

Perspective

New AI for Quantum Computing: From Quantum Optimization to Quantum Intelligence

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HOW far are we from quantum computers that serve everyone? More than a century has passed since quantum mechanics reshaped our understanding of nature, and in 2025, the Nobel Prize in physics once again honored breakthroughs in quantum mechanics for macroscopic quantum tunneling, a sign that quantum theory is stepping from abstraction into the tangible world. Yet for most people, quantum computers still seem as distant as the early mainframes once were. When Thomas Watson of IBM predicted that only a handful of computers would suffice for global needs almost 80 years ago, few could imagine that within decades, personal computers would become household tools. Today, diverse prototypes are steadily scaling up in qubit number and control precision, from superconducting qubits to trapped ions and photonic chips. Meanwhile, the quantum processing unit (QPU) is beginning to merge seamlessly with CPUs and GPUs into a unified computational fabric. As advances in quantum computing, quantum optimization, and quantum Artificial Intelligence (AI) continue to emerge (as discussed below), a new wave of AI, especially autonomous intelligence, is rapidly unfolding [1], and its coevolu-

tion with quantum technologies is opening a promising pathway toward the next generation of intelligent systems under the paradigm of quantum intelligence.

Advances in Quantum Computing

Quantum computing has evolved from laboratory prototypes to quantum processing units (QPUs) that begin to operate in industrial environments, as illustrated in Fig. 1. A leading hardware approach is based on superconducting qubits, a platform with large qubit capacity (thousands of qubits) and advanced engineering maturity, but with a strong reliance on low-temperature superconducting hardware. Representative examples include the *IBM Condor* and *Google Willow*. A specialized branch *D-Wave Advantage 2TM* has pioneered the development of large-scale annealers that specialize in solving optimization problems by exploiting quantum tunneling. In contrast, photonic quantum processors leverage the polarization and path degrees of freedom of photons to operate at room temperature; however, their scalability is challenged by the probabilistic nature of photon-mediated gates. Representative systems include *Xanadu Borealis* and *Jiuzhang Series* [2]. Meanwhile, ion-trap systems achieve high-fidelity quantum gates through electromagnetic confinement and laser manipulation, although their operational speed and scalability are constrained by the serial nature of individual ion addressing, as demonstrated by *Quantinuum H-Series* [3] and *IonQ Forte*. Another promising approach is Silicon spin-qubit processors, which benefit from high compatibility with standard complementary metal-oxide-semiconductor (CMOS) manufacturing. This technology uses quantum dots to confine electron spins with electrostatic gates and manipulates them via microwave pulses, with key developments including *QuTech* research and *Intel Tunnel Falls*. Similarly, neutral atom quantum computers, which manipulate neutral atoms with fine-tuned laser fields to initialize and manipulate qubits, are distinguished by their unique flexibility and exceptional scalability, with representative platforms including *QuEra Aquila* and *Atom Computing AC1000*. Topological quantum processors, in contrast, encode *Majorana zero modes* [4] for fault-tolerant computation. Although the most technologically nascent, this Microsoft-pioneered approach is exemplified by the *Microsoft Majorana 1* prototype. These diverse hardware paradigms are driving QPU development toward higher-dimensional quantum-state control, greater noise resilience, and deeper integration with classical computing.

As QPU technology advances toward practical deployment, quantum computing is transitioning from a single-purpose algorithmic platform to a hybrid intelligent computing paradigm jointly powered by CPUs, GPUs, and QPUs. The *PSNC Hybrid Quantum Cluster*

