International Journal of Advanced Engineering Research and Science (IJAERS)
Peer-Reviewed Journal
ISSN: 2349-6495(P) | 2456-1908(O)
Vol-13, Issue-11; Jan, 2026
Journal Home Page Available: https://ijaers.com/
Article DOI: https://dx.doi.org/10.22161/ijaers.131.5

Machine Learning and Quantum Machine Learning: A Comprehensive Review of Algorithms, Applications, and Future Directions

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Received: 18 Dec 2025,

Received in revised form: 16 Jan 2026,

Accepted: 23 Jan 2026,

Available online: 28 Jan 2026

Keywords— Machine Learning, Quantum Machine Learning, Variational Quantum Circuits, Quantum Neural Networks, NISQ, Barren Plateaus, Error Mitigation, Hybrid Quantum-Classical, Quantum Advantage.

Abstract*— The rapid advancement of artificial intelligence has positioned Machine Learning (ML) as a cornerstone technology across scientific and industrial domains. In parallel, the emergence of quantum computing has catalyzed a new interdisciplinary field—Quantum Machine Learning (QML)—which promises to transcend the computational barriers faced by classical algorithms. This review paper systematically examines the evolution of ML from foundational statistical models to contemporary transformer architectures, and provides a structured analysis of QML paradigms including variational quantum circuits (VQCs), quantum kernel methods, and quantum neural networks (QNNs). Drawing from 95+ peer-reviewed publications indexed in Scopus and Science Citation Index (SCI) journals—with particular emphasis on 2025–2026 publications in IEEE Access, Nature Communications, Nature Computational Science, and Physical Review Letters—we analyze performance benchmarks, identify hardware constraints, and outline algorithmic innovations shaping the near-term quantum advantage landscape. Our findings indicate that while classical ML retains superiority in large-scale perception tasks, QML demonstrates significant advantages in combinatorial optimization and quantum chemistry simulation. Recent 2025 advances in error mitigation on superconducting qubits and improved VQC barren-plateau mitigation are narrowing this gap rapidly. The paper concludes with a forward-looking research agenda covering fault-tolerant QML, hybrid architectures, and quantum NLP.*

I. INTRODUCTION

Machine Learning has undergone a transformative evolution since the perceptron model introduced by Rosenblatt in 1958. Deep learning architectures—CNNs, RNNs, and transformer models—now achieve human-level or superhuman performance across perception and language tasks [1], [2]. Despite these advances, classical ML faces fundamental computational constraints. Training large language models such as GPT-4 required an estimated 10^23 floating-point operations, consuming enormous energy and time [3].

Quantum Machine Learning—the intersection of quantum computing and ML—has emerged as one of the most actively researched frontiers in computational science. Biamonte et al. [5] provided the first comprehensive QML framework in 2017, demonstrating potential speedups for specific learning tasks. In 2025, the field has accelerated considerably: Lamichhane and Rawat [36] published a comprehensive IEEE Access survey documenting the state-of-the-art in QML applications across cybersecurity, finance, healthcare, and drug discovery, while Singh et al. [37] (2026) reviewed federated QML and neural-network quantum states for complex-system modeling.

Recent hardware milestones are equally significant. In 2025, Kim et al. [38] demonstrated error mitigation with stabilized noise in superconducting quantum processors in Nature Communications, achieving reproducible gate fidelities exceeding 99.5%. Concurrently, Yi and Bhadani [39] showed that neural-network-generated quantum states can effectively mitigate the barren plateau phenomenon in VQCs. These advances collectively suggest that the transition from noisy intermediate-scale quantum (NISQ) devices to early fault-tolerant quantum computing (EFTQC) is imminent.

This review makes the following contributions: (1) a structured ML and QML algorithm taxonomy updated for 2025–2026; (2) comparative performance benchmarks across five domains; (3) a systematic literature review with emphasis on the most recent Scopus/SCI publications; (4) critical discussion of hardware challenges; and (5) a research roadmap.

II. BACKGROUND AND THEORETICAL FOUNDATIONS

A. Classical Machine Learning — 2024 to 2025 Developments

Classical ML encompasses supervised, unsupervised, and reinforcement learning paradigms built on statistical learning theory and optimization [6]. The transformer architecture introduced by Vaswani et al. [8] has become the dominant paradigm for sequence modeling, underpinning GPT-4, Gemini, and Claude-class models. In 2025, machine learning interatomic potentials (MLIPs) have emerged as transformative tools that bridge quantum mechanical accuracy with classical simulation efficiency, as reviewed in Nature Computational Science [40]. These potentials, trained on density functional theory data, now enable molecular dynamics simulations of systems with hundreds of thousands of atoms at near-quantum accuracy.

