

# The Evolutionary Inevitability of Predictive Processing: A Physical Constraint Argument

Boris Kriger

*Institute of Integrative and Interdisciplinary Research*  
boriskrigger@interdisciplinary-institute.org

## Abstract

This paper argues that predictive processing is not merely one computational strategy among many, but the only scalable and evolutionarily stable architecture for systems operating under realistic physical constraints. The argument proceeds from physical facts: finite neural conduction velocity, body scaling geometry, and computational intractability of exhaustive reasoning. We formalize this using information theory, proving that systems persisting under uncertainty must maintain internal states encoding information about future environmental states. The independent convergence of biological and artificial systems on predictive architectures suggests a universal constraint. We address major criticisms of predictive processing—including unfalsifiability concerns and alternative frameworks—and propose the Predictive Viability Law as a general principle. We conclude with predictions for next-generation AI systems.

## 1 The Problem: The Tyranny of Latency

Consider the fundamental constraint shaping every nervous system: neural signals travel at finite speed. The fastest myelinated axons conduct action potentials at roughly 100 meters per second—impressive until you realize what it means for survival.

When light strikes your retina, the signal must travel through the optic nerve, reach the lateral geniculate nucleus, proceed to primary visual cortex, and propagate through visual areas before any conscious percept emerges. This journey takes 50–150 milliseconds. Add motor planning and execution, and reaction times reach hundreds of milliseconds.

The implications are stark. By the time you perceive a present moment, it has already become the past. You experience the world as it was—a tenth of a second ago, perhaps more. This is not a bug in the system. This is physics.

## 2 The Selection Pressure: Milliseconds as the Currency of Survival

For billions of years, life has engaged in an arms race where reaction time is the primary currency. The predator that strikes faster catches prey. The prey that flees sooner survives. This pressure operates at millisecond resolution.

Consider a frog catching a fly. The fly detects movement and initiates escape within 30 milliseconds. The frog’s tongue strike is ballistic—once launched, it cannot be corrected. The difference between catching a meal and going hungry often comes down to single-digit milliseconds.

This creates what we might call the *speed imperative*: any neural architecture that does not maximize response speed will be outcompeted. Evolution optimizes ruthlessly, and in predator-prey interaction, it optimizes primarily for speed.

### 3 The Physical Ceiling: Why Faster Is Not Always Possible

If speed is so important, why not simply evolve faster neurons? The answer lies in biophysics, which imposes hard limits on conduction velocity.

The speed of an action potential depends on axon diameter, myelination, ion channel density, and temperature. Evolution has pushed all parameters toward their limits. Myelination increases speed roughly a hundredfold, but requires specialized glial cells and metabolic investment. Increasing axon diameter increases speed only with the square root—quadrupling size merely doubles speed.

Ion channel kinetics impose another limit. Channels must open and close at rates determined by protein physics. You cannot arbitrarily speed up conformational changes without compromising reliability.

The verdict: neural conduction velocity has a ceiling. Vertebrates reached this ceiling hundreds of millions of years ago. The selective pressure for speed did not disappear—it redirected toward a different solution.

### 4 The Only Solution: Prediction as the Escape from Latency

When you cannot react faster, the only option is to act before the event you are responding to. This is what prediction means: generating a response to a future state based on current information.

Consider a baseball outfielder catching a fly ball. If the fielder waited to see where the ball lands, they would never catch anything—the ball would arrive hundreds of milliseconds before they could reach it. Instead, the fielder predicts the landing point from the initial trajectory and begins moving immediately.

The flash-lag effect demonstrates this directly: a flash presented at the exact moment a moving object passes it is perceived as trailing behind. The visual system extrapolates the moving object’s position forward to compensate for neural delays, while the unpredictable flash cannot receive this compensation.

It should be noted that alternative explanations exist for the flash-lag effect. Eagleman & Sejnowski (2000) proposed a “postdiction” account, arguing that visual awareness attributes position based on information collected  $\sim 80$ ms after the flash rather than extrapolating forward. However, as Hogendoorn (2020) argues in a comprehensive review, 25 years of evidence converges to support motion extrapolation, particularly findings that objects can be perceived in locations where no physical stimulus energy was ever detected—something temporal explanations cannot account for.

Prediction, then, is not an optional cognitive enhancement. It is the only possible solution to the latency problem. Any organism that simply waited for sensory data to arrive before initiating response would be outcompeted.

### 5 The Scaling Problem: Body Size as a Second Derivation

There is a second, independent route to the same conclusion—one that makes the case even more geometrically inevitable. This route passes through the scaling relationship between body size and neural delay.

As organisms grow larger, conduction pathways lengthen linearly with body size. But neural conduction velocity does not scale up—it remains bounded by the same biophysical limits. Total neural delay grows with body size while signal propagation stays constant.

For small organisms, this is manageable. A fly’s nervous system spans millimeters. A purely reactive architecture can remain viable. But as body size increases, this strategy degrades. A signal from a giraffe’s hoof to its brain and back covers meters. At 100 m/s, the round-trip takes tens of milliseconds before any processing.

