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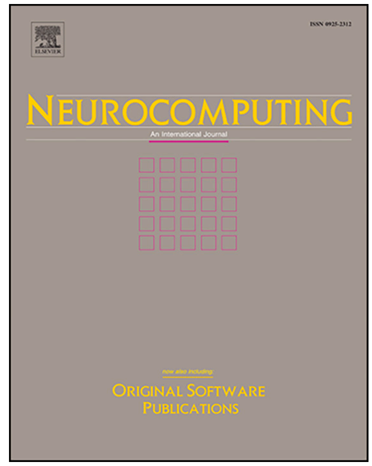

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Neuromorphic Quantum Computing: A Survey and Future Directions in Evolutionary and Gradient-Based Learning Strategies for Quantum Spiking Neural Networks

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Abstract

The convergence of quantum computing and neuromorphic engineering provides an important context for addressing the energy efficiency bottlenecks of classical deep learning and the noise constraints of Noisy Intermediate-Scale Quantum (NISQ) devices. Quantum Spiking Neural Networks (QSNNs), which integrate the biological plausibility of Spiking Neural Networks (SNNs) with the high-dimensional state space of quantum systems, have emerged as a promising paradigm for quantum-neuromorphic learning. However, the field faces significant theoretical and algorithmic challenges, primarily the "encoding mismatch" between discrete spikes and continuous quantum states, and the "double non-differentiability" arising from spiking dynamics and quantum measurements.

This paper provides a comprehensive survey of QSNNs from an algorithmic and architectural perspective. First, we establish a conceptual homology linking the integrate-and-fire mechanism of biological neurons to unitary quantum evolution and measurement-induced collapse. Second, we systemat-

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ically categorize existing quantum neuron models (e.g., measurement-driven, continuous evolution, and variational models). Third, we analyze existing training methodologies, synthesizing the divergent paths of evolutionary search and gradient-based tuning. Based on this literature synthesis, we identify a conceptual "Hybrid Co-Optimization Paradigm" as an important future research direction to mitigate the "barren plateau" problem. Finally, we review benchmarks spanning from classical imaging to emerging 2026 applications in genomics and 5G networks. Our analysis suggests an emerging shift towards hybrid architectures, indicating that bio-mimetic mechanisms (e.g., unmeasured qubit memory) may offer useful computational pathways for complex temporal tasks, although empirical quantum advantage over classical baselines remains an open challenge. We conclude by identifying critical hardware challenges, notably the "readout bottleneck," to guide future research toward hybrid neuro-quantum co-design.

Keywords: Quantum Spiking Neural Networks (QSNN), Neuromorphic Computing, Evolutionary Algorithms, Quantum Neural Architecture Search, Hybrid Learning

1. Introduction

1.1. Motivation: The Double Crisis and the Hybrid Pivot

The trajectory of modern artificial intelligence is currently constrained by two converging crises. On the classical front, deep learning faces an unsustainable "Energy Wall." As transistor scaling approaches the physical limits of Moore's Law, the energy consumption of large-scale models (e.g., LLMs) has grown exponentially, with training costs often exceeding gigawatt-hours and raising significant sustainability concerns [1, 2, 3, 4]. The von Neumann architecture, characterized by the separation of processing and memory units, imposes a significant latency and energy penalty known as the *von Neumann bottleneck*, driving the urgent need for alternative neuromorphic substrates [5, 6, 7]. This urgency has catalyzed a renaissance in classical neuromorphic hardware design, with foundational reviews highlighting the success of large-scale spiking platforms such as SpiNNaker, Intel Loihi, and the Tianjic chip [8, 9, 10, 11, 12]. Moreover, comprehensive surveys from 2024 to 2025 underscore a mature transition in the field, expanding from these foundational hardware architectures to advanced neuromorphic algorithm-hardware co-design and edge intelligence deployment [13, 14, 15].

Simultaneously, Quantum Computing (QC) has entered the Noisy Intermediate-Scale Quantum (NISQ) era [16, 17, 18]. While quantum processors promise exponential speedups via superposition and entanglement, they are plagued by short coherence times and high gate error rates. Traditional Variational Quantum Neural Networks (QNNs) require deep parameterized circuits to maintain sufficient expressivity [19, 20, 21], which invariably leads to severe signal degradation and the notorious "barren plateau" phenomenon, where gradients vanish exponentially with system size [22, 23].

In this context, recent perspectives advocate shifting from rigid quantum error correction to "engineered noise," drawing inspiration from the biological brain's ability to compute robustly in warm, noisy environments [24]. Spiking Neural Networks (SNNs)—the third generation of neural networks—offer an energy-aware computational model [25, 11]. By mimicking the brain's event-driven, sparse communication, SNNs can reduce energy consumption in suitable neuromorphic implementations. **Quantum Spiking Neural Networks (QSNNs)** emerge as a hybrid paradigm for exploring this double challenge: leveraging the high-dimensional state space of quantum mechanics to enrich the representational capacity of classical SNNs, while utilizing the event-driven sparsity and noise-aware design principles of neuromorphic computing to investigate more robust learning mechanisms under NISQ constraints, as illustrated in the convergence map in Figure 1.

Recent studies also suggest a gradual shift toward hybrid QSNN architectures. Rather than being limited to early proof-of-concept demonstrations or simple digit-classification tasks, recent work has begun to explore more specialized application settings, including genomic analysis and 5G resource allocation. In these studies, classical feature extraction, quantum kernels, and spiking or neuromorphic components are often combined to address data-scarce, noisy, or temporally structured tasks. This survey, therefore, focuses on near-term neuro-quantum co-design as a pragmatic research direction, while avoiding premature claims of quantum supremacy or general-purpose quantum advantage.

1.2. Implementation Paradigms: Digital vs. Analog

While broadly defined as integrating quantum evolution with spiking dynamics, QSNNs can be physically realized through two distinct paradigms, as categorized by Marković and Grollier [26]:

- **Digital QSNNs (Gate-Based):** Rely on discretized unitary operations ($U(\theta)$) in parametrized circuits. This approach, akin to digital

