Quantum Computing and Quantum Machine Learning: Emerging Algorithms and Computational Applications

Prof. Deepika Komal
Assistant Professor, Department of Computer Science
Dashmesh Khalsa College, Zirakpur, District Mohali, Punjab, India

***Abstract*—Quantum computing represents a fundamentally different approach to information processing, in which quantum-mechanical phenomena such as superposition, entanglement, and interference are used to manipulate information. During the last decade, advances in superconducting, trapped-ion, photonic and other quantum technologies have moved quantum computing from a primarily theoretical discipline towards experimentally accessible computing platforms. In parallel, Quantum Machine Learning (QML) has emerged at the intersection of quantum computing and artificial intelligence, investigating how quantum circuits, quantum kernels, variational algorithms and quantum representations can be incorporated into machine-learning workflows.**

This paper reviews emerging quantum algorithms and their computational applications with particular emphasis on Quantum Machine Learning. It examines important algorithmic developments including the Quantum Approximate Optimization Algorithm (QAOA), Variational Quantum Eigensolver (VQE), quantum kernel methods, Quantum Support Vector Machines (QSVM), Quantum Neural Networks (QNNs), Quantum Convolutional Neural Networks (QCNNs), quantum clustering and hybrid quantum-classical learning architectures. The study also considers contemporary quantum hardware and the limitations imposed by noise, decoherence, finite qubit connectivity, measurement overhead, data encoding and error correction. The paper uses secondary data from peer-reviewed research publications, institutional technical documentation and recent surveys of quantum computing and QML. Selected quantitative indicators are used to illustrate developments in processor size, error correction, computational throughput and algorithmic applications. Recent evidence shows that processors such as IBM Heron have reached 156 physical qubits, while IBM's Nighthawk platform introduced in 2026 is described with 120 programmable qubits and 458 physical qubits. Google's Willow processor demonstrated below-threshold surface-code error correction, representing an important development towards fault-tolerant quantum computing. However, these hardware milestones should not be interpreted as evidence that quantum computers have broadly replaced classical computing. Current QML research remains largely experimental and hybrid, with practical advantage dependent on the problem, dataset, encoding strategy, circuit depth and hardware characteristics.

The paper concludes that the most immediate computational opportunity lies in hybrid quantum-classical architectures in which classical processors and GPUs work alongside quantum processing units. Future research should focus on noise-resilient algorithms, efficient data loading, quantum-aware machine-learning architectures, benchmarking standards, error correction and application-specific quantum advantage.

***Index Terms*—Quantum computing; Quantum Machine Learning; quantum algorithms; quantum neural networks; quantum kernels; QAOA; VQE; quantum error correction; NISQ computing; hybrid computing.**

I. INTRODUCTION

Classical computing has transformed science, business and society through increasingly powerful processors, distributed computing and artificial intelligence. Nevertheless, several computational problems become increasingly difficult as their size grows. Combinatorial optimisation, molecular simulation, cryptographic analysis and certain high-dimensional learning problems can require computational resources that grow rapidly with input size. Quantum computing investigates whether fundamentally different information-processing mechanisms can address selected classes of these problems.

A classical computer represents information using bits that take the values 0 or 1. A quantum computer uses quantum bits, or qubits, whose states can exist in superpositions of computational basis states.

Entanglement creates correlations between quantum systems that cannot be represented through independent classical variables, while interference enables amplitudes associated with different computational paths to be amplified or cancelled. These principles do not imply that a quantum computer performs every calculation simultaneously in a simple classical sense. Instead, useful quantum algorithms carefully manipulate probability amplitudes so that measurement produces information about the desired solution.

Quantum algorithms have developed from theoretical proposals such as Shor's factoring algorithm and Grover's search algorithm to near-term variational approaches. Variational Quantum Algorithms are particularly relevant to current hardware because they combine relatively shallow parameterised quantum circuits with classical optimisation. VQE, QAOA and variational quantum classifiers are examples of this hybrid model.

