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Advances and Challenges in the Integration of Quantum Computing in Artificial Intelligence: A Systematic Review

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Abstract

The main objective of the research is to analyze the incorporation of quantum computing in artificial intelligence, focusing on applications, tools, and challenges. Through a systematic approach of literature review in academic databases, a growing interest in this integration was detected, particularly in fields such as physics, medicine, chemistry, and cybersecurity. It highlights the effectiveness of quantum algorithms in complex Artificial Intelligence issues such as factorization and unordered search. Challenges include the vulnerability of qubits and the demand for scalable quantum hardware. The research recognizes booming tools for quantum data modeling for Artificial Intelligence, examines innovative applications in materials design and agriculture, and suggests areas for future research. It highlights the importance of creating more efficient quantum algorithms and optimizing their integration.

Keywords: Methodologies, Machine Learning, Quantum Computing, QML, AI.

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1 Introduction

This review examines the emerging convergence between quantum computing and artificial intelligence (AI), a field that promises to address complex challenges in AI research and applications (Gray & Terashi, 2022; Peelam et al., 2024). It explores how quantum computing, based on qubits that take advantage of superposition and quantum entanglement, offers exponentially superior computational capabilities to classical computing. The article discusses proposed quantum algorithms that could revolutionize machine learning, cryptography, and molecular simulation (Carrasquilla, 2020; Huang et al., 2021). It also considers current challenges, such as the fragility of qubits and the need for scalable quantum hardware. This review provides an overview of the current state of the art and its intersection, taking into account its potential applications and the technical hurdles to be overcome for its integration (Noé et al., 2020; Bouchmal et al., 2023).

Before continuing, it is important to highlight the rationale proposed by (Yi, 2015), in which he details how artificial neural networks are employed in fault diagnosis in computer systems. Likewise, he mentions that the combination of AI algorithms, such as self-organizing maps (SOM) and backpropagation (BP) neural networks, is effective in the diagnosis of faults in networks (Valdez & Melin, 2023).

Alternatively, (Toscano et al., 2023) address the use of AI, focusing on convolutional neural networks (CNNs), to analyze scanning electron microscopy (SEM) micrographs to detect nanoparticles and to be able to accurately segment them. They also mention the attempt to use generative adversarial networks (GANs) to augment the data, although these may present difficulties in their use (Ngo et al, 2023).

Hong et al., 2024 mention that quantum computing utilizes qubits for information processing, assuming states of 0, 1, or both at the same time by quantum superposition. They also underscore the need for using a quantum approach to provide an efficient solution to complex problems, including accurate wind energy prediction, in line with sustainability and carbon emission reduction (In other concepts, the evolution of qubits in closed systems is governed by the Schrödinger equation, in which the representation of a qubit involves complex coefficients in a superposition of quantum states.

According to (Kessler et al., 2023) quantum computing is a part of computer science dedicated to studying and applying quantum algorithms, with Grover's quantum search algorithm as example, with it being fundamental in quantum computing software (Liu et al., 2024). This algorithm uses properties at a quantum scale, like superposition, to perform efficient searches on unordered data sets.

Babu et al., 2024 mention that quantum computing has been used to improve computational power in the healthcare field, specifically in the diagnosis of heart disease (Rasool et al., 2023). They also note that machine learning algorithms powered by quantum computing could make it easier to evaluate and treat complex health conditions in the healthcare industry (Hwang et al., 2023; Zeguendry et al., 2023; Pira & Ferrie, 2023).

Pooranam et al., 2023 highlight that a quantum processor is the key unit that powers a quantum computer. There are many kinds of quantum processors, like photonic, spintronic and ion traps, the latter of which offers improved qubit isolation and a more efficient use of qubits in processing operations.

According to (Gordienko et al., 2024) the integration of quantum technology in AI represents a critical need to reduce resource and energy consumption, especially in a context where sustainability is a priority. Moreover, it is imperative to optimize model architectures and deepen the understanding of "convolutional" operations to take full advantage of the benefits of this integration.

According to (Deng et al., 2024), integrating quantum computing in AI faces limitations because of the inefficiency of residue number systems (RNS) in handling real numbers, fundamental for training AI models. Although RNS are useful for integer operations, they are not directly applicable in AI, which creates challenges in optimizing time and energy consumption in model training.

2 Review Methodology

In this systematic review, the guide that (Kitchenham & Charters, 2007) presented will be used as reference, being essentially made up of three very important stages, which we adapted according to the most convenient criteria for the research.

The following is a chart of the development of the information review with the 3 steps in the review methodology Figure1.

