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Review article

Quantum artificial intelligence: A survey

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ABSTRACT

Quantum computing and artificial intelligence are two highly topical fields of research that can benefit from each other's discoveries by opening a completely new scenario in computation, that of quantum artificial intelligence. Indeed, on the one hand, artificial intelligence algorithms can be made computationally more efficient due to the potential speedup enabled by quantum phenomena; on the other hand, the complex development of quantum computing technologies and methodologies can be properly supported by the use of classical artificial intelligence approaches. The "entanglement" of these two disciplines is opening up completely new directions in computer science research, and this survey aims to provide a systematic and taxonomic overview of the work that has already been done and that which will begin in the near future.

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1. Introduction

The media has recently focused its attention on two computing disciplines that are transforming the way people live and will continue to do so in the years to come: **Artificial Intelligence (AI)** and **quantum computing**. It is evident that the influence of computer systems based on AI methodologies is becoming increasingly prevalent in the realm of human existence. Similarly, the potential of an alternative computing paradigm based on quantum mechanics is being touted as a means of exceeding the performance of modern supercomputers, opening up new scenarios in various application domains. This supports the positions of both AI and quantum computing as crucial foundations of contemporary information technology.

In his seminal work [1], Marco Somalvico, a pioneer of AI, defines the field as follows: "Artificial intelligence is a discipline belonging to computer science that studies the theoretical foundations, methodologies and techniques that enable the design of hardware and software systems capable of providing computers with performance that, to a common observer, would appear to be the exclusive domain of human intelligence". AI achieves this by means of the implementation of so-called intelligent agents capable of replicating different human intellectual abilities such as reasoning and decision making, problem solving, and learning [2]. Although these methods have been studied for several decades, it is only in recent years that they have had a major impact on people's daily lives due to the vast amount of data made available by the Internet and the increasing computational capabilities of computers. Today, AI is currently being used in various scenarios of daily life, from search and recommendation algorithms used in applications such as Netflix and Amazon to the navigation systems used by Tesla in its autonomous cars. Moreover, recent implementations of AI based on generative models, such as ChatGPT [3,4], have the potential to support, and in some cases replace humans, in work activities in different application domains, such as technology jobs, legal, marketing, and so on [5–8].

Quantum computing is a novel computational paradigm that uses quantum mechanical phenomena, such as superposition, entanglement, and interference, to explore solution spaces in fundamentally different ways, offering the potential to efficiently solve certain problems that are intractable for classical computational models [9], including probabilistic and deterministic Turing machines, and may even provide exponential advantages in specific cases. This challenges the *strong Church–Turing thesis*, which asserts that every physically reasonable computational device can be simulated by a Turing machine with at most polynomial slowdown. A case in point highlighting the potential advantages of quantum computing is Shor's quantum algorithm for the integer factorization problem [10], which involves the decomposition of a large integer into its prime factors. This algorithm can factor large numbers significantly faster than the best-known classical algorithms. While classical methods for factoring integers require time that grows exponentially with the size of the number, Shor's algorithm allows quantum computers to solve the problem in a polynomial time. Despite significant effort, no classical algorithm is known that can factor integers efficiently. If, as widely conjectured, there is no efficient classical algorithm for integer factorization, a problem that underpins the security of cryptographic schemes like RSA,[1] and quantum computers are physically realizable, then the strong Church–Turing thesis is fundamentally incorrect. An additional illustration of quantum efficiency is Grover's algorithm [12], which offers a substantial acceleration for unstructured search problems. These are problems in which the objective is to identify a specific solution from a set of possibilities that lack any inherent order or structure. In contrast to classical algorithms, which require time proportional to the total number of possible solutions, Grover's algorithm significantly reduces this time, achieving a quadratic speedup by requiring only the square root of the number of solutions to complete the search. Shor's and Grover's algorithms are among the most illustrative examples of quantum algorithms that offer enhanced performance compared to their classical counterparts. However, these algorithms currently provide only a theoretical advantage due to the limitations of the current generation of quantum computers, known as Noisy Intermediate-Scale Quantum (NISQ) devices,[2] which lack the reliability needed to consistently execute these algorithms. In 2019, however, this theoretical advantage was demonstrated in practice when Google researchers achieved the milestone of quantum supremacy [13], thereby proving that their quantum computer, Sycamore, was capable of completing a complex calculation in just 200 s, a task that would take a classical supercomputer 10,000 years.[3]

Although AI and quantum computing are traditionally considered distinct fields of computer science, their integration within the emerging domain of QAI can offer a dual benefit, as recently emphasized by Acampora et al. in the European White Paper on Quantum Artificial Intelligence [14]. On the one hand, the potential benefits induced by quantum phenomena in computation have opened the way to quantum implementation of AI algorithms, and indeed it is common today to encounter research studies on quantum neural networks (QNNs), quantum

[1] RSA (Rivest–Shamir–Adleman) is a widely used public-key cryptosystem that relies on the computational difficulty of factoring large composite integers as the basis for its security. It is commonly used in securing online communications and digital signatures [11].

[2] NISQ devices are primarily circuit-based, meaning they operate using the quantum gate model. These devices rely on quantum circuits composed of quantum gates applied to qubits to perform computations.

[3] In 2021, a team of Chinese researchers used the Sunway supercomputer to simulate a random quantum circuit from the Sycamore processor, accomplishing this task in only 304 s. This demonstrated that, although Sycamore's calculation was groundbreaking in its speed, it could still be replicated using classical supercomputers with a sufficiently advanced approach. The Google team said they were aware that this advantage could not be maintained for long, but they continue to think that this classical approach cannot keep up with quantum circuits in 2022 and beyond.

logic, and so on. This new direction of research will open up unimagined application scenarios in which the increasing amount of data to be processed to create AI models can be adequately managed thanks to the computational advantages of quantum computing [15–22]. Imagine, for example, the generative models that underpin applications such as ChatGPT, which could be managed more efficiently thanks to quantum algorithms [23]. Or consider the smart cities of the future, where thousands of sensors and actuators will interact to provide personalized services to millions of people; again, the efficiency of quantum computing can lead to enormous benefits in the generation and execution of AI models [24]. However, quantum computing is still an embryonic discipline due to the immature nature of the quantum processors used to run the current generation of quantum algorithms. In fact, NISQ devices are not yet advanced enough for fault tolerance or large enough to achieve quantum supremacy because they are sensitive to their environment (noisy) and prone to quantum decoherence. In this negative scenario, classical methods of AI can strongly support quantum computation to improve its ability to execute algorithms reliably. For example, neural networks can be used to "transform" quantum algorithms into a different form so that they are suitable to run reliably on a NISQ processor. Or, unsupervised machine learning algorithms or efficient search methods can be used to mitigate the errors generated by running quantum algorithms on NISQ devices. These are just a few examples of the symbiotic relationship between AI and quantum computing, which will be fully explored in this survey paper. This activity is carried out by defining and introducing a systematic and taxonomic vision of the field of QAI. The identified topics are then navigated hierarchically and the most valuable research results belonging to each node of the taxonomy are fully described. Finally, a discussion of future challenges and ethical issues related to the field of QAI is provided to guide researchers in properly initiating new activities in this fascinating area of computer science, opening the way towards the practical application of QAI once the NISQ era ends and Fault-Tolerant Quantum Computing (FTQC)[4] becomes available [25,26].

2. Motivations and related work

This section aims to provide an objective overview of the motivation of the survey, accompanied by a detailed analysis of related surveys.

2.1. The need for a structured survey on QAI

In recent years, there has been a marked increase in the number of academic papers related to QAI (see Section 4.3), indicative of the growing interest in this emerging research field. This increased interest underscores the need to perform a thorough analysis and methodically collect QAI research, providing researchers with a comprehensive understanding of current advances. This survey bridges this gap by first introducing a structured framework, based on a taxonomic approach, on which diverse methodologies, techniques, and applications within QAI can be categorized and systematically examined. This taxonomic definition offers researchers from the QAI a range of perspectives and benefits, including:

1. Organizing knowledge: A taxonomy is a classification system that organizes and categorizes knowledge into distinct groups. It serves to make the body of research more navigable by providing a structured framework that enables the systematic organization of diverse approaches, methodologies, and applications within QAI.
2. Enhancing understanding: Researchers can use the taxonomy to quickly grasp the fundamental concepts, components, and relationships within QAI, reducing the learning curve.
3. Facilitating comparisons: A structured framework enables systematic comparisons between different QAI methods, highlighting their strengths, weaknesses, and areas of applicability
4. Identifying research gaps: A comprehensive taxonomy can uncover underexplored areas, guiding researchers towards new and impactful directions.
5. Promoting interdisciplinary collaboration: By standardizing terminology and concepts, a taxonomic approach makes QAI more accessible to experts in AI, quantum computing, and related fields, fostering cross-disciplinary innovation.

This method will assist the computer science community in the progress of QAI theory and applications, with the aim of accelerating the shift from NISQ to FTQC by facilitating the creation of efficient quantum-enhanced AI algorithms and ensuring their real-world applicability.

2.2. Related surveys

Currently, there is only a brief survey of the field of QAI, which considers this field to be the combination of quantum-enhanced artificial intelligence and artificial intelligence for quantum computation [27]. Although the survey reviews around 70 contributions and represents an important initial effort to outline the field, some topics, such as quantum inference and AI-driven approaches to quantum pulse control, remain unaddressed. Therefore, it is necessary to expand this survey with a more comprehensive and exhaustive review of the literature, a formal taxonomic definition, and a critical evaluation of the field.

In contrast, other surveys consider the two subfields of QAI independently. For example, a pioneering study focused on quantum-enhanced artificial intelligence was published in 2010 [28]. This survey explores potential applications of quantum algorithms to learning problems, along with early approaches to quantum search and quantum game theory. Since 2017, several more comprehensive surveys have emerged on quantum-enhanced artificial intelligence. The first seminal work specifically dedicated to quantum machine learning (QML) was published in [29], where the authors laid the foundations for this emerging and promising research area. Subsequently, additional surveys in the field of QML have been presented in [30–34], while more focused reviews on QNNs can be found in [35,36]. Still, in [37], the authors present an overview of the integration of quantum mechanics with intelligent algorithms belonging to two research areas, that is, evolutionary computation and machine learning. The most recent survey in the field of QML is reported in [38], where the authors report 94 articles using QML techniques showing also their implementation using computational quantum circuits. Moreover, the survey discusses the most relevant applications in the field of QML such as image classification. As for the other research fields of the quantum-enhanced artificial intelligence area, a substantial literature review of various quantum walk formulations and their strengths and limitations is reported in [39], while, in [40], a review of emerging trends in quantum robotics is discussed. A recent survey [41] provides a comprehensive overview of quantum-enhanced artificial intelligence techniques designed for the NISQ era, highlighting both theoretical models and practical implementations across various AI domains.

Regarding the application of AI methodologies in the development of reliable quantum technologies, to our knowledge, the only existing survey is reported in [42], where the authors address quantum compilation using AI techniques. No surveys have been published exploring the application of AI to other specific quantum challenges, such as reducing quantum noise.

Starting from this literature analysis (see Table 1 for a summary), although the aforementioned surveys have made a substantial contribution to the field, their insights now require updating to reflect the significant advances in quantum computing that have occurred over recent years. It should be noted that the advent of operational NISQ

[4] FTQC enables reliable and scalable quantum computations, overcoming the limitations of NISQ systems in real-world applications.

Table 1
Summary of related surveys in chronological order.

Topics \ Surveys	[28]	[29]	[35]	[37]	[32]	[31]	[30]	[39]	[33]	[42]	[36]	[34]	[38]	[40]	[27]	[41]
Quantum search algorithms	x							x							x	x
Quantum evolutionary algorithms																x
Quantum game theory	x														x	
Quantum logic	x															
Quantum inference																x
Quantum cognition																
Quantum supervised learning	x	x	x	x	x	x	x		x		x	x	x		x	x
Quantum unsupervised learning		x		x	x	x	x								x	x
Quantum reinforcement learning															x	x
Quantum data processing		x				x	x									x
Quantum natural language processing															x	x
Quantum computer vision													x		x	
Quantum robotics														x	x	
Quantum circuit mapping										x					x	
Quantum routing strategy										x					x	
Quantum circuit synthesis										x					x	
Quantum tomography																
Quantum calibration		x													x	
Quantum pulse control																
Quantum error correction		x													x	
Quantum error mitigation															x	

devices has led to new developments that warrant further investigation. It can be concluded that there is a pressing need for a new survey that is more recent, more complete, and provides definitions, milestones, and future insights in the nascent research field of QAI.

3. A taxonomic and systematic vision for quantum artificial intelligence

In its pioneering nature, QAI is tentatively defined as a new field of research that investigates the relationships between classical computing methodologies associated with the domain of AI and quantum computing. This survey offers a more systematic and taxonomic definition of the field, beginning with a description of the individual research areas and the identification of the potential intersection areas.

3.1. Artificial intelligence: a set of methods to imitate humans

AI refers to the study and advancement of intelligent agents, systems capable of perceiving their environment and taking actions to achieve specific goals or perform tasks that typically require human intelligence. These tasks include, but are not limited to, speech recognition, decision making, and pattern identification. The overarching challenge of simulating intelligent behavior has been deconstructed into subproblems that focus on specific traits or capabilities expected from intelligent agents. According to the leading AI literature [2,43], the main capabilities that drive the development of intelligent agents are: *problem solving, knowledge representation, reasoning and planning, machine learning* and *communication, perception, and action*.

Problem solving is defined as the ability of intelligent agents to transform a given initial state into a desired goal state by performing a sequence of actions or steps. The objective is to find a solution that satisfies the constraints of the problem while optimizing for efficiency, cost, or other relevant metrics. AI employs a variety of problem solving techniques, including search algorithms such as breadth-first search, depth-first search, and heuristic methods such as A^* search. For problems that are more complex or large-scale in nature, evolutionary algorithms and random walks are employed. In environments involving multiple intelligent agents, where the outcomes depend on the actions of these agents, game theory provides a robust framework for problem solving. Incorporating these diverse strategies enables intelligent agents to address a wide range of challenges, from basic decision-making tasks to complex, dynamic systems.

Knowledge representation, reasoning, and planning are core capabilities that enable the design of intelligent agents capable of understanding their environment and making informed decisions. In knowledge-based systems, an agent's knowledge is represented as sentences in a formal language of knowledge representation, stored within a knowledge base. A knowledge-based agent combines this knowledge base with an inference mechanism to derive new information and guide its actions. These agents operate by storing facts and rules about the world, applying logical reasoning to infer new conclusions, and using these insights to determine appropriate actions. To achieve this, they rely on ontological engineering for structuring knowledge and implement various forms of mathematical logic, including propositional logic, first-order logic, fuzzy logic, and probabilistic inference techniques like Bayesian networks. The ability to represent and reason effectively allows intelligent agents to navigate complex environments, adapt to changing circumstances, and optimize decision making.

Machine learning is a branch of AI that enables computer systems to learn and improve their performance on a task by analyzing data rather than being explicitly programmed with specific rules. Instead of following predetermined instructions, a machine learning model identifies patterns and relationships in the data to make predictions, classify information, or make decisions. There are different types of learning: supervised learning, unsupervised learning, and reinforcement learning. In supervised learning, the agent observes the input–output pairs and learns a function that maps from input to output. Some examples of algorithms for supervised learning are support vector machine, logistic regression, linear regression, naive Bayes, decision trees, K-nearest neighbor algorithm, and neural networks. In unsupervised learning, the agent learns patterns in the input without explicit feedback. The most common unsupervised learning task is clustering: identifying potentially useful clusters of input examples. Clustering methods include hierarchical clustering, k-means, mixture models, DBSCAN, and the OPTICS algorithm. Another common task in unsupervised learning is anomaly or outlier detection, i.e., the identification of rare items, events, or observations that deviate significantly from the majority of the data and do not conform to a well-defined notion of normal behavior. Methods for anomaly detection include Z-score, Tukey's range test and Grubbs's test, local outlier factor, Isolation forest, replicating neural networks, autoencoders, variational autoencoders, and Long Short-Term Memory (LSTM) neural networks. In the domain of reinforcement learning, intelligent agents are designed to acquire decision-making capabilities through interactions with their environment. These agents execute actions, receiving feedback in the form of rewards or punishments depending on the outcomes of those actions. The objective of reinforcement learning is to devise a policy or strategy that maximizes cumulative rewards, also known as the return, over time. In contrast to supervised learning, where the correct answers are provided, the agent must explore its environment and exploit the most effective actions through trial and error. Reinforcement learning methods include Monte

Carlo methods, Q-learning, and SARSA, which aid the agent in estimating the value of different actions and refining its decision-making process.

In the context of AI, "communication, perception, and action" refer to the capabilities that allow an AI system to interact with its environment. Natural Language Processing (NLP), computer vision, and robotics belong to this area of AI. In fact, NLP allows intelligent agents to communicate successfully in a human language; computer vision enables agents to perceive their operational environments; and robotics is used by intelligent agents to manipulate objects and move in their environment. NLP is implemented by combining language models and machine learning capabilities. Computer vision uses image processing algorithms to detect edges, textures, optical flow, and regions of images, and machine learning algorithms such as neural networks to perform image classification. Robots use data from sensors with reasoning and learning algorithms to infer new knowledge to correctly set the status of actuators.

The aforementioned approaches are currently being utilized to implement sophisticated AI systems in various application scenarios, including e-Commerce, education, transportation, healthcare, and virtual assistants.

3.2. Quantum computing: benefits and design issues

Quantum computing is a significant technological breakthrough that has enormous potential to change the world of computing. Unlike classical bits, which represent binary states, quantum computing uses qubits that leverage quantum phenomena such as superposition, entanglement, and interference, enabling the exploration of multiple possibilities at once and significantly enhancing computational power for specific problems. This allows quantum computers to potentially solve hard problems more efficiently than classical computers. A comprehensive description of how quantum computers handle information and how to design quantum algorithms can be found in relevant books such as [44–46].

Despite the immense benefits that quantum computing may offer, designing and building quantum computers is a major challenge. At present, the process of manufacturing qubits is still in its infancy, and researchers have yet to develop a practical, large-scale quantum computer. Moreover, environmental factors such as noise and interference contribute to decoherence and lead to instability, which poses significant obstacles to the design and operation of quantum machines. For this reason, different technologies are being used to design and implement reliable and fully operational qubits. Of these, the most promising are those based on superconductors, neutral atoms, trapped ions, and photons. However, none of the above qubit realization technologies succeeds in minimizing the effects of quantum noise and making a quantum computer completely reliable. Consequently, there is a need to identify classical computation approaches that can assist and support the execution process of quantum circuits by minimizing the effects of noise and decoherence.

3.3. Quantum artificial intelligence

The preceding characterization of AI and quantum computing provides a foundation for the emerging research paradigm of QAI, in which these two disciplines exist in a symbiotic relationship, complementing and enriching each other. In fact, on the one hand, the potential increase in computation offered by quantum computing can support the design and implementation of new AI algorithms for problem solving, knowledge representation, reasoning and planning, machine learning and communicating, perceiving, and acting, opening up application scenarios unimaginable until now; on the other hand, AI techniques, such as machine learning, reasoning, and problem-solving algorithms, can improve the performance of quantum computers of NISQ era, because these methods can help to develop efficient methods for quantum compilation, pulse optimization, quantum error correction, and quantum error mitigation. This "entanglement" between AI and quantum computing can be systematized through a taxonomic approach that visualizes the different types of interaction between the two research areas, as shown in Fig. 1. A conceptual overview of the interplay between these fields was outlined in [27], upon which the present taxonomy builds by providing a structured and reproducible classification of such interactions. At the highest level of the hierarchy is the entire research area, divided into two macro areas: *quantum-enhanced artificial intelligence* and *artificial intelligence for quantum computation*.

