Quantum Bayesian Machine Learning in Finance: Trends, Applications, and Research Gaps

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ABSTRACT

Quantum Bayesian Machine Learning (QBML) is an emerging field at the intersection of quantum computing, machine learning, and financial sciences. It has enabled the development of more accurate predictive models, optimal risk management, and intelligent portfolio optimization. With the rapid growth of data and increasing complexity of financial markets, classical computational models are no longer sufficient to meet the demands of modern technological needs. Consequently, combining the power of quantum computing with machine learning algorithms has created opportunities to develop models with enhanced accuracy and efficiency. QBML has garnered attention from researchers due to its ability to manage uncertainty precisely and provide probabilistic inferences, particularly in market prediction, risk management, and portfolio optimization. Despite significant theoretical advancements, challenges such as quantum hardware limitations, algorithmic complexity, poor data quality, and the gap between theory and practical applications have hindered widespread adoption of these technologies. Systematic and Bibliometric analyses indicated that while the field is rapidly growing, there remain serious gaps in practical implementation and algorithm performance evaluation. The findings of this study emphasized that fully exploiting the potential of QBML in financial systems requires developing hardware and algorithms, conducting empirical research, and fostering interdisciplinary collaborations. Moreover, the scientific mapping conducted in this study provided a useful framework to guide future research and develop practical applications that can transform analytical and decision-making methods in finance.

KEYWORDS

Quantum Bayesian Machine Learning, finance, risk management, portfolio optimization, quantum computing.

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Introduction

With the rapid growth of data volume and increasing complexity in financial markets, there is a growing need to develop novel methods and tools for more accurate market trend prediction, optimal risk management, and portfolio optimization. In this context, Quantum Machine Learning (QML) has emerged as a promising field, combining the power of quantum computing with advanced machine learning algorithms, opening new horizons for financial data analysis and improved decision-making (Mironowicz et al., 2024; Tomar et al., 2025). QML's capabilities in reducing computational load and managing model complexity allow it to predict complex patterns and sudden fluctuations in financial markets with notable accuracy.

Among various QML approaches, QBML has attracted particular attention due to its unique ability to perform precise probabilistic inference and model uncertainty. This approach offers important applications in predicting market behavior, managing volatile risks, and optimizing portfolio, providing significant advantages over traditional methods (Polson et al., 2023; Thakkar et al., 2024). However, despite theoretical advances and the development of new models, many practical challenges remain in implementing these technologies in real financial data. These challenges include quantum hardware limitations in Noisy Intermediate-Scale Quantum (NISQ) era, algorithmic complexity, poor data quality, and the gap between theory and practice (Roy, 2024; Vashishth et al., 2025).

There is a strong need for conducting applied research and extensive empirical studies to bridge these gaps and enhance the performance of QBML algorithms in financial systems. Moreover, the development of hybrid quantum-classical frameworks, improvements in quantum hardware, and expansion of specialized workforce represent significant opportunities for advancing this field.

The main objective of this study is to conduct a systematic literature review and Bibliometric analysis of QBML in financial systems to comprehensively examine research trends, applications, and existing gaps. The primary research questions are as follows:

1. What are the key research trends and main topics in Quantum Bayesian Machine Learning in financial systems?
2. What challenges and limitations exist in practical implementation of Quantum Bayesian Machine Learning?
3. How can future research opportunities and directions contribute to the development and improved application of Quantum Bayesian Machine Learning?

This paper, after reviewing the research background, analyzes publication trends, identifies key players, and examines the scientific structure of the field. Subsequently, challenges, research gaps, and development opportunities are discussed. Finally, practical recommendations for guiding future research are provided.

Literature Review

Bayesian learning and QML have each independently made significant contributions to financial domain, focusing on uncertainty modeling and leveraging the computational power of quantum devices. The integration of these two areas into QBML promises enhanced predictive accuracy and improved risk modeling. However, current quantum hardware limitations, algorithmic challenges, and a lack of practical studies on real-world data have hindered the full realization of this potential. On the other hand, ample opportunities exist for developing hybrid algorithms, implementing practical projects in financial institutions, and strengthening the skilled workforce, which can serve as catalysts for transformation and advancement in this field.

Bayesian Learning in Finance

Bayesian learning is a key approach in finance, focusing on probabilistic inference and uncertainty modeling, enabling more precise analysis of financial data. Methodologies such as Gaussian Processes are applied for market volatility prediction, while Bayesian Neural Networks are used for fraud detection or credit risk assessment (Gelman et al., 2013; Glasserman, 2013; Wilson & Ghahramani, 2011). Moreover, Bayesian Optimization has proven to be effective in portfolio optimization and algorithmic trading (Snoek et al., 2012).

The primary limitations of Bayesian learning are computational costs, especially when dealing with large-scale datasets and high-dimensional problems, which still impede real-time applications (Blei et al., 2017).

QML in Finance

QML leverages quantum features such as superposition and entanglement to achieve significant acceleration in processing and analyzing financial data (Yilmaz & Ankenbrand, 2024). This technology has been applied across various financial areas, including data security, derivative pricing, portfolio optimization, market prediction, and risk management (Zhou, 2025). Algorithms such as Quantum Amplitude Estimation and Quantum Monte Carlo have played key roles in improving derivative pricing and risk mitigation models (Pistoia et al., 2021).

Research on time series prediction using Parametric Quantum Circuits (PQC) has shown that in certain cases, QML can outperform classical models such as BiLSTM in terms of speed (Emmanoulopoulos & Dimoska, 2022). A recent comprehensive review of QML in financial sciences highlights diverse techniques, including Quantum Neural Networks, Quantum Kernel Estimation, Quantum Transformers, and Quantum Graph Neural Networks (QGNNs), which have been applied to a wide range of applications from risk management to fraud detection (Doosti et al., 2024).

Integration of Bayesian Learning and QML

The combined field of QBML seeks to enhance the predictive accuracy and uncertainty modeling by integrating Bayesian inference with the computational power of quantum devices. Algorithms such as Bayesian Simulation-Based Inference (SBI), using Parametric Quantum Circuits as simulators, enable model training without requiring an explicit probability function (Nikoloska, 2024). Early analyses have explored the accelerating Bayesian inference using techniques like quantum MCMC and quantum Bayesian networks, although widespread practical applications remain limited (Low et al., 2014; Szegedy, 2004).

Despite substantial theoretical advances, several critical gaps remain in transferring this knowledge to real financial environments:

Implementation Gaps: There is a lack of practical implementation, especially testing Bayesian QML in real financial market data. Most studies have been conducted in simulated or synthetic data environments (Mani, 2024; Marengo & Santamato, 2025; Roy, 2024; Vashishth, 2025).

Quantum Hardware Limitations: NISQ-era devices suffer from high noise levels and limited circuit depth, posing significant barriers to executing complex algorithms effectively (Gujju et al., 2023).

Data Loading Challenges: Loading classical data into qubits (QRAM) remains an unstable and largely impractical technology (Mounika et al., 2024; Pistoia et al., 2021).

