International Journal of Cognitive Computing in Engineering 7 (2026) 26–39

Contents lists available at ScienceDirect

International Journal of Cognitive Computing in Engineering

journal homepage: www.keaipublishing.com/en/journals/international-journal-of-cognitive-computing-in-engineering/

Integrating artificial intelligence and quantum computing: A systematic literature review of features and applications

Vanessa García Pineda [a], Alejandro Valencia-Arias [b], Francisco Eugenio López Giraldo [a,*], Edison Andrés Zapata-Ochoa [a]

[a] Facultad de Ingenierías, Departamento de Electrónica y Telecomunicaciones, Instituto Tecnológico Metropolitano 050013, Colombia
[b] Vice-Rector for Research and Postgraduate Studies, Universidad de Los Lagos, 5290000, Chile

ARTICLE INFO

Keywords:
System architecture
Quantum computing
Artificial intelligence
Machine learning
Quantum optimization

ABSTRACT

Quantum Computing (QC) and Artificial Intelligence (AI) have emerged as key technologies in the evolution of Industry 6.0, driving advancements in automation and advanced analytics, and process optimization. Their integration holds the potential to revolutionize sectors such as data science, healthcare, finance, and cybersecurity by enabling faster and more efficient computations through qubits, superposition, and quantum entanglement. However, the lack of structured knowledge regarding specific QC methodologies and applications in AI hinders its optimal implementation and development. Consequently, this study aims to identify the applications and variables associated with QC-AI integration. To this end, a systematic literature review was conducted following the PRISMA 2020 methodology, drawing on studies from Scopus and Web of Science databases. This enabled the analysis of trends, limitations, and opportunities in this technological convergence. This study aims to systematically examine the intersection of quantum computing and artificial intelligence by identifying the key technological features, integration requirements, and sectoral applications that define the current state of the field. The review contributes by mapping existing research, highlighting methodological approaches, and revealing gaps that may guide targeted advancements in hybrid quantum AI systems. The insights generated have the potential to accelerate innovation in high-impact domains such as healthcare, finance, energy, and cybersecurity. The findings indicate that the main advances in QC applied to AI focus on quantum optimization, Quantum Machine Learning (QML), and post-quantum cryptography. Notably, sectors such as energy, healthcare, and finance have shown significant progress in adopting these technologies. For example, in healthcare, QML has been applied to simulate molecular interactions to accelerate drug discovery, and in finance, it enhances predictive models for market behavior. The study concludes that although QC demonstrates substantial potential to enhance AI, its broader adoption remains constrained by reliance on NISQ hardware, the need for effective error correction, and the limited scalability of hybrid quantum classical algorithms. Addressing these challenges will be essential to establishing QML as a cornerstone of technological innovation and digital transformation. Additionally, this review introduces an integrative framework that categorizes key AI QC convergence dimensions and proposes a classification of application areas based on technical requirements and algorithmic capabilities. These contributions aim to guide future experimental validations and hybrid model development.

1. Introduction

Quantum Computing (QC) and Artificial Intelligence (AI) are disruptive technologies that play a key role in the transition from Industry 5.0 to 6.0 (Murugan & Prabadevi, 2025a). Their integration drives autonomous operations through robotics, Machine Learning (ML), the Industrial Internet of Things (IIoT), blockchain, and cloud computing (Damaševičius & Misra, 2024; Duggal et al., 2022; Murugan & Prabadevi, 2025b; Pathak et al., 2024; Reddy et al., 2024). QC leverages quantum phenomena such as superposition and entanglement,

Peer review under the responsibility of KeAi Communications Co., Ltd

* Corresponding author.
E-mail addresses: vanessagarciap@itm.edu.co (V.G. Pineda), javalenciar@gmail.com (A. Valencia-Arias), franciscolopez@itm.edu.co (F.E.L. Giraldo), edisonzapatao@itm.edu.co (E.A. Zapata-Ochoa).

https://doi.org/10.1016/j.ijcce.2025.08.002
Received 14 April 2025; Received in revised form 18 August 2025; Accepted 20 August 2025
Available online 21 August 2025

enabling the parallel processing of multiple possibilities and, in certain cases, achieving exponential speedups over classical systems (Nguyen et al., 2024; Baniata, 2024). However, these advantages are problem-specific and have been rigorously proven only for certain algorithms, such as Shor's and Grover's (Moret-Bonillo, 2015).

AI has transformed data analysis, process automation, and real-time decision-making through ML and Deep Learning (DL) algorithms (Acemoglu & Restrepo, 2018). When combined with QC, these capabilities are amplified, enabling faster and more accurate solutions in fields such as healthcare and finance. In healthcare, quantum AI accelerates drug discovery by optimizing molecular interaction predictions (Espuny et al., 2021), while in finance, QC and AI improve risk management and predictive analytics through quantum optimization techniques (Go et al., 2020). In IoT, this convergence strengthens cybersecurity and resource management by enabling efficient analysis of massive datasets (Rishiwal et al., 2025), while in energy it supports smart grid optimization, renewable integration, and CO_2 emission reduction (Asl et al., 2024; Woolnough et al., 2023).

The terminology distinguishes between Quantum Artificial Intelligence (QAI), encompassing all AI enhanced by QC, and Quantum Machine Learning (QML), which specifically applies quantum algorithms to machine learning tasks (Nguyen et al., 2024; Solenov et al., 2018). QAI exploits superposition and entanglement to optimize decision-making processes or simulate intelligent agents (Murugan & Prabadevi, 2025a), while QML adapts classical ML models to quantum frameworks, often on Noisy Intermediate-Scale Quantum (NISQ) devices using hybrid algorithms such as QSVM or variational classifiers (Iyer & Bakshi, 2024; Said, 2023). This conceptual distinction is essential for analyzing the scope and capabilities of each approach.

Despite significant progress, AI–QC integration faces critical limitations: dependence on NISQ hardware with high error rates, lack of standardized methodologies, and insufficient conceptual frameworks for articulating applications and technical requirements (Ghodke et al., 2024). Additional challenges include error correction, scalability, and the development of post-quantum cryptography to counter future threats (Ghodke et al., 2024). These constraints hinder large-scale adoption and limit the application of quantum AI to complex problem-solving in domains such as data science, cybersecurity, and resource optimization (Dai & Nahum, 2020; Han et al., 2024).

This study aims to identify QC applications and methodologies applied to AI and to assess their impact on process optimization and complex problem-solving. The contributions are threefold: (i) providing a structured synthesis and classification of literature on QC–AI integration under NISQ constraints, (ii) presenting sector-based examples that illustrate opportunities and use cases, and (iii) outlining a forward-looking research agenda to guide the use of QC in enhancing AI. To achieve this, the study follows the PRISMA 2020 guidelines for systematic literature reviews, analyzing recent publications indexed in Scopus and Web of Science. To achieve this objective, the study addresses five guiding questions:

1. What achievements have been made in the development of quantum computers?
2. What are the main technical requirements for integrating artificial intelligence and quantum computing?
3. How does quantum computing contribute to the optimization of artificial intelligence models and algorithms?
4. Which industries demonstrate the greatest progress or potential in the use of quantum artificial intelligence?
5. What are the primary cybersecurity challenges posed by the emergence of quantum computing and artificial intelligence in future societies?

To address these questions, this article begins with the introduction of the topic, followed by a methodology section based on a systematic literature review conducted in accordance with the PRISMA 2020 guidelines. The subsequent sections present and discuss the results, highlighting key findings and their relevance. Finally, the paper concludes with a synthesis of the implications and provides recommendations for future research in QC applied to AI.

2. Methodology

The PRISMA 2020 statement provides an updated standard for conducting systematic literature reviews, ensuring transparency, reproducibility, and scientific rigor in research synthesis. According to Page et al. (2021), this framework optimizes documentation at each stage from the identification of studies to their final inclusion by establishing clear guidelines to minimize bias and error. In this study, PRISMA 2020 is employed to identify and analyze applications and methodologies at the intersection of QC and AI, an interdisciplinary field that demands rigorous approaches to integrate high-quality and relevant studies. This methodological approach systematically structures the search, selection, and evaluation processes, yielding reliable results that contribute to knowledge development in this emerging field.

2.1. Eligibility criteria

Specific eligibility criteria were established to guarantee the quality and relevance of selected studies. The inclusion criteria considered exclusively recent academic publications addressing developments in QC applied to AI. This encompassed articles published within the last ten years, written in English, and available as full-text publications in indexed journals. Specifically, studies published between January 2014 and March 2024 were considered, ensuring a comprehensive and current view of developments in the field over the last decade. All selected studies needed to demonstrate clear focus on quantum techniques applied to ML or AI, ensuring their relevance within the research's interdisciplinary scope.

The exclusion process was conducted in three phases: In the initial phase, duplicate or misclassified studies were identified and eliminated to ensure that each selected paper contributed uniquely to the analysis. In the second phase, articles lacking full-text access were discarded, as their inclusion would compromise comprehensive evaluation of methods and results. In the third phase, a qualitative assessment was conducted based on thematic relevance and methodological rigor. This involved evaluating the titles, abstracts, and full texts, prioritizing studies with novel and significant contributions to the field. Articles exhibiting insufficient methodological detail, weak results, or approaches misaligned with current trends in QC and AI were excluded. This approach enabled consolidation of a scientifically robust and thematically relevant body of literature for analysis.

2.2. Sources of information

The Scopus and Web of Science databases were selected for this study due to their extensive indexing of high-impact scientific research and multidisciplinary coverage. Both platforms incorporate relevant publications across technology, computing, and AI domains, making them essential resources for identifying advancements at the intersection of QC and AI.

Scopus is one of the most comprehensive databases, covering scientific, technical, medical, social, and humanities research. Its continuous updating and focus on indexing high-impact journals render it especially suitable for analyzing dynamic fields such as QC. Similarly, Web of Science is known for its rigorous selection of scientific journals, ensuring the inclusion of premium-quality papers. Additionally, it offers advanced bibliometric analysis tools to assess the influence and relevance of selected publications.

As highlighted by Mongeon and Paul-Hus (2016), Scopus and Web of Science function as complementary resources. While Scopus offers broader coverage in terms of publication volume, Web of Science prioritizes journals maintaining stricter standards and higher impact factors. These complementary characteristics ensure that combined use of both platforms effectively captures significant trends and developments at the QC–AI intersection.

On the other hand, to ensure methodological rigor and data reliability, this review limited its database selection to Scopus and Web of Science. These databases are widely recognized for their high impact factor coverage, robust indexing standards, and advanced bibliometric tools, ensuring high-quality and peer-reviewed sources relevant to the interdisciplinary domain of quantum computing and artificial intelligence (Agarwal et al., 2022; Murugan & Prabadevi, 2025a; Radanliev, 2025; Sotirelis & Grigoroudis, 2021). While other databases such as IEEE Xplore or PubMed offer relevant insights in technical or biomedical domains, they were excluded to maintain consistency in source quality and to prevent duplication during bibliometric synthesis. Additionally, inclusion of Google Scholar was avoided due to its lower selectivity and variable source credibility (Mongeon & Paul-Hus, 2016; Pranckutė, 2021). Future research may expand this scope to encompass broader repositories once quality filters and structured deduplication strategies are validated.

