# Cognitive Computation Beyond Optimality

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**Abstract**

Cognitive science has often modeled cognition as an efficiency-driven process, assuming that mental computation aims at optimizing performance under resource constraints. While this view has been successful in many domains, it struggles to explain cognitive phenomena in which inefficiency, ambiguity, and non-convergence play a functional role, such as creative insight, exploratory problem solving, and conceptual restructuring. In this paper, we argue that these forms of cognitive inefficiency are not mere by-products of limited resources, but reflect a deeper computational organization of cognition. We propose a quantum-algorithmic perspective in which cognitive processes are understood as inherently incomplete computations, where superposition, interference, and delayed resolution contribute to flexibility and context sensitivity. From this viewpoint, inefficiency emerges as a structural feature rather than a deviation from optimality. By rethinking cognitive computation beyond output-driven optimization, we introduce a process-based notion of cognitive optimality and discuss its implications for cognitive modeling and computer science.

**Keywords:** Cognitive inefficiency; Quantum cognition; Computational optimality; Incomplete computation; Creative cognition

## Beyond Efficiency as a Cognitive Ideal

Efficiency has long served as a central organizing principle in cognitive science. Across a wide range of theoretical frameworks, cognitive systems are commonly described as goal-directed processors that aim to achieve desirable outcomes while making economical use of limited resources. From early rational accounts of decision making (Simon, 1956) to contemporary computational models, cognition is frequently characterized in terms of performance optimization under constraints, whether framed as utility maximization, cost–benefit trade-offs, or resource-rational optimization (Lieder & Griffiths, 2020), with efficiency providing a unifying normative criterion (Anderson, 1990; Newell, 1990).

This efficiency-centered perspective has been highly productive, supporting influential models of perception, learning, and decision making, and fostering close connections between cognitive science and classical theories of computation. Within this paradigm, cognitive processes are typically evaluated with respect to their ability to converge toward well-defined solutions while minimizing costs related to time, error, or computational effort. Deviations from optimal behavior are therefore often interpreted as noise, approximation, or the expected consequence of bounded resources (Anderson, 1991; Gershman et al., 2015). At the same time, recent work has questioned whether algorithmic models optimized for efficiency on engineered hardware provide an adequate abstraction for neural computation, suggesting that biological cognitive systems may operate according to computational principles that differ fundamentally from classical efficiency-driven algorithms (Aimone & Parekh, 2023).

Despite its successes, an efficiency-centered view does not exhaust the range of phenomena that cognitive models are called upon to explain. Many cognitive activities—including creative thinking, open-ended problem solving, conceptual development, and everyday deliberation—do not naturally conform to well-specified optimization problems. In these domains, cognitive processes may unfold slowly, revisit intermediate states, or sustain ambiguity without clear signs of monotonic progress toward a single optimal outcome. Such patterns recur systematically across tasks and contexts, reflecting structural properties of cognitive computation rather than incidental deviations (Newell, 1990).

These observations motivate a reconsideration of the role of efficiency in cognitive explanation. Rather than treating inefficiency as a departure from an optimal baseline, we suggest that different modes of cognitive computation may operate in different contexts, pointing to qualitatively distinct computational regimes with different functional priorities.

In this paper, we advance a computational perspective that shifts attention away from output-driven optimization and toward the structure and dynamics of cognitive processes themselves. Rather than evaluating cognition primarily in terms of the efficiency or optimality of its final outcomes, we emphasize the internal trajectories through which cognitive states are generated and transformed over time. Drawing inspiration from principles developed in quantum computation, we suggest that certain forms of cognitive behavior are better understood as computations that remain open-ended, context-sensitive, and not necessarily convergent toward a single predefined solution. From this standpoint, inefficiency is not treated as a defect to be minimized, but as a computational resource that supports exploration, flexibility, and adaptive responsiveness in complex and uncertain environments. While the present contribution is primarily conceptual, it is not disconnected from empirical research: later in the paper, we briefly highlight empirical and computational findings that resonate with the structural assumptions developed here, without treating them as a validation of the proposed framework.


