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Natural Versus Artificial Intelligence in the Light of Quantum-Like Cognition

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Abstract

Contemporary discussions of the gap between natural and artificial intelligence often emphasize human capacities such as contextual reasoning, cognitive flexibility, and non-classical decision-making. This paper proposes that quantum and quantum-like models of cognition and decision processes offer a principled framework for addressing these differences. A growing body of empirical evidence shows that human reasoning systematically violates the assumptions of classical probability and logic, exhibiting contextuality, order effects, interference phenomena, and task incompatibility. Quantum probability theory and related quantum-like formalisms provide mathematically rigorous tools—based on Hilbert spaces, superposition, and entanglement—that capture these features more naturally than classical models. While quantum and quantum-like approaches share a common mathematical structure, they differ in physical implementation, motivating two complementary directions in artificial intelligence: quantum AI and quantum-like AI. Together, these approaches suggest a viable pathway toward narrowing, and potentially bridging, the divide between natural and artificial intelligence by grounding AI architectures in models aligned with the structure of human cognition.

Keywords: genuine quantum cognition; quantum-like cognition; artificial intelligence; natural intelligence; contextuality; human randomness; decision-making; physics-based computing

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1. Introduction

The aim of this article is to shrink the gap between natural and artificial intelligence by exploring genuine quantum and quantum-like modeling of consciousness, cognition, decision making, and AI. While current AI systems demonstrate remarkable proficiency in computation, pattern recognition, and optimization, they remain largely detached from the fluid, context-sensitive, and meaning-oriented processes that characterize human thought. Bridging this divide requires a conceptual and mathematical framework capable of describing the holistic, probabilistic, and context-dependent features of cognition—features that cannot be captured adequately within the classical paradigm of logic and probability. Genuine quantum and quantum-like models provide precisely such a framework, enabling a representation of cognitive dynamics where uncertainty, contextuality, and interference are not computational artifacts but intrinsic properties of the system itself. Now we describe the essence of such modeling, in particular, the commonality and difference between quantum and quantum-like approaches.

Since the first days of creation of quantum theory, it attracted interest of philosophers, psychologists, cognitive scientists as well as physicists as a possible methodological and mathematical tool for creation of a general well-structured and mathematically based theory of mental processes.[1]

Early attempts to link quantum concepts with cognition and consciousness include the correspondence between Pauli and Jung [56], who explored the idea of a psychophysical correspondence,

[1] This is the proper place to note that commonly the year 1925 is considered as the beginning of modern quantum theory — after Heisenberg's article [55]. So, in 2025 the scientific community celebrates 100 years of quantum theory.

and Umezawa and Vitiello [103,105,106], who developed a formalism of quantum field theory for brain dynamics. Further contributions came from Hamerof [47], who investigated microtubule-based quantum processes in neurons, and Penrose [89], who proposed a model of orchestrated objective reduction (Orch-OR) suggesting that consciousness may emerge from quantum computations within the brain (see also articles [48–52,89]). These foundational studies set the stage for what is now commonly referred to as *quantum consciousness* (or quantum theory of consciousness) [47,89,103,105,106]. In this paper we suggest to use the terminology *"genuine quantum consciousness"*; similarly modeling of cognition and decision-making on the basis of quantum physical processes in the brain is called *"genuine quantum cognition"* (Hameroff [53] and Fisher [36] used the term "quantum cognition").

While genuine quantum consciousness and cognition investigate mental processes through the lens of quantum physical theory, its mathematical structures inspired a broader, purely formal approach. This approach, known as *quantum-like cognition* [2], leverages the same quantum formalism—such as Hilbert spaces, superposition, interference, entanglement, decoherence, contextuality — to model consciousness, cognition, and decision-making without assuming that the brain operates via actual quantum physical processes [92] (see section 2). The quantum and quantum-like paradigms are thus closely related from a theoretical viewpoint, sharing mathematical foundations, but they differ fundamentally in their claims about underlying physical mechanisms.

Quantum methodology and formalism have rapidly expanded beyond physics, demonstrating remarkable success in applications such as consciousness, cognition, decision-making, psychology, the social and political sciences, biology, economics and finance [74]. This expansion has led to the emergence of a new research area: *quantum-like modeling* (QLM). The concept was first formalized by Khrennikov [61], who introduced it to describe the application of quantum structures to model contextuality and interference effects in non-physical domains. The intensive development of QLM has introduced groundbreaking perspectives to these fields; indeed, this surge of interest is now widely referred to as the quantum-like revolution [92].

In this paper, which focuses on comparing natural and artificial intelligence, we concentrate on modeling cognition, leaving the fascinating yet highly complex problem of consciousness—both natural and artificial—for future studies.

In the framework of this paper it is important to underline that QL cognition reflects better than classical cognitive models a few important behavioral features of humans (see, for example, monographs [13,15,16,27,54,60–62,75,92]).

Intensive development of quantum technologies, especially quantum computing, opens the door to development of (genuine) quantum artificial intelligence (QAI) [1,80]. This is the promising project, but its rigid coupling to creation of scalable quantum computers makes the possibility of its realization questionable.[3]

As a more realistic alternative for the QAI project, we consider the QL (or quantum inspired) artificial intelligence project (QLAI), implementation of the Hilbert space based AI models [17,70,73,75,77–79] on the classical computers [4–6]. In contrast to QAI, QLAI is not based on computational superiority of quantum computers or quantum simulators, its main aim is to create AI systems, e.g. robots and avatars which are behaviorally closer to humans.

We propose that quantum and quantum-like frameworks serve as a *bridge between natural and artificial intelligence*, reducing the perceived ontological distance. By interpreting human "randomness" not as noise but as a structured manifestation of quantum probability, and by equipping AI with quantum-inspired capacities for contextual decision-making, it becomes possible to view natural and artificial intelligence as points along a shared continuum rather than as categorically distinct. This perspective directly addresses the scope of the special issue: it highlights key differences between

[2] Some authors, e.g., Aerts et.al [2,3], Busemeyer and Bruza [27] use the term "quantum cognition" (cf. Hameroff [53] and Fisher [36] who used this term in genuine quantum physical framework).

[3] To clean one logical qubit from noise, one needs around 1000 physical qubits. To make a real step towards QAI, one needs quantum computers operating with around 1000 logical qubits - or 1 million physical qubits...

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brain and AI computation, explains non-algorithmic aspects of human cognition, and outlines how quantum models can inspire new architectures for artificial systems. In doing so, it reframes the contrast between natural and artificial intelligence as an opportunity to develop a *quantum-inspired synthesis of intelligence.*

The paper is primarily conceptual, presenting a program that seeks to unify natural and artificial intelligence on the foundation of quantum-inspired AI (QAI and QLAI). It might be useful as a thinking stimulator for experts in AI, computer science, QLM, generally consciousness studies/cognition and decision making, quantum physics, and philosophy of science.

2. Quantum-like Modeling and Quantum-like Cognition

QLM applies the mathematical formalism and methodology of quantum theory - such as Hilbert spaces, superposition, and entanglement, principles of uncertainty, complementarity, exclusion, and contextuality - to cognitive science, psychology, and decision-making, social and political sciences, economics and finance, and recently arts and literature; besides mentioned monographs see, for example, articles [11,12,21,28,30,37,40,41,85–87,108,109] and especially reviews [22,74,93]. This interdisciplinary approach challenges the classical probabilistic framework, particularly in explaining paradoxes in human cognition and mathematically modeling the basic effects of cognitive psychology such as the conjunction, disjunction, order and response replicability effects as well as contexuality in decision-making. Contextuality and then the interference effects in quantum probability theory were intensively explored in decision making including social science - crowd decisions [54,76].

QL cognition (as an important part of QLM) is a phenomenological approach based on the evidence that the quantum probability calculus in complex Hilbert space can be useful for mathematical shaping of mental processes and especially decision making (option selection).

But, recently QL cognition was coupled to information processing by oscillatory neuronal networks in the brain [77,78], theory of *QL oscillatory cognition.* Hence, neurophysiologically QL cognition can be coupled to the macroscopic information processors - neuronal networks. In contrast to Orch-OR theory, in QL oscillatory cognition the basic units of information processing are neurons. From this perspective, QL cognition can be coupled to biological computations (section 7).

