Quantum AI: Accomplishments and Obstacles in the Convergence of Quantum Computing and Artificial Intelligence

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ABSTRACT

Recently, Quantum Computing (QC) has garnered increasing attention due to significant advancements in the development of functional quantum computers, quantum materials, and quantum cryptography. In light of advancements in the physical construction and scaling of quantum computers, it is imperative to promote the development of quantum algorithms and methodologies tailored to these systems, maximising their inherent computational and communication capabilities. In the age of Big Data, several computationally intensive activities are within the domain of Artificial Intelligence (AI), encompassing those that are now computationally intractable owing to physical constraints. The inherent parallelism, computational efficiency, and representational capacity of quantum computing offers a superior alternative to binary computers, promising improved AI models. The Quantum Artificial Intelligence (QAI) idea will enable the identification of patterns that standard AI algorithms cannot detect, significantly reducing processing time by several orders of magnitude. This paper delineates the scientific advancements at the intersection of artificial intelligence and quality control. We commence by delineating both domains, fundamental concepts, and the chronology of pivotal advancements in the history of AI and QC, subsequently concentrating on the current study regarding the bidirectional methodologies wherein QC enhances AI and AI augments QC. Ultimately, we delineate prospective research directions for the nascent field of QAI and conclude.

Keywords: Quantum Artificial Intelligence; Artificial Intelligence; Quantum Computing; AI Algorithms

Introduction

Since the onset of the 20th century, the exploration of quantum theory has led to the development of quantum-based technologies, which are now influencing fields such as encryption, superconductors, and quantum computing (QC). These technologies have significant potential, providing enhancements in performance and viable solutions to previously insurmountable challenges associated with alternative technologies [1]. During the 1980s and 1990s, significant advancements in computation emerged, driven by quantum phenomena. Notably, these advancements included (1) hardware developments, with the recent milestone of quantum supremacy achieved by IBM's Eagle in November 2021, demonstrating a quantum device's capability to solve problems unattainable by contemporary binary computers; and (2) extensive initiatives in quantum computing technologies, exemplified by the European Commission-funded Quantum Flagship, initiated in 2018, aimed at creating a "Quantum Web" of interconnected quantum devices utilising quantum communication networks to share resources. Consequently, the conditions are ideally established for a significant progression in algorithmics that utilises quantum computational capabilities for complex issues, including those addressed by Artificial Intelligence (AI) methodologies [2].

Nonetheless, quantum supremacy does not inherently imply superiority in intelligence. In 1945, John Von Neumann delineated his architecture, and in 1948, Alan Turing wrote his renowned essay, Intelligent Machinery. Although the term 'Artificial Intelligence' was introduced at the renowned Dartmouth conference in the summer of 1956, and there were subsequent advancements in the field over the following decades, it was not until the late 1990s that AI proved effective in addressing real-world challenges, exemplified by Deep Blue's victory over Kasparov. Artificial intelligence has become essential in nearly all facets of civilisation. However, this does not apply to the more contemporary Quantum-based AI or to AI-driven Quantum methodologies. Consequently, the AI research community must be prepared in the short term to prevent a gap when the widespread adoption of quantum computers materialises (Fig. 1).

