



# Neural Quantum Architecture (HNQA): Toward Probabilistic Cognition in Deterministic Systems

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GitHub: <https://github.com/Picyboo-Cybernetics/picyboo-public-hnqa>

## Abstract

Modern neural networks are deterministic by design. They process input-output relationships with fixed weight matrices and produce stable but narrow results. Real cognition, in contrast, thrives on ambiguity—holding multiple possible interpretations simultaneously until one emerges as contextually dominant. Quantum computation offers a mathematical analogue of such uncertainty but lacks cognitive interpretability and practical integration pathways with classical learning systems.

This paper introduces the Hybrid Neural Quantum Architecture (HNQA), a theoretical model combining deterministic learning mechanisms with quantum-inspired probabilistic state encoding. HNQA aims to bridge the computational efficiency of neural networks with the state diversity inherent in quantum systems, enabling architectures that learn from uncertainty rather than minimizing it. We present the conceptual framework, functional model, theoretical benefits, and potential applications of this approach.

**Keywords:** Quantum Computing, Artificial Intelligence, Neural Networks, Probabilistic Learning, Uncertainty Modeling, Cognitive Systems, Information Theory, Computational Modeling, Hybrid Architecture

## 1. Introduction

Classical artificial intelligence systems rely fundamentally on static weight propagation and convergent optimization algorithms. Each input is mapped to a single outcome through deterministic transformations, reflecting computational certainty but also imposing cognitive rigidity. This approach has proven extraordinarily successful for well-defined tasks with clear input-output relationships, yet it fundamentally diverges from how biological cognitive systems operate.

In natural perception, reasoning, and judgment, biological systems do not immediately collapse to a single interpretation. Instead, they operate across competing internal states, maintaining multiple hypotheses simultaneously before contextual information or additional processing leads to resolution. A classic example is perceptual bistability, where the same visual stimulus can be interpreted in multiple ways, with the brain alternating between interpretations. Similarly, in language processing, ambiguous sentences maintain multiple parse trees until disambiguating context arrives.

Current stochastic techniques in artificial intelligence—including dropout regularization, Monte Carlo sampling, and Bayesian estimation—approximate this behavior artificially rather than structurally. These methods introduce randomness or maintain probability distributions over parameters, but they do so as engineering solutions layered atop fundamentally deterministic architectures. The uncertainty is simulated rather than intrinsic to the computational substrate.

HNQA proposes a fundamentally different approach: a new layer of computation where multiple potential states coexist naturally until contextual collapse occurs. This architecture mirrors both the competitive dynamics observed in neural populations and the superposition principles found in quantum mechanics, creating a bridge between deterministic learning efficiency and probabilistic state representation.

## 2. Problem Context

The motivation for HNQA emerges from several fundamental limitations in current artificial intelligence architectures and the challenges inherent in quantum computing approaches.

### 2.1 Deterministic Limitation

Classical neural networks can only represent uncertainty statistically, not intrinsically. When a network encounters ambiguous input, it must either commit to a single interpretation based on its learned weights or maintain separate forward passes for different hypotheses. There is no native mechanism for a single computational unit to exist in multiple states simultaneously. This forces a premature collapse of possibility space, potentially discarding information that could be valuable for downstream processing or future context integration.

### 2.2 Quantum Isolation

Quantum processors, conversely, can maintain superposed states and leverage interference patterns for certain computational advantages. However, these systems lack semantic interpretability in their raw form—quantum states represent mathematical abstractions in Hilbert space without direct correspondence to learned concepts or features. HNQA addresses this by inducing interpretable basis states through learning rather than assuming quantum states are inherently semantic. Moreover, current quantum systems sit outside mainstream learning workflows, typically requiring algorithmic reformulation rather than incremental integration.