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**Contributions.** This paper makes three contributions:

- We introduce the notion of *incomplete cognitive computation*, characterizing cognitive processes that are not defined by convergence to a solution or by optimization of a predefined objective function.
- We propose a *process-based* notion of cognitive optimality, shifting evaluation from outcome efficiency to the structure and dynamics of representational trajectories.
- We argue that a *quantum-algorithmic* perspective provides a principled computational language for formalizing such non-convergent, context-sensitive processes, in a way that is not captured by classical efficiency-based models.

## The Limits of Optimality in Cognitive Models

Efficiency-based models of cognition are not monolithic. Over time, the strong ideal of perfect rationality has been softened through increasingly sophisticated notions such as bounded rationality, approximate inference, and resource-rational optimization (Simon, 1956). These frameworks acknowledge that cognitive systems operate under constraints of time, memory, and computational capacity, and they have made substantial progress in explaining why behavior often departs from classical notions of optimality. Importantly, however, such departures are typically treated as second-order effects: cognition remains fundamentally oriented toward optimal solutions, albeit under imperfect conditions.

Even when optimality is relaxed, it continues to function as the implicit normative reference point against which cognitive performance is evaluated. Cognitive processes are thus interpreted as approximations to an ideal computation that would be realized in the absence of constraints. Within this view, inefficiency is tolerated or explained, but rarely embraced as an essential component of the computation itself. Related work on algorithmic decision making similarly frames deviations from optimal recommendations as forms of aversion, bias, or distrust, reinforcing the assumption that inefficiency reflects a misalignment between human behavior and optimal computational solutions (Mahmud et al., 2022). Experimental studies have shown that even highly specified heuristic models designed to improve decision efficiency often fail to capture the actual dynamics of human decision processes, revealing systematic violations of assumptions such as strict sequentiality, non-compensatoriness, and early convergence (Fiedler, 2010).

While this approach has proven effective for modeling well-defined tasks with stable goals, its limitations become apparent when addressing more open-ended forms of cognition. Creative thought, exploratory problem solving, and conceptual change do not merely approximate optimal solutions under constraints; they often lack a clearly defined objective function altogether. In such cases, the very notion of an optimal outcome becomes ill-specified, and the assumption that cognition is implicitly optimizing loses explanatory power.

Moreover, many cognitively relevant processes exhibit non-convergent dynamics that sit uneasily within optimization-based frameworks. Extended deliberation, persistent ambiguity, and oscillation between competing representations are typically interpreted as failures to settle on an optimal solution. Yet these dynamics frequently play a productive role, allowing cognitive systems to maintain flexibility, integrate conflicting information, and remain sensitive to contextual shifts. For such processes, convergence may not be the goal, but the cost of premature commitment.

These considerations suggest that the limitations of optimality-based models are not merely empirical, but conceptual. By anchoring cognitive explanation to an idealized notion of efficiency, these models struggle to capture forms of cognition in which indeterminacy, redundancy, and prolonged exploration are not side effects, but central mechanisms. Addressing these phenomena requires a computational perspective in which non-optimality is not an anomaly to be corrected, but a feature to be formally understood.

Several influential research programs have sought to accommodate deviations from classical optimality by incorporating computational constraints into normative models. In particular, the framework of *computational rationality* characterizes cognition as the optimization of expected utility under limits of time, memory, and computational capacity, treating observed suboptimal behavior as rational once such constraints are taken into account (Gershman et al., 2015). Closely related approaches in *resource-rational analysis* formalize cognitive strategies as solutions that optimally trade off performance against the cost of computation, thereby explaining heuristic and approximate reasoning as resource-efficient adaptations rather than failures of rationality (Lieder & Griffiths, 2020). Despite their differences, these approaches retain a common normative assumption: cognitive processes are ultimately evaluated with respect to a predefined objective function, and inefficiency is explained as the consequence of bounded resources rather than as a property of the computation itself.

