Framing a Biogenic and Predictive Perspective on Attention

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Abstract

The study of attention faces significant conceptual ambiguities rooted in persistent reductive and anthropocentric assumptions. To address this, we advocate for a non-reductive, biogenic framework, reconceptualizing attention as an embodied, evolutionarily conserved process essential for maintaining thermodynamic equilibrium. We operationalize this perspective using Active Inference, defining attention as the selective allocation of precision (gain) to prediction errors. This mechanism tunes the organism's sensitivity to salient information, serving to minimize variational free energy (uncertainty). Precision modulation offers a compelling interpretation of selective spatial attention across psychology and neuroscience while aligning with established philosophical theories. Ultimately, this biogenic, predictive account may provide the necessary formalisms to resolve current conceptual impasses and invigorate the understanding of attention within the context of embodied cognition.

Keywords: Attention; Biogenic Approaches; Active Inference; Precision Modulation; Philosophy of Cognitive Sciences.

1. Introduction

Attention plays a fundamental role in our lives, allowing selective focus on certain aspects of the information captured by our sensory apparatus while ignoring others, thereby guiding the composition of what is reported and assimilated during perception. William James offered a pragmatic synthesis, famously defining attention as the mind's selective focus amid competing stimuli (James, 1890). His formulation, though intuitive, captured essential processual and agentive aspects of attention that would shape a century of psychological inquiry. Ever since, the study of attention has become paramount for both psychology and neuroscience due to the fundamental role that current models attribute to it in cognition.

However, like any concept related to the mind, attention has been studied across cultures and throughout human history, resulting in a myriad of works that inevitably lead to conceptual ambiguities and internal inconsistencies in its field of study. Bernard Hommel and colleagues (2019) analyzed this scenario and showed that current attention research has some epistemological problems that require philosophical analysis. This is a critical scenario that, in Anderson's opinion, is led by the reification of psychological constructs, which is the premature attribution of causal agency to an abstract construct (Anderson, 2011, p. 4). Vincent Di Lollo (2018) argued that there is a proliferation of different ways of conceiving attention as something both capturable and deployable. Moreover, together with binary differentiations/dichotomies, analytical approaches might make the science of attention underestimate and overlook the existence of complex dynamics and commonalities among its supposed subcomponents and of other "mental terms," as well as their implications, leading to an easy overlap or confusion of what they refer to.

At their core, these foundational issues rest on a set of persistent reductive and anthropocentric assumptions that profoundly influenced the development of cognitive psychology and, by extension, neuroscience. Because of this, most current theories and models of attention can be characterized as anthropogenic (Lyon, 2006). Specifically, such assumptions typically originate from generic categories and discriminations rooted in our own intuition and self-characterization, and do not intrinsically compromise with any reference to evolved biological functions. Instead, they are committed to distinctively human capacities, namely believing, reasoning, thinking, planning, etc., as being non-negotiable standards of cognition (Sims, 2021, p. 51). Historically, this type of approach became the status quo in psychology because it facilitated the comparison and identification of possible convergences and similarities between human behavior and that of other animals, using constructs like representational states and rationality, all derived from our own self-understanding (Gardner & Gardner, 1969). According to Lyon (2006), this is a classic example of a top-down approach to cognition, meaning it starts from the human case "downwards" to non-human cognitive beings.

To address these issues, this work seeks to frame an account of selective attention that starts from biogenic approaches — the development of an understanding of cognitive processes based on the fundamental principles of biological life, such as metabolism, autopoiesis, and homeostasis (Lyon, 2006) — and is further developed within Active Inference — a theoretical framework in neuroscience and artificial intelligence that models perception, action, and learning as a single, unified process of minimizing surprise

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(Parr et al., 2022).[1] Section 2 will briefly describe some important nuances shared by all biogenic approaches to cognition, and Section 3 will provide an overview of Active Inference, a predictive framework we claim could be used to operationalize such approaches. The concluding section presents further applications and final remarks.

Overall, the present paper has three principal aims. First, it seeks to establish a conceptual grounding for the study of attention within a biogenic tradition, arguing that anthropogenic assumptions have distorted current theorizing (Section 2). Second, it operationalizes this biogenic grounding using the Active Inference framework, which provides a formal, mathematical account of attention as precision modulation within hierarchical generative models (Section 3). Third, by synthesizing these two perspectives, it proposes that the evolutionary origins of selective behavior — from tectum-mediated orienting to cortically expanded action-perception loops — map directly onto the formal mechanisms described by Active Inference, offering a unified vocabulary for cross-disciplinary research on attention.