## 2.3 Integration Instability

Previous attempts to combine quantum and classical computing domains have encountered significant challenges. Hybrid systems often suffer from noise amplification, where quantum decoherence undermines computational advantage, or gradient collapse, where the optimization signals needed for learning become vanishingly small or non-differentiable across the quantum-classical boundary. These integration instabilities have prevented the development of trainable systems that meaningfully leverage both paradigms.

## 2.4 Energy Disparity

Translating classical binary or real-valued data into amplitude-based quantum states introduces substantial energy overhead when using physical quantum hardware. However, HNQA is explicitly designed to function without physical quantum devices—the "quantum-like" transformations are linear-algebraic operations simulable on classical processors. Quantum state preparation, maintenance of coherence, and measurement all require resources that scale unfavorably compared to classical computation. HNQA sidesteps this by treating quantum-inspired operations as norm-preserving matrix transformations that can be efficiently implemented in standard numerical libraries. Physical quantum acceleration remains an optional future path rather than a prerequisite.

The central challenge, therefore, is to design a computational manifold that inherits the stability and trainability of classical learning while incorporating the representational diversity of quantum logic, all within an energy-efficient framework that provides measurable advantages for cognitively relevant tasks.

### 3. Conceptual Framework

HNQA addresses these challenges through a dual-layer architecture that maintains distinct but communicating computational substrates.

#### 3.1 Architectural Components

The architecture consists of two complementary layers operating in tandem. The first is a deterministic core, which functions as a conventional neural network performing supervised or reinforcement learning through standard backpropagation or policy gradient methods. This layer maintains learned weights, biases, and structured representations that capture stable patterns from training data. It provides the system with reliable, convergent behavior and serves as the primary interface for task-specific learning.

The second component is a probabilistic state layer, which maintains quantum-inspired representations encoding multiple activation probabilities for each computational node. Rather than a single activation value, each unit in this layer is represented by an amplitude vector describing a superposition of potential states. These states are not merely ensemble averages but genuine coexisting possibilities that can interfere constructively or destructively based on the computational context.

#### 3.2 Information Flow

Information flows cyclically between these layers in a structured manner. The deterministic layer optimizes learned structure through conventional gradient descent, identifying and reinforcing patterns that reduce task-specific loss functions. As it does so, it provides contextual signals to the probabilistic layer, indicating which state configurations align with successful task performance.

Simultaneously, the probabilistic layer encodes potential state variations that represent alternative interpretations or processing pathways. Rather than committing immediately to a single activation pattern, this layer maintains a distribution over possibilities. It feeds entropy-adjusted feedback to the deterministic core, effectively communicating the degree of certainty or ambiguity present in the current computational state. High entropy flags genuine ambiguity; low entropy signals confident convergence. The cycle preserves optionality without forfeiting trainability.

This bidirectional communication creates a dynamic balance. The deterministic core provides stability and learning capacity, while the probabilistic layer provides representational flexibility and the ability to defer commitment until sufficient information is available.

### **3.3 Theoretical Foundation**

The theoretical foundation draws from both neural competition models in neuroscience and quantum information theory. In biological neural networks, populations of neurons often encode competing hypotheses through mutual inhibition and winner-take-all dynamics. HNQA formalizes this through quantum-inspired superposition, where multiple hypotheses coexist as components of a state vector rather than as separate neural populations. This provides a more compact and mathematically elegant representation of cognitive uncertainty while remaining implementable on classical or quantum-classical hybrid hardware.

## 4. Functional Model

The operational cycle of HNQA consists of four primary phases that transform input data through probabilistic processing to actionable output.

### 4.1 Encoding Phase

Input data, whether sensory signals, textual tokens, or structured features, first enters the system through a classical encoding mechanism that transforms it into amplitude vectors suitable for probabilistic representation. This transformation maps each input feature to a point in a high-dimensional space where the coordinate values represent probability amplitudes rather than direct feature values.