Quantum Machine Learning extends this development into artificial intelligence. QML can be understood broadly as the use of quantum computation to perform, accelerate or transform machine-learning tasks, while machine-learning techniques can also be used to improve quantum systems. Recent literature identifies quantum kernels, quantum neural networks, variational circuits, quantum generative models and quantum-enhanced optimisation as major areas of research. A 2025 ACM Computing Surveys study reviewed more than 135 QML articles and highlighted hardware limitations, data encoding, scalability and benchmarking as major unresolved challenges. (DOI)

The importance of QML for Computer Science therefore lies not simply in replacing classical machine learning, but in investigating a new computational paradigm. Current quantum systems are generally noisy and contain relatively limited numbers of high-quality qubits. Consequently, practical QML research frequently employs hybrid architectures in which classical computers perform data preprocessing and optimisation while the quantum processor executes a parameterised circuit.

II. REVIEW OF LITERATURE

Shor (1994) introduced one of the foundational quantum algorithms for integer factorisation and discrete logarithms. His work demonstrated theoretically that a sufficiently powerful quantum computer could solve certain mathematical problems substantially more efficiently than known classical approaches. The study established an important connection between quantum computation and computational complexity and also highlighted the future implications of quantum computing for cryptographic systems.

Grover (1996) proposed the quantum search algorithm, demonstrating a quadratic speed-up for unstructured search compared with classical exhaustive search. Grover's algorithm became one of the fundamental examples of quantum algorithmic advantage and established the principle that quantum interference could be exploited to improve computational search procedures.

Peruzzo et al. (2014) introduced the Variational Quantum Eigensolver (VQE), a hybrid quantum-classical algorithm for estimating molecular ground-state energies. Their experimental demonstration on a photonic quantum processor showed how a relatively shallow quantum circuit could be combined with a classical optimisation procedure. VQE subsequently became an important framework for near-term quantum computing, particularly in chemistry, materials science and scientific simulation.

Farhi, Goldstone and Gutmann (2014) proposed the Quantum Approximate Optimization Algorithm (QAOA) for solving combinatorial optimisation problems. QAOA uses alternating parameterised quantum operations associated with a problem's cost function and a mixing function. The algorithm has since become one of the most extensively studied variational quantum approaches for optimisation problems such as graph partitioning, scheduling and routing.

Biamonte et al. (2017) provided a broad examination of Quantum Machine Learning and described the interaction between quantum computation and machine learning. Their work discussed quantum approaches to classification, clustering, dimensionality reduction, optimisation and other learning tasks. The study helped establish QML as an interdisciplinary field connecting quantum information science with artificial intelligence.

Preskill (2018) introduced the widely used concept of Noisy Intermediate-Scale Quantum (NISQ) computing. He explained that near-term quantum processors would contain useful but imperfect quantum resources and would be constrained by noise, limited circuit depth and the absence of complete fault tolerance. This framework remains particularly relevant to QML because many current quantum-learning algorithms are designed for shallow, noisy circuits.

Schuld and Petruccione (2018) examined supervised learning using quantum computers and developed a systematic theoretical foundation for quantum-enhanced machine learning. Their work addressed quantum representations of data, quantum classifiers and the relationship between quantum circuits and learning models. It contributed to the understanding of how classical machine-learning concepts can be reformulated within quantum computational frameworks.

Schuld and Killoran (2019) proposed a framework for understanding quantum machine learning through quantum feature spaces. Their work demonstrated how quantum circuits can map classical data into high-dimensional feature spaces and how quantum kernels can be used for supervised learning. This research became particularly influential in the development of quantum kernel methods and quantum-enhanced classification.

Havlíček et al. (2019) experimentally investigated supervised learning using quantum-enhanced feature spaces. Their study demonstrated a quantum classification approach based on a parameterised quantum circuit and compared its behaviour with classical kernel methods.
The research provided an important experimental foundation for the use of quantum feature maps in machine learning.

Cerezo et al. (2021) presented a comprehensive review of Variational Quantum Algorithms. Their study examined VQE, QAOA and related approaches while discussing optimisation, parameterised circuits, noise and scalability. The authors highlighted the importance of designing variational circuits that can be effectively trained on near-term quantum hardware. Their work is particularly relevant to QML because many quantum classifiers and quantum neural networks are based on variational circuits.

Gujju, Matsuo and Raymond (2024) reviewed supervised and unsupervised Quantum Machine Learning techniques designed for near-term quantum devices. Their study examined the practical challenges involved in implementing QML on contemporary hardware, including noise, limited qubit connectivity and computational overhead. The authors emphasised the importance of application-specific evaluation rather than assuming that quantum models automatically outperform classical alternatives.