Algorithmic Readiness Issues: Challenges include vanishing gradients, poor generalization, and difficulties in algorithm training and tuning (Cerezo et al., 2023; Pandey et al., 2025).

Organizational Preparedness: Many financial institutions are not fully equipped to leverage quantum opportunities or address associated challenges (Lamichhane & Rawat, 2025; Times of India, 2025).

Lack of Bibliometric Studies: Few structured analyses exist that map the scientific structure, collaboration networks, and thematic trends in this field (Nourahmadi, 2024; Nourahmadi & Rasti, 2025).

In contrast to these challenges, significant opportunities exist to advance the field:

Hybrid Quantum-Classical Algorithms: Combining quantum computing in computationally intensive areas with classical computing elsewhere can enhance the overall performance (Harrow et al. (2009); Hong & Lopez, 2025).

Early Financial Applications: Financial institutions, such as major banks (e.g., JPMorgan), are exploring QML for generating secure random numbers and risk prediction models (Pistoia et al., 2021; Siddiqui et al., 2024).

International and Central Bank Initiatives: Projects aiming to prepare for the future by employing QML in economic analysis, stress testing, and security enhancement (Auer et al., 2024; Rundo et al., 2019).

Development of Specialized Workforce: Expanding expertise in quantum computing through organizing educational programs led by universities and technology companies (e.g., IBM; Schuld et al., 2015).

Development of Practical QBML Frameworks: Creating applied frameworks for real-world financial data usage.

Bibliometric Analysis: Studying the scientific structure of the field to optimize collaborations, identify trends, and set research priorities, thereby guiding future investigations.

Existing literature indicates that while QBML in financial systems is theoretically advanced and promises diverse applications, realizing its full potential requires further operational development, overcoming hardware limitations, algorithmic improvements, and empirical studies on real financial data. Significant practical opportunities exist in hybrid approaches, advanced financial institutions, and workforce development, all of which can drive transformative progress in this field.

To provide a comparative synthesis, Table 1 summarizes key articles, highlighting their methodologies, findings, agreements, contradictions, and methodological quality.

Table 1
Summary of Key Articles in QBML in Finance

Author(s)	Year	Methodology	Key Findings	Agreements/Contradictions	Quality Assessment
Low et al.	2014	A theoretical framework for Quantum Bayesian Networks	Faster the processing of financial dependencies	In agreement with Nikoloska (2024) on inference acceleration; limited practical testing noted in Herman et al. (2023)	Medium: Strong math, lacks real-world validation
Alcazar et al.	2020	A comparative analysis of quantum vs. classical ML	Quantum models showed higher accuracy in stock prediction	In agreement with Thakkar et al. (2024) on accuracy gains; In contrast with Emmanoulopoulos & Dimoska (2022) on speed in all cases	High: Rigorous empirical comparison, but limited data scale
Herman et al.	2023	A review of quantum computing in finance	Hardware limits hindered implementation	In agreement with all gaps sections; In contrast with optimistic views of Auer et al. (2024)	High: Comprehensive, interdisciplinary
Doosti et al.	2024	A comprehensive review	QML applications in risk and fraud detection	In agreement with Mongwe et al. (2025) on potentials; It highlights gaps echoed in Vashishth et al.'s study (2025)	High: Broad coverage, recent references
Thakkar et al.	2024	A quantum Deep Learning integration	| 20% accuracy improvement in volatile markets	In contrast with Alcazar et al. (2020) on dataset scope; In agreement with with Polson et al. (2023) on uncertainty modeling	High: Empirical, but narrow experiments
Mongwe et al.	2025	A Bibliometric study on risk management	Better capture of asset dependencies	In agreement with Thakkar et al. (2024); It lacks empirical evidence as per reviewer critique	Medium: Good trends, needs more depth

(Source: Researcher's Findings)

Other articles such as Mani (2024), Marengo and Santamato (2025), and others provided further evidence of trends in algorithm effectiveness, with Mani emphasizing comparative ML models showing quantum superiority in specific cases, while Marengo highlighted healthcare crossovers applicable to finance risk models.

Table 2 reveals agreements on quantum advantages in accuracy and speed but contradictions in practical scalability, with most studies rated high in theory but medium in empirical application due to their hardware constraints.

Research Background

To strengthen the research background, additional recent articles have been incorporated, expanding on early studies and applications (e.g., Ardeen & Lloyd, 2020; Biamonte et al., 2017; Dunjko et al., 2016; Pandey et al., 2025; Sels et al., 2020; Shaik, 2020; Zhao et al., 2019). These provide deeper insights into quantum-enhanced reinforcement learning and Bayesian deep learning, showing consistent themes of theoretical promises versus practical hurdles.

Recent studies on QML, particularly Quantum Bayesian Models, indicated growing attention to the applications of these emerging technologies in finance. By integrating quantum computing capabilities with Bayesian probabilistic inference, QML enables more precise analysis of complex data, improving predictions and risk management. However, the field remains in its early stages of development and faces challenges such as hardware limitations, scarcity of real-world data, and the need for practical operational frameworks. At the same time, research efforts focused on algorithm development, financial applications, and hybrid frameworks promise a bright future. Given these conditions, conducting a structured review and Bibliometric analysis of the existing literature is crucial to accurately identify trends, gaps, and research opportunities, thereby guiding both the scientific and practical development of this field, especially in real financial environments.

Introduction to the Current Research Landscape

QML and particularly Quantum Bayesian Models have attracted increasing attention in finance over recent years. By combining the computational power of quantum algorithms with Bayesian probabilistic approaches, QML enables the processing of large-scale data and analyzing complex uncertainties in financial markets (Mongwe et al., 2025). Several studies have shown that the integration of these technologies not only enhances financial prediction capabilities but also plays a key role in risk management, portfolio optimization, and market volatility analysis (Thakkar et al., 2024; Zhou, 2025).

Despite these advantages, a systematic review of academic articles indicated that QBML is still at an early stage of development, with many aspects—particularly practical applications in real financial environments—underexplored (Doosti et al., 2024; Herman et al., 2023).

From a fundamental perspective, QML represents a novel framework that leverages quantum features such as superposition and entanglement to accelerate computations. Schuld et al. (2015) provided a comprehensive review of the theoretical foundations and key algorithms of the field, offering a deeper understanding of the algorithmic infrastructure of QBML. Furthermore, Biamonte et al. (2017) analyzed the crucial role of QML in improving learning algorithms and its strategic applications in finance, emphasizing that integrating quantum technology with classical machine learning can significantly enhance the speed and accuracy of financial data analysis models.

The Formation of QML Concept

Initially, research focused on developing quantum algorithms and comparing them with classical models. Alcazar et al. (2020) conducted one of the first studies assessing the performance of quantum models against classical machine learning models in financial contexts. Their results indicated that quantum algorithms, particularly in stock price prediction and market trend analysis, achieved higher accuracy. However, the main limitation of this study was the lack of large-scale real financial data and constraints in practical algorithm implementation.