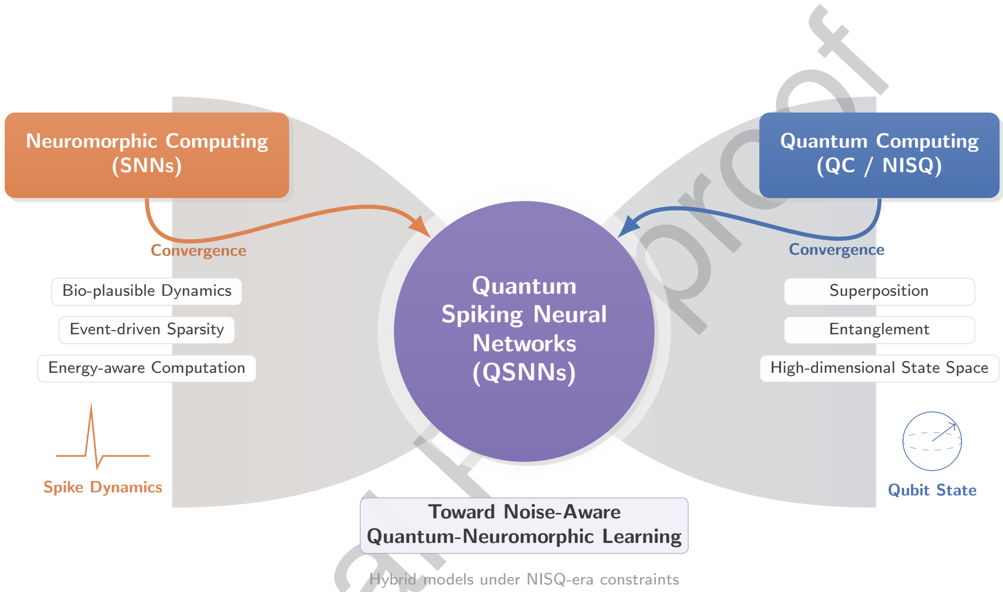

Figure 1: **Conceptual overview of Quantum Spiking Neural Networks (QSNNs).** The figure illustrates QSNNs as an emerging intersection between neuromorphic computing and NISQ-era quantum computing. The neuromorphic side emphasizes bio-plausible dynamics, event-driven sparsity, and energy-aware computation, whereas the quantum side highlights superposition, entanglement, and high-dimensional state-space representations. This convergence motivates noise-aware quantum-neuromorphic learning under current hardware and algorithmic constraints.

neuromorphic chips (e.g., TrueNorth), offers universality but requires error correction and handles information through gate sequences [26].

- **Analog QSNNs (Dynamics-Based):** Exploit the natural time-evolution of quantum Hamiltonians (e.g., quantum annealers or oscillator assemblies) to mimic neuronal integration directly. Here, the Hamiltonian $\hat{H}$ naturally maps to the recurrent connectivity of biological networks, offering a pathway to *Quantum Reservoir Computing* where dynamics are used for computation without deep gate sequences [26].

This survey primarily focuses on the Digital/Variational approach while acknowledging the physical foundations of the Analog paradigm.

1.3. Core Challenges: The Problem Statement

Despite the theoretical promise, the realization of QSNNs is hindered by two fundamental obstacles:

- **The Encoding Mismatch:** Classical SNNs rely on discrete, time-dependent spikes $s(t) \in \{0, 1\}$, whereas quantum computation operates on continuous complex probability amplitudes in Hilbert space ($|\psi\rangle \in \mathbb{C}^{2^N}$). Mapping the asynchronous, discrete nature of spikes to the synchronous, unitary evolution of quantum circuits requires novel transcoding protocols [27].
- **The Double Non-differentiability:** Optimization faces a compounded gradient problem. First, the spike generation function (Heaviside step) is non-differentiable. Second, the quantum measurement process (Born rule) induces a stochastic collapse that breaks the chain of derivatives needed for backpropagation. This paper addresses how to navigate this "derivative-free" landscape using hybrid evolutionary and surrogate gradient strategies.

1.4. Roadmap of This Survey

The remainder of this survey is structured to guide the reader from theoretical foundations to practical algorithmic implementations and future challenges.

Section 2 establishes the fundamental conceptual homology between the biological Leaky Integrate-and-Fire (LIF) mechanism and quantum unitary evolution, addressing the critical "Encoding Mismatch" problem.

Section 3 provides a systematic taxonomy of existing quantum neuron models, categorizing them into Measurement-Driven, Continuous Evolution, and Variational paradigms.

Section 4 analyzes existing learning strategies, contrasting gradient-based surrogate methods with evolutionary approaches, and highlights the fundamental trade-offs inherent in current NISQ-era optimizations.

Section 5 reviews performance benchmarks, explicitly highlighting the shift from standard image classification (e.g., MNIST) to emerging **temporal applications in genomics, fraud detection, and 5G resource allocation**.

Finally, **Section 6** identifies critical physical implementation bottlenecks, specifically the "Readout Bottleneck." Building upon our literature synthesis, this section also outlines future directions for Neuro-Quantum Co-Design, projecting a conceptual Hybrid Co-Optimization Paradigm as a theoretical blueprint for bridging discrete structural search and continuous parameter tuning, followed by the conclusion in **Section 7**.

2. Theoretical Framework

To conceptually ground the feasibility of Quantum Spiking Neural Networks (QSNNs), we must first establish a theoretical link between the dissipative dynamics of biological neurons and the unitary evolution of quantum systems. In this section, we formulate a **Conceptual Homology** that maps the membrane potential integration of a Leaky Integrate-and-Fire (LIF) neuron to the rotation of a qubit state vector.

2.1. Quantum-Classical Mapping: A Conceptual Homology

2.1.1. Classical Dynamics: The Dissipative Regime

The sub-threshold behavior of a biological neuron is standardly modeled by the Leaky Integrate-and-Fire (LIF) formalism. The evolution of the membrane potential $u(t)$ is governed by the first-order linear differential equation:

$$\tau_m \frac{du(t)}{dt} = -(u(t) - u_{rest}) + RI(t) \tag{1}$$

where τ_m is the membrane time constant, u_{rest} is the resting potential, and $I(t)$ is the synaptic input current. For numerical implementation on discrete neuromorphic hardware, this equation is solved via the Euler method. Letting Δt be the simulation time step and assuming $u_{rest} = 0$ for simplicity, the discrete update rule is derived as:

$$u[t] = \underbrace{\left(1 - \frac{\Delta t}{\tau_m}\right)}_{\alpha} u[t-1] + \underbrace{\frac{R\Delta t}{\tau_m} I[t]}_{x[t]} \tag{2}$$

Here, $\alpha \in (0, 1)$ represents the leakage decay factor, and $x[t]$ denotes the integrated input current at step t. The neuron essentially functions as a recursive accumulator with a forgetting mechanism.

2.1.2. Quantum Dynamics: The Unitary Regime

In the quantum domain, the evolution of a coherent state vector $|\psi(t)\rangle$ is governed by the time-dependent Schrödinger equation [28]:

$$i\hbar \frac{\partial}{\partial t}|\psi(t)\rangle = \hat{H}(t)|\psi(t)\rangle \tag{3}$$

where $\hat{H}(t)$ is the Hamiltonian operator encoding the system's energy. The formal solution for a discrete time interval Δt (assuming a time-independent Hamiltonian $\hat{H}$ over the step) is described by the unitary evolution operator $U(\Delta t)$:

$$|\psi(t)\rangle = e^{-i\frac{\hat{H}\Delta t}{\hbar}}|\psi(t-1)\rangle \tag{4}$$

2.1.3. Establishing the Conceptual Homology

The core theoretical challenge lies in mapping the linear, non-unitary integration of Eq. (2) to the unitary rotation of a qubit. We propose an **Angle-Encoding Homology**, as conceptually illustrated in Figure 2. Consider a single qubit state parametrized by polar angles (ϑ, φ) on the Bloch sphere:

$$|\psi(t)\rangle = \cos\left(\frac{\vartheta(t)}{2}\right)|0\rangle + e^{i\varphi}\sin\left(\frac{\vartheta(t)}{2}\right)|1\rangle \tag{5}$$

We define the mapping $\vartheta(t) \propto u(t)$, identifying the membrane potential with the rotation angle of the qubit (distinct from trainable circuit parameters θ). Let the input data $x[t]$ be encoded into the Hamiltonian via a Pauli-Y rotation generator, such that $\frac{\hat{H}\Delta t}{\hbar} = \frac{x[t]}{2}\hat{\sigma}_y$. The unitary operator then becomes a rotation gate $R_y(x[t])$. Applying this to the state at time $t-1$:

$$|\psi(t)\rangle = R_y(x[t])|\psi(t-1)\rangle \implies \vartheta(t) = \vartheta(t-1) + x[t] \tag{6}$$

Comparing Eq. (6) with the classical Eq. (2), we identify the structural correspondence and the divergence:

- **Integration Term (Homology):** The accumulation of the rotation angle ϑ in the quantum domain ($\vartheta(t) = \vartheta(t-1)+x[t]$) is mathematically homologous to the integration of input current in the classical domain.