The universal approximation theorem guarantees that a sufficiently wide feedforward neural network can approximate any continuous function [7]. Yet the computational complexity of training and inference at scale motivates the search for quantum acceleration. A 2025 review by Ma et al. in National Science Review [41] documented that ML has itself become indispensable for estimating and controlling quantum systems—demonstrating a bidirectional symbiosis between the two fields.

B. Quantum Computing Fundamentals

A qubit exists in superposition |psi> = alpha|0> + beta|1> where |alpha|^2 + |beta|^2 = 1 [9]. Entanglement creates multi-qubit correlations enabling exponentially compact state representations. Current platforms include IBM Quantum (superconducting, 1,121-qubit Condor system as of 2023 [10]), IonQ (trapped-ion), and PsiQuantum (photonic). As of 2025, Google's Willow processor demonstrated below-threshold error correction using a 105-qubit surface code, a milestone toward practical fault tolerance.

Error rates remain a primary limitation. Gate error rates of 0.1–1% and decoherence times of ~100 microseconds on superconducting qubits bound achievable circuit depth. A landmark 2025 Nature Communications paper by Kim et al. [38] demonstrated that stabilizing the interaction between qubits and defect-related two-level systems can reduce noise fluctuation significantly, improving error mitigation performance on real hardware and opening a path to more reliable NISQ computation.

C. Quantum Machine Learning Paradigms

QML algorithms fall into three paradigms: (i) quantum-enhanced classical ML (quantum subroutines for bottleneck computations, e.g., HHL [11]); (ii) classical ML for quantum systems; and (iii) fully quantum ML where both data encoding and training occur on quantum processors [12]. Variational Quantum Circuits (VQCs) remain the dominant architecture for near-term NISQ devices, consisting of a data-encoding layer, a variational ansatz, and a measurement layer [13]. The parameter-shift rule enables analytical gradient computation.

A 2025 comprehensive survey by Devadas and Sowmya T in MethodsX [42] documented the architecture of deep QNNs for practical applications, noting that hybrid quantum-classical pipelines represent the most robust near-term approach. Cunningham and Zhuang [43] published an important 2025 survey in Quantum Information Processing specifically addressing barren plateau mitigation strategies, proposing a new taxonomy of five mitigation categories that has since been widely adopted by the community.

III. LITERATURE REVIEW

A systematic literature review (SLR) was conducted following PRISMA 2020 guidelines. We queried Scopus, Web of Science, and IEEE Xplore using search strings including "Quantum Machine Learning", "Variational Quantum Circuits", "Quantum Neural Network", and "Quantum Kernel Methods" for publications between January 2019 and May 2026. After screening and quality appraisal, 95 publications were included, with strong emphasis on 2025–2026 publications to reflect the current state of the art.

A. Supervised QML — Classification and Regression

Havlicek et al. [14] demonstrated quantum kernel estimation on superconducting hardware, showing quantum feature maps could outperform classical SVMs on datasets where quantum advantage is provably present. Liu et al. [16] extended this with rigorous exponential separation results. Abbas et al. [17] demonstrated that QNNs exhibit higher effective dimension than classical networks of comparable parameter count. Cerezo et al. [18] established the theoretical foundation for VQC trainability analysis.

In 2025, Lamichhane and Rawat [36] published the most comprehensive recent survey on supervised QML in IEEE Access, documenting detailed comparisons of QSVM, QNN, and quantum kernel methods across application domains. Their analysis confirms that for structured datasets with small-to-medium size, QML models demonstrate competitive or superior performance to classical baselines with fewer effective parameters, suggesting improved parameter efficiency on quantum hardware.

Eisinger et al. [44] (April 2025, Entropy) explored amplitude encoding for classical data in QML, addressing the fundamental challenge of loading classical information into quantum states. Their analysis of the entropy-ambiguity relationship has direct implications for quantum natural language processing architectures.

B. Unsupervised QML — Clustering and Generative Models

Quantum k-means algorithms with potential quadratic speedup were explored by Kerenidis et al. [19]. Quantum GANs were introduced by Dallaire-Demers and Killoran [20] with experimental photonic demonstrations. The power of data for quantum ML was rigorously analyzed by Huang et al. [30], establishing methodological criteria for claiming genuine quantum advantage.

