyriacou, B.; Melnikov, A. Quantum Machine Learning for image classification. *Mach. Learn. Sci. Technol.* **2024**, *5*, 015040. [CrossRef]
7. De Leon, N.P.; Itoh, K.M.; Kim, D.; Mehta, K.K.; Northup, T.E.; Paik, H.; Palmer, B.; Samarth, N.; Sangtawesin, S.; Steuerman, D.W. Materials challenges and opportunities for quantum computing hardware. *Science* **2021**, *372*, eabb2823. [CrossRef]
8. Wang, P.; Luan, C.Y.; Qiao, M.; Um, M.; Zhang, J.; Wang, Y.; Yuan, X.; Gu, M.; Zhang, J.; Kim, K. Single ion qubit with estimated coherence time exceeding one hour. *Nat. Commun.* **2021**, *12*, 233. [CrossRef]
9. Murray, C.E. Material matters in superconducting qubits. *Mater. Sci. Eng. R Rep.* **2021**, *146*, 100646. [CrossRef]
10. Mercer, W.J.; Pashkin, Y.A. Superconductivity: The path of least resistance to the future. *Contemp. Phys.* **2023**, *64*, 19–46. [CrossRef]
11. Citro, R.; Guarcello, C.; Pagano, S. Josephson junctions, superconducting circuits, and qubit for quantum technologies. In *New Trends and Platforms for Quantum Technologies*; Springer: Cham, Switzerland, 2024; pp. 1–59.
12. Krasnok, A.; Dhakal, P.; Fedorov, A.; Frigola, P.; Kelly, M.; Kutsaev, S. Superconducting microwave cavities and qubits for quantum information systems. *Appl. Phys. Rev.* **2024**, *11*, 011302. [CrossRef]
13. Kockum, A.F.; Nori, F. Quantum bits with Josephson junctions. In *Fundamentals and Frontiers of the Josephson Effect*; Springer: Cham, Switzerland, 2019; pp. 703–741.
14. Lewis, B.R.; Templeton, G.F.; Luo, X. A scientometric investigation into the validity of IS journal quality measures. *J. Assoc. Inf. Syst.* **2007**, *8*, 35. [CrossRef]

15. Serenko, A.; Bontis, N. Meta-review of knowledge management and intellectual capital literature: Citation impact and research productivity rankings. *Knowl. Process. Manag.* **2004**, *11*, 185–198. [CrossRef]
16. Leydesdorff, L. Mapping interdisciplinarity at the interfaces between the Science Citation Index and the Social Science Citation Index. *Scientometrics* **2007**, *71*, 391–405. [CrossRef]
17. Savov, P.; Jatowt, A.; Nielek, R. Identifying breakthrough scientific papers. *Inf. Process. Manag.* **2020**, *57*, 102168. [CrossRef]
18. Klavans, R.; Boyack, K.W. Identifying a better measure of relatedness for mapping science. *J. Am. Soc. Inf. Sci. Technol.* **2006**, *57*, 251–263. [CrossRef]
19. Yalcin, H.; Daim, T. A scientometric review of technology capability research. *J. Eng. Technol. Manag.* **2021**, *62*, 101658. [CrossRef]
20. Zamani, M.; Yalcin, H.; Naeini, A.B.; Zeba, G.; Daim, T.U. Developing metrics for emerging technologies: Identification and assessment. *Technol. Forecast. Soc. Chang.* **2022**, *176*, 121456. [CrossRef]
21. Dhawan, S.M.; Gupta, B.M.; Mamdapur, G.M.N. Quantum Machine Learning: A scientometric assessment of global publications during 1999–2020. *Int. J. Knowl. Content Dev. Technol.* **2021**, *11*, 65–80.
22. Sood, S.K.; Agrewal, M. Quantum Machine Learning for computational methods in engineering: A systematic review. *Arch. Comput. Methods Eng.* **2023**, *31*, 1555–1577. [CrossRef]
23. Ahmadikia, A.A.; Shirzad, A.; Saghiri, A.M. A Bibliometric Analysis of Quantum Machine Learning Research. *Sci. Technol. Libr.* **2024**, *43*, 202–223. [CrossRef]
24. Walke, R.; Dhawan, S. Materials science research in India: A scientometric analysis. *DESIDOC Bull. Inf. Technol.* **2007**, *27*, 69–76. [CrossRef]
25. Schuhmacher, J.; Mazzola, G.; Tacchino, F.; Dmitriyeva, O.; Bui, T.; Huang, S.; Tavernelli, I. Extending the reach of quantum computing for materials science with machine learning potentials. *AIP Adv.* **2022**, *12*, 115321. [CrossRef]
26. Badillo, S.; Banfai, B.; Birzele, F.; Davydov, I.I.; Hutchinson, L.; Kam-Thong, T.; Siebourg-Polster, J.; Steiert, B.; Zhang, J.D. An introduction to machine learning. *Clin. Pharmacol. Ther.* **2020**, *107*, 871–885. [CrossRef] [PubMed]
27. Shandilya, S.K.; Datta, A.; Kartik, Y.; Nagar, A. Role of Artificial Intelligence and Machine Learning. In *Digital Resilience: Navigating Disruption and Safeguarding Data Privacy*; Springer: Cham, Switzerland, 2024; pp. 313–399.