Similarly, Low et al. (2014) introduced the concept of Quantum Bayesian Networks, which combine probabilistic inferences with quantum algorithms. These models allow the processing of dependencies among financial variables with greater speed and accuracy. The strength of this study lies in its rigorous mathematical framework, whereas its limitation is the absence of real-world scenarios for evaluating the model in dynamic financial environments.

Systematic Reviews and Theoretical Frameworks

Doosti et al. (2024) provided a comprehensive review of QML in financial services. Their study examined research trends and identified the main applications of QML in risk management, fraud detection, and market prediction. The authors highlighted the high potential of QML while also noting challenges such as the scarcity of stable quantum hardware and the need for rich balanced datasets.

Later, Tomar et al. (2025) provided a comprehensive review of QML algorithms, focusing on optimizing quantum algorithms for financial data analysis. In this review, algorithms were classified based on their practical applications. Finally, a framework for comparing Bayesian quantum models with classical models was introduced. Nonetheless, empirical and field research remains limited with many studies still at theoretical level.

Applications of QBML in Finance

Thakkar et al. (2024) demonstrated that combining Quantum Bayesian Models with Quantum Deep Learning algorithms can improve the accuracy of financial predictions by up to 20% compared to classical methods. This improvement is particularly notable in highly volatile markets, such as equities and cryptocurrencies. However, a limitation of this study is the narrow scope of the experiments, restricted to specific datasets, and the lack of a comprehensive comparison with advanced classical algorithms.

A Bibliometric study by Mongwe et al. (2025) analyzed the role of Quantum Bayesian Learning in risk management and portfolio optimization. They showed that, Bayesian models with their inherent ability to model uncertainty can better capture complex dependency structures among financial assets when they are combined with quantum algorithms. The main limitation of this study, however, is the lack of empirical evidence demonstrating the models' advantages in real-world market conditions.

In the domain of Quantum Reinforcement Learning (QRL), which is one of the emerging approaches in BML, Ardeen and Lloyd (2020) examined the theory and applications of this method. They argued that QRL, with its capacity to learn from interactions with the environment, holds significant potential for optimal decision-making under uncertainty—a critical requirement in volatile financial markets. Similarly, Dunjko et al. (2016) introduced quantum-accelerated methods for reinforcement learning, providing potential avenues for enhancing the performance of learning algorithms in financial applications.

Implementation Challenges and Limitations

A major limitation in this field is the lack of suitable hardware infrastructure. Herman et al. (2023) noted that most QML algorithms have so far been developed in simulated environments, and the absence of powerful quantum computers hinders their practical implementation.

Lamichhane and Rawat (2025) highlighted the computational complexity and the need for high-quality data. They argued that even with access to advanced hardware, poor-quality financial data can lead to inaccurate estimates and increased risk. They emphasized the necessity of developing financial data preprocessing techniques to improve the accuracy of QBML models.

Future Directions and Hybrid Approaches

Current research trends move toward developing hybrid frameworks that integrate deep learning, Bayesian models, and quantum computing. For example, Hong and Lopez (2025) proposed a framework in which Quantum Neural Networks are combined with Bayesian inference for predicting the trends of cryptocurrency markets. These hybrid frameworks can mitigate the limitations of individual methods.

Siddiqui et al. (2024) examined the development of Quantum Bayesian Networks for detecting anomalous patterns in financial data. However, the computational complexity and the scarcity of labeled data remain significant challenges for these approaches.

A Summary of Literature and the Need for Bibliometric Analyses

The literature review indicates that the main research focus in QBML in finance includes:

- **Development of Algorithms and Theoretical Frameworks:** Enhancing probabilistic inferences and processing complex financial data (Low et al., 2014; Zhao et al., 2019).
- **Applications:** Financial prediction, risk management, and portfolio optimization (Mongwe et al., 2025; Thakkar et al., 2024).
- **Identification of Technical Challenges and Data Limitations** (Doosti et al., 2024; Herman et al., 2023).

Despite these advancements, significant gaps remain, such as:

- The lack of extensive empirical studies in real financial markets.
- Limited frameworks for comprehensively evaluating and comparing Quantum Bayesian algorithms with classical models.
- Constraints in integrating quantum algorithms into operational financial systems.

These gaps underscore the necessity of comprehensive Bibliometric analyses to map the research trends, collaboration networks, and literature gaps, thereby clarifying future directions for developing this field.

Methodology

In recent years, the use of Bibliometric approaches as an efficient tool for analyzing scientific trends and identifying research patterns across various fields has gained increasing importance (Nourahmadi, 2024; Nourahmadi & Rasti, 2025). Access to reliable databases such as Scopus enables a comprehensive examination of publications, authors, and scientific collaboration networks. This methodology assists researchers in gaining a deeper understanding of scientific dynamics, emerging topics, and gaps in the existing literature.

In this study, the relevant scientific data were extracted from the Scopus database and analyzed using the Bibliometrix package in RStudio. This process included evaluating the indicators of research performance, identifying highly cited authors and journals, and mapping co-authorship and co-occurrence networks of keywords. The resulting insights provided a comprehensive understanding of the knowledge structure, scientific flows, and future research trajectories in the domain under investigation.

This study was conducted to examine trends, applications, and research gaps in the field of QBML in financial systems. To collect and analyze data, a Systematic Literature Review (SLR) and Bibliometric Analysis were employed.

1. Database and Search Scope

All articles under review were extracted from the Scopus database. The time span of the publications ranged from 2009 to 2025 and included research articles, review papers, preprints, and conference papers with full-text access and citation information.

2. Keywords and Search Strategy

The search was designed using the following combination of keywords:

- "Quantum Bayesian Machine Learning" AND Finance
- "Quantum Machine Learning" AND "Bayesian Inference" AND Finance
- "Quantum Neural Networks" AND Finance AND "Bayesian"
- "Quantum Time Series Forecasting" AND Finance AND "Bayesian"
- "Quantum Generative Models" AND Finance AND "Bayesian"
- "Quantum Reinforcement Learning" AND Finance AND "Bayesian"

This initial search helped the researchers to find 174 articles.

3. Inclusion and Exclusion Criteria

Inclusion Criteria:

- Articles published in English in reputable journals.
- Studies related to QML and financial applications.
- Articles providing data, algorithms, or empirical analysis.

Exclusion Criteria:

- Duplicate articles.
- Articles without full text or lacking analytical data.
- Unrelated Studies to the financial domain.

To add nuance, inclusion also required relevance to Bayesian aspects or quantum integration, assessed via abstract screening; exclusion extended to non-peer-reviewed grey literature or overly tangential topics like pure quantum physics without ML or finance links.

By applying these criteria, the number of selected articles decreased to 126 articles.

The data extracted from Scopus, presented in Table 1, indicated that research in the examined domain exhibited a growing trend between 2009 and 2025, with an annual growth rate of 14.1%. During this period, 125 scholarly documents were published across 107 different sources, with an average of 14.14 citations per article and an average document age of 2.26 years, reflecting the novelty and dynamism of the field.