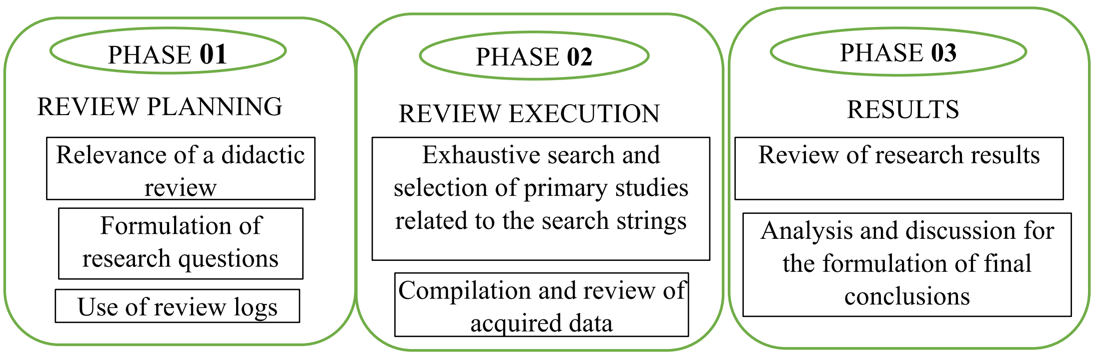

Figure 1: Chart of the Development of the Information Review. Prepared by the Authors

Review Planning

To obtain a more precise understanding of quantum computing and its integration in artificial intelligence, it is crucial to analyze the experiences developed so far and determine whether they have been optimal. Likewise, it is essential to access a wide range of research articles that address this specific context. In other words, we seek to explore research that addresses the union of quantum computing and artificial intelligence. To facilitate this process, systematic review planning emerges as a method that offers best practices for collecting and analyzing relevant sources of information. The desired information was collected from various repositories of scientific articles, such as Academic Search Complete, Taylor & Francis Online, Science Direct, IEEE Xplore, Scopus, and Web of Science, among other databases. Likewise, review schemes were developed in which key search words were identified to delimit and establish limits in the study area, focusing on experiences, activities, or theories related to the implementation of quantum computing in artificial intelligence.

Within the framework of this review, outlines will be developed that identify specific search keywords to delimit and establish boundaries in the area of study on experiences, activities, or theories related to how quantum computing is implemented in business artificial intelligence.

This will allow for a systematic review that is thorough, picking existing literature where quantum computing and artificial intelligence meet in enterprise contexts Table 1.

Table 1: Search Questions For Entrepreneurial Business Models

ID	Research Question	Motivation
Q1	What are the implementation cases of quantum computing in artificial intelligence?	To identify specific examples of quantum computing being integrated into business artificial intelligence models to address challenges and generate innovative solutions.
Q2	What tools, methods, or approaches are used to apply quantum computing in the development of AI models?	To investigate the specific techniques and procedures used in the convergence of quantum computing with AI.
Q3	What are the most significant challenges facing research applying quantum computing to enterprise artificial intelligence?	To propose a brainstorming that seeks innovative solutions and strategies to address the difficulties identified in the application of quantum computing to artificial intelligence.

Review Execution

Initial Search, the search process began on November 21, 2023, initially by searching for the terms "Artificial Intelligence", "Quantum Computing" and "Machine Learning" in the ScienceDirect and Scopus databases. Then, the search was extended using Boolean operators such as AND, OR being AND the most used in this search. The use of the aforementioned operators gave us several prominent results. However, these were either repetitive or encompassed a different idea, as they provided a broad idea of what aspect of vocabulary to use to be most effective in this search.

Likewise, they helped to verify the degree of connection or link they have about the topic of quantum computation in artificial intelligence. Since the results acquired in ScienceDirect and Scopus were very minimal and did not provide any additional referenced information, it was decided to remove them from the review process.

Systematic Search, continuing with the systematic search, additional repositories such as ScienceDirect, Taylor & Francis, Web of Science and Scopus were explored. The results were limited to articles published between the years 2019 and 2023. From the first experience, search terms were adjusted to obtain better results in the information repositories. The results obtained were used as a basis for continuing the systematic review.

Assessing the quality of the included studies for this systematic review was crucial to warrant a valid and reliable set of results, for which specific criteria were applied, prioritizing experimental and quasi-experimental studies, and considering internal validity by analyzing the control of bias and confounding, as well as the methodological rigor and relevance of the studies concerning the three research questions formulated.

On the other hand, although these can provide valuable information, their variable quality and lack of peer review make them less preferred sources for this review. Additionally, it is necessary to mention that this approach will strengthen the credibility of our findings and provide a clear context for interpreting the results and suggesting areas for future research Table2.

Table 2: Source and Search Strings of Information

Source	Search string	Cant. Res.
Scopus	Quantum Machine Learning AND Artificial Intelligence	981
Web of Science	Quantum Computing AND Machine Learning	2663
Taylor & Francis	Quantum Computing AND Artificial Intelligence	4214
Science Direct	Quantum Computing AND Artificial Intelligence	4732

Exclusion Criteria

To filter the articles obtained, the following exclusion criteria were applied in table 3:

Table 3: Table of Exclusion Criteria

Exclusion Criteria
Articles whose publication date was more than 5 years old were excluded.
Review and early access articles were discarded, and articles that were not broadly related to the search string were excluded.
Articles that did not have a strong focus on the research topics were excluded.

Additional filters, to advance in the selection of research articles, additional filters will be implemented to refine the choice.

The first filter, an initial review of the titles, abstracts, and conclusions of the articles will be carried out, performing a quick reading and a superficial review to identify those most relevant and directly related to the topic of study.

Second filter, a more exhaustive evaluation will be carried out, performing a complete reading and detailed analysis of the studies that have passed the first filter. This stage focuses on a thorough understanding of the methodology, results, and conclusions of the selected articles.