Interference of probabilities plays the crucial role in QLM, especially in QL cognition – in the analysis of the probabilistic structure of the disjunction effect. In the series of author's works (see, e.g., the monographs [60–62]) quantum interference was formulated in the purely probabilistic terms as *quantum formula of total probability* (FTP) in which the classical FTP part, see (1), is disturbed by an additional interference term (see formula (3), section 2.1). If this term is positive (negative), then interference is constructive (destructive) and probability can increase (decrease) comparing with the output of classical FTP. If the interference term is zero, then formula for quantum FTP is reduced to classical one.

We note that constructive interference is the seed of the superior computational power of quantum computing [69] (see appendix B on a brief discussion). However, we don't connect straightforwardly QLM and quantum computing. Here we in the same boat with Penrose [89] who sharply distinguished human and artificial intelligences. The studies on oscillatory neuronal networks connect computations performed by circuits of neurons with quantum inspired computation (see articles [77,78] connecting QLM modeling with quantum inspired computation via functioning of the oscillatory neuronal networks in the brain).

In QL cognition, conjunction, disjunction, and order effects arise as consequences of probability updating based on quantum conditioning. We highlight that quantum probability inference is non-Bayesian. Therefore, QL cognition and generally QLM can be regarded as formal frameworks for a particular class of non-Bayesian probabilistic inference. This observation is important for understanding the connection between QLM and AI. As is well known, AI encompasses not only classical Bayesian inference but also a variety of non-Bayesian approaches - many of which are typically developed in an ad hoc manner. In contrast, QL probabilistic inference is grounded in a coherent and well-established

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theoretical structure—quantum theory itself through its definition of conditional probability through state's projection (or more generally on the basis of quantum instrument theory).

In the textbook presentation quantum-theoretical conditioning is based on the projection postulate as the machinery for the state (and hence probability) update. This update naturally arises if a quantum observable A is represented as a Hermitian operator, its spectral projections are employed for the state update of the projection type. But, the careful analysis of the QL cognition counterpart of quantum measurement theory demonstrated that one can not proceed solely with projection observables and the corresponding projection state update. In article [63] it was shown that projections do not cover the combination the order efefct and response replicability effect (see appendix C). This problem stimulated application of the quantum instrument theory [83,84] in QL cognition [85–87].

By summarizing, we say that a key advantage of QL cognition is the ability to explain cognitive inconsistencies without assuming irrationality of decision makers, instead attributing them to contextual dependencies and interference effects. Despite skepticism from some classical decision theorists, the approach has gained traction in fields like behavioral economics and finances, molecular biology and genetics, AI, and neuroscience. Overall, QL cognition and generally QLM represents a promising and mathematically rigorous framework for understanding complex human behavior, offering novel insights beyond classical probability theory.

2.1. Classical and Quantum Probability, Interference

Classical probability was mathematically formalized by Kolmogorov (1933) [81]. This is the calculus of probability measures. Probability P is defined on σ-algebra of events $\mathcal{F}$, represented as subsets of some set Ω. the sample space (or the space of elementary events); probability is normalized by one, $P(\Omega) = 1$. The main property of measure-theoretic probability is its additivity: if two events A_1, A_2 are disjoint, $A_1 \cap A_2 = \emptyset$, then the probability of disjunction of these events equals to the sum of probabilities:

$$P(A_1 \vee A_2) = P(A_1) + P(A_2).$$

To make theory mathematically powerful - to develop integration theory - additivity should be extended to countable additivity. Additivity of probability in combination with the Bayes formula for conditional probability leads to FTP:

$$P(A) = P(B)P(A|B) + P(\bar{B})P(A|\bar{B}). \tag{1}$$

where $\bar{B}$ is negation of event B. Observables are mathematically represented as random variables - measurable functions from $\Omega \to \mathbb{R}$.

Quantum probability is the calculus of complex amplitudes or in the abstract formalism vectors belonging to complex Hilbert space $\mathcal{H}$. Thus, instead of operations on probability measures one operates with vectors. We can say that *quantum probability is a vector model of probabilistic reasoning.* Each complex amplitude ψ gives the probability by the Born's rule: probability is the square of the absolute value of the complex amplitude:

$$P = |\psi|^2, \tag{2}$$

see section 2.2 for this formula in the abstract complex Hilbert space formalism.

By operating with complex probability amplitudes, instead of the direct operation with probabilities, one can violate the basic laws of classical probability theory, in particular, FTP (1) which is transformed to quantum FTP (or FTP with interference term):

$$P(A) = P(B)P(A|B) + P(\bar{B})P(A|\bar{B}) + 2cos\theta\sqrt{P(B)P(A|B)P(\bar{B})P(A|\bar{B})}, \tag{3}$$

where the angle θ describes the interference between probability $P(A)$ and conditional probabilities. This angle has purely probabilistic meaning. The additional term in equality (3) is called the interference term. If $\cos\theta = 0$, quantum FTP is reduced to classical FTP - no interference; if $\cos\theta < 0$, then this is destructive interference - probability of event A is less than it should be due to classical FTP; if $\cos\theta > 0$, then this is constructive interference - probability of event A is larger than it should be due to classical FTP. Constructive interference is the powerful tool of quantum and QL computations; in particular, such interference is behind quantum computational supremacy [69].

Appearance of the interference term in quantum FTP is a consequence of representation of probabilities through complex amplitudes, see Born's rule (2), and the following property of complex numbers: generally $|z_1 + z_2|^2 \neq |z_1|^2 + |z_2|^2$.

2.2. *Quantum-Theoretic Representation of Decision Processes*

In this section we outline, in concise form, the QL formalism commonly employed for modeling decision-making processes. Application of this formalism to QL cognition for the order effect is presented in appendix A, with comparison of classical and quantum probability descriptions. We note that the process of decision making can be considered as biological computation (section 7), see section 2.2, as computation generating, for example, the order effect.

For clarity, we restrict ourselves to the finite-dimensional setting, as is standard in the majority of studies on QLM. Let $\mathcal{H}$ denote a complex Hilbert space equipped with an inner product $\langle\cdot|\cdot\rangle$ and the corresponding norm $||\psi||^2 = \langle\psi|\psi\rangle$. Pure states are described, up to a phase, by normalized vectors belonging $\mathcal{H}$. In the Dirac notation, a pure state is denoted as $|\psi\rangle$.

The set of all density operators on $\mathcal{H}$ is denoted by the symbol $\mathcal{D} = \mathcal{D}(\mathcal{H})$. Each element $\hat{\rho} \in \mathcal{D}$ is a positive, Hermitian operator of unit trace that $\langle\hat{\rho}\psi|\psi\rangle \geq 0$ for any state $|\psi\rangle$, $\hat{\rho}^\star = \hat{\rho}$, i.e. $\langle\hat{\rho}\psi|\phi\rangle = \langle\hat{\rho}\phi|\psi\rangle$, and Træ $= 1$. By conventional terminology, such operators describe *mixed quantum states*, i.e., statistical ensembles of pure states.

Within the QL framework, the internal cognitive states of a decision maker are represented either by normalized vectors $|\psi\rangle \in \mathcal{H}$ (pure states) or, more generally, by density operators $\hat{\rho} \in \mathcal{D}$ (probabilistic mixtures of pure states). We remark that any pure state can be presented as a density operator: $\hat{\rho}_\psi = |\psi\rangle\langle\psi|$, the orthogonal projector on the vector $|\psi\rangle$. Thus, $\mathcal{D}$ serves as the state space of the cognitive system.

Cognitive observables - questions, tasks, or traits - are represented by Hermitian linear operators $\hat{A} : \mathcal{H} \to \mathcal{H}$. The spectrum of A corresponds to the set of possible outcomes of a cognitive measurement. In the finite-dimensional case, this spectrum is discrete, consisting of eigenvalues $x_1, \ldots, x_n$, which label possible responses to the question represented by operator $\hat{A}$.

