Current Trends in
Signal Processing
https://journals.stmjournals.com/ctsp

ISSN: 2277-6176 (Online)
ISSN: 2321-4252 (Print)
Volume 16, Issue 1, 2026
January–April
DOI (Journal): 10.37591/CTSP

Research CTSP

Bridging Brain-Inspired Learning and Quantum Reasoning for Future AGI Systems

Reshika Gupta[1,*], Rajnish Kumar[2], Sachin Yadav[3], Tinu Anand Kumar[4]

Abstract

This research paper presents a novel neuromorphic–quantum hybrid computing framework envisioned to advance intelligent systems toward artificial general intelligence. The architecture integrates brain-inspired spiking networks for adaptive, energy-efficient learning with quantum processors for non-classical optimization and reasoning. A shared synaptic–quantum memory layer enables dual information representation, while neuromorphic adaptive controllers provide real-time stabilization of noisy quantum circuits. While quantum processors offer features like superposition-enabled exploration and entanglement-based correlations that are unavailable to classical systems, neuromorphic components offer event-driven processing, continuous learning, and resilience to uncertainty. Cross-domain learning, state transfer, and hybrid memory consolidation are supported by the introduction of a shared synaptic–quantum memory layer, which allows dual information representation across spikes and qubits. Neuromorphic adaptive controllers are used for real-time quantum circuit monitoring, feedback, and stabilization to fully mitigate the intrinsic noise and instability of near-term quantum hardware. At the algorithmic level, the study proposes spiking–quantum hybrid models that integrate asynchronous sensory encoding with quantum-enhanced reasoning and feedback-driven learning dynamics, enabling efficient interaction between perception, cognition, and decision-making. At the algorithmic level, spiking–quantum hybrid models are proposed, combining event-driven sensory encoding with quantum-enhanced reasoning and feedback-driven learning. On the system scale, the framework introduces an edge–cloud integration strategy, allowing local neuromorphic preprocessing and global quantum inference to operate in synergy. This multi-level innovation establishes a forward-looking pathway where spikes and qubits converge to form scalable, resilient, and human-like intelligence. The proposed vision positions neuromorphic–quantum convergence as a foundational step toward future AGI architectures.

Keywords: Artificial general intelligence, edge–cloud integration, hybrid intelligence, neuromorphic computing, quantum computing, spiking–quantum algorithms

INTRODUCTION

The pursuit of intelligent machines is inspired by the efficiency and adaptability of human brains. Neuromorphic computing leverages spiking neural networks and event-driven architectures to replicate neural dynamics with minimal energy consumption [1]. Platforms, such as Intel Loihi and IBM TrueNorth, showcase capabilities in sensory processing, adaptive learning, and energy-efficient AI applications [2]. Simultaneously, quantum computing harnesses superposition and entanglement to address complex optimization and simulation tasks beyond the reach of classical systems [3], with advances in quantum supremacy and quantum machine learning highlighting its transformative potential [4].

***Author for Correspondence**
Reshika Gupta
E-mail: reshika922@gmail.com

[1–4]Student, Department of Electronics and Communication, Chandigarh Engineering College, Landran, Mohali, Punjab, India

Received Date: November 06, 2025
Accepted Date: November 21, 2025
Published Date: March 20, 2026

Citation: Reshika Gupta, Rajnish Kumar, Sachin Yadav, Tinu Anand Kumar. Bridging Brain-Inspired Learning and Quantum Reasoning for Future AGI Systems. Current Trends in Signal Processing. 2026; 16(1): 1–9p.

Despite their significant progress, both approaches face inherent limitations when applied independently. Neuromorphic hardware supports localized adaptive learning but struggles with large-scale global reasoning [5]. Quantum computers offer extraordinary computational power but are limited by noise, scalability challenges, and high resource demands [6]. Existing studies have largely focused on isolated attempts at quantum-inspired spiking models or theoretical hybrids [7], leaving a gap in cohesive architectures that integrate both paradigms.