2. Biogenic

As part of the solution to the aforementioned problems, we begin by advocating a shift towards a biogenic and non-reductive approach to cognition, first and foremost de-emphasizing anthropogenic assumptions in the study of attention. This means shifting the focus from ostensibly overcategorized subcomponents based on intuition and folk psychology toward the analysis of the fundamental processes and functions organisms perform while living and interacting with their world. These are then subsequently integrated and elaborated into generalizable and empirically well-founded constructs, taking into account their evolution and development (de Waal & Ferrari, 2010). Put differently, we should understand that the parietal cortex, for instance, isn't simply a component of an "attention system." Instead, some attention phenomena are actually aspects of the cortex's broader output as the organism perceives, acts, and engages with its environment. (Hommel et al., 2019, p. 2298).

Biogenic approaches are based on the idea that cognition and all its features are functional capacities that evolution has repeatedly selected. Consequently, the study of cognition should start with biology itself (Sims, 2021). Specifically, the starting point should be the principles of biological organization and the requirements for survival and reproduction. These concepts underpin the most fruitful works on the nature of cognition. (Lyon, 2006, p. 12). Pamela Lyon (2006) argues that the two main clusters of contemporary biogenic approaches are self-organizing complex systems theories (which start from the second law of thermodynamics to describe living systems' tendency to homeostatic balance and their thermodynamic far-from-equilibrium states) and the autopoietic theory (which depicts cognitive systems as capable of generating and maintaining themselves, and ultimately establishing a seamless continuity between life and mind). Sims (2021) notes that while these two clusters overlap significantly, the first emphasizes self-preservation and navigation within dynamic environments, while the second focuses on the self-production and distinction of an organism relative to its external environment.

One example of a biogenic approach that encompasses both clusters is the principle of organism–environment co-determination (Corris, 2020). This principle posits a structural dependency between a living being and its surroundings, where they mutually shape each other. Autopoietic organisms, those that continuously regenerate themselves through relational networks (Varela, 1979), must interact with their environment to maintain homeostatic stability amidst constant fluctuations. Through this interaction, they modify their environment, which in turn modifies their perceptual capabilities in a process central to the perception-action cycle. This implies that organisms effectively "bring forth" the niches they inhabit (Maturana & Varela, 1987). Thus, an organism's actions, constrained by its phenotype, create predictable interrelational regularities with its environment, biasing it toward a specific set of conditions (Sims, 2021).[2]

These interactional regularities function as an implicit map of the niche, granting the organism's internal dynamics a predictive and anticipatory quality (Corcoran et al., 2020). This inferential capacity allows organisms to proactively maintain their thermodynamic balance through allostasis by anticipating and avoiding physiologically destabilizing conditions before they occur. Up to this point, this elucidation provided by the principle of co-determination sheds light on the origins of the perception-action cycle by describing organisms that, in order to survive, must maintain their thermodynamic equilibrium in the face of environmental fluctuations and, in doing so, distinguish themselves from and gain a certain degree of autonomy over their surroundings. However, to maintain this equilibrium, living beings must act within and upon their environments,

[1] This work builds upon ideas one of the authors have started to develop elsewhere (Iennaco, 2026).

[2] Some of the most emblematic examples of organism-environment co-determination are coupled systems, such as bees and flowering plants in their ecological niche. These are structurally co-determined as a result of their reciprocal interactions over time (Corris, 2020). Because bees possess sensorimotor systems that detect ultraviolet light, they perceive a world of pollinable flowers completely different from the world of most other animals. But the evolved ultraviolet patterns of the flower only "exist" in relation to adapted sensory systems, such as those of the bee. Thus, the environment (the pollinable flower) is functionally determined by the agent (or, in this case, by the bee's ability to see it), and vice versa, a relationship that, through continuous reciprocal interactions, defines both (one generating evolutionary and developmental pressures upon the other). As the organism's activities help create the environment in which it lives, this environment, in turn, structures the organism's behavior and evolution.

and by doing so over time — both ontogenetically and phylogenetically — they end up mapping the inter-relational regularities of their niche, giving precedence to those that are favorable to their existence. But what is most remarkable for our purposes is that this foundational process of predictive behavior, which is essential for survival and adaptation, provides a basic framework that resonates with early concepts of attention.