Lu et al. (2024) examined the classifications, challenges and possible solutions associated with Quantum Machine Learning. Their research identified data encoding, noise, scalability, circuit design and optimisation as major challenges. The study also discussed different categories of QML algorithms and their potential applications, highlighting the need for improved methods capable of operating effectively on realistic quantum hardware.

Devadas and Sowmya (2025) conducted a comprehensive review of QML and its integration with artificial intelligence. Their study examined quantum-enhanced learning approaches, applications and technological challenges. The authors discussed areas including optimisation, classification, healthcare, finance and scientific computing, while emphasising that practical QML remains dependent on improvements in quantum hardware, error correction and algorithmic efficiency.

Qi, Yang, Chen and Chen (2025) examined the interaction between quantum computing and machine learning and presented QML as an interdisciplinary field combining quantum information processing with conventional AI. Their work discussed quantum neural networks, quantum kernels, variational approaches and the role of hybrid quantum-classical architectures. The study highlighted the importance of evaluating QML algorithms against strong classical baselines and realistic computational workloads.

Rodríguez-Díaz et al. (2025) provided an extensive survey of Quantum Machine Learning covering its

foundations, algorithms, software frameworks, data representation and applications. The review examined more than 135 QML studies and identified hardware limitations, data encoding, scalability and benchmarking as continuing challenges. The authors emphasised that the practical value of QML must be established through rigorous comparisons with classical approaches rather than through theoretical speed-up claims alone.

Google Quantum AI (2025) reported experimental progress in quantum error correction using the Willow superconducting quantum processor. The associated research demonstrated below-threshold surface-code behaviour, in which increasing the error-correction code distance reduced the logical error rate. This result represents an important development towards fault-tolerant quantum computing because reliable logical qubits are necessary for executing large-scale quantum algorithms.

IBM Quantum (2025) reported continuing improvements in its Heron processor family, including a 156-qubit processor and improvements in two-qubit gate performance and circuit-processing throughput. IBM's reported CLOPS measurements demonstrated progress in the speed at which quantum circuits can be executed. These developments are significant for QML because repeated execution and measurement of quantum circuits can become a major computational bottleneck.

Gokhale, Dhote and Delhibabu (2026) reviewed quantum machine-learning algorithms, applications and emerging advantages, examining the development of QML from theoretical concepts towards application-oriented research. Their review highlighted opportunities in optimisation, artificial intelligence and scientific computing while identifying scalability, noise, data representation and hardware limitations as continuing areas requiring research.

The literature reviewed from 1994 to 2026 demonstrates a clear progression from foundational quantum algorithms towards experimentally accessible quantum machine-learning systems. Early research concentrated primarily on theoretical computational speed-ups, whereas later studies increasingly focused on variational algorithms, quantum kernels, hybrid architectures, hardware noise and practical applications. Recent literature indicates that the central research challenge is no longer simply developing quantum algorithms, but establishing when and under what conditions these algorithms can provide measurable computational benefits compared with advanced classical methods.

III. NEED OF THE STUDY

The need for studying quantum computing and QML arises from the rapid convergence of quantum information science, artificial intelligence and high-performance computing. Classical machine learning continues to achieve strong results, but increasing model complexity can require substantial computational resources. Quantum computing provides an alternative computational model that may eventually improve selected optimisation, simulation and learning tasks.

For Computer Science education and research, understanding QML is increasingly important because future computational systems are likely to integrate heterogeneous resources rather than depend exclusively on CPUs or GPUs. IBM's current roadmap explicitly describes a quantum-centric computing model in which quantum processors are integrated with classical high-performance computing resources. (IBM)

There is also a need to distinguish theoretical quantum advantage from demonstrated practical advantage. Claims of quantum speed-up depend strongly on assumptions concerning input preparation, data loading, circuit execution, error mitigation and classical post-processing. A careful review can therefore help students and researchers understand both the opportunities and limitations of emerging quantum algorithms.

IV. STATEMENT OF THE PROBLEM

Despite rapid progress in quantum hardware and algorithms, several problems restrict the practical adoption of Quantum Machine Learning.