It is often convenient to work with matrix representations of these operators in a chosen orthonormal basis of $\mathcal{H}$. According to the Born rule, the expectation value of an observable A in a state $\hat{\rho}$ is given by

$$\langle A\rangle_{\hat{\rho}} = \mathrm{Tr}(\hat{\rho}\hat{A}). \tag{4}$$

A key property of this expression is its linearity with respect to both the state and the observable, similar to the linearity of expectation values in classical Kolmogorov probability theory [81], where averages are defined as integrals with respect to probability measures.

Any Hermitian operator A admits a spectral decomposition,

$$\hat{A} = \sum_\alpha \alpha\, \hat{E}_A(\alpha), \tag{5}$$

where $\hat{E}_A(\alpha)$ denotes the orthogonal projector onto the eigenspace $\mathcal{H}_A(\alpha)$ corresponding to the eigenvalue α. For a pure state $|\psi\rangle \in \mathcal{H}$, the probability of obtaining the outcome $A = \alpha$ is given by Born's rule:

$$P_\psi(A = \alpha) = \|\hat{E}_A(\alpha)\psi\|^2 = \langle\hat{E}_A(\alpha)\psi|\psi\rangle. \tag{6}$$

A measurement yielding the result $A = \alpha$ induces a transformation (or "back-action") of the system's state,

$$|\psi\rangle \longrightarrow |\psi\rangle_{A=\alpha} = \frac{\hat{E}_A(\alpha)|\psi\rangle}{\|\hat{E}_A(\alpha)|\psi\rangle\|}. \tag{7}$$

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This is the well-known *projection postulate*, originally formulated in its general form by Lüders. While this rule is often attributed to von Neumann, it should be noted that von Neumann's treatment in [107] was limited to observables with non-degenerate spectra; in the degenerate case, he considered more general forms of state update, which later developed into the theory of quantum instruments [83,84].

For mixed states described by density operators, the Born rule for probabilities takes the form

$$P_{\hat{\rho}}(A = \alpha) = \mathrm{Tr}(\hat{\rho}\, \hat{E}_A(\alpha)). \tag{8}$$

A measurement resulting in $A = \alpha$ produces the corresponding post-measurement state

$$\rho \longrightarrow \hat{\rho}_\alpha = \frac{\hat{E}_A(\alpha)\, \hat{\rho}\, \hat{E}_A(\alpha)}{\mathrm{Tr}[\hat{E}_A(\alpha)\, \hat{\rho}\, \hat{E}_A(\alpha)]}. \tag{9}$$

To describe decision making (bio-computation) we used the textbook theory of quantum measurements. This framework is formal and it doesn't clarify the structure of measurement, see section 8.2 for modeling this process.

2.3. Classical Versus Quantum Rationality, Classical Versus Quantum Logic

Writing this section was stimulated by the following statement from the report of one of the reviewers:

"It seems to me there is a major tension between quantum cognition and AI. As the author points out, the former is very useful for understanding many departures of human behavior from classical probability and decision making, making it a good descriptive theory. The goal of AI, however, is not to describe human behavior, but rather to improve it. Many of the violations of classical probability and decision making described by quantum cognition are considered "irrational" from the point of classical theory. Therefore, developing AI that reproduces these behaviors may be considered building systems that are not "rational" according to classical standards."

In this statement, the key phrase is "that are not "rational" according to classical standards." In a series of works, e.g., [62,71,72,74,75], I have argued that the classical approach to rationality—grounded in Bayesian probability inference and the Savage Sure Thing Principle[4] - should be generalized to a quantum rationality, based on quantum state updates, either projective or more generally within the framework of quantum instrument theory. This is the good place to remark that Savage Sure Thing Principle can be mathematically formalized as validity of FTP (1) and hence violation of this principle to violation of classical FTP [62]. And as was noted in section 2.1 this can be formalized within quantum theory as quantum FTP (3) - FTP with interference term.

Already, Kahneman, Shafir, and Tversky [57,58,98] demonstrated that classical decision theory is limited by its reliance on classical probability. Nevertheless, many scientists continue to adhere strictly to classical probability theory and Bayesian rationality, often overlooking both empirical evidence and novel possibilities emerging from QLMs of decision making.

Consequently, the next generation of AI systems—including robots and avatars—should be designed to follow quantum rationality, grounded in quantum rather than classical probability updates [6,18]. Logically, this corresponds to a transition from classical to *quantum logic*, enabling reasoning and decision-making processes that accommodate phenomena such as interference, superposition, and contextuality [64,87]. Quantum logic relaxes the formal constraints of classical Boolean logic, most notably the distributive law governing conjunction and disjunction [100]. By operating within this broader logical framework, a quantum decision-maker can access a more expansive spectrum of possible outcomes than a classical counterpart. Crucially, such departures from classical reasoning

[4] The Sure Thing Principle is a cornerstone of rational decision theory. It was formulated by LSavage as a normative rule for how a "rational" person should make choices under uncertainty: "If you would prefer Action A to Action B if you knew that event E happened, and you would also prefer Action A to Action B if you knew that event E did not happen, then you should prefer Action A to Action B even if you do not know whether E happened or not."

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do not result in arbitrary or ad hoc choices; rather, these decisions remain structurally consistent and rational when viewed through the lens of quantum logic.

We conlclude this section by citation from paper [72] which might stimulate further AI-research in robotics (up to practical implementation and production of QL robots):

"One can imagine a quantum-like robot—an autonomous system which information processing is based on the laws of quantum information and probability, but which is a macroscopic classical system."

Recently some steps towards practical realization of such AI systems were done in article [6,23].

Table 1. Comparison of Logic Frameworks in Robotics

Feature	Classical Robot (Boolean)	Quantum-like Robot (Khrennikov)
Logic	Distributive $A \wedge (B \vee C)$	Non-distributive (Hilbert space)
Probability	Law of Total Probability (LTP)	Violation of LTP (Interference)
Decision Rule	Savage Sure-Thing Principle	Contextual/Quantum Rationality
Environment	Closed or Bayesian	Open Quantum System

3. Quantum Versus Quantum-like Cognition and AI

We emphasize once again that in cognitive studies quantum theory can be applied in two different framework - to genuine quantum and quantum-like cognitive modeling.

It is important to note that *genuine quantum cognition* is closely linked to the physical microworld. For instance, Umezawa and Vitiello [103,105,106] emphasized the role of the quantum vacuum state of the electromagnetic field (see also [32]), while Penrose even considers the possible involvement of quantum-gravitational processes. Consequently, experimental verification of predictions from genuine quantum cognition is extremely challenging due to the fine spatial, temporal, and thermal scales involved. The quantum physical approach to cognition was criticized by many authors.

In contrast, QL systems operate at macroscopic scales, typically involving human participants, and can be studied experimentally. Numerous studies have confirmed usefulness of QLM for cognitive effects such as conjunction and disjunction effects, order and response replicability effects, and their combinations (see section 2).

Overall, genuine quantum and QL modeling predict a variety of cognitive effects that are difficult to capture with classical models:

- **Interference:** Conjunction and disjunction effects.
- **Incompatibility of observables (noncommutativity):** Order effects.
- **Contextuality:** Dependence of responses on the experimental context.
- **Entanglement:** Correlations between cognitive variables that cannot be explained classically.

At this point, it is worth mentioning the notion of quantum nonlocality. In physics, violations of the Bell inequalities – "supercorrelations" - are commonly interpreted as the evidence of "spooky action at a distance." While this perspective could be formally applied to genuine quantum cognition, QLM avoids such interpretations, as this would imply paranormal mental phenomena. Instead, QLM generally interprets the Bell inequalities as the tests of contextuality [21], emphasizing a purely theoretical and operational approach to cognitive effects. (See also [13,26,33,38,39,79] on analysis of supercorrelations within QLM.) Contextuality is in turn coupled to observables' incompatibility (formalized within Bohr's principle of complementarity). The existence of incompatible observables is crucial for violation of the Bell inequalities [66]. Another crucial point is the existence of entangled states. QLMs employing entangled states can, for example, model associations when compositionality is violated (e.g., in memory or conceptual combination).