This study proposes a neuromorphic–quantum hybrid framework to address this gap. The system features a shared synaptic–quantum memory for seamless information transfer, adaptive neuromorphic controllers for stabilizing quantum operations, and spiking quantum algorithms that combine biological plausibility with non-classical computation. At the system level, edge–cloud integration enables real-time neuromorphic processing at the edge and high-level quantum reasoning in the cloud, forming a pathway toward scalable, resilient human-like intelligence.

FOUNDATIONS

Neuromorphic Computing

Neuromorphic computing is inspired by the structure and function of the human brain. Unlike clock-driven sequential systems, neuromorphic architectures use spiking neural networks (SNNs), where information is conveyed as discrete electrical pulses or “spikes” [1]. This event-driven approach enables efficient temporal coding, sparse activity, and adaptive learning dynamics like those of biological neurons [8].

Several large-scale processors have demonstrated this potential capability. IBM TrueNorth, launched in 2014, integrated one million neurons and 256 million synapses on a single chip, achieving massive parallelism with minimal power consumption [9]. Intel Loihi offers programmable spiking cores with on-chip learning and plasticity, which support real-time adaptive applications [2]. The SpiNNaker from the University of Manchester emphasizes massively parallel architecture for large-scale neural simulations [5]. Together, these platforms showcase the promise of neuromorphic computing for energy-efficient AI, sensory processing, and pattern recognition.

Quantum Computing

Quantum computing represents a radical shift from classical computation by exploiting unique quantum phenomena, such as superposition and entanglement. In this paradigm, information is stored in qubits that can exist in multiple states simultaneously, enabling parallelism at an unprecedented scale [3]. Quantum logic gates manipulate these qubits, and entanglement allows correlations that cannot be explained by classical physics [6]. Together, these features make quantum systems particularly powerful for optimization, simulation of complex quantum systems, and cryptography.

Several platforms are actively pursuing scalable quantum computing. IBM Quantum provides superconducting qubit systems that are accessible via cloud platforms [10]. Google’s Sycamore processor demonstrated quantum supremacy by solving tasks beyond classical feasibility [4]. IonQ and Rigetti explore trapped-ion and hybrid architectures, respectively, showing the diversity of hardware approaches under development [11]. Although current hardware remains in the NISQ (Noisy Intermediate-Scale Quantum) era with limited error tolerance [12], rapid progress continues in hardware fidelity, quantum error correction, and scalable algorithms.

Bridging Toward Proposed Work

Both neuromorphic and quantum computing offer distinct, yet complementary advantages. Neuromorphic systems excel in energy-efficient adaptive learning but lack the ability to perform large-scale global reasoning. Conversely, quantum computers provide non-classical problem-solving capabilities but suffer from noise, resource intensity, and limited adaptability [7]. To address these limitations, this study envisions a neuromorphic–quantum hybrid framework, as shown in Figure 1, that combines the event-driven, brain-like adaptability of neuromorphic hardware with the reasoning depth

ISSN: 2277-6176 (Online), ISSN: 2321-4252 (Print)