In parallel, quantum-inspired formalisms have been introduced in cognitive modeling to account for systematic violations of classical probability and decision theory. Quantum cognition models employ mathematical structures such as Hilbert spaces and quantum probability as descriptive tools, without claims about the physical implementation of cognition (Busemeyer & Bruza, 2012). Related work has emphasized how quantum probabilistic representations can capture contextual effects and information-processing limitations within bounded rationality frameworks (Blutner, 2016).

The present work builds on these insights while departing from their shared normative focus. Rather than explaining inefficiency as a consequence of resource constraints imposed on an underlying optimization problem, we consider inefficiency as a structural feature of cognitive computation in domains where a global objective function may be ill-defined or dynamically shifting. This shift motivates a computational perspective that emphasizes process dynamics over solution optimality, setting the stage for the quantum-algorithmic account developed in the following sections.

## Structural Inefficiency in Cognition

If inefficiency were merely the result of noise, distraction, or limited resources, its systematic presence across cognitive phenomena would be difficult to explain. Instead, many forms of higher-level cognition rely on processes that are slow, redundant, ambiguous, or non-convergent. These are not incidental side effects, but recurrent patterns that indicate a functional role for inefficiency in cognitive computation, particularly in problem-solving contexts characterized by non-monotonic search and exploration (Newell & Simon, 1972).

Empirical work across clinical, psychometric, and metacognitive domains supports this view. Measures of cognitive inefficiency do not straightforwardly align with dysfunction or maladaptive behavior, and reduced efficiency often fails to map onto objective cognitive impairment (Basagni & Navarrete, 2025; Hidary, 2013). Moreover, inefficiency can arise from multiple structured sources within the computational process itself, even in tasks with well-defined optimality criteria, rather than from undifferentiated noise (Shekhar & Rahnev, 2021). These reinforce the need to treat non-optimal dynamics as organized components of cognition, rather than as deficits or implementation-level limitations (Pantsar, 2021).

Creative insight provides a paradigmatic illustration of productive inefficiency. Moments of sudden understanding are often preceded by extended periods of exploration, false starts, and apparently unproductive reasoning. Rather than progressing monotonically toward a solution, cognitive trajectories wander through representational spaces, revisiting intermediate states and sustaining incompatible interpretations. From an efficiency-oriented perspective, such behavior appears wasteful; functionally, however, it enables conceptual reorganization that would be inaccessible under strictly convergent dynamics. This characterization is consistent with classic and contemporary accounts of creative insight, which emphasize prolonged exploration, incubation, and representational restructuring prior to solution emergence (Smith, 1995; Wallace, 1926).

Similar dynamics have been documented in conceptual change, learning, and decision making. Maintaining competing representations and delaying commitment can preserve flexibility, support robustness to contextual change, and prevent premature fixation, challenging the view that indecision necessarily reflects suboptimal processing (Carey, 2009; diSessa, 1993; Kruglanski, 2013).

Taken together, these phenomena suggest that inefficiency is not an accidental deviation from an otherwise optimal process, but a structural feature of cognition at higher levels of abstraction. Rather than being eliminated, inefficiency is actively maintained and sometimes strategically amplified. Once inefficiency is treated as constitutive rather than incidental, the central question shifts from why cognition fails to optimize to how such non-optimal dynamics are computationally organized. This reframing sets the stage for a computational perspective in which inefficiency is formally integrated into the architecture of cognitive processes.

## A Quantum View of Cognitive Computation

The observations outlined in the previous sections motivate the search for a computational framework in which inefficiency, non-convergence, and indeterminacy are not treated as anomalies, but as integral components of the process. Classical models of computation, however, are poorly suited for this task. They are fundamentally oriented toward well-defined inputs, deterministic or probabilistic transitions, and termination in an output that can be evaluated against a predefined notion of optimality. While approximations and heuristics can be introduced, the underlying computational logic remains convergent and goal-directed.