2.3. Search strategy

To identify relevant records, specific search strings were constructed for each database, aligned with the study inclusion criteria. These search strings incorporated Boolean operators such as AND and OR, along with carefully selected key terms, to target publications focusing on quantum techniques applied to ML and AI.

The search string used in **Scopus** was `TITLE("quantum comput*" AND ("machine learning" OR "artificial intelligence"))`, which limited the search to article titles to prioritize directly relevant studies. The string employed in **Web of Science** was adapted to the platform-specific syntax as `TS=("quantum comput*" AND ("machine learning" OR "artificial intelligence"))`.

The search process was refined by iteratively revising the initial results. Ambiguous terms were eliminated, and Boolean operators were modified to maximize precision and relevance in study selection. These adjustments ensured consistency across both databases while maintaining strict alignment with the inclusion criteria.

2.4. Selection process

The selection process involved three stages. In the first stage, duplicate studies were identified and removed using automated tools to ensure that each retained record represented a unique contribution. In the second stage, a pre-selection was carried out by reviewing titles and abstracts for compliance with the inclusion criteria. In the third stage, the full texts of the pre-selected articles were reviewed in depth to assess their thematic relevance and methodological quality.

Each stage of the selection process was documented in accordance with the PRISMA 2020 guidelines, systematically recording the number of studies identified, excluded, and ultimately included. This rigorous process guaranteed transparency and reproducibility. This selection process is summarized and visually structured through the PRISMA flow

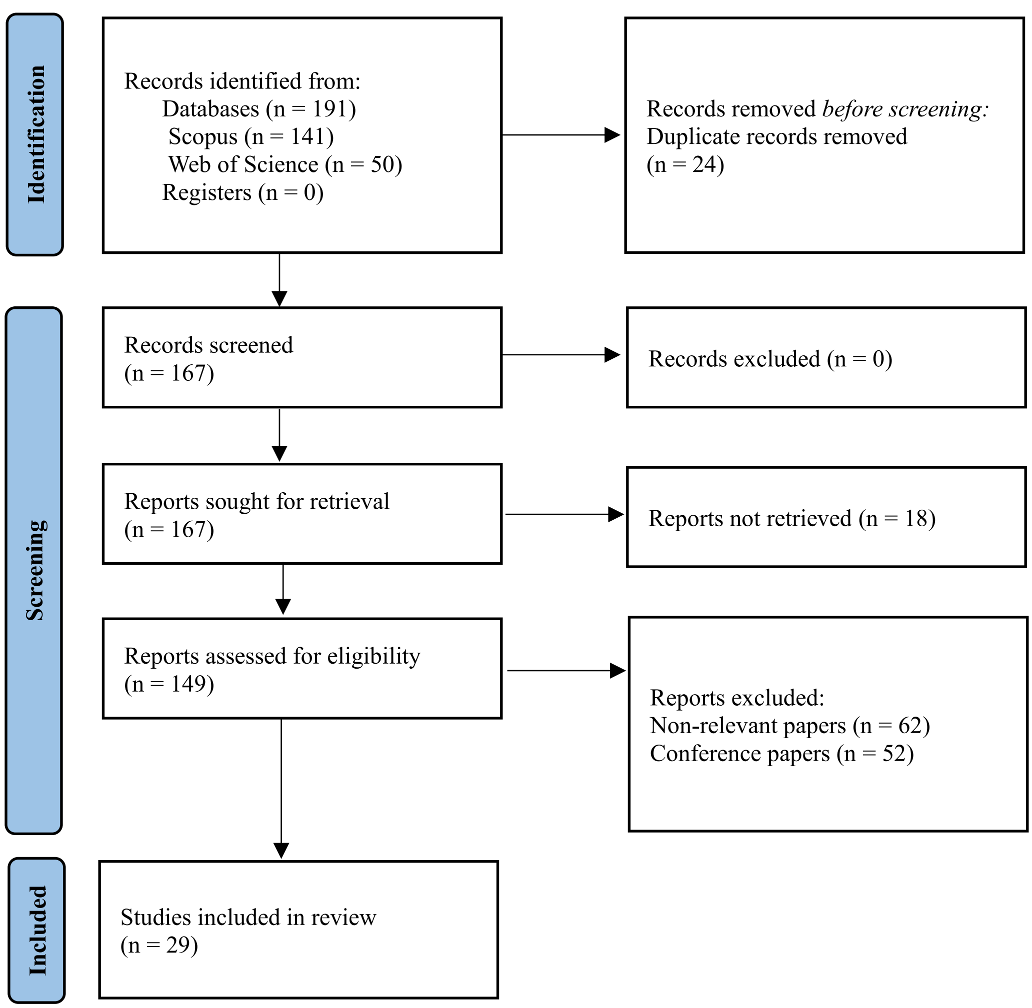

Fig. 1. PRISMA Flow diagram. Own work based on data from Scopus and Web of Science.

diagram (Fig. 1), which details the steps taken from initial identification through to final inclusion.

To ensure the robustness of the selected studies, the quality assessment process extended beyond thematic relevance. A set of methodological rigor criteria were applied in the final phase of selection, where studies were included only if they presented transparent methodological designs, peer-reviewed validation, and reproducible outcomes aligned with the PRISMA 2020 framework (Haddaway et al., 2022; Page, McKenzie, Bossuyt, Boutron, Hoffmann, Mulrow, Shamseer, Tetzlaff & Moher, 2021). Additionally, novelty was evaluated by prioritizing studies that introduced innovative applications, hybrid quantum–classical frameworks, or optimization schemes applied in practical sectors such as energy, cybersecurity, or healthcare (Kishor, 2023; Shrivastava et al., 2024).

Furthermore, studies were considered high-quality if they demonstrated implementation or simulation results on real or emulated quantum devices (e.g., IBM Q, IonQ), as shown by Martina et al. (2022), and if they incorporated machine learning-based optimization schemes, such as reverse engineering or QUBO formulations (Castaldo et al., 2021; Mao et al., 2023). This approach ensured the inclusion of technically rigorous and conceptually novel literature, reinforcing the scientific credibility and relevance of the synthesis.

2.5. Data processing

Microsoft Excel served as the primary tool for managing and analyzing the collected data. The selected references were recorded in a spreadsheet, with variables including authors, year of publication, methodology employed, and main findings. This facilitated the organization and classification of studies by thematic and methodological relevance, enabling the identification of patterns and trends within the analyzed data. Excel was also used to generate graphs and tables, providing clear and concise visualization of the research findings. This approach ensured efficient, accurate, and transparent data processing throughout the study.

2.6. Risk of bias

The risk of bias in the selected studies was assessed through careful consideration of methodological rigor, results transparency, and possible author conflicts of interest. Biases inherent in the use of specific databases and search terms were also acknowledged, as they may limit the diversity and comprehensiveness of the studies retrieved. Additionally, reporting bias was considered, recognizing that some relevant studies might remain unpublished due to negative or inconclusive results. To mitigate these risks, strict selection and analysis criteria were applied, ensuring alignment between the research objectives and the included studies. This approach reinforced the integrity and reliability of the findings.

With the selected studies established through this rigorous process, the following section presents the results derived from their analysis, organized according to the research questions posed.

3. Results

The results of this study are organized according to the research questions to ensure a clear and structured presentation of the findings. The following subsections explore developments in QC, the main technical requirements for integrating AI and QC, the contribution of these technologies to algorithm and model optimization, the sectors with the greatest potential in QAI applications, and the cybersecurity challenges associated with these technologies. Table 1 presents the studies selected for detailed analysis, providing the foundation for the discussion and conclusions. It outlines each study's methodology, country of origin, application sector, and variables addressed.

Quantum AI (QAI) has demonstrated significant advancements across diverse sectors. In autonomous systems, variational quantum algorithms enable real-time optimization of route planning under uncertainty, reducing energy use and latency in self-driving vehicles (Lappala, 2024). In healthcare, QAI accelerates drug discovery and diagnostics by simulating molecular interactions with high precision; studies show quantum-enhanced simulations improve drug target interaction predictions and optimize medical imaging protocols (Espuny et al., 2021; Subrahmanian et al., 2022; Shrivastava et al., 2024). Hybrid quantum classical models have also unveiled new chemical properties and reduced simulation cycles in preclinical research (Liu, 2024). In cybersecurity, quantum support vector machines (QSVM) improve DDoS attack detection sensitivity (Said, 2023), while quantum key distribution integrated with ML strengthens critical communications security (Kishor, 2023). Finance benefits from quantum optimization in portfolio selection, enabling rapid evaluation of vast investment scenarios (Go et al., 2020; Marshall et al., 2022). Additionally, quantum simulations of perovskite quantum dots offer tunable optoelectronic properties for photonics and quantum communications (Kishor, 2023).

The feature distribution in QC research emphasizes quantum simulations (10 mentions), hybrid quantum–classical algorithms, and NISQ architectures (8 mentions each), followed by quantum circuit compilation and noise resilience. Quantum simulations are central for modeling complex quantum phenomena in chemistry and materials science, while NISQ devices face limitations due to noise and decoherence (Kusyk et al., 2021). Hybrid approaches, such as the Variational Quantum Eigensolver (VQE), bridge quantum and classical computing to address these constraints (Perdomo-Ortiz et al., 2018). Noise mitigation strategies, including zero-noise extrapolation and AI driven error correction, enhance qubit coherence and computational stability (Schuhmacher et al., 2022; Abdelgaber & Nikolopoulos, 2020). Although less frequent, photonic processors, generative models, and quantum annealing highlight niche but promising research areas.

Publication trends from 2017 to 2023 reveal a growing global focus on practical quantum algorithms and hybrid models, especially post 2019, driven by advancements in NISQ hardware and accessible quantum simulators (Usman et al., 2020; Wu et al., 2021). This growth aligns with expanding applications in high-complexity domains, from logistics optimization to large-scale biomedical data analysis. However, persistent technical challenges such as scalability, error correction, and efficient data encoding limit widespread adoption. The integration of AI into QC, particularly through hybrid frameworks, remains a promising pathway to overcome these barriers, with future research expected to deepen sector specific implementations in areas like drug discovery, secure communications, and sustainable energy systems Fig. 2.

The analysis of Fig. 3 shows that the most frequent technical requirements for AI QC integration are neural network integration (11 mentions), machine learning integration, and hybrid quantum classical approaches (10 each), followed by efficient encoding techniques and error mitigation (5 each), with less frequent needs such as data embedding strategies, quantum hardware, and scalable frameworks (3 each), and rare mentions of qubit connectivity, gate noise reduction, and blockchain integration (1 each). Neural network ML integration leverages quantum parallelism and superposition to enhance classification and prediction (Nguyen et al., 2024), while efficient encoding and error mitigation improve computational fidelity for applications in biomedicine and cryptography (Solenov et al., 2018), and data embedding optimizes quantum state representation for QAI algorithms (Abdelgaber & Nikolopoulos, 2020). Hardware scalability and qubit connectivity are critical for complex algorithm execution (Cherbal et al., 2024), and hybrid approaches enable efficient training of AI models for tasks like molecular simulation. Sector-wise, QML applications stand out in healthcare, finance, and cybersecurity, supporting drug discovery through improved molecular simulations (Espuny et al., 2021), portfolio management via quantum optimization (Si Mohammed et al., 2024), and the development of post-quantum cryptography to address emerging encryption threats.