We can state this as a scaling law: *small organisms can afford to react; large organisms must anticipate.*

## 6 The Tyrannosaurus Test: Prediction at Scale

Consider *Tyrannosaurus rex* as a test case. Here was an organism of massive body size—multiple metric tons—operating as an active predator. At tyrannosaur scale, purely reactive control is physically incoherent.

Successful predation would require: tracking prey trajectory, anticipating evasive maneuvers, coordinating head and jaws with body momentum, timing the strike to intercept prey at a future location, managing enormous inertia during turns. None of this can be accomplished reactively.

If *T. rex* was an active predator—and paleontological evidence suggests it was—it had no choice but to operate on predictive models. This does not imply cognitive sophistication. A predictive brain is not necessarily an intelligent brain. The predictions may have been narrow and hard-wired, but within that domain, exquisitely calibrated.

## 7 The Two Transitions: From Optional to Necessary to Macroscopic

Prediction pressure is not constant across body sizes. There appear to be two critical transitions.

The first transition occurs from small to medium size. Conduction delays become significant, reactive strategies fail, and predictive architectures offer maximum advantage. Medium-sized organisms in dynamic niches face the strongest selection for fine-grained sensorimotor prediction.

The second transition occurs at very large sizes. A large herbivore may not need millisecond-precise reactions—it can afford to be slower. But prediction does not disappear; it becomes macroscopic—concerned with terrain, long-term trajectories, body dynamics at larger timescales.

## 8 The Medium Matters: Water, Air, and the Physics of Prediction

The argument thus far has focused on neural conduction speed and body size. But there is a third critical factor: the physical medium in which the organism operates. Water, air, and land impose radically different constraints on movement, sensing, and the necessity of prediction.

### 8.1 The Aquatic Amplification

Water intensifies the prediction problem in several ways simultaneously:

**Movement is costly and slow:** Water is ~800 times denser than air. Every movement requires overcoming substantial viscous drag. Acceleration and deceleration are energetically expensive and temporally extended. An aquatic predator cannot make rapid course corrections the way a terrestrial one can—momentum commits it to trajectories that must be anticipated, not merely reacted to.

**Large body sizes are common:** Buoyancy support allows aquatic organisms to achieve sizes impossible on land. Sharks, orcas, dolphins, and whales operate at scales where neural conduction delays are substantial. A great white shark at 6 meters, or an orca at 8 meters, faces round-trip signal delays measured in tens of milliseconds—before any processing occurs.

**Sensory constraints compound the problem:** Vision is limited by turbidity and light attenuation. Many aquatic predators rely heavily on mechanoreception (lateral line), electroreception, or echolocation—modalities that provide information about prey position with inherent delays. Sound travels faster in water than air ( $\sim 1,500$  m/s vs  $\sim 340$  m/s), but this advantage is offset by the need to process complex echoes and the distances involved.

**Prey evasion is three-dimensional:** Unlike terrestrial pursuit, aquatic predation occurs in a full 3D volume. Prey can escape in any direction. Predicting the trajectory of a fish evading in three dimensions requires more sophisticated models than tracking prey constrained to a surface.

The implication is clear: aquatic environments create a perfect storm for predictive necessity. Large bodies + slow/costly movement + sensory delays + 3D pursuit = extreme selection pressure for anticipatory control. It is no accident that dolphins and orcas—among the most neurologically sophisticated non-human animals—are large aquatic predators. Their cognitive complexity may be less a product of social demands (though those matter) and more a consequence of the physics of hunting in water at scale.

**Dolphins as a case study:** Dolphins use echolocation to hunt fish in murky water. The time between emitting a click and receiving the echo creates an inherent sensory delay. Meanwhile, the dolphin is moving, and so is the prey. Successful interception requires predicting where the fish will be when the dolphin arrives—not where it was when the echo returned. The dolphin’s brain must run a forward model that integrates its own trajectory, the prey’s likely evasive maneuvers, and the hydrodynamics of both bodies. This is not optional sophistication; it is the minimum viable architecture for the task.

## 8.2 The Aerial Extreme

If water amplifies prediction demands, air takes them to an extreme—particularly for fast-moving fliers:

**Speed magnifies latency costs:** A peregrine falcon diving at 300+ km/h covers nearly a meter in the time it takes for a visual signal to travel from retina to motor cortex. At such speeds, purely reactive control is mathematically impossible. The falcon must predict prey position, wind effects, and its own aerodynamic trajectory multiple time steps ahead.

**Three-dimensional navigation at speed:** Aerial predators operate in a 3D environment with no friction to slow them down. A dragonfly catching a mosquito mid-flight performs calculations that would challenge an aerospace engineer—predicting the intersection point of two independently moving objects in three dimensions, while itself being buffeted by turbulence.

**Insects and the minimal brain solution:** Interestingly, flying insects like dragonflies achieve remarkable interception accuracy with tiny nervous systems. How? Their small size means minimal conduction delays, and their sensory-motor loops are extremely tight. This supports the scaling argument: prediction becomes necessary when delays become significant relative to task demands. Dragonflies can afford more reactive strategies because their entire nervous system operates in microseconds.