After applying these refined filters, a technique recognized in formal research known as "snowballing" will be employed. This technique involves adding additional articles after applying the initial filters, as these may provide more recent and relevant information, thus enriching the content of the systematic review.

The following Figure 2 depicts the search process and filters used in the repositories, with exact figures to illustrate the efficiency of the process:

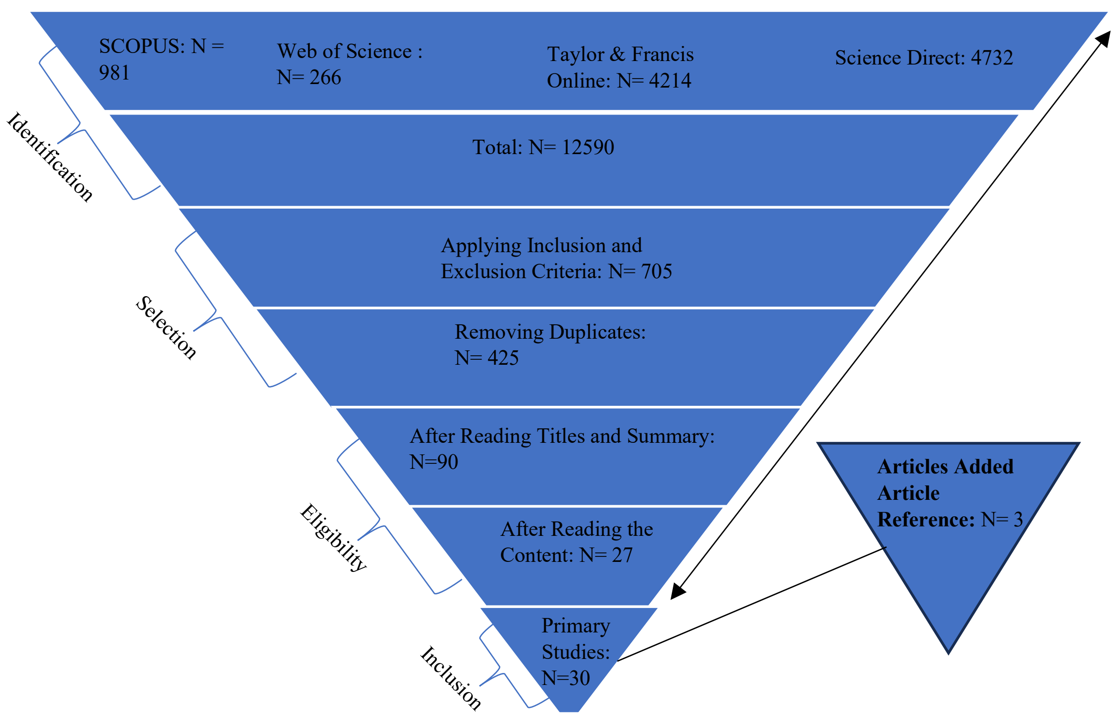

Figure 2: Search and Filtering Process of Articles

From the 12590 articles initially identified, inclusion and exclusion criteria were applied. To optimize the review process, additional filters were used, such as the elimination of duplicates by comparing each database (DB) using Excel, to avoid redundancies and speed up the analysis.

Next, an in-depth reading of each of the most relevant sections of each article was carried out, focusing mainly on the titles, summaries, and conclusions. Greater emphasis was given to those papers that were considered more important or had a broader relationship with the topic of study. Following the application of these initial filters, an additional search was carried out to identify possible new developments using the "snowball" technique. The "snowballing" strategy involved adding new articles discovered in this additional search to the studies already filtered in earlier stages. After completing this process, we obtained a final set of 48 primary studies that met the relevance criteria and provided valuable information for the systematic review.

Review Results

The 30 selected studies show a variety of content regarding the application of the soft model methodology in entrepreneurial business models.

3 Results and Discussion

The research papers indicate a heightened involvement in how to apply quantum computing in the field of artificial intelligence. It is worth mentioning that the reference numbers in the tables are numbers whose only purpose is to order the articles attached per question, which are purely representative of each question.

Q1. What are the cases of implementation of quantum computing in artificial intelligence?

In Table 4, based on the results obtained, the information will be analyzed in detail according to the questions established at the beginning of the systematic review.

Table 4: Implementation Areas of Quantum Computing

N° Ref.	Title	Description
1	Parameterized quantum circuits as machine learning models	Key approaches are emphasized, including advanced quantum algorithms that leverage quantum software engineering to enhance core machine learning solutions.
2	Quantum machine learning: from physics to software engineering	Important approaches are highlighted, such as improved quantum algorithms, using quantum software engineering to improve fundamental machine-learning solutions.
3	Quantum Machine Learning Applications in the Biomedical Domain: A Systematic Review	The report highlights that quantum technologies, including quantum machine learning, have proven to be powerful tools across diverse fields, including chemistry, agriculture and healthcare.
4	Tensor networks for quantum machine learning	It is mentioned that tensor networks have proven to be a successful paradigm in machine learning, and are currently being applied in the novel field of quantum machine learning to solve problems that could not be efficiently addressed with classical computers.
5	Quantum Machine Learning: A Review and Case Studies	It is noted that traditional machine learning is still demanding in terms of resources, especially for training advanced models, and that the current trend requires high-speed computing hardware.
6	Unlocking the Potential of Quantum Machine Learning to Advance Drug Discovery	The study mentions that the quantum machine learning (QML) algorithms are applied in the pharmaceutical area for drug discovery and production.