Quantum-enhanced artificial intelligence aims to use quantum mechanical principles such as superposition, entanglement, and interference to define new subfields of AI such as *quantum problem-solving*, *quantum knowledge representation*, *reasoning and planning*, *QML* and *quantum communication, perception, and action*. Quantum problem solving employs quantum-mechanical principles to aid in the development of search algorithms that are more proficient in exploring the solution space of a given problem. Quantum computation may aid knowledge representation by utilizing quantum logic and vector spaces to efficiently store and retrieve information. Quantum reasoning and planning may enhance the efficiency of smart systems by deducing novel knowledge through the development of parallel inference mechanisms. QML has the potential to improve the storage of machine learning model parameters with the added benefit of improving training time and model accuracy. Finally, quantum computing opens new possibilities to design efficient algorithms for communication, perception, and action, such as new methods for NLP, computer vision, and robotics.

Artificial intelligence for quantum computation is a research area focused on using intelligent methodologies, such as reasoning and learning, to address the critical issues that still affect the design of reliable quantum computers and algorithms. It is composed of three sub-fields: *AI for quantum compilation*, *AI for quantum characterization*, and *AI for reducing quantum noise*. In the field of AI for quantum compilation, intelligent methodologies, such as search algorithms and machine learning, are employed to address issues pertaining to quantum compilers, including circuit mapping and routing. In the field of AI for quantum characterization, logic, inference engines, and machine learning are employed to facilitate the development of more efficient approaches for pulse control, calibration, and state tomography in quantum processors. Finally, in AI to reduce quantum noise, inference engines, evolutionary algorithms, as well as supervised and unsupervised machine learning algorithms, are used to enhance the performance of quantum error correction and mitigation schemes.

Table 2 provides a comprehensive list of concepts denoted as *keyword classes* related to the taxonomy used to collect papers in this survey. In fact, this list of keyword classes provides a framework for the methodology that will be used in collecting the papers that are deemed most appropriate for presentation in our survey.

4. Methodology

This section is devoted to describing how the papers reported in this survey were collected. An exhaustive and objective search of the relevant academic literature was conducted, encompassing both formal peer-reviewed publications, such as conference papers and journal articles. Two distinct methodologies were used for the right and left subtrees of the hierarchy in Fig. 1 reflecting the disparate levels of advancement in research activities related to the two corresponding macro-areas: quantum-enhanced artificial intelligence and artificial intelligence for quantum computation.

4.1. Methodology: Quantum-enhanced artificial intelligence

In regard to the left subtree of the hierarchy, the most pertinent literature was identified by the following criterion. For each leaf node in the left subtree, a list of keyword classes corresponding to different

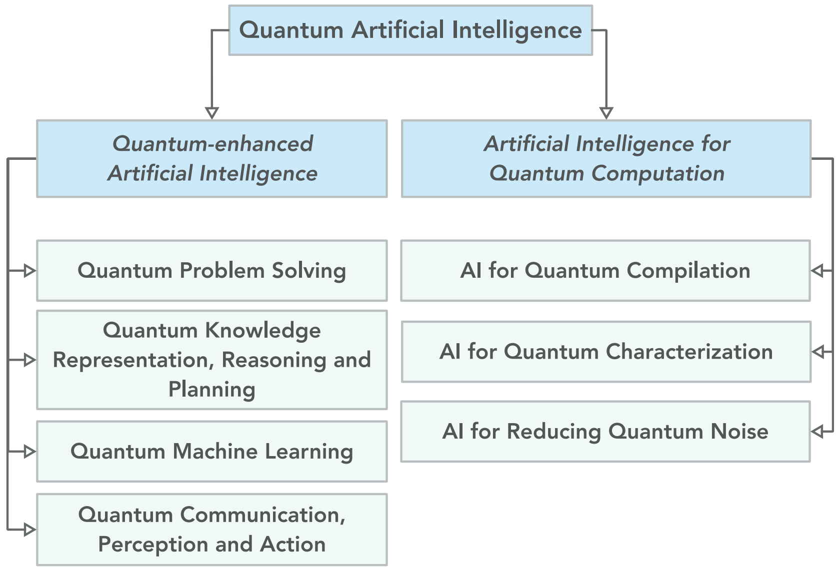


Fig. 1. Quantum artificial intelligence: a taxonomic view.

Table 2
Sub-fields of QAI and related keywords.

Quantum-enhanced Artificial Intelligence	
Sub-field	*Keyword classes*
Quantum problem solving	Quantum search algorithms Quantum evolutionary algorithms Quantum game theory
Quantum knowledge representation, reasoning and planning	Quantum logic Quantum inference Quantum cognition
Quantum machine learning	Quantum supervised learning Quantum unsupervised learning Quantum reinforcement learning Quantum data processing
Quantum Communication, Perception, and Action	Quantum natural language processing Quantum computer vision Quantum robotics
Artificial Intelligence for Quantum Computation	
Sub-field	*Keyword classes*
AI for quantum compilation	Quantum circuit mapping Quantum routing strategy Quantum circuit synthesis
AI for quantum characterization	Quantum tomography Quantum calibration Quantum pulse control
AI for reducing quantum noise	Quantum error correction Quantum error mitigation

research subareas of a specific field of quantum-enhanced artificial intelligence has been identified (see Table 2). For example, quantum search algorithms are a subarea of quantum problem solving, and quantum supervised learning is a subarea of QML. Subsequently, these keyword classes were used as Scopus queries in a Python script based on the Pybliometrics library.[5] This was done with the objective of collecting a list of papers related to the specific subarea and extracting from those papers other correlated keywords that contain the word "quantum". These keywords were then analyzed, considering their occurrences, in order to extract the complete set of keywords, which were subsequently used as Scopus queries. A query was generated for each keyword considering the Scopus field codes *Authkey* and *Title*, with the objective of collecting the papers presented in this survey.

In order to identify an appropriate set of research for this survey, the Scopus query also considered the subject area, the year of publication, and the number of citations of the papers. All papers in the computer science field were collected for this survey because it is mainly addressed to this community. Only papers published from 2016 onward were considered, as this was the year in which the first computers of the NISQ era were released.[6] Regarding the number of citations, articles that ranked above the 95th percentile of all relevant publications in a given year were extracted. All searches were conducted on articles written in the English language. It is also worth noting that to avoid duplicates, a paper extracted by two or more Scopus queries using different keywords was collected under the item "hybrid" for each keyword class. The set of documents collected was then subjected to an expert-based analysis to ascertain their compatibility with the survey objectives and the class in which it was placed, as determined by the Python script.

4.2. Methodology: Artificial intelligence for quantum computation

With regard to the right subtree of the hierarchy, it should be noted that due to the lower maturity of the search field, as evidenced by the statistical data presented in the following section, the most relevant literature was identified using an alternative methodology. In particular, for each leaf node in the right subtree, a list of keyword classes corresponding to different research subareas of quantum computation in which AI can contribute has been identified (see Table 2). Subsequently, all keyword classes related to a specific subfield were utilized in a Scopus query considering field codes *Authkey* and *Title*, in conjunction with keywords associated with the AI domain. This was done with the objective of collecting papers pertaining to artificial intelligence for quantum computation. Moreover, also for the right subtree of the hierarchy, the Scopus query also took into account the subject area, that is 'computer science,' and the year of publication, that is, from 2016 onward. As in the first area, the collected set of

[5] https://pybliometrics.readthedocs.io/en/stable/

[6] Although John Preskill formally introduced the term 'NISQ' in 2018, the first significant steps into this era began in 2016, when major technology companies unveiled 5-qubit and 16-qubit quantum processors, marking the early development of noisy intermediate-scale quantum devices.

documents was then critically analyzed to check the compatibility of each manuscript with the survey objectives and the class in which it was placed by the Python script.

4.3. Statistics

The results of our systematic review of the literature on QAI in the field of computer science indicate that more than 3000 articles have been published since 2016. Of these, only slightly more than 150 are affiliated with the right subtree of the taxonomy. This suggests that there is a notable difference in the level of maturity mentioned above between the two research fields of QAI.

4.3.1. Statistics for quantum-enhanced artificial intelligence

As illustrated in Fig. 2, the field of quantum-enhanced artificial intelligence has seen a notable acceleration in research activity since 2016. In fact, the number of articles published from 2016 to the present (nine years) exceeds the total number of articles published prior to 2016 across all subfields within this research area. To provide a more detailed analysis, Fig. 3 illustrates the evolution of the field over the years since 2016, with a focus on its subfields. It should be noted that, given the large number of papers pertaining to the domain of quantum-enhanced artificial intelligence, the selected papers analyzed for this survey represent the 95th percentile in terms of the number of citations, as discussed in Section 4.1. Consequently, the number of papers subjected to analysis within each subfield of quantum-enhanced artificial intelligence is presented in Fig. 4.

In order to more accurately assess the level of interest within the research community in relation to the topics covered by the keyword classes, Fig. 5 presents the number of papers collected for each keyword class within each subfield of the quantum-enhanced artificial intelligence area, as well as the number of manuscripts belonging to the 95th percentile. As illustrated in Fig. 5(a), the field of quantum game theory has a relatively limited publication history compared to the other two subfields within the broader domain of quantum problem solving: namely, quantum search algorithms and quantum evolutionary algorithms. However, it should be noted that the number of papers extracted using the keyword "quantum search algorithms" has been slightly increased by some works on *quantum-inspired* random walks [47,48]. Similarly, the number of papers related to the quantum evolutionary algorithms of keyword class "quantum evolutionary algorithms" is significantly influenced by research in the field of quantum-inspired evolutionary computation [49–52]. The field of quantum-inspired computation was established prior to the advent of the NISQ era. Its principal objective was to develop classical algorithms that were inspired by, and drew upon, the fundamental principles of quantum mechanics. As these quantum-inspired approaches were not designed to be executed on NISQ quantum computers, they were not included in this survey. Fig. 5(b) illustrates that quantum logic is the subject with the highest number of publications in the subfield of quantum knowledge representation, reasoning, and planning. It is important to note that the number of papers in this area has been inflated by the inclusion of several works, such as [53,54], which pertain to quantum computational logic applied to the synthesis of quantum circuits for quantum algorithms. These have been omitted from this survey because they do not focus on knowledge representation, reasoning, and planning. Fig. 5(c) illustrates that the majority of papers in the subfield of QML refer to quantum supervised learning. However, the number of papers extracted using this keyword class is slightly increased by the presence of some quantum-inspired algorithms for machine learning tasks [55,56]. Similarly, the papers identified through the keyword class "quantum unsupervised learning" also include a few papers related to quantum-inspired algorithms for clustering, such as [57,58]. Once more, as the focus of the survey is exclusively on actual quantum approaches, these have been excluded from the discussion. As illustrated in Fig. 5(d), most of the papers in the subfield of quantum communication, perception, and action are related to quantum computer vision. However, it should be noted that this area also encompasses some papers that were initially included in the domain of quantum supervised learning. Consequently, these papers will be exclusively addressed within the context of quantum supervised learning.

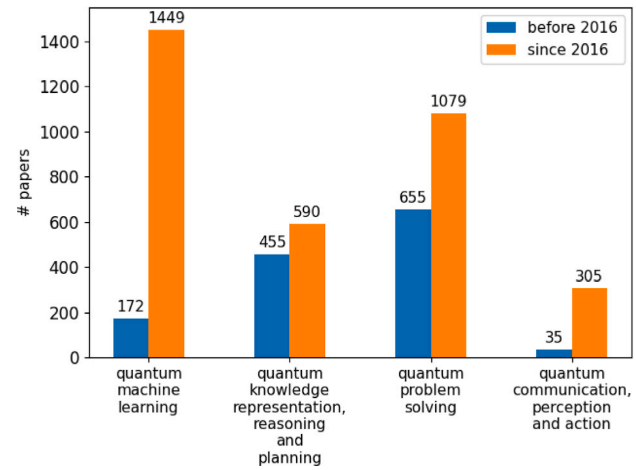


Fig. 2. Number of papers published in the search field of quantum-enhanced artificial intelligence before and from 2016.

4.3.2. Statistics for artificial intelligence for quantum computing

To provide information on the research domain of AI techniques for quantum computing, Fig. 6 illustrates the number of publications within each subfield. It is evident that the most developed subfield pertains to the utilization of AI methodologies to mitigate quantum noise. However, it should be noted that the number of articles in this subfield has been slightly inflated by the inclusion of some articles that are related to quantum noise but do not employ or introduce AI techniques to address the problem. These articles have been omitted from the analysis. An example is provided in [59], in which a study on the effects of quantum noise on quantum genetic algorithms is detailed, but no methodology is outlined to reduce quantum noise.

Similarly, for a fair comparison, it is worth noting that the number of papers in the second most mature subfield related to the exploitation of AI methods to quantum characterization has also increased, as evidenced by papers such as [60,61], which are erroneously extracted because they do not deal with AI techniques.

5. Quantum-enhanced artificial intelligence

This section presents the contributions of the computer science community to the field of quantum algorithms for AI. It is organized according to the left subtree of the proposed taxonomy of QAI, and Table 3 reports the summary of the cited papers.

5.1. Quantum problem solving

Problem solving is the process by which an intelligent agent transforms a given initial state into a desired goal state by selecting and executing a sequence of actions that satisfies the constraints of the problem, using different strategies, such as search algorithms, evolutionary computation, and game theory. Quantum computing has the potential to significantly transform problem solving in AI by exploiting its unique ability to process information using quantum superposition, entanglement, and interference. This can lead to faster solutions to complex problems that are hard to solve on classical machines. Building on these considerations, this section analyzes three key aspects of quantum problem solving: quantum search algorithms, quantum evolutionary algorithms, and quantum game theory.

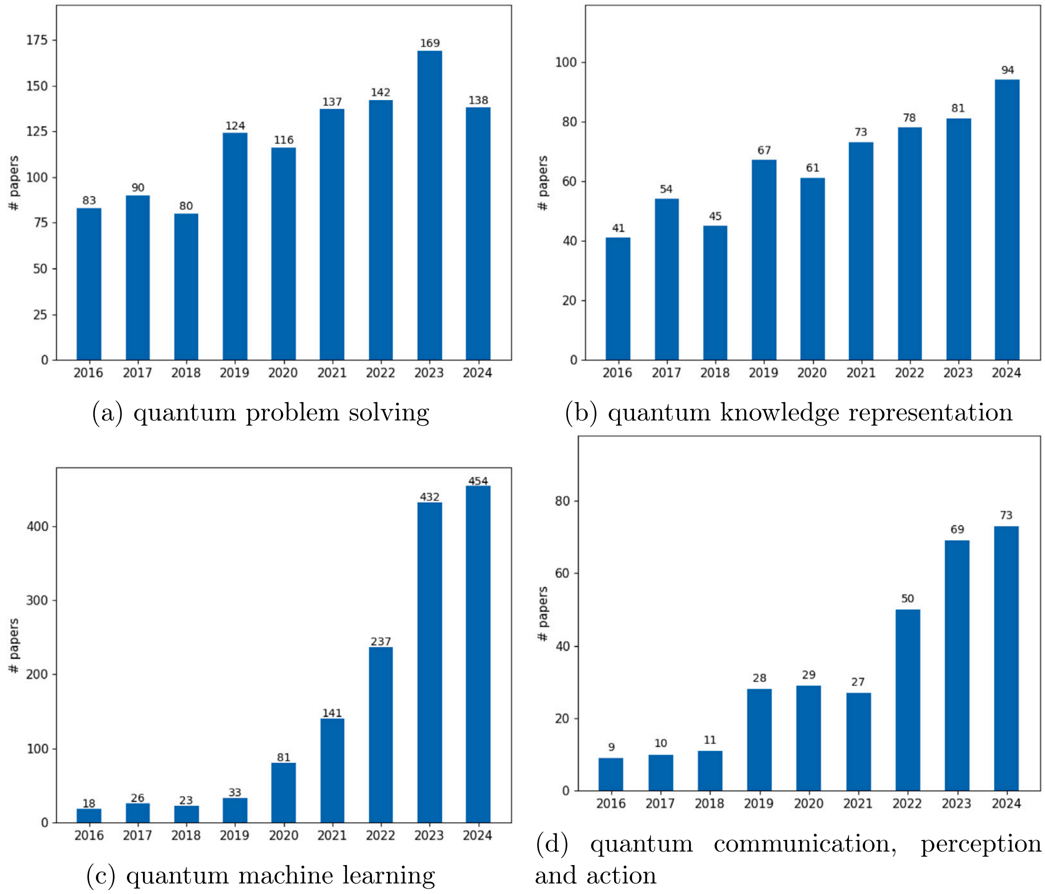


Fig. 3. Number of papers published in the field of quantum-enhanced artificial intelligence over years since 2016 by considering the sub-fields separately.

Table 3
A literature overview of quantum-enhanced artificial intelligence.

Quantum-enhanced Artificial Intelligence			
AI Field	*Classical approaches*	*Quantum approaches*	*References*
Problem Solving	Search Algorithms	Grover's Search Algorithm	[62–70]
		Quantum Random Walks	[71–106]
	Quantum Evolutionary Algorithms	Genetic Algorithms	[107–113]
		Other Evolutionary Algorithms	[114–116]
	Game Theory	Quantum Game Theory	[117–136]
Knowledge Representation	Logic	Quantum Logic	[137–145]
		Quantum Automata	[146–153]
		Quantum Fuzzy Logic	[154–158]
	Inference	Quantum Fuzzy Inference	[159,160]
		Quantum Probabilistic Inference	[161–187]
	Cognition	Quantum Cognition	[188–200]
Machine Learning	Unsupervised Learning	Quantum Regression	[201,202]
		Quantum Neural Networks	[203–223]
		Quantum Recurrent Neural Networks	[224–228]
		Quantum Convolutional Neural Networks	[229–238]
		Quantum classifiers	[239–253]
		Quantum k-Means Algorithm	[254–260]
		Quantum Generative Models	[261–272]
		Quantum Autoencoders	[273–275]
	Reinforcement Learning	Quantum Reinforcement Learning	[276–286]
	Data processing	Quantum Data Preprocessing	[287–289]
		Quantum Feature Maps and Kernels	[290–295]
		Quantum State Processing	[296,297]
Communication, Perception and Action	Natural Language Processing	Quantum Natural Language Processing	[298–305]
	Computer Vision	Quantum Image Representation	[306–315]
		Quantum Image Processing	[316–332]
	Robotics	Quantum Robotics	[333–338]

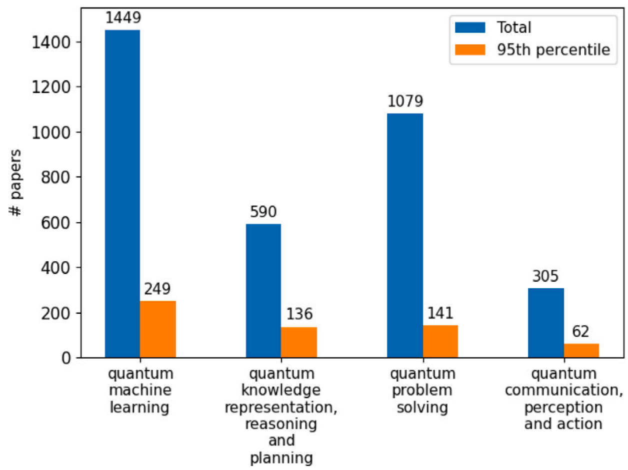


Fig. 4. Number of papers analyzed in this survey for the field of quantum-enhanced artificial intelligence is the 95th percentile.