First, current quantum processors remain susceptible to noise and decoherence. Second, classical datasets must be encoded into quantum states, and this data-loading stage can itself require significant computational resources. Third, increasing circuit depth can amplify errors. Fourth, measurement-based

estimation may require many circuit executions to obtain sufficiently accurate expectation values.

Another problem is the difficulty of demonstrating a meaningful advantage over highly optimised classical machine-learning algorithms. A quantum model may perform well on a particular dataset while still requiring substantial classical preprocessing or offering no practical computational advantage.

The central problem addressed by this study is therefore how emerging quantum algorithms and QML architectures can be understood in terms of their computational mechanisms, available hardware, potential applications and current technical limitations.

V. OBJECTIVES OF THE STUDY

1. To examine the fundamental concepts underlying quantum computing and Quantum Machine Learning.
2. To review emerging quantum algorithms including VQE, QAOA, quantum kernels and variational quantum circuits.
3. To examine major Quantum Machine Learning architectures such as QSVM, QNN and QCNN.
4. To analyse current quantitative developments in quantum processor capacity, error correction and computational performance.
5. To identify computational applications of quantum algorithms in optimisation, machine learning, chemistry, materials science, cybersecurity and other fields.
6. To examine the technical limitations affecting present-day QML systems.
7. To identify research gaps and future directions for quantum-enhanced machine learning.

VI. DATA AND METHODOLOGY

This study is designed as a narrative research review based on secondary data. The analysis combines peer-reviewed literature, recent review studies and technical information released by major quantum-computing research organisations.

The literature considered includes research on quantum algorithms, variational quantum computing, quantum kernels, quantum neural networks, quantum error correction and near-term quantum hardware. Recent surveys were used to identify algorithmic categories and application areas, while institutional technical sources were used for current processor specifications.

The study uses the following analytical dimensions:

- Qubit capacity: Number of physical or programmable qubits reported for a processor.
- Circuit depth: Number and arrangement of quantum operations that can be executed before accumulated noise becomes problematic.
- Gate fidelity: Accuracy with which quantum gates are implemented.
- Quantum error rate: Frequency of incorrect quantum operations or measurements.
- CLOPS: Circuit Layer Operations Per Second, used by IBM as a measure of quantum processing throughput.
- Algorithmic complexity: The computational scaling associated with an algorithm under its theoretical assumptions.
- Data-encoding cost: Computational resources required to transform classical data into quantum states.
- Model performance: Accuracy or objective-function performance of QML models relative to appropriate classical baselines.
- Scalability: Ability of an algorithm or architecture to remain useful as data size, circuit size and problem complexity increase.

The study deliberately avoids treating qubit count as a standalone measure of computational usefulness. A processor with more qubits may not outperform a smaller system on a specific problem if connectivity, fidelity, error rates or algorithmic requirements are unfavourable.

V. DATA & RESULTS

The reviewed evidence indicates substantial progress in quantum hardware, while practical QML remains predominantly hybrid and experimental.

1. Development of Quantum Hardware

Current processor development illustrates the rapid expansion of available physical quantum resources.

Quantum technology indicator	Reported value	Significance
IBM Heron processor	156 physical qubits	Demonstrates scaling of superconducting quantum hardware
IBM Nighthawk, 2026	120 programmable; 458 physical qubits	Emphasises programmable qubits within a larger physical architecture
IBM Heron r3 fleet	330,000 CLOPS reported by IBM	Indicates improvement in circuit-processing throughput
Google Willow	Superconducting processor	Demonstrated below-threshold surface-code error correction
Willow surface-code experiments	Distance-5 and distance-7 memories	Evidence of progress towards logical error suppression

IBM reported 156-qubit Heron processors and improvements in two-qubit error performance and circuit throughput. In 2025, IBM reported a Heron configuration with a median two-qubit error rate around 3×10^{-3} in a specified benchmark and a CLOPS value of 250,000 for that system.

IBM subsequently reported a Heron fleet throughput of 330,000 CLOPS in 2025. These figures should be interpreted as hardware-specific benchmark indicators rather than universal measures of quantum advantage. Google's Willow work is particularly relevant to error correction. The associated Nature publication reports below-threshold surface-code memories in which logical error suppression improves as the code distance is increased.