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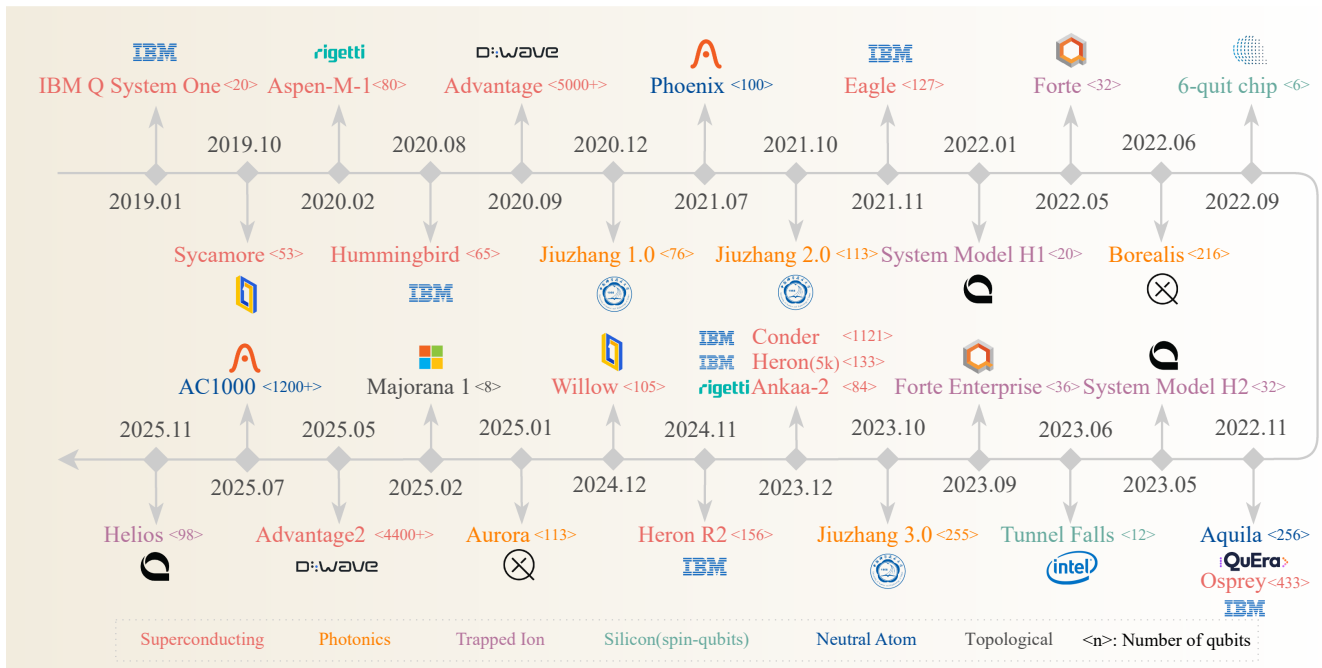


Fig. 1. Milestones in Quantum Computing Hardware Development.

demonstrates a multi-user, multi-QPU/GPU/CPU hybrid supercomputing architecture that highlights efficient cross-layer resource orchestration and collaborative computation [5]. The *IBM Quantum-Centric Supercomputing* architecture weaves quantum processors and classical nodes into a unified computational fabric through the *Qiskit Runtime*, enabling near-real-time quantum-classical hybrid execution [6]. Meanwhile, *NVIDIA CUDA-Q* and *NVQLink* provide a unified programming framework and high-speed interconnects, achieving up to 400 Gb/s throughput with latency below 4 μ s, enabling real-time calibration, error correction, and hybrid algorithm coupling [7]. Through these heterogeneous fusion and intelligent control mechanisms, quantum computers are evolving from conventional “algorithm executors” into intelligent systems endowed with self-learning and self-optimization capabilities.

Advances in Quantum Optimization

In the noisy intermediate-scale quantum (NISQ) era, constrained by limited qubit counts and insufficient connectivity, the variational quantum algorithm (VQA) has emerged as a key approach to finding high-quality approximate solutions by combining shallow quantum circuits with classical optimizers. These algorithms, as shown in Fig. 2, exploit the properties of quantum superposition and entanglement to enable parallel exploration of exponentially large solution spaces, while leveraging the quantum tunneling effect to avoid local optima. Building on these principles, two major classes of core algorithms have been established: variational quantum algorithms such as quantum approximate optimization algorithm (QAOA) [8] and variational quantum eigensolver (VQE) [9], which integrate parameterized quantum circuits with classical optimization loops, demonstrating potential in combinatorial optimization and ground-state solving. The second is quantum annealing (QA) [10], a quantum adiabatic computing paradigm that finds applications from logistics scheduling to financial modeling through Hamiltonian evolution. Together, these methods are steadily driving the transition of quantum computing from theory to practical deployment.

In the NISQ era, constrained by limited qubits and noisy hardware, quantum optimization faces intertwined challenges of noise, convergence, and resource scarcity: decoherence and gate errors rapidly degrade superposition and entanglement, causing reliability to decay with circuit depth; variational quantum algorithms suffer from barren plateaus and numerous spurious local optima; and hard limits on qubit counts and measurements restrict realistic problem mapping

and amplify the tension between noise and convergence. To address these bottlenecks, the research focus is shifting from static, hand-crafted algorithms to intelligent generative systems that dynamically perceive problem structure and hardware conditions. Instead of relying on fixed Ansätze, reinforcement learning-based generative mechanisms autonomously evolve circuit architectures and parameters, reducing dependence on expert design and alleviating barren plateaus, while noise-adaptive compilation optimizes gate sequences and error mitigation in response to real-time device characteristics.