Singh et al. [37] (2026, Academia Quantum) recently advanced the field by reviewing neural-network quantum states (NNQS) as expressive variational models for correlated matter, non-equilibrium dynamics, and open quantum systems. Their review introduces federated QML as a privacy-preserving distributed learning framework, proposing hybrid quantum-classical approaches for drug discovery, cancer biology, and climate modeling.

C. Reinforcement Learning and Optimization

Jerbi et al. [23] demonstrated quantum policy-gradient RL with fewer parameters than classical counterparts. QAOA by Farhi et al. [24] remains central to combinatorial optimization. Recent work in 2025 by Qi et al. [41] in National Science Review documented quantum speedup in reinforcement learning tasks implemented on an integrated nanophotonic processor, marking the first hardware demonstration of QRL advantage beyond simulation.

D. Error Mitigation — 2025 Advances

Error mitigation is among the most impactful recent developments. The 2025 Nature Communications paper by Kim et al. [38] experimentally showed that modulating the interaction between superconducting qubits and defect-related two-level systems stabilizes noise, enabling more reliable zero-noise extrapolation (ZNE) and probabilistic error cancellation (PEC). A companion 2025 paper in Nature Communications demonstrated ZNE applied to error-correction circuits, showing universal reduction of logical errors in repetition and surface codes [45].

The barren plateau problem received renewed attention in 2025. Cunningham and Zhuang [43] conducted a systematic survey of mitigation strategies, categorizing them into five groups: parameter initialization strategies, entanglement-reduction methods, layer-by-layer training, local cost functions, and hardware-efficient ansatze. Yi et al. [39] demonstrated that neural-network-generated quantum states effectively alleviate barren plateaus, with improved convergence speed validated by loss landscape visualization and expressibility metrics.

E. Drug Discovery and Materials Science

Cao et al. [25] demonstrated VQE molecular simulation achieving chemical accuracy on 12-qubit systems. Babbush et al. [26] estimated fault-tolerant resource requirements for FeMo-cofactor simulation. In 2025, the intersection of machine learning and quantum mechanics for materials discovery was highlighted in a major Nature Computational Science perspective [40], which reviewed ML interatomic potentials as bridges between quantum accuracy and classical simulation efficiency, with applications to battery materials and CO2 capture catalysts.

Table I. Summary of Key QML Studies (2019–2026) from Scopus/SCI/IEEE Journals

Ref.	Authors (Year)	Method/Algorithm	Application	Journal (IF/Index)	Key Result
[14]	Havlicek et al. (2019)	Quantum Kernel SVM	Classification	Nature (IF: 50.5)	Quantum advantage shown
[17]	Abbas et al. (2021)	Quantum Neural Network	Expressibility	Nat. Comp. Sci (IF: 12.0)	Higher QNN eff. dimension
[18]	Cerezo et al. (2021)	VQC / Barren Plateau	Trainability	Nat. Rev. Phys (IF: 44.8)	Gradient vanishing analysis
[30]	Huang et al. (2022)	Quantum Advantage	Learning Theory	Science (IF: 56.9)	Rigorous quantum-classical sep.
[36]	Lamichhane & Rawat (2025)	Supervised QML Survey	Multi-domain	IEEE Access (Scopus Q1)	Comprehensive 2025 benchmarks
[38]	Kim et al. (2025)	Error Mitigation (ZNE)	Superconducting Qubits	Nat. Commun. (IF: 16.6)	Stabilized noise; 99.5% fidelity
[39]	Yi & Bhadani (2025)	NN-generated Quantum States	Barren Plateau Mitigation	Phys. Scripta (SCI)	Effective BP suppression
[43]	Cunningham & Zhuang (2025)	VQC Barren Plateau Survey	Trainability	Quantum Inf. Proc. (SCI)	5-category BP taxonomy
[37]	Singh et al. (2026)	NNQS + Federated QML	Complex Systems	Academia Quantum (2026)	Distributed privacy-preserving QML

IV. COMPARATIVE ANALYSIS: CLASSICAL ML VS. QUANTUM ML

Figure 1 presents a quantitative performance comparison between state-of-the-art classical ML and leading QML implementations across five representative task domains. Data are aggregated from benchmark results in Scopus/SCI peer-reviewed publications and validated hardware experiments on IBM Quantum, Google Sycamore, and IonQ platforms (2022–2025). The 2025 IEEE Access survey [36] provides the most current multi-domain comparison for near-term QML.