Table 1
Studies included in the review. Own work based on data from Scopus and Web of Science.

Title	Country	Methodology	Sector	Studied variables	Reference
Application of quantum machine learning using the quantum variational classifier method to high energy physics analysis at the LHC on IBM quantum computer simulator and hardware with 10 qubits	USA (with international collaborations: University of Wisconsin, CERN, Fermilab, etc.)	Experimental implementation and benchmarking of the quantum variational classifier; comparison with classical methods (SVM, BDT)	High-energy physics	Quantum variational classifier, data encoding, signal–background discrimination, QML vs. CML comparison, performance evaluation and optimization	Wu et al. (2021)
Can artificial intelligence benefit from quantum computing?	Spain (University of La Coruña)	Conceptual and comparative review; analysis of theoretical foundations and potential applications in AI and QC	AI–QC intersection	Conceptual framework, energy efficiency, reversible computing, AI–QC synergies, theoretical perspectives	Moret-Bonillo (2015)
Entanglement-based machine learning on a quantum computer	China (University of Science and Technology of China)	Experimental demonstration on quantum platform; implementation of entanglement-based quantum circuits for ML tasks	QML, quantum information processing	Entanglement-based algorithms, experimental implementation, circuit fidelity, comparison with classical models	Cai et al. (2015)
Extending the reach of quantum computing for materials science with machine learning potentials	Switzerland / USA / UK	Development of ML potentials from quantum simulation data; error analysis and predictive model training	Materials science	ML potentials, quantum simulation error/noise, QC–ML integration, molecular dynamics optimization	Schuhmacher et al. (2022)
Fitting a collider in a quantum computer: tackling the challenges of quantum machine learning for big datasets	Portugal (University of Minho) / UK	Experimental benchmark comparing QML and classical methods; feature selection and grid search applied to high-energy data	High-energy physics	Feature selection, event classification, QML algorithm performance in HEP, large dataset handling	Peixoto et al. (2022)
Framework for atomic-level characterisation of quantum computer arrays by machine learning	Australia (University of Melbourne, with international collaborations)	Theoretical development supported by large-scale STM image simulations, using CNNs for atomic-level characterization	Qubit Characterization in quantum devices (Atomic metrology and materials)	STM image analysis, DL, atomic precision, dopant identification, defect modeling	Usman et al. (2020)
Harvesting Chemical Understanding with Machine Learning and Quantum Computers	Not specified	Perspective article reviewing how ML and QC can transform chemical understanding; qualitative analysis and forecasting	Theoretical and computational chemistry; chemical modeling and simulation	ML vs. QC paradigms, Schrödinger equation solutions, hierarchical modeling, impact on traditional chemical concepts	Liu (2024)
High Dimensional Quantum Machine Learning With Small Quantum Computers	Netherlands (Leiden) / Switzerland	Development and simulation of QML models using variational circuits; experimentation on QC simulators	General QML applications	Circuit partitioning, variational quantum circuits, dimensionality reduction, circuit optimization	Marshall et al. (2022)
High-fidelity control of spin ensemble dynamics via artificial intelligence: from quantum computing to NMR spectroscopy and imaging	USA (University of Minnesota, Mayo Clinic)	Experimental study using evolutionary algorithms and AI to design optimized RF pulses with inhomogeneity compensation; validation in NMR and MRI experiments	Healthcare; spectroscopy and imaging (NMR, MRI, control of spin)	Quantum control, evolutionary algorithms, RF pulse optimization, design of experiments, inhomogeneity compensation	Subrahmanian et al. (2022)
Hybrid Entanglement Distribution between Remote Microwave Quantum Computers Empowered by Machine Learning	USA (University of Arizona, USC)	Theoretical proposal and simulation; development of a hybrid CV–DV protocol for entanglement distribution with ML optimization	Quantum computer connectivity (microwave QC)	Entanglement distribution, hybrid CV–DV protocol, microwave-optical transduction, ML optimization, superconductor integration	Zhang et al. (2022)
Implementation of Quantum Machine Learning for Electronic Structure Calculations of Periodic Systems on Quantum Computing Devices	USA	Hybrid quantum–classical approach using restricted Boltzmann machines and IBM-Q simulations to calculate the electronic structure of periodic systems	Materials science; computational chemistry (calculation of electronic structures)	Hybrid quantum–classical algorithms, ML potentials, electronic calculations, quantum device benchmarking	Sureshbabu et al. (2021)
Machine learning and quantum computing for reactive turbulence modeling and simulation	USA (University of Pittsburgh)	Perspective and review article discussing potential ML and QC applications in reactive turbulence modeling using limited data	Mechanical engineering; combustion and turbulence	Turbulence modeling, ML in fluid dynamics, QC integration for simulations, data and scalability challenges	Givi (2021)
Machine learning method for state preparation and gate synthesis on photonic quantum computers	Canada	Hybrid quantum–classical algorithm; photonic circuit optimization using ML methods (including genetic algorithms)	QC; photonics	State preparation, gate synthesis, circuit optimization, hybrid quantum–classical algorithms, ML for QC optimization	Arrazola et al. (2019)
Machine-learning-inspired quantum optimal control of nonadiabatic geometric quantum computation via reverse engineering	China	Quantum control optimization using neural networks with periodic feature enhancement (reverse engineering)	QC; quantum technology	Nonadiabatic quantum control, geometric computation, ML optimization, reverse engineering, noise robustness	Mao et al. (2023)
Noise fingerprints in quantum computers: Machine learning software tools[Formula presented]	Italy / Portugal	Development of a hybrid ML software for classifying noise fingerprints in quantum devices; reproducible validated approach	QC; noise characterization	Noise classification, ML (SVM etc.), software tool integration, noise analysis in NISQ devices, impact of noise on QC	Martina et al. (2022)

(continued on next page)

Table 1 (*continued*)

Title	Country	Methodology	Sector	Studied variables	Reference
Noise-robust optimization of quantum machine learning models for polymer properties using a simulator and validated on the IonQ quantum computer	Japan (Asahi Kasei Corporation)	Hybrid quantum–classical approach; robust optimization using the SGD method and the parameter-shift rule, validated on IonQ device	Computer materials; polymer property prediction	Robust optimization in NISQ device, regression for polymer properties, noise mitigation, hybrid quantum–classical algorithms	Ishiyama et al. (2022)
Nuclear Physics in the Era of Quantum Computing and Quantum Machine Learning	Spain	Critical review (perspective) of QC and QML applications in nuclear physics; qualitative discussion	Nuclear physics	Nuclear models, quantum simulation, QML in nuclear physics, particle identification and classification, QML in nuclear experiments	García-Ramos et al. (2024)
Opportunities and challenges for quantum-assisted machine learning in near-term quantum computers	USA and UK (NASA, UCL, Cambridge Quantum Computing Limited, etc.)	Perspective and review article analyzing QAML opportunities and challenges in NISQ devices; hybrid approaches and unsupervised ML applications	General ML applications in QC with a focus on complex ML tasks (generative models)	QAML, hybrid approaches, scalability, data challenges, barren plateau optimization and suppression	Perdomo-Ortiz et al. (2018)
Quantum computation with machine-learning-controlled quantum stuff	Canada (Perimeter Institute for Theoretical Physics)	Theoretical study proposing a conceptual framework and an ML algorithm to optimize the control of quantum stuff and thereby implement QC; formulation of the optimization as an ML problem	QC; quantum control and optimization; theoretical foundations	Quantum control, ML-based optimization, quantum tomography, hybrid quantum–classical algorithms, conceptual formulation	Hardy and Lewis (2020)
Quantum computer-based feature selection in machine learning	Germany (DHBW Stuttgart, DHBW Ravensburg, Fraunhofer, Freiburg)	Reformulation of the feature selection problem as a QUBO problem; comparison of quantum (annealing, gate-based QAOA) and classical optimization methods; small dataset experiments	ML applied to feature selection problems in supervised learning	Feature selection, QUBO formulation, quantum vs. classical optimization, algorithm convergence	Hellstern et al. (2024)
Quantum Computing and Healthcare: Drug Discovery and Molecular Simulation with Machine Learning	India	Systematic literature review and secondary data synthesis; descriptive and deductive approach	Healthcare; Pharmaceutical	AI–QC integration, molecular simulation, integration frameworks, ethical considerations	Shrivastava et al. (2024)
Quantum computing and machine learning for Arabic language sentiment classification in social media	Egypt (Minia University, Deraya University)	Comparative experimental study; evaluation of quantum and classical algorithms (e.g., Random Forest) for sentiment analysis	Natural language processing (Arabic document classification)	Sentiment analysis, quantum vs. classical algorithms, classification metrics, processing efficiency	Omar and Abd El-Hafeez (2023)
Quantum Computing and Machine Learning for Cybersecurity: Distributed Denial of Service (DDoS) Attack Detection on Smart Micro-Grid	Canada	Implementation of a Quantum Support Vector Machine (QSVM) model integrating QC and ML for DDoS detection	Energy (smart micro-grid) and cybersecurity	Cybersecurity, DDoS attack detection, ML, QC, smart grid applications	Said (2023)
Quantum Machine Learning: Bridging The Gap Between Classical and Quantum Computing	Not specified	Literature review and conceptual analysis	Information technology; QC	ML integration in QC, hybrid quantum–classical algorithms, quantum simulation	Ghodke et al. (2024)
Quantum optimal control with quantum computers: A hybrid quantum–classical algorithm featuring machine learning optimization	Italy	Hybrid quantum–classical algorithms; ML-based optimization	Quantum technology; computational chemistry	QC, optimal control, optimization	Castaldo et al. (2021)
Review and significance of cryptography and machine learning in quantum computing	India (ABES Institute of Technology)	Critical review; literature synthesis on cryptography, ML, and QC	Information security; post-quantum cryptography	Cryptography–ML integration, QC strategies, risk–benefit analysis, systematic review	Kishor (2023)
Security in internet of things: a review on approaches based on blockchain, machine learning, cryptography, and quantum computing	Not specified	Systematic comparative literature review on IoT security	IoT security	IoT security, blockchain, ML, cryptography, QC, solution taxonomy	Cherbal et al. (2024)
Survey on Quantum Circuit Compilation for Noisy Intermediate-Scale Quantum Computers: Artificial Intelligence to Heuristics	USA (New York City College of Technology, City College of the City University of New York)	Systematic review analyzing quantum circuit compilation methods for NISQ devices (AI and heuristic techniques)	Quantum circuit compilation in NISQ devices	Circuit mapping, optimization, AI-based methods (genetic algorithms, graph optimization), hardware limitations	Kusyk et al. (2021)
The Potential of Quantum Computing and Machine Learning to Advance Clinical Research and Change the Practice of Medicine	USA (Saint Louis University)	Perspective review with clinical case study; discussion of potential diagnostic and therapeutic applications; narrative based on practical examples	Clinical research and medical practice (diagnosis, treatment, medical data security)	Clinical applications, medical imaging, early diagnosis, quantum encryption, healthcare transformation	Solenov et al. (2018)

The analysis of the reviewed studies (Fig. 4) evidences that Quantum AI significantly enhances model optimization, with the most recurrent advances in predictive models (11 mentions), molecular simulations (9 mentions), and both noise-resilient optimization and gate implementation (8 mentions each). Predictive models integrate AI's data-driven techniques, such as neural networks or logistic regression, with QC's ability to estimate quantum electronic states more accurately than classical methods (Iyengar et al., 2024), while in molecular

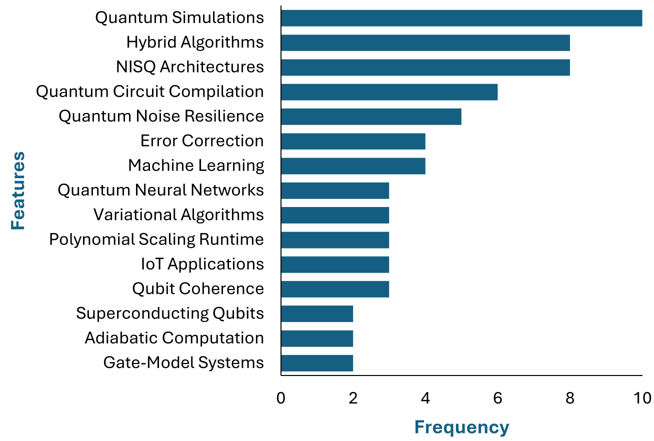

Fig. 2. Frequency of features in the development of quantum computers. Own work based on data from Scopus and Web of Science.