7	Quantum Computing for Healthcare: A Review	This study mentions how quantum computing can bring efficiency to healthcare systems, within which are operational areas such as drug discovery, DNA sequence analysis, and improving healthcare operations.
8	Quantum Computing: The Future of Big Data and Artificial Intelligence in Spine	The study highlights the potential of quantum computing to circumvent the limits of traditional analytics platforms, giving way to more advanced tools in data science and deep analytics.

The brief descriptions of the studies provide a more accurate picture of the contexts in which the use of quantum computing in AI is currently being applied. These initiatives are intended to contribute accurate and important information about the study in question.

Table 5 below presents some studies related to the areas that implement quantum computing in artificial intelligence.

Table 5: Areas Implementing Quantum Computing.

Area
Quantum physics and chemistry.
Machine Learning and Data Science
Health and Medicine
Telecommunications
Security and Information Technology
Agriculture and Environment

For a better appreciation of the above table, Figure 3 is shown for a clear understanding.

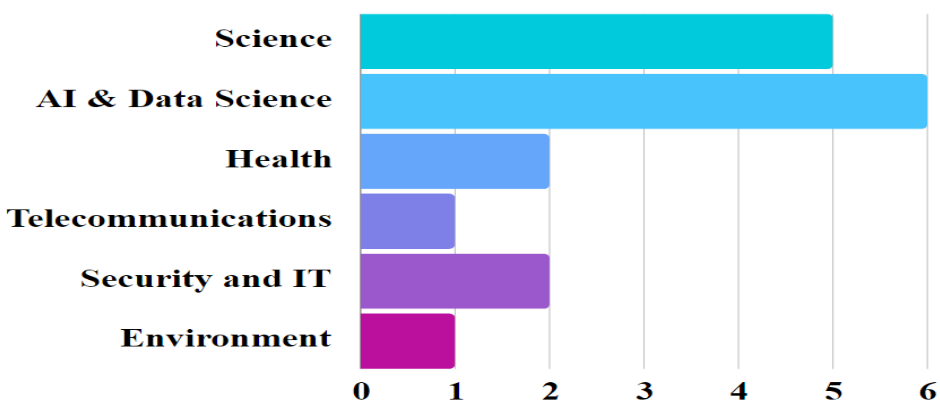

Figure 3: Areas of Implementation of Quantum Computing

Machine Learning and Data Science (AI and CDD) stand out as a domain, accounting for 35.3% of the studies on the integration of quantum computing in artificial intelligence. Quantum Physics and Quantum Chemistry (Science) follow closely with 29.4% (Smith et al., 2021; Raucci et al., 2023). In contrast, Telecommunications and Environment have a lower representation, both with 5.9%. Although these latter percentages are lower, they should not be underestimated, as they also offer significant opportunities (Phillipson, 2023). In summary, there is a more diverse regard for potentially using quantum computing in fields such as medicine and computer security, suggesting a shift in how we face current challenges.

Khan et al., 2023, consider that quantum computing has an important role in several areas, such as big data search in large repositories, prime number factorization, number theory, cybersecurity, polynomial evaluation, interpolation, ML, and AI (Rakhmanovich et al., 2025; Shoutao et al., 2023).

On the other hand, (Pandey et al., 2023) highlight the close relationship between quantum computing and ML. They point out that the rapid growth of data may exceed the capacity of traditional ML algorithms, while quantum computing offers an efficient solution for processing large volumes of data.

Dutta et al., 2023 mention the use of quantum circuits and architectures to tackle issues in AI, such as constraint optimizations, performing probabilistic inference, and continuously learning from noisy data, would greatly enhance the efficiency and performance of AI algorithms across various applications (Benedetti et al., 2019).

Areas and Fields of application of quantum computation in AI

Quantum Physics and Chemistry

- The application of quantum computing in high-energy physics to address the computational challenge related to the large data sets of the Large Hadron Collider (LHC).
- High-energy physics (HEP) research is advancing considerably with the integration of QML, particularly in the analysis of large data sets, such as those generated by the LHC. This reflects a move towards quantum application in simulation and large-scale data processing.
- Quantum computing applied to AI spans several fronts, highlighting its quantum parallelism capabilities in problems such as factorization and unstructured search.
- Machine learning and data science
- Traditional machine learning is resource-intensive, and the current trend demands high-speed hardware, driving research in quantum computing to overcome these limitations.
- Improved quantum algorithms, supported by quantum software engineering, optimize key machine learning solutions.
- Parameterized quantum circuits are presented as highly expressive models for machine learning, suggesting their implementation in AI algorithms.
- Health and Medicine
- The integration of quantum computing in drug discovery and personalized medicine shows its potential to benefit from advanced artificial intelligence techniques in medical data analysis and outcome prediction.
- In addition, mention is made of its promising use in biology and medicine, such as biomolecule simulation and cancer classification, highlighting its usefulness in areas of medical research (Cordier et al., 2022).
- Telecommunications
- The research indicates that quantum computing has a notable impact in the field of telecommunications. Concrete cases of the application of quantum computing in the telecommunications sector are presented.
- The research also points to the possibility of implementing global quantum networks, which could revolutionize connectivity on an international level (Durga & Sudhakar, 2023).
- Security and Information Technology (Alisawi et al., 2023).
- The usage of quantum computing fundamentals in the Internet of Things (IoT) is highlighted to increase accuracy, speed, and security (Guru Prasad & Badrinarayanan, 2025). Several case studies are cited, such as network optimization, faster execution of computations on end devices,