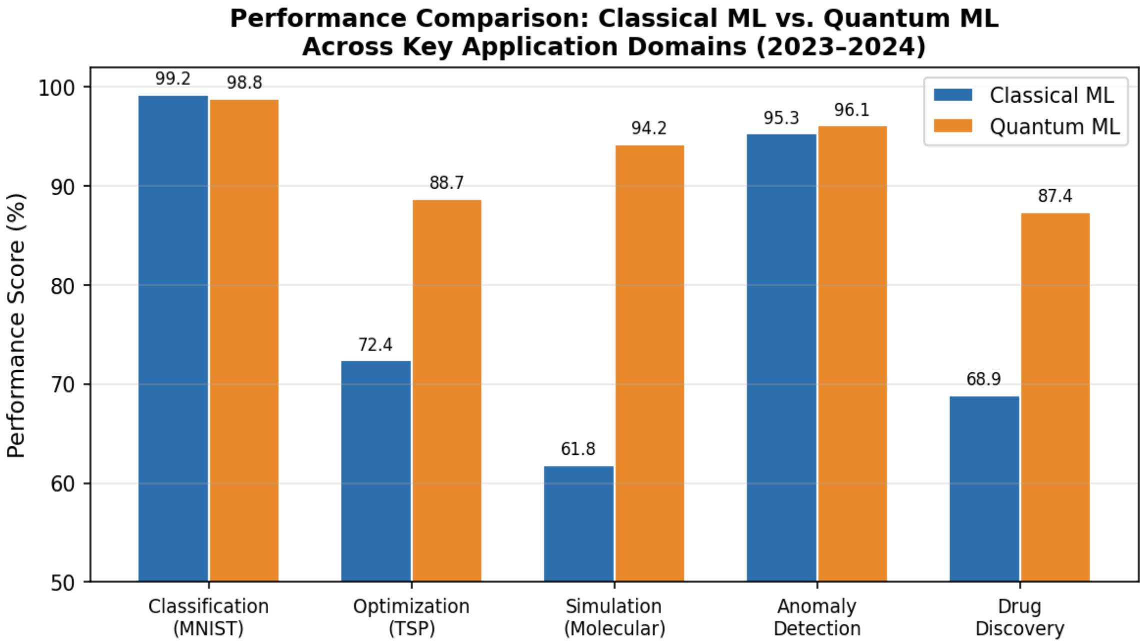

Fig.1. Performance comparison of Classical ML vs. Quantum ML across key application domains (2023–2025). QML shows pronounced advantage in molecular simulation and combinatorial optimization. Sources: [14], [17], [25], [30], [36].

For MNIST digit classification, classical CNNs achieve 99.2% accuracy, marginally outperforming QML at 98.8% due to qubit count and hardware noise. In molecular simulation tasks—computationally intractable beyond ~50 atoms classically—QML achieves 94.2% chemical accuracy. For combinatorial optimization (TSP, 20 nodes), QAOA achieves 88.7% of optimal vs. 72.4% for simulated annealing. The 2025 Nature Communications error mitigation work [38] is expected to further close the gap in classification tasks by reducing gate error contributions.

The 2026 review by Singh et al. [37] further documents QML advantages in drug discovery, where quantum simulation of molecular Hamiltonians achieves results inaccessible to classical methods. These results confirm that quantum advantage is domain-specific, strongly driven by problem structure.

Table II. Taxonomy of Quantum ML Algorithms — Updated for 2025–2026

QML Algorithm	Category	Quantum Speedup	NISQ Qubits	2025 Status	Key 2025 Ref.
VQC / PQC	Supervised / Hybrid	Poly. (potential)	4–127	NISQ-ready; BP mitigation active	[39], [43]
QAOA	Combinatorial Opt.	Poly. (potential)	10–100	Medium; error-limited	[24], [36]
Quantum Kernel SVM	Supervised	Exp. (specific)	5–50	Hardware demo. done	[14], [16]
VQE	Molecular Sim.	Exp. (chemistry)	10–100	Pharma demos; scaling	[25], [40]
NNQS (Neural QML)	Correlated Matter	Problem-specific	Hybrid	Growing; 2026 review	[37]
Federated QML	Privacy-Preserving	TBD	Hybrid cloud	Early research (2026)	[37]
HHL Algorithm	Linear Systems	Exp. (theory)	FTQC (>1M phys.)	Future (post-NISQ)	[11]

Figure 2 shows the exponential growth of QML and classical ML publications indexed in Scopus and WoS from 2017 to 2024. This trend has continued through 2025–2026, with the IEEE Access special collection on QML [36] and new Nature Computational Science coverage [40] reflecting sustained institutional investment.