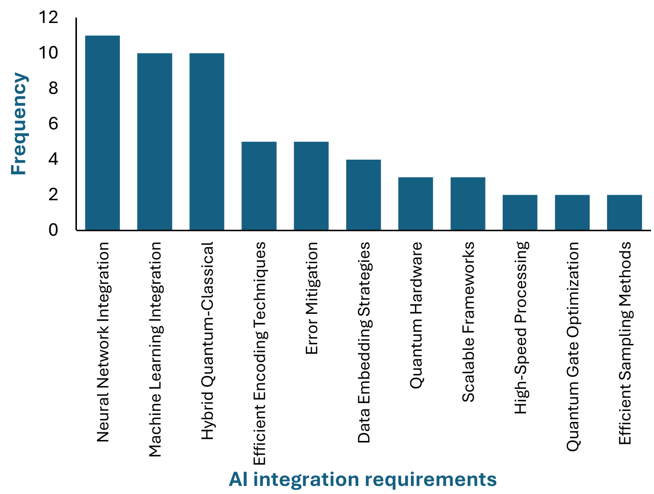

Fig. 3. Frequency of technical requirements for AI–QC integration. Own work based on data from Scopus and Web of Science.

simulations, Machine Learning Potentials enable stable long-timescale dynamics (Schuhmacher et al., 2022). Noise resilient optimization mitigates decoherence and circuit imperfections, improving algorithms like VQE, and gate implementation focuses on error correction to increase fidelity (Gyongyosi, 2020). Advances in real-time processing (5 mentions) stem from ML-based dynamic calibration of quantum circuits, which enhances noise resilience and hardware performance (Wichert, 2016). Less frequent contributions include tree search optimization, pattern recognition, network optimization, feature selection, security protocols, resource allocation, cancer diagnostics (2 mentions each), and isolated cases of signal discrimination, data compression, decision-making, and drug discovery (1 mention each), reflecting a research landscape where high-impact areas coexist with emerging, niche applications.

In terms of the geographical distribution of studies on QAI applications, As shown in Fig. 5, the United States leads the publication count in the area of quantum AI applications, followed by Portugal, Italy, the United Kingdom, and Canada with three studies each. For their part, Switzerland, Spain, China, Egypt, Germany, and India have two studies each. Russia, the Netherlands, Poland, Japan, Colombia, and Malaysia report one study each. This indicates that, while participation is global, there is a strong concentration of QAI research in North America and some regions of Europe and Asia.

The leading contributions from the U.S., China, and EU countries indicate the geographical concentration of quantum R&D funding and infrastructure. The U.S., for example, benefits from joint academic–industry initiatives (e.g., IBM, Google, and NASA's Quantum AI Lab). Meanwhile, contributions from institutions in Italy, Russia, and Latin America reveal emerging regional interest, often centered on experimental simulators or conceptual frameworks (Wichert, 2016).

The results also highlight the main challenges in quantum cybersecurity. Fig. 6 summarizes the most frequently discussed cybersecurity challenges in quantum AI, highlighting noise resilience and scalability issues. The most frequent categories are noise resilience (9 mentions), scalability challenges (8 mentions), and noise mitigation (6 mentions). Other major challenges include data security, error correction, and decoherence issues (4 mentions each). Categories with slightly lower frequencies include measurement errors, standardized architectures, control parameter noise, hybrid protocol noise, and hardware limitations (3 mentions each). Less frequent but still relevant challenges are quantum-resistant encryption, qubit connectivity, and quantum key distribution (2 mentions each), while photonic system imperfections, quantum programming complexity, and IoT cybersecurity are the least

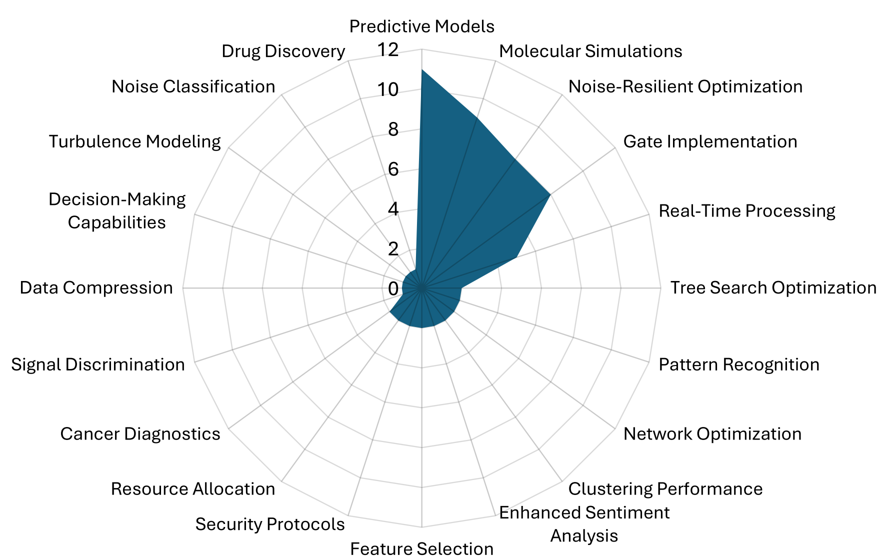

Fig. 4. Contributions of quantum AI to model optimization. Own work based on data from Scopus and Web of Science.

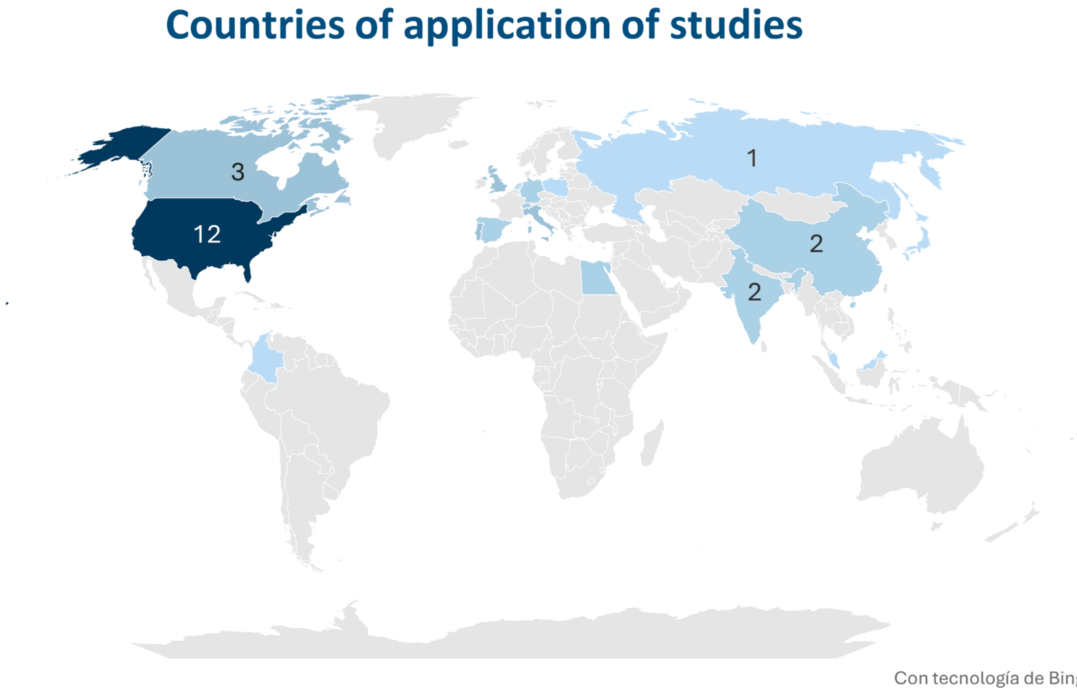

Fig. 5. Countries of application of QAI studies. Own work based on data from Scopus and Web of Science.

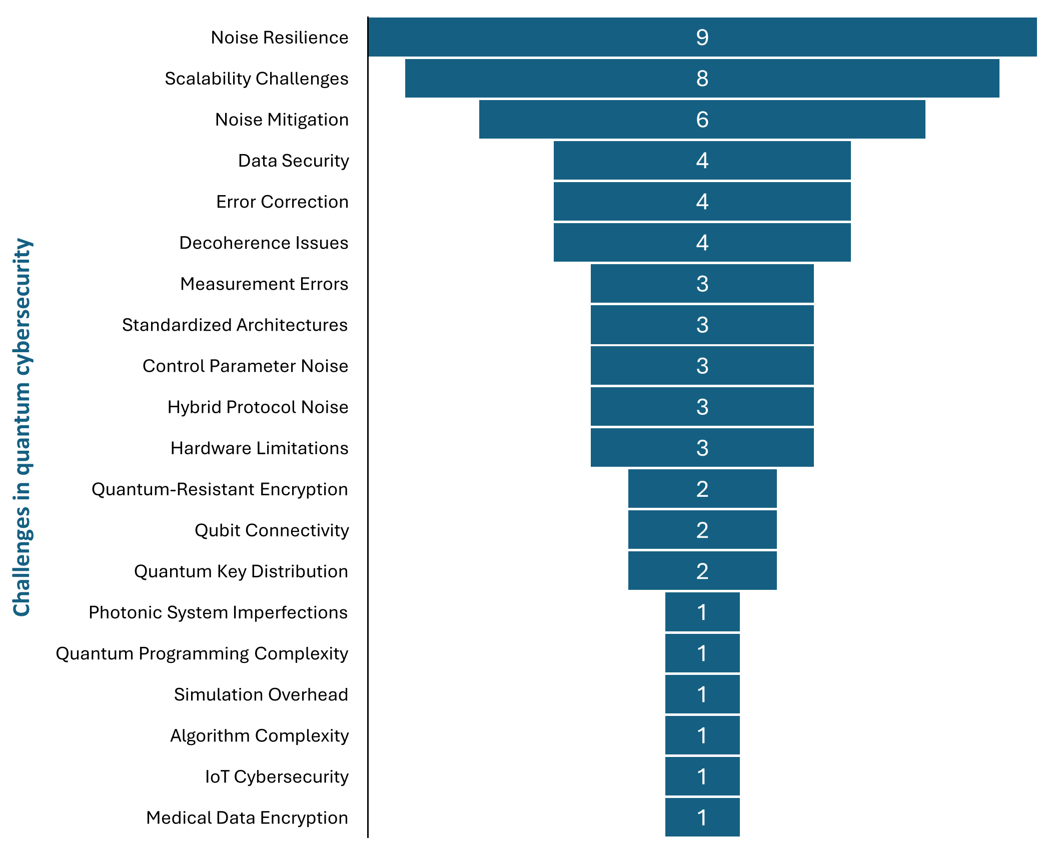

Fig. 6. Challenges in quantum cybersecurity. Own work based on data from Scopus and Web of Science.

frequent (1 mention each).