**Birds occupy the critical zone:** Birds are large enough that conduction delays matter, but operate at speeds where those delays are maximally costly. This predicts that avian brains should show sophisticated predictive mechanisms—and they do. The avian pallium, functionally analogous to mammalian cortex, is highly developed in raptors and other aerial predators.

### 8.3 Medium-Specific Predictions

This analysis generates testable predictions:

(1) Aquatic predators of a given body size should show more developed predictive neural circuits than terrestrial predators of similar size, because the costs of reactive errors are higher in water.

(2) Fast aerial predators (falcons, swifts, dragonflies at their scale) should show neural specializations for trajectory prediction that exceed those of similar-sized terrestrial animals.

(3) Organisms that transition between media (e.g., diving birds, flying fish) should show hybrid predictive strategies adapted to the different physics of each medium.

(4) The evolution of echolocation in aquatic (dolphins) and aerial (bats) hunters represents convergent solutions to the same problem: maintaining predictive information in environments where visual prediction is limited.

The medium, then, is not merely a backdrop for the latency argument—it is a multiplier. Water and air each impose their own physics on the prediction problem, creating distinct selection pressures that shape neural architecture in predictable ways.

### 8.4 Alternative Sensory Modalities: The Double Latency Problem

The argument thus far has primarily considered vision, where the stimulus—light—travels at approximately 300,000 km/s, effectively instantaneous from the perspective of biological organisms. The latency problem in vision arises solely from neural conduction within the organism. But many organisms rely on sensory modalities where the signal itself propagates slowly through the external medium, creating a *double latency problem*: delay in the environment plus delay in the nervous system.

**Echolocation as the paradigm case:** Bats and dolphins independently evolved echolocation—active sensing through emitted sound waves and their returning echoes. Sound travels at  $\sim 340$  m/s in air and  $\sim 1,500$  m/s in water. For a bat detecting a moth 5 meters away, the round-trip time for the acoustic signal alone is  $\sim 29$  milliseconds. For a dolphin tracking a fish 10 meters distant, the acoustic delay is  $\sim 13$  milliseconds. These delays occur *before* any neural processing begins.

The total latency for an echolocating predator is therefore: acoustic propagation time (out and back) + cochlear transduction + auditory nerve conduction + central auditory processing + motor planning + motor execution. For a bat, this can easily exceed 50–80 milliseconds. During this time, both predator and prey are moving. Successful interception requires predicting not where the prey was when the echo was emitted, but where it will be when the strike arrives—a prediction spanning two cascading temporal gaps.

**Electrolocation and the slow-field problem:** Weakly electric fish (Gymnotiformes and Mormyridae) sense their environment through self-generated electric fields. These fields propagate at effectively instantaneous speeds, but their spatial resolution degrades rapidly with distance, and the fish must integrate temporal changes in field distortions to track moving objects. The computational challenge is analogous: the fish must predict where a prey item or obstacle will be by the time it can respond, not where it was when detected. Studies of electric fish reveal sophisticated predictive mechanisms in their electrosensory systems, including forward models of expected field distortions during self-movement (Sawtell et al., 2005).

**Mechanoreception and the lateral line:** Fish and aquatic amphibians detect water movements through the lateral line system. Pressure waves from approaching predators or fleeing prey travel through water at speeds determined by fluid dynamics—fast, but not instantaneous, and subject to complex patterns of reflection and distortion. The organism receiving this information must disentangle self-generated water movements from external signals and predict the source’s future position. This requires precisely the kind of forward modeling that predictive processing describes.

**Infrared sensing in pit vipers:** Pit vipers detect thermal radiation through specialized pit organs. While infrared radiation travels at light speed, the thermal detection mechanism itself introduces latency—the pit membrane must warm or cool in response to incident radiation, a process governed by thermodynamics rather than electronics. The snake must predict prey movement during the strike based on thermal “images” that are inherently smoothed and delayed by this physical constraint.

**The generalized principle:** What unites these cases is that the latency constraint generalizes beyond neural conduction. Any sensory modality where the physical signal propagates slowly, where transduction introduces delays, or where environmental factors add noise and temporal uncertainty faces the same fundamental problem: the information an organism receives describes a world that no longer exists. The only solution is the same—prediction.

This observation strengthens the central argument. Vision, with its effectively instantaneous stimulus propagation, represents a *best case* for reactive control—and prediction is still necessary. For organisms relying on echolocation, electrolocation, mechanoreception, or other “slow” modalities, the necessity is even more acute. The convergent evolution of sophisticated predictive neural circuits in echolocating mammals (bats and cetaceans, separated by ~95 million years of evolution) and electrosensing fish (Gymnotiformes and Mormyridae, independently evolved on different continents) provides powerful evidence that prediction is not just one computational strategy but the universal response to the physics of signal propagation in time.

## 9 The Implication: Predictive Architecture as Physical Necessity

We now have two independent derivations of the same conclusion. The first proceeds from selection pressure for speed. The second proceeds from body scaling. Both converge on a single claim: predictive processing is not one possible architecture among many—it is the only scalable and evolutionarily stable architecture for any nervous system facing temporal constraints.