Table 2. Genuine Quantum Cognition vs Quantum-like Cognition

Aspect	Genuine Quantum Cognition	Quantum-like Cognition
Scale	Microscopic / physical	Macroscopic / behavioral
Experimental accessibility	Extremely difficult	Feasible and numerous studies exist
Physical assumptions	Based on actual quantum processes (e.g., microtubules, vacuum fields)	No assumption of physical quantum processes
Core quantum features	Interference, noncommutativity, entanglement, contextuality	Interference, noncommutativity, entanglement, contextuality
Interpretation of Bell-type inequalities	Can involve nonlocal effects	Contextuality tests only, avoids paranormal interpretations
Typical applications	Modeling consciousness, micro-level cognitive effects	Decision-making, memory, reasoning, cognitive biases
Practicality	Mostly theoretical	Experimentally testable

We recall that in cognitive science, probability theory, and semantics, *compositionality* is the principle that the properties, meaning, or statistical behavior of a composite system are fully determined by the properties of its components and the rule by which they are combined. Formally, let X and Y be random variables (for example, cognitive variables). A compositional model assumes that joint structures are determined by the marginal structures of X and Y, possibly together with classical correlations. In probabilistic terms, this corresponds to factorizable or classically correlated joint distributions. In vector-space models, compositionality is often implemented via tensor products combined with separable states or product representations.

Empirical studies in cognition and decision making show that compositionality is frequently violated. A canonical example is conceptual combination: the meaning or feature statistics of a compound concept (e.g. "pet fish") cannot be inferred from the individual concepts ("pet" and "fish") alone. The joint behavior exhibits emergent associations that are not reducible to classical combinations. Mathematically, such violations correspond to joint structures that are *non-separable*: they cannot be written as convex mixtures of product states. This is directly analogous to entanglement in quantum theory.

The theoretical and mathematical insights from genuine quantum and QL cognition have inspired two complementary approaches in AI :

QAI explores the use of physical quantum computational devices to implement AI algorithms. Leveraging quantum principles such as superposition, entanglement, and quantum parallelism, QAI can potentially accelerate training and inference in large-scale models (e.g., LLMs), enhance optimization over complex loss landscapes, enable compact high-dimensional representations, and improve probabilistic sampling. However, the practical realization of QAI is currently limited by hardware constraints and the requirement for noise-resilient quantum processors.

QLAI takes inspiration from the mathematical structures of quantum theory without assuming any underlying physical quantum processes. Its goal is to reproduce human-like behavioral patterns observed in decision-making, reasoning, and language tasks. QLAI models focus on capturing interference, contextuality, and non-classical correlations in cognition, making it a more immediately realistic approach to AI development. While QAI emphasizes computational advantages, QLAI emphasizes behavioral fidelity, leveraging QL principles to model cognition and generate human-like responses.

Table 3. Quantum AI vs Quantum-Like AI

Aspect	Quantum AI (QAI)	Quantum-Like AI (QLAI)
Underlying principle	Physical quantum computation (superposition, entanglement)	Mathematical quantum formalism applied to behavioral modeling
Goal	Acceleration, optimization, high-dimensional computation	Reproduction of human cognitive and behavioral patterns
Randomness	True quantum randomness	Modeled stochasticity, can reproduce cognitive interference effects
Hardware	Requires quantum processors (NISQ or future fault-tolerant devices)	Classical hardware sufficient
Practicality	Limited by current quantum hardware	Realistic and implementable with current technology
Applications	Large-scale AI models, LLMs, generative tasks	Decision-making, reasoning, human-like language models, cognitive simulations

4. Quantum AI: Potential Advantages over Classical AI

Quantum computation provides a new paradigm for AI, particularly for large-scale models such as *Large Language Models* (LLMs). While classical AI relies on conventional hardware and algorithms, quantum AI leverages quantum computational principles such as superposition, entanglement, and quantum parallelism. The potential advantages of quantum AI over classical approaches can be summarized as follows:

Quantum algorithms such as Harrow-Hassidim-Lloyd (HHL) can solve linear systems exponentially faster under specific conditions, potentially accelerating matrix operations at the core of neural network training; quantum annealing and variational quantum algorithms may improve convergence on complex, high-dimensional, non-convex loss landscapes, potentially finding better minima in training large networks; true quantum randomness can provide more unbiased and high-quality random initialization of weights and stochastic processes in LLMs, potentially improving convergence and generalization; since n qubits naturally encode 2^n amplitudes, quantum systems allow exponentially high-dimensional feature representations, which could reduce memory and computational requirements for embeddings; quantum superposition and interference can improve sampling efficiency from complex probability distributions, benefiting generative models like LLMs; entanglement enables encoding correlations that are difficult to represent classically, potentially improving the modeling of relational and semantic structures in language; and near-term hybrid quantum-classical architectures can serve as co-processors in classical LLM pipelines, improving efficiency for submodules such as attention mechanisms or combinatorial search.

Table 4. Comparison of Classical AI (LLM-style) vs Quantum AI

Aspect	Classical AI (LLM)	Quantum AI
Computation	Deterministic matrix operations	Potential exponential speedup for linear algebra under specific conditions
Optimization	Gradient descent, stochastic methods	Quantum annealing / variational algorithms for complex loss landscapes
Representation	High-dimensional embeddings, stored explicitly	Quantum states encode exponentially large feature spaces in logarithmic qubits
Sampling	Monte Carlo, softmax-based sampling	Quantum superposition and interference for efficient probabilistic sampling
Expressivity	Classical correlations captured by network	Entanglement allows modeling complex relational and semantic correlations
Hardware	Classical GPUs / TPUs	Quantum processors or hybrid quantum-classical devices
Practicality	Fully mature and deployable	Limited by current NISQ devices, mostly theoretical/experimental

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Overall, quantum AI offers a theoretically promising framework for accelerating, enhancing, and extending classical AI approaches, especially for large-scale and generative models, while current hardware limitations mean that near-term advantages are likely to be realized through hybrid quantum-classical architectures.

5. Quantum-like AI: Potential Advantages over Classical AI

QLAI explores the mathematical formalism and methodology of quantum theory to extend the capabilities of classical AI, while remaining implementable on standard digital computers or simulators. QLAI provides a range of potential advantages over classical approaches:

- **Contextual and non-commutative reasoning:** QLAI captures cognitive and informational processes where the order of observations or decisions affects the outcome. This non-commutativity enables modeling of context-dependent reasoning and cognitive order effects, which classical probabilistic frameworks cannot represent.
- **Superposition of cognitive or informational states:** Instead of committing to a single definite alternative, QLAI represents coexisting, potentially incompatible possibilities through superposed states, allowing smoother and more flexible reasoning transitions among competing hypotheses or meanings.
- **Interference-based decision dynamics:** QL interference between probability amplitudes can generate constructive or destructive effects in decision probabilities, providing a natural explanation for empirically observed deviations from classical Bayesian reasoning such as conjunction or disjunction fallacies.
- **Non-Bayesian probability update:** In QLAI, inference and learning proceed via state update rules inspired by the quantum projection postulate or, more generally, by quantum instruments. These updates capture contextual and measurement-dependent changes of belief states, extending beyond the static and commutative nature of Bayesian updating.
- **Entanglement-driven correlations:** The use of tensor product spaces allows modeling of holistic, non-factorizable correlations between features, concepts, or agents—providing a natural framework for complex relational and collective behaviors without ad hoc coupling mechanisms.
- **Compact representation of uncertainty:** Encoding information in complex probability amplitudes allows a more compact and geometrically meaningful representation of uncertainty than large classical probability tables, supporting efficient simulation of cognitive or semantic processes.
- **Unified symbolic and sub-symbolic integration:** The Hilbert-space formalism enables a principled combination of symbolic operations (as projectors or observables) and distributed representations (as state vectors or density matrices), thus bridging logical reasoning and connectionist computation within a single mathematical framework.
- **Computational and modeling efficiency:** QLAI exploits the linear-algebraic structure of quantum theory to perform parallel inference and dimensional compression in high-dimensional semantic spaces. This can reduce the computational cost of representing and updating complex relational structures, offering scalable advantages even on classical hardware.

In summary, QLAI employs the mathematical structure of quantum theory to extend the expressive and inferential capacity of classical AI without requiring quantum hardware. By integrating superposition, contextuality, interference, and entanglement into cognitive modeling and decision processes, QLAI provides a unified and computationally efficient framework for representing uncertainty, relational meaning, and dynamic belief updating. This paradigm thus bridges the gap between probabilistic reasoning, symbolic inference, and sub-symbolic learning, offering a powerful theoretical foundation for next-generation cognitive and semantic architectures.