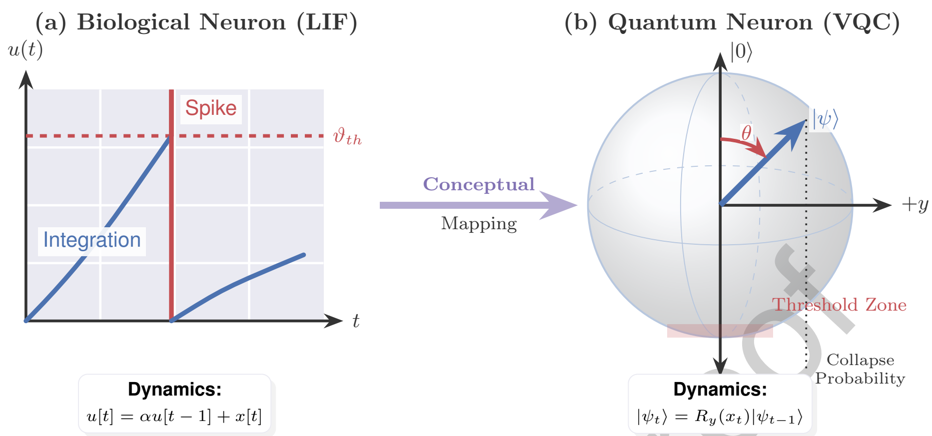

Figure 2: **Conceptual Homology between Biological and Quantum Neurons. (a)** Biological LIF Neuron dynamics, where information is encoded in the membrane potential $u(t)$ (blue curve). The neuron integrates input current until crossing the threshold ϑ_{th}, triggering a spike (red). **(b)** Quantum VQC Neuron dynamics, where information is encoded in the rotation angle ϑ of the qubit state $|\psi\rangle$ on the Bloch Sphere. The unitary operator $R_y(x_t)$ accumulates input data into the phase. The "Spike" corresponds to a projective measurement collapsing the state to $|1\rangle$ with probability $P(1) = \sin^2(\vartheta/2)$.

- **Leakage Term (The Mismatch):** The classical decay factor $\alpha < 1$ inherently violates the unitarity condition ($U^\dagger U = I$), as quantum operations must preserve the norm (energy conservation).

To address this "Dissipation-Unitary Gap," modern QSNN architectures typically adopt a **Learned Re-uploading** strategy, where the parameters of the Variational Quantum Circuit (VQC) are trained to approximate the decay dynamics through non-linear feature mapping layers. Alternatively, theoretical frameworks based on open quantum systems propose utilizing controlled dissipation and environment interactions not as errors, but as computational resources for implementing non-linear activation and forgetting mechanisms [24]. Thus, the quantum neuron can be characterized here as a **Unitary Integrator with Measurement-Induced Non-linearity**, providing a conceptual basis for investigating how classical accumulators may be represented through quantum Hilbert space evolution.

2.1.4. Limitations of the Mapping: Stochasticity vs. Measurement Collapse

While the angle-encoding homology provides a useful intuitive bridge, it is crucial to emphasize that this mapping is a **conceptual analogy rather than a rigorous mathematical isomorphism**. The transition from classical membrane potential to quantum probability amplitude entails fundamental physical divergences that limit direct equivalence:

- **Nature of Stochasticity:** In a biological LIF neuron, firing is generally deterministic upon reaching the threshold ϑ_{th}, though biological noise (e.g., ion channel fluctuations) can introduce stochasticity. Conversely, the "spike" in a quantum neuron is governed by Born's rule. A measurement collapses the state $|\psi\rangle$ to $|1\rangle$ with probability $P(1) = \sin^2(\vartheta/2)$. This stochasticity is not noise, but an intrinsic, unavoidable feature of quantum mechanics.
- **The Reset Mechanism and State Destruction:** A biological neuron resets its potential ($u(t^+) = u_{rest}$) after spiking, but the physical substrate (the cell) remains intact to continue integrating input. In contrast, a projective quantum measurement is fundamentally destructive. Once measured, the superposition is irreversibly collapsed. To evaluate temporal inputs continuously, the quantum state must either be repeatedly re-prepared (incurring substantial overhead) or necessitate advanced non-destructive measurement techniques (such as utilizing ancilla qubits), which adds hardware and control complexity.

Consequently, formalizing a strict isomorphism remains an open theoretical problem. Current variational models address this limitation by utilizing the homology purely as an architectural inspiration rather than a strict physical translation.

2.2. Encoding Strategies: Bridging the Discrete-Continuous Gap

The efficacy of a QSNN is heavily dependent on how classical temporal data is mapped onto the quantum state. As highlighted in foundational QML reviews, the process of uploading classical data into the quantum Hilbert space remains a critical bottleneck that dictates the overall computational advantage [29]. Drawing from the framework established by Marković and Grollier [26], we categorize encoding strategies based on their physical realization and information density.

2.2.1. Rate Encoding (Qubit-Based)

In rate encoding, the firing rate r of a presynaptic neuron is mapped to the rotation angle (probability amplitude) of a single qubit. This corresponds to the **"Qubit Encoding"** paradigm in quantum literature [26, 30]. For a normalized input $x \in [0, 1]$, the qubit is prepared in the state:

$$|\psi\rangle = \sqrt{1-x}|0\rangle + \sqrt{x}|1\rangle \tag{7}$$

A measurement in the computational basis yields $|1\rangle$ (a "spike") with probability $P(1) = x$. While robust, this method requires multiple "shots" (repeated measurements) to estimate the rate, incurring high latency on NISQ devices.

2.2.2. Temporal Encoding (Phase-Based)

To exploit the temporal dynamics of SNNs, phase encoding (or Time-to-First-Spike, TTFS) maps the arrival time of a spike t_s to the relative phase ϕ of a qubit. Through a phase-shift gate $R_z(\phi)$, information is stored in the superposition:

$$|\psi\rangle = \frac{1}{\sqrt{2}}(|0\rangle + e^{i\phi(t_s)}|1\rangle) \tag{8}$$

This approach is more information-dense and bio-plausible. In the classical neuromorphic domain, strict temporal coding has demonstrated extreme energy efficiency, achieving high-accuracy image classification with as few as two spikes per neuron [31]. Translating this sparse temporal efficiency into the quantum regime allows the network to compute with complex numbers, but it requires precise control over quantum coherence times.