Advances in Quantum AI

In the Quantum for AI paradigm, quantum computing not only promises acceleration beyond classical limits but also reshapes AI model design by exploiting quantum parallelism and fast linear algebra. As shown in Fig. 2, early algorithms such as QPCA [11] and QSVM [12] established the computational basis with exponential speedups for eigenvalue decomposition and linear system solving in high-dimensional settings. Building on this, quantum neural architectures including QGANs [13], QCNNs [14], and QLSTM [15] exploit superposition, entanglement, and logarithmic-depth circuits to achieve efficient generative modeling, topological pattern recognition, and long-range sequence modeling.

At the frontier of quantum-LLM integration, QSANN [16] and the Quixer quantum Transformer [17] demonstrate that quantum self-attention and quantum singular value transformations can achieve performance competitive with classical baselines, while QuanTA [18] uses quantum-inspired tensor adaptation to overcome the expressiveness limits of LoRA in LLM fine-tuning.

Despite NISQ-era constraints, these advances establish a theoretical foundation for next-generation AI, even as powerful quantum algorithms threaten classical cryptography: Shor-type attacks could break RSA/ECC [19], motivating the deployment of quantum-safe primitives such as quantum key distribution (QKD) as a foundational security layer. Conversely, in the AI for Quantum paradigm, AI becomes a core enabler for practical quantum computing: Transformer-based quantum error correction (QEC) decoders [20], learning-based quantum error mitigation (QEM), and deep reinforcement learning for gate synthesis and qubit mapping [21] together endow quantum devices with emerging capabilities for autonomous noise awareness and dynamic adaptation, accelerating progress toward scalable, fault-tolerant quantum computation.

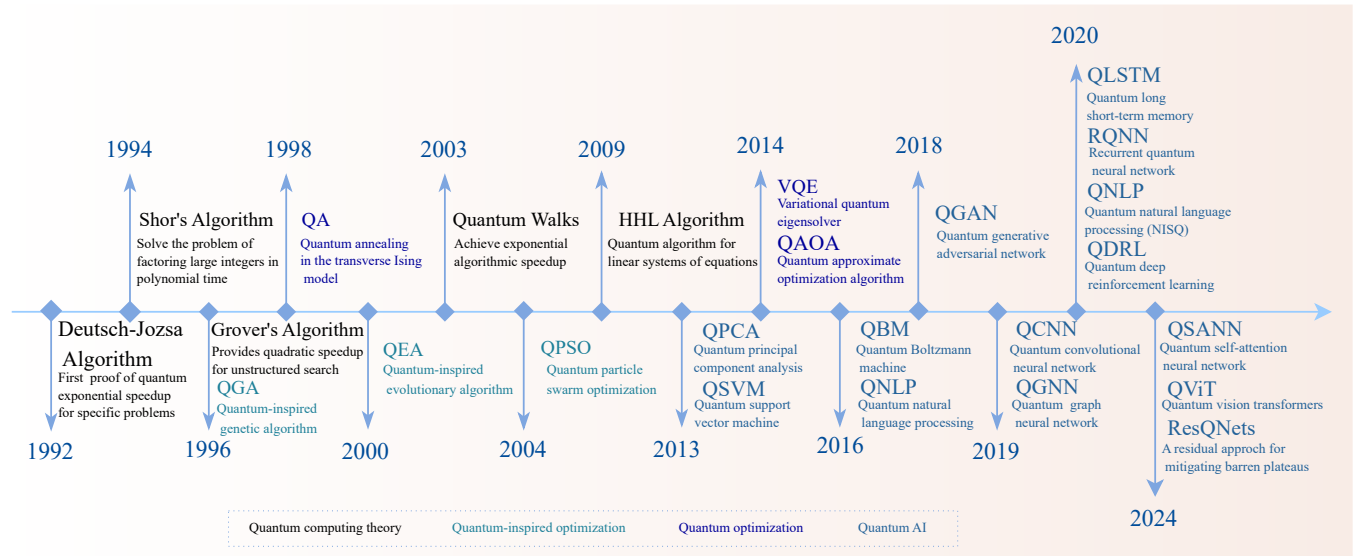


Fig. 2. The Evolution of Quantum Algorithms: From Theoretical Foundations to NISQ-Era Applications.