The most frequently cited limitations scalability, NISQ hardware constraints, and lack of error correction are consistent with findings in the literature. As emphasized by Baniata (2024) and Ghodke et al. (2024), these technical barriers hinder the deployment of fully quantum models and necessitate hybrid quantum–classical architectures for practical implementations. Moreover, limitations in quantum data encoding and quantum RAM (QRAM) underscore the need for infrastructure co-development alongside algorithmic innovation.

The findings discussed in the previous section underscore the relevance of quantum AI integration across diverse sectors. Based on these insights, the next section synthesizes the implications and outlines recommendations for future research.

4. Discussion

This section contextualizes and analyzes the findings related to the applications and methodologies of QC in AI. It begins by examining the results obtained, identifying emerging trends, current challenges, and research opportunities. These findings are then compared with existing literature to highlight points of convergence and divergence, as well as potential underlying causes. Based on the results, a conceptual framework is proposed that synthesizes the essential components for integrating QC into AI, offering a structured foundation for future research and applications. Theoretical, policy-related, and practical implications are discussed next, considering their relevance for academic research, policymaking, and industry implementation. Finally, the limitations of this study both methodological and technological are addressed, and avenues for future research are suggested.

4.1. Analysis of results

The results show a diverse range of methodologies and applications in QC, with notable advances in quantum simulations, hybrid quantum–classical algorithms, and NISQ architectures. These align with the expansion of digital technologies, AI, and QC, and with García-Ramos et al. (2024) on the early development of quantum simulations and QML in nuclear physics. However, the limited presence of quantum annealing and generative models reflects methodological and technical constraints that call for future research to enhance scalability and efficiency. While progress in NISQ devices is significant, Preskill (2025) notes that they still lack the error correction needed for practical applications, and Harrow et al. (2023) warn that "quantum advantage" claims require rigorous benchmarking against classical algorithms. Similarly, Huang et al. (2020) critiques early supremacy demonstrations like Google's Sycamore, emphasizing their limited practical utility, while Gyongyosi and Imre (2020) and Harrow and Lowe (2025) highlight hardware limitations in coherence time, gate fidelity, and interconnectivity.

The study identifies a variety of technical requirements for AI–QC integration, particularly neural networks, ML techniques, and hybrid approaches, consistent with Hardy and Lewis (2020) on quantum circuit optimization on scalability challenges in wireless networks. Less frequent elements, such as gate noise reduction and blockchain integration, reveal unresolved issues and research opportunities. Blockchain is increasingly relevant in QAI architectures to secure distributed quantum data processing pipelines vulnerable to adversarial and quantum attacks (Kishor, 2023). In infrastructures such as energy grids, blockchain ensures integrity and provenance in QML-based cybersecurity tasks, including DDoS detection (Said, 2023).

QAI's contributions to model optimization are particularly evident in predictive modeling, molecular simulations, and noise-resilient optimization. For example, Givi (2021) demonstrates the synergy of QC and ML in simulating turbulent reactive flows, and He et al. (2024) highlight applications in computational chemistry for solving the Schrödinger equation. While these areas are advancing rapidly, applications like signal detection and drug discovery appear less frequently, suggesting technical limitations that must be addressed for broader adoption.

Geographically, QAI research is concentrated in North America and Europe, with the United States leading scientific production (He et al., 2024). Countries such as Portugal, Italy, and the United Kingdom also show strong activity, while emerging regions participate less, reflecting infrastructure and funding gaps. Wichert (2016) underscores the potential of QC in symbolic AI, which could expand research into new regions. The limited representation of countries like Colombia and Malaysia highlights the need for stronger international collaboration to bridge disparities in quantum technological development.

Key challenges in quantum cybersecurity include noise resilience, scalability, and error mitigation. Subrahmanian et al. (2022) stress controlling spin dynamics to improve quantum operation fidelity, while Nguyen et al. (2024) and Ishiyama et al. (2022) emphasize that noise in QKD can increase error rates and system vulnerability. Scalability limitations, as discussed by Cherbal et al. (2024) and Nguyen et al. (2024), hinder the deployment of large-scale secure quantum networks, leaving them exposed to bottleneck and side-channel attacks. Addressing these vulnerabilities will require layered, hybrid safeguards and robust error correction to ensure security in practical quantum–classical architectures.

Moret-Bonillo (2015) examines the relationship between AI and QC, emphasizing energy efficiency and processing speed as critical aspects. The low presence of topics such as quantum IoT and quantum-resistant cryptography indicates the need for further research in these areas. Data security and error correction remain key challenges, requiring progress in standardized architectures and optimization of inter-qubit connectivity Table 2 summarizes the main AI applications in QC currently under study. Each application is associated with relevant tools, quantum aspects, technical requirements, and AI techniques described in various studies.

The proposed workflow for AI and QC integration, including preprocessing, hybrid optimization, and final application, is depicted in Fig. 7. Based on the above, Fig. 7 illustrates the general workflow and proposed operational model for integrating AI with QC, from input data to final application. The AI+QC operational model is structured as a sequence of interconnected processes that facilitate the synergy between both fields. In the initial stage, data requirements are identified, which may include structured data (e.g., tables, databases) or unstructured data (e.g., text, images, biomedical signals). In certain cases, these may involve quantum big data to represent information more efficiently in Hilbert space (Perdomo-Ortiz et al., 2018). This data must then undergo quantum preprocessing, in which quantum encoding techniques are applied to transform classical information into quantum states that can be exploited by QML algorithms (Hellstern et al., 2024).

In the second stage of the model, AI+QC optimization is performed to accelerate computations using hybrid quantum–classical algorithms such as QAOA, QSVM, and Quantum Generative Adversarial Networks (QGANs) (Mao et al., 2023). These algorithms enable tasks such as classification, combinatorial optimization, and synthetic data generation, playing a crucial role in applications like post-quantum cryptography, fraud detection, and predictive analysis in financial markets. Executing these processes requires appropriate quantum architectures, which may consist of NISQ quantum computers, superconducting qubits, or quantum photonics systems (Castaldo et al., 2021).

Subsequently, the processed information is applied in AI+QC solutions across key sectors such as biomedicine, logistics optimization, natural language processing, and cybersecurity. These developments enable, for instance, more accurate quantum simulations for drug discovery, optimized routing in logistics and transportation, enhanced quantum encryption systems, and the creation of more efficient AI models for processing large-scale datasets (Wichert, 2016).

4.2. Comparison of results

The relationship between quantum computing (QC) and artificial intelligence (AI) presents significant opportunities and challenges, with confirmed advances in predictive models, molecular simulations, and noise-resilient optimization, as well as improvements in cybersecurity and large-scale data processing (Kishor, 2024; Dunjko & Briegel, 2018; Singh & Kumar, 2024). These findings align with studies highlighting the synergy between ML and QC in pattern detection, resource optimization, and data allocation (Krenn et al., 2023), although notable differences emerge, such as the still nascent application in IoT (Cherbal et al., 2024) and the technical barriers to adopting quantum-resistant cryptography. Despite the transition from theoretical proposals to

Table 2
Key advances in AI and QC applications across different contexts. Own work based on data from Scopus and Web of Science.

Application	Description	Tools	QC contribution	Technical requirements	AI techniques	Reference
Autonomous systems	AI–QC integration to enhance autonomous industrial operations, with a focus on the digital transformation of the oil and gas sectors.	Quantum reinforcement learning; TensorFlow Quantum	Quantum optimization for autonomous operation planning and execution	Autonomous control systems integrated with quantum hardware and advanced sensors	Reinforcement learning and probabilistic models for real-time decision making	Duarte and Deville (2024); Jayan and Babu (2025); K et al. (2024)
Healthcare	Use of QC and ML to simulate molecular and biomolecular interactions and accelerate drug discovery.	IBM Qiskit; D-Wave; TensorFlow Quantum; integration frameworks	Quantum state simulation for modeling molecular interactions	High-performance quantum hardware for chemical and biomolecular simulations	Deep neural networks; supervised and unsupervised learning	Jeyalakshmi et al. (2024); Pujahari et al. (2025); Sangeetha et al. (2024)
Cybersecurity	Application of AI and QC to enhance cyberattack detection/response (including DDoS) and implement advanced security protocols.	Quantum key distribution; QSVM; post-quantum algorithms	Encryption and security protocols based on quantum mechanics principles	Secure network infrastructure with quantum processing capability	ML for anomaly detection; DL for pattern analysis	Rodriguez (2025)
Cryptography	Development of quantum-resistant encryption techniques combining traditional methods with ML to enhance communication security.	Post-quantum cryptography frameworks; entanglement-based algorithms	Quantum entanglement for secure key generation and encryption protocols	Secure communication infrastructure supporting quantum hardware	Generative adversarial networks; pattern analysis for security protocol evaluation	Cherbal et al. (2024); Kishor (2023); Radanliev (2025)
Bioinformatics	Early cancer cell detection via optical biosensors and EEG signal analysis for brain monitoring, combining ML with QC.	Optical biosensors; Lasso regression; Bayesian neural networks; adversarial convolutional architectures and federated neural networks for EEG	Quantum optimization for biomedical and neurophysiological data processing	Biomedical imaging and neurophysiological signal processing platforms integrated with QC	DL for classification, feature selection, and pattern analysis in biomedical data	Murugan and Prabadevi (2025a); Said (2023)
Finance	Market movement prediction and portfolio optimization using quantum techniques combined with deep learning to model and mitigate financial risks.	Quantum Monte Carlo; Qiskit Finance	Risk optimization and financial scenario simulation through quantum algorithms	Capability to process large financial datasets using quantum hardware	Deep neural networks and reinforcement learning for market prediction	Iyer and Bakshi (2024); Said (2023)
Perovskite Quantum Dots for Photonic and Quantum Applications	Synthesis, characterization, and modeling of luminescent perovskites. It covers fabrication methods (HI, LARP, antisolvent) and surface engineering strategies to optimize optoelectronic properties, as well as their integration into devices like LEDs, solar cells, sensors, and potential QC applications (qubits and quantum memory).	Synthesis methods (Hot Injection, Ligand-Assisted Reprecipitation, antisolvent); characterization techniques (XRD, TEM, PL, UV–Vis spectroscopy); DFT and QMC simulations; ML frameworks for material discovery and device optimization	Exploitation of quantum confinement effects to tune emission; electronic structure simulation and optoelectronic property modeling; exploration of Perovskite Quantum Dots as elements of quantum architectures (qubits, gates, memory)	Precise control of synthesis parameters (temperature, precursor ratios); surface passivation strategies; scalable purification methods; advanced characterization equipment	ML algorithms for property prediction and optimization; experimental data analysis; simulations to model Perovskite Quantum Dot behavior	Jayan and Babu (2025)

implementation on real quantum hardware, challenges persist in scalability, error correction, and hybrid quantum–classical integration, with domains such as biomedicine, IoT, and quantum neural networks requiring further experimental validation and infrastructure improvements.