5.1.1. Quantum search algorithms

Search algorithms in AI are techniques used by intelligent agents to explore a set of possible solutions to a problem to find an optimal or satisfactory result. They guide the agent's decision making by systematically examining different states or actions within a problem space, starting from an initial state and moving towards a goal state, using two different approaches: uninformed search and informed search [2].

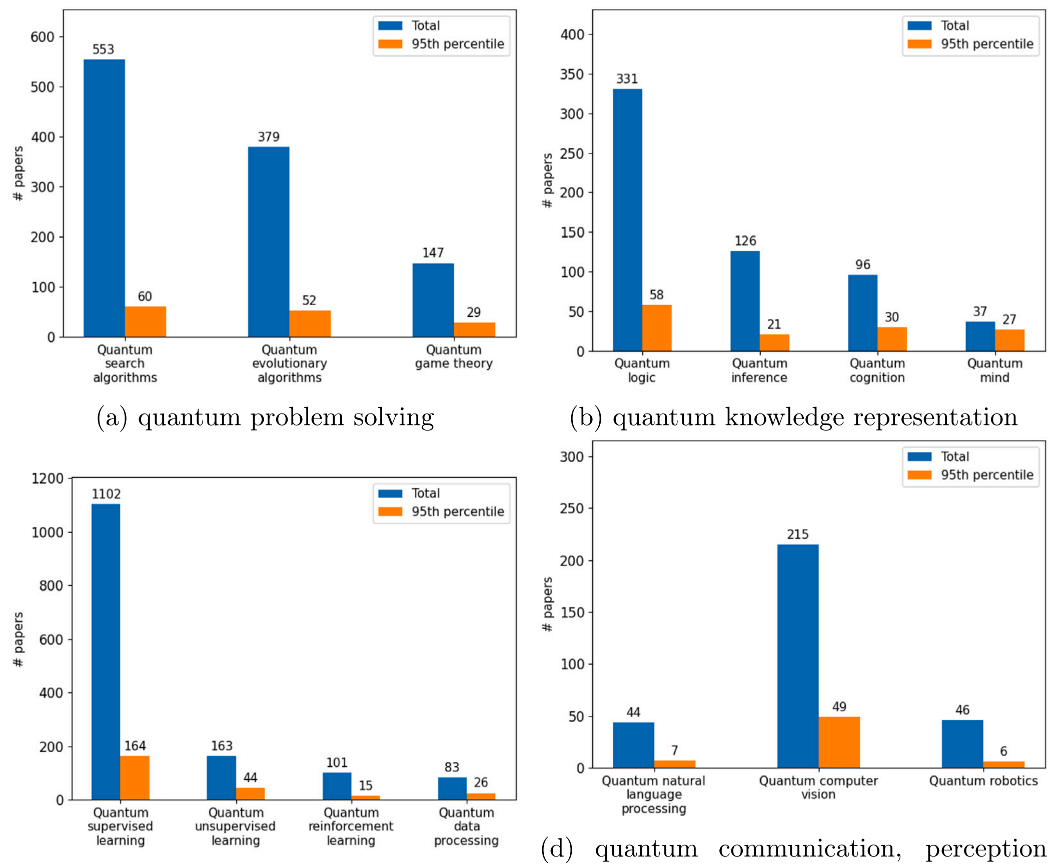
Among quantum search algorithms, two main classes emerge: the first is related to all algorithms originated by the groundbreaking Grover's search algorithm (GSA), and the second class of search algorithms is related to quantum random walks (QRWs). GSA is a quantum-informed search that uses an oracle to find solutions but differs from the classical search by exploiting quantum parallelism and interference instead of heuristics. QRWs are considered uninformed search algorithms because they do not have any knowledge of the structure or properties of the search space to guide the search process. Instead, each step in a random walk is determined at random, regardless of how close or far it is from a goal or optimal solution. Both approaches aim to improve the efficiency of the classical search algorithms employed in different contexts of AI such as optimization, combinatorial problems, graph traversal, and decision processes.

As is well known in the relevant literature, the GSA is utilized to perform searches in unsorted databases by amplifying the probability of the correct result through iterative quantum interference. This process achieves a quadratic speed-up over classical search methods. The computational benefit of this approach has led to its utilization in a variety of application scenarios. In communication systems, GSA is proposed to maximize the localization accuracy in grids [64], to speed up the processing of quantum data in 6-G quantum Internet networks as in [65]. In wireless sensor networks, GSA is used to select energy-efficient cluster heads. [66]. In machine learning, GSA is used to speed up classical deep learning methods [67] or to perform pattern recognition on quantum data [68]. Furthermore, Kim et al. in [69] investigate the application of GSA to cryptosystems, specifically focusing on the time-space complexity for AES and SHA-2.[7] Finally, [70] introduces a variant of GSA to perform searches in structured datasets. Although GSA has been extensively used in practical applications, its efficacy is significantly constrained by the limitations imposed by NISQ computers. Consequently, other pertinent research has examined the impact and reduction of noise in GSA, as evidenced by studies reported in [62,63]. These studies demonstrate that once an acceptable level of error is attained, the quadratic speed-up in search obtained by GSA can be used effectively in a diverse range of domains.

QRWs were introduced by Aharonov et al. in 1993 as the quantum counterpart to classical random walks (CRWs) [26]. These random walks aim to model and analyze the behavior of systems or processes that appear random or unpredictable over time. They have applications in various application scenarios, including AI. Although CRWs rely on probabilistic steps to describe the movement of entities through space or time, QRWs utilize the principles of superposition and interference, allowing a quantum particle to evolve on a graph or lattice in a fundamentally different way. This quantum approach provides unique statistical properties and computational advantages, such as faster mixing times and enhanced search capabilities, making QRWs a valuable tool in both theoretical studies and practical applications. In fact, as demonstrated in [71,74], QRWs consistently exhibit superior computational efficacy compared to CRWs. This superiority is observed despite the fact that QRW behavior can undergo significant alterations in response to strategic placement of marked locations, a phenomenon that has been thoroughly examined in [72,73].

In general, QRWs can be divided into two categories: discrete-time quantum random walks (DT-QRWs) [75] and continuous-time quantum random walks (CT-QRWs) [76]. In the former case, the evolution of the quantum walker occurs in discrete time steps. At each discrete time step, the quantum walker performs a specific quantum operation. In the latter case, the evolution is continuous rather than occurring in discrete steps. The walker's dynamics are characterized by a continuous-time Hamiltonian, enabling smooth transitions between different positions. DT-QRWs are generally simpler to implement on a NISQ computer compared to CT-QRWs because they can be executed using a sequence of unitary operations (quantum gates), which aligns with the architecture of existing quantum hardware. This assertion is supported by a substantial body of research, which demonstrates the capacity of DT-QRWs to execute beneficial operations on NISQ devices, with or without the assistance of error mitigation schemes [77–79]. These results have paved the way for the practical application of QRWs across various domains. For example, in [80] a QRW is used to simulate neutrino oscillation from the perspective of open quantum systems. In addition, in [81], QRWs with chaotic system's outputs are used to implement a new pseudorandom number generator system. In [82], DT-QRWs are explored on simplicial complexes, a higher-order generalization of graph structures. Another example is reported in [83], where QWalkVec, a quantum walk-based node embedding method, is proposed to integrate the depth-first search and breadth-first search processes on a graph. Still, in [84], a DT-QRW is used to detect communities in real-world networks. Other significant application domains for QRWs include communication, security and encryption protocols, as well as graph-based machine learning. In particular, the first QRW-based communication protocol has been introduced [85]. In [86] QRWs are used to implement perfect state transfer to move a quantum state from a sender to a receiver without loss or distortion. In [87] QRWs are used for the identification of important edges in complex networks, an important task for unmanned aerial vehicles. In the field of security protocols, QRWs have been used for the implementation of quantum key distribution [88] used for information sharing and data protection in 5G networks [89–92]. QRWs have been used in the context of image encryption wherein quantum states are employed for the storage of images [93,94]. Furthermore, QRWs have been utilized in conjunction with classical encryption schemes, such as AES, to achieve substantial encryption effects [95,96], or in conjunction with the Henon mapping to develop an image security algorithm [97,98]. These QRW-based image encryption strategies find applications in critical domains, such as medical imaging [99,100]. In the area of machine learning QRWs achieved important results, as reported

[7] AES (Advanced Encryption Standard) is a symmetric encryption algorithm standardized by the National Institute of Standards and Technology (NIST) in 2001. SHA-2 (Secure Hash Algorithm 2) is a family of cryptographic hash functions also developed by NIST, commonly used for data integrity verification and digital signatures.



(a) quantum problem solving (b) quantum knowledge representation

(c) quantum machine learning (d) quantum communication, perception and action

Fig. 5. Number of papers published in the field of quantum-enhanced artificial intelligence over years since 2016 by considering the sub-fields separately.

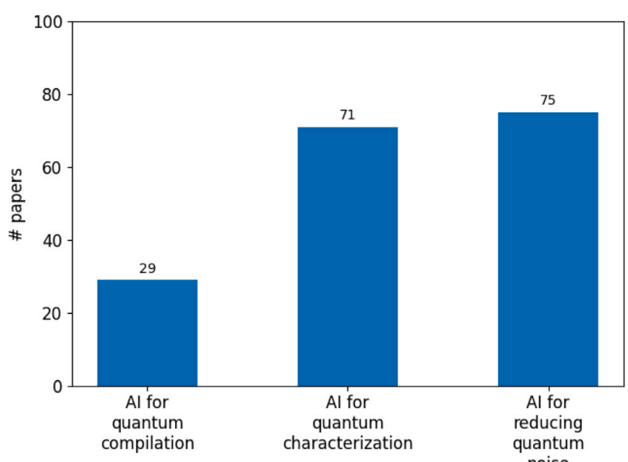


Fig. 6. Number of papers analyzed in this survey for the field of artificial intelligence for quantum computing.

in [101] where a quantum walk-based optimizer is used to update the neurons' weights of a neural network for binary classification. Furthermore, the use of QRWs has been demonstrated in the probing of graph structures within a properly designed family of graph kernels [102], or in improving the performance of graph neural networks by using a new diffusion operator [103]. Additionally, in [104] the authors focus on integrating a quantum spatial graph convolutional layer based on QRWs with a traditional convolutional layer. In [105] QRWs are successfully used in a quantum clustering algorithm for graph-based data. Finally, Loke et al. in [106] propose a scalable quantum PageRanking scheme based on QRWs, which achieves better performance than classical schemes for specific network configurations. These advancements demonstrate how QRWs enhance AI through faster search, optimization, and graph-based learning, providing potential quantum speedups and new computational capabilities over classical approaches.

5.1.2. *Quantum evolutionary algorithms*

Evolutionary algorithms are a class of optimization techniques inspired by natural selection and used by intelligent agents to solve complex problems by iteratively improving candidate solutions. These algorithms simulate the process of evolution, in which a population of potential solutions evolves over time through mechanisms analogous to reproduction, mutation, and selection. The population-based design of these algorithms makes them ideal for quantum computers, where quantum superposition can represent an entire population using few registers, and quantum interference and entanglement enable more efficient navigation of the solution space with quantum evolutionary operators.[8]

A significant part of the actual quantum evolutionary algorithms is based on a hybrid approach, where some components of the algorithm are implemented on a quantum computer and the remaining components are implemented on classical devices. For example, in [107] the well-known quantum amplitude amplification algorithm is used to implement a quantum genetic selection operator, named Quantum

8 Quantum-inspired evolutionary algorithms emerged by applying quantum principles to classical optimization methods. However, these algorithms are not compatible with quantum computers and are not covered in this survey.

Genetic Sampling (QGS). Due to its quantum characteristic, which allows a non-zero probability of introducing new genetic material into the population of candidate solutions, QGS provides an increased population diversity in genetic evolution and reduces the possibility that the optimization process converges to low quality solutions. QGS has been used to successfully address complex optimization problems in the electromagnetic domain, thus demonstrating its superiority as a selection operator [108]. Another quantum-based selection operator has been introduced in [109]. In this research, the selection process is implemented using a binary quadratic model encoding fitness and distance between candidate solutions of a population and a quantum annealing system sampling low-energy solutions as the most suitable to be evolved by evolutionary operators. The Hybrid Quantum Genetic Algorithm (HQGA) proposed in [110] is the first quantum approach that implements an entire evolutionary process (recombination and mutation) on actual IBM quantum computers by defining concepts such as quantum chromosome, entangled crossover, rotation mutation, and quantum elitism, while fitness evaluation is calculated on a classical device (see Fig. 7). Another example of a quantum genetic algorithm is provided in [111], where recombination, fitness evaluation, and selection are completely managed within a quantum circuit, and only a minimal interaction with classical components is needed. This approach enables the evolution of a population primarily within the quantum realm, circumventing measurements during the algorithm's iterations. However, its efficacy is currently constrained by the range of objective functions that can be optimized. In addition, another implementation of quantum genetic algorithm is provided in [113], to solve a machine learning problem, such as feature selection, on NISQ devices.

Genetic algorithms and operators are not the only evolutionary computing methods implemented on quantum computers. For example, in [114] a Quantum Multiverse Optimization algorithm is proposed. This research introduces a class of optimization algorithms inspired by the concept of a multiverse, which suggests that multiple parallel universes or solutions can coexist and interact to explore and exploit a problem's search space. The quantum implementation uses a quantum representation of the search space for a given optimization problem and the integration of the quantum interference and operators to enable a more efficient interaction among the different universes and obtain a suitable suboptimal solution of the objective function. Furthermore, Ghosh et al. in [116] propose a quantum ant colony optimization algorithm that exploits actual quantum computers. Specifically, the algorithm utilizes adaptive quantum circuits to represent the dynamic pheromone-updating strategy in real IBMQ devices, thereby facilitating the solution of the single source single destination shortest path problem.

5.1.3. Quantum game theory

Game theory is a mathematical framework that studies strategic interactions between rational decision makers, or players, who aim to maximize their individual payoffs. A key concept in game theory is the Nash equilibrium, which states that no player can improve their outcome by changing their strategy alone. In multiobjective scenarios, the Pareto front represents solutions where no player can improve without worsening another's outcome. In the domain of AI, game theory finds application in adversarial search algorithms, which simulate competitive environments and predict interactions among intelligent agents with conflicting goals. The concept of repeated game theory extends this by analyzing interactions across multiple rounds, allowing strategies to evolve based on past outcomes, with the potential to foster cooperation or punishment.

Quantum game theory refers mainly to the implementation of game theory principles using quantum mechanical phenomena. In particular, quantum entanglement, quantum transitions, and quantum networks are used to model the strategies and interactions of the players. Entanglement links players' strategies, allowing them to coordinate actions

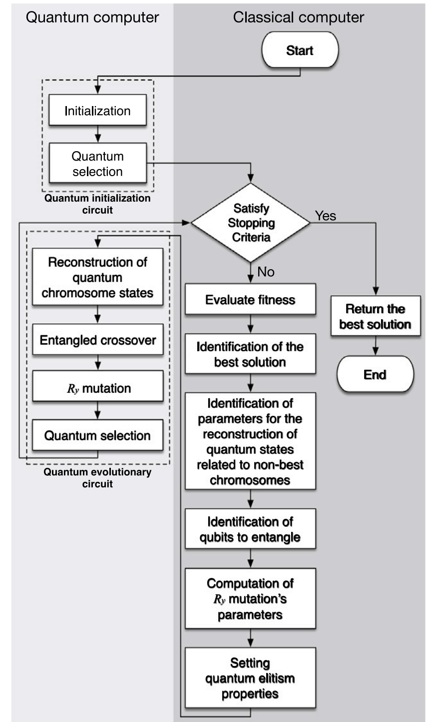


Fig. 7. The flowchart of a hybrid quantum genetic algorithm proposed in [110].

with stronger correlations than classical strategies. This creates cooperative outcomes that are otherwise unstable, improving equilibrium efficiency. Quantum transitions describe how players' strategies evolve dynamically using quantum operations. By applying unitary transformations, strategies shift between states, enabling richer strategic possibilities compared to static classical moves. Quantum networks connect players through quantum channels, enabling secure communication and shared entangled resources. This structure supports interactions that are decentralized, strategic, and enhanced by the advantages of quantum information.

Quantum entanglement is used to implement different quantum versions of the Prisoner's Dilemma game [117–121]. In particular, the research conducted in [122] demonstrates that the utilization of quantum-entangled states in different games ensures the preservation of Nash inequalities up to a threshold value of quantum noise. Moreover, the research presented in [123] uses quantum entanglement in infinitely repeated quantum games, a scenario in which players engage in a game an infinite number of times. This research proves that quantum games behave very differently when played forever, and it helps explain how players can get better outcomes by understanding these new rules of infinite quantum play. Moreover, the research presented in [124] uses a nuclear magnetic resonance setup in a two-qubit system to implement the Eisert–Wilkens–Lewenstein strategy protocol, based on an entangling quantum gate, to find better solutions for the quantum version of the Battle of the Sexes games. In [125,126] quantum entanglement is used to address duepoly problems, whereas in [127] quantum transitions are used to address the Angel problem. Finally, in [128], the authors detail the successful implementation of the Mermin magic square game and a new Doily game on an IBM quantum computer. Quantum networks have been used to implement a distributed version of the Prisoners' Dilemma game [129] using two different design schemes: the client–server scheme based on state transmission between nodes of the network and the peer-to-peer scheme devised in remote quantum operations.

These research activities, which have been conducted in the domain of quantum game theory, have laid the foundation for a variety of applications. In particular, applications of quantum game theory have been designed in the following areas: low carbon transportation [130]; load balance in ad hoc networks [131]; the interaction between two heterogeneous governments in environmental governance [132]; the study of the price identity of replicator(–mutator) dynamics [133]; the verification of news [134] and the promotion of green buildings in sustainable development [135]. Furthermore, quantum game theory has a significant impact on the field of economics. For example, in [136] Ikeda et al. examined a quantum economy, where agents engage in the production and consumption of quantum goods. In this model, agents interact with neighbors bilaterally through bartering, engaging in transactions for the goods they have produced. The entanglement of quantum strategies renders distinctive aspects of quantum games inaccessible to explanation through conventional classical game theory. This conclusion also provides novel insights into theories of mechanism design, auction, and contract in the quantum era.

5.1.4. Critical discussion

Quantum problem solving uses quantum computational principles to tackle complex challenges, often outperforming classical approaches in certain contexts. The three approaches-quantum search algorithms, evolutionary algorithms, and game-theoretic models-are at different stages of maturity, reflecting their different levels of progress and potential as we transition from the NISQ era to the FTQC era.