Quantum computation offers a radically different perspective. Without appealing to any claims about the physical realization of cognitive processes, the quantum computational formalism provides a set of structural principles that align naturally with many features of higher-level cognition. In particular, notions such as superposition, interference, and measurement describe modes of computation in which multiple potential states coexist, interact, and are selectively resolved, rather than being sequentially eliminated in the search for a single optimal solution (Nielsen & Chuang, 2010). This approach aligns with broader work on quantum-like modeling in cognitive science, where quantum probability and related formalisms are applied without commitment to quantum physical mechanisms (Khrennikov, 2020). Recent work has further demonstrated that such formalisms can be used to model the dynamics of cognitive states in Hilbert space without ontological commitments, providing mathematically explicit accounts of belief updating and contextual effects beyond classical probabilistic frameworks (Brody, 2023).

Superposition captures the idea that a computational system can simultaneously represent mutually incompatible states. In cognitive terms, this corresponds to the sustained coexistence of alternative interpretations, hypotheses, or action plans. Rather than committing early to a single representation, cognitive systems often maintain a space of possibilities that remains deliberately unresolved. From a classical standpoint, this appears inefficient; from a quantum-algorithmic perspective, it is a legitimate and computationally expressive state of the system.

Interference further enriches this picture. In quantum algorithms, computational paths do not merely coexist; they interact in ways that can amplify or suppress particular outcomes. Analogously, cognitive processes often involve interactions between competing representations, where partial ideas combine, cancel, or reshape one another over time. Insight, for example, may emerge not from the linear accumulation of evidence, but from the constructive interference of previously unproductive cognitive trajectories. Importantly, such dynamics do not guarantee convergence to an optimal outcome, nor do they require a well-defined objective function in advance (Ambainis, 2003; Kempe, 2003).

**Example.** Consider a quantum walk defined over a graph encoding a conceptual space. Unlike classical search procedures, the walk does not progress monotonically toward a target state. Instead, multiple paths evolve in superposition, and their interference can transiently amplify configurations that were not locally optimal. In cognitive terms, such dynamics provide a natural computational account of insight, where productive solutions emerge from the interaction of previously unpromising trajectories rather than from efficient goal-directed search.

Measurement, or more generally resolution, plays a distinct and critical role. In quantum computation, measurement is not a passive readout, but an active operation that collapses a superposed state into a specific outcome, irreversibly discarding alternative possibilities. Cognitive commitment exhibits a similar structure. Decisions, interpretations, or beliefs often crystallize abruptly, not because all alternatives have been exhaustively evaluated, but because contextual factors trigger a resolution. Delayed measurement, a well-known strategy in quantum algorithms, finds a natural analogue in cognition: postponing commitment preserves flexibility and allows further interaction among competing representations.

From a computational perspective, delaying measurement increases the depth of interaction among computational paths at the cost of postponing resolution. Analogously, cognitive indecision can be understood not as a failure to select an option, but as a strategy that maximizes representational interaction before commitment, trading short-term efficiency for longer-term adaptability.

Within this framework, cognitive processes can be understood as *incomplete quantum algorithms*. By incompleteness, we do not mean failure or approximation, but the absence of a requirement to converge toward a single, predefined solution. Many cognitive computations are valuable precisely because they remain open-ended, exploratory, and sensitive to context. Their computational power lies not in guaranteed termination, but in the structure of the trajectories they generate through representational space.

> **Definition (Incomplete Cognitive Computation).** We define an incomplete cognitive computation as a computational process $C = (S, T, \Pi)$ where $S$ is a space of representational states, $T$ a set of transition operators, and $\Pi$ a context-dependent resolution procedure, such that termination is not required and no global objective function is defined a priori.