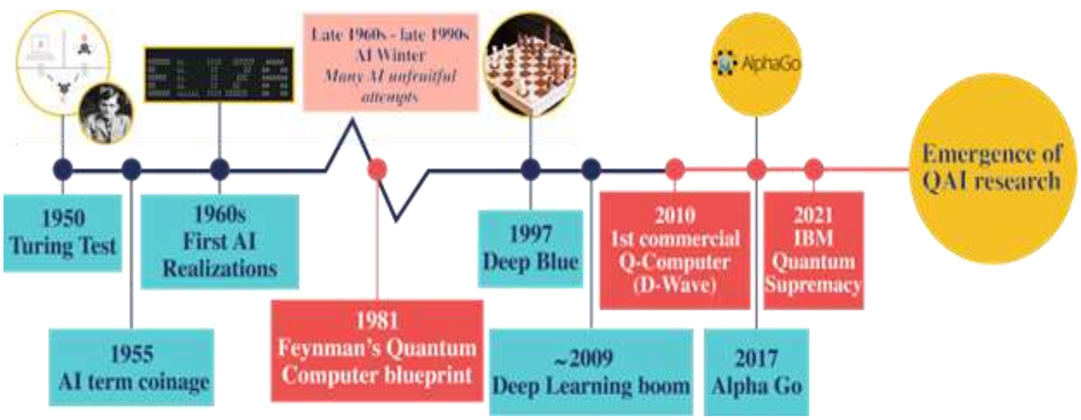

Figure 1. Chronology of developments in classical machines and classical artificial intelligence compared to quantum machines and quantum artificial intelligence.

A Concise Overview of Quantum Computing

The term quantum computing was first coined by Richard Feynman in 1981 and has since had a rich intellectual history. Figure 3 depicts a timeline of major events in this area. Noteworthy in the timeline is that while there were somewhat larger gaps between events earlier on, recently, the field has started experiencing a more rapid series of developments. For example service providers have begun offering niche quantum computing products, as well as quantum cloud computing services (e.g., Amazon Braket). Recently, Google's 54-qubit computer accomplished a task in merely 200 s that was estimated to take around over 10,000 years on a classical computing system [3]. Nevertheless, quantum computing is still in its infancy stages, and it will take some time before quantum computing chips reach desktops or handhelds. An important factor inhibiting the commoditization of quantum computing is the fact that controlling quantum effects is a delicate process, and any noise (e.g., stray heat) can flip 1s or 0s and disrupt quantum effects, such as superposition. This requires qubits to be fully operated under special conditions, such as very cold temperatures, sometimes very close to absolute zero. This also motivates research exploring fault-tolerant quantum computing [4]. Considering this fast-paced development of quantum computing, this is an opportune time for healthcare researchers and practitioners to investigate its benefits to healthcare systems.

The Build of Hardware since traditional computing systems handle user data and network components, it is ideal for a quantum computing system to be able to interface with and make efficient use of traditional computing systems. In order to run efficiently, qubit systems need to be controlled in a carefully orchestrated fashion, which can be handled using conventional computing principles. To understand the hardware components of an analogue gate-based quantum computing system, it is possible to map it into various layers. Each layer is responsible for performing a different quantum operations and comprise the following: the quantum control plane, the measurement plane, and the data plane. The control processor plane, which supports the host processor and is responsible for network access, user interfaces, and storage arrays, uses measurement outcomes to determine the algorithm's required sequence of operations and measurements.

The Quantum Data Plane

It is the main component of the quantum computing ecosystem. It broadly consists of physical qubits and the structures required to bring them into an organized system. It contains support circuits required to identify the state of qubits and perform gated operations. It does this for the gate-based system or controlling “the Hamiltonian for an analog computer” [5]. Control signals that are sent towards selected qubits set the Hamiltonian path, thereby controlling the gate operations for a digital quantum computer. For gate-based systems, a configurable network is provided to support the interaction of qubits, while analog systems depend on richer interactions in qubits enabled through this layer. Strong isolation is required for high qubit fidelity. It limits connectivity as each qubit may not be able to directly interact with every other qubit. Therefore, we need to map computation to some specific architectural constraints provided by this layer. This shows that connection and operation fidelity are prime characteristics of the quantum data layer. In conventional computing systems, the control and data plane are based on silicon technology. Control of the quantum data plane needs different technology and is performed externally by separating control and measurement layers. Analog qubit information should be sent to the specific qubits. Control information is transmitted through (data plane) wires electronically, in some of the systems. Network communication is handled in a way that it retains high specificity, affecting only the desired qubits without influencing other qubits that are not related to the underlying operation. However, it becomes challenging when the number of qubits grows; therefore, the number of qubits in a single module is another core component of the quantum information plane.