Quantum search algorithms are arguably the most mature of the three. GSA and QRWs represent fundamental advances, with GSA providing quadratic speeds up for unstructured search problems and QRWs excelling at graph-based search tasks. Despite the noise challenges in NISQ devices, researchers have demonstrated significant progress in error mitigation through innovations such as local diffusion operators and scalable quantum circuits to support the efficient implementation of GSA. GSA has found broad applications, from optimizing machine learning models to improving cryptographic protocols. Similarly, QRWs have shown promise in communication protocols, graph-based machine learning, and advanced encryption techniques. The transition to FTQC will unlock their full potential by enabling deeper circuits and error-free implementations, which are critical to scaling these algorithms to real-world problems involving large data sets or complex network structures.

Quantum evolutionary algorithms are less mature but have transformative potential, especially in optimization problems. Hybrid quantum–classical approaches, such as QGS, have already demonstrated advantages in population diversity and solution quality. Other classical–quantum implementations of evolutionary algorithms, such as HQGA, demonstrate the feasibility of encoding evolutionary processes directly in quantum computers, although the approach is characterized by classical evaluations of fitness functions due to the limitations imposed by NISQ devices. FTQC will address these limitations by enabling direct encoding and evaluation of fitness functions within the quantum computational framework. This will allow for seamless quantum-native evolutionary processes, eliminating the inefficiencies caused by quantum–classical data exchange.

Quantum game theory is the least mature, but offers intriguing possibilities for modeling strategic interactions using quantum phenomena such as superposition and entanglement. Current implementations, such as those for the Prisoner's Dilemma and other classical games, have demonstrated the potential for quantum strategies to reach new equilibria and solutions under noise. As FTQC becomes feasible, the robustness of quantum game-theoretic models will improve, enabling applications in AI-driven decision making, autonomous systems, and adversarial problem solving. This could lead to breakthroughs in fields such as economics, cybersecurity, and robotics.

5.2. Quantum knowledge representation, reasoning and planning

Intelligent agents use formal logic to construct structured representations of a complex world, allowing them to effectively model relationships, entities, and dynamic changes. They use inference engines to process these logical representations and derive new knowledge and beliefs, or formulate decisions and generate action plans to efficiently achieve their goals. This integration of formal logic, reasoning, and action-oriented inference enables intelligent agents to function autonomously and respond to complex real-world challenges. Quantum computing can support this area of AI by representing knowledge structures more efficiently through superposition and entanglement. These properties allow qubits to store and process exponentially more information than classical bits. This capability can improve the encoding of fuzzy reasoners, or probabilistic knowledge bases, by handling more states simultaneously and enabling faster inference processes.

5.2.1. Quantum logic

Quantum logic refers to a framework for reasoning and making deductions within the realm of quantum mechanics. In classical logic, which governs everyday reasoning, statements are either true or false, and logical operations like AND, OR, and NOT follow well-defined rules. However, in the quantum domain, the behaviors of logic systems and their associated variables are described by principles that diverge from the tenets of classical logic. In particular, quantum logic attempts to formalize reasoning within this new scenario, taking into account phenomena such as superposition and entanglement. It involves the development of new reasoning schemes based on alternative mathematical frameworks built on quantum logic gates and quantum circuits to manipulate quantum states and perform quantum computations. Some researchers have attempted to formalize quantum logic using ad hoc mathematical theories, such as in [137]. This paper explores how semilattices and global valuations in the topos approach to quantum mechanics can offer a more abstract and unified way to model quantum systems. This framework could inspire new methods for handling uncertainty, logic, and information in quantum computing and AI, improving AI's ability to manage complex probabilistic scenarios. One particularly useful paradigm of quantum logic for quantum computing is known as quantum computational logic [138]. In this framework, formulas are interpreted as representing quantum information, specifically qubit systems or mixtures of qubit systems. Logical connectives are understood as reversible quantum gates that operate on these quantum states. This paradigm can also be extended to higher-dimensional quantum states, known as qudits, as discussed in [139]. Within the paradigm of quantum computational logic, numerous researchers are focusing their efforts on exploring the feasibility of replicating classical Arithmetic Logic Units (ALUs). The authors in [140–142] focus on the efficient construction of a control modular adder in terms of both the number of qubits and the quantum gates required. Still, in [143], a quantum reversible adder is proposed using qutrit instead of qubits and based on ternary Toffoli gates which are built on top of the ion-trap realizable ternary 1-qutrit gates and 2-qutrit Muthukrishnan–Stroud gates. The design of ALUs based on quantum logic could significantly impact AI by speeding up computations and improving efficiency in tasks such as optimization and machine learning.

Additional notable findings within the domain of quantum logic have been achieved in the realm of quantum program verification. In [144], an automated quantum program verification approach is proposed using dynamic quantum logic. Experiments demonstrate its effectiveness by successfully verifying five quantum protocols: Superdense Coding, Quantum Teleportation, Quantum Secret Sharing, Entanglement Swapping, and Quantum Gate Teleportation. In [145], a new quantum Hoare logic is introduced to analyze probabilistic behavior in quantum measurements and assess the correctness of quantum programs. Experiments demonstrate its effectiveness by formally verifying the correctness of complex quantum algorithms, including the

Harrow-Hassidim-Lloyd (HHL) and Shor's algorithms. Quantum logic and program verification can boost AI by accelerating computations and improving algorithm efficiency through quantum parallelism. Verified quantum programs ensure the reliability and correctness of AI systems, which is crucial for high-stakes applications.

Two other significant fields within Quantum Logic are represented by quantum finite automata and quantum fuzzy logic, which extend the classical concepts of finite automata and fuzzy logic, respectively. Instead of being strictly in one state, a quantum finite automaton can exist simultaneously in a superposition of states. This allows for potentially faster computation in certain cases, particularly when dealing with problems that involve massive parallelism or complex superposition states. Various studies assess the capability of quantum finite automata compared to their classical counterparts [146–148]. Among these, a comparison between probabilistic finite automata and quantum finite automata arises in [149], where the authors prove the ability of quantum finite automata to be more succinct than probabilistic finite automata, with respect to specific problems. In [150], variants of quantum finite automata were developed using different quantum mechanics approaches, such as Schrödinger's and Heisenberg's formalisms. In contrast, [151] proposed a method for learning measure-one quantum finite automata combining active learning with nonlinear optimization. The versatility of quantum finite automata is further demonstrated in [152,153], where they were applied to solve the Prisoner's dilemma in quantum game theory. Quantum finite automata have the potential to significantly impact AI by improving efficiency and computational power. Their ability to handle probabilistic states and leverage the unique properties of quantum mechanics can enhance pattern recognition and learning in AI systems.

Fuzzy logic and quantum computing are two distinct theoretical frameworks that address different types of uncertainty: fuzzy logic models vagueness and imprecision in reasoning, while Quantum Computing manages the probabilistic nature of quantum states. Despite their differences, they share several points of connection, creating opportunities for synergy in handling complex, uncertain systems and paving the way for the development of quantum-based fuzzy logic. This potential is illustrated in [154], where lattice theory serves as a foundational tool to model their similarities. Additionally, [155–157] demonstrate that quantum computing can be used to perform Atanassov's intuitionistic fuzzy logic operations, offering faster solutions to challenging problems compared to classical logic and conventional computing approaches. A practical example demonstrating the advantages of combining fuzzy logic and quantum computing is presented in [158], where a fuzzy-based quantum key distribution protocol is integrated into a cognitively managed multi-level authentication system for nuclear command and control centers. The synergistic use of quantum computing and fuzzy logic can significantly enhance AI by enabling intelligent agents to better model environments characterized by uncertainty and imprecision.

5.2.2. Quantum inference and cognition

Inference and cognition are two critical processes in AI that relate to how systems make decisions and simulate human-like thinking. Inference refers to the process of drawing conclusions or making decisions based on available data, rules, or knowledge. Cognition refers to the simulation of human-like mental processes to try to replicate how humans understand and interact with the world. Quantum computing supports cognition and inference by using superposition and entanglement to process data more efficiently, accelerating inference tasks, and improving adaptability in cognitive processes.

In the domain of quantum inference, two primary sub-areas have emerged: the first is quantum fuzzy inference, and the second is quantum probabilistic inference. The former area is more recent and arises from the quantum aspects of fuzzy logic previously discussed. Its primary objective is to enhance classical fuzzy inference, which relies on linguistic rules, by employing quantum mechanical principles. The first work on quantum fuzzy inference is presented in [159], where the authors introduce Quantum Fuzzy Inference Engine (QFIE), an efficient quantum algorithm based on a quantum oracle to parallel fire fuzzy rules (see Fig. 8). QFIE leverages quantum superposition to process multiple inputs simultaneously, making it exponentially faster than classical engines to run fuzzy rules. The approach is tested in a benchmark scenario, such as the inverted pendulum control problem, and is also applied to control a particle accelerator at CERN [160].

Quantum probabilistic inference has achieved greater levels of consolidation and is supported by a more extensive body of literature [161–164]. The works by Yukalov and Sornette [165,166] are crucial, as they show how quantum theory can model human decision-making. They propose that decision-making can be understood through quantum rules, with behavioral probabilities modeled as quantum probabilities. This approach reflects the dual nature of decision-making, combining rational utility evaluation with subconscious attraction assessment. These papers laid the foundation for what is now known as quantum decision theory (QDT). Furthermore, drawing from these assumptions, Yukalov and Sornette underscore the necessity for AI to be formalized in a quantum manner to account for the dual nature of human decision-making processes. In a recent development, Gao and Deng [167] have provided additional validation for the aforementioned assumption. They have done so by underscoring the efficacy of quantum theory in modeling uncertain states prior to the execution of a judgment in an inference process. Also, in [168], QDT models human decision-making in sensor-human interfaces for rapid state change detection. By analyzing human decision peculiarities, the authors provide theoretical guarantees for the optimal detection policy, highlighting its robustness and performance. The framework's effectiveness is demonstrated through the Prisoner's Dilemma, where QDT captures deviations from classical decision-making principles. In [169], QDT is used to develop an innovative computational trust model. The authors link quantum principles, like interference and entanglement, to trust decision-making, showing that these quantum phenomena can capture subjective aspects often missed by classical models. This integration enhances the model's ability to accurately represent complex trust decisions. The modeling of human behavior by quantum probability theory is also the focus of Nguyen et al. in [170], which demonstrates how this theory, in conjunction with Bohmian mechanics for modeling economic data, could have a substantial impact on econometrics. Similarly, quantum probability theory is exploited in the field of customer experience analytics [171], into joint multi-modal sarcasm, sentiment, and emotion analysis [172] and in studying irregular physical, visual, and behavioral events of individuals with anxiety disorders in academic environments [173]. QDT is extended to the multi-criteria group decision-making model by the works in [174,175], where the concept of quantum interference is used to model the interference effects among decision makers' opinions. Among the applications of quantum interference in the context of group decision-making models several works arise: in [176], the authors propose a VIKOR-based linguistic distribution assessments model considering asymmetric interference effects in a quantum decision scenario; in [177] a quantum interference methodology is exploited to develop a decision model based on trust measure in a social network group. In the field of QDT and quantum inference, a great focus is on quantum Bayesian networks (QBNs). They represent the quantum counterpart of classical Bayesian networks (CBNs). In [178] the differences between classical and quantum Bayesian reasoning are shown through a model inspired by a scenario of the well-known Monty Hall game. As pointed out in [179], with respect to classical CBNs, QBNs could be valid alternatives to large-scale networks, in particular in the context of influence estimation in multi-step process chains.

Even for smaller case studies, QBNs can already be implemented in actual quantum devices. In fact, in [180,181] the authors proposed a way to translate CBNs into equivalent quantum circuits and to use the quantum amplitude amplification protocol to perform the sampling

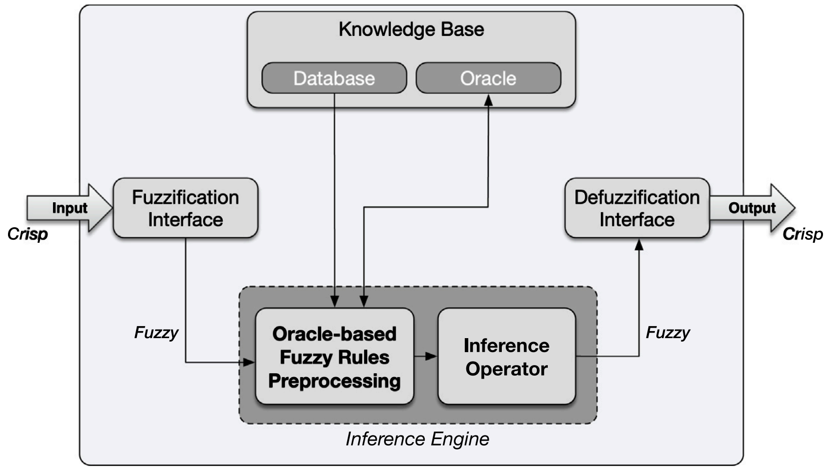


Fig. 8. The architecture of a quantum oracle-based fuzzy inference engine [159].

process. In detail, the research in [181] applies this QBN in the context of the reliability assessment of power networks in response to wildfire events in the United States. Similarly, the authors in [182] compare the performance of a 4-node QBN for the prediction of stock implemented on nine different IBM Quantum devices. However, as pointed out in [183], quantum circuits developed to represent Bayesian networks are prone to quantum noise and strictly limited by the maximum number of shots that can be performed on quantum hardware. To solve these issues, the authors proposed a hybrid model in which the quantum circuit generates samples to perform likelihood-weighted sampling and Markov chain Monte Carlo-based sampling. The potentiality of causal graphical models based on quantum probability is also highlighted in [184], where it is shown that the use of quantum or classical models is convenient depending upon the representation of events constructed by the reasoner. The implementation of QBNs has also been exploited in the context of bike sharing systems both for rebalancing [185] and demand forecasting [186]. Considering the success of QBNs as proved by the aforementioned works, the authors in [187] were encouraged to develop a library providing high-level functions for Bayesian inference.

To conclude this discussion, the relationship between QDT and quantum cognition and consciousness must be highlighted. Indeed, as probabilistic outcomes of certain human decisions do not agree with the axioms of classical probability theory [188,189], as well as classical physics was long found to be unaccommodating for a causally effective human consciousness theory. The field of Quantum Cognition provides an alternative probabilistic model to explain such paradoxical findings, based on the idea that a cognitive property may be indeterminate, i.e., its properties do not have well-established values prior to observation [190]. This thesis is also supported by [191,192], where it is pointed out how certain human cognitive decision-making processes are best described by quantum mechanical processes. For instance, in [193] it is highlighted how non-formalizable aspects of human consciousness like emotions, feelings, thoughts, and insights must be taken into account during decision-making and analytical conversations with AI support and non-local semantics like quantum cognition could better deal with these aspects. From a more theoretical perspective, in [194], a new modeling framework for structured concepts using a category-theoretic generalization of conceptual spaces and a quantum algorithm is introduced. In detail, the authors use Gärdenfors' classical framework of conceptual spaces, in which cognition is modeled geometrically through the use of convex spaces, which in turn factorize in terms of simpler spaces called domains. Concepts from the domains of shape, color, size, and position are learned by a hybrid classical–quantum network trained to perform concept classification, where the classical image processing is carried out by a convolutional neural network (CNN), and the quantum representations are produced by a parameterized quantum circuit. Differently, as pointed out in [195] most of the approaches in the field of Quantum Cognition rely upon Projective Measurement of the quantum systems, i.e., measurements where it is assumed the orthogonality of the measurement operators. However, the assumption of an orthogonal relationship between meanings is difficult to justify in general cognitive systems, and models are easy to construct only for special scenarios. This is why, Aliakbarzadeh and Kitto propose a quantum cognition framework based on positive operator valued measure where there are no assumptions about the orthogonality of two operators, and suddenly there is no longer a need to frame measurements in a simple $\{yes, no\}$ basis. The quantum cognition domain is extended also to human language in [196], where is given to the words the meaning of quanta. The similarity is supported by proposing Bose–Einstein statistics in human language due to the presence of "indistinguishability" in it, as well as "indistinguishability" occurring also in quantum mechanics leading likewise to the presence of Bose–Einstein statistical structure. Despite, the potentiality of quantum cognition, some researchers believe that the human brain is neither an electric power machine nor a digital computer, but a dynamic equilibrium of neuron ensembles of bipolar quantum agents. According to [197], quantum computing alone is not enough to describe an analytical paradigm for equilibrium-based Quantum Cognition and Quantum Intelligence. Therefore, the authors propose a Quantum-Neuro-Fuzzy Associative Memory to bridge this gap. The synergy between quantum cognition and fuzzy logic is also highlighted in [198], where a digression about how important Zadeh's theory of fuzzy sets was to arrive at the modern description of quantum cognition is presented. By modeling in a quantum way the human brain, it is possible to model in a quantum way also the concept of generation of consciousness. This approach is formulated in [199], where the authors assert that the generation of consciousness and the resonance of thinking are precisely the result of the quantum collapse of mutual entanglement. This theory is tested by constructing a musical appreciation system. Finally, it is worth noting that even if QDT emerges as an approach to efficiently model human decision-making processes, the study in [200] proves that this theory can also be used to model process estimation in qubit systems. Indeed, it is shown how QDT can be exploited to discriminate whether or not a given unitary perturbation has been applied to a qubit system, and to determine the amplitude of the minimum detectable perturbation.

In summary, quantum inference and cognition enhance AI by improving the way systems reason under uncertainty and model complex decisions. Quantum inference enables faster and more efficient reasoning by using superposition to evaluate multiple possibilities simultaneously, improving performance in learning and optimization. Quantum cognition, inspired by human thought processes, captures nonclassical behaviors such as ambiguity and context dependency, making AI more adaptive and human-like.

5.2.3. Critical discussion

The section explored how quantum computing frameworks can redefine classical logic and inference, aiming to simulate aspects of human reasoning, cognition, and knowledge representation. Quantum logic offers a departure from classical true/false paradigms by incorporating principles such as superposition and entanglement. Efforts in this domain include developing quantum computational logic to model logical connectives as reversible quantum gates, extending to systems of higher-dimensional quantum states like qudits. This approach promises efficient implementations of arithmetic logic units and opens avenues for innovations in quantum program verification using dynamic quantum logic and quantum Hoare logic. These tools are being applied to verify quantum protocols and algorithms, signaling practical advances in reasoning about quantum systems. FTQC will enhance these methods by enabling stable and scalable quantum logic systems and precise implementations of quantum arithmetic. Its error correction will ensure robust program verification, enabling exploration of richer logical constructs and advancing tools for reasoning in quantum mechanics and AI.

The integration of quantum mechanics into finite automata and fuzzy logic demonstrates how quantum computing enhances classical frameworks by dealing with problems involving massive parallelism. Quantum finite automata offer more compact representations and faster computations in some scenarios compared to probabilistic automata. Similarly, the fusion of quantum mechanics with fuzzy logic yields methods to tackle problems involving uncertainty more effectively, as seen in different application scenarios, such as key distribution in secure systems. FTQC promises to push these advances further by allowing for reliable quantum operations at scale, improving the precision of quantum fuzzy logic systems, and expanding the applicability of quantum finite automata to even more complex and large-scale real-world problems.