2. Major Emerging Quantum Algorithms

Algorithm	Principal computational task	Current relevance
VQE	Ground-state and eigenvalue estimation	Chemistry and materials
QAOA	Combinatorial optimisation	Routing, scheduling, graph problems
Quantum Kernel Methods	Classification and similarity estimation	Machine learning
QSVM	Supervised classification	Small and structured datasets
QNN/VQC	Classification and regression	Hybrid QML
QCNN	Quantum pattern recognition	Structured/image-like data
Quantum Generative Models	Distribution learning and generation	Generative modelling
Grover's algorithm	Unstructured search	Quadratic search improvement
Shor's algorithm	Integer factorisation/discrete logarithms	Cryptography, future fault-tolerant systems

VQE and QAOA are particularly important because they can be implemented using relatively shallow parameterised circuits. Their hybrid architecture is compatible with current NISQ systems.

3. Quantum Kernel Learning

Quantum kernel methods use quantum circuits to map classical observations into high-dimensional quantum feature spaces. The similarity between encoded observations can be estimated through quantum measurements. A classical support-vector machine or related optimiser can subsequently use the resulting kernel.

The approach is attractive because it does not require a complete quantum replacement for the classical machine-learning pipeline. However, quantum kernel methods can face difficulties involving circuit concentration, noise, kernel estimation cost and classical preprocessing.

4. Variational Quantum Classifiers and Quantum Neural Networks

A QNN can be represented conceptually as:

Classical input → Quantum encoding → Parameterised quantum circuit → Measurement → Classical output

The parameters of the circuit are updated by a classical optimisation algorithm. This structure creates a hybrid computational loop.

A major challenge is the barren-plateau problem, in which gradients can become extremely small as circuits become deeper or more expressive. When gradients become difficult to estimate, optimisation can become inefficient. Consequently, QML research increasingly examines circuit architecture, parameter initialisation, problem-specific ansatz design and gradient-free optimisation.

5. Quantum Optimisation

QAOA and other quantum optimisation methods have been investigated for graph partitioning, scheduling, routing, portfolio optimisation and constraint problems. These applications are relevant to Computer Science because they connect quantum algorithms with combinatorial optimisation, algorithms and complexity theory.

However, a theoretical quantum formulation of an optimisation problem does not automatically establish practical superiority. Classical algorithms, heuristics and specialised solvers remain highly competitive for many real-world instances.

6. Applications in Scientific Computing

Quantum simulation is one of the most important long-term applications of quantum computers. Molecular energy calculations, materials modelling and chemical reaction simulation can potentially benefit from quantum representations of quantum systems.

VQE has therefore received extensive attention in computational chemistry. The expected benefit comes from the natural representation of quantum states by quantum hardware rather than from a generic speed-up applicable to every chemical computation.

7. Applications in Cybersecurity

Quantum computing has major implications for cryptography. Shor's algorithm theoretically threatens widely used public-key systems based on integer factorisation and discrete logarithms when sufficiently large fault-tolerant quantum computers become available.

Grover's algorithm provides a quadratic speed-up for unstructured search and has implications for symmetric cryptography. These theoretical results have contributed to the development and adoption of post-quantum cryptographic approaches.

8. Applications in Healthcare and Bioinformatics

QML has been investigated for medical classification, genomic analysis, molecular property prediction and drug discovery. Potential applications include identifying patterns in biological datasets, classifying medical images and estimating molecular properties.

Nevertheless, healthcare applications require especially careful benchmarking. Small quantum datasets or artificially reduced datasets can produce impressive experimental results without demonstrating an advantage on clinically realistic workloads.

9. Applications in Finance and Logistics

Quantum optimisation and QML have been investigated in portfolio construction, fraud detection, risk analysis, vehicle routing and supply-chain optimisation. These problems often involve combinations of discrete and continuous variables.

The computational attraction of quantum optimisation arises from the possibility of representing complex combinatorial spaces through quantum states. However, practical performance depends on encoding overhead, circuit depth, error mitigation and the availability of a sufficiently powerful quantum processor.

10. Hybrid Quantum-Classical Computing

The evidence reviewed indicates that hybrid computing represents one of the most important architectures for near-term quantum applications.