2.2.3. Theoretical Trade-offs: Capacity vs. Expressivity

Integrating the analysis from Marković and Grollier [26], we compare the scalability of these approaches:

- **High-Capacity Amplitude Encoding:** One could theoretically map a vector $\mathbf{x}$ of size 2^N into the amplitudes of N entangled qubits ($\sum x_i|i\rangle$). While offering exponential storage capacity, Marković et al. note that this method suffers from two critical bottlenecks for neuromorphic computing: (1) state preparation depth scales exponentially, and (2) unitary evolutions are strictly linear, making it difficult to introduce the non-linearity required for neural activation without complex measurement schemes [26].

- **Expressive Qubit/Product Encoding:** Conversely, the Rate Encoding described in Sec. 2.2.1 (mapping inputs to individual qubit rotations) is less memory-dense but computationally superior. The tensor product structure of the state space naturally generates an exponential number of non-linear basis functions [26]. This property is crucial for Variational Quantum Neurons, as it allows the network to approximate complex functions with shallower circuits compared to pure amplitude encoding.

3. Taxonomy of Quantum Neuron Models

The design space of quantum neurons is vast. While broader surveys on Quantum Machine Learning (QML) have extensively mapped the landscape of classical-quantum hybrid optimization and theoretical scaling limits (e.g., Biamonte et al. [27], Cerezo et al. [32]), the specific intersection of QML with asynchronous, event-driven spiking dynamics requires a dedicated architectural analysis. Based on how non-linearity—the essential ingredient for neural computation—is introduced into the linear framework of quantum mechanics [33, 34], we categorize existing literature into three distinct streams (see Table 1).

3.1. Measurement-Driven Models

Pioneered by Tacchino et al. [35], this class of models mimics the biological threshold mechanism directly via the **measurement collapse postulate**. In this framework, the perceptron's integration is unitary, but the activation is triggered by a projective measurement. If the qubit is measured in state $|1\rangle$, a spike is propagated; otherwise, the system is reset.

- *Pros:* This directly emulates the stochastic nature of biological ion channels and is relatively easy to implement on hardware.
- *Cons:* Measurement is destructive. It destroys the quantum superposition (coherence), preventing information from propagating deep into a multi-layer network without complex re-encoding schemes.

3.2. Continuous Evolution and Continuous-Variable (CV) Models

Approaches like those based on **Quantum Random Walks** or Hamiltonian simulation attempt to keep the dynamics entirely unitary, where information propagates as a wave packet on a graph [38].

Table 1: **Taxonomy and Comparison of Representative Quantum Neuron Models.** We categorize existing models into three streams: Measurement-Driven (discrete collapse), Continuous Evolution (Hamiltonian dynamics), and Variational (VQC-based). Abbreviations: Amp. (Amplitude), Rot. (Rotation), NISQ (Noisy Intermediate-Scale Quantum).

Model Category	Representative Work	Encoding Strategy	Non-linearity Source	Key Pros	Key Cons
Measurement-Driven	Tacchino et al. (2019) [35]	Basis Encoding	Projective Measurement	Bio-plausible	Destroys Coherence
	Kristensen et al. (2021) [36]	Angle Encoding	Reset/Dissipation	Natural Dynamics	Complex Control
Continuous Evolution	Killoran et al. (2019) [37]	CV Displacement	Kerr Non-linearity	Photonic Bandwidth	Non-Gaussian Gate Scaling
	Dernbach et al. (2019) [38]	Graph State	Quantum Walk	Temporal Dynamics	Deep Circuits
Reservoir / Analog	Marković et al. (2020) [26]	Hamiltonian Dyn.	Readout Only	No Quantum Training	Input Embedding Cost
	Fujii & Nakajima (2017) [39]	Ensemble Injection	Unitary Dynamics	Hardware Friendly	State Prep. Cost
Variational (Our Focus)	Schuld et al. (2021) [40]	Re-uploading	Serial Encoding	**Theory Strong**	Deep Depth
	Zhang et al. (2022) [41]	Hybrid	Architecture Search	**Automated**	High Training Cost

A prominent, highly scalable extension of this paradigm is the **Continuous-Variable Quantum Neural Network (CV-QNN)**. Pioneered by Killoran et al. [37], CV-QNNs operate on the continuous phase space of quantum modes (qumodes) rather than discrete two-state qubits. By utilizing **photonic quantum computing architectures**—specifically Gaussian operations (e.g., squeezing, displacement) intermixed with non-Gaussian gates (e.g., the Kerr effect)—CV-QNNs physically realize the non-linear activation functions necessary for deep learning natively within the optical substrate.

- *Pros:* CV-QNNs and analog photonic neuromorphic systems naturally support high-bandwidth information processing and can intrinsically implement complex non-linearities without the destructive measurement collapse required in gate-based qubit models.
- *Cons:* Physical implementation heavily relies on advanced optical setups, and executing highly deterministic non-Gaussian gates with high fidelity remains a significant hardware challenge for scaling.

3.3. Quantum Reservoir Models and Analog Neuromorphic Systems

A related direction in neuromorphic and quantum learning literature is **Quantum Reservoir Computing (QRC)**, originally introduced by Fujii and Nakajima [39]. QRC provides an analog and dynamical alternative to fully gate-based variational quantum models. Instead of optimizing many internal circuit parameters, QRC exploits the transient dynamics of a quantum system as a fixed or weakly tunable reservoir, while learning is usually concentrated in a classical readout layer. In this setting, temporal inputs are mapped into a high-dimensional quantum state space, where the resulting reservoir states may provide useful features for downstream prediction or classification tasks.

- *Mechanism:* The quantum substrate evolves under a fixed or externally driven Hamiltonian $\hat{H}$. Representative implementations and proposals include nuclear magnetic resonance (NMR) spin ensembles [39], dynamically driven superconducting resonators [26], and quantum dot arrays [42, 43]. Related analog and physical-computing approaches have also been explored in photonic and Ising-machine-based systems, including Coherent Ising Machines (CIMs) for sampling and training spiking-based Deep Belief Networks [44]. Because the internal dynamics are mainly determined by the physical substrate, QRC can reduce the need for deep parameterized quantum circuits and repeated gradient-based

optimization. This makes it a potentially relevant model class under NISQ-era constraints, although the actual advantage depends on hardware noise, input encoding, measurement cost, and task-specific benchmarking.
- *Relevance to SNNs:* QRC is conceptually close to recurrent spiking systems, liquid-state machines, and reservoir-based neuromorphic models. These systems all rely on rich internal dynamics, fading memory, and nonlinear temporal responses to encode time-dependent signals. For QSNNs, QRC therefore suggests a possible route for processing spike trains, event streams, and other temporal data without requiring all internal quantum dynamics to be directly trained. However, current QRC-based approaches remain limited by noise sensitivity, input–output overhead, hardware-specific reservoir dynamics, and the lack of standardized benchmarks against classical reservoirs, SNNs, and variational quantum baselines.

3.4. Variational Models (The Focus of This Work)

The third and most promising category utilizes **Variational Quantum Circuits (VQCs)** or Parameterized Quantum Circuits (PQCs) to approximate neuronal behavior. Here, the "synaptic weights" are the rotation angles θ of quantum gates (e.g., $R_x(\theta), CNOT$).

