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Quantum Computing and Artificial Intelligence: Current Applications, Challenges, and Future Prospects

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Research Article

Keywords: Artificial intelligence, Quantum computing, Machine learning, NISQ

Posted Date: October 30th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11350591/v1

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Additional Declarations: No competing interests reported.

Abstract

Artificial intelligence (AI) and quantum computing represent a new frontier in computing, offering the promise of solving problems previously considered unsolvable. This article aims to provide an in-depth analysis of the current state of research at the intersection of quantum computing and artificial intelligence. We will explore the basic concepts, major applications, and challenges of quantum machine learning (QML). We will start by offering a definition of the motivation for the convergence of quantum computing and artificial intelligence. We will then proceed to offer a description of the basic algorithmic frameworks for quantum machine learning, such as quantum differential algorithms (VQA) for near-term quantum (NISQ) devices and the prospects for error-tolerant quantum algorithms such as the Harrow-Hassidim-Lloyd algorithm. We will then proceed to offer a methodical analysis of the current applications of quantum machine learning in finance, cybersecurity, materials science, among other fields. We will then proceed to discuss the basic challenges facing the implementation of quantum machine learning, while offering a glimpse of the future of quantum-enhanced artificial intelligence.

1 Introduction

Artificial Intelligence (AI) and Quantum computing (QC) and, both of upon their own, have progressed at a rapid pace, converting technological ecosystems along the way and discussing new opportunities in various fields.

Quantum computing draws on principles of quantum mechanics to make calculations that are unresolvable by even the most powerful classical supercomputers [1]. The emergence of Artificial Intelligence (AI), particularly machine learning (ML), which has proven to be highly effective in pattern recognition, data analysis and even making decisions across various industries [2]. Quantum AI, also termed Quantum Machine Learning (QML), is an interdisciplinary field at the intersection of quantum physics and machine learning with huge potential for providing new problem-solving techniques and scientific breakthroughs [3].

Motivation to combine QC with AI arises because classical computing is proving ineffective with increasing complexity of datasets and computations. Despite having achieved several astounding breakthroughs using classical AI algorithms, this approach does have a bottleneck when it comes to training and inference as data and computing resources take an exponentially exploding form; high-dimensional feature spaces (realizing a situation where the dimensionality of features is simply too huge) or complex verification problems [4]. Quantum computing holds out the vision of an escape from these constraints by offering us algorithmic primitives that allow us to manipulate information in regions unavailable to classical computation. Quantum algorithms, on the other hand, can provide exponential speedups for some problems like factoring large numbers or searching unsorted databases, which has major implications for cryptography and information retrieval [5].

This article provides a high-level overview of the current state of quantum computing and artificial intelligence. We summarise the current state of affairs in this emerging field. In the following sections,

we will cover the methodology that informs QML, before discussing application areas arising from the intersection of these disciplines. We will then move on to challenges that we believe need to be addressed for quantum-aided AI to become mainstream in industry and work environments. Finally, we will provide a high-level discussion of the future potential impact of quantum-enhanced AI. This review aims to provide a valuable resource for interested individuals to learn about and contribute to this exciting field, which combines quantum computing and artificial intelligence.

2 Methods

Quantum Machine Learning (QML) involves algorithms that are inspired by quantum computing principles or incorporate them into artificial intelligence practices. This section describes the basic algorithmic framework and hardware which provides this synergy, for both present day Noisy Intermediate- Scale Quantum (NISQ) devices and for the forthcoming Fault-Tolerant quantum computing (FTQC) era.

2.1 Variational Quantum Algorithms

A major class of QML algorithms to access the potential power of NISQ devices featuring a mildly small number of qubits that can suffer from noise are known as Variational Quantum Algorithms (VQAs) [6]. VQAs work through a hybrid quantum-classical optimization workflow where the circuit parameters of a parameterized quantum circuits (PQC) that prepare a quantum state are iteratively tuned toward minimizing some cost function by means of a classical optimizer. The general structure of a VQA can be described as follows, as illustrated in Fig. 1:

a. Quantum State Preparation: Input data is encoded into a quantum state, often through a feature map F($\mathbf{x}$) that maps classical data $\mathbf{x}$ to a quantum state $|\psi(\mathbf{x})\rangle$ [7].
b. Parameterized Quantum Circuit (PQC): A quantum circuit $U(\boldsymbol{\theta})$ with adjustable parameters $\boldsymbol{\theta}$ is applied to the prepared state [8]. In this circuit, alternating layers of one-qubit rotations and gates of entanglement are used.
c. Measurement: An observable H is measured on the output state to obtain an expectation value $\langle H\rangle = \langle\psi(\mathbf{x})|U^{\dagger}(\boldsymbol{\theta})HU(\boldsymbol{\theta})|\psi(\mathbf{x})\rangle$.
d. Classical Optimization: The expectation value serves as a cost function, which is then minimized by a classical optimizer that updates the parameters θ for the next iteration of the quantum circuit execution.

Mathematically, the objective is to find optimal parameters θ^* such that:

$$\boldsymbol{\theta}^* = \arg\min L(\boldsymbol{\theta}) = \arg\min\langle\psi(\mathbf{x})|U^{\dagger}(\boldsymbol{\theta})HU(\boldsymbol{\theta})|\psi(\mathbf{x})\rangle \quad (1)$$

Two prominent use cases for VQAs are the Variational Quantum Eigensolver (VQE) for chemistry and materials science, and the Quantum Approximate Optimization Algorithm (QAOA) Applied to

combinatorial optimization [9]. Despite their promise, VQAs face challenges in the form of barren plateaus where gradients vanish exponentially with respect to the number of qubits, rendering optimization challenging [10].

2.2 Fault-Tolerant Quantum Algorithms

While NISQ devices are crucial for near-term exploration, the full potential of QML is expected to be realized with the advent of Fault-Tolerant Quantum Computers (FTQC). It will be easier to develop and implement more complex and robust quantum algorithms because of the high-fidelity capabilities of FTQC devices in executing deep quantum circuits [11]. The important algorithms related to AI in the FTQC era are:

-Harrow-Hassidim-Lloyd (HHL) Algorithm: This algorithm offers an exponential speedup for solving systems of linear equations, **Ax = b**, where **A** is a sparse, well-conditioned matrix. The quantum algorithm can find **x** in **O(log NK^2)** time (N is the dimension of **A** and **K** is its condition number), compared to **O(NK)** or **O(N log N)** for classical methods, making it highly relevant for applications in big data analysis and machine learning [12].

- Quantum Phase Estimation (QPE): QPE is a basic subroutine for many quantum algorithms like Shor's algorithm for factoring and quantum simulation. In QML, it can serve purposes such as Quantum Principal Component Analysis (QPCA) for feature extraction from quantum data [13].

-Quantum Support Vector Machines (QSVMs): these algorithms utilize quantum feature maps to embed data in a higher-dimensional Hilbert space, which may offer improved separability compared to classical SVMs. The quantum kernel method, a variant of QSVM, estimates the inner product between quantum states (which can be classically intractable) [14].

2.3 Hardware and Architecture Considerations

The advancement of QML is significantly impacted by the development of quantum hardware. There are several physical qubit implementations being investigated, each with unique benefits and difficulties. Some of the most popular qubit technologies and their features are compiled in Table 1.

Table 1
Technology comparison of the leading qubits

Qubit t echnology	Advantages	Challenges
Superconducting Qubits	High gate fidelity, scalable architectures	Low operating temperatures, decoherence
Trapped Ions	Long coherence times, high connectivity	Slow gate operations, complex laser systems
Photonic Qubits	Room temperature operation, fast gate operations	Probabilistic gates, scalability
Topological Qubits	Intrinsic fault tolerance	Extremely challenging to realize

To facilitate the full transition from NISQ to FTQC, major improvements in qubit coherence, error correction and interconnectivity are necessary. The Quanta team from Google's Quantum AI has published plan towards useful quantum computing in five stages, with a focus on the planned logical qubits that could be built using quantum error correction techniques [15]. This roadmap emphasizes the importance of specialized hardware and software co-design to translate theoretical quantum advantages into practical applications [16].

3 Results

The synergy between quantum computing and artificial intelligence has resulted in new applications in different fields, which shows that quantum-enhanced solutions have a higher potential to achieve better results than classical counterparts for a limited number of tasks [17]. This section outlines key application areas where Quantum AI is currently being explored and developed.