Unlike classical algorithms, incomplete cognitive computations are not defined by correctness with respect to an output, nor by termination guarantees, but by the structure of their internal trajectories and their sensitivity to contextual resolution. This perspective also reframes inefficiency as a computational resource. In quantum algorithms, non-determinism, noise, and limited circuit depth are not always obstacles to be eliminated; in many contemporary settings, particularly in near-term quantum computation, they define the regime in which computation actually occurs (Preskill, 2018). Similarly, cognitive systems operate under conditions where exhaustive optimization is neither feasible nor desirable. Inefficiency, in this sense, reflects a mode of computation optimized not for speed or precision, but for adaptability and expressiveness.

Crucially, the proposed quantum-algorithmic view does not imply that cognition is quantum mechanical in a physical sense. The relevance of quantum computation here is structural rather than ontological. It provides a formal language in which non-convergence, contextuality, and productive indeterminacy can be treated as first-class computational principles. By adopting this perspective, inefficiency ceases to be a deviation from an idealized model and becomes a defining feature of cognitive computation itself.

In summary, a quantum-algorithmic framework captures cognitive processes that resist classical optimality, framing non-convergence as a functional feature rather than a deficiency.

## Why a Quantum-Algorithmic Formalism?

The appeal of a quantum-algorithmic perspective is not merely metaphorical. Rather, it lies in the fact that quantum computation satisfies a set of *structural criteria* that are difficult to realize simultaneously within computational frameworks commonly used in cognitive modeling, such as dynamical systems, stochastic search, or attractor-based models.

**Criterion 1: Coexistence without Reduction.**
Quantum computation allows multiple, mutually incompatible computational states to coexist in superposition without being reduced to a probabilistic mixture. Unlike classical representations, where alternatives are encoded as mutually exclusive options or probability distributions, superposition provides a formal mechanism for representing sustained ambiguity and the parallel maintenance of incompatible hypotheses without premature commitment.

**Criterion 2: Interaction without Selection.**
In quantum algorithms, coexisting computational paths can interact through interference, reshaping outcome probabilities without requiring explicit selection or elimination. Classical models typically enforce competition via thresholding or pruning mechanisms, whereas interference enables representational restructuring through interaction alone, capturing cognitive phenomena in which ideas combine, suppress, or amplify one another prior to decision or resolution.

**Criterion 3: Resolution as a Computational Operation.**
Quantum computation treats resolution as an explicit computational operation (measurement), which collapses a superposed state into a specific outcome and discards alternatives. This contrasts with classical models, where commitment typically emerges through gradual convergence. The explicit separation between evolution and resolution provides a principled account of delayed commitment and context-driven decision making in cognition.

Together, these criteria motivate a quantum-algorithmic formalism as a structural framework for non-convergent, context-sensitive cognitive computation.

## Rethinking Cognitive Optimality

The quantum-algorithmic perspective introduced in the previous section motivates a reconsideration of what it means for a cognitive process to be optimal. Classical notions of cognitive optimality are typically output-driven: a computation is successful insofar as it converges to a solution that maximizes utility, minimizes cost, or satisfies a predefined objective function. Within this framework, efficiency is measured in terms of speed, accuracy, and resource consumption, and deviations from optimality are interpreted as errors or limitations (Anderson, 1991).

Such criteria are well suited to domains in which goals are stable and success conditions are clearly specified. However, many forms of cognition do not conform to this structure. In exploratory problem solving, learning, and creative thought, adaptive success cannot be reduced to the quality of the final outcome, but depends on the structure of the process itself, namely on the trajectory it generates through a space of representations, hypotheses, or interpretations.

From a computational standpoint, rather than optimizing a scalar objective function $f(x)$ over outputs, a process-based notion of optimality evaluates properties of the computational trajectory $\tau = (s_0, s_1, \ldots, s_t)$ generated over the state space $S$. From this perspective, rapid convergence may be less desirable than sustained exploration, particularly in environments characterized by uncertainty or change.

**Definition (Classical Cognitive Optimality).** A cognitive process is classically optimal if it computes an output that maximizes (or minimizes) a predefined objective function under given resource constraints, and if the process converges toward this solution within bounded time.