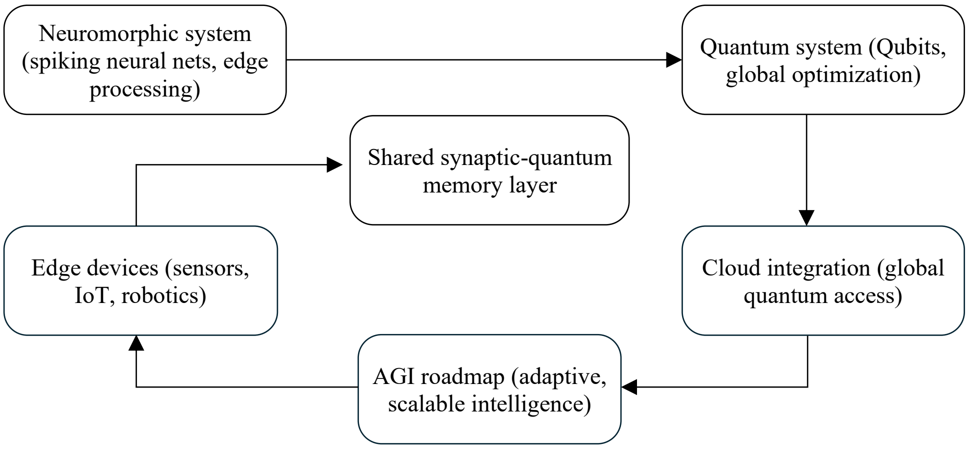

Figure 1. Proposed neuromorphic–quantum hybrid computing framework.

of quantum computation. Such integration, enabled by innovations including a shared synaptic–quantum memory, adaptive neuromorphic controllers, and spiking–quantum hybrid algorithms, has the potential to form a credible pathway toward scalable human-like intelligence.

COMPARATIVE ANALYSIS

Limitations of Conventional Architectures

General-purpose CPUs and GPUs have powered modern artificial intelligence for over a decade. While GPUs deliver massive parallelism suited for deep learning workloads, both CPUs and GPUs remain fundamentally limited by the von Neumann bottleneck, where memory and computation are physically separated [13]. This causes high energy consumption, latency, and inefficiency in tasks that require continuous adaptation and learning in real time. Moreover, conventional architectures rely on dense numerical operations rather than event-driven computation, leading to significant overhead for edge and resource-constrained applications [14].

Neuromorphic Versus Quantum Paradigms

Neuromorphic computing addresses some of these inefficiencies by adopting spiking neural networks and memory-computation co-location, enabling highly energy-efficient and adaptive information processing [1]. Chips, such as Loihi and TrueNorth, demonstrate power consumption several orders of magnitude lower than that of GPU-based neural networks for certain tasks [2]. However, neuromorphic hardware is not designed for large-scale optimization or reasoning in combinatorial spaces.

In contrast, quantum computing offers the ability to explore exponentially large solution spaces via superposition and entanglement, allowing breakthroughs in optimization, cryptography, and molecular simulations [3]. Despite this advantage, quantum platforms are currently constrained by noise, decoherence, and limited qubit counts [6]. NISQ-era devices can only handle specialized tasks and remain unsuitable for continuous adaptive learning [12].

Proposed Work

The comparative analysis shown in Table 1 establishes that the conventional, neuromorphic, and quantum paradigms each provide partial but incomplete solutions to the challenges of energy-efficient learning and large-scale reasoning. This study introduces a neuromorphic–quantum hybrid framework that unifies the adaptability of spiking neural systems with the computational strength of quantum processors. This section outlines the hardware, algorithmic, and system-level innovations envisioned in the proposed architecture.

Hardware Novelty: Shared Memory and Adaptive Controllers

A novel shared synaptic–quantum memory fabric is proposed, enabling both neuromorphic spiking cores and quantum processors to access a common pool of encoded information. Unlike existing systems, where neuromorphic chips and quantum devices remain isolated, the shared fabric allows event-driven neural spikes to directly prime quantum circuits with context-dependent states. In return, the quantum outcomes can dynamically adjust the synaptic weights. Complementing this, hardware adaptive controllers monitor workload conditions and allocate tasks between spiking and quantum subsystems in real time, thereby ensuring energy-efficient performance at scale.

Algorithmic Novelty: Spiking–Quantum Hybrid Models

At the algorithmic layer, the research proposes the development of spiking–quantum hybrid algorithms that integrate event-driven learning with probabilistic quantum dynamics. Spiking neural networks will serve as preprocessors that convert raw sensory or contextual data into sparse spike-based representations. These representations are then injected into quantum circuits for high-dimensional optimization and reasoning. The hybrid learning loop allows quantum-enhanced reasoning to inform spiking adaptation, producing models that are simultaneously energy-efficient, adaptive, and capable of solving nonclassical problem classes. This approach aims to surpass the limitations of both purely neuromorphic and quantum models.