application of quantum security, quantum sensors, and quantum digital marketing strategies (Kondori & Peashdad, 2015).

- The information deals with the use of machine learning methods to investigate the detection of practical imperfections in quantum key distribution systems (CVQKD) (Sandoval et al., 2025; Sajjan et al., 2022). This case represents an example of the integration of quantum computing into information security, specifically in the area of quantum key distribution (Haidar et al., 2023; Tychola et al., 2023).
- Agriculture and the Environment
- It is mentioned that quantum technologies, such as quantum machine learning, have shown to be powerful tools in a variety of fields, from chemistry to agriculture to healthcare (Avramouli et al., 2017; Guan et al., 2021; Maheshwari et al., 2022).

Estimates and Opportunities

Despite significant advances when incorporating quantum computing in contexts like as high-energy physics, machine learning and medicine, there are still technological barriers that limit its large-scale adoption, particularly in terms of quantum hardware. Trends indicate that research is focused on improving simulation and massive data processing, optimizing quantum models to overcome the limitations of traditional systems. However, gaps remain in practical implementation, especially in sectors such as information security, where quantum technologies face stability and accuracy challenges. Going forward, research directions must address these challenges by increasing the efficiency of algorithms and the reliability of quantum infrastructures, which will enable wider adoption in fields such as personalized medicine, agriculture, and telecommunications.

Q2. What tools, methods, or approaches are used to apply quantum computing in the development of artificial intelligence models?

Table 6 shows the tools or methods used for the application of quantum computing, with some details such as the title and a brief description.

Table 6: Tools or Methods that Were Used for the Application of Quantum Computing

N° Ref.	Title	Description
1	Quantum Machine Learning Overview	The analysis highlights the superior performance of quantum algorithms, such as the Quantum Support Vector Machine algorithm (QSVM), in contrast to classical variants, like Support Vector Machine (SVM), in terms of accuracy. This involves comparing both classical and quantum approaches to address specific ML problems.
2	Parameterized quantum circuits as machine learning models	A particular approach that fuses quantum and classical components is employed for activities such as supervised learning and generative model creation.
3	Quantum machine learning: from physics to software engineering	Specific methods, such as the hybridization of quantum and classical neural networks, are being investigated to better model generalization and enhance accuracy while using less computational resources.
4	Quantum machine learning for chemistry and physics	The information highlights the use of machine learning (ML), including training on quantum hardware, to advance chemistry and electronic structure computation, employing new and improved algorithms, and both classical and quantum computational styles.

5	Quantum Machine Learning: A Review and Case Studies	The information describes the move from basic quantum theory to the use of quantum AI algorithms, such as quantum neural networks (QNN), variational quantum classifiers (VQC), and other classical equivalents in specific tasks.
6	An invitation to distributed quantum neural networks	The study explores the development of distributed deep learning foundations in QNN, highlighting aspects linked to dataset distribution and quantum modeling.
7	A review of quantum computing and deep learning algorithms and their applications	The analysis remarks the importance of quantum algorithms and their ability to manage information in quantum operations and offers insight into how quantum principles can be powerful tools in the creation of artificial intelligence models.
8	A Survey of Recent Advances in Quantum Generative Adversarial Networks	The study specifically mentions the adaptation of the classical generative adversarial network (GAN) to the quantum domain, thus creating quantum GANs also known as Qu GANs. This implies the possibility of having fully quantum or hybrid quantum-classical architectures. In addition, methods for training Qu GANs are discussed, including the application of loss functions such as maximum likelihood, Wasserstein distance or total variance.

The techniques and methods used to apply quantum computing in artificial intelligence do not differ much from those used in the previously mentioned activities.

In Table 7 the search data have been grouped and ordered according to the tools used in different contexts of application of quantum computing in artificial intelligence.

Table 7: Tools Used for the Implementation Of Quantum Computing

Tools
Quantum algorithms
Quantum approaches and data modeling
Computer resources
Molecular structure and modeling
Experimental machine learning

Figure 4 shows the distinctive tools present in the studies that employed quantum computing in artificial intelligence. It is worth mentioning that each bar represents the frequency with which the different tools are mentioned in the investigations.