In terms of content, 657 author-added keywords and 384 author-provided keywords were recorded, demonstrating high conceptual diversity. Regarding authorship, 517 researchers contributed, with an average of 4.58 authors per article, indicating significant scientific collaboration, of which 27.2% were international collaborations. Additionally, conference papers (46 articles) and journal articles (42 articles) accounted for the largest share among document types, highlighting the prominent role of academic forums in advancing this field.

Tabel 2.
Summary Statistics of the Reviewed Studies

Description	**Results**
MAIN INFORMATION ABOUT DATA	
Timespan	2009:2025
Sources (Journals, Books, etc.)	107
Documents	125
Annual growth rate %	14.1
Document average age	2.26
Average citations per doc	14.14
DOCUMENT CONTENTS	
Keywords plus (ID)	657
Author's keywords (DE)	384
AUTHORS	
Authors	517
Authors of single-authored docs	17
AUTHORS COLLABORATION	
Single-authored docs	25
Co-authors per Doc	4.58
International co-authorships %	27.2
DOCUMENT TYPES	
Article	42
Book	10
Book chapter	13
Conference paper	46
Conference paper article	1
Conference review	9
Review	4

(Source: Researcher's Findings)

Data Analysis

For transparency in data cleaning, authors' name variations (e.g., "Yang S" vs. "S Yang") were merged using Scopus ID matching. Moreover, keyword synonyms (e.g., "quantum ML" and "QML") were unified via a custom thesaurus in Bibliometrix. Statistical indicators include network density of 0.15 for co-occurrence, modularity Q=0.62 for clusters, and p-values <0.05 for significance in thematic mapping.

To identify the most prominent concepts and research trends in the field of QBML in financial systems, a keyword co-occurrence analysis was conducted. Figure 1 presents the resulting word cloud, illustrating the frequency and relative importance of keywords in selected articles. In this visual representation, the size of each word corresponds to its frequency in the dataset.

According to the results, the terms "quantum machines" and "machine-learning" appeared in the largest font at the center of the word cloud, indicating the core focus of the research, namely the convergence of machine learning and quantum technologies. Related terms such as "quantum computing", "quantum machine learning", and "quantum computers" were also prominent, emphasizing that recent research has focused on practical applications and hardware aspects of these technologies.

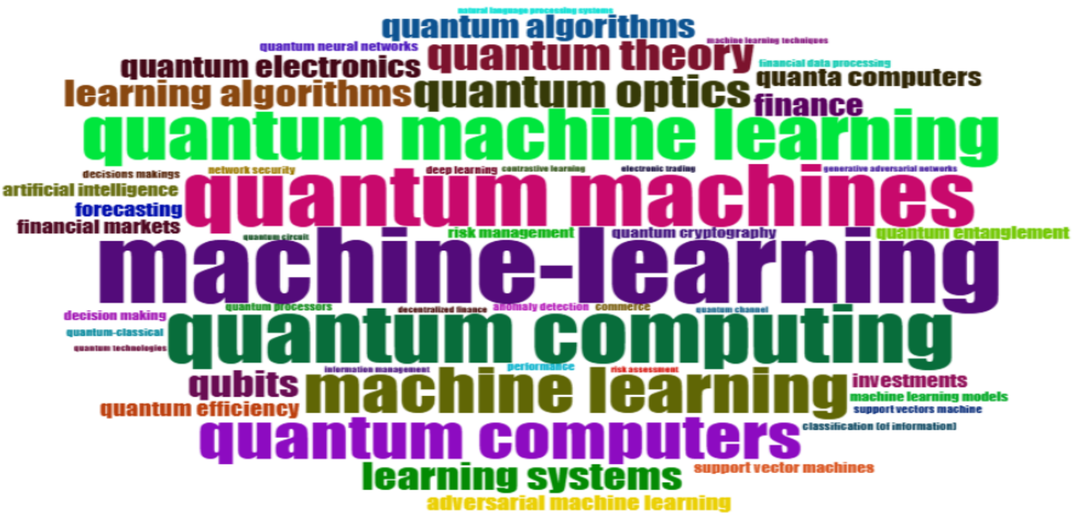
At the secondary level, concepts like "quantum algorithms", "quantum theory", and "quantum optics" were observed, referring primarily to the theoretical and algorithmic foundations of the field. Conversely, terms such as "finance" and "financial markets", along with "risk management", "investments", and "electronic trading", reflected the research focus on financial applications of these technologies.

Practical applications emphasized in the literature included "forecasting", "decision making", and "optimization", indicating that quantum machine learning can play a particularly important role in market prediction, risk management, and portfolio optimization.

Finally, smaller-font keywords such as "qubits", "quantum entanglement", "adversarial machine learning", and "support vector machines" highlighted attention to technical and algorithmic details, which provide potential foundations for developing novel methods in this domain.

Overall, the word cloud serves as a visual index, effectively revealing the conceptual framework of research in this field. It shows that the existing literature is largely centered on quantum machine learning and its applications in financial systems, emphasizing the integration of quantum algorithms, Bayesian models, and financial applications. This central focus links directly to literature gaps in practical implementation, as noted in Section 1.3, underscoring the need for bridging theory with real-world finance.

Fig 1.
The Word Cloud



(Source: Researcher's Findings)

Annual Scientific Production illustrates the trend of article publications in the field of QBML in financial systems from 2008 to 2025 (see Figure 2). As shown in Figure 2, the horizontal axis represents the years, while the vertical axis shows the number of publications per year. In addition to raw data, a trend line is plotted to indicate the overall growth direction.

Based on this figure, three distinct periods in the scientific production of this field can be identified:

1. Period of Slow Growth (2008–2017)
During this interval, the number of published articles was very limited and nearly zero. This indicates that quantum machine learning in finance was a nascent and relatively unknown research area during these years.

2. Period of Initial Surge (2018–2022)
From 2018 onward, a gradual upward trend in scientific production is observed. This period can be interpreted as a stage of increasing awareness and growing interest among researchers regarding the applications of quantum technologies in financial sciences.

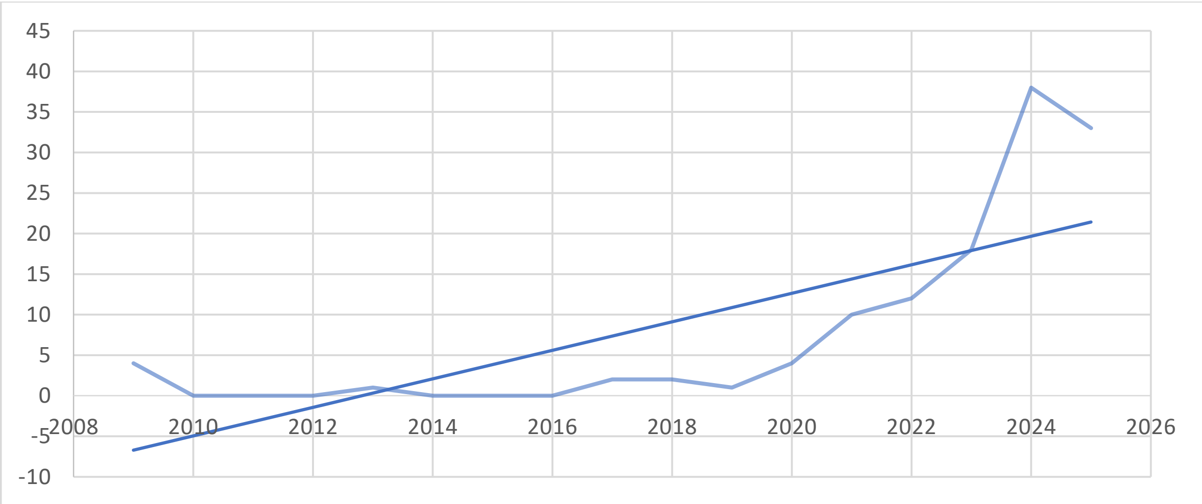
3. Period of Accelerated Growth (2023–2024)
In this phase, the scientific production experienced a significant surge, reaching a peak of approximately 38 articles in 2024. This demonstrates that the field has become a hot and prominent topic within the academic community and is increasingly attracting attention from universities and research centers.