3.1 Optimization Problems

The real-world applications of optimization are vast and include but are not limited to logistics and supply chain management, financial modeling, and drug discovery. Many classical algorithms are vulnerable to the combinatorial explosion of possibilities in large-scale optimization problems. The quantum algorithms, especially VQAs such as QAOA, seem promising solutions for a wide variety of such cases. As a matter of fact, quantum-enhanced stochastic gradient descent algorithms have been studied for optimizing machine learning models, which can result in faster convergence rates and even better performance [18]. The ability of quantum computers to explore exponentially large solution spaces using superposition and entanglement appears to provide a unique advantage for finding optimal or near-optimal solutions more efficiently than their classical counterparts [19, 20].

3.2 Financial Modeling and Analysis

Quantum AI has immense potential in the financial sector, as the sector relies on predictions, risks, and complex calculations. Portfolio optimization, fraud detection, and pricing derivatives are a few instances of such projects that can be implemented with the help of quantum AI. To cite an example, specific quantum machine learning techniques are in development to examine stochastic volatility models, which are vital in understanding the market volatility in the financial sector [21]. The HHL algorithm, which can provide an exponential speedup in solving linear equations, can significantly speed up Monte Carlo simulations for risk management and asset pricing, thus providing more precise information to the market in a timely manner [12]. This teasing speedup is illustrated on Fig. 2.

3.3 Cybersecurity

The emergence of quantum computers represents both a challenge and an opportunity for cybersecurity. Although Shor’s algorithm would render most public-key encryption schemes useless, quantum computing has also inspired algorithms promising greater security [22]. Quantum AI is also being investigated for creating quantum-resilient cryptography algorithms and enhancing intrusion detection

systems. Quantum machine learning approaches can also help in detecting cyber threats by analyzing network traffic patterns and identifying anomalies that are indicative of cyber-attacks more effectively than classical methods, consequently strengthening cybersecurity defenses against advanced attacks [23]. Post-Quantum Cryptography (PQC) is an active research field aiming at devising new cryptographic primitives secure against future quantum computers [24].

3.4 Materials Science and Drug Discovery

This application of quantum AI has the potential to revolutionize discoveries in both materials' science and drug discovery. Computationally expensive tasks such as simulating molecular interactions and predicting the properties of materials could be greatly accelerated using quantum approaches [1, 2]. Quantum machine learning model training on quantum chemical data can be done to predict known material properties or to find new probable drug candidates with certain expected properties. When fueled by quantum algorithms, generative AI has the promise to revolutionize the way new molecules and materials are designed by manipulating large chemical spaces more efficiently to find successors of software or important compounds such as high-temperature superconductors, catalysts, and personalized medicine [25].

3.5 Healthcare and Medical Diagnostics

For instance, Quantum AI can assist in the diagnosis, specific treatment plans, as well as the development of drugs in a more efficient manner. The algorithms of machine learning, as applied in quantum computing, have the potential to process vast databases in the medical field, including the consideration of the genome as well as images, while identifying patterns that could be indicative of diseases or drug efficacy. Quantum technology in the form of qubit algorithms in image processing can help in obtaining accurate images and results in medical diagnostic tests, thus helping in early disease detection. Moreover, quantum computing technology can simulate complex biological processes with unprecedented accuracy, thus helping in the speedy discovery of new drugs and therapeutics through better predictions about the formulation of drug molecules and overall drug success [26].

4 Discussion

However, the intersection of quantum computing and artificial intelligence is a vast area with lots of potential, as well as huge challenges. It is important to overcome these challenges in order to realize the potential of Quantum AI. The following part of the review highlights the current challenges, as well as the future of the intersection of quantum computing and artificial intelligence.

4.1 Current Challenges

4.1.1 Hardware Limitations and Noise

Currently, Quantum Computing, and by extension Quantum AI, faces one major hindrance, which is quantum hardware. Noisy Intermediate-Scale Quantum (NISQ) devices have various noise issues, which

affect their performance [6]. Quantum gates, which form quantum circuits, have to operate ideally and orthogonally, but due to noise, their actual operation is not ideal, thus causing errors in computation, which affect precision, a requirement of many quantum computing processes. Quantum error correction methods have been established, but these methods require a lot of qubits to encode logical qubits, something that is not possible now and is not expected to happen any time soon. Another major hindrance is the transition from Noisy Intermediate-Scale Quantum to Fault-Tolerant Quantum Computing [15].