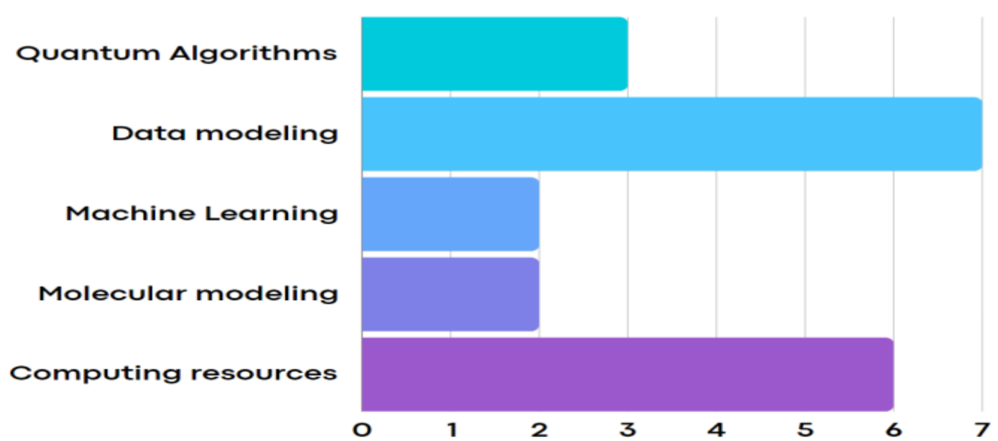

Figure 4: Tools Used in Quantum Computing

The predominance of the use of quantum data modeling methods and the need for suitable computational resources stand out; these together represent 65% of the total number of studies. This result underlines the importance of adapting specific quantum computing tools for their integration in the field of artificial intelligence.

In contrast, experimental machine learning and molecular modeling are positioned at a lower level, each comprising only 10% of the studies. Although their use is lower compared to the other tools mentioned above, their relevance should not be underestimated, as they also offer significant opportunities for the advancement of research in this field (Richings & Habershon, 2022).

Chao et al., 2023 mention using parameterized quantum circuits and quantum tensor networks to enhance the reinforcement learning of AlphaZero by replacing its classical neural network and extracting key features from the game data, achieving performance comparable to classical AlphaZero (Rieser et al., 2023). However, its implementation is complex due to scalability challenges and depends on the development of current quantum technology (Melnikov et al., 2023).

On the same plane, (Jia et al., 2019) suggest that integrating quantum computing in geological research could benefit AI models and their development, especially through the use of Big Data, which enables the analysis of large volumes of geological information and improves decision making. However, they point out that the lack of consensus in the scientific community on the feasibility of the concept of "quantum geology" represents an obstacle to its acceptance and practical application Gray, 2022).

On the other hand, (Pophale & Gadekar, 2021) highlight the key role of advanced and experimental Big Data analysis techniques in handling diverse and massive datasets, which overcome the limitations of traditional computing, as they can process large volumes of data in a significantly shorter time than classical methods (Mallow et al., 2022). However, there are still challenges in their practical application in real-world situations.

Methods and Approaches involved in the integration of quantum computing in AI.

Quantum Algorithms

- The importance of using quantum algorithms such as QSVM and classical approaches such as SVM to analyze and evaluate the relationships between paradigms within common AI implementation problems is highlighted.
- Among other of the most widely used quantum algorithms important for their capabilities are QNNs and the variational quantum classifier VQC.
- Machine Learning algorithms, including deep neural networks and support vector machines, can be used to design chaos-based encryption algorithms.

Quantum approaches and data modeling

- The implementation of distributed deep learning concepts in these quantum neural networks is explored, highlighting aspects linked to the distribution of data sets and quantum models.
- Methods such as hybrid quantum-classical neural networks are investigated to better model generalization and reduce computational resources.
- The adaptation of the classical adversarial generative network to the quantum domain involves the creation of Quantum Adversarial Generative Networks (Qu GAN), exploring fully quantum or hybrid architectures.

- Quantum and classical components are merged in activities such as supervised learning and generative model building, allowing a convergence between the two approaches.

Computer resources

- Tools such as OpenView and mild-fermion facilitate the implementation of adaptive methods inspired by quantum chemistry, simplifying model-building calculations.
- The application of various forms of machine learning, trained on quantum hardware, enables advances in chemistry from materials design to the calculation of electronic structures.
- Machine learning algorithms trained on quantum hardware drive advances in materials design and energy photovoltaics.

Structure and molecular modeling

- The ability to manage quantum information accelerates complex problem-solving in artificial intelligence, showing the potential of quantum principles in model building.
- Machine learning approaches, such as deep neural networks, are used to predict quantum-mechanical energies and forces and address molecular dynamics.

Experimental machine learning

- Quantum computing is applied in high-energy physics for simulation and analysis of large data sets.
- Reinforcement Learning (RL) and Deep Learning (DRL) techniques with Quantum Machine Learning are used to tackle routing challenges in 6G SDN networks.

Estimates and Opportunities

The integration of quantum computing in the development of artificial intelligence models shows clear trends towards combining quantum-classical approaches, with an increase in the use of quantum algorithms such as QSVM and hybrid neural networks to improve efficiency and accuracy. However, significant gaps remain, such as the lack of standardization in tools and the limited scalability of quantum algorithms for industrial applications. As for future directions, advances in quantum hardware and the development of new tools are expected to optimize these approaches, enabling their application in more complex areas, such as quantum cryptography and molecular simulation.