- *Mechanism:* The non-linearity is often induced effectively by "data re-uploading" strategies or by measuring only a subset of qubits (ancilla) while keeping the data qubits coherent.
- *Relevance:* This model is particularly amenable to hybrid training. As we will discuss in Section 4, VQC-based neurons provide a differentiable (via parameter shift) substrate that supports both evolutionary search for topology (EQNAS) and gradient descent for parameter tuning.

4. Learning Algorithms and Optimization Strategies

4.1. Gradient-Based Adaptation: Overcoming the Non-Differentiability Constraint

The fundamental optimization challenge in training Spiking Neural Networks (SNNs)—both classical and quantum—stems from the intrinsic non-differentiability of the spike generation mechanism. As extensively characterized in recent reviews of neuromorphic hardware and direct-learning methodologies [45, 46], the Leaky Integrate-and-Fire (LIF) model accumulates membrane potential $U(t)$ continuously, yet the output firing is a discrete binary event triggered only when $U(t)$ crosses a threshold ϑ [45]. Formally, this activation is governed by the Heaviside step function:

$$S_{out}(t) = H(U(t) - \vartheta) \tag{9}$$

Since the derivative of the Heaviside function is the Dirac Delta function $\delta(x)$, the gradient $\nabla_\theta \mathcal{L}$ vanishes almost everywhere during backpropagation, resulting in the notorious "dead neuron" problem that inhibits parameter updates in deep architectures [47]. In the classical neuromorphic domain, this fundamental non-differentiability has inspired a wealth of foundational research into Surrogate Gradient (SG) methodologies and approximate backpropagation techniques [48, 49, 13, 50, 51]. The quantum adaptation of these principles forms the basis of modern QSNN training.

To circumvent this blockage in the quantum domain, Andrés et al. (2025) proposed the *Quantum Leaky Integrate-and-Fire* (QLIF) model, which reformulates the integration process by replacing classical tensor operations with a parameterized Variational Quantum Circuit (VQC) [52]. Crucially, to enable the optimization of quantum rotation parameters via classical gradient descent, they adopt a **surrogate gradient** approach. *This methodology effectively decouples the forward inference dynamics from the backward learning dynamics:* while the forward pass retains the precise, binary spiking behavior essential for neuromorphic efficiency, the backward pass navigates a smoothed optimization landscape by substituting the non-differentiable Heaviside derivative with a continuous proxy (e.g., arctangent). This ensures that error signals can successfully propagate through the discrete quantum measurement outcomes to update the VQC ansatz [53]. Building on this hybrid trajectory, recent frameworks by Saggi et al. [54] have demonstrated that directly integrating biological LIF spiking mechanisms with variational quantum circuits can significantly enhance feature representation for complex multiclass classification tasks, further solidifying the empirical viability of VQC-SNN co-design.

4.2. Evolutionary Quantum Architecture Search (EQNAS): From Parameters to Topology

While surrogate gradients facilitate parameter optimization within a fixed ansatz, they do not address the critical challenge of topology discovery—specifically, identifying the optimal quantum gate arrangement to maximize expressivity while minimizing circuit depth. To address the limitations of manual ansatz design, Li et al. (2023) introduced *Evolutionary Quantum Neural Architecture Search* (EQNAS), treating the circuit structure as a dynamic, evolving entity [55, 56].

Central to this approach is the novel concept of the "Quantum Chromosome," where the genetic information of the network architecture is encoded not in classical bits, but in qubits. This methodology resonates with the foundational "quantum computational neuro-genetic" framework proposed by Kasabov [57], who early on envisioned the integration of genetic information processing principles with quantum probabilities to model complex biological systems. In this framework, a single gene representing a quantum gate is maintained in a superposition state:

$$|\psi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{10}$$

Consequently, a single quantum chromosome of length N implicitly encodes a probability distribution over the entire search space of 2^N architectures. Unlike classical evolutionary algorithms that must maintain a large population of discrete instances, this approach leverages **quantum implicit parallelism** to represent the entire population within a single quantum state, allowing for a highly efficient exploration of the combinatorial landscape through probability amplitude manipulation.

The optimization mechanism in EQNAS fundamentally departs from backpropagation. Instead of computing error gradients, the algorithm iteratively updates the probability amplitudes of quantum genes using *Quantum Rotation Gates*. By applying a rotation $U(\Delta\theta)$ conditioned on the fitness of collapsed architectures, the system steers the superposition towards high-performance configurations, effectively bypassing the differentiability constraints [58]. Furthermore, to mitigate premature convergence, Li et al. incorporated an "Entirety Interference Crossover" strategy. This mechanism exploits quantum coherence to enable global information exchange, demonstrating superior robustness against the noise inherent in NISQ devices compared to gradient-based counterparts.

As evidenced by the dichotomy between gradient-based adaptation (Section 4.1) and evolutionary search (Section 4.2), neither approach is universally optimal for NISQ devices. Pure gradient methods suffer from barren plateaus in random deep circuits, while pure evolutionary methods incur exponential computational costs. Indeed, the expressivity and trainability of deep parameterized quantum circuits have been extensively documented as a central bottleneck in modern QML, prompting a vast body of literature dedicated to understanding and mitigating exponential gradient decay [22, 59, 60, 61, 23]. This fundamental trade-off necessitates a transition towards hybrid optimization strategies, which we will explore theoretically as a primary future research direction in Section 6.

5. Applications and Benchmarks

Before analyzing the empirical landscape, we must explicitly establish the limitations of cross-study comparisons. The performance metrics summarized in the subsequent benchmarks (Table 2 and Table 3) are aggregated to illustrate macro-trends in architectural evolution, **not to imply direct algorithmic superiority**. Meaningful side-by-side comparisons are currently confounded by two primary inconsistencies in the literature:

1. **Preprocessing Discrepancies:** Methods like PCA dimensionality reduction or heavy down-sampling drastically simplify the learning task before the data ever reaches the quantum circuit. A model achieving 95% on heavily preprocessed MNIST cannot be directly compared to one processing raw pixels.
2. **Simulation vs. Hardware Reality:** The vast majority of reported "state-of-the-art" results assume ideal, noise-free simulators. As explicitly highlighted in Konar et al. [62], moving from simulation to physical NISQ hardware can result in an accuracy degradation of over 30% due to gate infidelities and readout errors.

Consequently, the following empirical results should be interpreted strictly as theoretical capability demonstrations rather than standardized leaderboard metrics.

5.1. Image Classification: Breaking the Dimensionality Curse

Image classification remains the standard "sanity check" for validating quantum neuromorphic architectures. However, mapping high-dimensional classical data (e.g., 28×28 MNIST pixels) onto the limited qubit space of NISQ devices presents a severe bottleneck.

Early works, such as the measurement-driven models by Tacchino et al. [35], utilized aggressive down-sampling techniques (e.g., resizing to 4×4) to fit images onto 2-4 qubits. While demonstrating biological plausibility, these approaches suffered from significant information loss.