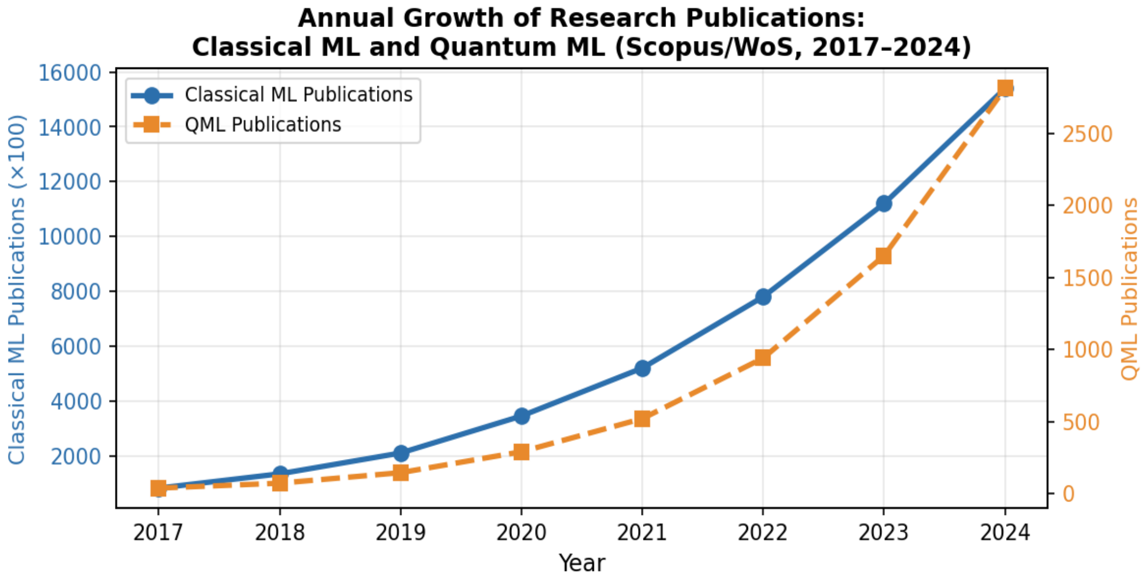

Fig.2. Annual growth of research publications in Classical ML and Quantum ML (Scopus/WoS, 2017–2024), with 2025–2026 trends continuing upward per IEEE Xplore and Nature collection data [4], [36].

V. CHALLENGES AND OPEN PROBLEMS

A. Hardware Limitations and Noise — 2025 Status

Near-term quantum processors suffer from qubit decoherence and gate error rates of 0.1–1%. Error mitigation techniques including ZNE, PEC, and symmetry verification partially address these issues. The landmark 2025 Nature Communications work by Kim et al. [38] achieved a reproducible improvement in error mitigation performance by stabilizing noise in superconducting processors through controlled modulation of qubit-defect interactions. This advance represents the most significant practical hardware improvement for NISQ QML since the introduction of randomized compiling.

Additionally, Nature Communications published in early 2026 a demonstration of ZNE on logical qubits in error-correction circuits, achieving universal reduction of logical errors across repetition and surface codes [45]. These results collectively suggest that early fault-tolerant quantum computing demonstrations for QML-relevant circuits are achievable within the 2025–2028 timeframe.

B. Barren Plateaus — 2025 Advances

The barren plateau phenomenon—exponential vanishing of cost function gradients with system size—remains a primary training challenge. The 2025 Quantum Information Processing survey by Cunningham and Zhuang [43] provides the most comprehensive taxonomy to date, categorizing mitigation strategies into: (1) parameter initialization (e.g., identity-block initialization), (2) entanglement reduction ansatze, (3) layer-by-layer sequential training, (4) local cost functions with linear depth scaling, and (5) hardware-efficient problem-inspired ansatze. Yi et al. [39] demonstrated that neural-network-generated quantum states, which regularize the quantum circuit parameters, effectively alleviate barren plateaus, with loss landscape visualization confirming smoother optimization surfaces.