6. Is LLM a Quantum-like System?

At the same time, we recognize that the interplay between classical AI (such as LLMs) and QLAI is profoundly complex. Many foundational issues remain opaque and require further investigation.

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A primary concern is determining whether LLMs genuinely perform classical Bayesian updates. As noted in [31]:

"Large language models demonstrate remarkable in-context learning capabilities, adapting to new tasks without parameter updates. While this phenomenon has been successfully modeled as implicit Bayesian inference, recent empirical findings reveal a fundamental contradiction: transformers systematically violate the martingale property, a cornerstone requirement of Bayesian updating on exchangeable data. This violation challenges the theoretical foundations underlying uncertainty quantification in critical applications."

Recent work by [35] flagged these martingale violations as evidence against true Bayesian inference. However, [31] suggests that these apparent "failures" do not stem from flawed learning algorithms, but rather from the specific way Transformers encode positional information.

If LLMs are essentially performing classical Bayesian inference, then any observed QL effects may lack fundamental value, potentially being mere artifacts of classical probabilistic processing. This problem remains a subject of intense debate within the AI research community...

The debate over the Bayesian nature of LLMs is not merely academic; it strikes at the heart of the QL hypothesis in cognition. In human decision-making, QL effects – such as, for example, the order effect and violation of the law of total probability – are often attributed to the non-commutative nature of information processing. If the martingale violations in Transformers are simply "bugs" caused by positional encoding, then the LLM remains a classical agent (at least in this aspect). However, if these violations reflect a deeper, non-classical way of aggregating context, it may suggest that LLMs are inadvertently mirrors of the QL structures found in human language and thought. This intersection between implicit Bayesian inference and QLM represents a new frontier for understanding artificial "intuition."

It is highly probable that modern LLMs are already performing a form of contextual reasoning, a phenomenon closely tied to what we call *in-context learning* (ICL) [25]. Currently, the AI research community is actively debating whether ICL represents a fundamental shift in how models process information.

While it is theorized that ICL significantly enhances the efficiency and adaptability of LLMs, we currently lack a universally accepted framework to explain its mechanics. Heuristically, the way ICL dynamically reconfigures a model's output based on surrounding prompts mirrors the contextual reasoning formalized in QLMs. Specifically, both systems rely on the idea that the meaning of a variable is not absolute, but is defined by its relationship to the operators (or tokens) surrounding it. While this remains a compelling conjecture, it offers a promising path toward understanding why non-commutative structures might be superior for artificial intelligence.

From QLM-viewpoint, ICL reminds the contextual model of emotional coloring in that emotions determine contexts for perceptions and decision making [68].

7. Quantum and Quantum-like Approaches to Biological Computation

Quantum physics and, in particular, quantum information theory have become powerful sources of inspiration for understanding biological phenomena and developing bio-inspired computational paradigms. Recent research suggests that quantum effects—such as superposition, entanglement, and coherence—may play functional roles in living systems. Examples include the remarkable efficiency of excitonic energy transfer in photosynthesis, avian magnetoreception, and certain enzymatic reactions. These findings indicate that biological systems may exploit quantum information principles to optimize energy transfer, signal processing, and molecular decision-making, revealing an additional layer of information processing beyond classical biochemical interactions.

Even when physical quantum effects are not directly operative, the *quantum formalism* itself provides a powerful mathematical language for modeling the probabilistic, contextual, and holistic nature of biological dynamics. The QLM framework has been successfully applied to describe contextual dependencies and interference effects in biological networks, such as gene regulation, cellular signaling,

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and genetic or epigenetic evolution [9–13,19]. This approach extends beyond classical probability theory by representing states as density operators and processes as non-commutative transformations, thereby capturing the non-classical correlations inherent in biosystems. Importantly, all living systems are *open* systems—an isolated biosystem is dead, as Schrödinger famously emphasized in *"What Is Life?"* [99].

The theory of open quantum systemsprovides the most general formalism for describing the dynamics of systems interacting with their environments, making it a natural framework for modeling biological information processing. Schrödinger [99] highlighted the fundamental feature of living systems: their apparent escape from the increase of disorder, seemingly violating the second law of thermodynamics. He introduced the concept of "negative entropy" to account for this stability—a biosystem maintains order by exporting entropy to its surroundings. Modern open quantum system theory gives this idea a rigorous mathematical foundation: order-preserving dynamics emerge naturally from system–environment interactions [10,19,20,59]. Under suitable assumptions,[5] the evolution of an open quantum system is described by the *Gorini–Kossakowski–Sudarshan–Lindblad* (GKSL) equation [8,9,13,14,74,75], see Eq. (10) below.

The concept of *biological computation* rests on the recognition that living systems fundamentally process information rather than merely simulating computation metaphorically. Across all levels of organization—from molecules to organisms—biological entities perform operations of storing, transforming, and transmitting information. This computation is inherently distributed: local molecular interactions collectively give rise to global functionality. Cells can be viewed as information-processing systems whose internal states (gene expression, metabolism, membrane potentials) evolve in response to both external and internal cues. Their regulatory and signaling networks perform logic-like operations—feedback, inhibition, amplification—forming distributed circuits that ensure robustness and adaptability. DNA itself functions as both storage and computational substrate: its sequences encode instructions, regulatory elements act as logic gates, and repair or epigenetic mechanisms implement error correction and programmability. Synthetic biology extends these principles through engineered DNA-based computation.

The distributed, stochastic, and context-dependent nature of biological computation requires a formalism capable of representing both probabilistic and holistic information dynamics. Quantum information theory within the QLM framework offers precisely such a tool: it encodes correlations, interference, and adaptive dynamics in a compact operator-based form. Moreover, quantum information concepts inspire novel computational paradigms for bio-inspired AI. By leveraging principles of superposition, entanglement, and coherence—either physically or in simulation—QL approaches can emulate the distributed and adaptive computation observed in living systems. These methods have potential applications in synthetic biology, neural network architectures, and artificial intelligence, unifying insights from quantum theory, biology, and computation into a coherent framework of *QL biological information processing*.

8. Decoherence Based Physical, Biological, and AI Information Processing

8.1. Decoherence and Its Role in Quantum Control Theory

Decoherence is one of the fundamental phenomena in quantum information processing. It originates from the unavoidable interaction between a quantum system and its environment, leading to the loss of phase coherence between components of a superposition state. As a consequence, interference effects and entanglement decay, and the system's evolution transitions from quantum to effectively classical. In quantum computing, this process is typically regarded as detrimental, since it destroys the superposition and entanglement that carry quantum information. Thus, a large part of the effort in implementing and scaling quantum technologies is devoted to protecting systems from decoherence through error correction, dynamical decoupling, and environmental isolation.

[5] A key assumption is that the environment's influence on the system dominates over the system's feedback on the environment.

However, decoherence is not purely destructive. In the broader context of open quantum systems and quantum control theory, controlled or *engineered decoherence* can be harnessed as a powerful resource [88,94,102,104]. By tailoring system–environment interactions, one can use dissipation to drive a system toward specific steady states or to stabilize entanglement. This approach is often referred to as *reservoir engineering* or *dissipative quantum control*. In such settings, decoherence acts not as noise but as a mechanism for robust quantum-state preparation and stabilization.

Notable examples include dissipative preparation of entangled Bell states, autonomous quantum error correction, and decoherence-assisted energy transport observed in biological and condensed-matter systems. The key insight is that, when properly engineered, environmental coupling can impose desired dynamical constraints and steer the system toward target quantum states or subspaces. Hence, while uncontrolled decoherence remains the main obstacle to scalable quantum computation, controlled decoherence has emerged as a constructive tool in modern quantum control theory.