Table 2: **Comprehensive Benchmark of Quantum Neuromorphic Architectures (2019–2025).** This table aggregates 13 key studies, highlighting the shift from simple measurement-driven models to complex hybrid architectures. **Note:** Direct quantitative comparisons across rows are limited due to significant variations in classical preprocessing, encoding methodologies, and the pervasive gap between idealized simulations and physical NISQ hardware (as discussed in Section 5).

Reference	Year	Paradigm	Dataset	Input Preproc. (Raw → Encoded)	Qubits	Encoding	Accuracy (Sim / HW)
				Phase I: Early Exploration & Measurement-Driven (2019–2021)			
Tacchino [35]	2019	Measure-Driven	MNIST	$28 \times 28 \rightarrow 4 \times 4$	2	Rate	86.0% / ∼70%
Ajayan [63]	2021	Hybrid SNN-QC	CIFAR-10	$32 \times 32 \rightarrow 784$ (Gray)	1	Angle (R_y)	88.6% / -
				Phase II: Systematic Optimization & Architecture Search (2022–2023)			
Chen [64]	2022	QSNN-QUIP	MNIST (2-class)	$28 \times 28 \rightarrow 14 \times 14 \rightarrow 25$ feats	∼21	Block Temporal	∼99.9% / -
Zhang [41]	2022	Diff. NAS	MNIST	$28 \times 28 \rightarrow 16$ feats (PCA)	8	Angle	91.1% / -
Konar [62]	2023	Surrogate Grad	CIFAR-10	**32x32 (Full Res.)**	∼5	Amplitude	**98.2%** / 59.9%
Li [55]	2023	Evolutionary	CIFAR-10	Downsampled to 4×4	5-10	Angle	58.6% / -
				Phase III: Hybrid Architectures & Specialized Tasks (2024–2025)			
Brand [65]	2024	QSNN (QLIF)	MNIST	$28 \times 28 \rightarrow 784$ (Spikes)	1/neuron	Rotation (R_x)	88.2% / -
Pandey [66]	**2025**	**Hybrid QAttn**	**Skin Cancer**	**Hybrid** (32^2 **Q** / 150^2 **C**)	**18**	**NEQR**	**91.0%** / -
Sharma [67]	2025	Hybrid QSNN	PCOS (Medical)	$224 \times 224 \rightarrow$ Tensor	-	Implicit	99.5% / -
Islam [68]	2025	Hybrid CNN+PQC	OASIS-2 (MRI)	$128 \times 128 \rightarrow$ 2-3 feats	2-3	ZZFeatureMap	97.5% / -
Nhan [69]	2025	Spiking Hybrid	F-MNIST	Image → SNN Feats	18	Re-uploading	82.2% / -
Muniasamy [70]	2025	Hybrid Q-Conv	Brain Tumor	$512 \times 512 \rightarrow 64 \times 64$	4	Angle (Scan)	88.0% / -
Niu [71]	2025	Hybrid Q-Filter	Pavement	$640 \times 640 \rightarrow 64 \times 64$	16	Angle/Amp	77.9% / -

* **Trend Analysis:** The table reveals a clear transition from simplistic down-sampling (2019) to sophisticated hybrid encoding (2025) like NEQR and Feature Mapping.

1 Note the "Simulation-Hardware Gap" explicitly quantified in Konar et al. (98% vs 60%), highlighting the NISQ noise barrier.

Table 3: **Benchmarks on Temporal and Dynamic Tasks (2024–2026).** These studies report potential advantages of hybrid QSNN-related architectures in temporal and dynamic tasks such as genomics and 5G resource allocation. Note the shift towards bio-mimetic memory architectures.

Reference	**Year**	**Task & Dataset**	**Memory & Encoding**	**Key Innovation / Advantage**
Andres [72]	2024	RL for Energy Eff.	**Mem:** Dual-Stage (Hypothalamus) **Enc:** Amp. (QSNN) + Angle (QLSTM)	**Continual Learning:** Mitigates catastrophic forgetting via bio-inspired consolidation.
Chen [73]	2025	DVS Event Streams	**Mem:** Unmeasured Qubits (Native) **Enc:** Rotation Angle $R_x(\phi)$	**Hardware Efficiency:** Single-shot stochastic spiking without destroying state.
Andres [52]	2025	Fraud Detection	**Mem:** Hybrid QSNN-QLSTM **Enc:** Spike Encoding	**Robustness:** $> 99\%$ F1-Score with minimal data; robust to noise.
Abdullayev [74]	2025	Genomics (Splice)	**Mem:** QLSTM + Voxel Modules **Enc:** Nucleotide Vectors	**Speedup:** Quantum-inspired backprop updates weights 30% faster.
Dhanasree [75]	**2026**	**5G Resource Alloc.**	**Mem:** Hierarchical Edge Comp. **Enc:** Positional Encoding	**Real-Time:** 0.08s reported latency via edge-cloud collaboration; potential relevance to telecom scenarios.

The Evolution of Encoding Strategies

Recent advances have mitigated the information loss problem via increasingly sophisticated embedding strategies, marking an "Encoding Upgrade" from simple rate coding to dense representations:

- **Amplitude Encoding (High Compression):** As demonstrated by Konar et al. [62], this method compresses N features into $\log_2 N$ qubits, allowing processing of full-resolution inputs (32×32). While efficient, it requires deep state-preparation circuits that are prone to noise, leading to a performance gap between simulation and hardware (see Table 2).
- **Hybrid Scanning (Spatial Locality):** Approaches like Quantum CNNs (QCNN) use a small quantum kernel to scan images in a sliding-window fashion. This avoids the need for hundreds of qubits while preserving local spatial correlations [76, 77].
- **Novel Enhanced Quantum Representation (NEQR):** As a representative 2025 hybrid encoding approach, Pandey et al. [66] employ NEQR to encode position and intensity information simultaneously. This provides a more expressive alternative to early down-sampling methods, enabling the handling of complex textures in medical imaging.

The 2025 Hybrid Shift: From Generic Benchmarks to Specialized Hybrids

A critical analysis of the literature from 2024 to 2025 (summarized in Table 2) suggests an emerging shift in the field, characterized by three emerging trends:

1. **From General to Specialized Domains:** While the 2019–2023 era focused heavily on generic datasets like MNIST and CIFAR, recent studies have explored applications in high-stakes, data-scarce domains. Notable examples include Skin Cancer detection [66], Brain Tumor classification [70], and Pavement Distress identification [71]. This trajectory directly parallels the evolution of classical SNNs, which are increasingly being deployed in noise-intensive, real-time industrial applications such as fault diagnosis [78]. This shift indicates that QSNNs are moving beyond academic toy problems to find their niche in **"High-Value, Low-Sample"** scenarios where quantum kernels may offer better generalization than classical deep learning.
2. **The Increasing Use of Hybrid Architectures:** Pure end-to-end quantum models are increasingly giving way to **hybrid architectures**

(e.g., Classical Feature Extractor + Quantum Core). As hardware noise remains a constraint, recent works [66, 68] demonstrate that delegating high-dimensional feature extraction to classical CNNs and reserving the quantum circuit for the high-complexity classification kernel may offer a practical balance between performance and feasibility.

3. **Evolutionary Co-Design:** To navigate this complex design space, Evolutionary strategies (EQNAS) [55] have become increasingly relevant. By automatically discovering circuits that balance the trade-off between gate count (noise depth) and accuracy, evolutionary approaches are pushing benchmarks from $\sim 80\%$ (fixed ansatz) to over 90% (evolved ansatz), bridging the gap between theoretical potential and NISQ reality.