This is a strong claim—perhaps too strong in its original formulation. We should qualify: predictive processing is the only architecture that remains viable at scale in dynamic, temporally demanding niches. Organisms in static environments or those small enough for negligible delays may persist with simpler architectures.

## 10 Corollary: The Impossibility of Passive Perception

If the foregoing argument is sound, a strong corollary follows: perception cannot be passive reception. The classical view—that the brain simply receives sensory data and outputs representations—is physically impossible.

Passive perception would require waiting for data. Waiting means responding to the past. Responding to the past means systematic failure in temporally demanding tasks. Systematic failure means extinction. Therefore, passive perception cannot exist in any organism shaped by selection for rapid response.

What exists is perception as controlled hallucination. The brain generates predictions, compares them against incoming data, and updates based on prediction errors. The percept is the prediction, not the raw input.

## 11 The Convergence: Why Artificial Systems Rediscover the Same Architecture

Artificial intelligence systems, designed by humans on entirely different substrates, have independently converged on predictive architectures. Large language models are prediction engines.

This convergence is not coincidental—it reflects the same underlying constraint in a different medium.

For biological systems, the limiting resource is time. For artificial systems, it is computation—the combinatorial explosion when attempting exhaustive reasoning. Different constraints, but the same structural problem: the impossibility of thinking everything through before acting.

Consider generating text without prediction. At each token, the system would need to evaluate all continuations, compute consequences, verify correctness, and select optimally. This is intractable. The only solution that scales is prediction based on learned statistical structure.

The trade-off is identical. Predictive systems make errors. Brains hallucinate—perceiving patterns that are not there. Language models hallucinate—generating plausible-sounding falsehoods. These are not bugs but necessary costs of prediction as strategy.

## 12 What Prediction Means: A Unified Definition

This paper has invoked “prediction” in several contexts: sensorimotor extrapolation, internal body models, anticipatory control, and next-token prediction. Are these genuinely instances of the same phenomenon?

**Definition:** A system engages in prediction if and only if it maintains internal states that carry information about states of a target variable not directly accessible to current observation, and these internal states influence the system’s outputs.

This definition has three components: (1) internal states, (2) information about inaccessible states, and (3) influence on output. Under this definition, all discussed cases qualify:

Sensorimotor extrapolation: the visual system represents moving objects “ahead” of their last observed position. Internal body models: the cerebellum generates predicted limb positions. Predator-prey anticipation: neural states encode future prey position. Language models: hidden states encode information about likely future tokens.

The key insight: “prediction” does not require explicit temporal reasoning or conscious foresight. It requires only that internal states carry information about states not directly accessible to current observation.

## 13 Prediction as the Basis for Intuition

The unified definition has a striking implication for intuition. We propose that intuition is not a separate cognitive faculty but the subjective experience of predictive processing operating below the threshold of conscious access.

Consider an experienced chess player who “feels” a position is dangerous, or a clinician who “senses” something is wrong before explicit diagnosis. These judgments arrive fully formed, without conscious reasoning, yet are often remarkably accurate.

The predictive framework provides a direct answer: intuition is prediction that has become so compressed, automatic, and fast that it no longer registers as inference. The chess player’s brain has encoded statistical regularities from thousands of games; when a new position is presented, these patterns generate predictions without explicit calculation.

**The speed of intuition is not magical; it is architectural.** Conscious reasoning is slow because it serializes information through working memory. Intuitive prediction bypasses this bottleneck by operating on distributed, parallel representations.

This explains several puzzling features: why intuition improves with expertise (more data for learning regularities), why it is domain-specific (different domains have different regularities), why it can be wrong (models trained on limited or biased data), and why it feels like perception rather than inference (same predictive machinery, applied to abstract domains).

## 14 Critiques, Alternatives, and Boundary Cases

### 14.1 The Unfalsifiability Objection

A persistent criticism of predictive processing is that it is unfalsifiable—that any observation can be accommodated by adjusting parameters like “precision weighting” (Bowman et al., 2023; Litwin & Miłkowski, 2020). Critics argue that when prediction errors are large, defenders claim precision was low; when errors are small, precision was high; when organisms seek prediction errors, precision weighting explains it away.

This criticism has force against certain implementations of predictive coding but less force against the argument presented here. Our claim is not about specific neural implementations or precision parameters. It is about a constraint: systems with finite latency in punishing environments must encode information about future states to survive. This is falsifiable in principle—one would need to demonstrate a system that persists indefinitely in a dynamic, punishing environment with zero predictive capacity.

More generally, we distinguish between predictive processing as a framework (which may indeed be too flexible) and prediction as a necessary computational strategy (which follows from physical constraints). The framework may be unfalsifiable; the necessity claim is not.

### 14.2 The *C. elegans* Challenge

The nematode *C. elegans* presents an apparent counterexample: 302 neurons, a fully mapped connectome, and behavior that appears largely reactive (White et al., 1986). If prediction is necessary, why does *C. elegans* succeed with such a minimal nervous system?

The answer lies in the boundary conditions of our argument. *C. elegans* is small enough (~1mm) that conduction delays are negligible—signals traverse the entire nervous system in microseconds. It operates in relatively stable environments (soil, bacterial lawns) with low temporal demands. The “punishing” criterion is met only weakly; most behaviors are chemotaxis and feeding that tolerate substantial latency.