4.3. Proposed conceptual framework

Fig. 8 illustrates the relationship between QC and AI, integrating the main findings of this study into a structured model. The diagram presents the interaction between quantum computer architecture and development, the requirements for integration with AI, and key applications such as model optimization and advanced simulations. It also incorporates the geographical distribution of research and highlights challenges in quantum cybersecurity, including error mitigation and scalability. Finally, it identifies essential factors for the adoption of these technologies, such as access to quantum hardware and the establishment of regulatory frameworks. Fig. 8 outlines the conceptual framework that synthesizes the study's findings on QAI integration.

4.4. Critical methodological limitations and industry prospects

The literature on quantum computing (QC) and artificial intelligence (AI) highlights critical methodological limitations that hinder large-scale adoption, chiefly the reliance on Noisy Intermediate-Scale Quantum (NISQ) devices, which constrain algorithmic depth, circuit fidelity, and scalability (García-Ramos et al., 2024). Even advanced methods like variational quantum eigensolvers and parameter-shift learning face

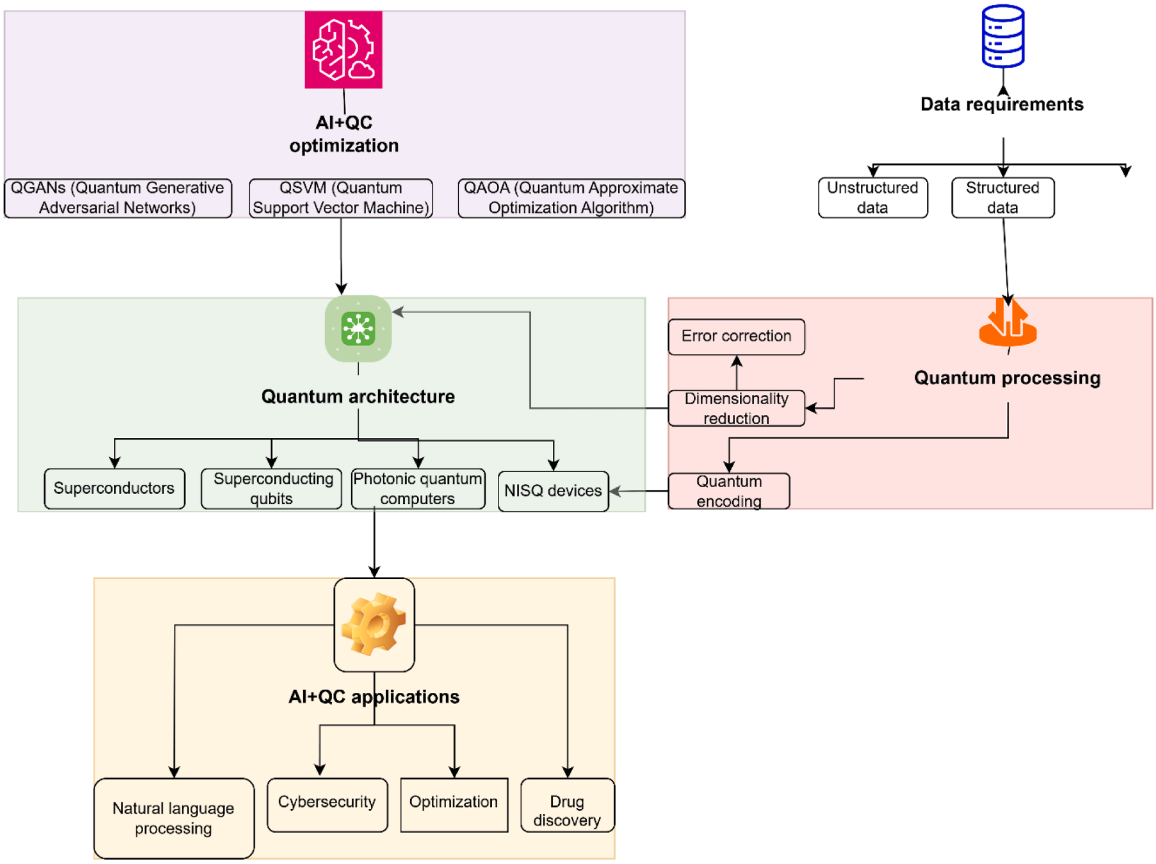

Fig. 7. AI+QC operational model. Own work using Drawio based on data from Scopus and Web of Science.

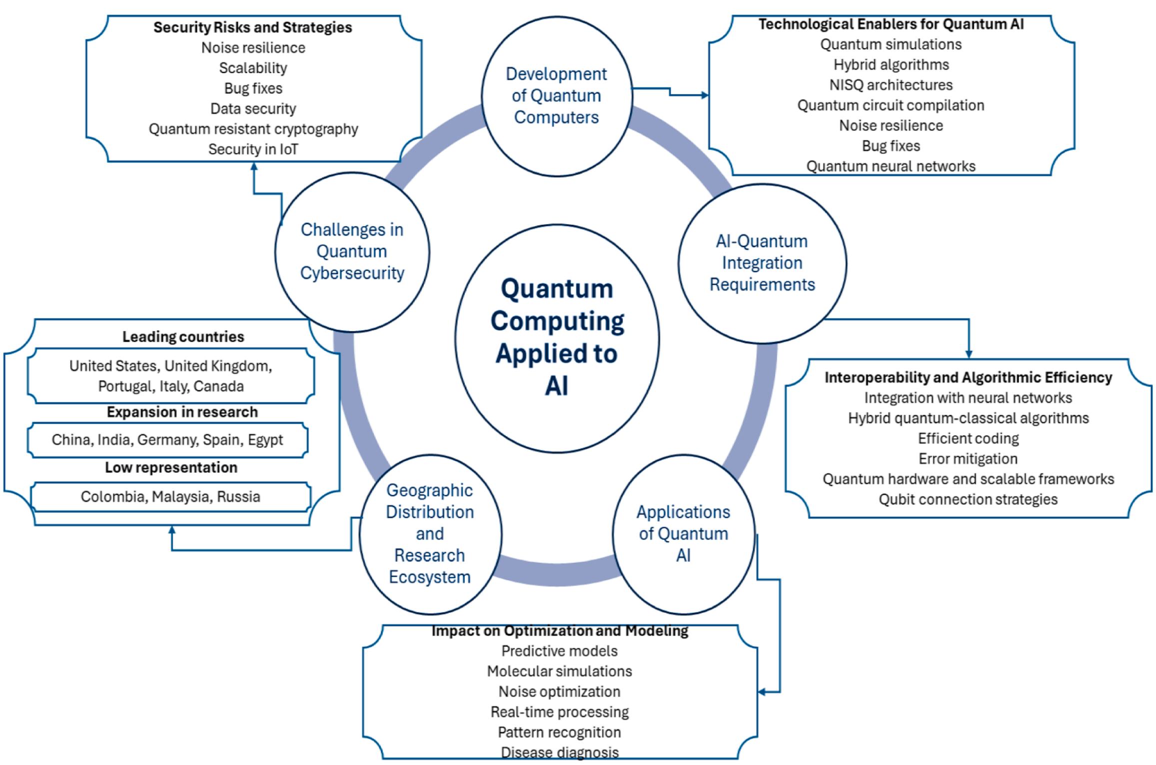

Fig. 8. AI+QC conceptual framework. Own work based on data from Scopus and Web of Science.

decoherence and stochastic measurement issues, while data encoding strategies often neglect trade-offs that introduce representational bias. Approaches such as QUBO-based feature selection remain dataset-specific and noise-sensitive, frequently underperforming against classical baselines (Hellstern et al., 2024), and the use of synthetic datasets in fields like materials science and drug discovery limits real-world applicability (Cai et al., 2015; Schuhmacher et al., 2022). Industrially, most QC–AI applications remain proofs of concept, lagging in accuracy and efficiency compared to classical models (Peixoto et al., 2022; Wu et al., 2021), with deployment hindered by hardware instability, regulatory challenges, and lack of standardized APIs (Ghaemi Asl et al., 2024; Subrahmanian et al., 2022). Overstated claims of quantum advantage are further compounded by insufficient robustness testing and benchmarking (Perdomo-Ortiz et al., 2018), underscoring the need for noise-aware evaluation protocols, interpretable QML outputs, and reproducible cross-platform validation to advance from theoretical promise to operational impact.

4.5. Implications

Despite significant advances in QC and AI, several barriers hinder their development and large-scale implementation. A primary limitation is the reliance on NISQ devices, which are characterized by high error rates and limited scalability. This type of hardware restricts the execution of complex quantum algorithms, as cumulative errors and qubit instability reduce computational fidelity. Furthermore, QML models often require datasets specifically tailored for quantum algorithms, complicating their training and applicability to real-world problems.

Another key challenge is the integration of hybrid quantum–classical algorithms, which aim to combine the efficiency of classical computing with the optimization and learning capabilities of quantum systems. However, these algorithms require continuous adaptation due to the absence of standardized development tools and advanced quantum simulation software, delaying their practical implementation. Additionally, the lack of effective quantum error correction methods remains a critical obstacle to enhancing the reliability of current quantum devices. In the field of cybersecurity, post-quantum cryptography still faces challenges in terms of practical implementation, which poses a vulnerability to the future capabilities of quantum computers to compromise conventional encryption systems.

4.6. Limitations

This study faces limitations related to access to quantum hardware, selection of studies, reproducibility of experiments, and scalability of the approaches analyzed. Access to advanced quantum hardware, on the one hand, is limited and often dependent on specialized infrastructure, restricting the experimental validation of proposed models. This limitation hinders large-scale testing and affects the precision of results. On the other hand, the selection of studies may introduce bias, as QC and AI are rapidly evolving fields, and some approaches may have been excluded due to limited data availability or the exclusion of recent publications. Moreover, the fast-paced technological development also complicates the reproducibility of experiments, as quantum algorithms and architectures change frequently, making it difficult to replicate studies under consistent conditions. Finally, scalability remains a persistent challenge because many quantum models face barriers when applied to complex systems, necessitating further research to evaluate their feasibility in real-world scenarios.

4.7. Future research directions

Future research in quantum AI should focus on developing more stable quantum hardware—particularly superconducting, photonic, and hybrid qubits less affected by noise—while optimizing hybrid quantum–classical models to boost efficiency in machine learning and optimization tasks and advancing encoding and data structuring methods to create datasets tailored for quantum algorithms. Progress in quantum error correction will be key to enabling accurate, scalable computations, and in cybersecurity, the deployment of post-quantum cryptographic systems will be essential to counter future quantum threats. Expanding sector-specific applications, such as logistics optimization, drug discovery, and materials simulation, will further consolidate quantum AI's role in the digital transformation. Illustrating this potential, Mahmoudi et al. (2025) demonstrated that a quantum-inspired particle swarm optimization method can significantly reduce energy consumption in IoT networks while maintaining service quality, reinforcing hybrid and quantum-inspired approaches as practical bridges between current NISQ limitations and scalable, real-world solutions.