4.1.2 Barren Plateaus in Variational Quantum Algorithms

"Barren plateaus" is a major challenge for Variational Quantum Algorithms (VQAs), which is a key aspect of NISQ-VQML. When the number of qubits or the number of layers in the quantum circuit increases, gradients in the cost function landscape decay exponentially [10]. This is because the learning process is in a state of standstill as the gradients become extremely low, making it challenging for classical optimizers to learn the optimal parameters for the quantum circuit. This is likely to be a major challenge for variational quantum algorithms (VQAs), as presented in Fig. 3.

4.1.3 Data Encoding and Input/Output Problem

A major challenge that still exists is in efficiently encoding classical data into quantum states and extracting useful information from quantum measurements. The “input/output problem” concerns the challenge of loading classical data large enough to fill up quantum registers and then, performing measurements that yield classically usable results without destroying quantum superposition [4]. An active area of research is designing quantum feature maps that encapsulate the relevant information in classical data and which are implementable on current hardware. There is also the additional complication of limited bandwidth for moving data between classical and quantum processors.

4.1.4 Algorithmic Development and Theoretical Foundations

While theoretical speedup is extremely promising, the creation of practical quantum algorithms that provide a significant advantage over classical ones for real-world AI tasks still appears to be in its infancy. There are many proposed QML algorithms, but still some of them are only studied theoretically or need resources that current hardware cannot provide [20]. More rigorous theoretical underpinnings are needed to establish when and how quantum algorithms give an actual advantage, beyond heuristically motivated considerations towards provable quantum speedups for problems relevant to AI [3].

4.2 Future Prospects and Research Directions

4.2.1 Hybrid Quantum-Classical Architectures

Hybrid quantum-classical architecture would likely dominate the near future of Quantum AI development. This architecture uses both quantum and classical computer resources, where computationally expensive subroutines such as quantum state preparation, quantum Fourier transform, etc., can be offloaded to their equivalent classical counterparts, which have better performance, while allowing control logic and data preprocessing + optimization to remain classical computers. This architecture would allow quantum features to evolve gradually as hardware improves, making it available before the completion of FTQC while still exploiting quantum advantages as they emerge [27].

4.2.2 Quantum-Enhanced Optimization and Sampling

Quantum algorithms, especially, have natural affinity towards optimization problems or sampling, both of which could potentially be of primary importance to many AI tasks. Future studies aim to discover sophisticated quantum optimization algorithms that navigate complex energy landscapes better compared to classical alternatives. Quantum sampling techniques, whether quantum anneal or quantum Monte Carlo, have potential to enable faster exploration of probability distributions, thus enabling faster progress in popular generative models or reinforcement learning techniques [28].

4.2.3 Novel Quantum Machine Learning Models

One of the best future directions is to develop entirely new QML models that are quantum by their very nature, rather than quantum extensions of classical algorithms. This includes quantum neural networks (QNNs) with new architectures, quantum Boltzmann machines, quantum generative adversarial networks, etc. They could potentially utilize the inexplicable postulates of quantum mechanics to "learn" patterns and data in ways that classical algorithms could not, opening doors to fundamental innovation in conventional AI [29].

4.2.4 Interdisciplinary Collaboration and Workforce Development

To advance Quantum AI, there is a need to have teams of experts from various fields such as quantum physics, computer science, mathematics, and domain area experts. There is a need to have cross-disciplinary cooperation to advance from theory to reality [17]. In addition, there is a need to have a huge investment in workforce development and education to train new generations of researchers and engineers well-versed in quantum computing, as well as digital terrain [1].

4.2.5 Ethical and Societal Implications

However, as Quantum AI technologies advance and become more refined in the future, they will also present ethical and societal challenges that will have to be addressed appropriately. Such as concerns about data privacy and potential job losses due to bias in algorithms and artificial intelligence. In order to undertake some form of proactive research in responsible AI development and governance frameworks in spite of this and to ensure that Quantum AI is developed and used in a way that benefits everyone [2].