8.2. Decision Making via Decoherence

A state of biosystem S can be represented by a density matrix $\rho = \rho_S$, interpreted as informational state. The evolution of ρ captures the system's information processing, including both internal dynamics and interactions with the environment E. This evolution can be formally described using the *Gorini–Kossakowski–Sudarshan–Lindblad* (GKSL) equation:

$$\frac{d\hat{\rho}}{dt}(t) = -i[\hat{H}, \hat{\rho}(t)] + \hat{L}[\hat{\rho}(t)], \quad \hat{\rho}(0) = \hat{\rho}_0, \tag{10}$$

where $\hat{H}$ is a Hermitian operator, Hamiltonian, encoding the system's internal information processing, and $\hat{L}$ is a superoperator capturing information flows between S and its environment $\mathcal{E}$, interaction superoperator. he GKSL equation describes the process of state decoherence generated by the interaction of a system S with its environment $\mathcal{E}$. Typical GKSL dynamics are characterized by the rapid destruction of superpositions: a pure initial state, represented by a normalized vector in $\mathcal{H}$, evolves into a probabilistic mixture described by a density operator. Our interest lies in applications to biological systems, particularly cognition. In such models, decoherence exhibits a special character — the states of biological systems should decohere without collapsing into disorder, meaning that entropy should not increase monotonically (cf. section 8.1 on quantum control theory).

Special examples of such biologically relevant dynamics were analyzed in [20,59]. In these works, we investigated the evolution of the von Neumann entropy $E = E(t; \hat{\rho}_0)$ for quantum states evolving in accordance with the GKSL equation. For a special class of operators $\hat{H}$ and $\hat{L}$, the entropy function $E(t; \hat{\rho}_0)$ exhibits a characteristic *camel-like* profile: (a) during the initial stage of interaction between the system S and its environment $\mathcal{E}$, the entropy increases, approaching its maximal value $E_{\max} = E(t_{\max}; \hat{\rho}_0)$; (b) at the second stage, the entropy decreases, reflecting the adaptation of S to $\mathcal{E}$; (c) finally, the entropy stabilizes at a value E_{fin} corresponding to the entropy of the steady state

$$\hat{\rho}_{\text{steady}} = \lim_{t \to \infty} \hat{\rho}(t).$$

It is crucial that for the class of the GKSL equations studied in [20], E_{fin} is smaller than $E_{\max}$ (in contrast to the second law of thermodynamics) or even $E_{\text{fin}} \leq E_0 = E(t_0)$.

In general, we interpret *the steady states of GKSL dynamics as the outputs of biological QL computations* performed by the system S interacting with its environment $\mathcal{E}$ (physical, biological, ecological, social, political, or informational) [8].

In [65,67], the GKSL equation was employed to model brain's mental (psychological) functions. In this framework, a question or problem is mathematically represented by the initial density operator $\hat{\rho}_0$, while the corresponding steady-state operator $\hat{\rho}_{\text{steady}}$ represents the output of a mental function F. The internal dynamics of F are governed by the Hamiltonian $\hat{H}$, and its interaction with the environment—other mental functions—is described by interaction superoperator $\hat{L}$. The evolution

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toward the steady state represents a process of decoherence. Therefore, QL computation based on convergence to a steady state can be characterized as *computation via decoherence*.

We also mention article [97] in that theory of open quantum systems was used to simulate the real experimental data demonstrating ambivalence in decision making via recoding of eye tracking. The researchers specifically challenged the traditional drift diffusion model. Standard models usually assume that when we make a decision, we move somewhat steadily (if noisily) toward one choice. In [97] it was argued that for ambivalent decisions—where pros and cons are roughly equal and hard to compare—the process is much more turbulent and QLMs based on theory of open quantum systems can be useful.

We remark that the GKSL equation describes quantum Markovian dynamics, a class of processes characterized by memoryless evolution. Although Markovianity imposes strong constraints, these dynamics are relatively simple, amenable to numerical simulation [13], and thus useful for AI implementations of biological computation.

Biological functions

QLM for computation via decoherence is not restricted to modeling brain functioning. Generally, within QLM the Hamiltonian $\hat{H}$ and interaction superoperator $\hat{L}$ together encode a *biological function* F, which represents the mapping from environmental inputs to biological outputs. In practice, F may correspond to processes such as glucose/lactose gene regulation in *Escherichia coli* or epigenetic mutations [9–13,19].

Formally, F is represented as a quantum observable: a Hermitian operator $\hat{F}$ with spectral decomposition

$$F = \sum_x x \hat{E}_F(x),$$

where x labels possible outputs and $\{\hat{E}_F(x)\}$ are the corresponding projectors.

The outputs of the biological function emerge as the system approaches a *steady state* of the GKSL dynamics:

$$\lim_{t\to\infty} \hat{\rho}(t) = \hat{\rho}_{\text{steady}}, \tag{11}$$

which is diagonal in the eigenbasis of $\hat{F}$:

$$\hat{\rho}_{\text{steady}} = \sum_x p_x \hat{E}^F(x), \quad p_x \geq 0, \quad \sum_x p_x = 1. \tag{12}$$

Here, $\hat{\rho}_{\text{steady}}$ represents a classical statistical mixture of the informational states underlying F, and probabilities are given by

$$p_x = \mathrm{Tr}\Big(\hat{\rho}_{\text{steady}} \hat{E}^F(x)\Big).$$

Biologically, this means that F produces output x with probability p_x, even for a single biosystem repeatedly interacting with its environment.

The steady state captures stabilization under the influence of a specific environment $\mathcal{E}$. In reality, convergence is never complete; fluctuations persist indefinitely. Nevertheless, the formalism of (11) provides a rigorous description of damping and stabilization in biological information processing.

Importantly, steady states are not necessarily unique and may depend on the initial conditions. Biologically, this non-uniqueness reflects adaptability and plasticity: the same biosystem can stabilize into different functional states under varying environmental conditions.

Decoherence is one of the fundamental features of quantum information processing. It is typically regarded as a detrimental environmental effect that destroys superposition and entanglement, thereby disrupting quantum computations. In essence, much of the effort devoted to the realization and scaling of quantum computers is aimed at suppressing decoherence. However, even within genuine quantum physics, decoherence can play a constructive role as a tool in quantum control theory (see Section 8.1).

In a series of works [8,9,13,14,74,75], we have explored this positive aspect of decoherence to model the process of decision-making. Decoherence-based models provide a promising framework for unifying natural and artificial forms of intelligence. In this view, decoherence processes occurring in nature can be interpreted as instances of natural physical computation. Our bioinformational approach to GKSL dynamics and decoherence thus establishes, at the level of mathematical modeling, a unification of biological and physical computation—bridging the quantum and quantum-like domains.

Finally, the application of this model to artificial intelligence (e.g., [74,75]) further integrates natural intelligence—physical and biological, quantum and QL—with artificial intelligence, thereby narrowing the conceptual and methodological gap between them.

Decoherence based intelligence is open system intelligence; here information processing in a system S (physical, biological, AI) is induced by interaction with its environment $\mathcal{E}$. We remark that here "interaction" is not a force-like classical interaction, but information interaction via signaling.

Decoherence is a fundamental feature of quantum information processing, typically regarded as a detrimental environmental effect that destroys superposition and entanglement, thereby disrupting quantum computations. However, even within genuine quantum physics, decoherence can play a constructive role as a tool in quantum control theory.

In a series of works [45], we have explored this positive aspect of decoherence to model the process of decision-making. Decoherence-based models provide a promising framework for unifying natural and artificial forms of intelligence. In this view, decoherence processes occurring in nature can be interpreted as instances of natural physical computation. Our bioinformational approach to GKSL dynamics and decoherence thus establishes, at the level of mathematical modeling, a unification of biological and physical computation—bridging the quantum and quantum-like domains.

Finally, the application of this model to artificial intelligence further integrates natural intelligence—physical and biological, quantum and QL—with artificial intelligence, thereby narrowing the conceptual and methodological gap between them.

8.3. Open Computation and Natural-Born Intelligence

Gunji et al. [45] theory of open computation contrasts with traditional closed computation by emphasizing the dynamic interaction between a system and its environment, leading to emergent behaviors that are not predetermined by fixed algorithms. In this framework, intelligence arises from the system's interactions with its environment, rather than from internal computations alone.

Gunji introduces the concept of *Natural-Born Intelligence* (NBI), which is characterized by adaptability and responsiveness to external stimuli [42,43]. Unlike classical AI, which is often designed with specific goals and constraints, NBI is grounded in the system's capacity to engage with and adapt to its surroundings [45].