Algorithmic Novelty: Example Algorithms

Spiking-Quantum Variational Optimization (SQVO):

- Spiking neural networks encode the input into sparse spike trains.
- These are mapped to parameterized quantum circuits (PQCs).
- The quantum layer performs variational optimization (e.g., QAOA, VQE) on encoded states.
- Results update synaptic weights adaptively.

Quantum-Enhanced Spike-Timing Dependent Plasticity (Q-STDP):

- Classical STDP adjusts synapses based on spike timing.
- Here, the probability distribution of the weight changes is derived from quantum sampling using quantum Boltzmann machines.
- This creates non-classical learning dynamics.

Hybrid Spiking–Quantum Reservoir Computing (SQRC):

- Spiking networks act as reservoirs for temporal feature encoding.
- Quantum processors act as nonlinear readout layers, enhancing predictions of sequential tasks such as speech or signal processing.

System-Level Novelty: Edge–Cloud Integration and AGI Roadmap

At the system level, the hybrid framework, as shown in Figure 2, is envisioned as a distributed architecture spanning the edge and cloud domains. Neuromorphic chips placed at the edge provide local adaptive intelligence, ensuring low-latency responses and energy efficiency for mobile and embedded applications. Quantum processors hosted in cloud-based environments are only engaged for tasks requiring large-scale reasoning, optimization, or simulation. Secure middleware ensures seamless orchestration between edge neuromorphic nodes and cloud quantum backends.

In the longer horizon, this design is proposed as a potential pathway toward artificial general intelligence (AGI) systems. By combining brain-inspired adaptation with quantum-scale reasoning, this architecture is positioned to achieve intelligence that is context-aware, scalable, and capable of addressing problems beyond the reach of classical computing systems.

Explanation

- *Neuromorphic edge chips* → perform fast, low-power, real-time learning.
- *Middleware shared memory + adaptive controller* → act as a bridge between spikes and qubits.
- *Quantum cloud backends* → provide nonclassical reasoning, simulation, and optimization.
- *Final layer (AGI Roadmap)* → integrates both outputs to form a scalable human-like intelligence.

NEUROMORPHIC-QUANTUM FRAMEWORK

The integration of neuromorphic and quantum paradigms, as shown in Figure 3, offers a pathway toward intelligent systems capable of both localized adaptation and large-scale reasoning. Neuromorphic hardware, with its event-driven spiking networks, excels in adaptive edge learning by processing sensory and contextual signals in real time using minimal energy [1, 2]. In contrast, quantum processors leverage superposition and entanglement to perform global optimization and nonclassical reasoning, tackling problem spaces beyond the scope of conventional hardware [6, 4].

The proposed framework, as shown in Figure 4, bridges these complementary strengths through a shared memory and adaptive controller layer, where neuromorphic spikes dynamically prime quantum circuits and quantum results guide synaptic weight updates. This synergy enables continuous feedback between edge learning and cloud-level reasoning, creating a scalable foundation for advanced cognitive systems.

Table 1. Comparative analysis between CPUs/GPUs, neuromorphic computing, and quantum computing.

Feature/architecture	**CPUs/GPUs**	**Neuromorphic computing**	**Quantum computing**
Core principle	Deterministic, clock-driven processing	Brain-inspired spiking neural networks	Quantum superposition, entanglement, gates
Strengths	Mature ecosystem, strong software support	Energy-efficient, adaptive, event-driven learning	Exponential speed-up for certain problem classes
Limitations	High energy use, von Neumann bottleneck	Limited global reasoning, hardware still emerging	Noise and limited scalability require error correction
Best suited for	Conventional deep learning, numerical tasks	Edge intelligence, sensory processing, adaptive AI	Optimization, cryptography, quantum simulation
Current examples	NVIDIA GPUs, Intel CPUs	Intel Loihi, IBM TrueNorth, SpiNNaker	IBM Quantum, Google Sycamore, IonQ