5 Conclusion

Quantum computing and artificial intelligence, a new frontier in the development of science and technology, a perfect storm of the ideal kind. The article offered a comprehensive overview of Quantum AI as it is today: its basics, its potential, its limitations, the hurdles still to be overcome in the journey towards fully exploiting its potential. The territory of machine learning from a quantum perspective: a territory with great potential, ranging from the more efficient in terms of resource usage hybrid quantum-classical approaches of Variational Quantum Algorithms, leveraged on near-term/intermediate-scale NISQ technology, to the more futuristic classes of theoretically too-powerful algorithms, like fault-tolerant quantum ones, for HHL, etc.

We explained how through its computational advantage that breaks the classical boundary, Quantum AI is set to revolutionize several domains such as optimization, finance, cybersecurity, material science and healthcare. But the journey ahead is not without challenges. There is still intensive R&D to do in areas such as hardware limitations, noise, the barren plateau problem and complexities data encoding. When commercial, demonstrable fault-tolerant quantum computers and the powerful quantum error correction tools that support them exist, then we can usher in a new paradigm of quantum-native algorithms.

The future of Quantum AI will be characterized by continued development of hybrid designs, quantum optimization and sampling techniques, as well as the creation of completely new quantum ML models. It will take strong interdisciplinary collaboration and workforce development efforts to succeed in this space. Furthermore, since domain-specific center of excellence type of powerful technologies are becoming mature more issues will arise which need to be addressed in the contextualization if such technologies. The aggressive evolution of quantum AI embodies our desire to grasp and enhance compute capabilities, bringing a new era where once impossible complex issue can be solved by the wisdom of nature.

Declarations

Funding: The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Consent to Participate declaration: Not applicable.

Ethics declaration: Not applicable.

Data Availability: Data sets generated during the current study are available from the corresponding author on reasonable request.

Competing Interest: The authors have no relevant financial or non-financial interests to disclose.

Author Contribution

Achraf and Ismail wrote the manuscript, and Moulay Brahim supervised the project .