*C. elegans* does not refute the argument; it illustrates the boundary conditions. Very small organisms in stable environments can afford reactive architectures. But *C. elegans* could not be scaled up to even moderate body sizes without fundamental architectural changes.

### 14.3 The Relevance Problem: Which Predictions to Make?

A significant objection concerns not whether to predict, but what to predict. The “relevance problem” (also known as the frame problem) asks how a system determines which predictions are worth making among the infinite possible futures. Simply predicting is insufficient if the system cannot context-sensitively prioritize information—a hurdle that has famously stalled complex AI agents.

This is a genuine challenge, and we must address it directly. The Predictive Viability Law establishes that some predictive capacity is necessary for persistence, but does not specify which predictions are required. This appears to leave a gap in the argument.

**Resolution via precision weighting:** Within predictive processing, the relevance problem is addressed through precision weighting—the dynamic adjustment of how much weight different predictions and prediction errors receive based on their estimated reliability and relevance to current goals (Feldman & Friston, 2010; Hohwy, 2020). Predictions about fast-changing, survival-relevant environmental features receive higher precision; predictions about stable or irrelevant features receive lower precision.

**Evolutionary pre-tuning:** For biological systems, evolution has pre-solved much of the relevance problem. Organisms do not start from scratch deciding what to predict; they inherit neural architectures that are already tuned to predict survival-relevant features—motion



of predators, location of food, dynamics of their own bodies. The relevance structure is encoded in the genome before any individual learning occurs.

**The relevance problem as a refinement, not a refutation:** Importantly, the relevance problem does not undermine the necessity of prediction—it specifies an additional constraint on what kinds of prediction are viable. A system that predicts irrelevant features will be outcompeted by one that predicts relevant features, but a system that predicts nothing will be outcompeted by both. The relevance problem is a selection pressure within the space of predictive architectures, not an alternative to prediction itself.

We acknowledge that our formal model (Section 16) does not fully capture the relevance problem. Future work should extend the Predictive Viability Law to incorporate relevance as an additional constraint, perhaps by decomposing  $I$  into task-relevant and task-irrelevant components and showing that only the former contributes to survival probability.

## 14.4 Ecological Psychology and Direct Perception

Gibson (1979) ecological psychology offers an alternative framework: perception is direct, not inferential. Organisms perceive affordances—action possibilities specified by invariant information in the optic array—without constructing internal models. This directly contradicts predictive processing’s claim that perception is controlled hallucination.

However, the tension may be more apparent than real. Gibson was right that the environment is richly structured and that much information is directly available. But “directly available” still requires time to propagate through nervous systems. Even if perception is “direct” in the sense of not requiring symbolic inference, it still faces the latency problem. The question is not whether perception is representational (a philosophical dispute) but whether temporal constraints require anticipation (a physical fact).

A reconciliation is possible: ecological information specifies what to predict. Affordances may be the content of predictions rather than alternatives to them.

## 14.5 Feedforward Models and Direct Control: The Cost-Benefit Boundary

The claim that PP is the “only” scalable architecture must be weighed against feedforward models and direct control mechanisms that may be more efficient in certain regimes.

**Feedforward architectures:** Classical feedforward models (Hubel & Wiesel, 1962; Marr, 1982) process information bottom-up without recurrent, generative dynamics. These are computationally simpler and may suffice for tasks with low temporal demands. The early visual system appears largely feedforward for the first  $\sim 100$ ms of processing.

**Direct control:** In low-complexity environments, the cost of maintaining a generative world model may exceed the benefit. A thermostat does not predict; it reacts. For systems in environments with low volatility ( $H \approx 0$ ) or weak punishment ( $\kappa \approx 0$ ), reactive control may be optimal.

**The cost-benefit formalization:** Let  $C_{\text{pred}}$  be the cost of predictive machinery and  $C_{\text{err}}$  be the cost per error. Prediction is favored when:

$$C_{\text{err}} \cdot P(\text{error} \mid \text{reactive}) > C_{\text{pred}} + C_{\text{err}} \cdot P(\text{error} \mid \text{predictive}) \quad (1)$$

This fails when error probability is low without prediction, errors are cheap, or predictive machinery is expensive. Our claim should be refined: prediction is necessary where this inequality holds—which includes all dynamic, temporally demanding niches with significant latency.

## 14.6 The Hierarchical Grounding Trilemma

A sophisticated objection concerns hierarchical structure. If predictions at one level require higher-level predictions, what grounds the highest level? Three possibilities:

(1) **Infinite regress:** Every prediction requires a higher prediction, extending infinitely. But brains are finite.

(2) **Arbitrary termination:** The hierarchy terminates with “foundational” priors that appear arbitrary.

(3) **Circular causation:** Predictions mutually cause each other, appearing viciously circular.

**Our response:** We adopt (2) but deny it is problematic. The highest-level priors are products of evolutionary selection—tuned over millions of years to maximize fitness. They are justified not by higher predictions but by survival. The hierarchy terminates in evolutionary adequacy, not metaphysical necessity.