In the realm of quantum inference and cognition, research highlights the potential of quantum mechanics to simulate human decision-making processes. Quantum fuzzy inference leverages quantum speedups in control systems, while QDT models the dual rational and subconscious aspects of human choices. QDT has shown utility in fields as diverse as econometrics, trust modeling, and customer analytics. QBNs further extend this reasoning, offering scalable alternatives to classical networks, though practical implementations remain constrained by hardware limitations. Moreover, quantum cognition bridges cognitive science and quantum mechanics, offering models that better capture indeterminate or paradoxical aspects of human thought, showing that the synergy between quantum principles and cognitive science remains a fertile ground for innovation. FTQC can significantly improve these methods by enabling the direct simulation of complex quantum states and faster, more accurate inference processes. This improvement could lead to more precise quantum decision-making models, faster updates and reasoning in QBNs, and a deeper exploration of paradoxical cognitive patterns in quantum cognition.

5.3. Quantum machine learning

An intelligent agent with machine learning capabilities can adapt its behavior based on experience and continuously improve its performance. QML integrates quantum computing with machine learning to enhance this process by using quantum principles such as superposition and entanglement for faster and more efficient computation. Research in QML encompasses key areas of machine learning, including supervised learning, where models are trained on labeled data to make predictions; unsupervised learning, which aims to uncover hidden patterns and structures in unlabeled data; and reinforcement learning, where agents learn by interacting with their environment to maximize rewards.

5.3.1. Quantum supervised learning

Supervised learning methods rely on input–output data pairs to train a model, allowing them to perform data-driven tasks such as regression and classification on unseen data. Although the use of quantum algorithms for regression is relatively underexamined in the academic literature, there have been a few significant instances. For example, the algorithm presented in [201] uses the HHL algorithm to implement a linear regression, while the method of quantum regression developed in [202] combines an autoencoder with a "dressed quantum circuit" to predict the behavior of fiber optic temperature sensors. In contrast to regression, numerous quantum approaches have been developed and implemented for classification problems. In this context, the impressive success of artificial neural networks (ANNs) has inspired researchers to explore their quantum counterparts, QNNs. These quantum versions aim to overcome some of the key limitations of classical ANNs, such as the difficulty in determining optimal architectures, limited memory capacity, and the high computational cost of training algorithms. With the aim of exploring the potential of quantum computing to address the latter limitation, in 2016, in [203], da Silva et al. proposed a theoretical model of quantum perceptron, denoted as QPF, and a quantum learning algorithm called Superposition based Architecture Learning (SAL). QPF is a direct extension of the classical perceptron, in which each input neuron and each weight correspond to one qubit, while SAL conducts a nonlinear search in both the neural network parameters and architecture space simultaneously in polynomial time. However, the authors did not conduct empirical evaluations of these theoretical proposals, citing the need for a quantum computer with thousands of qubits or a classical simulator requiring terabytes of memory. As quantum technology advances and quantum computers become more accessible, Mangini et al. [204] introduced a generalized perceptron model on a qubit-based quantum register (see Fig. 9), extending the proposal in [339], to accept continuous- instead of discrete-valued input vectors, without increasing the number of qubits. The proposed quantum neuron has shown promise in classifying linearly nonseparable two-dimensional data, particularly in pattern recognition tasks with grayscale images. An initial instance of a QNN is discussed in [205]. In this context, a quantum circuit realizes a network employing a periodic activation function, derived from the cosine of a linear combination of n inputs and k weights. In particular, the circuit demands only $O(n \log_2 k)$ qubits and $O(nk)$ quantum gates, suggesting a prospective exponential speed-up in contrast to a corresponding classical ANN that involves k^n neurons. Another notable result in this field is presented in [206], where Abbas et al. numerically demonstrate that a class of QNNs achieves significantly higher effective dimension and faster training compared to similar feedforward networks, highlighting a potential advantage for QML. In [207], QNNs have been implemented by parameterized quantum circuits, known as VQCs, where a classical optimizer adjusts the circuit parameters to perform a specific data-driven task (see Fig. 10). In this research, the authors compare performance for several different parameterizations on two classical machine learning datasets, Iris and MNIST, and on a synthetic dataset of quantum states by using ibmqx4 quantum computer. The appeal of VQCs lies in their hybrid quantum–classical design, which makes them well suited for NISQ devices. However, their practical use is limited by trainability issues, primarily due to barren plateaus in cost-function landscapes as the number of qubits grows. To address this issue, in [208] Skolik et al. investigate a layerwise learning approach for VQCs. In this strategy, the depth of the circuit is gradually increased during optimization, with only subsets of parameters updated at each step to mitigate barren plateaus. Since the impact of barren plateaus depends heavily on the choice of cost function, Kashif et al. in [209] empirically analyzed the effects of local (measured single qubit) versus global (measured all qubits) cost functions in QNNs. They examined two scenarios, binary and multiclass classification, across various QNN widths and depths, proving that global cost functions significantly improve multi-class classification performance, while both cost functions perform equally

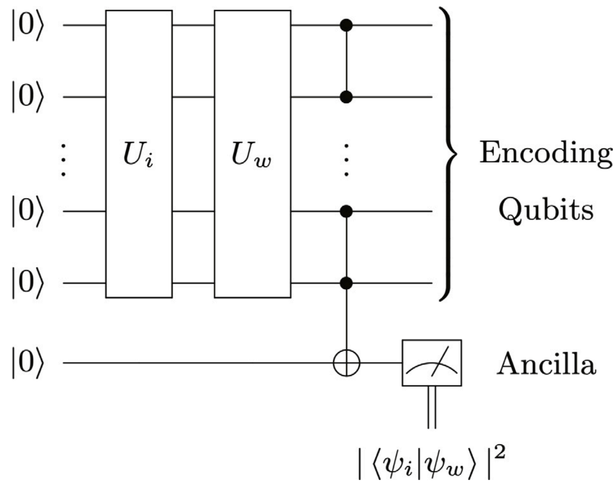


Fig. 9. Quantum circuit model of a perceptron with continuously valued input (i) and weight vectors (w) [204].

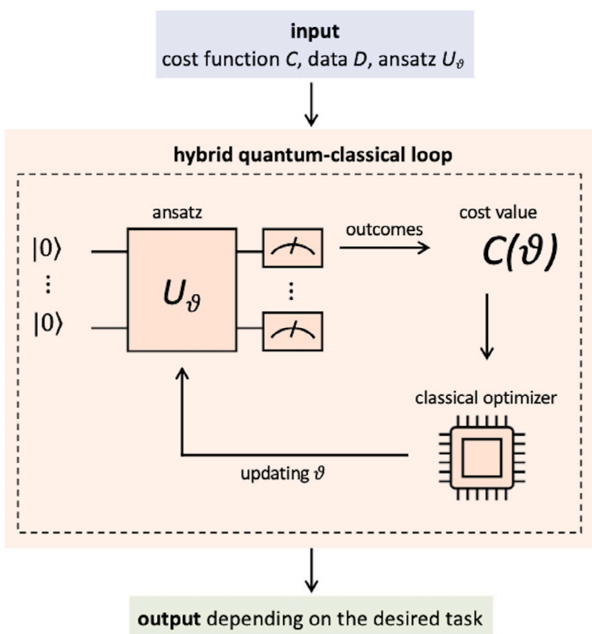


Fig. 10. The workflow of a variational quantum algorithm [340].

for binary classification. In the same context, the study presented in [210] explores the theory of overparameterization in QNNs, aiming to investigate how attributes of these networks, such as the number of parameters M, influence the loss landscape and, subsequently, inform the design of scalable QNN architectures.

Another approach addressing training issues in VQCs is presented in [211]. In this study, the authors propose to decouple the circuit search and parameter training by introducing two novel concepts known as SuperCircuit and SubCircuit. The SuperCircuit is constructed with multiple layers of pre-defined parameterized gates and trained by iteratively sampling and updating the parameter subsets, the SubCircuits, of it. In recent work [212], issues related to QNN training have been explored within the emerging domain of geometric QML. The principal notion is that architectures, like equivariant QNNs, should be engineered to incorporate the symmetries inherent in the problem. In [213], a comprehensive theoretical framework is presented for designing equivariant QNNs for virtually any relevant symmetry group. The authors developed several methods to construct equivariant layers within QNNs and analyzed their respective advantages and limitations.

Over the years, researchers have also worked to demonstrate the feasibility of implementing more complex deep learning architectures, such as recurrent neural networks (RNNs) and CNNs, on NISQ devices. In [224], authors introduce a quantum RNN cell comprising parameterized quantum neurons. This approach, integrated with amplitude amplification, facilitates nonlinear activation through polynomials of input and cell state, enabling prediction of class probabilities at each step. The quantum RNN is tested on MNIST classification by sequentially processing each image pixel. The results show that using a network with only 12 qubits, the accuracy of the test set exceeds 95% for differentiating the digits '0' and '1'. Another example is presented in [225], where Chen et al. proposed a quantum adaptation of LSTM, a type of RNN proficient in processing data exhibiting temporal dependencies (refer to Fig. 11). In particular, they replaced conventional ANNs in LSTM cells with VQCs, fulfilling the dual functions of feature extraction and data compression. The experimental findings showed that, with a comparable number of parameters, this quantum LSTM shows a more consistent and faster decrease in loss compared to its classical version. Other more recent examples of quantum LSTM are reported in [226,227]. For CNNs, in [229], Henderson et al. introduced a new concept of quantum convolution, the *quanvolutional layer*, which will be used in hybrid classical–quantum architectures (see Fig. 12). Specifically, these quanvolutional layers process input data by transforming them locally via a series of random quantum circuits, analogously to the transformations executed by random convolutional filter layers in CNNs. Moreover, in [230], Hur et al. propose a fully parameterized quantum CNN for the classification of classical data that only uses two-qubit interactions throughout the algorithm. The authors investigate the performance of the quantum CNN by differentiating the structures of parameterized quantum circuits, quantum data encoding methods, classical data preprocessing methods, cost functions and optimizers on MNIST and Fashion MNIST datasets. As shown in the results, the quantum CNN models performed noticeably better than the CNN models under similar training conditions. Similarly, also in [231], a quantum CNN is implemented and tested on the MNIST dataset.

Aside from neural and deep networks, quantum counterparts for additional classifiers have been introduced in the literature. For example, in [239], a proposal for a quantum version of k-nearest neighbor algorithm is given. Another example is reported in [240], where an ensemble of quantum classifiers is proposed for multi-class classification problems. Moreover, in [241], a quantum Variational Distance-based Centroid Classifier is introduced. This is a hybrid approach that combines the Quantum One-Class Classifier and parameterized quantum circuits to improve the feasibility of multiclass classification on NISQ devices, as it eliminates the need for a label qubit and uses a single-qubit measurement, regardless of data size. Still, in [242], Zhang et al. proposed a quantum algorithm for multi-class classification tasks, aiming to manipulate multiple training samples with a higher expression ability. In particular, in this approach, the training data are loaded into parameterized operators which are applied to the basis of the quantum state in a quantum circuit composed of two registers denoted *sample register* and *label register*. In this context, the Support Vector Machine (SVM) is the most widely recognized classical classifier that has seen various quantum adaptations proposed in recent years. Two primary formulations have emerged: a quantum adaptation of the SVM itself or a quantum adaptation of kernels for use in the classical SVM framework. The first remarkable result in the first formulation is reported in [341], where Blank et al. present a quantum algorithm for the construction of a kernelized binary classifier with a quantum circuit as a weighted power sum of the quantum state fidelity of training and test data. The underlying idea of the classifier is to perform a swap test on a quantum state that encodes data in a specific form. To demonstrate the proof-of-principle, the proposed swap-test classifier is used to solve a toy problem using the IBM Q 5 Ourense quantum processor. Another example is reported in [342], where Zhang et al. have proposed a quantum SVM, named RN-QSVM, based on the regularized quantum Newton method. From the experimental session, it has been demonstrated that RN-QSVM provides advantages in terms of accuracy, robustness, and complexity compared to other quantum and classical models. In further detail, in [343], Zhang et al. propose a quantum SVM based on the regularized quantum Newton method, named AEQSVM. This approach overcomes the limitations provided by the typical use of the swap test to compute the inner product. Precisely, as the swap test is destructive, the typical quantum SVM must be repeated in preparing qubits and manipulating operations, whereas AEQSVM overcomes this constraint by adding auxiliary qubits instead of repeating the algorithm. Moreover, in [344], Huang et al. have introduced a quantum version of fuzzy SVM, named QFSVM. This proposal is based on the efficiency of quantum computing in processing large amounts of data, combined with fuzzy capability to handle complexity and uncertainty problems effectively. Specifically, QFSVM allows different training samples to contribute differently in predicting an optimal hyperplane to separate two classes with maximum margin. The proposed algorithm can determine whether a sample belongs to the positive or negative class while achieving good generalization performance. Compared to the classical fuzzy SVM, the computational complexity of QFSVM decreases exponentially with the number of training samples. More recently, in [345], an anti-noise quantum support vector machine algorithm has been proposed to classify data on real quantum computers by properly customizing the quantum circuit. As for the second formulation of a quantum SVM, the introduction of quantum kernels in the classical SVM allows quantum computers to compute (hopefully faster) nontrivial kernel matrices. For example, in [346], canonical coherent states are proposed to calculate specific nonlinear kernel functions in the context of SVMs. Precisely, the authors describe the evaluation of radial kernels through a positive operator-valued measure on a quantum optical system based on canonical coherent states. Moreover, in [347], the authors extend the linear quantum SVM with the kernel function computed through Quantum Kernel Estimation (QKE), to form a decision tree classifier constructed from a decision-directed acyclic graph of quantum SVM nodes denoted as the Quantum Random Forest. In addition, in [348], John et al. have proposed various general-purpose optimization methods and best practices to improve the practical utility of kernel-based quantum classification algorithms. Recently, a quantum kernel self-attention mechanism is introduced in [349] to combine the data representation merit of quantum kernel methods with the efficient information extraction capability of the self-attention mechanism.

These studies on quantum classification have prompted the community to explore the robustness of quantum classifiers [214,243,244] and their application in various domains, including communication networks [245], medicine and healthcare [215–217,232–235,246–249,350,351], attack detection [352], energy management [228], aviation [218], finance [219,220], image classification [221,222,236,237,250–252,353], speech recognition [238], traffic sign classification [223], symbol detection in the context of vehicular technology [253], remote sensing [354], consumer reaction time demand response predictive management [355], real-time malware analysis [356], solving of the one-dimensional advection–diffusion equation [357] and applied physics [358].

5.3.2. Quantum unsupervised learning

Unsupervised learning methods attempt to detect patterns in the data without explicit guidance. Quantum computers offer multiple possibilities for aiding in such tasks, particularly in prototype-based clustering, generative tasks, and autoencoders. In prototype-based clustering, quantum algorithms can speed up distance calculations and centroid updates, improving efficiency for large datasets. For generative tasks, quantum models can sample from complex distributions more effectively, potentially enhancing data generation. In autoencoders, quantum circuits can improve feature extraction and data compression

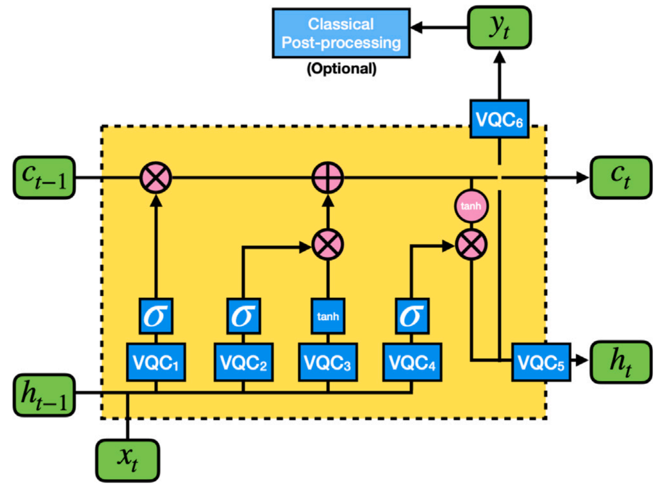


Fig. 11. Quantum Long Short Term Memory architecture proposed in [225]. Each VQC box represents a parameterized quantum circuit. The σ and tanh blocks represent the sigmoid and the hyperbolic tangent activation function, respectively. x_t is the input at the time t, h_t is for the hidden state, c_t is for the cell state, and y_t is the output. $\otimes$ and $\oplus$ represent element-wise multiplication and addiction, respectively.

by capturing correlations more efficiently, leading to faster training and reduced complexity. In general, quantum computing has the potential to accelerate these tasks and handle more complex models with greater scalability.

For prototype-based clustering, a quantum variant of k-means has been described in [254], where the closest centroids are computed using the Grover's algorithm. Due to the excessive computational demands of the core subroutines in quantum k-means on quantum computers, the study in [255] introduces a quantum k-means algorithm reliant on a trusted server within quantum cloud computing. This approach offers improved load reduction on the client side while enhancing data privacy protection in the cloud compared to the conventional quantum k-means algorithm. An application of quantum k-means is reported in [256], where a recommender system uses the quantum clustering algorithm to perform a prediction process. The results demonstrate that employing the quantum version of k-means achieves a logarithmic reduction in time complexity compared to the classical algorithm. Also in [257], a QML system based on quantum k-means is proposed for the recommendation of image descriptors. Moreover, in [258], the quantum k-means algorithm is used to detect heart disease. Another notable variant, proposed in [260], introduces the first quantum version of the fuzzy k-means algorithm, offering a lower time complexity and higher accuracy. This approach encodes training data into quantum states, uses a swap test to measure similarity between sample points and cluster centers, and applies Grover's algorithm to identify the cluster with the highest membership degree, determining the test sample's classification.