A typical workflow is:

Classical data → preprocessing → quantum encoding → quantum circuit → measurement → classical optimiser → parameter update → repeated quantum execution

This structure enables classical CPUs and GPUs to perform tasks for which they are already highly effective while quantum processors are reserved for specialised computational subroutines.

IBM's current roadmap explicitly describes quantum-centric computing in which quantum processors operate together with classical high-performance computing systems.

VI. INTERPRETATION OF FINDINGS

The findings indicate that quantum computing is progressing along two interconnected paths: hardware development and algorithmic development. Increasing qubit numbers are important, but qubit count alone does not determine practical computational capability. Error correction represents a particularly important issue. Google's Willow results demonstrate progress towards operating below the surface-code threshold, but a fully fault-tolerant computer capable of executing very large algorithms remains a substantially larger engineering challenge.

The QML literature similarly indicates that practical advantage cannot be inferred simply from the presence of a quantum circuit. The complete computational pipeline must be considered, including data preparation, encoding, circuit execution, repeated measurements, classical optimisation and post-processing.

An important finding is therefore the shift from the question "How many qubits does a computer have?" to "How effectively can the available qubits execute a particular algorithm for a particular problem?"

For QML, dataset characteristics are equally important. Quantum models may be particularly interesting when the underlying problem has a structure that can be naturally represented through quantum states or quantum feature maps. Conversely, classical machine learning may remain preferable when datasets are very large, easily processed by GPUs, or expensive to encode into quantum states.

VII. DISCUSSION

Quantum computing and QML represent an important research direction within Computer Science because they combine concepts from algorithms, complexity theory, artificial intelligence, optimisation, information theory and hardware architecture.

The literature suggests that QML should not currently be viewed as a universal replacement for classical machine learning. Instead, it is better understood as an emerging computational paradigm whose useful domain remains under investigation.

One major advantage of hybrid architectures is that they allow researchers to exploit existing classical infrastructure. Quantum circuits can be treated as specialised computational components inside larger machine-learning workflows. This approach is compatible with the development of quantum-centric supercomputing architectures.

The principal technical challenges are interconnected. Noise affects quantum circuits; error correction requires additional physical qubits; additional qubits increase engineering complexity; deeper circuits create more opportunities for errors; and data encoding can become expensive.

Another challenge is benchmarking. QML experiments should compare quantum models against strong and appropriately tuned classical baselines. Accuracy alone is insufficient. Researchers should also report training time, inference time, number of circuit executions, data-loading cost, hardware characteristics, error-mitigation overhead and statistical uncertainty.

Reproducibility is equally important. Quantum experiments can vary substantially according to hardware calibration, compiler settings, circuit transpilation, shot count and noise conditions. Standardised benchmarks and openly available datasets can improve the comparability of results.

Recent QML reviews emphasise precisely these issues, including hardware constraints, scalability, data encoding and the need for meaningful comparisons with classical methods.

For Computer Science education, QML creates opportunities to introduce students to quantum gates, circuits, optimisation, machine learning and computational complexity within a single interdisciplinary framework. Tools such as quantum programming frameworks can allow students to experiment with simulators and cloud-accessible quantum processors.

The most significant conceptual development is therefore not simply the creation of a new type of processor, but the emergence of heterogeneous computational systems in which CPUs, GPUs and QPUs cooperate.

VIII. CONCLUSION

Quantum Computing and Quantum Machine Learning represent an emerging frontier in Computer Science. Quantum computing introduces a computational model based on superposition, entanglement and interference, while QML investigates how quantum

resources can be incorporated into learning, optimisation and data-processing systems.

The review shows that important progress has been achieved in both hardware and algorithms. Modern quantum processors have moved into the hundreds of physical qubits, while recent error-correction experiments have demonstrated progress towards logical quantum computation. IBM's Heron processors and Google's Willow processor illustrate different aspects of this development.

At the algorithmic level, VQE, QAOA, quantum kernels, QSVMs, QNNs and QCNNs provide several frameworks for investigating quantum-enhanced computation. Their current applications include optimisation, scientific simulation, machine learning, cybersecurity, healthcare, finance and logistics.

However, the evidence does not support the conclusion that quantum machine learning has already achieved broad practical superiority over classical machine learning. Current systems remain constrained by noise, data encoding, measurement overhead, circuit depth, limited qubit quality and error-correction requirements.