For a given input vector  $x$ , the encoding produces an amplitude vector  $\psi$  where each component  $\psi_i$  represents a probability amplitude. This encoding preserves information content while distributing it across a superposition of states. This is analogous to how a quantum system encodes classical information in the amplitudes of its wavefunction, but implemented in a manner compatible with both classical simulation and potential quantum acceleration.

Assume  $\psi \in \mathbb{R}^n$  or  $\mathbb{C}^n$  with  $\|\psi\|_2=1$ ; transforms  $T$  satisfy  $T^T T=I$  (real) or  $T^\dagger T=I$  (complex).

The encoding process is learned during training, with the system discovering optimal mappings that facilitate downstream processing. Unlike fixed encoding schemes, this adaptive encoding allows HNQA to discover representations where probability mass naturally concentrates on basis states that correspond to meaningful cognitive or computational distinctions.



## 4.2 Quantum-like Transformation

Amplitude vectors undergo norm-preserving transforms (orthogonal/unitary), keeping  $\|\psi\|_2^2=1$  and enabling interference that suppresses inconsistent combinations and reinforces coherent ones via learned phase relations. In HNQA, this allows the system to explore multiple interpretations simultaneously, suppressing combinations that violate learned constraints while reinforcing coherent interpretations.

These transformations are parameterized and learned, much like weight matrices in conventional networks. However, they operate on probability amplitudes rather than activations, enabling a richer space of possible transformations. The learning process discovers transformation matrices that productively interfere different hypotheses, effectively implementing soft logical operations over uncertain states.

## 4.3 Collapse Mechanism

At appropriate points in processing, the system must select a dominant interpretation from the maintained superposition of possibilities. This collapse mechanism is context-dependent and can be triggered by various factors including accumulated evidence, task requirements, or resource constraints.

HNQA implements a differentiable, gradual collapse: attention-like weights concentrate probability on context-supported hypotheses, while non-selected paths persist at reduced amplitude for rapid reconsideration. Rather than instantaneous projection to a single basis state, HNQA implements soft collapse where probability mass gradually concentrates on the most contextually supported interpretation.

Critically, non-selected paths do not entirely disappear. Instead, they remain latent in the system's state representation with reduced but non-zero amplitude. This enables the system to rapidly reconsider alternative interpretations if subsequent information

contradicts the initially dominant choice. It also provides a form of implicit memory for paths not taken, which can inform future processing when similar ambiguities arise.

#### **4.4 Gradient Adjustment**

The final phase involves updating the learnable parameters of both the deterministic core and the probabilistic transformations. This presents a unique challenge: how to backpropagate error signals through probabilistic state representations without collapsing them prematurely or losing gradient information.

HNQA addresses this through entropy-aware gradient adjustment. Classical backpropagation reinforces stable patterns by adjusting parameters to reduce task loss. HNQA extends this by incorporating an entropy regularization term that prevents premature convergence to deterministic representations. When the system encounters genuinely ambiguous situations during training, the gradient adjustment maintains controlled entropy in the probabilistic layer, learning to preserve uncertainty rather than artificially resolving it.

Conversely, when training data provides clear disambiguating signals, the entropy term allows probability mass to concentrate appropriately. This creates a learned calibration where the system's internal uncertainty corresponds to genuine ambiguity in the task domain rather than merely reflecting undertraining or model uncertainty.

## 5. Expected Benefits

The proposed architecture offers several theoretical advantages over purely deterministic or purely quantum approaches.

### 5.1 Native Uncertainty Handling

By maintaining probabilistic states as a fundamental computational primitive rather than a statistical approximation, HNQA provides native handling of uncertainty. The system does not need to artificially generate multiple samples or maintain explicit probability distributions over parameters. Instead, uncertainty is directly represented in the amplitude structure of the state layer, providing a more compact and computationally natural representation.

### 5.2 Enhanced Generalization

The maintenance of alternative hypotheses during processing enables improved generalization behavior. Rather than committing prematurely to a single interpretation based on partial evidence, HNQA can defer commitment until sufficient disambiguating context is available. This reduces the tendency toward overconfident predictions on ambiguous inputs, a known limitation of standard neural architectures. The entropy-aware training also naturally regularizes the system, as maintaining controlled uncertainty prevents overfitting to spurious patterns in training data.