Regarding generative tasks, in [261], Situ et al. propose a Quantum Generative Adversarial Network (QGAN) to generate classical discrete distributions. This model features a hybrid classical–quantum architecture, with a parameterized quantum circuit acting as the generator and a classical neural network serving as the discriminator. The quantum circuit is composed solely of simple one-qubit rotation gates and two-qubit controlled-phase gates, which are readily implementable on current quantum devices. In addition, in [262], the authors introduce a method to model classical continuous probability distributions using a variational quantum circuit. The quantum generator encodes a classical random variable in a quantum state, while a parameterized quantum circuit is trained to approximate the target distribution. This quantum generator can be combined with either a classical neural network or

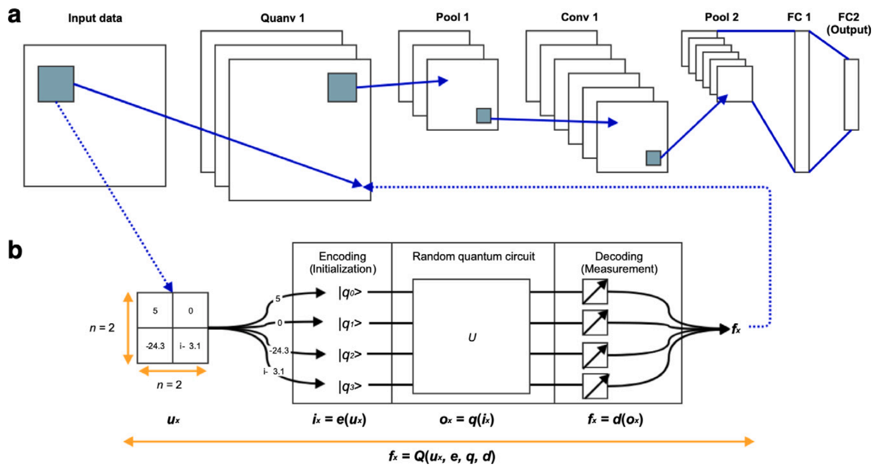


Fig. 12. The upper portion of the figure, denoted by **a**, shows the quanvolutional layer in a full network stack proposed in [229]. The quanvolutional layer contains several quanvolutional filters (three in this example) that transform the input data into different output feature maps. The bottom portion of the figure, denoted by **b**, shows am in-depth look at the processing of classical data into and out of the random quantum circuit in the quanvolutional filter.

another parameterized quantum circuit as the discriminator model. Moreover, in [263], a QGAN is used to facilitate efficient learning and loading of generic probability distributions, implicitly given by data samples, into quantum states. The loading requires $O(poly(n))$ gates and can thus enable the use of potentially advantageous quantum algorithms, such as Quantum Amplitude Estimation. In addition, the work in [264] presents a quantum Bayesian inference technique for the estimation of model parameters that takes advantage of a QGAN customized to efficiently load training data. Finally, the study presented in [265] focuses on optimizing the structure of a quantum generator to minimize the parameters required for image generation tasks and make the quantum generator suitable for current quantum devices. The good performance of the proposed quantum generator was demonstrated on two well-known datasets, namely MNIST and Fashion-MNIST. Also in [266], a QGAN is used to generate synthetic images using the MNIST dataset. In other research work, the focus was on improving the efficiency of QGANs. For example, in [267] the authors propose a robust implementation based on Rigetti's Quantum Cloud Services and a comparison on-hardware of several components of quantum generative models such as two circuit ansatzes with varying entangling connectivity graphs and circuit depths. Moreover, in [268], the authors address the inflexibility problem by adopting the variable-depth VQC model to automatically change the structure of the quantum circuit according to the qBAS score[9] in the generative learning tasks. In recent years, QGANs have been applied to various problems. For example, in [269], a QGAN featuring a hybrid quantum generator, capable of supporting various numbers of qubits and quantum circuit layers, along with a classical discriminator, is used for the discovery of small molecule drugs. As shown in the experiments, the proposed hybrid approach can learn molecular distributions as efficiently as its classical counterpart, but with fewer than 20% of the parameters of typical generative adversarial network. In [270], a fully connected QGAN has been implemented and applied in mathematical finance, with a particular focus on volatility modeling. Still, in [271], a QGAN is introduced and tested with application to the quantum anomaly detection problem that cannot be handled using existing methods. Recently, a comparative study was carried out in [272] to investigate QGANs and Quantum Circuit Born Machines. The study has been carried out on six low-dimensional synthetic and two real financial data sets. The key finding is that, for all data sets, the tested quantum models require parameters similar to or fewer than their classical counterparts.

[9] The qBAS score is an instantiation of the F1 score widely used in the context of information retrieval.

For autoencoders, Ding et al. in [273] have demonstrated the feasibility of implementing quantum autoencoders using approximate quantum adders in the Rigetti cloud quantum computer, showcasing their applicability in state-of-the-art superconducting quantum technologies. Another example is in [274], where the authors present an enhanced feature quantum autoencoder, named EF-QAE, composed of a variational quantum algorithm capable of compressing quantum states of different models with higher fidelity. The key idea of the algorithm is to define a parameterized quantum circuit that depends upon adjustable parameters and a feature vector that characterizes such a model. As shown in the experiments, EF-QAE improves the performance compared to the standard quantum autoencoder using the same amount of quantum resources, but at the expense of additional classical optimization.

Finally, Zhu et al. in [275] have proposed quantum autoencoders for quantum gates as a means of compressing quantum computations, with the aim of minimizing quantum communication between the client and the server in the context of cloud computing.

5.3.3. Quantum reinforcement learning

Reinforcement learning involves the design of intelligent agents capable of interacting with the external environment to perform specific tasks, such as reaching a goal or achieving certain rewards. By providing a simplified overview of the environment, including the goal and potentially hazardous locations controlled by adversaries, the reinforcement learning model seeks a path that achieves the objective while minimizing costs. In this way, the reinforcement learning model effectively learns a policy that dictates the action to be taken in a given state. However, as environments become increasingly complex, conventional computing approaches face obstacles and demand greater computational power. Consequently, the use of quantum computing emerges as a promising approach to address these challenges. In particular, in [276], theoretical aspects about quantum reinforcement learning such as the quantum agent-environment interaction, quantum improvements in learning, and the cost of oraculization are described.

In practice, variational quantum approaches represent the methodology for implementing more suitable quantum reinforcement learning algorithms for NISQ devices. In particular, in [277], the authors have demonstrated a proof-of-principle implementation of VQCs to approximate the deep Q-value function for decision-making and policy-selection reinforcement learning tasks, incorporating experience replay and target network methodologies. In addition, they have emphasized the utilization of a quantum information encoding scheme, which effectively decreases the number of model parameters in comparison to ANNs. In [278], Lockwood and Si introduce and demonstrate the potential of VQCs in the variations of the Double Deep Q Network using the CartPole and Blackjack OpenAI Gym environments. Later, in [279], the impact of VQCs design choices such as angle embedding, encoding block architecture, and post-processing on the training capabilities of quantum reinforcement learning agents is investigated. The experiments show how to design a quantum reinforcement learning agent in order to solve classical environments with continuous action spaces and benchmark quantum agents against classical feedforward ANNs. Also in [280], Deep Q learning is implemented with the support of parameterized quantum circuits. The performance of this approach shows that it collects roughly four times more rewards in a given time and takes significantly fewer episodes to converge compared to the classical approach. Moreover, in [281], a novel quantum reinforcement learning approach is introduced that merges the Advantage Actor-Critic algorithm with VQCs by substituting parts of the classical components. This approach addresses the concerns of reinforcement learning scalability while maintaining high performance. In addition, in [282], an approach for gradient-free quantum reinforcement learning is introduced using evolutionary optimization. This approach is evaluated in the Coin Game environment and, as shown in the experimental results, it performs significantly better compared to an ANN with a similar amount of trainable parameters. Quantum reinforcement learning has also been used in some applications, such as spatio-temporal prioritization in Metaverse [283] or coordination in Metaverse [284] and reuse of rockets in space missions [285]. Finally, the study in [286] introduces a novel model that integrates quantum spiking neural networks and quantum LSTM architectures designed for reinforcement learning tasks in energy-efficient environments.

5.3.4. Quantum data processing

Classical data processing techniques are methods used to prepare and analyze data in traditional computing. They include tasks such as data cleaning to correct errors, feature selection to identify important variables, and normalization to scale data for better model performance. Other techniques, such as dimensionality reduction, simplify complex datasets by reducing the number of features while retaining key information. These methods help ensure that data are accurate, relevant and ready for analysis, making them essential for machine learning and data science tasks. Quantum data preprocessing extends classical techniques by using quantum computing capabilities. It involves encoding classical data into quantum states, allowing for more efficient storage and manipulation of information, and developing methodologies capable of processing quantum states to produce information from them.

For example, in [287], a quantum-based feature selection algorithm for the multi-classification problem, called QReliefF algorithm, is proposed. Initially, all the features of the sample are encoded in the quantum state. Subsequently, the similarity is encoded via the estimation of the amplitude, and the k-nearest neighbors in each class are determined using the Grover's method to update the weight vector. Then, features are selected on the basis of the final weight vector and a threshold. The proposed algorithm outperforms the classical ReliefF algorithm in efficiency and resource use. Moreover, in [288], a hybrid quantum feature selection algorithm has been introduced, which combines a classical approach based on correlation coefficient graphs with quantum oracles to determine the suitability of a dataset for the reduction of dimensions. If the dataset meets the criteria, the algorithm efficiently estimates high correlation values using quantum parallel amplitude estimation and amplitude amplification techniques. This approach demonstrates significant improvements in query complexity compared to several popular classical feature selection algorithms. Finally, in [289], a new method is explored to search for the best characteristics in the context of fraud detection using the characteristics of the feature map of the quantum SVM.

As for the encoding of the classical data in quantum states, the definition of so-called Quantum Feature Maps (QFMs) provides a typical way to encode the classical data in the Hilbert space of quantum states. In this context, real-valued features can be encoded within the angles of rotational gates or the probability amplitudes of a quantum register. Alternatively, by maintaining the binary representation of the data, these attributes can be mapped onto the computational quantum basis states. Especially for this last case, where a large number of qubits could be required, in [290], the authors have proposed a new method to embed discrete features with parameterized quantum circuits (see Fig. 13), thus improving the quantum random access coding with a strategy for training a QFM called quantum metric learning. The proposed trainable embedding not only requires as few qubits as the quantum random access coding but also overcomes its limitations to classify inputs whose classes are based on hard Boolean functions. Moreover, one can also consider the embedding of class labels in quantum states via QFM. In [291], by embedding both features and class labels in a quantum register, the authors have demonstrated the implementation of a novel machine learning framework, which does not require any optimization algorithm to perform a classification task. Studies on QFMs embrace also the investigation of the kernel function and, consequently, how quantum circuits can encode the outcome of the kernel function into the Hilbert space. Hence, in this section, quantum kernels will be addressed as data processing techniques beyond their use in quantum support vector machine reported in Section 5.3.1. In detail, a quantum kernel function can be defined as the inner product of two quantum feature vectors in a Hilbert space. As mentioned above, this method of constructing quantum kernels is referred to as QKE. Two primary methods are commonly employed to evaluate quantum kernels: the inversion test and the SWAP test.

However, these conventional methods become impractical for large datasets as they scale quadratically with the dataset size. Accordingly, in [292], the authors have proposed the utilization of randomized measurements for evaluating quantum kernels: their method generally exhibits exponential scaling in qubit number, thereby achieving significant speed-up when executed on intermediate-sized quantum computers. Instead, in [293], the authors show the first experimental demonstration of a quantum kernel machine that achieves a scheme where the dimension of the feature space greatly exceeds the number of data using nuclear spins in solid.

The promising capabilities of QKE methods to surpass their classical counterparts have encouraged their application in real-world scenarios, where the empirical demonstration of the quantum advantage is crucial. For example, in [294], the authors have empirically identified regimes in which quantum kernels could provide an advantage in healthcare. Instead, in [295], the authors have demonstrated a tangible advantage over state-of-the-art classical algorithms operating on real-world datasets for drug discovery.

Finally, quantum state discrimination refers to methods commonly used in quantum information processing to distinguish between different quantum states and selectively extract or manipulate specific states from a larger ensemble. These approaches attempt to improve the performance of QML algorithms by properly discriminating quantum states encoding classical data. For example, in [296], the authors have proposed a hybrid quantum–classical classification scheme of input states, which is nondestructive and deterministic for certain inputs, while probabilistic, in the general case, with the main goal of improving the classification of quantum states.

5.3.5. Critical discussion

The domain of quantum supervised learning has witnessed a mixture of outcomes in the realm of regression and classification tasks. Quantum regression remains an under-explored field, with a few notable approaches using algorithms such as HHL or combining autoencoders with quantum circuits. In contrast, classification has witnessed

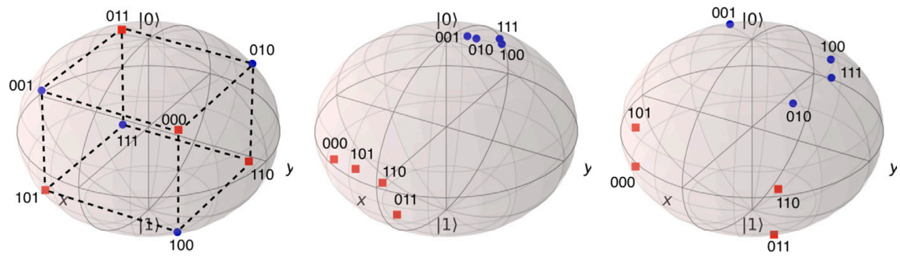


Fig. 13. The embeddings of 3-bit discrete features into one-qubit quantum states drawn as colored dots on Bloch spheres proposed in [290]. The blue dots denote those with parity 1, and the red dots parity 0.

substantial advances, particularly through the use of QNNs. Early theoretical models, such as QPF, have laid the foundation for applications in image classification and pattern recognition. These models leverage the high-dimensional Hilbert space to efficiently manage large data environments. However, challenges such as barren plateaus and noise-induced errors in NISQ devices continue to constrain their practical application. The maturity of quantum supervised learning methods exhibits significant variability. Classification tasks, aided by advances in QNNs and quantum-enhanced SVMs, have shown the greatest promise, with real-world applications in healthcare, finance, and communication networks. The potential for quantum computing to enhance the capabilities of quantum supervised learning is promising, particularly with the development of FTQC, which has the potential to enable scalable, noise-resilient algorithms. This transition could also enable deeper architectures such as quantum CNNs, RNNs and LSTMs, extending the applicability of quantum supervised learning to time series analysis, high-resolution imaging, and beyond.

Unsupervised quantum learning, which includes clustering, generative tasks, and autoencoders, is a promising area of QML, with varying levels of maturity across its subfields. Quantum clustering, particularly quantum k-means, has seen moderate progress. Algorithms such as quantum fuzzy k-means and cloud-based implementations exemplify efforts to optimize performance and privacy. Applications in recommendation systems and medical diagnostics underscore the utility of quantum clustering. However, current implementations face challenges posed by noise and resource limitations of NISQ devices, which hinder scalability and precision. The advent of FTQC has the potential to address these issues, enabling more robust clustering solutions with higher accuracy and reduced computational overhead. Generative tasks, such as those using QGANs, are at an earlier stage of development but show significant potential. Current quantum–classical generative architectures enable the modeling of complex distributions for applications in areas such as image generation and drug discovery. However, the limited depth of the quantum circuits in the NISQ devices restricts their capabilities. In the FTQC era, the development of deeper circuits and improved error correction holds the potential to unlock more efficient generative modeling, thus broadening the range of applications to include high-dimensional data synthesis and advanced anomaly detection. Quantum autoencoders, though less mature, are vital for the compression of quantum data and the optimization of quantum communication. Early implementations demonstrate feasibility, but challenges, such as resource demands and classical optimization overhead, persist. The FTQC approach has the potential to enhance the functionality of quantum autoencoders, facilitating high-fidelity quantum state compression and efficient manipulation of data, particularly in quantum simulations and cryptographic applications.

Quantum reinforcement learning is a recent development that integrates the principles of quantum computing with reinforcement learning to enhance the efficiency and scalability of decision-making agents in complex environments. Although classical reinforcement learning has achieved significant success, it struggles with high-dimensional state spaces and computational intensity, particularly in intricate settings. Quantum reinforcement learning, by leveraging the parallelism and entanglement properties inherent to quantum mechanics, has the potential to address these limitations. Current quantum reinforcement learning implementations frequently use VQCs to approximate Q-value functions, integrate experience replay, and refine policy selection strategies. Initial studies demonstrate the feasibility of quantum reinforcement learning in standard reinforcement learning tasks, such as those simulated in the CartPole and Blackjack environments, where hybrid quantum–classical approaches have been shown to outperform their classical counterparts in terms of convergence speed and resource efficiency. The employment of quantum information encoding schemes has demonstrated significant potential in reducing model complexity when compared to classical neural networks. Furthermore, gradient-free methods, such as evolutionary optimization for quantum reinforcement learning, have demonstrated potential for applications in nondifferentiable or rugged environments. Finally, the integration of advanced quantum architectures, such as quantum spiking neural networks or quantum LSTMs, suggests the potential for future breakthroughs in the handling of spatio-temporal dependencies and dynamic environments. However, these algorithms are constrained by noise, decoherence, and the restricted qubit count of NISQ devices. The transition to FTQC is expected to catalyze quantum reinforcement learning's growth, enabling the development of more sophisticated quantum memory management and the creation of deeper quantum circuits, as well as error correction. These improvements could facilitate the application of quantum reinforcement learning to complex real-world scenarios, such as autonomous systems, advanced robotics, and energy-efficient optimization tasks.

Quantum data processing is evolving beyond classical techniques, incorporating quantum computing's strengths such as superposition and entanglement. Classical methods like feature selection are being enhanced with quantum versions, such as the QReliefF algorithm, which improves efficiency and resource consumption. Furthermore, quantum–classical approaches, founded upon quantum oracle design, have been introduced to efficiently execute feature selection, as evidenced by reduced query complexity. However, scaling for larger datasets remains challenging. Another key development is the encoding of classical data into quantum states using QFMs, which offer potentially more efficient data representations. However, scaling QFMs and QKEs for large datasets remains a challenging endeavor, despite the potential offered by randomized measurements. Finally, discrimination and filtering of quantum states are methods used in quantum information to distinguish and selectively extract or manipulate specific quantum states from a larger ensemble. The transition from NISQ to FTQC technologies is poised to markedly enhance quantum data processing by facilitating the development of more scalable and robust algorithms. This transition has the potential to unlock the full potential of quantum feature selection, QFMs, and QKEs, rendering them more effective for real-world applications. Furthermore, quantum state discrimination could become more efficient with FTQC, providing a potential advantage over classical classification methods.

5.4. Quantum communication, perception and action

When Alan Turing proposed his test for intelligence, he based it on language because of its universal scope and because language captures so much of intelligent behavior. Consequently, intelligent agents must have the ability to process natural language to exhibit intelligent behavior comparable to that of humans. In addition, humans obtain information about their surroundings through vision. Therefore, intelligent agents must utilize computer vision techniques to collate large image collections from which they can extract visual knowledge. Finally, the interaction of humans with their environment is achieved through a mechanical approach based on the utilization of the human body's arms and legs. Consequently, an intelligent agent can emulate this behavior by utilizing robotic components. The application of quantum principles offers the potential for the development of a new generation of highly efficient computational approaches for the processing of natural language, computer vision, and robotics.

5.4.1. Quantum natural language processing

Today, NLP predominantly relies on large pre-trained deep learning models, such as LSTM. In fact, in [298], a protocol based on quantum LSTM is proposed for NLP to perform various tasks in general but specifically to translate a sentence from English to Persian. The proposed method uses quantum circuits of sentences as input for the quantum LSTM cell. In addition, Di Sipio et al. in [299] have successfully trained a quantum LSTM network [225] (previously discussed in Section 5.3.1) to perform the parts-of-speech tagging task using numerical simulations. In [300], Katyayan et al. have suggested the use of QML models to improve question-answer systems. Specifically, they have conducted the question classification task via quantum SVM and variational quantum classifiers. Moreover, in [301], a variational quantum circuit-based approach is used in the field of sentimental analysis in bilateral conversations. Moreover, in [302], Bouakba et al. investigated the potential of employing ensemble learning to improve prediction of quantum text classification tasks. Focusing on the NISQ era, in [303], Meichanetzidis et al. have conducted the first implementation of an NLP task on a NISQ processor, using the Categorical Distributional Compositional model. Specifically, sentences are instantiated as parameterized quantum circuits, word meanings are embedded in quantum states using parameterized quantum circuits, and the sentence's grammatical structure faithfully manifests as a pattern of entangling operations, composing the word circuits into a sentence circuit. The circuits' parameters are trained using a classical optimizer in a supervised NLP task of binary classification. Still, in [304], some experiments are reported showing that some tasks in NLP can be performed using quantum computers. For example, in this work, a case study on topic classification has been implemented, in which word-topic weights are implemented as fractional rotations of individual qubits, and a phrase is classified based on the accumulation of these weights onto a scoring qubit, using entangling quantum gates. Later, the first application of quantum transfer learning in the area of NLP was introduced in [305]. In this work, short texts (e.g. SMS) are classified with classical–quantum transfer learning, which was originally applied only to image processing [247]. In detail, this work proposed the application of the pre-trained BERT (Bidirectional Encoder Representations from the Transformers) model, whose VQC is fine-tuned for text processing. As shown in the experiments, this approach is characterized by high precision as well as a lower loss function.