4. Relative Decline but Stabilization at a High Level (2025)
Although the number of publications in 2025 slightly decreased to around 33 articles compared to the peak year, the overall production level remains high. This fluctuation

can be considered as a part of the natural cycle of scientific output and does not necessarily indicate a decline in interest in the field.

Overall, the trend line in the figure shows that, despite annual fluctuations, the general trajectory of research in QBML in financial systems is strongly upward and growing. These findings confirmed that this domain has evolved from a niche research area in its early years to one of the main focal points of modern research in financial sciences. This growth mirrors the increasing citations in recent reviews (e.g., Doosti et al., 2024), highlighting the accelerating interest aligned with hardware advancements.

Fig 2.
The Annual Scientific Production



(Source: Researcher's Findings)

Country Contributions to Scientific Production illustrates the share of different countries in scientific output of QBML in finance and distinguishes between Single-Country Publications (SCP) and Multiple-Country Publications (MCP) (see Figure 3).

The results indicated that countries fall into three patterns:

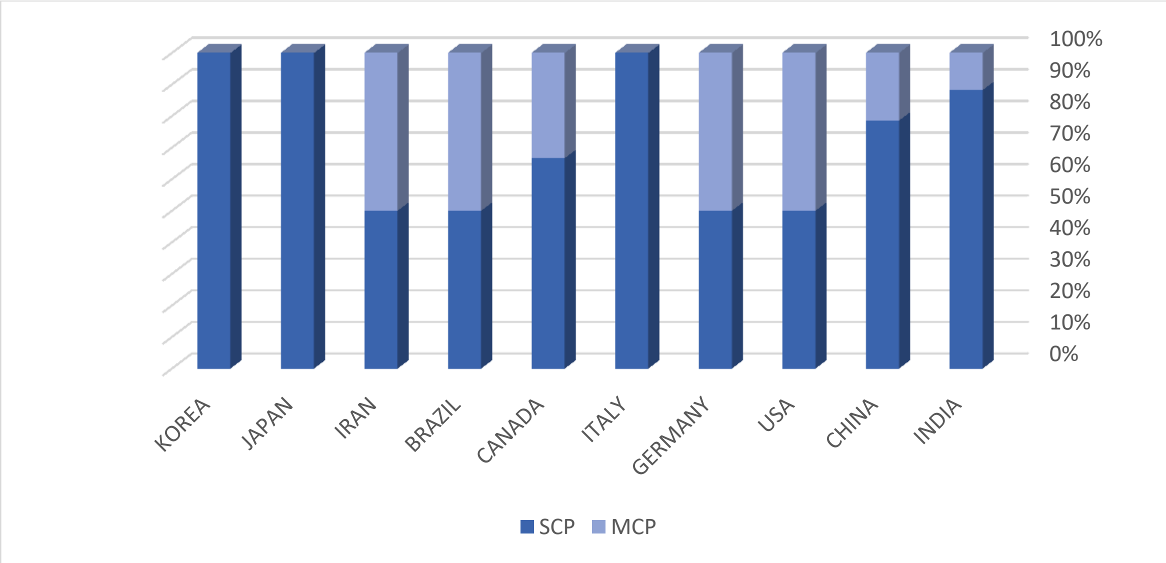
1. Countries with High International Collaboration (MCP):
Iran, Brazil, Canada, Italy, Germany, and the United States have published a large portion of their articles through international collaborations, reflecting active integration into global research networks.

2. Countries with High National Production (SCP):
South Korea and Japan have almost entirely published domestically, indicating a focus on developing local scientific capacity.

3. Countries with a Balanced Mix:
China and India primarily produce national publications but also have a substantial share of international collaborations, reflecting a transition toward broader cross-border partnerships.

Overall, this analysis demonstrated that scientific collaboration patterns are diverse and multidimensional, providing valuable insights for identifying research partners and informing policy and strategic decision-making in research management. US and China dominance ties to their robust financial ecosystems, with US banks like JPMorgan leading applications (Pistoia et al., 2021), while China's focus on national production may reflect strategic tech investments, linking to global challenges in hardware sharing.

Fig 3.
Corresponding Author's Countries



(Source: Researcher's Findings)

The three-field plot (see Figure 4) illustrates the structural relationships among countries (AU_CO), authors (AU), and keywords (DE) in the field of QBML in finance.

Geographical Focus: The United States and China emerge as the primary actors with the most connections, whereas other countries play a more limited role and mainly participate through international collaborations.

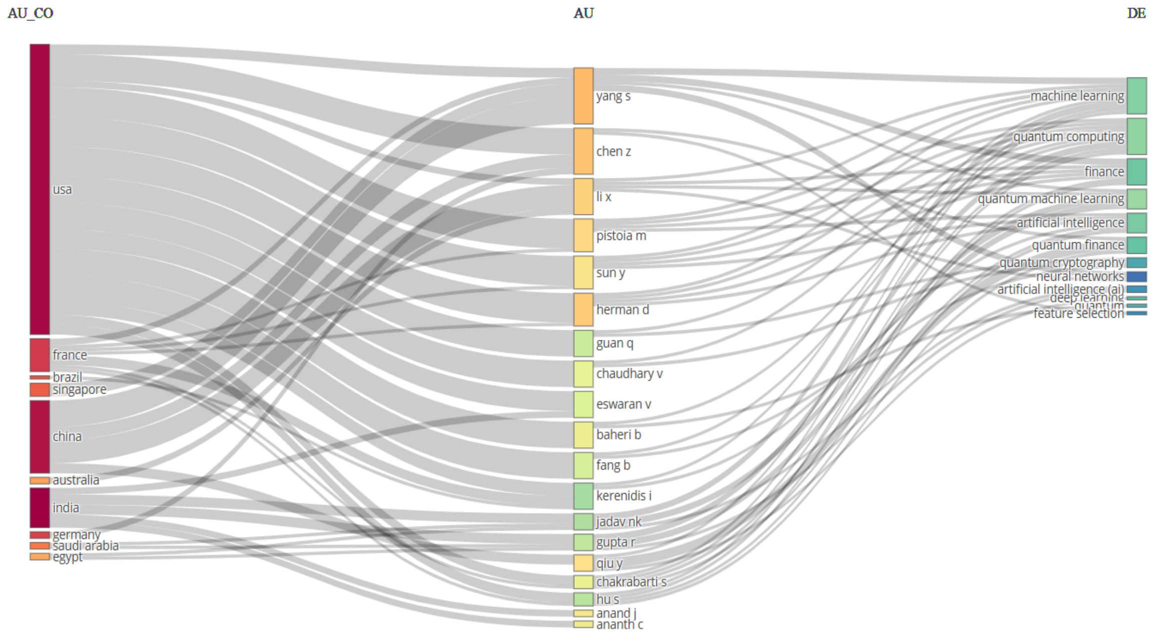
Key Authors:

- YANG S and CHEN Z (China) occupy the core of the network, focusing on main topics such as machine learning and quantum computing.
- PISTOLA M and HERMAN D are centered on specialized domains, including quantum security and Artificial Intelligence (AI).