This connects to the Predictive Viability Law: the priors that persist are those enabling  $I(X; Y_{t+\tau}) > 0$  for survival-relevant variables. Evolution grounds the hierarchy by selecting for priors that work. The circularity objection is defused: mutual influence between levels is coherentist, not viciously circular, with the whole system grounded by viability—pragmatic rather than foundationalist justification.

## 14.7 Comparative Analysis of Frameworks

To clarify the empirical landscape, we compare three major frameworks on their solutions to the latency problem:

Table 1: Framework Comparison

	Predictive ing	Process- ing	Ecological ogy	Psychol- ogy	Reactive Control
<b>Latency So- lution</b>	Anticipation via learned internal models		Direct pickup of invari- ant information		None—fast reflexes
<b>Core Mecha- nism</b>	Prediction error mini- mization		Affordances; perception-action coupling		Hardwired sensorimotor mappings
<b>Scalability</b>	High		Medium		Low
<b>Limitations</b>	Potential unfalsifiability		Does not address neural delays		Cannot scale to large bodies

This comparison reveals that each framework has a natural domain of applicability. Reactive control works for small organisms. Ecological psychology captures much of perception-action in medium-scale, richly structured environments. Predictive processing becomes necessary—not merely useful—when body size creates significant delays or when environments are dynamic and punishing.

## 14.8 Testable Predictions of the Predictive Viability Law

A theory is only as good as its testable predictions. The Predictive Viability Law generates several empirically tractable predictions:

**Prediction 1 (Latency-Scaling Relationship):** Across species, the sophistication of predictive mechanisms should correlate with body size and ecological temporal demands.

**Prediction 2 (EEG/MEG Latency Effects):** In humans performing interception tasks, prediction error signals should appear earlier relative to action execution as task difficulty increases.

**Prediction 3 (Disruption Studies):** Artificially increasing effective latency should produce systematic errors predictable from the model.

**Prediction 4 (Simulation Falsification):** Agent-based simulations should demonstrate that non-predictive agents ( $I = 0$ ) show survival probability decay  $P(\text{survive } n \text{ steps}) = p_0^n \rightarrow 0$ .

**Prediction 5 (AI Development):** Artificial systems scaled to operate in real-time physical environments with significant latency will independently converge on predictive architectures.

## 14.9 Alternative Explanations for AI Convergence

One might argue that AI systems are predictive not because prediction is computationally necessary, but because that is what we know how to train. Next-token prediction is a convenient objective for gradient descent; other architectures might work but we have not found them.

This is a legitimate alternative hypothesis. We cannot rule out that some non-predictive architecture could achieve comparable performance if only the right training signal were discovered. However, several considerations favor the necessity interpretation: (1) diverse approaches (symbolic AI, reinforcement learning, evolutionary computation) have all converged on prediction-like mechanisms when scaled; (2) the computational intractability of exhaustive verification is substrate-independent; (3) predictive architectures emerged before their theoretical necessity was understood.

### 14.10 Softening the Central Claim

In light of these considerations, we refine our central claim. Instead of: “Predictive processing is the only viable architecture,” we propose: “Predictive processing is the only scalable and evolutionarily stable architecture for adaptive systems operating under realistic physical constraints in dynamic, temporally demanding environments.”

This formulation acknowledges boundary cases (small organisms, static environments) while preserving the core insight: wherever latency matters and the environment punishes errors, prediction will dominate.

## 15 Toward a General Principle

The preceding sections have traced predictive architecture in two domains: biological nervous systems and artificial intelligence. In both cases, resource limitations that prohibit exhaustive processing drive systems toward prediction. Are we observing a more general principle?

We propose—tentatively—that a general principle may be at work: in any competitive system where outcomes depend on response speed, and where response speed is constrained by finite operation latency, predictive strategies will tend to emerge as the dominant solution.

Evidence for generality: High-frequency trading systems have converged on predictive strategies. Military doctrine emphasizes anticipation. Game-playing AI learns to predict opponent behavior. In each case: competition plus latency constraint yields prediction.

We must be cautious. Not all systems face competitive pressure. Not all competitive systems are latency-constrained. The principle describes a tendency rather than an exceptionless law—a basin of attraction, not a logical necessity.

## 16 Formal Framework: The Predictive Viability Law

We now formalize the arguments using information theory.

### 16.1 System Definition

Consider an adaptive system  $S = (X, A, U, \tau)$  where  $X$  is internal states,  $A$  is actions,  $U : X \rightarrow A$  is the update rule, and  $\tau > 0$  is response latency. The environment  $E = (Y, P)$  has states  $Y$  and transition probability  $P(Y_{t+\tau} | Y_t)$ .

Define a viability region  $V \subset Y$ . The system persists iff it remains in  $V$ . The environment must be *punishing*: incorrect actions increase  $P(Y_{t+\tau} \notin V)$ .

## 16.2 Formal Statement

**Predictive Viability Law:** For any adaptive system with latency  $\tau > 0$  in a punishing, non-stationary environment, continued persistence requires:

$$I(X; Y_{t+\tau} | Y_t) > 0 \quad (2)$$

That is, internal states must encode information about future environmental states beyond what is available in present observation.