5.2. Temporal Data Processing: Beyond Static Images

While image classification focuses on spatial features, an important motivation of Spiking Neural Networks lies in processing temporal data. In classical deep learning, Recurrent Neural Networks (RNNs) and LSTMs are the standard for sequential data, but often struggle with high computational costs and the "vanishing gradient" problem over long sequences.

QSNNs introduce a novel paradigm via **Quantum Recurrence**. As detailed in **Table 3**, recent studies (2024–2026) have moved beyond theoretical speculation to report encouraging results in complex dynamic tasks by leveraging bio-mimetic mechanisms.

Mechanisms of Temporal Processing: Intrinsic Phase & Memory

Unlike classical neurons that require explicit feedback loops to store history, a qubit's state naturally evolves in time. The accumulated rotation angle $\vartheta(t)$ in a VQC serves as an intrinsic memory buffer.

- **Native Quantum Memory:** Chen et al. (2025) [73] extend this mechanism by introducing **unmeasured memory qubits**. By keeping a subset of qubits coherent (unmeasured) across time steps, their QRNN architecture achieves *single-shot stochastic spiking*. This innovation not only preserves quantum information but also enables hardware-friendly local learning algorithms, partly addressing the destructive nature of standard projective measurements.
- **Bio-mimetic Consolidation (QSNN-QLSTM):** Building upon classical architectural efforts to integrate Long Short-Term Memory (LSTM)

into spike-based hardware for extended temporal dependencies [79], Andres et al. (2025) [52] propose a dual-stage "Hypothalamus-Hippocampus" quantum architecture. This hybrid model assigns short-term sensory processing to a fast-reacting QSNN (simulating the Hypothalamus) and long-term consolidation to a QLSTM (simulating the Hippocampus). In credit card fraud detection tasks, this bio-inspired synergy combined the event-driven noise immunity of SNNs with the long-term dependency capture of LSTMs, achieving a $> 99\%$ **F1-score** with minimal training data.

Real-Time Applications: From Genomics to 5G

The application scope has begun to extend beyond simple benchmarks. Abdullayev (2025) [74] reports that quantum-inspired architectures can support genomic sequence processing tasks, such as Gene Splice Junction analysis, with 30% faster weight updates than classical counterparts in their experimental setting. Furthermore, Dhanasree et al. [75] report a Hierarchical Quantum Edge Computing framework for 5G resource allocation, with a reported latency of 0.08s. These results suggest potential relevance to selected real-time edge scenarios, although broader deployment still requires further validation under realistic hardware and workload constraints.

6. Challenges and Future Perspectives

Despite the algorithmic advancements discussed in this survey, deploying QSNNs on physical hardware remains a formidable challenge. Drawing from Marković and Grollier's framework [26], we highlight the critical bottlenecks and emerging architectural shifts.

6.1. The Quantum-to-Classical I/O Bottleneck

The most significant disparity between theory and practice lies in the interface between classical data and quantum states. As identified in recent surveys [26], this "Quantum-to-Classical bottleneck" manifests in three distinct dimensions:

- **Input Latency (The Encoding Cost):** Encoding classical analog data (e.g., pixel intensities) into quantum states requires deep encoder circuits or specialized Quantum Random Access Memory (QRAM) [80, 81, 82, 83]. As frequently cautioned in the literature, the depth of these state preparation circuits often scales exponentially with the data size, potentially negating any theoretical computational speedup gained in the subsequent processing stage [26, 84, 27].

- **Destructive Measurement Dynamics:** In biological neurons, membrane potential is monitored continuously. In quantum systems, detecting if a "quantum neuron" has spiked requires a projective measurement. If the result is $|0\rangle$ (no spike), the superposition is irrevocably destroyed, forcing a system reset. This discontinuity hinders the continuous integration dynamics required for true temporal processing.
- **Sampling and Reconstruction Overhead:** Extracting a reliable classical decision involves estimating expectation values or performing Quantum State Tomography, which suffers from severe scaling bottlenecks [84, 85]. Recovering the full probability distribution requires an exponential number of measurements relative to system size, although recent advances like Classical Shadows offer partial mitigation [26, 86, 85]. Combined with the $O(1/\epsilon^2)$ shot noise scaling, this readout step often introduces a latency bottleneck entirely absent in classical neuromorphic chips.

To confront these NISQ-era hardware limitations, parallel research tracks in Quantum Error Mitigation (QEM) and classical shadow tomography have provided essential, albeit resource-intensive, complementary strategies for improving readout fidelities [18, 87, 88, 85].

6.2. Future Directions: Neuromorphic Quantum Co-Design and Hybrid Optimization

To address these I/O limitations and noise constraints, we identify several key paradigms:

- **Pulse-Level Control:** Instead of abstract logic gates (CNOT, R_x), future QSNNs may operate directly at the analog pulse level [89]. By optimizing microwave pulses, evolutionary algorithms can better align with the native physics of the quantum processor, reducing some overhead associated with gate decomposition inefficiencies.
- **Hybrid Neuro-Quantum Processors (N-QPU):** A potential architecture involves a classical SNN serving as a sparse controller, routing information to small, highly entangled quantum kernels (QPUs) only for computationally intensive tasks. This may reduce measurement frequency while preserving useful expressivity.

- **Quantum Data Learning:** To alleviate the I/O bottleneck, future research may further investigate implicit learning paradigms or "Quantum Data Learning," where inputs are inherently quantum states (e.g., from quantum sensors) [26]. This approach may reduce costly encoding and reconstruction steps, offering a possible route for reducing data-loading overhead in quantum-neuromorphic systems.

6.2.1. A Conceptual Outlook: The Hybrid Co-Optimization Paradigm

Beyond hardware co-design, our synthesis of current learning algorithms (Section 4) motivates the Hybrid Co-Optimization Paradigm as an important trajectory for future algorithmic research. The field currently faces a trilemma between *Training Complexity*, *Barren Plateau Risk*, and *Resource Efficiency* (as summarized in Table 4).

To address this trade-off, we abstract a **conceptual Hybrid Co-Optimization Paradigm** as a blueprint for future empirical studies. Rather than relying exclusively on gradient or evolutionary methods, future frameworks can integrate their complementary strengths via a two-phase hand-off mechanism (see Figure 3):

1. **Phase I: Coarse-Grained Topological Search (Evolutionary).** Future algorithms can initially explore the discrete search space using EQNAS to identify a noise-aware candidate topology, reducing early-stage exposure to barren plateaus without optimizing continuous variables.
2. **Phase II: Fine-Grained Parameter Tuning (Gradient).** Upon selecting the candidate topology, the system transitions to a fine-grained tuning regime using surrogate gradients (e.g., the Parameter Shift Rule). By utilizing a "warm start" inherited from Phase I, the gradient optimizer can support local parameter refinement.