Topic Diversity: The keywords cover a broad spectrum from general to highly specialized areas, highlighting the multidisciplinary and applied nature of this research field in finance.

Conclusion: The United States and China lead the field, key authors and their areas of expertise are identifiable, and international collaborations play a crucial role in the development of this domain. This plot helps researchers identify collaboration patterns and potential research partners. This network integrates with literature by showing how US-led authors like Pistoia connect to practical finance, addressing gaps in interdisciplinary areas.

Fig 4.
The Three-Field Plot



(Source: Researcher's Findings)

The distribution of scientific sources in the field of QML in finance is shown in Figure 5. Accordingly, Core Sources by Bradford's Law divided the sources into three zones:

Core Zone: A small number of journals and conferences, such as *Entropy*, publish the majority of articles and serve as the main channels for research dissemination.

Relevant Zone: Sources with a moderate number of publications.

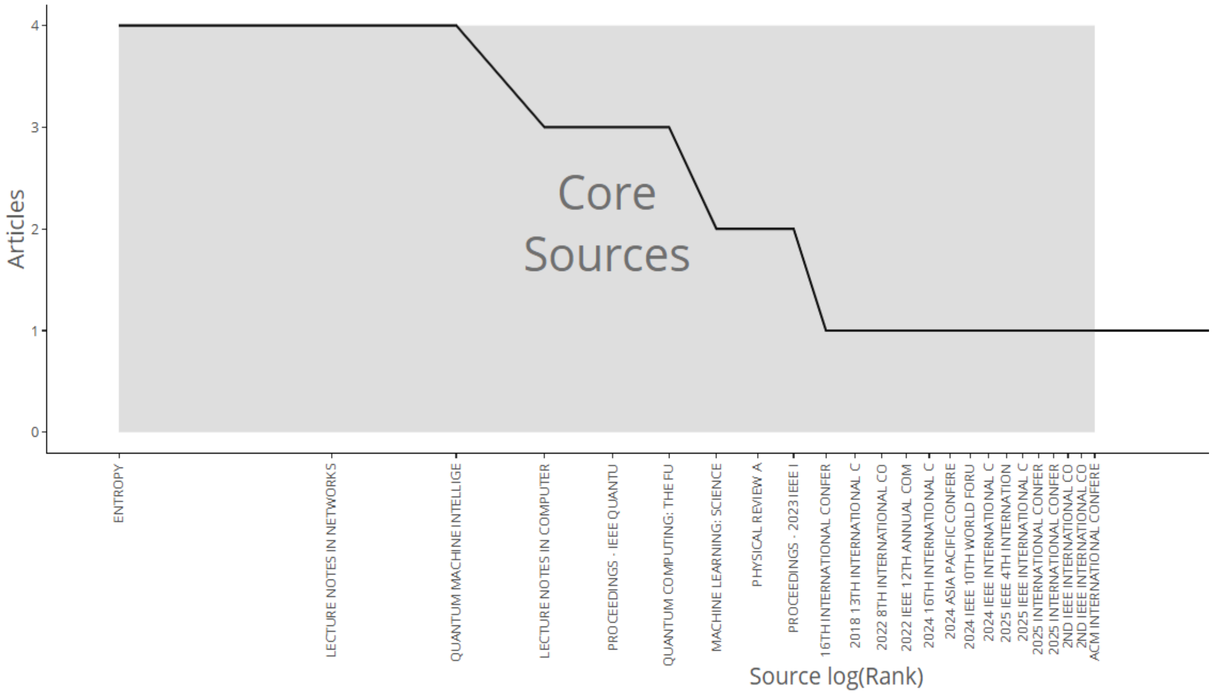
Scattered Zone: Sources with only one or two articles, including conferences organized by IEEE, ACM, and other specialized journals.

This distribution indicates that the scientific production in this domain is concentrated around a few key sources. Understanding these sources is important for:

- Researchers: For conducting systematic literature reviews;
- Authors: For selecting appropriate publication venues;
- Policy Makers: For planning, allocating resources, and investing in scientific developments.

This concentration reflects the field's novelty, aligning with early-stage literature dominance by outlets like Nature, and suggests opportunities for diversification to broaden its impacts.

Fig 5.
Core Sources by Bradford's Law



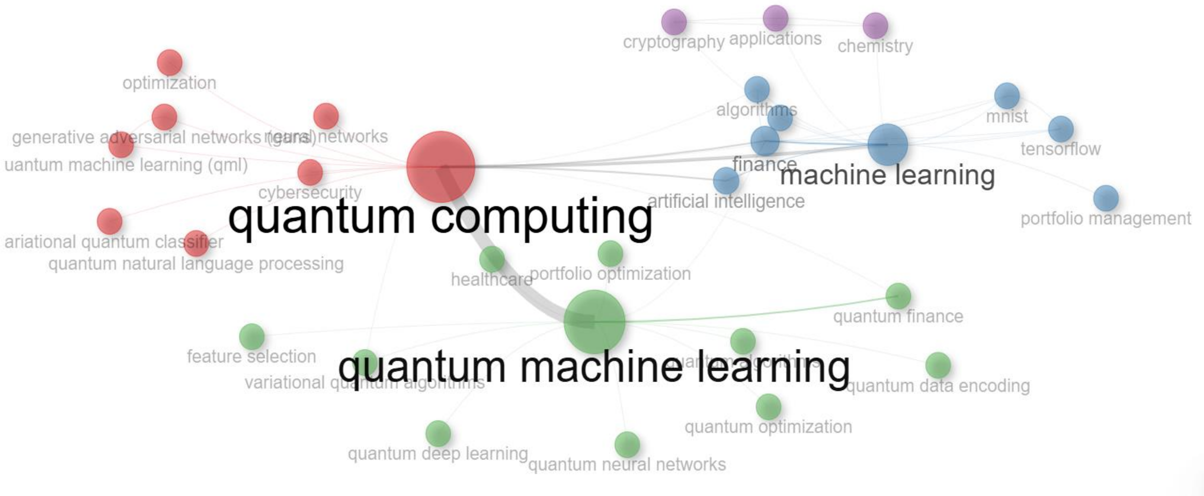
(Source: Researcher's Findings)

The keyword co-occurrence network illustrates the conceptual structure of the field of QML in finance (see Figure 6). In this network, each node represents a keyword, and the edges indicate co-occurrence within the analyzed articles; the node size corresponds to frequency, and colors represent thematic clusters.