28. Biamonte, J.; Wittek, P.; Pancotti, N.; Rebentrost, P.; Wiebe, N.; Lloyd, S. Quantum Machine Learning. *Nature* **2017**, *549*, 195–202. [CrossRef] [PubMed]
29. Poddar, H. Unravelling the secrets of artificial neural networks and perceptrons. In *Deep Learning in Engineering, Energy and Finance: Principals and Applications*; CRC Press: Boca Raton, FL, USA, 2024; Volume 1, p. 25.
30. Çelik, Ö. A research on machine learning methods and its applications. *J. Educ. Technol. Online Learn.* **2018**, *1*, 25–40. [CrossRef]
31. Muggleton, S. Alan Turing and the development of Artificial Intelligence. *AI Commun.* **2014**, *27*, 3–10. [CrossRef]
32. Rosenblatt, F. The perceptron: A probabilistic model for information storage and organization in the brain. *Psychol. Rev.* **1958**, *65*, 386. [CrossRef]
33. Basu, J.K.; Bhattacharyya, D.; Kim, T.H. Use of artificial neural network in pattern recognition. *Int. J. Softw. Eng. Its Appl.* **2010**, *4*, 23–33.
34. Rumelhart, D.E. *Foundations*; The MIT Press: Cambridge, UK, 1989; Volume 1.
35. Rumelhart, D.E.; Hinton, G.E.; Williams, R.J. Learning representations by back-propagating errors. *Nature* **1986**, *323*, 533–536. [CrossRef]
36. Valkenborg, D.; Rousseau, A.J.; Geubbelmans, M.; Burzykowski, T. Support Vector Machines. *Am. J. Orthod. Dentofac. Orthop.* **2023**, *164*, 754–757. [CrossRef]
37. Miraftabzadeh, S.M.; Di Martino, A.; Longo, M.; Zaninelli, D. Deep Learning in Power Systems: A Bibliometric Analysis and Future Trends. *IEEE Access* **2024**, *12*, 163172–163196. [CrossRef]
38. Rhee, J.; Veloso, P.; Krishnamurti, R. Three decades of machine learning with neural networks in computer-aided architectural design (1990–2021). *Des. Sci.* **2023**, *9*, e25. [CrossRef]
39. Wang, W.; Yang, Y.; Wang, X.; Wang, W.; Li, J. Development of convolutional neural network and its application in image classification: A survey. *Opt. Eng.* **2019**, *58*, 040901. [CrossRef]
40. Khurana, S.; Nene, M. Quantum Machine Learning: Unraveling a New Paradigm in Computational Intelligence. *Quantum* **2024**, *74*, 1–24.
41. Tychola, K.A.; Kalampokas, T.; Papakostas, G.A. Quantum Machine Learning—An overview. *Electronics* **2023**, *12*, 2379. [CrossRef]
42. Preskill, J. Quantum computing 40 years later. In *Feynman Lectures on Computation*; CRC Press: Boca Raton, FL, USA, 2023; pp. 193–244.
43. Berthiaume, A.; Feynman, R.P. Quantum computation. In *Complexity Theory: Retrospective II*; Springer: Cham, Switzerland, 1997; Volume 2, p. 23.
44. Jeswal, S.; Chakraverty, S. Recent developments and applications in quantum neural network: A review. *Arch. Comput. Methods Eng.* **2019**, *26*, 793–807. [CrossRef]
45. Schuld, M.; Petruccione, F. *Machine Learning with Quantum Computers*; Springer: Cham, Switzerland, 2021; Volume 676.

46. Monz, T.; Nigg, D.; Martinez, E.A.; Brandl, M.F.; Schindler, P.; Rines, R.; Wang, S.X.; Chuang, I.L.; Blatt, R. Realization of a scalable Shor algorithm. *Science* **2016**, *351*, 1068–1070. [CrossRef]
47. Fluhrer, S. Reassessing Grover's Algorithm. Cryptology ePrint Archive. 2017. Available online: https://eprint.iacr.org/2017/811 (accessed on 11 March 2025).
48. Abbas, H. Quantum Machine Learning-Models and Algorithms: Studying quantum machine learning models and algorithms for leveraging quantum computing advantages in data analysis, pattern recognition, and optimization. *Aust. J. Mach. Learn. Res. Appl.* **2024**, *4*, 221–232.
49. Bonner, R.; Freivalds, R. A survey of quantum learning. In *Quantum Computation and Learning*; Arkitektkopia: Västerås, Sweden, 2003; Volume 106.