The decoherence-based model of decision-making aligns with Gunji's theory of open computation by highlighting how environmental interactions lead to the emergence of structured, context-dependent choices. In both paradigms, intelligence arises not from fixed algorithms but from the dynamic interplay between a system and its environment. By modeling decision-making through decoherence, we can understand how quantum systems, through their interactions with the environment, transition from superposed states to definite outcomes, mirroring the emergence of decisions in open systems. Incorporating Gunji's concepts into this framework enriches our understanding by providing a theoretical foundation for how such interactions can lead to emergent behaviors and intelligence.

Integrating decoherence-based models with Gunji's theory of open computation (cf. also with [44]) provides a robust framework for understanding intelligence as an emergent property of systems interacting with their environments. This approach bridges the gap between quantum mechanics and classical decision-making processes, offering a unified perspective on the nature of intelligence.

NBI, open computation, and decoherence-based decision-making together provide a unified framework for understanding a broad spectrum of intelligence - from chemical reactions and information processing by DNA, RNA, and proteins within cells and cell signaling to mental processes, ecological processes, and social behavior. This unifying perspective naturally extends to coupling with A, including its QAI and QLAI.

9. Natural and Artificial Intelligence: Bridging the Gap

We now comment on ten central issues in the study of natural versus artificial intelligence formulated in this special issue, emphasizing how quantum and quantum-like approaches provide unifying perspectives; we also add principle 11 of purely quantum(-like) nature.

1. **Key differences between computation in the brain and computation in AI:** Classical AI relies on deterministic or classically probabilistic algorithms, while the brain exhibits contextual, interference-based, and non-commutative information processing. Quantum and QL models reproduce these features mathematically, thereby reducing the structural divide between neural cognition and machine intelligence.
2. **Distinguishing AI from humans:** Traditional distinctions, such as creativity, intuition, and adaptability, often rest on features poorly captured by classical computation. Genuine quantum and QL cognition formalizes these “non-classical” traits, offering a framework where AI (QAI/QLAI) can replicate human-like contextual judgments, “interference of minds”, non-Beyesian probability inference order and other psychological effects, nonlocal information processing (“mental entanglement”), employment of nonclassical logic, and bounded rationality, thus narrowing the distinction between AI and human information processing and behavior (of say robots, avatars and humans).
3. **Key characteristics of computing in the brain:** Empirical studies in QL cognition and decision making show that the brain processes information in superposed, context-dependent ways that defy Boolean logic. Quantum probability encodes such characteristics (e.g., cognitive interference, violation of the sure-thing principle). Embedding these into AI systems (QAI/QLAI) would create information processing architectures that align more closely with natural computation.
4. **Characteristics of non-algorithmic human decision-making:** Human decisions often appear inconsistent, but QLMs show they follow a higher-order probabilistic logic. By adopting such models, AI can move beyond rigid algorithmics toward flexible, context-driven reasoning, bringing artificial decision-making closer to human processes. This is the good place to remark that more generally QLM is based on general probability theory extending quantum probability and logic [77,78]. Mathematically general probability theory is based on ordered Banach spaces. Any such model is based on the very natural and general mathematical structure - convex state space; for example, some matrix space space, as space of covariance matrices normalized by trace.
5. **Can AI characterize human randomness?** Human “randomness” is not purely stochastic—it often follows structured but non-classical distributions. QLMs capture this structured randomness through probabilistic interference. Implementing these models in AI enables machines to better simulate and anticipate human variability, reducing one of the starkest divides. Realization of QAI would lead to implementation of irreducible quantum randomness [107] which reminds randomness of human thought process and decision making. May be this would generate of say robot or avatar based free will.
6. **Weaknesses of AI:** Current AI struggles with contextuality, meaning, and adaptability in dynamic environments. These weaknesses correspond to areas where quantum and QL cognition excel. QAI/QLAI architectures can therefore address limitations such as lack of transferability and rigidity by embedding probabilistic contextuality directly through operating with noncommutative variables - represented mathematically by Hermitian operators in complex Hilbert space (or ordered Banach space).
7. **Unique strengths of human beings:** Humans excel at meaning-making, creativity, and adaptive inference under uncertainty. QLMs show that these strengths are grounded in non-classical probability and contextual reasoning. Integrating these into AI provides a blueprint for machines that can partially share such strengths, while still benefiting from classical computation.

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8. **Natural intelligence applications in digital technologies:** Internet-of-Things (IoT) systems, blockchain, and related digital technologies require distributed, adaptive, and sometimes unpredictable decision-making. Embedding QL decision frameworks into these technologies allows systems to mimic natural intelligence's flexibility and resilience, making them more aligned with human users and social environments.
9. **Potentials of AI and ML to augment human capabilities:** By adopting QL cognitive models, AI can become a true augmentative partner rather than a rigid tool. For example, QLAI can provide decision support that respects human context sensitivity, cognitive framing, and bounded rationality—complementing, rather than replacing, natural intelligence.
10. **Automated reasoning and decision-making systems:** Automated systems designed under classical logics face limitations in uncertain, contradictory, or context-rich domains. Quantum-inspired reasoning frameworks allow such systems to process information in ways closer to human cognition, offering more adaptive and holistic decision support.
11. **Role of decoherence in unifying natural and artificial intelligence:** Decoherence is a fundamental feature of quantum information processing, traditionally viewed as detrimental to superposition and entanglement. However, decoherence can play a constructive role in modeling decision-making and cognition. In this framework, decoherence processes in the brain and other natural systems can be interpreted as instances of natural computation, while their mathematical modeling in AI (QAI/QLAI) bridges the quantum and quantum-like domains. By adopting decoherence-based architectures, artificial intelligence can be aligned more closely with natural intelligence, creating a conceptual and methodological unification of physical, biological, and artificial information processing.

Conclusion

Taken together, these ten issues highlight the persistent gap between natural and artificial intelligence. Quantum and quantum-like models of cognition address precisely the domains where AI appears weakest—contextuality, interference, order-dependence, and structured randomness—thereby offering a unifying paradigm. By embedding these models into AI (through QAI or QLAI), the differences between natural and artificial intelligence can be not only diminished but reframed as part of a shared probabilistic logic of cognition.

10. Appendix A: Conditional and Sequential (Join) Probabilities; Order Effects

Classical Kolmogorov formulation [81].

Let $(\Omega, \mathcal{F}, P)$ be a probability space and $A, B \in \mathcal{F}$ events. The conditional probability of B given A (assuming $P(A) > 0$) is defined by the Bayes formula (the definition of conditional probability in Kolmogorov theory):

$$P(B \mid A) = \frac{P(A \cap B)}{P(A)},$$

for $P(A) > 0$.

The sequential (or sequential joint) probability of observing A first and then B (interpreted as "the probability that A occurs and, given that, B occurs") is

$$P(A \text{ then } B) = P(A)\, P(B \mid A) = P(A \cap B).$$

Symmetry of the joint event implies the usual (non-sequential) identity

$$P(A \cap B) = P(B \cap A),$$

but note that the decomposition into $P(A)P(B \mid A)$ versus $P(B)P(A \mid B)$ highlights the operational asymmetry introduced by measurement order in sequential protocols: different conditional probabilities imply different sequential probabilities. In classical probability, however, both decompositions agree on the *joint* probability (they are equal because $P(A \cap B)$ is a single number independent of description).

Quantum measurement formulation

In QLM of binary questions one represents a respondent's belief state by a (pure) state vector $|\psi\rangle$ in a finite dimensional Hilbert space $\mathcal{H}$. Each binary question (observable) A has two answer subspaces with associated projectors $\{\hat{E}_A^y, \hat{E}_A^n\}$ ("yes"/"no") and similarly for B with $\{\hat{E}_B^y, \hat{E}_B^n\}$.