5. Conclusions

This systematic literature review provides a structured synthesis of the integration between quantum computing (QC) and artificial intelligence (AI) from both technological and application-oriented perspectives. It identifies key technical requirements, integration features, and sector-specific use cases, with healthcare, finance, cybersecurity, and energy emerging as leading domains. The reviewed studies reveal methodological diversity and highlight the limitations of the NISQ era, particularly the need for noise mitigation and improved qubit fidelity to achieve more stable QC systems. Advances such as quantum simulations and hybrid quantum–classical algorithms have proven essential tools in computational chemistry and combinatorial optimization, although their scalability and error rates still limit their applicability to more complex problems.

AI–QC integration demonstrates transformative potential, especially through quantum neural networks and hybrid algorithms, which have shown notable improvements in processing capacity and optimization performance. These contributions enable applications in biomedicine, post-quantum cryptography, and cybersecurity. However, significant challenges remain in efficient quantum data encoding and error correction, both of which are critical for broader adoption. In practical terms, combining quantum algorithms with machine learning techniques has enhanced predictive model accuracy, reduced processing times, and expanded the ability to analyze complex datasets, with promising results in financial forecasting, drug discovery, and materials simulation. Nevertheless, the limited availability of accessible quantum hardware continues to hinder large-scale experimental validation.

Geographically, research in quantum AI is concentrated in North America and Europe, with pronounced disparities in developing regions due to constraints in infrastructure and access to advanced computational resources. Democratizing these technologies will require fostering international collaboration and expanding access through cloud-based quantum platforms. In conclusion, the application of QC in AI has the potential to transform multiple sectors, but large-scale adoption depends on advancements in hardware, refinement of hybrid algorithms, and robust error mitigation strategies. Future research should prioritize improving qubit coherence, enhancing post-quantum cryptography, and developing scalable quantum architectures, thereby ensuring the feasibility of these emerging technologies in real-world scenarios.

CRediT authorship contribution statement

Vanessa García Pineda: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Alejandro Valencia-Arias:** Writing – review & editing, Supervision, Methodology, Formal analysis. **Francisco Eugenio López Giraldo:** Writing – review & editing, Supervision, Conceptualization. **Edison Andrés Zapata-Ochoa:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The development of this research was supported for the APC payment by the Higher Education Institution Metropolitan Technological Institute (Instituto Tecnológico Metropolitano - ITM) which provided support in payment of 75 % the APC of this item through the call for projects and strategies for the strengthening of the science, technology and innovation system of the ITM through project PF24206 and Universidad de Los Lagos which provided support in payment of 25 % of the APC. The authors also thank ITM Translation Agency (traducciones@itm.edu.co) for translating the manuscript into English.

References

Abdelgaber, N., & Nikolopoulos, C. (2020). Overview on Quantum computing and its applications in artificial intelligence. In *Proceedings - 2020 IEEE 3rd International Conference on Artificial Intelligence and Knowledge Engineering, AIKE 2020* (pp. 198–199). https://doi.org/10.1109/AIKE48582.2020.00038

Acemoglu, D., & Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review, 108*(6), 1488–1542. https://doi.org/10.1257/aer.20160696

Agarwal, S., Bhardwaj, G., Saraswat, E., Singh, N., Aggarwal, R., & Bansal, A. (2022). *Insurtech Fostering Automated Insurance Process using Deep Learning Approach*, 386–392.

Arrazola, J. M., Bromley, T. R., Izaac, J., Myers, C. R., Brádler, K., & Killoran, N. (2019). Machine learning method for state preparation and gate synthesis on photonic quantum computers. In *Quantum science and technology, 4*. https://doi.org/10.1088/2058-9565/aaf59e

Baniata, H. (2024). SoK: Quantum computing methods for machine learning optimization. *Quantum Machine Intelligence, 6*(2), 47. https://doi.org/10.1007/s42484-024-00180-1

Cai, X. D., Wu, D., Su, Z. E., Chen, M. C., Wang, X. L., Li, L., Liu, N. L., Lu, C. Y., & Pan, J. W. (2015). Entanglement-based machine learning on a quantum computer. *Physical Review Letters, 114*(11). https://doi.org/10.1103/PhysRevLett.114.110504

Castaldo, D., Rosa, M., & Corni, S. (2021). Quantum optimal control with quantum computers: A hybrid algorithm featuring machine learning optimization. *Physical Review A, 103*(2). https://doi.org/10.1103/PhysRevA.103.022613

Cherbal, S., Zier, A., Hebal, S., Louail, L., & Annane, B. (2024). Security in internet of things: A review on approaches based on blockchain, machine learning, cryptography, and quantum computing. *The Journal of Supercomputing, 80*(3), 3738–3816. https://doi.org/10.1007/s11227-023-05616-2

Dai, Z., & Nahum, A. (2020). Quantum criticality of loops with topologically constrained dynamics. *Physical Review Research, 2*(3), Article 033051. https://doi.org/10.1103/PhysRevResearch.2.033051

Damaševičius, R., & Misra, S. (2024). *The rise of industry 6.0* (pp. 478–494). doi:10.4018/979-8-3693-2081-5.ch020.

Duarte, L. T., & Deville, Y. (2024). Quantum-assisted machine learning by means of adiabatic Quantum computing. In *2024 IEEE Mediterranean and Middle-East Geoscience and Remote Sensing Symposium (M2GARSS)* (pp. 371–375). https://doi.org/10.1109/M2GARSS57310.2024.10537323

Duggal, A. S., Malik, P. K., Gehlot, A., Singh, R., Gaba, G. S., Masud, M., & Al-Amri, J. F. (2022). A sequential roadmap to industry 6.0: Exploring future manufacturing trends. *IET Communications, 16*(5), 521–531. https://doi.org/10.1049/cmu2.12284

Espuny, M., da Motta Reis, J.S., Monteiro Diogo, G.M., Reis Campos, T.L., de Mello Santos, V.H., Ferreira Costa, A.C., Gonçalves, G.S., Tasinaffo, P.M., Vieira Dias, L.A., da Cunha, A.M., de Souza Sampaio, N.A., Rodrigues, A.M., & de Oliveira, O.J. (2021). *COVID-19: The importance of artificial intelligence and digital health during a pandemic* (pp. 27–32). doi:10.1007/978-3-030-70416-2_4.

García-Ramos, J. E., Sáiz, Á., Arias, J. M., Lamata, L., & Pérez-Fernández, P. (2024). Nuclear physics in the era of Quantum computing and Quantum machine learning. *Advanced Quantum Technologies*. https://doi.org/10.1002/qute.202300219

Ghaemi Asl, M., Ben Jabeur, S., Nammouri, H., & Bel Hadj Miled, K. (2024). Dynamic connectedness of quantum computing, artificial intelligence, and big data stocks on renewable and sustainable energy. *Energy Economics, 140*, Article 108017. https://doi.org/10.1016/j.eneco.2024.108017

Ghodke, V., Musrif, P., Karhale, S., & Patwardhan, S. (2024). View of Quantum machine learning_ bridging the gap between classical and quantum computing. *Journal of Electrical Systems*, (10), 20. https://journal.esrgroups.org/jes/article/view/6006/4244.

Givi, P. (2021). Machine learning and quantum computing for reactive turbulence modeling and simulation. *Mechanics Research Communications*, 116. https://doi.org/10.1016/j.mechrescom.2021.103759

Go, E. J., Moon, J., & Kim, J. (2020). Analysis of the current and future of the artificial intelligence in financial industry with big data techniques. *Global Business Finance Review, 25*(1), 102–117. https://doi.org/10.17549/gbfr.2020.25.1.102

Gyongyosi, L. (2020). Unsupervised quantum gate control for gate-model quantum computers. *Scientific Reports, 10*(1). https://doi.org/10.1038/s41598-020-67018-1

Gyongyosi, L., & Imre, S. (2020). Optimizing high-efficiency quantum memory with Quantum machine learning for near-term quantum devices. *Scientific Reports, 10*(1), 135. https://doi.org/10.1038/s41598-019-56689-0

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020 : An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open synthesis. *Campbell Systematic Reviews, 18*(2). https://doi.org/10.1002/cl2.1230

Han, T., Lu, Z., Yao, Y., Yang, J., Seo, J., Yoon, C., Watanabe, K., Taniguchi, T., Fu, L., Zhang, F., & Ju, L. (2024). Large quantum anomalous Hall effect in spin-orbit proximitized rhombohedral graphene. *Science, 384*(6696), 647–651. https://doi.org/10.1126/science.adk9749

Hardy, L., & Lewis, A. G. M. (2020). Quantum computation with machine-learning-controlled quantum stuff. *Machine Learning: Science and Technology, 2*(1), Article 015008. https://doi.org/10.1088/2632-2153/abb215

Harrow, A.W. (2023). *Approximate orthogonality of permutation operators, with application to quantum information*. doi:10.1007/s11005-023-01744-1.

Harrow, A. W., & Lowe, A. (2025). Optimal quantum circuit cuts with application to clustered hamiltonian simulation. *PRX Quantum, 6*(1), Article 010316. https://doi.org/10.1103/PRXQuantum.6.010316

He, X., Lu, T., Rong, C., Liu, W., Ayers, P. W., & Liu, S. (2024). Energetic information from information-theoretic approach in density functional theory as quantitative measures of physicochemical properties. *Journal of Chemical Theory and Computation, 20*(14), 6049–6061. https://doi.org/10.1021/acs.jctc.4c00697

Hellstern, G., Dehn, V., & Zaefferer, M. (2024). Quantum computer based feature selection in machine learning. *IET Quantum Communication*. https://doi.org/10.1049/qtc2.12086

Huang, H.-Y., Kueng, R., & Preskill, J. (2020). Predicting many properties of a quantum system from very few measurements. *Nature Physics, 16*(10), 1050–1057. https://doi.org/10.1038/s41567-020-0932-7

Ishiyama, Y., Nagai, R., Mieda, S., Takei, Y., Minato, Y., & Natsume, Y. (2022). Noise-robust optimization of quantum machine learning models for polymer properties using a simulator and validated on the IonQ quantum computer. *Scientific Reports, 12*(1). https://doi.org/10.1038/s41598-022-22940-4

Iyengar, S. S., Ricard, T. C., & Zhu, X. (2024). Reformulation of all ONIOM-type molecular fragmentation approaches and many-body theories using graph-theory-based projection operators: Applications to dynamics, molecular potential surfaces, machine learning, and quantum computing. *Journal of Physical Chemistry A, 128*(2), 466–478. https://doi.org/10.1021/acs.jpca.3c05630

Iyer, R., & Bakshi, A. (2024). Artificial intelligence and quantum computing techniques for stock market predictions. *Deep learning tools for predicting stock market movements* (pp. 123–146). Wiley. https://doi.org/10.1002/9781394214334.ch5

Jayan K, D., & Babu, K. (2025). Luminescent perovskite quantum dots: Progress in fabrication, modelling and machine learning approaches for advanced photonic and quantum computing applications. *Journal of Luminescence, 277*, Article 120906. https://doi.org/10.1016/j.jlumin.2024.120906

Jeyalakshmi, M. S., Asif Sayyad, A., Deepak, A., Shrivastava, A., Kakoli Rao, A., Chakrapani, I. S., Kumar, N., & Badhoutiya, A. (2024). International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Quantum Computing and Healthcare: Drug discovery and Molecular Simulation with machine learning. *Original Research Paper International Journal of Intelligent Systems and Applications in Engineering IJISAE*, (Issue 14s). www.ijisae.org.