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Figures

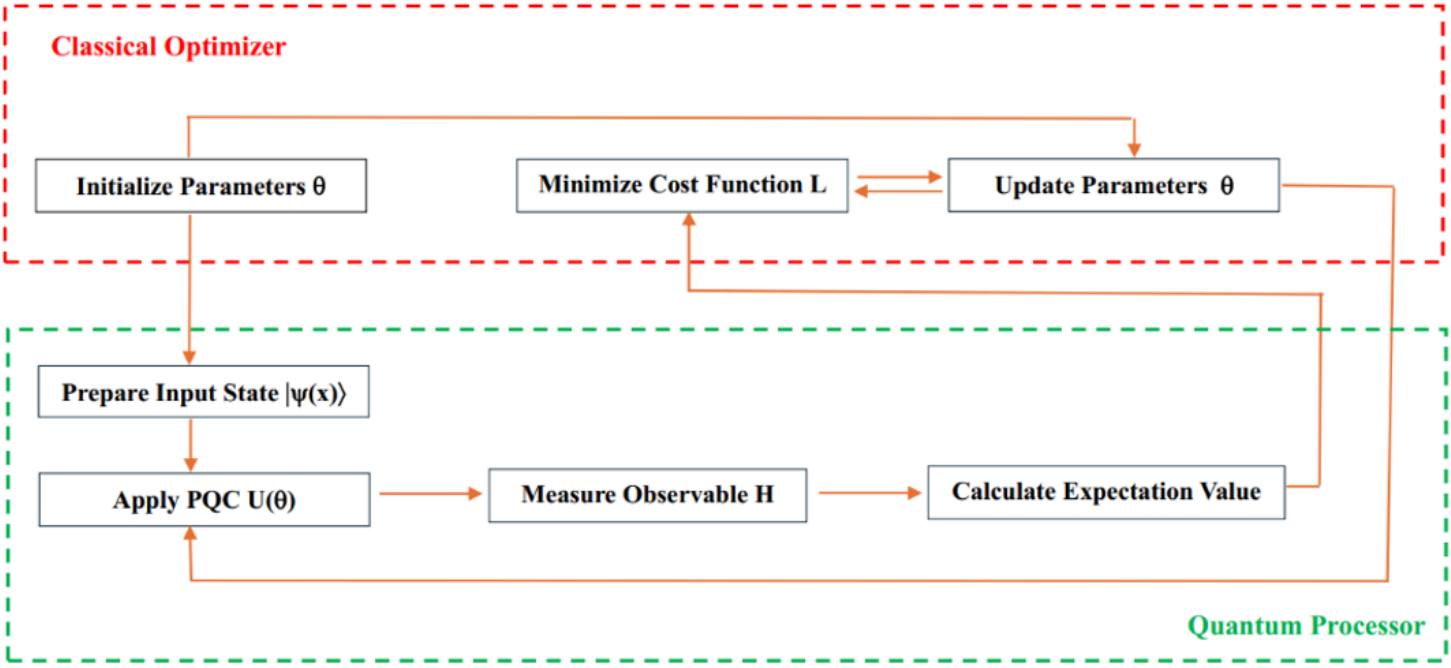


Figure 1

The general structure of a VQA

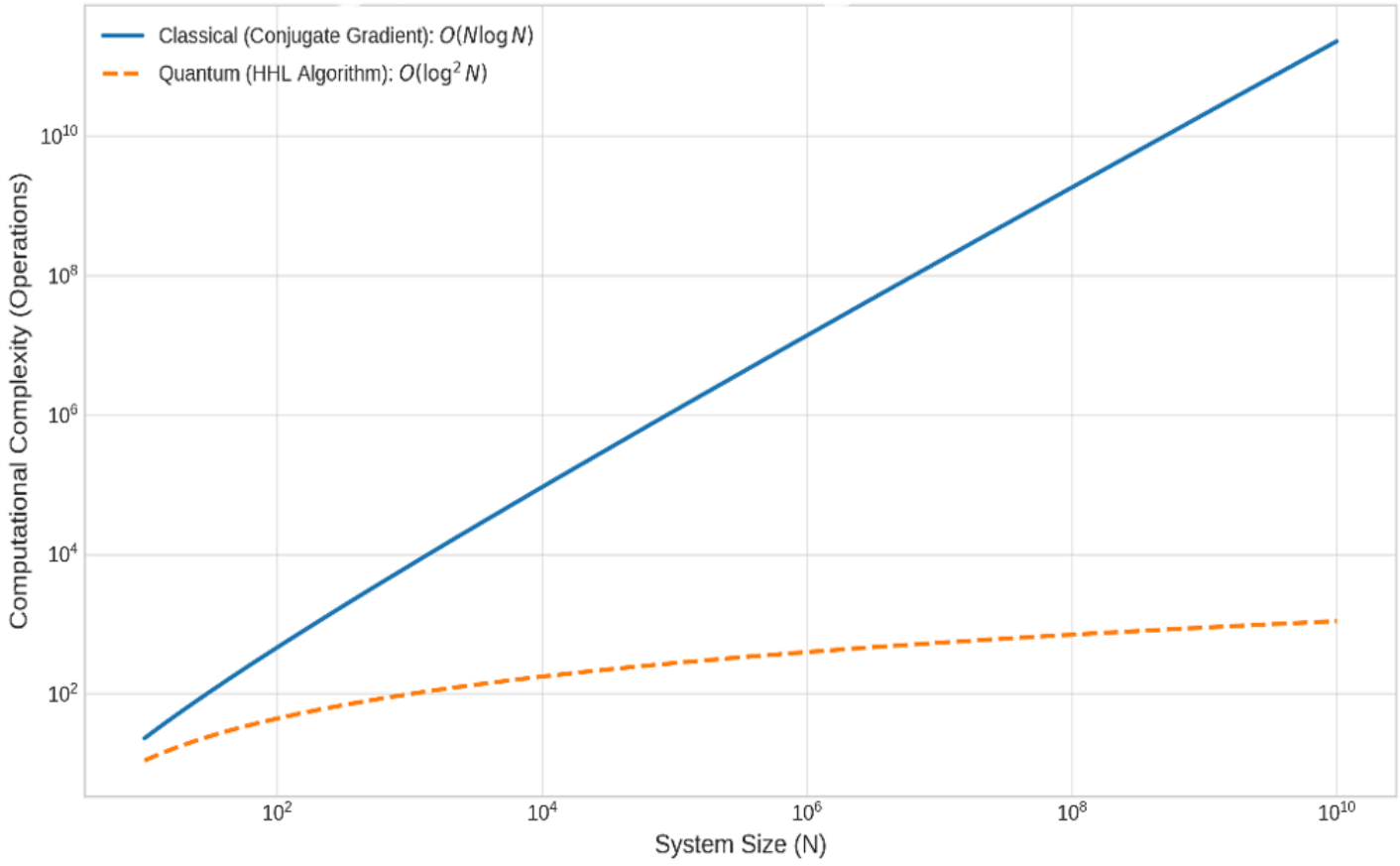