Philosophical analyses have long questioned the identification of cognitive competence with algorithmic optimality, noting that human problem solvers routinely employ strategies that are computationally suboptimal yet cognitively appropriate under realistic constraints (Pantsar, 2021).

**Definition (Process-Based Cognitive Optimality).** A cognitive process is process-optimal if it sustains the generation, interaction, and transformation of representations in a manner that remains adaptive to contextual changes, independently of convergence to an output.

From a computational perspective, process-based optimality can be characterized in terms of *representational productivity*, defined as the ability of a cognitive computation to maintain diversity, interaction, and transformability among its internal states over time. This notion shifts evaluation from final performance to the structure and dynamics of the computational trajectory.

Under classical optimality, inefficiency is treated as a cost to be minimized; under process-based optimality, it functions as a mechanism that preserves flexibility and prevents premature convergence. Cognitive performance is thus better characterized in terms of process productivity than output optimality alone. These differences are particularly salient in decision making under uncertainty. When relevant information is incomplete or rapidly changing, maintaining multiple competing possibilities and delaying commitment can enhance long-term adaptability, even though such behavior appears inefficient from an output-driven perspective. Delayed resolution preserves sensitivity to contextual shifts and reduces the risk of premature fixation on suboptimal commitments, a dynamic discussed extensively in studies of decision making and exploration–exploitation trade-offs (Kahneman & Tversky, 1979; Sutton & Barto, 2018).

Similar considerations apply to learning and creative cognition, where adaptive success depends less on rapid convergence than on the capacity to generate, revise, and reorganize representations over time. In these domains, locally inefficient trajectories may be globally productive, enabling forms of conceptual change and insight inaccessible under strictly efficiency-driven dynamics (Carey, 2009).

Reconceptualizing cognitive optimality along these lines aligns naturally with the quantum-algorithmic framework discussed earlier. Just as quantum algorithms may trade guaranteed convergence for expressive computational dynamics, cognitive systems may sacrifice efficiency in order to sustain richer forms of computation. Optimality, in this view, becomes contextual and temporal, tied to the unfolding of cognitive processes rather than to their termination.

## Implications for Cognitive Modeling

Adopting a process-based and quantum-algorithmic perspective on cognition has several concrete implications for how cognitive models are constructed, evaluated, and interpreted.

Classical cognitive models are typically evaluated in terms of convergence speed, accuracy, or proximity to an optimal solution. A process-based framework instead suggests that models should also be assessed with respect to the structure of their internal trajectories, including the diversity of representations maintained over time and the degree of interaction among coexisting states. From this perspective, non-convergent or slowly converging models may exhibit higher cognitive adequacy in domains where exploration is functionally central.

Many experimental paradigms implicitly penalize indecision, variability, or prolonged deliberation by treating them as noise or suboptimal performance. The present framework suggests that such behaviors may instead reflect productive computational dynamics. As a consequence, task designs that enforce early commitment or reward rapid convergence may systematically underestimate cognitive competence in exploratory or creative domains.

In standard modeling approaches, behavioral variability is often absorbed into noise parameters or treated as an implementation-level limitation. Within a process-based view, variability can instead be interpreted as a signature of ongoing representational interaction and delayed resolution. This shift encourages cognitive models that represent variability as part of the computational process, rather than relegating it to residual error.

## Indicative Empirical Evidence

This section briefly reviews empirical and computational findings that bear on the nature of non-convergent cognitive dynamics. It does not provide an empirical validation of the proposed framework, but highlights convergences between existing evidence and the structural assumptions underlying a process-based, non-convergent view of cognition.

**Creative insight and incubation.** A first class of evidence comes from studies of creative insight, which consistently report extended phases of exploration, apparent impasse, and representational instability preceding the emergence of a solution. Such dynamics are difficult to reconcile with monotonic search or optimization-based accounts, and instead suggest iterative restructuring and delayed integration of partial representations. Connectionist models of creative problem solving explicitly reproduce incubation effects and non-linear transitions to insight, emphasizing the functional role of intermediate, non-convergent phases in creative cognition (Helie & Sun, 2010). Neurocognitive evidence further supports this view, showing that insight is often preceded by distributed and unstable patterns of neural activity rather than by gradual convergence toward a solution (Kounios & Beeman, 2014).