Q3. What are the most significant challenges facing research applying quantum computing to business artificial intelligence?

Table 8 below identifies the difficulties present in quantum computation in the articles written.

It is possible to identify common challenges and challenges in its implementation and application, however, these difficulties aside, quantum computing will continue to be a valuable tool for AI researchers and developers. This allows for rapid knowledge acquisition and agile adaptation while these areas are being explored.

Table 8: Difficulties Present in the Implementation of Quantum Computing

N°. Ref.	Title	Description
1	Quantum Machine Learning Overview	Reference is made to the challenges present when integrating classical and quantum computing to increase processing speed. In addition, it highlighted the need to make significant efforts in the advancement of quantum hardware to ensure adequate resources.
2	Machine learning for quantum matter	The research suggests that there are challenges in actively exploring common ground between machine learning and quantum physics of many-body systems.
3	Open-source variational quantum eigen solver extension of the quantum learning machine for quantum chemistry	It is noted that current quantum hardware, especially NISQ processors, experience substantial errors. OpenVQE and its associated modules are proposed as tools capable of overcoming these challenges by creating and implementing adaptive VQE algorithms.
4	An invitation to distributed quantum neural networks	The review refers to vulnerabilities arising due to the particular characteristics of quantum data in distributed deep learning approaches and quantum neural networks.
5	From classical to quantum machine learning: survey on routing optimization in 6G software-defined networking	The research identifies and explores unresolved research questions in the usage of Reinforcement Learning (RL), Deep Reinforcement Learning (DRL), and Quantum Machine Learning (QML) techniques in Software-Defined Networking (SDN) routing in 6G networks. This indicates that there are outstanding challenges that need to be considered to effectively use these techniques in enterprise contexts.
6	Secure Continuous-Variable Quantum Key Distribution with Machine Learning	The information highlights the importance of security in the Continuously Variable Quantum Key Distribution (CVQKD) system and mentions the current possibility that disparities between real objects and ideal models can lead to vulnerabilities.
7	Predicting Molecular Photochemistry Using Machine-Learning-Enhanced Quantum Dynamics Simulations	The article mentions that simulating molecular photochemistry is a permanent challenge because it involves the precise intervention of electronic structure in a molecular level, along with nuclear dynamics and the effect of non-adiabatic couplings.
8	Towards provably efficient quantum algorithms for large-scale machine learning models	The study points out that large-scale AI models face common difficulties in terms of computational costs and carbon emissions because of the immense resource usage in model training.

Table 9 below summarizes and categorizes the challenges encountered in the studies that applied quantum computing techniques in the field of artificial intelligence.

Table 9: Challenges Present in Quantum Computing Applied to Artificial Intelligence

Challenges
Technological integration
Simulation and modeling
AI Implementation

To improve the understanding of the data, Figure 5 is provided, which consists of a bar chart designed to represent the information in a clearer and more accessible way.

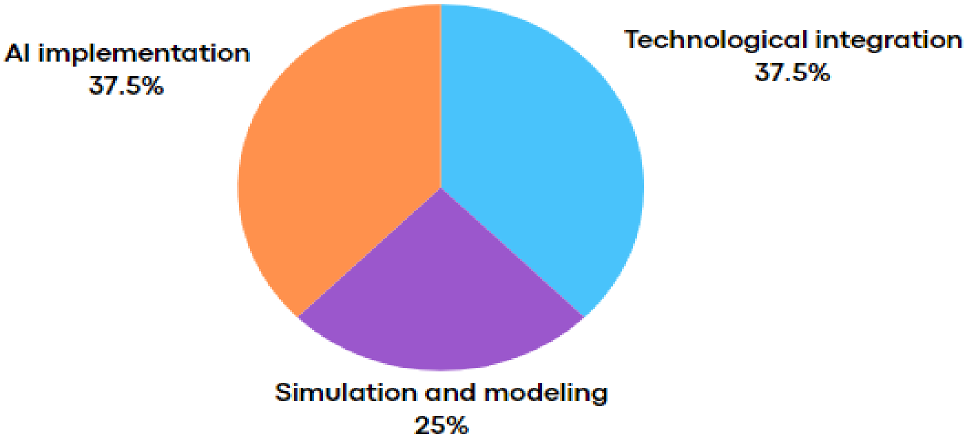

Figure 5: Challenges Encountered In Quantum Computing

It is observed that the main challenge identified in the implementation of quantum computing in artificial intelligence is technology integration and AI implementation, which together comprise the vast majority of the total related studies, at 75%. This result highlights the complexity and importance of achieving effective harmonization between quantum technologies and existing AI systems.

On the other hand, although simulation and modeling have a smaller percentage compared to the other problems, it is crucial to acknowledge the relevance of these aspects for the successful integration of quantum computing in artificial intelligence solutions.

Navaux et al., 2023 consider some challenges for software developers when dealing with parallelization of applications and non-functional needs, such as power consumption and resilience.

Damaser et al., 2024 suggest that one of the challenges is computational complexity, particularly when dealing with complex systems and large volumes of data. They also mention the need to understand and adequately model emergent interactions and nonlinear behaviors in complex systems.