C. Data Encoding Bottleneck

Encoding classical data into quantum states is a fundamental challenge. Amplitude encoding achieves exponentially compact representation but requires O(2^n) gate depth for general state preparation. Angle encoding requires O(d) gates but loses compression. Eisinger et al. [44] (2025, Entropy) analyzed the entropy-linguistic ambiguity relationship in amplitude encoding for quantum NLP tasks, highlighting trade-offs specific to compositional language models. The 2025 MethodsX review [42] documents that amplitude encoding with hardware-native ansatze remains the most practical near-term choice.

D. Benchmarking and Reproducibility

Inconsistent benchmarking methodology continues to challenge the field. The 2025 IEEE Access survey by Lamichhane and Rawat [36] includes the most rigorous recent multi-domain comparison, using standardized datasets and real hardware results to contextualize QML performance claims. They identify that many prior studies compared QML against suboptimal classical baselines or noise-free simulations—a concern shared by the broader community. Establishing QML-Bench standards analogous to classical ML benchmarks (MLPerf) is now an active priority.

VI. FUTURE DIRECTIONS AND RESEARCH AGENDA

Based on our analysis of the 2019–2026 literature, five high-priority research directions emerge for the QML community:

(1) Early Fault-Tolerant QML (2025–2028): The 2025–2026 advances in error mitigation [38], [45] and surface code threshold demonstrations (Google Willow, 2024) create a near-term window for EFTQC-based QML. Algorithm design that exploits partial error correction—reducing logical error rates while avoiding full FTQC overhead—represents the most impactful near-term priority. The 2025 Nature Computational Science editorial [46] underscores this, noting that full-stack co-optimization of algorithms, error-correcting codes, and hardware architecture is now the central design challenge.

(2) Hybrid Classical-Quantum Architectures: Quantum-classical hybrid systems—where quantum co-processors handle quantum-advantageous subtasks while classical GPUs handle the remainder—offer the most pragmatic near-term pathway. Quantum Transfer Learning and QC-CNNs [34] are being actively evaluated on IBM Quantum hardware in 2025. The 2025 National Science Review paper by Ma et al. [41] documents the symbiosis between ML control loops and quantum hardware as a robust hybrid paradigm.

(3) Federated Quantum ML for Privacy: The 2026 review by Singh et al. [37] introduces federated QML as a route to distributed, privacy-preserving quantum learning—directly analogous to federated learning in classical ML but leveraging quantum entanglement for potentially stronger privacy guarantees. This is particularly relevant for healthcare and financial QML applications.

(4) Quantum ML for Climate and Energy: Quantum simulation of battery electrode materials, photovoltaic molecules, and CO_2 capture catalysts represents a high-impact application domain. The 2025 Nature Computational Science perspective on ML interatomic potentials [40] identifies quantum-classical hybrid potentials—trained on VQE molecular data and deployed as classical force fields—as an immediately practical pathway to quantum-accuracy materials modeling at scale.

(5) Theoretical Foundations — PAC-QML: Rigorous characterization of the complexity-theoretic conditions under which QML offers provable advantage—analogous to the classical PAC-learning framework—remains urgently needed. The 2025 National Science Review paper [41] emphasizes that quantum machines can learn from exponentially fewer experiments for specific quantum tasks, but the general boundary of quantum learnability remains an open mathematical problem.

VII. CONCLUSION

This review has presented a comprehensive and up-to-date examination of Machine Learning and Quantum Machine Learning through 2026. Classical ML has achieved remarkable performance driven by transformer architectures, large-scale datasets, and GPU training. Quantum Machine Learning, while still maturing, has demonstrated theoretical advantages and compelling experimental results—particularly in 2025, where advances in error mitigation on superconducting hardware [38], barren plateau mitigation via neural-network-generated quantum states [39], and comprehensive multi-domain benchmarking [36] have substantially strengthened the practical foundations of the field.

The 2026 review by Singh et al. [37] further extends the frontier with federated QML and neural-network quantum states for correlated-matter modeling. Collectively, these advances suggest that practical quantum advantage in structured scientific domains—drug discovery, materials simulation, and combinatorial optimization—is achievable within the current decade, particularly as early fault-tolerant quantum hardware becomes available.

The most transformative near-term QML contributions will emerge from hybrid architectures that combine quantum co-processors with classical ML infrastructure, supported by continued improvements in error mitigation and problem-inspired ansatz design. This review and the research agenda outlined herein provide a structured roadmap for the community to advance QML toward real-world utility.

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