**Delayed commitment in decision and learning.** Related patterns have also been documented in decision making and learning. Behavioral and eye-tracking studies reveal prolonged deliberation, oscillations between competing alternatives, and delayed commitment even in well-defined tasks, suggesting that variability and indecision can support flexibility rather than reflect processing failure (Rosner et al., 2022). Similarly, learning and conceptual change exhibit regressions, temporary destabilization of representations, and non-linear trajectories that violate assumptions of smooth convergence toward an optimal internal model. At the neurophysiological level, creative tasks have been associated with oscillatory dynamics reflecting the coexistence of multiple representational states prior to resolution (Yu et al., 2023).

**Non-monotonic computational dynamics.** From a computational perspective, these empirical patterns are mirrored by models in which cognitive dynamics unfold as non-monotonic trajectories rather than as goal-directed optimization processes. In particular, implementations based on continuous-time quantum walks over semantic graphs show how interference-driven dynamics can transiently amplify conceptually remote but task-relevant representations, leading to time-localized and probabilistic insight events without requiring convergence to a unique optimal state (Pavone & Faro, 2025).

Taken together, these findings challenge output-driven accounts that assess cognitive performance primarily in terms of convergence or optimality. Within the framework of *incomplete cognitive computation*, non-convergent dynamics are instead expected and functionally meaningful, as the value of cognitive processing lies in the structure of its internal trajectories rather than in guaranteed termination, in line with dynamical views of cognition (van Gelder, 1998).

# Conclusions

The present contribution is best understood not as a predictive theory, but as a conceptual and computational reframing that clarifies how inefficiency is modeled and evaluated in cognitive science. Rather than proposing a formal or empirical model, our goal has been to make explicit the computational assumptions that shape prevailing interpretations of inefficiency, viewing formal and empirical instantiations as downstream consequences of this shift.

This paper has argued for rethinking cognitive computation beyond efficiency and optimality as normative ideals. We have suggested that many forms of higher-level cognition are better understood as processes in which inefficiency, non-convergence, and indeterminacy play a functional and often indispensable role. Rather than treating these features as limitations to be minimized, we have proposed that they constitute a structural dimension of cognitive computation.

At the core of this proposal lies a quantum-algorithmic perspective that reframes cognition as a form of computation oriented toward exploration rather than guaranteed convergence. Drawing on structural principles from quantum computation we have outlined a framework in which cognitive processes can be understood as inherently incomplete algorithms, operating in regimes where optimization is neither fully specified nor always desirable.

The implications for cognitive science are twofold. First, this perspective challenges output-driven accounts that evaluate cognitive success solely in terms of efficiency or accuracy. Second, it offers a principled way to model phenomena such as creativity, prolonged deliberation, and conceptual restructuring without relegating them to anomalies. Inefficiency thus becomes a feature to be explained, rather than a residual absorbed into noise or bounded rationality.

From the standpoint of computer science, the proposed framework suggests a broader class of computational models that we refer to as *cognitive quantum algorithms*. These are not algorithms designed to terminate with an optimal output, but structured computational processes whose value lies in their internal dynamics, including exploratory behavior, non-convergence, and context-driven resolution.

This view resonates with contemporary developments in quantum computation, particularly in settings where limited depth, noise, and non-determinism define the computational landscape rather than merely constrain it (Preskill, 2018), and where guarantees on convergence time and solution optimality are traded for increased expressive power and adaptability (Arora & Barak, 2009).

Several limitations of the present work should be acknowledged. The account developed here is primarily conceptual and does not aim to provide a complete formal model or direct empirical validation. Future research may explore explicit computational instantiations, simulations, or experimental paradigms that operationalize the proposed ideas, particularly by investigating how degrees of inefficiency interact with task structure and environmental uncertainty.

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