(Henchir et al., 2023) reaffirmed energy consumption as one of the constant difficulties and also mentioned another equally important challenge such as speed when designing the architecture at the hardware level in integrated systems. It also highlights the need to develop Edge Computing Systems (ECS) that are energy-efficient, compact, and fast.

Difficulties and challenges of implementing quantum computation in AI

Technological integration

- Integrating classical and quantum computing presents challenges to increasing processing speed, requiring significant advances in quantum hardware.
- Actual quantum hardware, especially Noisy Intermediate Scale Quantum processors (NISQ), experience substantial errors requiring the development of adaptive algorithms to overcome these obstacles.
- In regards to Quantum Key Distribution system security (CVQKD), disparities between real devices and ideal models can lead to vulnerabilities, raising challenges and concerns in integrating quantum computing into information security.

Simulation and Modeling

- Direct simulation of molecular photochemistry remains challenging due to the need to accurately address molecular electronic structures, the dynamics of atomic nuclei, and the impact of non-adiabatic couplings.
- There are challenges in exploring the interactions of machine learning and quantum physics of many-body systems.

AI Implementation

- The application of RL, DRL, and QML techniques in SDN routing in 6G-type networks faces unresolved research questions, which limits their normal and recurrent use in enterprise contexts.
- There are also other challenges in terms of economic, accessibility, and environmental means. This highlights the need to make these models more sustainable and efficient.
- Vulnerabilities in quantum systems arise because the particular characteristics of quantum data pose challenges in distributed deep learning approaches and QNNs, underscoring the difficulties and concerns associated with integrating quantum computing into the AI domain.

Estimates and Opportunities

Research applying quantum computing to enterprise artificial intelligence faces significant challenges in several key areas. In technology integration, NISQ quantum processors and disparities between real devices and ideal models represent critical hurdles, especially in quantum security. In simulation and modeling, the challenge lies in handling the complexity of molecular photochemistry and many-body systems, which requires advances in algorithms and simulation techniques. In addition, the application of AI in enterprise contexts, such as SDN routing in 6G networks, faces economic, environmental, and affordability barriers, highlighting the need for more sustainable and efficient solutions.

General Aspects of the Findings

Quantum computing is revolutionizing several fields of artificial intelligence. In machine learning, quantum algorithms such as quantum parameterized circuits and tensor networks offer better, more efficient answers to complex problems. In biomedicine, it is used to accelerate drug discovery and DNA analysis. It also improves molecular simulation and big data handling in chemistry and quantum physics. In telecommunications, cybersecurity, as in quantum key distribution it provides superior data security. These innovations could transform AI, optimizing processes in various industries and opening up new opportunities for the implementation of advanced technologies in healthcare, physics, and information security.

Key quantum computing tools and methods in artificial intelligence include algorithms like the Quantum Support Vector Machine (QSVM), which offers higher accuracy than traditional methods. Hybrid quantum-classical models improve supervised and generative learning and quantum neural networks (QNN) are effective in handling large volumes of data. In addition, quantum data modeling facilitates the application of quantum and classical technologies. These innovations make artificial intelligence more accurate and efficient, potentially revolutionizing areas that rely on big data processing.

Integrating quantum computing into artificial intelligence faces several major challenges. The fragility of qubits, the need for advanced hardware, and the difficulty of simulating complex phenomena are technical hurdles. In addition, high computational and energy costs limit scalability in enterprises, and quantum security vulnerabilities require more robust systems. Overcoming these challenges is crucial to enable companies to take full advantage of these technologies and improve performance and security in various applications.

4 Conclusions

The study has achieved its goal by providing a generalized view of how quantum computing improves efficiency and decision-making in various fields of artificial intelligence. It highlights how high-energy physics, materials design, and medicine benefit from its use, as well as how high-energy physics and quantum machine learning work together to perform deeper analysis of sizable data sets with less resources.

However, as the systematic research undertaken indicates, several limits should be taken into account when tackling the integration of quantum computing in artificial intelligence. First of all, the size of the studies that were analyzed was lower than anticipated, indicating that to have a more comprehensive and effective perspective, more research utilizing various research methodologies may be required. Furthermore, the absence of a discussion of the theoretical or motivational foundations of the papers retrieved raises the possibility of a lack of a thorough comprehension of the writer's perspectives on applying quantum computing in AI. Moreover, it is pertinent and fair to acknowledge that the integration of both factors concentrates on distinct levels of abstraction, implying that a thorough and flexible comprehension is required for efficient execution. It is therefore hoped that these constraints would be seen as chances for additional study and investigation.

Future research will be foundational to increase the understanding of how quantum computing can enhance the development of AI. It is estimated that new lines of study may focus on the design of advanced quantum algorithms, targeted towards optimizing predictive models and classifying complex data, key areas where quantum AI promises to revolutionize efficiency and accuracy. It will also be critical to explore hybrid quantum-classical approaches, which merge the better features of both approaches to overcome current limitations and facilitate more seamless integration. As new quantum hardware technologies emerge, it will be equally important to investigate how these advances can be optimized to take full advantage of quantum algorithms, as well as to develop infrastructures that enable greater accessibility to these innovations.

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