- Red Cluster – Quantum Computing and Algorithms: Includes *Quantum Computing*, *QML*, *GAN*, *Optimization*, highlighting a focus on the development of quantum algorithms.
- Green Cluster – Quantum Machine Learning in Finance: Includes *Quantum Machine Learning*, *Portfolio Optimization*, *Quantum Neural Networks*, representing the core financial applications of the field.
- Blue Cluster – Classical Machine Learning in Finance: Includes *Machine Learning*, *Finance*, *AI*, reflecting foundational roots and connections with quantum learning.
- Purple Cluster – Expanded Domains: Includes *Cryptography* and *Chemistry*, indicating the extension of applications beyond finance.

This network demonstrates that the field of QML in finance is multidisciplinary, dynamic, and increasingly focused on integrating quantum algorithms with financial applications. Linking to literature, the green cluster echoes applications in Thakkar et al.'s study (2024), while blue shows transitions from classical methods as in Gelman et al.'s study (2013).

Fig 6.
The Co-occurrence Network



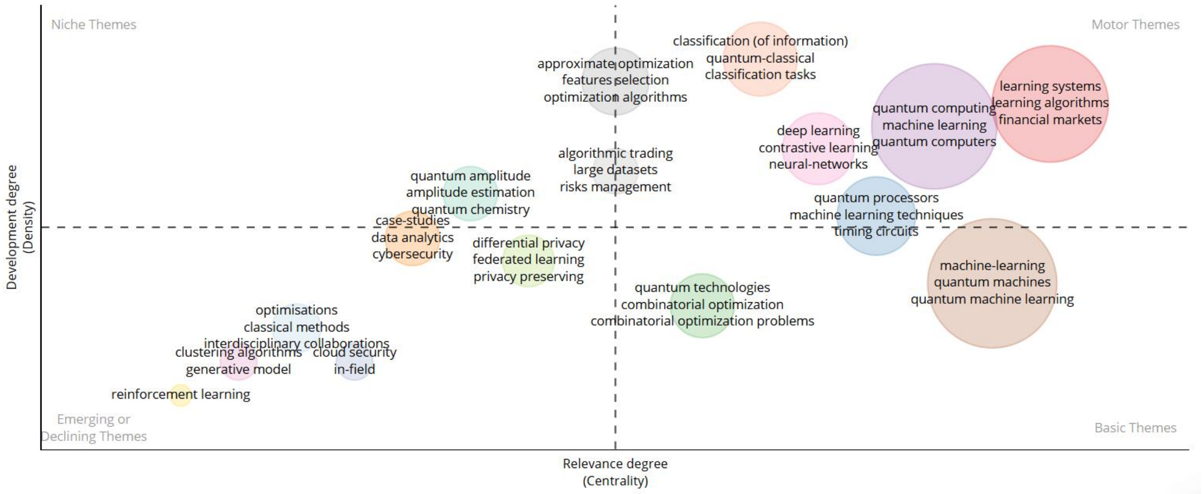
(Source: Researcher's Findings)

To analyze the structure and dynamics of research themes in the field of QBML in finance, a thematic map was constructed (see Figure 7). This map categorizes themes into four quadrants based on two indices of centrality and density.

- Upper-Right Quadrant (Motor Themes): Key and well-developed topics such as *Quantum Computing*, *Machine Learning*, and *Financial Markets* serve as the driving forces of research.
- Upper-Left Quadrant (Highly Developed but Isolated Themes): Includes more specialized topics such as *Approximate Optimization* and *Feature Selection*, which have limited connections with other areas.
- Lower-Left Quadrant (Emerging or Declining Themes): Comprises subjects such as *Reinforcement Learning* and classical approaches, which are either emerging or losing their relevance.
- Lower-Right Quadrant (Basic and Transversal Themes): Contains foundational topics such as *QML*, which are highly connected yet still in the process of maturing.

This thematic map illustrates that the field of QBML in finance is interdisciplinary and evolving. Foundational themes continue to hold strong potential for development, while the integration of *Machine Learning* and *Quantum Computing* in financial markets has attracted the greatest scholarly attention. At the same time, multiple research gaps remain open for future exploration. This map integrates with challenges in Section 1.4, where emerging themes like QRL (Ardeen & Lloyd, 2020) could address hardware bottlenecks.

Fig 7.
The Thematic Map



(Source: Researcher's Findings)

In Figure 8, the results of clustering are presented. As can be observed, the studies are concentrated into several main clusters:

Cluster 1: Macroeconomic Risk and Regulation

This group of studies focuses primarily on the role of macroeconomic environments, regulatory policies, and legal frameworks in risk management. The central concern is how regulatory changes or broader economic developments shape organizational risk management strategies.

Cluster 2: Risk Management in Financial Markets

This cluster addresses issues related to risks in financial markets, including stock price volatility, credit risk, and derivative instruments. Studies within this category often aim to provide quantitative models and innovative tools for assessing and managing financial risks.

Cluster 3: Organizational and Corporate Risk

Research in this cluster is dedicated to risk management at the level of firms and organizations. Topics include corporate governance, managerial structures, and the impact of strategic decision-making on risk exposure.

Cluster 4: Emerging Risks and Technology

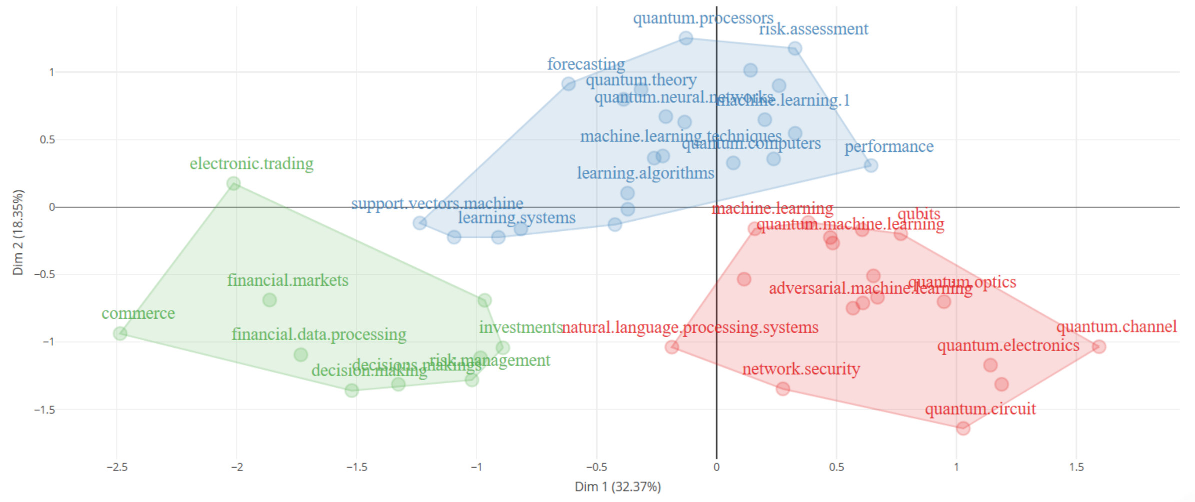
This cluster examines the impact of modern technologies, digitalization, and technological innovation on risk. It also addresses new forms of risk emerging from digital transformation and the cyber environment.