The Plane for Quantum Control and Measurement

The role of the quantum plane is to convert digital signals received from the control processor. It defines a set of quantum operations that are performed in the quantum data plane on the qubits. It efficiently translates the data plane’s analog output of qubits to classical data (i.e., binary), which are easier to be handled by the control processor. Any difference in the isolation of the signals leads to small qubit signals that cannot be fixed during an operation, thus resulting in inaccuracies in the states of qubits. Control signals shielding is complex, since such signals must be passed via the apparatus that is used for isolating the quantum data plane from the environment. This could be performed using vacuums, cooling, or through both required constraints. Signal crosstalk and qubit manufacturing errors gradually change with the configuration change in the system. Even if the underlying quantum system allows fast operations, the speed can still be limited by the time required to generate and send a precise pulse.

Plane of Control and Host Processor

This plane recognizes and invokes a series of quantum gate operations to be per- formed by the control and measurement plane. This set of steps implements a quantum algorithm via the host processor. The application should be custom-built, using specific functionalities of the quantum layer that are offered by the software tool stack. One of the critical responsibilities of the control processor plane is to provide an algorithm for quantum error correction. Conventional data processing techniques are used to perform different quantum operations that are required for error correction according to computed results. This introduces a delay that may slow down the quantum computer processing. The overhead can be reduced if the error correction is carried out in a comparable time to that of the time needed for the quantum operations. As the computational task increases with the machine size, the control processor plane would inevitably consist of more ele- ments for increasing computational load. However, it is quite challenging to develop a control plane for large-scale quantum machines [6].

One technique to solve these challenges is to split the plane into components. The first component being a regular processor that can be tasked to run the quantum program, while the other component can be customized hardware to enable direct interaction with the measurement and control planes. It computes the next actions to be performed on the qubits by combining the controller's output of higher-level instructions with the syndrome measurements. The key challenge is to design customized hardware that is both fast and scalable with machine size, as well as appropriate for creating high-level instruction abstraction. A low abstraction level is used in the control processor plane. It converts the compiled code into control- and measurement-layer commands. The user will not be able to directly interact with the control processor plane. Subsequently, it will be attached to the computing machine to fasten the execution of a few specific applications. Such kind of architectures have been employed in current computers that have accelerators for graphics, ML, and networking. These accelerators typically require a direct connection with the host processors and shared access to a part of their memory, which could be exploited to program the controller [7].

Quantum Computing and Artificial Intelligence

Since the 1980s and 1990s, quantum computing and quantum algorithmics have experienced substantial advancements, including Feynman's foundational design for a quantum computer, Shor's quantum algorithms for number factorisation and discrete logarithms, as well as quantum key distribution, which are pertinent to cryptography and cryptanalysis. Additionally, Grover's quantum algorithm for unordered search facilitates the identification of entries within data structures, and quantum pattern matching aids in locating substring occurrences within a string. In the domain of Quantum Machine Learning (QML), various initiatives have emerged at the intersection of Quantum Computing and Artificial Intelligence, including the quantum annealing algorithm for optimisation problems [24], quantum constraint satisfaction for 3-SAT problems [8], quantum adiabatic algorithms for NP-complete combinatorial optimisation [2], quantum Principal Component Analysis (PCA) for identifying principal components in datasets [3], the quantum k-NN algorithm for complexity reduction in clustering [6], and quantum training of Boltzmann machines and neural networks to exceed the theoretical performance of their binary equivalents [5]. These endeavours have facilitated more organised and concentrated study in the emerging domain of Quantum AI.

Since Feynman's foundational blueprint in 1981, and the inaugural successful physical quantum computer by D-Wave in 2010, various physical implementations of quantum computers have been proposed, including quantum gate arrays, one-way quantum computers, adiabatic quantum computers, and topological quantum computers, culminating in the attainment of quantum supremacy in 2019 (Google Inc., 53 qubits), 2020 (USTC China, 76 qubits), and 2021 (IBM Eagle, 127 qubits). This milestone in quantum computing, in conjunction with significant advancements in other fields such as advanced AI techniques like Deep Learning, increased computational power and data accessibility, and High-Performance Computing, has laid the groundwork for research into a forthcoming AI that enables quantum computers to learn from quantum information. This Quantum AI (QAI) would utilise advancements in several transformative technologies, including medical Magnetic Resonance Imaging (MRI), superconductors, quantum computing and communication, quantum cryptographic key distribution, and quantum measurement. This field, commonly known as quantum machine learning, exists at the convergence of artificial intelligence and quantum computing. Many of the preliminary strategies have focused on classical AI to diminish its computing complexity and accelerate learning processes [46]. Other studies have focused on quality control to devise alternate learning algorithms and facilitate improved solutions. The suggested solutions encompass quantum clustering [34], quantum autoencoders [9], and quantum reinforcement learning [1]. Nonetheless, these solutions have been suggested individually, devoid of a cohesive framework that facilitates a smooth transition from conventional AI to quantum AI and permits their collaboration throughout this process.