The near-term research direction is therefore likely to involve hybrid quantum-classical systems. In such architectures, classical computing resources perform preprocessing and optimisation while quantum processors execute specialised quantum circuits.

Future progress will depend not only on increasing qubit numbers but also on improving fidelity, connectivity, error correction, compiler technology, quantum algorithms and benchmarking methodologies. The development of reliable evidence for application-specific quantum advantage will be particularly important.

IX. POLICY AND INDUSTRIAL IMPLICATIONS

1. Promote quantum-computing education: Computer Science curricula should introduce quantum information, quantum algorithms and QML alongside classical algorithms and machine learning.
2. Develop hybrid computing infrastructure: Universities and research institutions can integrate classical HPC resources with cloud-accessible quantum processors for experimental research.
3. Support interdisciplinary research: Quantum computing requires collaboration among computer scientists, mathematicians, physicists, AI researchers and domain specialists.
4. Establish benchmarking standards: Research programmes should require transparent reporting of datasets, classical baselines, circuit depth, qubit numbers, shots, error rates and computational overhead.
5. Strengthen cybersecurity preparedness: Organisations should monitor the development of post-quantum cryptography because sufficiently capable fault-tolerant quantum computers could affect existing public-key cryptographic systems.
6. Encourage reproducible QML research: Researchers should provide code, datasets, circuit specifications and experimental parameters wherever possible.
7. Develop quantum-skilled human resources: Universities should create training programmes combining quantum programming, machine learning, algorithms and high-performance computing.
8. Evaluate industrial applications systematically: Companies exploring quantum technologies should conduct application-specific feasibility studies rather than assuming that quantum processing will automatically improve performance.

X. RESEARCH GAPS AND FUTURE SCOPE

Several research gaps remain.

First, quantum data encoding requires greater attention. Many QML experiments begin with relatively small classical datasets, whereas industrial AI systems frequently involve millions or billions of observations.

Efficient mechanisms for loading and representing large classical datasets remain essential.

Second, quantum error correction must become more resource-efficient. Google's below-threshold error-correction experiments represent important progress, but practical fault-tolerant computation will require large numbers of reliable logical qubits.

Third, QML requires stronger benchmarking. Future research should compare quantum models against modern classical methods rather than weak or outdated baselines. Benchmarking should include computational cost and not merely predictive accuracy.

Fourth, barren plateaus and optimisation instability remain significant issues for variational circuits. Future work should investigate problem-specific circuit structures, layerwise training, improved initialisation and alternative optimisation methods.

Fifth, quantum generative AI deserves further research. Quantum generative models could potentially provide new approaches to probability distribution learning, but their scalability and practical advantage remain open questions.

Sixth, quantum reinforcement learning is still an emerging research area. Future studies may investigate whether quantum representations can improve policy optimisation or exploration in appropriately structured environments.

Seventh, quantum-classical compiler technology requires further development. Efficient compilation can reduce circuit depth and transform abstract algorithms into hardware-compatible circuits.

Eighth, application-specific quantum advantage should become the central benchmark. Rather than asking whether quantum computers are faster in general, researchers should identify particular computational problems for which a complete quantum-classical workflow provides a measurable advantage.

Finally, the future of quantum computing is likely to be heterogeneous. Quantum processors are unlikely to operate independently of classical computing infrastructure. Instead, future systems may integrate CPUs, GPUs, specialised accelerators and QPUs within common computational workflows.

The continuing development of quantum hardware, error correction and QML algorithms therefore provides a substantial research opportunity for Computer Science.

The transition from experimental demonstrations to reliable application-specific computational advantage will depend on progress across the entire stack—from quantum hardware and error correction to algorithms, compilers, data representation and machine-learning architecture.

REFERENCES

[1] J. Biamonte, P. Wittek, N. Pancotti, P. Rebentrost, N. Wiebe, and S. Lloyd, “Quantum machine learning,” *Nature*, vol. 549, pp. 195–202, 2017, doi: 10.1038/nature23474.