### 5.3 Interpretability Through State Maps

The probabilistic state layer provides a window into the system's internal reasoning process. By examining which basis states carry significant probability mass at different processing stages, researchers and users can understand what alternative interpretations the system is considering and how confident it is in its choices. This offers substantially

richer interpretability than examining hidden layer activations in standard networks, where the meaning of individual unit activations is often opaque.

#### **5.4 Hardware Compatibility**

The architecture is designed with flexibility in implementation substrate. While the quantum-inspired transformations could potentially leverage actual quantum hardware for acceleration, they can also be efficiently simulated on classical processors or neuromorphic hardware. The norm-preserving structure of the transformations is well-suited to parallel implementation, and the gradual collapse mechanism avoids the measurement bottlenecks that plague pure quantum approaches. This positions HNQA as forward-compatible with emerging hybrid quantum-classical systems while remaining practically implementable on current technology.

#### **5.5 Cognitive Plausibility**

From a theoretical neuroscience perspective, HNQA provides a more plausible model of cognitive processing than standard feedforward networks. The maintenance of competing hypotheses and context-dependent resolution aligns with observations from neural population dynamics and behavioral studies of decision-making under uncertainty. While HNQA is not intended as a literal model of biological neural circuits, its architectural principles better capture key aspects of cognitive computation, potentially enabling more human-like reasoning capabilities in artificial systems.

## **6. Use Cases and Applications**

The theoretical advantages of HNQA translate into several promising application domains where uncertainty handling and probabilistic reasoning are central requirements.

### **6.1 Adaptive AI Governance**

Decision-making systems in policy, resource allocation, and autonomous vehicle control must often operate under uncertainty while providing calibrated confidence estimates. HNQA enables models that naturally represent decision confidence through their internal state entropy, allowing for adaptive governance where systems can flag decisions requiring human oversight when internal uncertainty exceeds safe thresholds. The ability to maintain multiple policy options simultaneously until decisive evidence emerges enables more robust decision-making in dynamic environments.

### **6.2 Quantum-Enhanced Cybersecurity**

Security systems require sources of unpredictability that are both cryptographically secure and computationally efficient. HNQA's probabilistic dynamics can interface with hardware-backed quantum randomness where available. In classical deployments it yields complex patterns that are hard-to-predict but lack cryptographic guarantees and must be combined with standard cryptographic primitives for key generation or traffic shaping. This is particularly valuable for randomizing network traffic patterns and implementing unpredictable defensive strategies in adaptive security systems.

### **6.3 Cognitive Simulation and Human-AI Interaction**

Understanding and simulating human cognition requires models that capture perceptual ambiguity, emotional valence uncertainty, and the gradual resolution of competing interpretations. HNQA provides a formal framework for modeling these phenomena,

enabling simulation of how humans process ambiguous information, how confidence develops over time, and how context influences interpretation. This has applications in human-AI interaction design, where systems must understand and appropriately respond to human uncertainty, and in cognitive science research, where HNQA could serve as a computational model for testing theories of perception and decision-making.

#### **6.4 Advanced Data Compression**

HNQA suggests exploratory compression schemes that keep multiple encoding hypotheses in superposition and collapse context-dependently at decode time. This is exploratory; rigorous benchmarks against modern codecs are required.

#### **6.5 Scientific Discovery and Hypothesis Generation**

In domains where multiple theoretical models compete to explain observed data—such as particle physics, molecular biology, or economic forecasting—HNQA provides a natural framework for maintaining multiple hypotheses simultaneously and allowing them to compete through interference as new data arrives. Rather than prematurely committing to a single model, the system can track the evolving plausibility of different theoretical frameworks, effectively implementing a form of automated Bayesian model comparison with the computational efficiency of neural networks.