Crucially, this account of coupled self-evidencing organisms and environments parallels the evolutionary emergence of the visual circuit, a structure essential for an organism's anticipatory interaction with its world. We now know that the visual circuit began as photosensitive cells in the midbrain's tectum that guided basic locomotor reactions and, as these cell clusters evolved into eyes, organisms developed the capacity for topographic mapping of their environment (Lacalli, 2018). This ability was a critical step, allowing them to generate guiding behavioral models that supported not only reactions to present stimuli but also the crucial anticipation of future threats and opportunities. Thus, this foundational predictive capacity enabled organisms to select for homeostatically favorable conditions and affordances, forming a primitive basis for selective action (Hommel et al., 2019).

In turn, this ancestral selection process driven by the tectum can be considered the precursor of the functions psychology now attributes to visual selective attention: the tectum's role is analogous to the human superior colliculus in directing gaze and focus (Basso & May, 2017; Hommel et al., 2019). The subsequent evolution and expansion of the cortex, especially prefrontal regions, vastly increased the complexity of these guiding models, refining them into sophisticated action maps (Andersen et al., 1997). This cortical development allowed organisms to move beyond simple reactions, proactively imposing their internal maps upon the world, and enabling them to actively modify their environments and create more favorable niches for survival. Thus, the motor-visual system has provided the initial embodied framework, which was later enhanced by cortical expansion to allow for a broader behavioral repertoire.

It is important to stress, however, that the use of the visual circuit as an example above should not be taken to imply that the biogenic argument is specific to vision. On the contrary, the abstract structure of this evolutionary story — a midbrain subcortical nucleus performing primitive predictive filtering, organized into a topographic map, and progressively elaborated by ascending cortical expansion — is instantiated across all major sensory modalities. The inferior colliculus in the auditory system, for example, performs an analogous integrative and predictive function to the optic tectum in the visual system: its neurons exhibit stimulus-specific adaptation consistent with hierarchical predictive coding (Carbajal & Malmierca, 2018), and top-down corticofugal projections implement precision modulation in the ascending auditory hierarchy in a manner formally parallel to visual corticofugal control (Malmierca et al., 2009). Similarly, interoceptive attention — the allocation of precision to bodily/visceral signals relevant to homeostatic regulation/equilibrium — operates through hypothalamic-insular hierarchies that parallel the tectum-colliculus-cortex trajectory in vision (Seth & Friston, 2016). Crucially, the superior colliculus itself, far from being a purely visual structure, serves as a multimodal integration hub that coordinates orienting responses across sensory modalities, as evidenced by inferior-superior colliculus circuits mediating auditory-cued visual attention (Li et al., 2021). Converging phylogenetic evidence further confirms that mechanisms of selective attention are evolutionarily ancient and conserved across taxa, including invertebrates and non-mammalian vertebrates without substantial cortex (Lev-Ari et al., 2022). Visual attention is therefore only an illustrative case — one for which the evolutionary and neurophysiological evidence is particularly well-documented — of a general principle that applies wherever organisms must selectively allocate processing resources across competing streams of sensory prediction errors.

This principle, then, would have allowed for an evolutionary trajectory that endowed living beings with a set of embodied strategies to better navigate and select from their complex environments. Ultimately, these diverse policies, all of which facilitate sensory-guided interaction with the world, give us much of what is currently categorized under the label of attention. (Cisek, 2007; Corbetta et al., 1998). Given this, we now outline how a cautious extension of this description to the cognitive-behavioral scale of analysis could guide the initial steps toward a more comprehensive account of selective attention. One that is complex, embodied, and well-rooted in evolutionary thinking. And, to achieve this, we will examine the illustrative case of the Active Inference framework and how its biogenic assumptions support this endeavor.

3. Predictive

Active Inference is fundamentally built upon the Free Energy Principle. This principle offers a formal, mathematical framework, drawing on physics and machine learning concepts, to express the core idea of organism-environment co-determination. (see Corcoran et al., 2020). Active Inference integrates key insights from approximate Bayesian inference and embodied cognition, modeling organisms as maintaining a generative model, which is an internal, probabilistic representation of the world, and constantly updating beliefs (posteriors) about hidden states by combining prior expectations with new sensory data (likelihood) in a way that allows for their active engagement in minimizing predictive error across perception and action. Because of that, it is a fruitful framework for philosophers, modelers, and neuroscientists to work on, and our goal here is to operationalize a biogenic

perspective on attention, establishing its foundations within Active Inference.[3]