## 16.3 Proof Sketch

(1) Latency creates temporal gap: action selected at  $t$  takes effect at  $t+\tau$ . (2) If  $I(X; Y_{t+\tau} | Y_t) = 0$ , actions are calibrated for present, not future. (3) In non-stationary environments, present  $\neq$  future. (4) In punishing environments, miscalibrated actions increase termination probability. (5) Over time,  $P(\text{survive } n \text{ steps}) = p^n \rightarrow 0$  for any  $p < 1$ . (6) Therefore, persistence requires  $I(X; Y_{t+\tau} | Y_t) > 0$ .  $\square$

## 16.4 Boundary Conditions

The law does not hold when: (1) environment is fully random (prediction impossible), (2) environment is not punishing (errors tolerable), (3) system is externally sustained (not autonomous), (4) persistence does not depend on action, (5) latency is zero (instantaneous response).

## 16.5 Quantitative Model and Simulation Framework

Let  $p(I)$  = probability of surviving one step given predictive capacity  $I$ . For purely reactive systems ( $I = 0$ ):

$$P(\text{survive } n \text{ steps} | I = 0) = p_0^n \rightarrow 0 \text{ as } n \rightarrow \infty \quad (3)$$

Without prediction, extinction is certain; it is merely a matter of time.

**Extended Model with Environmental Parameters:** We can parameterize the survival function more precisely. Let:

- $H = H(Y_{t+\tau} | Y_t)$  = environmental volatility (entropy of future given present)
- $\kappa$  = punishment severity (probability of termination given wrong action)
- $I$  = predictive capacity (mutual information between internal states and future)
- $I^*$  = maximum achievable prediction given environmental structure

Then per-step survival probability can be modeled as:

$$p(I, H, \kappa) = 1 - \kappa \cdot \frac{H - \min(I, H)}{H} \quad (4)$$

This captures: (a) higher volatility  $H$  increases error probability; (b) predictive capacity  $I$  reduces errors up to what is predictable; (c) punishment  $\kappa$  converts errors into termination probability.

## 17 Conclusion: From Is to Must Be, and What Comes Next

Most discussions of predictive processing ask whether brains work this way. The argument here suggests the more fundamental question is whether brains could work any other way—and under realistic physical constraints, the answer is no.

We have provided both intuitive and formal arguments. The intuitive argument: neural conduction is finite, survival requires speed, speed has limits, body size amplifies delay, and beyond certain thresholds prediction is the only viable strategy. The formal argument: systems with zero predictive capacity face exponentially decaying survival probability.

We have addressed the unified definition of prediction, showing that sensorimotor extrapolation, internal models, and language model generation are instances of the same abstract structure. We have engaged with criticisms—unfalsifiability, alternative frameworks, boundary cases—and refined the central claim accordingly.

### 17.1 Predictions for Future AI

If the argument is sound, it generates predictions for AI development:

**Multimodal foundation models will be predictive.** As AI systems scale to handle vision, language, action, and other modalities, they will inevitably adopt predictive architectures—not because designers choose prediction, but because no other architecture scales.

**Hallucination cannot be eliminated without sacrificing capability.** Hallucination is the cost of prediction under uncertainty. Systems that never hallucinate are systems that encode no predictive information—and such systems cannot perform at scale.

**World models will emerge in capable AI.** Any AI system operating in dynamic environments with latency constraints will develop internal models that encode predictive information about environmental dynamics—not by design, but by necessity.

### 17.2 Final Reflection

Predictive processing is not a “cognitive fashion” or passing paradigm. It may be the universal answer of adaptive systems—biological or artificial, terrestrial or otherwise—to competition, latency, and the physical limits of information processing.

The world of direct perception, of exhaustive reasoning, of stimulus-response chains uncomplicated by anticipation—this world never existed and cannot exist. The physics and mathematics forbid it. Every brain that ever evolved and every AI that ever scaled was already, and always, predicting.

## References

- Bowman, H., Collins, D. J., Nayak, A. K., & Cruse, D. (2023). Is predictive coding falsifiable? *Neuroscience & Biobehavioral Reviews*, 154, 105404.
- Chemero, A. (2009). *Radical embodied cognitive science*. MIT Press.
- Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, 36(3), 181–204.
- Clark, A. (2016). *Surfing uncertainty: Prediction, action, and the embodied mind*. Oxford University Press.
- Colombo, M., & Wright, C. (2018). First principles in the life sciences: The free-energy principle, organicism, and mechanism. *Synthese*, 198(14), 3463–3488.