Figure 2

Theoretical Speedup of Quantum HHL Algorithm vs Classical Methods

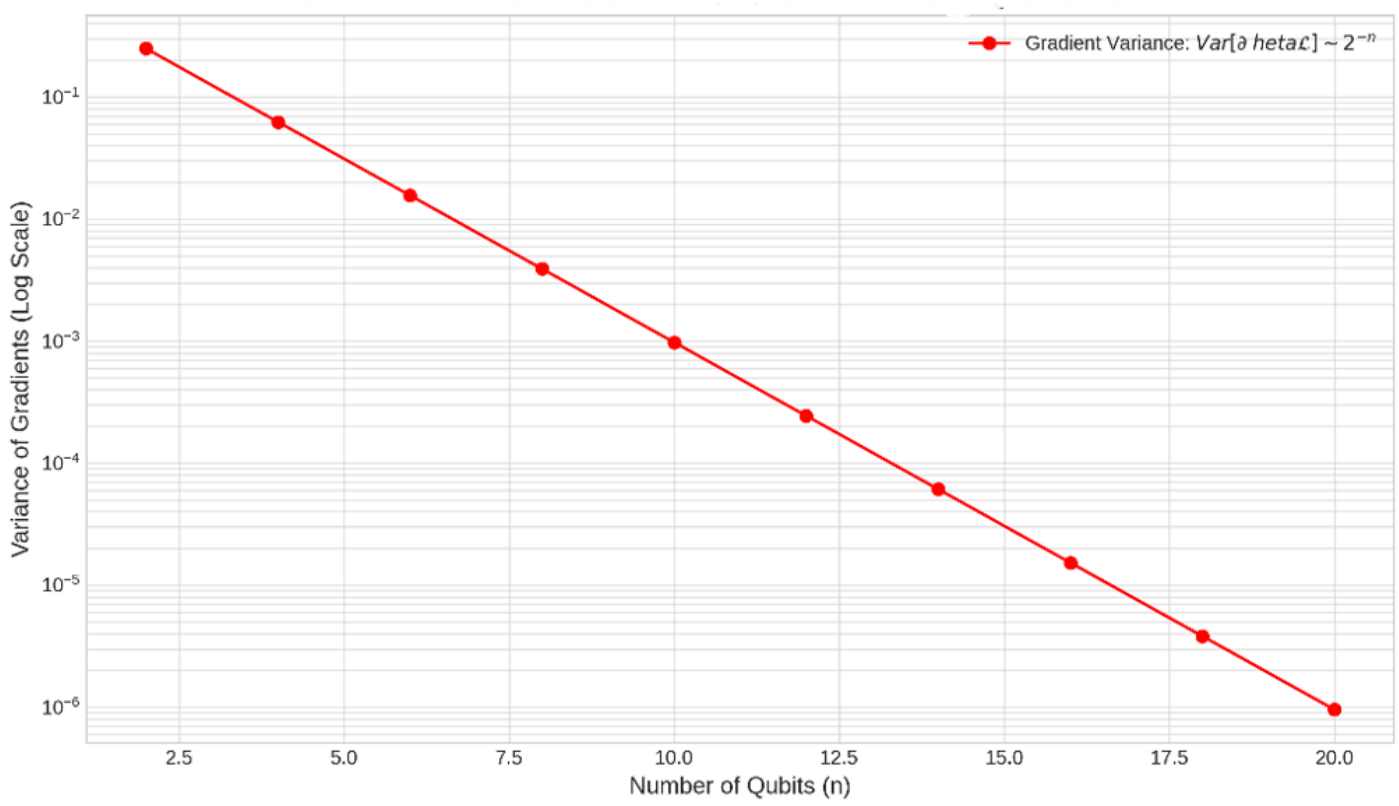


Figure 3

The Barren Plateau Phenomenon in Variational Quantum Circuits