K, A., R, L. H., K, N. H., K, S., & L, Y. C (2024). Machine learning approach for Parkinson's disease prediction through Quantum computing techniques. In *2024 S International Conference on Advances in Information Technology (ICAIT)* (pp. 1–6). https://doi.org/10.1109/ICAIT61638.2024.10690380

Kishor, K. (2023). 12 Review and significance of cryptography and machine learning in quantum computing. *Quantum-Safe cryptography algorithms and approaches* (pp. 159–176). De Gruyter. https://doi.org/10.1515/9783110798159-012

Kusyk, J., Saeed, S. M., & Uyar, M. U. (2021). Survey on quantum circuit compilation for noisy intermediate-scale quantum computers: Artificial intelligence to heuristics. *IEEE Transactions on Quantum Engineering, 2*. https://doi.org/10.1109/TQE.2021.3068355

Lappala, A. (2024). The next revolution in computational simulations: Harnessing AI and quantum computing in molecular dynamics. *Current Opinion in Structural Biology, 89*, Article 102919. https://doi.org/10.1016/j.sbi.2024.102919

Liu, S. (2024). Harvesting chemical understanding with machine learning and quantum computers. In *ACS physical chemistry au* (Vol. 4, pp. 135–142). American Chemical Society. https://doi.org/10.1021/acsphyschemau.3c00067

Mahmoudi, Y., Zioui, N., & Belbachir, H. (2025). An improved quantum-inspired particle swarm optimisation approach to reduce energy consumption in IoT networks. *International Journal of Cognitive Computing in Engineering, 6*, 313–322. https://doi.org/10.1016/j.ijcce.2025.01.010

Mao, M. Y., Cheng, Z., Xia, Y., Oleś, A. M., & You, W. L. (2023). Machine-learning-inspired quantum optimal control of nonadiabatic geometric quantum computation via reverse engineering. *Physical Review A, 108*(3). https://doi.org/10.1103/PhysRevA.108.032616

Marshall, S.C., Gyurik, C., & Dunjko, V. (2022). *High dimensional quantum machine learning with small quantum computers*. doi:10.22331/q-2023-08-09-1078.

Martina, S., Gherardini, S., Buffoni, L., & Caruso, F. (2022). Noise fingerprints in quantum computers: Machine learning software tools[Formula presented]. *Software Impacts*, 12. https://doi.org/10.1016/j.simpa.2022.100260

Mongeon, P., & Paul-Hus, A. (2016). The journal coverage of Web of Science and Scopus: A comparative analysis. *Scientometrics, 106*(1), 213–228. https://doi.org/10.1007/s11192-015-1765-5

Moret-Bonillo, V. (2015). Can artificial intelligence benefit from quantum computing? *Progress in Artificial Intelligence, 3*(2), 89–105. https://doi.org/10.1007/s13748-014-0059-0

Murugan, M., & Prabadevi, M. N. (2025a). Artificial intelligence, Quantum computing, autonomous operation, emotional intelligence: Key drivers of industry 6.0 and sustainabile development goals (SDG-8,9,12,17) for business sustainability in the oil and gas industry. *Journal of Lifestyle and SDGs Review, 5*(2), Article e04549. https://doi.org/10.47172/2965-730X.SDGsReview.v5.n02.pe04549

Murugan, M., & Prabadevi, M. N. (2025b). Artificial intelligence, Quantum computing, autonomous operation, emotional intelligence: Key drivers of industry 6.0 and sustainabile development goals (SDG-8,9,12,17) for business sustainability in the oil and gas industry. *Journal of Lifestyle and SDGs Review, 5*(2), Article e04549. https://doi.org/10.47172/2965-730X.SDGsReview.v5.n02.pe04549

Nguyen, H. T., Krishnan, P., Krishnaswamy, D., Usman, M., & Buyya, R. (2024). *Quantum Cloud Computing: A Review, Open Problems, and Future Directions*. http://arxiv.org/abs/2404.11420.

Omar, A., & Abd El-Hafeez, T. (2023). Quantum computing and machine learning for arabic language sentiment classification in social media. *Scientific Reports, 13*(1). https://doi.org/10.1038/s41598-023-44113-7

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., & Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery, 88*, Article 105906. https://doi.org/10.1016/j.ijsu.2021.105906

Pathak, S., Arora, K., & Quraishi, S.J. (2024). *Strategic challenges of Human resources management in the industry 6.0* (pp. 169–190). doi:10.4018/978-1-6684-9596-4.ch009.

Peixoto, M.C., Castro, N.F., Romão, M.C., Oliveira, M.G.J., & Ochoa, I. (2022). *Fitting a collider in a quantum computer: Tackling the challenges of quantum machine learning for big datasets*. doi:10.3389/frai.2023.1268852.

Perdomo-Ortiz, A., Benedetti, M., Realpe-Gómez, J., & Biswas, R. (2018). Opportunities and challenges for quantum-assisted machine learning in near-term quantum computers. In *Quantum science and technology, 3*. Institute of Physics Publishing. https://doi.org/10.1088/2058-9565/aab859

Pranckutė, R. (2021). Web of science (WoS) and Scopus: The titans of bibliographic information in Today's academic world. *Publications, 9*(1), 12. https://doi.org/10.3390/publications9010012

Preskill, J. (2025). Beyond NISQ: The megaquop Machine. *ACM Transactions on Quantum Computing, 6*(3), 1–7. https://doi.org/10.1145/3723153

Pujahari, R. M., Khan, R., & Yadav, S. P. (2025). Integration of quantum artificial intelligence in healthcare system. *Quantum computing for healthcare data* (pp. 139–166). Elsevier. https://doi.org/10.1016/B978-0-443-29297-2.00005-8

Radanliev, P. (2025). Cyber diplomacy: Defining the opportunities for cybersecurity and risks from Artificial Intelligence, IoT, Blockchains, and Quantum computing. *Journal of Cyber Security Technology, 9*(1), 28–78. https://doi.org/10.1080/23742917.2024.2312671

Reddy, C. K. K., Doss, S., Pamulaparty, L., Lippert, K., & Doshi, R. (2024). *Industry 6.0*. CRC Press. https://doi.org/10.1201/9781003517993

Rishiwal, V., Agarwal, U., Yadav, M., Tanwar, S., Garg, D., & Guizani, M. (2025). A new alliance of Machine Learning and Quantum Computing: Concepts, attacks, and challenges in IoT networks. *IEEE Internet of Things Journal*. https://doi.org/10.1109/JIOT.2025.3535414, 1–1.

Rodriguez, A. G. (2025). Cybersecurity implications of quantum computing and its combined use with artificial intelligence. *UNISCI Journal, 23*(67), 137–153. https://doi.org/10.31439/UNISCI-223

Said, D. (2023). Quantum Computing and Machine learning for cybersecurity: Distributed denial of service (DDoS) attack detection on smart micro-grid. *Energies, 16*(8), 3572. https://doi.org/10.3390/en16083572

Sangeetha, M., Senthil, P., Alshehri, A. H., Qamar, S., Elshafie, H., & Kavitha, V. P. (2024). RETRACTED ARTICLE: Neuro quantum computing based optoelectronic artificial intelligence in electroencephalogram signal analysis. *Optical and Quantum Electronics, 56*(4), 544. https://doi.org/10.1007/s11082-023-06187-5

Schuhmacher, J., Mazzola, G., Tacchino, F., Dmitriyeva, O., Bui, T., Huang, S., & Tavernelli, I. (2022). Extending the reach of quantum computing for materials science with machine learning potentials. *AIP Advances, 12*(11). https://doi.org/10.1063/5.0099469

Shrivastava, A., Badhoutiya, A., Jeyalakshmi, M. S., Asif Sayyad, A., Deepak, A., Kakoli Rao, A., Chakrapani, I. S., & Kumar, N. (2024). Quantum Computing and Healthcare: Drug Discovery and Molecular Simulation with Machine Learning 1 International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Quantum Computing and Healthcare: Drug Discovery and Molecular Simulation with Machine Learning. In *Original research paper international journal of intelligent systems and applications in engineering ijisae, 2024*. Issue 14s www.ijisae.org.

Si Mohammed, K., Serret, V., Ben Jabeur, S., & Nobanee, H. (2024). The role of artificial intelligence and fintech in promoting eco-friendly investments and non-greenwashing practices in the US market. *Journal of Environmental Management, 359*, Article 120977. https://doi.org/10.1016/j.jenvman.2024.120977

Solenov, D., Brieler, J., & Scherrer, J. F. (2018). The potential of quantum computing and machine learning to advance clinical research and change the practice of medicine. *Missouri Medicine, 115*(5), 463–467. www.research.ibm.com/ibm-q/network/.

Sotirelis, P., & Grigoroudis, E. (2021). Total Quality Management and Innovation: Linkages and evidence from the agro-food industry. *Journal of the Knowledge Economy, 12*(4), 1553–1573. https://doi.org/10.1007/s13132-020-00683-9

Subrahmanian, M. V., Pavuluri, K. D., Olivieri, C., & Veglia, G. (2022). High-fidelity control of spin ensemble dynamics via artificial intelligence: From quantum computing to NMR spectroscopy and imaging. *PNAS Nexus, 1*(4). https://doi.org/10.1093/pnasnexus/pgac133

Sureshbabu, S. H., Sajjan, M., Oh, S., & Kais, S. (2021). Implementation of quantum machine learning for electronic structure calculations of periodic systems on Quantum computing devices. *Journal of Chemical Information and Modeling*. https://doi.org/10.1021/acs.jcim.1c00294

Usman, M., Wong, Y. Z., Hill, C. D., & Hollenberg, L. C. L. (2020). Framework for atomic-level characterisation of quantum computer arrays by machine learning. *Npj Computational Materials, 6*(1). https://doi.org/10.1038/s41524-020-0282-0

Wichert, A. (2016). Artificial intelligence and a universal quantum computer. *AI Communications, 29*(4), 537–543. https://doi.org/10.3233/AIC-160699

Woolnough, A. P., Hollenberg, L. C. L., Cassey, P., & Prowse, T. A. A. (2023). Quantum computing: A new paradigm for ecology. *Trends in Ecology & Evolution, 38*(8), 727–735. https://doi.org/10.1016/j.tree.2023.04.001

Wu, S. L., Chan, J., Guan, W., Sun, S., Wang, A., Zhou, C., Livny, M., Carminati, F., Di Meglio, A., Li, A. C. Y., Lykken, J., Spentzouris, P., Chen, S. Y. C., Yoo, S., & Wei, T. C. (2021). Application of quantum machine learning using the quantum variational classifier method to high energy physics analysis at the LHC on IBM quantum computer simulator and hardware with 10 qubits. *Journal of Physics G: Nuclear and Particle Physics*, (12), 48. https://doi.org/10.1088/1361-6471/ac1391

Zhang, B., Wu, J., Fan, L., & Zhuang, Q. (2022). Hybrid entanglement distribution between remote microwave quantum computers empowered by machine learning. *Physical Review Applied, 18*(6). https://doi.org/10.1103/PhysRevApplied.18.064016