- Doerig, A., Schurger, A., & Herzog, M. H. (2023). Hard criteria for empirical theories of consciousness. *Neuroscience of Consciousness*, 2023(1), niad002.
- Eagleman, D. M., & Sejnowski, T. J. (2000). Motion integration and postdiction in visual awareness. *Science*, 287(5460), 2036–2038.
- England, J. L. (2013). Statistical physics of self-replication. *Journal of Chemical Physics*, 139(12), 121923.
- Feldman, H., & Friston, K. J. (2010). Attention, uncertainty, and free-energy. *Frontiers in Human Neuroscience*, 4, 215.
- Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews Neuroscience*, 11(2), 127–138.
- Friston, K. (2019). Waves of prediction. *Nature Reviews Neuroscience*, 20(12), 727–728.
- Friston, K., FitzGerald, T., Rigoli, F., Schwartenbeck, P., O’Doherty, J., & Pezzulo, G. (2017). Active inference: A process theory. *Neural Computation*, 29(1), 1–49.
- Friston, K., & Stephan, K. E. (2007). Free-energy and the brain. *Synthese*, 159(3), 417–458.
- Furutachi, S., et al. (2024). Cooperative thalamocortical circuit mechanism for sensory prediction errors. *Nature*, 633, 398–406.
- Gibson, J. J. (1979). *The ecological approach to visual perception*. Houghton Mifflin.
- Helmholtz, H. von. (1867). *Handbuch der physiologischen Optik*. Voss.
- Hogendoorn, H. (2020). Motion extrapolation in visual processing: Lessons from 25 years of flash-lag debate. *Journal of Neuroscience*, 40(30), 5698–5705.
- Hohwy, J. (2013). *The predictive mind*. Oxford University Press.
- Hohwy, J. (2020). New directions in predictive processing. *Mind & Language*, 35(2), 183–204.
- Hubel, D. H., & Wiesel, T. N. (1962). Receptive fields, binocular interaction and functional architecture in the cat’s visual cortex. *Journal of Physiology*, 160(1), 106–154.
- Kwisthout, J., & van Rooij, I. (2020). Computational resource demands of a predictive Bayesian brain. *Computational Brain & Behavior*, 3, 174–188.
- Lau, H. (2022). *In consciousness we trust: The cognitive neuroscience of subjective experience*. Oxford University Press.
- Litwin, P., & Miłkowski, M. (2020). Unification by fiat: Arrested development of predictive processing. *Cognitive Science*, 44(7), e12867.
- Marr, D. (1982). *Vision: A computational investigation*. W.H. Freeman.
- Nijhawan, R. (1994). Motion extrapolation in catching. *Nature*, 370, 256–257.
- Parr, T., Benrimoh, D. A., Vincent, P., & Friston, K. (2018). With an eye on uncertainty: Modelling blind inference as a parametric Bayesian active inference problem. *Scientific Reports*, 8(1), 1–15.
- Parr, T., Da-Costa, L., Friston, K., & Frith, C. (2021). Markov blankets in the brain. *Network Neuroscience*, 5(1), 1–28.

- Pezzulo, G., Rigoli, F., & Friston, K. (2015). Active inference, homeostatic regulation and adaptive behavioural control. *Progress in Neurobiology*, 134, 17–35.
- Rao, R. P., & Ballard, D. H. (1999). Predictive coding in the visual cortex: A functional interpretation of some extra-classical receptive-field effects. *Nature Neuroscience*, 2(1), 79–87.
- Raven, M. J. (2015). Ground. *Philosophy Compass*, 10(5), 322–333.
- Richter, D., Kietzmann, T. C., & de Lange, F. P. (2024). High-level visual prediction errors in early visual cortex. *PLOS Biology*, 22(11), e3002829.
- Sawtell, N. B., Williams, A., & Bell, C. C. (2005). From sparks to spikes: Information processing in the electrosensory systems of fish. *Current Opinion in Neurobiology*, 15(4), 437–443.
- Schaffer, J. (2016). Grounding in the image of causation. *Philosophical Studies*, 173(1), 49–100.
- Schrödinger, E. (1944). *What is life? The physical aspect of the living cell*. Cambridge University Press.
- Seth, A. K. (2015). Presence of mind: Predictive processing and the phenomenology of presence. *Journal of Consciousness Studies*, 22(9–10), 154–181.
- Seth, A. K., & Hohwy, J. (2021). Predictive processing as a systematic basis for identifying the self. In *The philosophy and science of self-control* (pp. 1–22). Routledge.
- Sprevak, M. (2023). An introduction to predictive processing models of perception and decision-making. *Topics in Cognitive Science*.
- Sun, Z., & Firestone, C. (2020). The dark room problem. *Trends in Cognitive Sciences*, 24(5), 346–348.
- Thomas, E. R., Haarsma, J., Nicholson, J., Yon, D., Kok, P., & Press, C. (2024). Predictions and errors are distinctly represented across V1 layers. *Current Biology*, 34(10), 2265–2271.
- Van Gelder, T. (1995). What might cognition be, if not computation? *Journal of Philosophy*, 92(7), 345–381.
- Vopson, M. M. (2022). The mass-energy-information equivalence principle. *AIP Advances*, 9(9), 095206.
- White, J. G., Southgate, E., Thomson, J. N., & Brenner, S. (1986). The structure of the nervous system of the nematode *Caenorhabditis elegans*. *Philosophical Transactions of the Royal Society B*, 314(1165), 1–340.
- Wiese, W. (2018). Vanilla predictive processing: A first approximation. In *Philosophy and predictive processing* (pp. 1–18). MIND Group.
- Williams, D. (2020). Predictive coding and thought. *Synthese*, 197(4), 1749–1775.