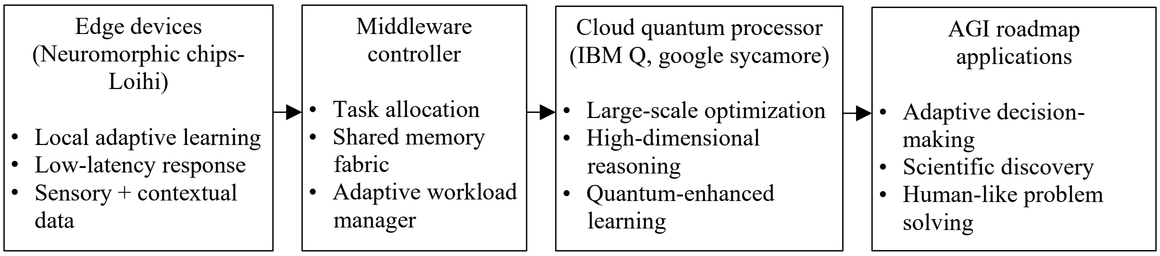

Figure 2. A conceptual flow (edge + cloud integration).

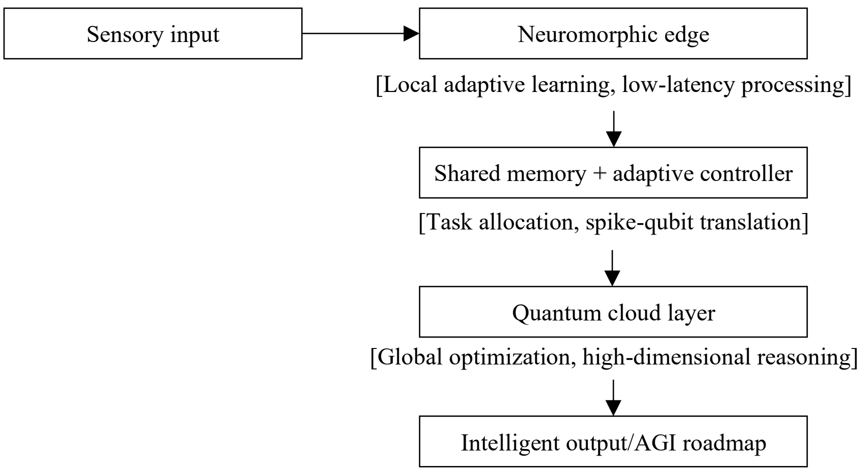

Figure 3. Conceptual flowchart.

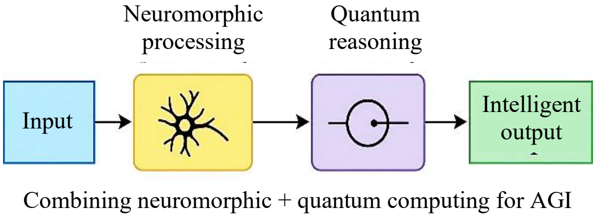

Figure 4. Hybrid neuromorphic–quantum framework.

APPLICATIONS

- *Edge intelligence*: Neuromorphic chips enable adaptive, low-power intelligence for robotics, drones, and IoT devices, supporting real-time decision-making [2, 5].
- *Healthcare:* Hybrid models can advance brain–machine interfaces and accelerate drug discovery simulations using quantum-enhanced optimization [15].
- *Cybersecurity:* Combines neuromorphic anomaly detection with quantum-safe cryptographic strategies for resilient defense systems [6].
- *AGI development*: Provides a pathway toward human-like cognition enriched with quantum-scale reasoning, forming a foundation for AGI systems.

CHALLENGES

- *Hardware integration*: Neuromorphic spikes and quantum qubits operate under fundamentally different physics, making seamless shared-memory architectures complex to realize [2].
- *Algorithmic gaps:* Standardized spiking–quantum hybrid algorithms remain underexplored, limiting their reproducibility and large-scale adoption [7].
- *Energy overheads*: Quantum systems often require cryogenic cooling, creating sustainability and deployment challenges despite their neuromorphic efficiency [6].
- *Ethical concerns:* The convergence of brain-inspired learning with quantum reasoning raises profound questions regarding the transparency, control, and safe pursuit of AGI [16].