Classical AI relies on information storage (data) and manipulation (algorithms), but quantum AI is underpinned by quantum information storage (quantum data) and manipulation (quantum algorithms). Quantum data manifests as quantum binary digits (qubits), but quantum algorithmics pertain to actions performed on qubits, such as quantum logic gates. Although qubits may be realised in several physical systems (e.g., trapped ions, spin qubits, resonant cavities, or semiconductor qubits), the quantum properties of matter in each are essential for quantum computing, offering distinct benefits. The properties encompass: quantum superposition, wherein qubit states exist concurrently as a combination of $|0\rangle$ and

|1⟩ values [10]; decoherence, the dissipation of information from a quantum system to its environment [6]; collapse, the irreversible reduction of a superposed quantum state to a singular state [5]; entanglement, the correlation of two or more quantum particles, maintaining interdependent states despite significant separation [3]; and quantum tunnelling, the ability of quantum wave functions to traverse potential barriers [2]. Consequently, QAI must be supported by three components: data, methods, and a computational environment. This cohesive framework may enable researchers to create quantum artificial intelligence algorithms that modify data within the quantum domain, hence accelerating machine learning processes and using quantum computing features. Pioneering efforts in QML have yielded recommendations for algorithms aimed at addressing specific problems. Currently, there is an absence of a technical framework to organise the emerging subject of Quantum Artificial Intelligence (QAI) research, which would aid in the creation of novel QAI algorithms. Additionally, the challenge of converting binary data into quantum states and vice versa (quantization/dequantization) remains unresolved. Moreover, in the near future, conventional AI and quantum AI will coexist, necessitating a conceptual ecosystem within the AI research community that fosters cooperation and synergy between both methods, therefore smoothing the transition. To this end, the emerging discipline of QAI will confront the following essential challenges, as outlined in Table 1. In the subsequent part, we examine the cutting-edge developments pertaining to QAI, focussing on the dimensions of data, algorithmics, and computational frameworks quantum artificial intelligence

Data Dimension

As previously stated, quantum computing (QC) relies on quantum information storage and manipulation through quantum binary digits (qubits) [16], as well as operations performed on qubits, such as quantum logic gates [51]. Qubits encode information distinctively from traditional two-state bits: in a qubit, both |0⟩ and |1⟩ values coexist simultaneously with a probability owing to superposition, until the state is collapsed by observation or measurement. The information representation capacity of qubits grows exponentially relative to binary representation [50]: a single qubit may concurrently represent two values, whilst N qubits can represent up to 2N values simultaneously, in contrast to N bits, which can represent just one of 2N values. In Quantum AI, the superposition of qubits and the concurrent operation on distinct points of a superposed qubit facilitate extensive parallel computations, presenting the potential to address complex problems that are currently impractical or demand excessive time and resources [9-18].

Table 1. Problems to be addressed by Quantum Artificial Intelligence.

Scientific problem	Description
Input problem	The cost of reading input data can potentially surpass the computational gain of quantum algorithms, limiting the obtained speed-up

Output problem	To translate the output of quantum algorithms as a binary string, it is necessary to learn an exponential number of bits, which makes some applications of QAI unfeasible
Noise problem	Random fluctuations in quantum states propagate very fast and can lead to the complete loss of information, which is at the root of the large effort in quantum error correction. This is particularly relevant for QAI because it entails series of unitary operations on large data volumes: quantum errors could invalidate entire analyses
Benchmarking problem	Some incipient benchmarks exist for the assessment of quantum algorithmic performance in specific cases; however, there is a lack of a solid benchmarking framework for the evaluation of QAI performance in comparison to classical AI
Costing problem	While theoretical bounds suggest that QAI algorithms will offer big advantages in solving large problems, it is currently not possible to estimate the actual number of quantum gates required to create a quantum circuit for a given algorithm

Computational Framework

For instance, developing a computational framework tailored to Quantum Artificial Intelligence (QAI) that enables the coexistence and collaboration of classical and quantum AI processes, with the objective of facilitating a seamless transition between the two in the near future.