From a theoretical complexity standpoint, this decoupled trajectory may reduce the effective search burden by separating architecture-level exploration from parameter-level refinement, with an approximate cost $\mathcal{C}_{hybrid} \approx \mathcal{O}(\text{poly}(N)) + \mathcal{O}(\text{poly}(M))$ under favorable assumptions. Compared with pure evolutionary search and randomly initialized variational circuits affected by barren plateaus, this conceptual framework provides a theoretical basis for developing more scalable QSNN optimization strategies.

Table 4: **Systematic Analysis of Computational Complexity and Optimization Risks (2021–2025).** This table surveys 11 recent frameworks, revealing a trilemma between *Training Complexity*, *Barren Plateau (BP) Risk*, and *Resource Efficiency*. The bottom row summarizes our proposed conceptual Hybrid Co-Optimization Paradigm as a future trajectory for empirical investigation

Optimization Paradigm	**Representative Work**	**Complexity**	**BP Risk**[1]	**Critical Limitation / Trade-off**
Hybrid SNN	Ajayan et al. [63]	Low	Low	**Info Loss:** Low qubit count but relies heavily on classical compression.
Diff. NAS	Zhang et al. [41]	High	Moderate	**Dependency:** Finds optimal circuits but relies on PCA preprocessing.
Evolutionary	Li et al. [55]	High $\mathcal{O}(G \cdot P)$	**None**	**Scalability:** Immune to BP but search cost scales exponentially.
Surrogate Grad	Konar et al. [62]	Medium $\mathcal{O}(E \cdot M)$	**High**	**Training Difficulty:** High accuracy but struggles with deep circuit gradients.
PSO (Hardware)	Karamuftuoglu et al. [90]	Offline (PSO)	None	**Area Overhead:** Inductances occupy most chip area; limited connectivity.
Surrogate Grad	Brand et al. [65]	Low	Low	**Entanglement:** Efficient noise utilization but lacks entanglement capability.
Tensor Networks	Abdullayev et al. [74]	Low	None	**Quantum Advantage:** Faster classical sim, but no path to quantum supremacy.
Hybrid PQC	Islam et al. [68]	High	**High**	**Stagnation:** 99.9% fewer params than CNN, but suffers severe stagnation.
Surrogate Grad	Nhan et al. [69]	Medium $\mathcal{O}(E \cdot M)$	Mitigated	**Noise Sensitivity:** Ultra-compact model but degrades fast under NISQ noise.
Parallel VQC	Yurtseven et al. [91]	Medium $\mathcal{O}(E \cdot M)$	Low	**Expressivity:** Accuracy gains limited by 4-qubit hardware restriction.
QAttn-CNN	Pandey et al. [66]	Optimized $\mathcal{O}(\log N)$	Mitigated	**Overhead:** NEQR requires ∼18 qubits for small 32×32 patches.
Hybrid Co-Opt	**Future Outlook**	$\mathcal{O}(N_{topo} + N_{tune})$	**Mitigated**[2]	**Theoretical Synthesis:** Decouples topology search (evolutionary) from parameter tuning (gradient), which may alleviate scaling bottlenecks under favorable assumptions.

[1] BP Risk: Barren Plateau Risk (Exponential decay of gradients variance).
[2] For the future-outlook row, "Mitigated" denotes a conceptual expectation under favorable assumptions, not an empirically validated result.
* Note how recent methods (2025) like Islam et al. and Pandey et al. achieve high parameter efficiency but still face significant optimization challenges (Stagnation/Overhead), motivating further investigation of hybrid approaches.

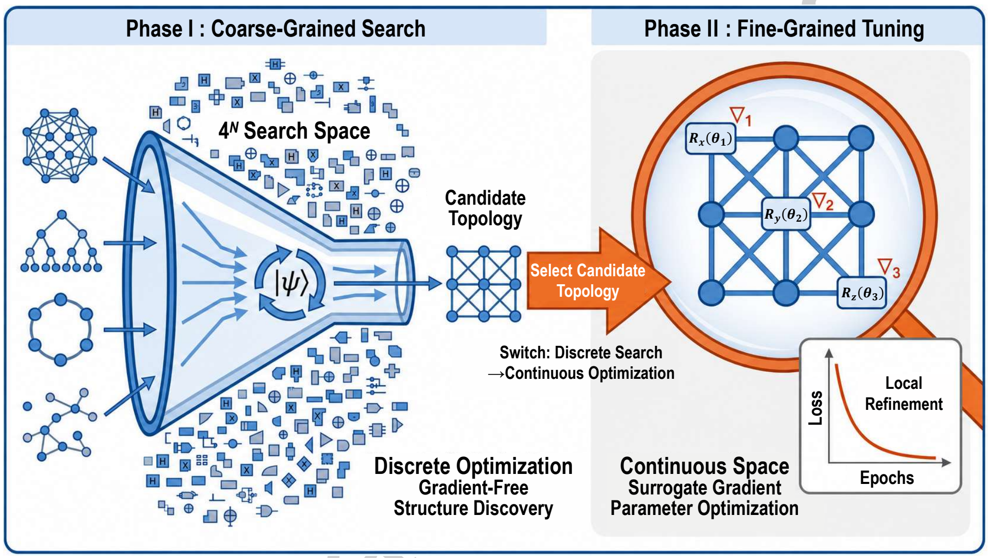

Figure 3: **Conceptual Blueprint of a Hybrid Co-Optimization Paradigm for Future Research.** Abstracted from our literature synthesis, this schematic illustrates a potential two-phase trajectory to address NISQ-era bottlenecks. **Phase I (Left):** The discrete structural search space (4^N) is explored via evolutionary methods (e.g., EQNAS). The central representations of the "Quantum Chromosome" ($|\psi\rangle$) evolve within the loop to identify a noise-aware candidate topology while reducing early-stage exposure to barren plateaus. **Phase II (Right):** Once the candidate topology is selected, the system transitions to a fine-grained tuning regime. Specific parameterized gates (e.g., $R_x(\theta_1), R_y(\theta_2)$) are optimized using surrogate gradients (∇) and the Parameter Shift Rule, supporting local parameter refinement.

7. Summary and Conclusions

The convergence of Quantum Computing and Neuromorphic Engineering represents an emerging research frontier with the theoretical potential to address the growing energy constraints and computational bottlenecks of modern AI. In this survey, we have established a conceptual homology between the biological integrate-and-fire mechanism and quantum unitary evolution, providing a heuristic foundation for Quantum Spiking Neural Networks (QSNNs).

By systematically reviewing the literature, we categorized existing quantum neurons into measurement-driven, continuous evolution, and variational paradigms. In particular, our analysis highlights an important algorithmic trend: relying solely on gradient-based adaptation (e.g., surrogate gradients) may be insufficient for some challenging optimization landscapes of NISQ devices, especially when barren plateaus and measurement noise are present. Based on these empirical trends, we identify a **conceptual Hybrid Co-Optimization Paradigm** as an important future trajectory—leveraging evolutionary search to discover candidate topological structures, followed by fine-grained gradient tuning. As benchmarked on image and temporal tasks, emerging hybrid architectures demonstrate encouraging exploratory results, though achieving empirical quantum advantage remains a long-term open challenge. Future progress will likely depend not only on algorithmic improvements, but also on the holistic co-design of quantum algorithms, neuromorphic models, hardware constraints, and input–output interfaces.

Declaration of Competing Interest

None.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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