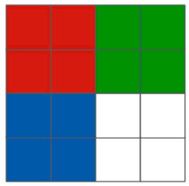
5.4.2. Quantum computer vision

The way in which an image is represented on a quantum computer is crucial in the design of quantum algorithms for computer vision. It significantly influences the types of image processing tasks that can be performed and the level of effectiveness with which they are executed. Quantum image representation techniques can be classified into four primary categories: (1) qubit lattice-based methods, where each pixel of the digital image is stored in a qubit; (2) entanglement-based methods, where the employment of entangled qubits enable the reconstruct images; (3) flexible representation of quantum images (FRQI) methods, where the gray level and the position of the image are expressed as a normalized quantum superposition state; (4) novel enhanced quantum representation (NEQR) methods, where the grayscale value of each pixel in the image is stored in the basis state of a qubit register [306]. Drawing inspiration from FRQI, a multichannel representation for quantum images (MCRQI) has been devised, employing quantum rotation gates to capture channel information for triple-color RGB images. However, MCRQI requires three qubits per pixel to store color data, limiting its ability to execute certain digital image processing operations, such as complex color manipulations. With the aim of improving MCRQI, Sang et al. have introduced a novel quantum representation for digital color images, named NCQI, in [307]. This method utilizes the basis states of a qubit register to encode the color value of each pixel (see Fig. 14). Consequently, to store a color digital image in a quantum computer, two entangled qubit registers are employed, encompassing both color values and pixel positions. Using this quantum representation of the images, a two-domain quantum color image watermarking scheme based on the least significant bit algorithm has recently been proposed in [308]. Later than NCQI, in [309], Li et al. have proposed a bitplane representation of quantum images (BRQI). This method employs $(n+4)$ or $(n+6)$ qubits to store grayscale or RGB color images consisting of 2^n pixels. Compared to NEQR and NCQI, BRQI significantly increases storage capacity, 16 times and 2^{18} times, respectively. Recently, a more efficient technique to store the bit planes of an image in quantum states has been proposed [310]. This technique has 10% less quantum cost and four times less time complexity compared to the BRQI model for grayscale images, and 30% less quantum cost and four times less time complexity compared to another quantum representation model of color digital images, named QRCI [359].

Regarding NEQR methods, in [311], Miyake et al. have proposed a new quantum grayscale image watermarking scheme by using simple and small-scale quantum circuits. In [312], Şahin et al. have introduced a quantum representation of multi-wavelength images to perform image processing at different wavelengths. This model uses the basis states of a qubit register to store the values at different wavelengths of each pixel of the image. In particular, it uses three separate registers to hold the position, wavelength, and color values of each pixel, while keeping the whole image in the superposition of the three registers. Later, Zhu et al. in [313], have proposed a multimode quantum image representation, still a NEQR-based method capable of representing images of any size in multiple color modes while reducing the number of qubits required. Later, Chen et al. in [314], have combined the strengths of the FRQI and NEQR models to introduce a novel method of presenting quantum images based on the HSI color space model.[10] In [315], different quantum data representations and algorithms are used and evaluated in the context of radio interferometry. As shown in the experiments, the Quantum Probabilistic Image Encoding (QPIE) offers an excellent algorithmic speedup without sacrificing image fidelity. In particular, this encoding technique represents grayscale image pixels as probability amplitudes within the statevector of a potential quantum state, which require a minimal number of qubits, specifically, $\log_2 n$ qubits for the representation of n pixels. However, QPIE encodings may not be suitable for high-fidelity image analysis required by extended source structure or cosmological studies.

The quantum image representation model also serves as the foundation for quantum image encryption to efficiently protect visual information. Considering FRQI methods, in [316], Song has introduced a new approach to the preparation of quantum noise images. This

[10] HSI model uses two qubits to represent hue (H) and saturation (S) and multibinary qubits to represent intensity (I).



$$
\begin{aligned}
|I\rangle = \frac{1}{\sqrt{2^4}}\Big[& \big|\underbrace{00000000}_{B}\underbrace{00000000}_{G}\underbrace{11111111}_{R}\big\rangle \otimes \left(|0000\rangle + |0001\rangle + |0100\rangle + |0011\rangle\right) \\
& + \big|\underbrace{00000000}_{B}\underbrace{11111111}_{G}\underbrace{00000000}_{R}\big\rangle \otimes \left(|0010\rangle + |0011\rangle + |0110\rangle + |0111\rangle\right) \\
& + \big|\underbrace{11111111}_{B}\underbrace{00000000}_{G}\underbrace{00000000}_{R}\big\rangle \otimes \left(|1000\rangle + |1001\rangle + |1100\rangle + |1101\rangle\right) \\
& + \big|\underbrace{11111111}_{B}\underbrace{11111111}_{G}\underbrace{11111111}_{R}\big\rangle \otimes \left(|1010\rangle + |1011\rangle + |1110\rangle + |1111\rangle\right)\Big]
\end{aligned}
$$

Fig. 14. A 4 × 4 color image and its quantum representation expression of NCQI [307].

method aims to establish evaluation and testing schemes for quantum image authentication and secure communication. In [317], Zhout et al. have proposed a new quantum image encryption scheme using iterative generalized Arnold transforms and quantum image cycle shift operations. For NEQR images, in [318], Li et al. have instead proposed a block-based image scrambling scheme for the generalized model of NEQR. It can be used both for grayscale and color images, and also for $2^n \times 2^m$ images. Meanwhile, in [319], a quantum block image encryption scheme has been designed based on the Quantum Arnold Transform (QArT) and the Sine Chaotification Model (SCM). In order to flexibly manipulate image blocks, the authors have proposed a quantum block image representation model for block image, which encodes pixel gray values and position information of image blocks into two entangled qubit sequences. QArT is applied to scramble the positions of the image blocks, and the final ciphertext image is obtained by quantum XOR operations, which are completed with a pseudo-random sequence generated from SCM. Once more employing QArT to scramble pixel positions, in [320], Liu et al. have introduced a novel quantum image encryption algorithm based on bit-plane permutation and a sine logistic map. The image to be encrypted is represented here by the NEQR model. The bit-plane cross-exclusive OR and shift operations have been designed accordingly to change the pixel values. The final ciphertext image is obtained through a diffusion process utilizing a sine logistic map, which extremely enlarges the key space. Continuing to adopt the NEQR model, in [321], Musanna et al. have proposed a quantum 3-D Baker map to scramble a 3-D quantum representation of an image and an encryption scheme utilizing basic quantum gates such as C-NOT, Toffoli, and Ripple-carry adder due to their computational efficiency. However, Guo et al. have introduced an image encryption algorithm in [322], employing a Feistel structure. This choice is motivated by the fact that the Feistel structure decryption process closely mirrors the reverse operation of encryption. Within the field of quantum secure communications, in [323], Abd El-Latif et al. have proposed a quantum steganography approach to hide a quantum secret image in a quantum cover image, as well as a quantum image watermarking to hide a quantum watermark gray image in a quantum carrier image. The proposed approaches have been demonstrated through a scenario of sharing medical images between two remote hospitals. Moreover, in [324], a novel Multi-Modal Quantum Watermarking scheme is proposed for both types of grayscale and color images. To enhance the robustness, the authors of this paper propose the Block Bit-plane Centrosymmetric Expansion method, which utilizes controlled quantum gates to extend the watermark, making the method resistant to noise and geometric attacks.

Later, Qu et al. in [325], have presented a large payload quantum image steganography protocol. This protocol is based on quantum image expansion and Grover's algorithm. It adopts the quantum log-polar image representation to prepare the quantum image. Subsequently, a quantum expansion technique is employed to generate a superposition of multiple image copies, each with the same size angle difference as the carrier. Following this, a secret message is embedded in one of the quantum image copies, with a specific rotation angle encoded. To accurately extract the embedded secret message, the Grover's algorithm is utilized to locate the correct quantum image copy. Finally, in [326], a blind watermarking scheme is proposed and evaluated for multimode quantum image representation based on three-dimensional coordinate images on the IBM Quantum Lab platform.

Quantum image processing has the potential to reduce both image storage and the number of gate operations. The wavelet transform is widely used in image processing and has led to the development of quantum versions. In detail, Quantum Wavelet Transform (QWT) is classified as 1-D or multidimensional according to the types of data it acts on, being one-dimensional or multidimensional. Moreover, QWT can be used repeatedly, and then the level of QWT describes the number of times QWT works on the data. In [327], Li et al. have presented the general theory of the multilevel 2-dimensional QWT, and have also designed the circuits for the multilevel 2-D-QWT. Later, in [328], Li et al. have introduced a multi-level 3-dimensional QWT theory to implement the wavelet transform for quantum videos. Meanwhile, in [329], Shukla et al. have proposed a hybrid classical–quantum approach for the evaluation of multi-dimensional Walsh–Hadamard transforms and its applications to quantum image processing.

Edge detection is also an important task in image processing, significantly affecting subsequent research in feature extraction, description, and target recognition. In [330], Ma et al. have employed the Sobel operator to calculate the gray gradient for NEQR images. Empirical results have shown that their algorithm can extract an edge with dimension $2^n \times 2^n$ when the computational complexity is $O(n^2 + 2^{q+3})$. Later, in [331], Chetia et al. introduced a quantum-improved Sobel edge detection algorithm with nonmaximum suppression and double threshold techniques for NEQR images.

In conclusion, numerous computer vision tasks are based on large machine learning models utilizing CNNs with rapidly expanding trainable parameters. The ever-growing demand for computing resources necessary to train these models has prompted the exploration of alternative frameworks, such as Optical Neural Networks and quantum computing, as suggested in [332]. In this study, Parthasarathy et al. have introduced the Quantum Optical CNN to address the computational bottleneck due to the increasing number of parameters.

5.4.3. Quantum robotics

In navigating complex and challenging robotic tasks, achieving robust, intelligent, and adaptive control in unpredictable or hazardous situations, or when faced with multi-criteria control objectives, relies on quantum computing principles. In [333], a case study with a robotic dance, where the thinking and moving mechanisms are modeled according to quantum–classic decision making. This research adopts the D'Ariano–Faggin formalism to model the elaboration of multi-sensory stimuli and the corresponding decision making in terms of movement response. The case study with improvised dance is based on a collection of poses, whose combination is presented in response to external and periodic multi-sensory stimuli. The dancer's inner state and reaction to classic stimuli is modeled through a quantum circuit. Moreover, in [334], the authors propose a new quantum circuit, implemented thanks to the IBM quantum experience platform, to make a robot fly. The proposed quantum robot shows the behavior of 'fear', and its movement is deterministic in nature. The behavior of this quantum robot was tested in a game, where it can always avoid accidents. Moreover, robotics aims to understand and replicate structures and mechanisms found in nature, including phenomena such as self-organized collective behavior, known as swarm intelligence. In [335], the main technical challenge addressed is the development of a formalism that encompasses both local and global aspects of robotic swarm behavior, integrating a quantum-based approach to bridge the gap between the realm of robots and the rapidly evolving field of quantum computing. In [336], the same authors have refined these ideas by providing a mathematical model to describe swarms using nested matrices and reversible logic gates to represent pairwise interactions. The authors have established a link between local and global swarm behavior, with the emergence of global behavior from simple local pairwise interactions. Therefore, these local interactions have been captured using a quantum circuit. To validate the approach, the authors have specifically focused on an ant foraging scenario because of its significance in nature and recent applications in robotics. An additional practical instance of quantum computing aiding robot swarms is documented in [337]. This study involves creating aquatic robot swarms tasked with purifying the Venice canals, using computers based on gondolas for interaction. In detail, quantum computing is used both to design the telecommunication-based model of an aquatic robotic swarm and to formalize the interaction and synchronization between the "heads" of the swarms, that is, between gondolas. Finally, in [338], quantum multi-agent reinforcement learning has been used for Internet-connected autonomous multi-robot control and coordination in smart factory applications.

5.4.4. Critical discussion

Quantum NLP, a key element in the achievement of intelligent behavior analogous to human cognition, has seen substantial advancements in quantum-enhanced artificial intelligence. Preliminary endeavors, including the formulation of quantum LSTM networks and variational quantum classifiers for tasks such as sentiment analysis and question answering, have shown considerable promise. For instance, Meichanetzidis et al.'s work on parameterized quantum circuits for binary classification tasks demonstrates the potential of quantum circuits to model linguistic structures. Moreover, quantum transfer learning, as evidenced by recent studies, is poised to play a pivotal role in quantum NLP, offering an efficient means to fine-tune pre-trained models for text processing. However, these early-stage implementations face substantial limitations due to the inability of current NISQ systems to handle large datasets or perform complex optimizations at scale. The evolution of quantum NLP will depend on overcoming these limitations through error correction techniques and the increased qubit coherence and connectivity enabled by FTQC.

Quantum Computer Vision also represents a promising area in which quantum computing could offer groundbreaking advancements. The primary challenge in quantum image processing pertains to the representation and manipulation of images in quantum states. To address this challenge, various quantum image encoding techniques have been investigated, including FRQI and NEQR. These techniques have been explored to improve the efficiency of storing and processing digital images. These approaches have been shown to reduce computational complexity and could potentially enable faster processing of large image datasets. In the NISQ era, these methods have demonstrated initial success in image watermarking, encryption, and basic image processing tasks, such as edge detection. However, translating these methods into real-time applications in dynamic environments remains a significant challenge. The transition to FTQC is expected to enhance the efficiency of quantum image processing by reducing noise and enabling more precise quantum gates for image manipulation. Consequently, quantum computer vision can achieve significant advancements in domains such as object recognition, pattern matching, and image analysis at scales that were previously impractical with classical systems.

Quantum robotics, which aims to emulate human-like actions and decision-making, is arguably the most nascent of these fields. The application of quantum computing in robotics has been explored in tasks such as swarm intelligence, robotic dance, and autonomous multirobot coordination. Research has demonstrated how quantum principles can enhance decision making and behavior modeling, allowing robots to make efficient and adaptive decisions in complex environments. For instance, quantum-enhanced swarm behavior models, such as those developed by Mannone et al. signify a substantial advancement in the integration of quantum mechanics with multi-robot coordination systems. These systems hold considerable promise for applications such as autonomous robotic fleets in disaster response or industrial settings. Furthermore, the integration of quantum reinforcement learning and enhanced decision-making algorithms will empower robots to perform more sophisticated actions in dynamic, unpredictable environments. However, the current state of quantum robotics is hindered by the limited scalability of quantum systems. However, the advent of FTQC will likely enable the development of more robust quantum circuits and error correction, allowing quantum robotic systems to handle larger, more complex tasks with greater precision.

6. Artificial intelligence for quantum computation

This section presents the contributions of the AI community to the design of classical algorithms aimed at addressing the drawbacks of NISQ computers (see Table 4).

6.1. AI for quantum compilation

Quantum compilation is the process of transforming a high-level quantum algorithm into an optimized sequence of low-level instructions that can be executed on quantum hardware with specific properties and constraints. It involves several steps, including circuit mapping, routing, and circuit synthesis. In detail, circuit mapping refers to the task of assigning logical qubits in the algorithm to physical qubits on the device. In fact, a given quantum processor is characterized by a so-called *coupling map*, according to which qubits can interact. Consequently, the quantum circuit mapping must take into account the structure of the processor in such a way as to minimize the transportation of logical qubits from one physical qubit to another during the computation phase, which is a greatly noisy operation that strongly affects the reliability of the output. The routing task, instead, refers to the adjustment of the circuit to respect hardware connectivity by inserting operations such as SWAP gates.[11] Finally, circuit synthesis consists of transforming high-level gates into a sequence of basic gates that the hardware supports [421,422]. The whole quantum compilation procedure aimed to optimize the circuit to minimize the number of gates, reduce the gate depth, and address constraints imposed by the underlying hardware architecture such as the physical connectivity of qubits. Finding an optimal mapping and routing strategy is a problem that is NP-hard and several strategies to find pseudo-optimal solutions have been proposed in the literature in the last years.

In [360], the quantum circuit mapping problem was formulated as a classification task and solved using deep neural networks. In particular, for a given quantum processor, the authors proposed to collect a dataset that based on the features of the physical device and the quantum circuit has labeled the best mapping provided by testing different mapping strategies. Subsequently, the deep neural network is trained on it and results in a fast mapping strategy achieving a good level of optimization compared to the several strategies used to build the dataset. Machine learning, and in particular reinforcement learning, is also used in the more recent mapping strategies proposed in [361–363].

[11] The SWAP gate is a two-qubit gate that swaps the quantum states of the two qubits.

Table 4
A literature overview of artificial intelligence for quantum computation.

Artificial Intelligence for Quantum Computation			
AI Field / *Quantum issue*	*Machine learning*	*Problem solving*	*Reasoning*
Quantum circuit mapping	[360–366]	[367]	
Quantum routing strategy	[368]	[369]	
Quantum circuit synthesis	[370–372]	[373–375]	[376]
Quantum tomography	[377–394]		
Quantum calibration	[395,396]		
Quantum pulse control	[397]	[398]	
Quantum error mitigation	[399–406]	[407,408]	[409,410]
Quantum error correction	[411–419]	[420]	

Moreover, in [364], the authors use reinforcement learning combined with a A* search to solve the qubit mapping problem. In detail, the authors propose a reinforcement learning-based model to solve the initial mapping problem and a dynamical extract-and-route framework that iteratively extracts a subcircuit and uses A* search to determine when and where to insert additional gates. Still, in [365], the authors present a novel approach to circuit partitioning in the context of multicore quantum architectures that uses reinforcement learning to decide how a quantum algorithm can fit within the different cores of the quantum computer. The success of reinforcement learning in quantum compilation has encouraged the authors in [366] to develop a software framework based on OpenAI gym equipped with environments that are specifically tailored for quantum compilation. Finally, in [367], an evolutionary deep neural network is introduced that learns the qubit layout initialization of the most advanced and complex IBM heuristic used in today's quantum machines.

Reinforcement learning has also been used to develop an efficient routing strategy in [368]. In detail, this work proposes a strategy based on a modified version of the deep Q-learning paradigm that results in a routing procedure more efficient than the state-of-the-art quantum compilers available from IBM's Qiskit and CQC's t $|ket\rangle$ across a range of NISQ devices up to 50 qubits. In addition, in [369], the authors apply an A* search algorithm to determine how to insert a sequence of additional SWAP and BRIDGE operations into the subcircuit to obtain a high-quality routing solution with the minimum number of additional gates.