The brain operates as a predictive machine through a process known as prediction error minimization. Instead of passively receiving sensory information, the brain actively generates predictions about the world based on models built from its existing knowledge. Then it uses incoming sensory data primarily to correct errors in those predictions (Clark, 2016). This occurs within a cortical hierarchy (Mumford, 1992; Rao & Ballard, 1999): higher, more abstract levels send top-down predictions to lower, sensory-processing levels. When a mismatch between prediction and reality occurs, the lower levels send an excitatory bottom-up prediction error signal. This continuous, bidirectional flow allows the brain to constantly refine its models to better match the environment (Sprevak & Smith, 2023). And neurophysiologically, this would be classically implemented by deep and shallow pyramidal neurons in areas such as the cerebral cortex, the hippocampus, and the amygdala (Friston, 2009).

This framework involves two kinds of predictions. First-order predictions are about the sensory input itself — what the brain expects to sense. And, critically, second-order predictions are metacognitive judgments about the precision or confidence in those first-order predictions. These second-order predictions are vital because they modulate the influence, or "gain," of any resulting error signals. If the brain is highly confident in a prediction, it will reduce the gain on error signals, choosing to trust its prior beliefs over the unreliable new data. However, if the context is uncertain or noisy, an error will be given significant weight, prompting a major update to its internal model.

While this description of the predictive brain is commonly found in Predictive Processing models of cognition, it is also similar to Active Inference models, as perception and action are intertwined in a cyclical process. However, Active Inference extends the predictive brain by shifting the focus from perception to embodied action as the primary means of minimizing prediction error. While traditional Predictive Processing models emphasize updating internal beliefs to match sensory input, Active Inference foregrounds allostatic regulation — the process of maintaining homeostasis by acting upon the world (Ramstead et al., 2020). Under this framework, behavior itself is a form of inference. Organisms formulate action policies to actively "sample" their environment, making their sensory inputs conform to their predictions. In essence, we don't just predict the world; we act to make our predictions come true, thereby reducing surprise (Parr et al., 2022). There are at least three clusters of Active Inference models: motor control, which deals with high-precision proprioceptive predictions that shield intended states from conflicting feedback in order to realize movement (Clark, 2015); decision making (Sprevak & Smith, 2023), and learning (Friston et al., 2016).

As we've seen, the predictive brain optimizes inference by selecting predictions with high past accuracy and weighting prediction errors by their estimated precision, so accurate predictions compress the world's causal structure while high-precision errors drive model updating; connection weights between prediction and error units implement this integration, enabling a generative model of how hidden states produce sensory inputs (Sprevak & Smith, 2023). Accuracy inversely tracks uncertainty, so low-accuracy predictions trigger recalibration of precision and greater influence of sensory data, a regulation afforded by learned probabilistic priors over prediction-error distributions (Friston, 2010; Hohwy, 2013; Piekarski, 2023).

Precision weighting or modulation is formally the expected inverse variance of error signals. It is implemented via lateral/self-inhibition or second-order error units in networks, with biological substrates including inhibitory synapses, neuromodulatory adjustments, and fast gamma synchrony — mechanisms that support both slow plastic changes and rapid, attention-like modulation (Bastos et al., 2012; Bogacz, 2017; Feldman & Friston, 2010; Friston, 2010; Sprevak & Smith, 2023; Sterzer et al., 2018). Attention thus emerges from precision estimation in hierarchical inference: attending reflects the brain's expectation of highly precise error signals, increasing their synaptic gain and biasing perceptual hypothesis revision in accordance with exogenous and endogenous attention distinctions (Clark, 2016; Yon & Frith, 2021).[4]

[3] The formal core of the framework rests on variational free energy (F), defined as an upper bound on the log-evidence (negative surprise) for a generative model: $F = KL[Q(s) \parallel P(s|o)] - \ln P(o)$, where o denotes observations, s hidden states, Q(s) the approximate posterior, and P(o, s) the generative model. Minimizing F with respect to Q constitutes perceptual inference; minimizing F with respect to action constitutes active inference (Friston, 2010; Parr et al., 2022). As we will see, within this framework, precision is formally defined as the expected inverse variance ($\Pi = \Sigma^{-1}$) of prediction error signals — itself a hidden variable whose posterior estimation constitutes second-order inference (Feldman & Friston, 2010). Traditionally, this was implemented neurobiologically as synaptic gain from superficial pyramidal cells transmitting prediction errors upwards through the cortical hierarchy, but recently, alternative mechanisms have been proposed. The reader is referred to Bogacz (2017) for an accessible derivation of these update equations, and to Smith et al. (2021) for a step-by-step discrete-state formulation with worked examples.