[2] M. Cerezo, A. Arrasmith, R. Babbush, S. C. Benjamin, S. Endo, K. Fujii, J. R. McClean, K. Mitarai, X. Yuan, L. Cincio, and P. J. Coles, “Variational quantum algorithms,” *Nature Reviews Physics*, vol. 3, pp. 625–644, 2021, doi: 10.1038/s42254-021-00348-9.

[3] R. M. Devadas and T. Sowmya, “Quantum machine learning: A comprehensive review of integrating AI with quantum computing for computational advancements,” *MethodsX*, vol. 14, Art. no. 103318, 2025, doi: 10.1016/j.mex.2025.103318.

[4] E. Farhi, J. Goldstone, and S. Gutmann, “A quantum approximate optimization algorithm,” *arXiv preprint arXiv:1411.4028*, 2014.

[5] S. S. Gokhale, R. R. Dhote, and R. Delhibabu, “A review of quantum machine learning algorithms, applications, and emerging advantages,” *Discover Computing*, vol. 29, Art. no. 226, 2026.

[6] Google Quantum AI, “Quantum error correction below the surface code threshold,” *Nature*, vol. 638, pp. 920–926, 2025, doi: 10.1038/s41586-024-08449-y.

[7] L. K. Grover, “A fast quantum mechanical algorithm for database search,” in *Proc. 28th Annu. ACM Symp. Theory Comput.*, 1996, pp. 212–219, doi: 10.1145/237814.237866.

[8] Y. Gujju, A. Matsuo, and R. Raymond, “Quantum machine learning on near-term quantum devices: Current state of supervised and unsupervised techniques for real-world applications,” *Physical Review Applied*, 2024.

[9] V. Havlíček, A. D. Córcoles, K. Temme, A. W. Harrow, A. Kandala, J. M. Chow, and J. M. Gambetta, “Supervised learning with quantum-enhanced feature spaces,” *Nature*, vol. 567, pp. 209–212, 2019, doi: 10.1038/s41586-019-0980-2.

[10] IBM Quantum, “IBM Quantum processors and advances in quantum circuit performance,” IBM Quantum Research and Technology, 2025.

[11] IBM Quantum, “IBM Quantum processor types and hardware specifications,” IBM Quantum Documentation, 2026.

[12] W. Lu, Y. Lu, J. Li, A. Sigov, L. Ratkin, and L. A. Ivanov, "Quantum machine learning: Classifications, challenges, and solutions," *Journal of Industrial Information Integration*, Art. no. 100736, 2024.

[13] A. Peruzzo, J. McClean, P. Shadbolt, M.-H. Yung, X.-Q. Zhou, P. J. Love, A. Aspuru-Guzik, and J. L. O'Brien, "A variational eigenvalue solver on a photonic quantum processor," *Nature Communications*, vol. 5, Art. no. 4213, 2014, doi: 10.1038/ncomms5213.

[14] J. Preskill, "Quantum computing in the NISQ era and beyond," *Quantum*, vol. 2, Art. no. 79, 2018, doi: 10.22331/q-2018-08-06-79.

[15] J. Qi, C.-H. H. Yang, S. Y.-C. Chen, and P.-Y. Chen, "Quantum machine learning: An interplay between quantum computing and machine learning," in *Proc. IEEE Int. Symp. Circuits Syst. (ISCAS)*, 2025.

[16] F. Rodríguez-Díaz, D. Gutiérrez-Avilés, A. Troncoso, and F. Martínez-Álvarez, "A survey of quantum machine learning: Foundations, algorithms, frameworks, data and applications," *ACM Computing Surveys*, vol. 58, no. 4, Art. no. 91, 2025, doi: 10.1145/3764582.

[17] M. Schuld and N. Killoran, "Quantum machine learning in feature Hilbert spaces," *Physical Review Letters*, vol. 122, Art. no. 040504, 2019, doi: 10.1103/PhysRevLett.122.040504.

[18] M. Schuld and F. Petruccione, *Supervised Learning with Quantum Computers*. Cham, Switzerland: Springer, 2018.

[19] P. W. Shor, "Algorithms for quantum computation: Discrete logarithms and factoring," in *Proc. 35th Annu. Symp.* Foundations *Comput. Sci.*, 1994, pp. 124–134.

[20] IBM Quantum, "Quantum-centric computing and advances in quantum processing performance," IBM Research and IBM Quantum, 2025.