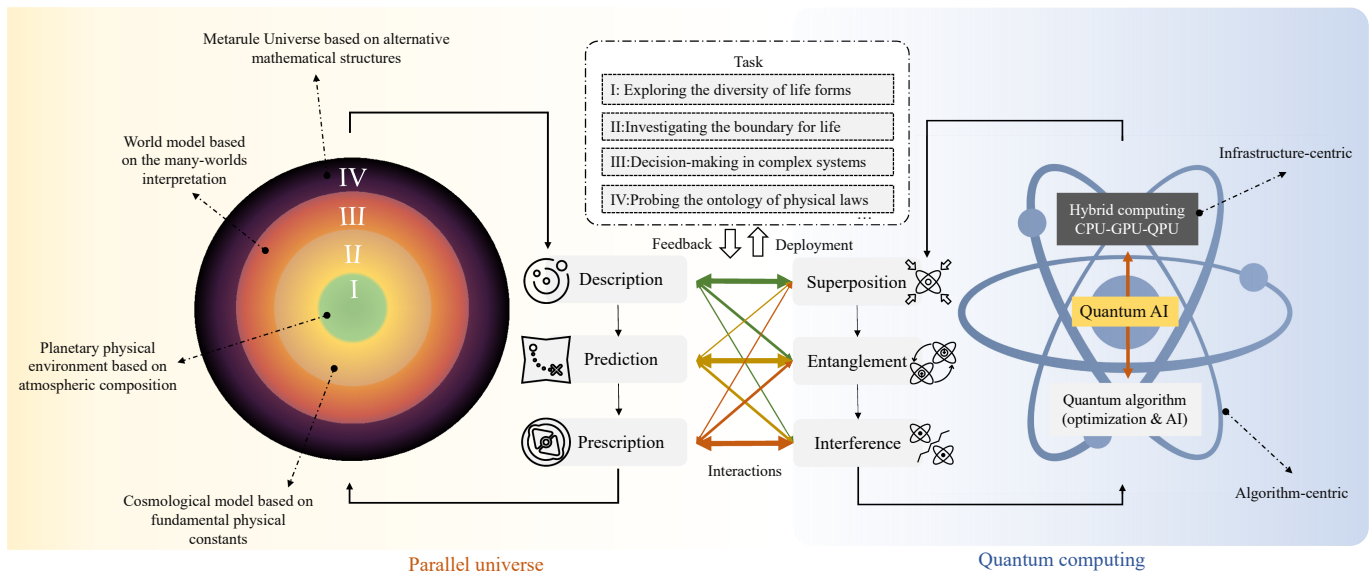


Fig. 3. A Parallel-Universes-Inspired Quantum Intelligence Framework Based on the ACP Methodology.

Quantum Intelligence

Advances in quantum computing hardware and algorithms are opening new pathways for understanding physics, the philosophical dimensions of human potential [22], and artificial general intelligence (AGI), primarily by providing a fast mechanism for exploring diverse possibilities.

At the macroscopic level, Max Tegmark's multiverse framework Parallel Universes [23] postulates four levels of parallel universes: a Level I Universe that shares our physical constants but differs in initial particle configurations; a Level II Universe with different physical constants; a Level III Universe arising from branching realities induced by quantum measurements; and a Level IV Universe dedicated to the ontology of physical laws and mathematical structures.

At the microscopic level, Parallel Intelligence [24] introduces the ACP method (Artificial Systems, Computational Experiments, and Parallel Execution) for agents and subsequently evolves into the digital quadruplets framework, consisting of the physical agent, descriptive agent, predictive agent, and prescriptive agent, to systematically model, understand, and guide intelligent behaviors.

These theories share a common objective: to construct extended or alternative spaces around our current world and to channel the result-

ing insights back into reality. Building on this perspective, we propose an integrated architectural vision of quantum intelligence: a quantum-driven computational framework for the development of AGI that systematically links representation, interaction, decision-making, and learning. As illustrated conceptually in Fig. 3, quantum superposition is used to encode diverse system states within a unified Hilbert space, providing a rich representational basis and thereby enabling descriptive intelligence. On top of this state space, quantum entanglement models the strong couplings and joint evolution among different components of the system, capturing high-order dependencies and supporting predictive intelligence. Further, quantum interference together with amplitude amplification is employed to computationally explore and evaluate exponentially many decision paths in parallel, guiding the search for high-quality solutions and realizing prescriptive intelligence. Through large-scale observation and simulation of complex systems, and through continuous interaction between virtual and physical spaces, the framework supports the training, adaptation, and coordination of various intelligent agents and offers a structured route to explore and understand complex phenomena, from life and cognition to fundamental physical laws across multiple levels of abstraction.

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