Networks for Quantum Communications

The use of different quantum states of light to complete specific communication tasks is the focus of quantum communication (QC), a subfield of quantum technologies. There has been a significant uptick in interest in the possibility of QC finding usage in business settings. Quantum random-number generation (QRNG) and quantum key distribution (QKD) are two of the most prominent QC technologies. Together, these features have the potential to enable the ideal secrecy protocol that can withstand external assaults, and QKD makes private communication possible by letting distant entities share a secret key. Building a quantum communication network that links quantum computers together to accomplish computation, synchronisation, and network security with quantum enhancements is the objective of the quantum Internet. The IETF's quantum Internet research group known as Qirg is in charge of the quantum Internet's standardisation efforts [19-27].

Quantum Communication on Higher Dimensions

Contemporary trends in technology have had a significant impact on quantum information. It is clear from the research that high-dimensional quantum states, particularly in the context of quantum communication, are becoming more and more intriguing. A huge amount of information may be stored in Hilbert space, and it is also resistant to noise. A combination of integrated photonics and bulk optics was also used by the authors to investigate "multiple photonic degrees of freedom for generating high-dimensional quantum states" in order for the quantum states to propagate, several channels were created, such as single-mode, free-space connections, aquatic channels, multicore, and multimode fibres.

How Quantum Computing Can Be Scaled

Because the many-body Hilbert vector space of highly linked, constantly interacting quantum states grows with the number of particles, simulating such states is difficult. Applying transfer learning techniques is one of the most encouraging ways to increase scalability. The rule states that ML models may be reused to tackle various types of problems that are related but not identical. We can take use of transfer learning protocols influenced by physics by reusing aspects of the neural network's quantum states.

Boltzmann machines, which are very basic neural networks, may accurately mimic the behaviour of many-body quantum systems, according to the validated results. In transfer learning, one task is taught on a smaller system and then applied to a bigger system using the same trained model. Here, scalability may be achieved via the application of transfer learning protocols influenced by several branches of physics. An further purpose for FPGAs is to simulate quantum computing algorithms, which can outperform software-based simulations in terms of performance. One major obstacle, however, is the amount of hardware power needed to simulate quantum systems. Scalable FPGA-based technologies may provide more scalability in this area [28-30].

Lack of Criticism

Since the parts of a quantum computer are in a delicate entangled state, fault tolerance is crucial. This results in the high fidelity of quantum computations by making them resistant and introducing strategies to tackle quantum difficulties. This opens the door for quantum computers to do calculations that were previously intractable on classical computers. On the other hand, systems relying on such calculations would be severely impacted in the event of a qubit or measurement mechanism mistake during processing. There are serious problems with the method of mistake correction itself. Using auxiliary qubits to monitor qubits—which continuously analyse logical faults for rectification and detection—is a possible technique to monitor these systems. While auxiliary qubits have shown some encouraging outcomes, it is important to be aware that faults in these components might cause errors in the qubits, which in turn can cause even more errors in the operation. Error the system might be able to fix the code when certain bits are incorrect if it is incorporated among the qubits. It aids in the propagation of faulty errors by making sure that a single defective gate or time stamp causes a single defective gate.

Conclusion

This document provides a comprehensive analysis of advancements at the intersection of Quantum Computing and Artificial Intelligence. We have highlighted the mutual advantages of Quantum Computing for Artificial Intelligence and vice versa, leading to the establishment of a novel scientific domain that integrates both fields, namely Quantum

Artificial Intelligence. We have identified the primary basic challenges encountered in QAI, along with prospective research avenues essential for fully realising the potential of QAI. This innovative scientific domain emerges as a very promising technology that is already yielding results, and we anticipate it will have a significant influence in the imminent future, owing to the forthcoming availability of medium-scale quantum computers.

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