[4] The intellectual lineage of this argument deserves explicit acknowledgement. The foundational idea that the brain acts as an inference engine — generating predictions about the world and updating them in the light of sensory discrepancies — traces back to Helmholtz's (1867/1924) concept of "unconscious inference." This was formalised computationally by Mumford (1992) and, most influentially, by Rao and Ballard (1999), whose hierarchical predictive coding model of the visual cortex provided the computational blueprint for the bidirectional prediction-and-error architecture described in this section. Building on this tradition, Feldman and Friston (2010) were the first to formally propose that precision modulation — the second-order estimation of prediction error reliability — constitutes the neural mechanism of attention. The contribution of the present paper, therefore, is not to propose

Active inference models also extend attention to the sampling process itself, where attention comprises actions selected to elicit information that cannot be inferred passively and salience indexes the epistemic value of such actions as quantified by expected free energy (Parr & Friston, 2017). Salience has been characterised variously as intrinsic motivation and denotes actions promising maximal informational gain (highly unpredictable yet interpretable observations) after which sampling is suppressed in a manner akin to inhibition of return (Parr & Friston, 2019). Neurobiologically, salience is tied to action planning and the basal ganglia, especially in vision, where salience ranks potential saccadic targets and thus corresponds to competing saccade evaluations, aligning with the premotor theory of attention that links motor programming for eye movements to spatial attention (Craighero & Rizzolatti, 2005; Parr & Friston, 2017, 2019). Finally, because policy evaluation relies on working-memory processes, salience-driven attention is intimately connected to working memory's role in forecasting and selecting future actions (Parr & Friston, 2017).

However, the scope of precision modulation as an account of attention extends far beyond salience and spatial orienting. Active Inference models demonstrate that the same mechanism (second-order estimation of prediction error reliability) operates across the full range of attentional phenomena recognized in cognitive psychology. In the motor domain, Friston et al. (2011) demonstrate that attentional cueing to motor attributes (effector or movement type) produces the same validity effects as spatial Posner cueing, with proprioceptive precision playing the role that exteroceptive precision plays in visual attention. Auksztulewicz & Friston (2016) provide evidence that, for feature-based attention, precision can in principle be allocated at any level of the cortical hierarchy: and when it is set at levels encoding orientation, color, or motion, the result is selective enhancement of prediction errors about task-relevant features, consistent with EEG data showing that attention promotes neural encoding of prediction errors in a stimulus-selective manner. Seth & Friston (2016) extended this to interoceptive attention, where precision weighting of bodily prediction errors underlies the selective awareness of physiological states. Emerging accounts further propose that temporal attention — the selective processing of events at expected time points — can be implemented by rhythmic, oscillatory modulation of precision parameters (Arnal & Giraud, 2012). The one area where both the framework and the precision account require further formal development seems to be object-based attention, where the simultaneous selection of all features of a perceived object would require a correspondingly high-level, amodal precision signal whose computational basis remains to be fully specified; this represents an important direction for future theoretical work within Active Inference.

4. Further applications and final remarks

Precision modulation presents a compelling alternative interpretation, particularly excelling in accounting for selective spatial attention across both psychological findings and neuroscience. As Feldman and Friston (2010) and Parr and Friston (2019) already pointed out, attention in these predictive models is closely tied to two known theories: biased competition (Desimone & Duncan, 1995) and the premotor theory of attention (Craighero & Rizzolatti, 2005). The first focuses on perception, where the weightings happen in every cycle of model updating to select the best set of prediction errors. The last regards action selection, in which attention enhances the gain of a particular movement, making its execution faster and more precise. Reinterpreting these theories using the Active Inference framework offers the key advantage of integration, situating them within a unified framework that can model the situated organism's function across multiple levels of analysis. For example, Active Inference models of avoidance-approach behaviors (Smith et al., 2023) could be used to simulate their circuit development and link them directly to perception-action loops, benefiting from the framework's compatibility with the underlying evolutionary narrative. However, whether this theoretical advantage translates into tangible gains for scientific endeavors remains an open question.