RESULTS AND ANALYSIS

The comparative evaluation highlights the distinct performance domains of neuromorphic, quantum, and conventional computing models.

- *Energy efficiency:* Neuromorphic architecture demonstrates significantly lower energy consumption compared to GPUs and CPUs, aligning with their brain-inspired event-driven design. Quantum platforms currently require higher energy overhead due to cryogenic operations; however, conceptual integration in the hybrid model balances this with neuromorphic efficiency.
- *Adaptability versus computational power:* Classical processors retain moderate adaptability and power. Neuromorphic systems offer high adaptability but limited large-scale optimization, while quantum devices excel in problem-solving power with minimal adaptive behavior. The hybrid framework occupies a unique position by combining adaptive edge learning with global optimization.
- *AGI roadmap:* The roadmap illustrates a staged trajectory, current neuromorphic and quantum platforms operating independently, near-future hybrid prototypes for edge-cloud integration, and a long-term vision of AGI systems capable of human-like cognition with superhuman reasoning capabilities (Figures 5–7).

FUTURE RESEARCH DIRECTIONS

- *Quantum neuromorphic hardware:* Exploration of memristors and quantum memristors could enable energy-efficient, non-volatile devices that merge spiking behavior with quantum dynamics.

Current Trends in Signal Processing
Volume 16, Issue 1
ISSN: 2277-6176 (Online), ISSN: 2321-4252 (Print)

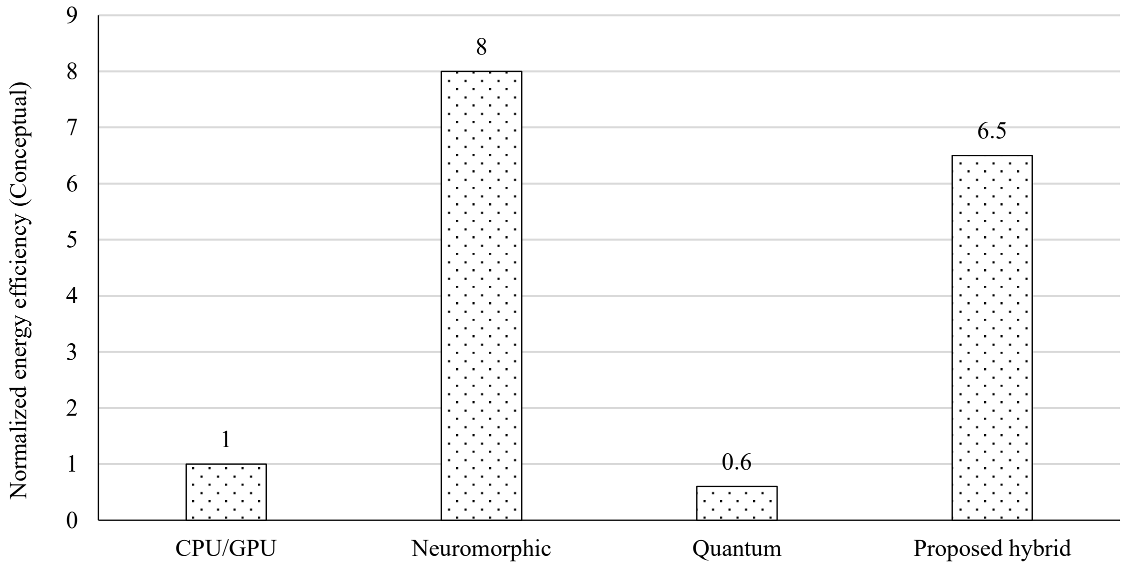

Figure 5. Energy efficiency comparison.