If question A is asked first and outcome $x \in \{y, n\}$ is obtained, the Lüders (projection) update gives the post-measurement (unnormalized) state $\hat{E}_A^x|\psi\rangle$. The probability of observing $A = x$ then $B = y$ (sequential joint probability) is

$$p(A{=}x \text{ then } B{=}y) \;=\; \big\| \hat{E}_B^y \, \hat{E}_A^x \, |\psi\rangle \big\|^2 \;=\; \langle\psi| \, \hat{E}_A^x \, \hat{E}_B^y \, \hat{E}_A^x \, |\psi\rangle.$$

This is the natural quantum analogue of the classical sequential probability $P(A)P(B \mid A)$. If the projectors for A and B commute (i.e. $\hat{E}_A^x \hat{E}_B^y = \hat{E}_B^y \hat{E}_A^x$ for all x, y), then

$$\big\|\hat{E}_B^y \hat{E}_A^x |\psi\rangle\big\|^2 = \big\|\hat{E}_A^x \hat{E}_B^y |\psi\rangle\big\|^2,$$

and no order effect arises: the probability of obtaining answers x, y is the same whether we ask A then B or B then A. Conversely, if the projectors do not commute, in general

$$p(A{=}x \text{ then } B{=}y) \neq p(B{=}y \text{ then } A{=}x),$$

and an order effect appears as a direct consequence of non-commutativity. Thus, in the quantum framework the origin of order effects is structural: incompatible (non-commuting) measurement operators change the state in different ways depending on the order of applied projectors.

Application: the order effect (interpretation and diagnostics).

From the quantum formula for sequential probabilities one obtains clear diagnostics:

- Large or systematic differences between $p(A \text{ then } B)$ and $p(B \text{ then } A)$ indicate incompatible observables in the model, i.e. non-commuting projectors; the quantum model explains the direction/magnitude of order effects through the geometry (angles/phases) between the answer subspaces.
- If additional empirical constraints (e.g. response replicability) are present, one may need the more general instrument/POVM framework (Ozawa & Khrennikov [85–87]).

Empirical example: the Clinton–Gore poll.

A canonical survey example of an order effect is the Gallup split-ballot item reported and discussed in the literature [82]. In that study respondents were randomly assigned to two orders of the two questions:

"Do you generally think Bill Clinton is honest and trustworthy?"
"Do you generally think Al Gore is honest and trustworthy?".

Reported proportions ("Yes") were approximately:

$$\begin{array}{lcl} \text{Order: Clinton then Gore} & : & \text{Clinton yes } \approx 50\%, \;\; \text{Gore yes } \approx 60\% \\ \text{Order: Gore then Clinton} & : & \text{Gore yes } \approx 68\%, \;\; \text{Clinton yes } \approx 57\%. \end{array}$$

These asymmetric percentages are a classic order effect: the measured marginal ("Yes") rates depend on question order. Quantum models of question order effects [108,109] provide a compact account of such data via non-commuting projectors.

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Measurement theory of quantum-like cognition.

Although projective measurements are widely employed in QL cognition, for example, in studies of the question order effect [108,109], their use becomes problematic when one attempts to account for more complex combinations of cognitive effects. As shown in [85–87], a more advanced framework of quantum measurement theory, namely *quantum instrument theory*, is required in such cases. Recently, in article [37] we described a class of measurements specifically suited to genuine quantum cognition. This class differs essentially from the types of measurements typically considered in quantum physics. This distinction demonstrates that, although both quantum physics and QL cognition are grounded in the same mathematical theory, they rely on fundamentally different operational realizations of that theory.

Quantum Instruments.

The projective formulas above assume ideal (von Neumann-Lüders) projective measurements. More generally, a measurement is described by a family of *quantum instruments* [83,84] (or Kraus operators) $\{M_a\}$ satisfying $\sum_a M_a^\dagger M_a = I$. For a state ρ the sequential probability of outcome a then b is

$$p(a \text{ then } b) = \mathrm{Tr}\big(M_b\, M_a\, \rho\, M_a^\dagger\, M_b^\dagger\big),$$

and the post-measurement state after outcome a is

$$\rho_a = \frac{M_a\, \rho\, M_a^\dagger}{\mathrm{Tr}\big(M_a\, \rho\, M_a^\dagger\big)}.$$

Quantum instruments permit richer modelling (noise, response replicability, partial collapse) and can sometimes reconcile empirical phenomena that projective models alone cannot (see e.g. Ozawa & Khrennikov [85–87]).

Appendix B: Complementarity as the Root of Supremacy of Quantum Computing

Here we briefly present the arguments of article [69] that the root of supremacy of quantum computing is complementarity - the existence of complementary contexts and incompatible observables.

We argue that Bohr's complementarity principle implies (by its connection to probability) that [69]:

" ... probabilistic algorithms may proceed without the knowledge of joint probability distributions (jpds). The computation of jpds is exponentially time consuming. Consequently, classical probabilistic algorithms, involving the computation of jpds for n random variables, can be outperformed by quantum algorithms (for large values of n). Quantum probability theory modifies the classical formula for the total probability (FTP). Inference based on the quantum version of FTP leads to a constructive interference that increases the probability of some events and reduces that of others. The physical realization of this probabilistic advantage is based on the discreteness of quantum phenomena (as opposed to the continuity of classical phenomena)."

The last sentence is crucial for understanding why the mere manipulation of superpositions is not sufficient to achieve quantum computational supremacy. For example, continuous waves can also form superpositions, as in classical optics. However, quantum advantage requires not only the superposition of states, but also observables capable of extracting information from these states in the form of discrete outcomes, such as those registered by photodetectors.

The foundational role of this property of (certain) quantum observables was already emphasized by Bohr [91].

Since entanglement itself is a particular form of superposition, it is likewise not sufficient for attaining quantum superiority.

This naturally leads to the following question: *Can quantum superiority be achieved without entanglement, relying solely on quantum interference effects?* In [69], we argued that the answer to this question is affirmative.

In one sentence: Quantum supremacy arises because quantum theory violates the classical assumption of a single, context-independent probability space — and this violation is captured most fundamentally by complementarity.

Appendix C: Response Replicability Effects

Suppose Alice is asked a question A and she answers, for example, "yes," and suppose that if she is immediately asked the same question again, she responds "yes" with probability one. We call this property $A-A$ response replicability.

In physics, $A-A$ response replicability is a common feature of basic quantum experiments and is formalized by *the projection postulate*.

Now, consider another feature characteristic of human behavior in special contexts, which we call $A-B-A$ **response replicability**. Suppose that after answering question A with "yes," Alice is asked a different question B and provides some answer. Later, she is asked A again. If she repeats her original answer "yes," then $A-B-A$ response replicability occurs.

The combination of $A-A$, $A-B-A$, and $B-A-B$ response replicability is referred to as the response replicability effect.

In contrast to the order effect that was tested experimentally in the way matching the QL setting, the response replicability effect was not tested precisely in the QL setting. However, in experimental psychology one can find a plenty of experimental studies that are similar (some of them are practically identical) to the QL $A-B-A$ scheme.

One of the closest empirical analogues of the $A-B-A$ scheme appears in studies of *response consistency* and *answer stability* (see, e.g., [101]-[96]).

Experimental Structure

Participants are typically asked:

1. Question A (attitude, preference, moral judgment, evaluation);
2. An intervening question or task B;
3. Question A again.

The intervening task B is often cognitively demanding, context–changing, or interpretively incompatible with A.

Empirical Findings

Across decades of research in attitude psychology and survey methodology, these studies consistently report:

- very high probabilities of answer repetition for A;
- strong test–retest reliability even under contextual disturbance;
- minimal spontaneous answer reversals.

In quantum–like terms, these findings correspond precisely to $A-B-A$ replicability with incompatible observables.

Conclusion: Although $A-B-A$ replicability has rarely been isolated as a named experimental paradigm, its empirical content has been observed for decades in studies of response consistency, interference, source memory, and commitment. These results support the view that human cognition combines contextuality with memory persistence, a combination that motivates the development of extended quantum–like measurement frameworks [85–87].

At the same time, a straightforward experimental verification of the response replicability effect in combination with a statistically significant order effect is crucial for the foundations of quantum-like (QL) cognition. To date, only one such experiment has been conducted (Busemeyer & Wang [29]),

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which reported a violation of the response replicability effect. However, both the experimental design and the interpretation of its results have been questioned by several experts in QL cognition (see the comments on the journal's webpage).

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