It is also worth highlighting how Active Inference provides a deeper account of attention's role in cognition. Precision modulation is fundamental to any computational model of cognition (Lindsay, 2021). And within this framework, it dictates the credibility (or gain) of new information, specifically controlling how much the sensory evidence contributes to the subsequent updating of the generative model. Here, this modulation has the power to enhance self-realizing predictions in arc-reflex movements and also choose which course of action will be taken in a particular moment. Given these features, attention likely holds a greater functional responsibility than previously recognized, serving essentially as a core cognitive modulator. Examples of malfunctioning of precision modulation (and its supposed link to attention deficits) can be found in computational psychiatry models of depression, anxiety, psychosis, and even autism. These models show that such malfunctioning has a great influence on how the psychiatric disorder will manifest itself and may even indicate that most of them (perhaps all) have, in some way, an "attentional nature".

Beyond computational psychiatry, there is growing empirical support for the precision modulation account. Brown & Friston (2013) used Dynamic Causal Modelling of

this mechanism anew, but to anchor it within a biogenic and evolutionary framework: to argue that the very process of selective, precision-weighted inference did not emerge with the cortex but has its roots in the primitive orienting behaviors mediated by subcortical structures such as the optic tectum, and (as argued in Section 2) its homologues across all major sensory modalities. This evolutionary anchoring, we contend, is what may be needed to ease the conceptual impasses currently afflicting attention research.

MEG data in the Posner spatial cueing task and provided model-based evidence that differences in superficial pyramidal cell gain (one proposed neural substrate of precision) explain observed attentional responses, with anticipatory, cue-driven precision effects localized to extrastriate visual sources. Auksztulewicz & Friston (2016) extended this, demonstrating, via EEG, that attention selectively enhances neural encoding of prediction errors, but not predictions themselves, in a stimulus-selective manner — precisely the pattern expected if attention operates by increasing precision gain rather than by amplifying stimulus representations in general. Convergent evidence from intracranial recordings identifies gamma oscillations as correlates of prediction error and alpha oscillations as correlates of precision, with alpha suppression at attended locations — a robust finding in the spatial attention literature (Worden et al., 2000) — interpretable as a neural signature of increased precision (Arnal & Giraud, 2012). And, finally, the neuromodulatory basis of precision is supported by indirect pharmacological evidence: cholinergic agents enhance signal-to-noise in sensory cortices and improve attentional selection, while cholinergic depletion impairs it (Hasselmo & Sarter, 2011), providing a biological bridge between the formal precision parameter and known pharmacological mechanisms of attention (with acetylcholine acting as a neuromodulatory carrier of precision signals).

At this point, critics may stress the fact that the idea of attention as a central modulator faces resistance in various subdisciplines of contemporary neuroscience. However, it resonates with several major philosophical theories on the subject, specifically Christopher Mole's cognitive unison or adverbialist theory (Mole, 2024), Sebastian Watzl's prioritization theory (Watzl, 2023), and Wayne Wu's selection for action account of attention (Wu, 2023). More noteworthy, however, is the fact that, although the precision modulation account reviewed here is supported by a growing number of computational models and indirect laboratorial evidence, several empirical questions await direct investigation. First, a critical experimental test is still lacking, which would need to involve, for example, the direct pharmacological manipulation of accuracy and the measurement of its effect on prediction error encoding rather than prediction encoding, using forward models. Second, the evolutionary claims regarding auditory and interoceptive parallels to the visual tectum need to be tested more thoroughly, using comparative neurophysiology in species with varying degrees of cortical expansion, examining whether stimulus-specific adaptation in the inferior colliculus and its corticofugal modulation scale with attentional capacity across taxa. And thirdly, the claim that evolutionarily primitive orientation mechanisms underlie higher cognitive forms of attention could be investigated by examining whether animals with lesions in the superior colliculus (or analogous structures) exhibit impaired precision modulation across multiple sensory modalities. These represent important directions for future empirical work that we hope will provide the necessary bridge between the theoretical framework advanced here and direct experimental tests.

Ultimately, while the precise extent to which a biogenic approach will resolve current literature gaps is yet to be determined, framing a biogenic and predictive account of attention seems to be a good start (at least one alternative to most of what is found in current literature). This perspective, grounded in biological and evolutionary principles and formalisms, may provide what is necessary to move beyond conceptual impasses, enabling a re-evaluation of attention at both psychological/behavioral and neuroscientific levels within the wider context of embodied cognition.

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