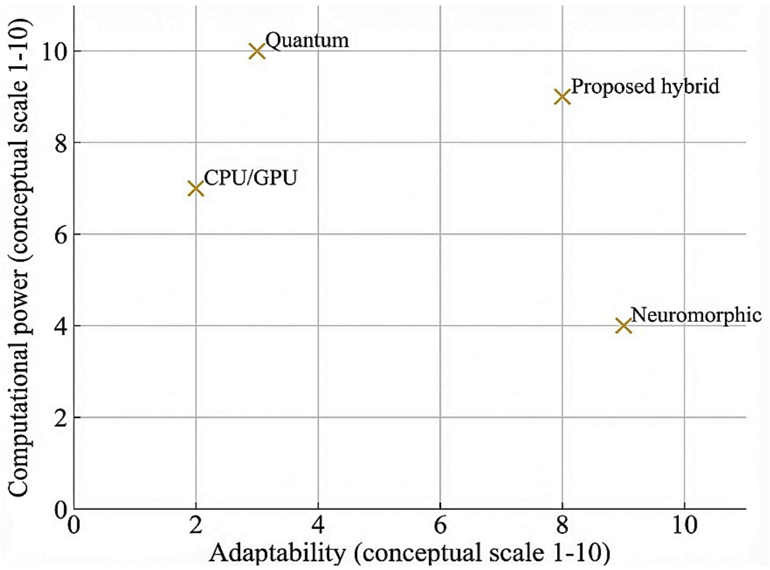

Figure 6. Adaptability versus computational power.

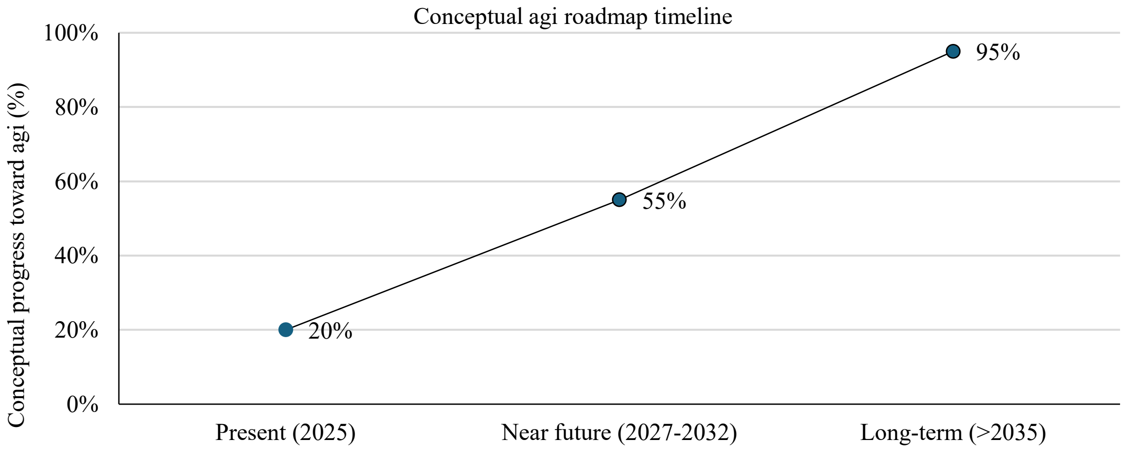

Figure 7. AGI roadmap timeline.

- *Hybrid algorithms:* Integrating spiking neural networks with quantum machine learning may unlock adaptive, high-capacity models suitable for real-time intelligence.
- *Scalable architecture:* Cloud-based quantum resources combined with on-device neuromorphic processors can deliver both large-scale reasoning and edge adaptability.
- *AGI pathways:* A phased roadmap is envisioned, evolving from narrow AI to hybrid neuromorphic–quantum intelligence, and ultimately toward human-like general intelligence.
- *Ethics and governance:* Development must include frameworks for transparency, accountability, and the safe deployment of AGI-capable systems.