The aims of a quantum compiler are not only the mapping and routing of quantum circuits on the hardware. Indeed, although nowadays quantum programming is still based on the manual arrangement of logic gates, for the successful development of quantum computation, it is of critical importance to raise the level of abstraction at the programming stage. In this context, quantum circuit synthesis plays a crucial role in translating high-level quantum algorithms into low-level gate sequences that quantum hardware can understand and execute. For example, in [370] Pires et al. proposed a way of synthesizing quantum circuits for the creation of Bell and GHZ states by using reinforcement learning. The capability of their approach to learn new circuits is shown to decrease as the number of qubits increased. Moreover, in [371], the authors introduce a reinforcement learning environment for quantum circuit synthesis, where circuits are constructed utilizing gates from the Clifford+T gate set to prepare specific target states. Still, in [373], a GPU-accelerated evolutionary search optimization based on genetic algorithms is proposed for the synthesis of quantum circuits. Also in [374], evolutionary algorithms and in particular genetic algorithms are used in the context of quantum compilation. In particular, the authors used genetic algorithms to compile multiple unitaries into a single trainable unitary through an optimization process. Another step towards a high level of abstraction in quantum computation is taken in [375], where a method is proposed to build N-bit unitary matrices by a properly trained variational quantum circuit through an optimization method like Nelder–Mead/Powell or Gradient descent methods. Instead, in [372], a deep neural network that uses information about a target unitary is used to propose parameterized quantum circuits that are likely to instantiate the target unitary. Finally, in [376] an ad hoc quantum synthesizer is introduced for ion trap and quantum dot technologies based on classical reversible logic and quantum cascades.

6.2. AI for quantum characterization

Quantum characterization is a comprehensive term that encompasses various processes to optimize and understand the behavior of quantum processors. This includes procedures for error diagnosis such as Quantum State Tomography (QST), calibration, and pulse control, all of which are critical to achieving high-fidelity quantum operations. In the literature, initial efforts have been made to improve these procedures using AI methods.

In particular, QST consists in determining the complete description of the state of a quantum system starting from some measurement data. QST can be executed by exploiting classical approaches like Maximum Likelihood Estimation [423] or innovative machine learning-based techniques [377–380]. Machine learning approaches seem to be more robust to the number of measurements used for QST [381–387]. Moreover, as highlighted in [388], there is a trade-off between rapid and high average reconstruction fidelity, whereas Maximum Likelihood Estimation results in a slower reconstruction even if characterized by lower variance. Remarkably, in [389], the authors developed a machine learning pipeline that does not require the training of a separate model for each missing measurement, making it potentially applicable to the estimation of the quantum state of large quantum systems where preprocessing is computationally infeasible due to the exponential scaling of the dimension of the quantum system. In contrast, the authors in [390] do not focus on the problem of making machine learning models robust to missing measurements, but on their necessity to match exactly the dimensionality of the system under consideration. To solve this issue, the authors propose a machine learning approach that can be trained once on m qubits and that can subsequently perform QST on any system of n qubits where $m \geq n$. With the goal of maximizing the performance of machine learning-based QST approaches, Lohani et al. in [391] show that it is not always optimal to engineer training sets to exactly match the expected distribution of a target scenario, and instead performance can be further improved by biasing the training set to be slightly more mixed than the target. In terms of performance, recently an attention mechanism-based generative network was proposed for QST in [392]. As shown in the paper, the proposed approach outperforms earlier neural network-based quantum state reconstruction tasks, also in noisy environments such as IBMQ quantum computers. Finally, in [393], a QST scheme that relies on approximating the probability distribution over the results of an informationally complete measurement in a variational manifold is represented by a complex machine learning model such as CNNs. In the paper, it is shown that the number of variational parameters used scales polynomially in system size. This compressed representation enables the reconstruction of states with high classical fidelity that outperforms standard methods such as Maximum Likelihood Estimation. To conclude, it is worth noting that a way to boost the efficiency of state tomography is via local measurements on reduced density matrices, but the reconstruction of the full state thereafter is hard. Therefore, in [394], a machine learning method is proposed to recover the ground states of k-local Hamiltonians from just the local information, where a fully connected neural network is built to carry out the task with up to seven qubits.

As for calibration, this procedure involves a series of steps related to qubits and gates such as tuning qubit frequencies and adjusting control parameters. Automated calibration that reduces the need for manual intervention and speeds up the process can be executed using machine learning techniques. In [395], an approach based on deep reinforcement learning is proposed for superconducting circuit calibration. In detail, a simplified model of a transmon qubit coupled to a cavity resonator is used to demonstrate a quantum circuit. To demonstrate the feasibility of this approach, the agent is trained in three distinct environments to achieve the best possible rewards. Also in [396], the authors use deep reinforcement learning for model-free quantum control. The proposed approach relies only on the measurement at the end of the control process and provides the ability to find the optimal control policy without access to the quantum systems during the learning process.

Finally, regarding the optimization of pulse control, procedures in this context are typically belonging to quantum optimal control theory aimed at addressing the control of physical qubits. Finding explicit pulse control sequences in such a framework is challenging, especially when an underlying physical model is unknown. In [397], a deep reinforcement learning method is proposed, which does not require any underlying gate model or qubit pre-calibration, capable of controlling a superconductive qubit via analog pulses acting in the IBM Qiskit Pulse environment. The method is applied to build a single qubit gate with high fidelity and short duration at pulse level. In particular, the reinforcement learning agent approximated the X90 gate at the physical layer on the IBM Armonk transmon superconductive qubit simulated by the Qiskit Pulse simulator. Moreover, some AI techniques have also been used in the realization of quantum gates. In particular, in [398], a quantum gate is realized using the gravitational search algorithm and by perturbing a three-dimensional harmonic oscillator with an electromagnetic field.

6.3. AI for reducing quantum noise

While quantum characterization helps to understand and mitigate the effects of noise on qubits, it does not completely eliminate noise. Noise can arise from various sources, including environmental factors, hardware imperfections, and limitations in control mechanisms. Therefore, noise remains a significant challenge in quantum systems, requiring ongoing research and development of specific techniques to reduce noise and achieve higher reliability of quantum computation. To reduce noise effects, two main approaches are known in the literature: the first consists of error mitigation techniques and the second consists of error correction schemes. Error mitigation consists of post-processing noisy quantum data with classical approaches in such a way as not to exploit further quantum hardware resources that are already limited at this stage. However, post-NISQ devices will be characterized by error correction approaches that will correct quantum errors by exploiting further quantum resources.

Let us begin by discussing the work that has emerged in our literature investigation in the field of error mitigation. In [399], deep neural networks are applied for error mitigation in the presence of different types of quantum noise. In particular, this approach focuses on the simulation of Trotterized dynamics of 2D spin lattice in the regime of high noise, when expectation values of bounded traceless observables are strongly suppressed. In addition, some research has focused on mitigating readout errors specifically. This is because readout errors are one of the sources of errors that greatly affect the reliability of the quantum computation. Focusing on readout error mitigation, this can be done at two levels. In [400], there is an example of a low-level data error mitigation technique. Indeed, the authors proposed an innovative way to classify kerneled data from qubit measurements by exploiting Gaussian mixture models with probability threshold. Differently, in [401,402,407–410], techniques are proposed to mitigate readout errors with higher level data. In these cases, ANNs, linear regression, genetic algorithms, competent memetic algorithms, and fuzzy clustering are used, respectively, to directly mitigate the output distribution of probability from noisy quantum circuits. However, these approaches can suffer from scalability issues when the number of qubits to be considered increases with the exponential growth of the probability distribution. In [403], a scalable quantum error mitigation approach is proposed that takes advantage of the conditional independence of distant qubits and incorporates transfer learning techniques. This method results in an exponential reduction in the size of the neural network used for mitigation. Moreover, [404], investigated how the quantum error increases accordingly to the depth of the quantum circuit, and a semi-supervised quantum error mitigation technique is proposed which combines unsupervised and supervised machine learning models. Similarly, in [405] a deep neural network-based error mitigation technique is proposed for digital quantum simulation consisting of multiple Trotter steps. This technique allows the user to effectively increase the number of trotter steps in the quantum circuit, i.e., to have reliable results even when it is increased its depth. In addition, in [406], the authors consider the tasks of reconstructing and classifying quantum states corrupted by the action of an unknown noisy channel using classical feedforward neural networks.

If all of the above researches focused on mitigating quantum errors, hereafter the topic will be about quantum error correction. Roughly speaking, error correction techniques consist of using some additional quantum resources to have some pattern of errors, and then according to a given pattern apply some other operations to correct the related error. The surface code is the most well-known approach for performing error correction, and patterns of error are often decoded by using AI techniques. An example is reported in [411], where a multidimensional Bose quantum error correction technique based on the neural network decoder is proposed. Another example is reported in [412] where different neural network-based decoders are compared. The authors show that the proposed RNN results in a better balance between decoding performance and execution time and is much easier to train than other neural network models. The suitability of neural networks as error decoding methods is also validated in [413], where a hardware implementation of this type of decoders is introduced. The experimental results show high decoding performance comparable to other state-of-the-art decoding algorithms whilst being well below the tight delay requirements ($\approx$ 440 ns) of current solid-state qubit technologies. Although neural network-based decoders are very promising, the main issue is related to scalability to larger code distances due to an exponential increase in the error syndrome space.[12] To bridge the gap in this direction in [414], a way to distribute decoders based on neural networks while maintaining a similar level of decoding performance is proposed. More recently, different variants of neural network decoders have been investigated, such as in [415] and in [416], where CNNs are proposed as decoders of surface code error syndromes and heavy hexagonal coding[13] respectively. Also in [417], the topic is to implement quantum error correction algorithms for errors in the heavy hexagonal code, but using reinforcement learning. Still, in [418], the authors propose a new decoding algorithm for surface codes, i.e., a type of topological code, by using CNNs tailored for the topological lattice structure of surface codes. In [419], a generative adversarial network is exploited as an error correction training model, and the problems of finding the error positions of the surface code and of decoding efficiency are addressed using Grover's algorithm and a reinforcement learning decoder. Instead, in [420], a genetic algorithm is developed to search for quantum circuits, particularly quantum error correction codes of stabilizers.

[12] The error syndrome space refers to the set of all possible outcomes of syndrome measurements performed on a quantum state. These measurements are used to detect and diagnose errors in the state without collapsing the encoded quantum information.

[13] Heavy hexagonal coding is an adaptation of surface codes to heavy-hexagonal lattice architectures where "heavy" qubits (i.e., with higher connectivity) and "light" qubits (i.e., with lower connectivity) are alternated.

6.4. Critical discussion

The integration of AI into quantum computation has emerged as a key solution to the myriad of challenges inherent in NISQ systems, such as quantum compilation, characterization, and noise reduction. This integration has a substantial impact on the maturation of quantum technologies and paves the way for the advent of FTQC devices.

In the context of quantum compilation, AI techniques, including deep neural networks and reinforcement learning, have exhibited considerable potential to perform circuit mapping, routing, and synthesis. Machine learning approaches have shown the ability to provide efficient solutions that improve traditional compilation strategies, a critical aspect for improving the performance of NISQ devices. As quantum hardware continues to evolve, AI-driven solutions will play a pivotal role in automating the compilation process and improving the level of abstraction in quantum programming, thus facilitating the scalability and complexity required for FTQC.

Another crucial area is quantum characterization, where AI has the potential to enhance the accuracy of QST and optimize qubit calibration processes. The inherent exponential nature of quantum systems poses a significant challenge to classical methods for quantum state reconstruction, particularly with respect to scalability. However, machine learning provides a promising solution by offering more robust and scalable approaches to reduce errors caused by noisy environments. Furthermore, AI-based methods play a crucial role in automating calibration, thereby reducing human intervention and accelerating the pace of quantum hardware development. These advances are of critical importance for the NISQ era, where error rates are high, and lay the foundation for more reliable FTQC systems by streamlining error correction and state estimation.

Finally, noise continues to represent a substantial challenge in the realm of quantum computing, with AI-based techniques for error mitigation and error correction demonstrating efficacy in addressing this issue. Error mitigation methodologies aid in noise reduction without necessitating additional quantum resources, while AI-empowered error correction techniques, such as neural network decoders for surface codes, have the potential to manage errors by leveraging additional qubit resources. These methods exhibit increasing scalability and have the potential to support the fault-tolerant paradigms necessary for FTQC in the future.

In conclusion, AI plays a critical role in overcoming the current limitations of NISQ systems, providing tools for compilation, error reduction, and characterization that are essential for scaling quantum computation. As the field progresses, AI techniques will continue to evolve, ensuring a smoother transition towards the FTQC era, where quantum computers will be able to execute reliable and complex computations. The maturity of AI-driven methods in these areas is crucial to optimize NISQ systems and unlock the full potential of quantum computation.

7. Future challenges and ethical issues

As evidenced by the large number of papers cited so far, QAI is a research topic that is attracting significant attention from the computer science community. The interaction between quantum computing and AI is bidirectional, allowing mutual benefits. Despite the strong interest, practical results in terms of computational benefits for AI methods or AI-based reliability for quantum computation are still far away because of some weaknesses that still negatively affect the interaction between the two disciplines. On the one hand, preliminary research suggests potential computational advantages in using quantum computing for reasoning, learning, and problem solving, but there is currently only minimal formal proof of quantum advantage. However, current AI approaches, while mature, are still unable to overcome the computational drawbacks of NISQ devices. In both cases, therefore, there is still a wealth of research avenues to be explored in order to establish the field more thoroughly. In the future, innovative approaches to the design of quantum algorithms that can provide significant speedups in AI will need to be explored in depth. Concepts such as reasoning, learning, and problem solving need to be rethought under a new vision, where these subfields of AI are natively redesigned computationally, taking quantum phenomena directly into account. Furthermore, recent research suggests that QAI could benefit significantly from the integration of multi-agent frameworks, which support distributed cognition, collaborative decision making, and scalable quantum-enhanced learning architectures [424–430]. Moreover, the integration of innovative quantum technologies, such as Quantum Random Access Memory (QRAM), could further enhance QAI by enabling scalable memory architectures that leverage quantum parallelism and coherent data access [431–435]. This may open new possibilities, allowing more efficient handling of information in a range of quantum-native AI tasks.

It is also important to emphasize the need to integrate AI techniques into high-performance computing environments to enable more efficient analysis and management of quantum information and ultimately to increase the reliability of current NISQ devices towards ideal behavior. Moreover, even if this survey focused on AI techniques to overcome the drawbacks of current NISQ devices, recently AI techniques are emerging as powerful tools to overcome issues in the design of quantum algorithms. For example, as shown in [436], genetic algorithms represent more efficient optimizers for training parameters of the Quantum Approximate Optimization Algorithm (QAOA) compared to traditional gradient-based and gradient-free methods. Starting from these considerations, the frontier research area of QAI will present serious challenges to the scientific community of computer scientists to accelerate the process towards the post-NISQ era of quantum computing, where practical applications will be successfully addressed.

In considering the interaction between quantum computing and AI, it is also important to consider future emerging research areas such as quantum neuroscience. Some frontier studies suggest that certain brain processes, including cognition and consciousness, may be based on quantum principles such as superposition, entanglement, coherence, and tunneling. First, research suggests that superposition could act as a mechanism for cognitive processes to consider multiple possibilities simultaneously, potentially leading to more efficient decision-making and problem-solving. Second, it has been theorized that entanglement could play a role in the integration of information across different brain regions, potentially contributing to the unity of conscious experience. Recent studies suggest that quantum coherence may play a role in synchronizing neural oscillations, which are crucial for cognitive functions such as attention, memory, and perception. In addition, quantum tunneling has been proposed as a potential mechanism for synaptic transmission and neuronal firing, which could affect the speed and efficiency of information processing in the brain. Although these results are based on theoretical models and speculative hypotheses rather than experimental data, and there is limited empirical evidence to support the idea that quantum phenomena play a significant role in brain function, there is a strong need to further investigate this aspect of QAI to pave the way towards a definitive recognition of quantum neuroscience as a research field upon which to build the future generation of general AI frameworks. In this case, new scenarios will be available to rethink breakthrough applications, such as those based on generative AI (ChatGPT, etc.), where real human brain processes are embedded in the generative process thanks to their potential quantum nature. Again, where quantum computing and AI interact to improve the field of neuroscience, the scientific community has many important challenges ahead to prove the quantum nature of brain processes and to use this theoretical framework to define new algorithms that can natively replicate the aforementioned processes and be used profitably in high-impact applications.

The efforts to address all aspects of the prospective challenges of QAI have the potential to accelerate the research and development of systems based on the principles of general artificial intelligence (GAI).

In contrast to conventional AI systems, which are designed to perform specific tasks within a limited domain, GAI systems are capable of generalizing their knowledge and skills to new and diverse situations, in a manner analogous to that observed in humans. These results will have the potential to profoundly impact research and society in numerous ways. The significant increase in computational power for AI will have significant ethical and social implications in relation to job displacement, algorithmic bias, data privacy, and control over AI systems to ensure that GAI technologies benefit society as a whole.

Although still utopian, these futuristic scenarios in QAI research open up new ethical dilemmas. The exponential speed at which QAI can train models could outpace our ability to fully understand or predict the outcomes of such systems, creating risks of unintended behavior or emergent properties that could be harmful to individuals or society. The complexity and opacity of QAI systems could also make it difficult to trace decision-making processes, undermining efforts to ensure accountability and transparency in AI deployments. Furthermore, data manipulation becomes a significant ethical issue, as the increased computational power of QAI could allow rapid processing of large amounts of personal or sensitive information, raising concerns about privacy violations and the potential for surveillance. The ability to analyze and predict human behavior more accurately could lead to the development of AI systems capable of influencing or controlling decision-making processes in ways that may not align with the interests or values of individuals, thus infringing on personal autonomy. Furthermore, the risks of power concentration are amplified in the QAI landscape. As access to quantum computing technologies could remain limited to a few powerful corporations or governments, there is a growing concern that such entities could leverage these capabilities for economic or political control, further deepening social inequalities and amplifying existing power imbalances. This concentration of advanced AI technologies could lead to the development of systems that disproportionately benefit the few while marginalizing entire groups or nations, exacerbating the digital divide. The rapid acceleration of QAI also calls for robust regulation to ensure that these technologies are used ethically and responsibly. Current governance frameworks may be insufficient to keep up with the pace of technological advancements, creating the risk of unchecked development and the possibility of harmful consequences, such as job displacement, economic disruption, or the weaponization of AI. Ethical guidelines must be developed that balance the potential benefits of QAI with the need to protect human rights, social justice, and public welfare. In sum, while QAI promises transformative advances in multiple sectors, its rapid development requires careful oversight and a commitment to ensure that its deployment prioritizes fairness, accountability, and the well-being of society as a whole.

8. Conclusions

In the last decade, the release of the first usable quantum computers has started a race towards designing quantum algorithms capable of demonstrating potential quantum advantage. This pioneering research has found fertile ground in various domains, including AI. Since then, the interaction between quantum computing and AI has become stronger and stronger, creating a real entanglement between the two disciplines, allowing them to gain mutual benefits. In this survey work, the interactions between these disciplines were first disentangled through a hierarchical representation that can strongly highlight, in a precise and timely manner, how quantum computing can support AI and vice versa. This taxonomic representation of this new branch of computer science enabled the development of a research methodology capable of collecting research papers that represent the state of the art in both the area of quantum-enhanced artificial intelligence and the area of artificial intelligence for quantum computation. These works serve as an important reference point for anyone who wishes to advance the field of QAI and propose new pioneering approaches. As stated previously, the field is vast and the potential for undertaking activities is numerous. In this context, the aim of the computer science community is to provide a basis for the development of reliable quantum computers capable of performing computationally efficient AI methods, while giving strong consideration to emerging ethical issues.

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.

Data availability

No data was used for the research described in the article.

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