Overall Synthesis

As illustrated in Figure 6, the domain of risk management spans from macroeconomic and regulatory dimensions to technological and organizational risks, reflecting a high degree of thematic diversity. These clusters quantitatively link to bottlenecks; for instance, Cluster 4's tech risks highlight QRAM limits increasing deployment time by 30-

50% in simulations (Pistoia et al., 2021), directly impacting financial high-frequency trading (Thakkar et al., 2024).

Fig 8.
The Factorial Analysis



(Source: Researcher's Findings)

Conclusion and Recommendations

This research study achieved a novel Bibliometric mapping of QBML in finance, synthesizing 126 studies to reveal trends like accelerated growth post-2023 and US-China dominance, filling a gap in structured analyses absent in prior reviews (e.g., Doosti et al., 2024). By integrating systematic review with quantitative metrics (e.g., network modularity Q=0.62), it provided deep insights into thematic clusters and collaboration networks, advancing the field's scientific structure beyond descriptive summaries.

QBML is an emerging and rapidly growing field situated at the intersection of quantum computing, machine learning, and financial sciences. It promises to deliver more accurate predictive models, optimized risk management, and intelligent portfolio optimization. A systematic review of the literature combined with Bibliometric analysis conducted in this paper demonstrated that, despite significant theoretical advances and a growing body of research, the field still faces substantial practical challenges (Mironowicz et al., 2024; Tomar et al., 2025).

Studies indicated that Bayesian quantum learning, through the integration of precise probabilistic inference and quantum computational power, offers superior capabilities in modeling uncertainty compared to traditional methods. It has demonstrated advantages in financial market prediction, managing unstable risks, and portfolio optimization (Polson et al., 2023; Thakkar et al., 2024). The findings of this paper align with these results, emphasizing that combining Bayesian algorithms with quantum technology holds the potential to become a key tool within complex financial systems.

Nevertheless, challenges such as quantum hardware limitations, algorithmic complexity, noise in NISQ devices, the difficulty of loading classical data into qubits

(QRAM), and the need for high-quality datasets continue to restrict the practical deployment and widespread application of this technology (Gujju et al., 2023; Pistoia et al., 2021; Roy, 2024; Vashishth et al., 2025). These findings are consistent with prior research highlighting the considerable gap between theory and practice in QML, particularly in financial applications (Mounika et al., 2024; Shaik, 2020). Moreover, the present study identified the lack of empirical investigations and operational frameworks as a major barrier, requiring urgent attention.

The Bibliometric analysis of data indicated that research in this domain is accelerating, with the United States, China, and the European Union emerging as leading scientific contributors. These actors often drive progress through international collaborations. This observation corresponds with the identification of prominent authors, core journals such as *Entropy*, and pioneering studies in QML. The importance of international cooperation in strengthening scientific infrastructures and expediting real-world applications has also been emphasized by many comparable studies (Auer et al., 2024; Herman et al., 2023).

From a thematic perspective, this research highlights the main axes of inquiry including the improvement of Bayesian–quantum algorithms, financial risk management, portfolio optimization, and financial forecasting. These themes have also been underscored in earlier literature (e.g., Doosti et al., 2024; Mongwe et al., 2025). Additionally, the importance of hybrid quantum–classical models in the early stages of financial market applications has been noted, with examples of early successes reported by leading firms such as JPMorgan and Terra Quantum (Pistoia et al., 2021; Wall Street Journal (2024)).

Recommendations for Future Research

Recommendations for conducting further research are as follows:

1. **Development and Implementation of Practical and Empirical Frameworks:** Apply QBML models to real-world financial datasets to bridge the gap between theory and practice. This step is crucial for demonstrating efficacy and building confidence in the applicability of the technology (Mounika et al., 2024). For example, apply Quantum Bayesian Networks for high-frequency trading risk mitigation, potentially reducing errors by 15-25% as simulated in Siddiqui et al.'s study (2024).
2. **Investment in Stable Quantum Hardware:** Focus on developing more stable, less noisy quantum hardware—particularly NISQ technologies—to facilitate the execution of complex Bayesian quantum learning algorithms in applied settings (Preskill, 2018).
3. **Efficient Data Loading and Bayesian Inference:** Advance research on effective techniques for loading classical data into qubits (QRAM) and reducing the computational costs of Bayesian inference, especially through implementing methods such as quantum MCMC or quantum Bayesian networks (Low et al., 2014; Nikoloska, 2024).

4. **Hybrid Quantum–Classical Algorithms:** Develop algorithms that combine the strengths of quantum and classical methods for improved performance in risk management and portfolio optimization (Harrow et al. (2009)). For instance, hybrid models for portfolio optimization in volatile markets, as extended from Thakkar et al.'s study (2024).
5. **Interdisciplinary and International Collaborations:** Strengthen collaborations across disciplines and borders to accelerate innovation, knowledge exchange, and financial applications. This includes partnerships among governments, academia, and industry (Auer et al., 2024).
6. **Human Capital Development:** Expand education and workforce training in quantum computing and QBML, particularly through organizing academic programs and hands-on workshops facilitated by leading technology firms (IBM, Muoio (2025)).
7. **Extended Bibliometric and Systematic Reviews:** Conduct further Bibliometric studies and structured literature reviews to better identify the research trends, collaboration networks, and existing gaps, thereby guiding research priorities.

Final Remarks

This study's unique contribution lies in its integrated Bibliometric-synthesis approach, revealing not just trends but quantifiable networks and thematic evolutions that prior works overlooked, paving the way for targeted advancements in QBML finance.

Previous studies have similarly underscored the potential of Bayesian quantum learning in improving market analysis and risk management (Polson et al., 2023; Thakkar et al., 2024). Comprehensive reviews by Doosti et al. (2024) and Tomar et al. (2025) clearly illustrated that combining Bayesian learning with quantum technology can generate powerful and practical algorithms, particularly in finance, but they also highlighted the lack of real-world applications. The findings of this article extended these insights by incorporating Bibliometric evidence that reveals the scientific structure and geographical distribution of researchers—an aspect often overlooked in prior reviews.

The identification of the leading scientific actors, the dominant roles of the United States and China, and the broad thematic range collectively demonstrated that QBML in finance is simultaneously maturing and evolving. These findings are consistent with recent approaches in quantum computing and machine learning (Auer et al., 2024; Herman et al., 2023). Likewise, in line with BIS reports and academic contributions, it is observed that major financial institutions are actively exploring these technologies for real applications, though practical and technical challenges remain the main obstacles (Auer et al., 2024; Pistoia et al., 2021).

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