## 7. Theoretical Challenges and Future Directions

While HNQA presents a promising theoretical framework, several challenges must be addressed in future research and development.

### 7.1 Formal Mathematical Modeling

The current conceptual framework requires rigorous mathematical formalization. Specifically, we need formal proofs of key properties including the conditions under which the gradient adjustment procedure converges, the relationship between entropy regularization strength and generalization performance, and the information-theoretic capacity of the probabilistic state layer compared to classical representations of the same dimensionality. Developing this formalism will enable precise analysis of HNQA's theoretical capabilities and limitations.

### 7.2 Classical Simulation Efficiency

Simulating quantum-like state evolution on classical hardware involves computational overhead. While HNQA is designed to minimize this through gradual rather than instantaneous collapse and through learned rather than exhaustive state exploration, the practical efficiency of classical implementations requires empirical investigation. Research is needed to identify which components of the architecture contribute most to computational cost and to develop optimized implementations that maintain the theoretical benefits while achieving practical efficiency.

### 7.3 Energy Efficiency Evaluation

A full energy budget is needed across training and inference, comparing GPUs, neuromorphic options, and hybrid quantum-classical paths. This analysis must account for both training and inference costs, and must consider different hardware substrates.

Only through rigorous energy accounting can we determine whether HNQA's theoretical advantages translate into practical benefits that justify its additional complexity.

#### **7.4 Integration with Existing Frameworks**

For HNQA to achieve practical adoption, it must integrate smoothly with existing machine learning frameworks and workflows. This includes developing differentiable implementations compatible with automatic differentiation systems, creating APIs that allow HNQA layers to be composed with standard neural network components, and establishing training protocols that work with existing optimization algorithms and learning rate schedules. Reducing the barrier to experimentation will accelerate research progress and practical validation.

#### **7.5 Empirical Validation**

Ultimately, HNQA's value will be determined through empirical validation on real-world tasks. Benchmark experiments are needed comparing HNQA against standard neural architectures and existing uncertainty-aware methods on tasks that specifically benefit from native uncertainty handling. These experiments should measure not only predictive accuracy but also calibration of uncertainty estimates, computational efficiency, and interpretability of decision processes.



## 8. Conclusion

The Hybrid Neural Quantum Architecture represents a theoretical bridge between deterministic learning and probabilistic cognition. By combining the stability and trainability of classical neural networks with quantum-inspired probabilistic state representations, HNQA offers a framework for artificial systems that handle uncertainty as a computational primitive rather than a statistical approximation.

The architecture addresses fundamental limitations in current AI systems, particularly their inability to naturally maintain multiple competing interpretations and their tendency toward overconfident predictions on ambiguous inputs. Through its dual-layer design, entropy-aware learning, and gradual collapse mechanisms, HNQA provides theoretical advantages in generalization, interpretability, and cognitive plausibility.

While significant research remains to validate these theoretical benefits and address practical implementation challenges, HNQA establishes a conceptual foundation for next-generation cognitive architectures. As quantum computing hardware matures and hybrid systems become more accessible, frameworks like HNQA will become increasingly relevant for applications requiring sophisticated uncertainty reasoning and human-like cognitive flexibility.

The path forward involves rigorous mathematical formalization, efficient classical simulation development, empirical validation across diverse tasks, and integration with emerging technologies such as the Tyra Protocol. Through these efforts, the vision of probabilistic cognition in artificial systems moves closer to practical realization.

## References

This conceptual paper builds upon general frameworks in neural computation and quantum information theory. Core references include foundational work on backpropagation and gradient-based learning in neural networks, principles of unitary transformation and quantum state evolution from quantum mechanics, and information-theoretic approaches to uncertainty quantification. The framework also draws inspiration from theoretical neuroscience models of neural population coding and decision-making under uncertainty. No proprietary or unpublished data were used in the development of this theoretical model.

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