50. Dunjko, V.; Briegel, H.J. Machine learning & artificial intelligence in the quantum domain: A review of recent progress. *Rep. Prog. Phys.* **2018**, *81*, 074001.
51. Lloyd, S.; Mohseni, M.; Rebentrost, P. Quantum algorithms for supervised and unsupervised machine learning. *arXiv* **2013**, arXiv:1307.0411.
52. Wittek, P. *Quantum Machine Learning: What Quantum Computing Means to Data Mining*; Academic Press: San Diego, CA, USA, 2014.
53. Rebentrost, P.; Mohseni, M.; Lloyd, S. Quantum Support Vector Machine for big data classification. *Phys. Rev. Lett.* **2014**, *113*, 130503. [CrossRef]
54. Schuld, M.; Sinayskiy, I.; Petruccione, F. The quest for a quantum neural network. *Quantum Inf. Process.* **2014**, *13*, 2567–2586. [CrossRef]
55. Lloyd, S.; Mohseni, M.; Rebentrost, P. Quantum principal component analysis. *Nat. Phys.* **2014**, *10*, 631–633. [CrossRef]
56. Schuld, M.; Petruccione, F. *Supervised Learning with Quantum Computers*; Springer: Cham, Switzerland, 2018; Volume 17.
57. Rosmanis, A. Hybrid quantum-classical search algorithms. *ACM Trans. Quantum Comput.* **2024**, *5*, 1–18. [CrossRef]
58. Alabi, M. A Revolution in Processing Capabilities and Its Possible Uses: Quantum Computing. 2024. Available online: https://www.researchgate.net/profile/Moses-Alabi/publication/386049161_A_Revolution_in_Processing_Capabilities_and_Its_Possible_Uses_Quantum_Computing/links/6740d985868c966b93228ba2/A-Revolution-in-Processing-Capabilities-and-Its-Possible-Uses-Quantum-Computing.pdf (accessed on 11 March 2025).
59. Chen, C. Science mapping: A systematic review of the literature. *J. Data Inf. Sci.* **2017**, *2*, 1–40. [CrossRef]
60. Hosseini, M.R.; Martek, I.; Zavadskas, E.K.; Aibinu, A.A.; Arashpour, M.; Chileshe, N. Critical evaluation of off-site construction research: A Scientometric analysis. *Autom. Constr.* **2018**, *87*, 235–247. [CrossRef]
61. Zhao, X.; Zuo, J.; Wu, G.; Huang, C. A bibliometric review of green building research 2000–2016. *Archit. Sci. Rev.* **2019**, *62*, 74–88. [CrossRef]
62. Shi, J.; Zhao, R.X.; Wang, W.; Zhang, S.; Li, X. QSAN: A near-term achievable quantum self-attention network. *IEEE Trans. Neural Netw. Learn. Syst.* **2024**, 1–14. . [CrossRef]
63. Li, G.; Zhao, X.; Wang, X. Quantum self-attention neural networks for text classification. *Sci. China Inf. Sci.* **2024**, *67*, 142501. [CrossRef]
64. Zhao, R.X.; Shi, J.; Li, X. Qksan: A quantum kernel self-attention network. *IEEE Trans. Pattern Anal. Mach. Intell.* **2024**, *46*, 10184–10195. [CrossRef]
65. Sharma, P.; Gupta, V.; Sood, S.K. Analyzing the contribution of material science in quantum cryptography: A scientometric study. *Int. J. Quantum Chem.* **2024**, *124*, e27280. [CrossRef]
66. Van Eck, N.; Waltman, L. Software survey: VOSviewer, a computer program for bibliometric mapping. *Scientometrics* **2010**, *84*, 523–538. [CrossRef]
67. Cobo, M.J.; López-Herrera, A.G.; Herrera-Viedma, E.; Herrera, F. SciMAT: A new science mapping analysis software tool. *J. Am. Soc. Inf. Sci. Technol.* **2012**, *63*, 1609–1630. [CrossRef]
68. Wang, W.; Lu, C. Visualization analysis of big data research based on Citespace. *Soft Comput.* **2020**, *24*, 8173–8186. [CrossRef]
69. Jacomy, M.; Venturini, T.; Heymann, S.; Bastian, M. ForceAtlas2, a continuous graph layout algorithm for handy network visualization designed for the Gephi software. *PLoS ONE* **2014**, *9*, e98679. [CrossRef] [PubMed]
70. Kaur, A.; Sood, S.K. Ten years of disaster management and use of ICT: A scientometric analysis. *Earth Sci. Inform.* **2020**, *13*, 1–27. [CrossRef]
71. Liu, Z.; Lu, Y.; Peh, L.C. A review and scientometric analysis of global building information modeling (BIM) research in the architecture, engineering and construction (AEC) industry. *Buildings* **2019**, *9*, 210. [CrossRef]