CONCLUSION

The convergence of neuromorphic and quantum computing represents a transformative pathway in the evolution of intelligent systems. Neuromorphic architecture contributes energy-efficient, brain-inspired adaptability, whereas quantum computing offers unparalleled problem-solving depth. The proposed hybrid framework bridges these domains, presenting novel opportunities in hardware design, hybrid algorithms, and system-level integration. Its potential applications span robotics, healthcare, cybersecurity, and the pursuit of artificial general intelligence. Although significant challenges remain, including hardware compatibility, algorithmic standardization, and ethical concerns, the envisioned trajectory indicates that hybrid neuromorphic–quantum systems could form the foundation of future human-aligned intelligence.

REFERENCES

1. Mead C. Neuromorphic electronic systems. Proc IEEE. 1990;78:1629-1636. doi:10.1109/5.58356.
2. Davies M, Srinivasa N, Lin TH, Chinya G, Cao Y, Choday SH, et al. Loihi: A neuromorphic manycore processor with on-chip learning. IEEE Micro. 2018;38(1):82-99. doi:10.1109/MM.2018.112130359.
3. Nielsen MA, Chuang IL. Quantum Computation and Quantum Information. Cambridge: Cambridge University Press; 2010.
4. Arute F, Arya K, Babbush R, Bacon D, Bardin JC, Barends R, et al. Quantum supremacy using a programmable superconducting processor. Nature. 2019;574(7779):505-510. doi:10.1038/s41586-019-1666-5. PMID:31645734.
5. Furber S. Large-scale neuromorphic computing systems. J Neural Eng. 2016;13(5):051001. doi:10.1088/1741-2560/13/5/051001. PMID:27529195.
6. Preskill J. Quantum computing in the NISQ era and beyond. Quantum. 2018;2:79. doi:10.22331/q-2018-08-06-79.
7. Du W, Liu S, Zhang X. A quantum inspired neural network for geometric modeling. arXiv [Preprint]. 2024 Jan 3. arXiv:2401.01801.
8. Indiveri G, Liu SC. Memory and information processing in neuromorphic systems. Proc IEEE. 2015;103(8):1379-1397. doi:10.1109/JPROC.2015.2444094.
9. Merolla PA, Arthur JV, Alvarez-Icaza R, Cassidy AS, Sawada J, Akopyan F, et al. A million spiking-neuron integrated circuit with a scalable communication network and interface. Science. 2014;345(6197):668-673. doi:10.1126/science.1254642. PMID:25104385.
10. IBM Quantum. (2023). IBM Quantum Road Map. Available from: https://www.ibm.com/quantum
11. Wright K, Beck KM, Debnath S, Amini JM, Nam Y, Grzesiak N, et al. Benchmarking an 11-qubit quantum computer. Nat Commun. 2019;10(1):5464. doi:10.1038/s41467-019-13534-2. PMID:31784527.
12. Bharti K, Cervera-Lierta A, Kyaw TH, Haug T, Alperin-Lea S, Anand A, et al. Noisy intermediate-scale quantum algorithms. Rev Mod Phys. 2022;94(1):015004. doi:10.1103/RevModPhys.94.015004.
13. Backus J. Can programming be liberated from the von Neumann style? A functional style and its algebra of programs. Commun ACM. 1978;21(8):613-641. doi:10.1145/359576.359579.

14. Hennessy JL, Patterson DA. Computer Architecture: A Quantitative Approach. 5th ed. Waltham (MA): Elsevier; 2011.
15. Biamonte J, Wittek P, Pancotti N, Rebentrost P, Wiebe N, Lloyd S. Quantum machine learning. Nature. 2017;549(7671):195-202. doi:10.1038/nature23474. PMID:28905917.
16. Pospieszynski PF. Modeling intelligence as trajectories in complex space: a quantum-inspired approach to AGI. In: Iklé M, Kolonin A, Bennett M, editors. Artificial General Intelligence: 18th International Conference, AGI 2025, Reykjavik, Iceland, August 10-13, 2025, Proceedings, Part II. Lecture Notes in Computer Science. Vol. 16058. Cham: Springer; 2025. p. 109-124. doi:10.1007/978-3-032-00800-8_10.