

UC Riverside

UC Riverside Previously Published Works

Title

A neurocomputational account of motivated seeing

Permalink

<https://escholarship.org/uc/item/00w6986q>

Journal

Trends in Cognitive Sciences, 30(1)

ISSN

1364-6613

Authors

Kim, Haena

Ballard, Ian C

Leong, Yuan Chang

Publication Date

2026

DOI

10.1016/j.tics.2025.06.005

Copyright Information

This work is made available under the terms of a Creative Commons Attribution-NonCommercial License, available at <https://creativecommons.org/licenses/by-nc/4.0/>

Peer reviewed

A neurocomputational account of motivated seeing

Haena Kim¹, Ian C. Ballard² & Yuan Chang Leong^{1,3,4}

¹ Department of Psychology, University of Chicago, Chicago, IL 60637, USA

² Department of Psychology, University of California, Riverside, CA 92521, USA

³ Neuroscience Institute, University of Chicago, Chicago, IL 60637, USA

⁴ Institute of Mind and Biology, University of Chicago, Chicago, IL 60637, USA

Corresponding author: ycluong@uchicago.edu (Y.C. Leong)

Website: <https://mcnlab.uchicago.edu/>

Abstract

Do goals, beliefs and desires affect visual experience? This question has long been controversial in cognitive science. There exists extensive literature documenting motivational effects on perceptual reports, but these findings could reflect biases in what people report seeing rather than what they see. Here, we propose that examining the underlying neurocomputational processes can provide new perspectives on this long-standing debate. We review evidence suggesting that motivation biases both perception and action, but does so via distinct neural systems: amygdala and locus coeruleus-norepinephrine activity enhances sensory representations for desirable stimuli, while striatal dopamine biases action selection toward goal-congruent actions. The neurocomputational approach provides a framework for advancing a mechanistic understanding of motivated seeing and how these biases are shaped by context.

Keywords: motivated seeing, perceptual decision-making, drift diffusion models, cognitive neuroscience, motivated cognition

The Intersection of Motivation and Vision

Imagine watching a close tennis match, where a crucial line call could decide the outcome of the game. The ball lands near the edge of the court, and fans on opposing sides insist that they saw it land either “in” or “out,” depending on which player they support. One possibility is that motivation biased the fans to see the outcome favorable to the player they root for. Another possibility is that the disagreement reflects biased subjective reports, rather than a genuine difference in perceptual experience.

Do goals, desires, and beliefs influence what people see? This has proven to be an enduring question in cognitive science [1–4]. In the 1940s-50s, the New Look movement challenged the then-prevailing notion that perception is a purely bottom-up process, arguing instead that perception is shaped by goals and needs [5]. For example, a seminal study found that 10-year-olds, particularly those from lower socioeconomic backgrounds, consistently overestimated the size of coins, which was interpreted as evidence that heightened subjective value influenced perceived size [6]. However, these studies were often faced with methodological critiques, with skeptics arguing that the effects could be explained by non-perceptual factors, including differences in familiarity, biases in what people remember, and decision biases [3,7–9]. With no convincing response to these criticisms, enthusiasm for the New Look waned, leaving the question of whether motivation affects perception unresolved.

The turn of the 21st century witnessed a renewed interest in the topic, with studies showing that ambiguous images are more likely reported as the interpretation associated with desirable outcomes [10,11], desirable objects are judged as closer [12], and physiological needs, such as thirst and hunger, speed up the recognition of words associated with satisfying those needs [13,14]. Nevertheless, much of this work has relied on participants' subjective reports as the primary dependent measure. Without direct access to an individual's perceptual experience, it remains challenging to determine whether motivation truly alters perception. This limitation highlights a fundamental challenge in understanding the relationship between motivation and visual processing.

Techniques in neuroscience and computational modeling provide powerful new tools to probe the mechanisms underlying perception. These include methods for measuring neural activity during visual processing and computational frameworks that link motivational states to sensory processing and decision-making. A central goal of this review is to advance a neurocomputational framework for studying how motivation shapes perceptual reports. By integrating behavioral, computational, and neural evidence, we propose a model in which motivation shapes perception and action through distinct neural pathways. Here, we focus on the phenomenon of **motivated seeing**, where individuals are biased to report perceiving desirable stimuli, but the approach is broadly applicable to investigating other motivational effects on perception.

A Neurocomputational Approach

A neurocomputational approach uses computational models to decompose observable behavior into latent cognitive processes, which are then mapped onto neural activity to identify

the computational role performed by neural structures. This approach is particularly valuable in the study of motivated seeing, as the same subjective report can result from distinct underlying processes. By combining computational model-fitting with neural data, we can dissociate these processes and examine how they are influenced by motivation.

Neurocomputational approaches have been highly successful in uncovering the cognitive and neural mechanisms underlying **perceptual decision-making** [15–17]. Perceptual decision-making refers to the act of selecting one option from a set of alternatives based on available sensory information. In the brain, sensory information is encoded in sensory areas and accumulated in downstream frontoparietal regions to determine a discrete response [18–20]. The decision process is well-described by mathematical models that formalize evidence accumulation as sequential sampling and integration of evidence towards a decision bound [21]. These models, known as “sequential sampling models,” provide a unifying theoretical framework for the study of perceptual decision-making across species (e.g., humans, monkeys, and rodents), sensory modalities (e.g., visual, auditory, and tactile) and measurement tools (e.g., single-unit recordings, EEG, and fMRI) [22,23].

The **drift diffusion model** (DDM) is a widely used variant of sequential sampling models that has been shown to account for behavior and neural activity during perceptual decision-making [24] (Box 1). It assumes that perceptual decisions are determined by the noisy accumulation of sensory evidence over time. When the evidence crosses one of two decision bounds, the corresponding response is made. Within the DDM framework, bias in perceptual decisions can arise from at least two distinct mechanisms [25]. First, the *starting point* of evidence accumulation can be shifted towards one of the decision bounds. This reduces the amount of evidence required to make a response, and is typically associated with a **response bias** independent of sensory processing. Second, the *rate* of evidence accumulation (i.e., the “drift rate”) can be biased in favor of a response, and reflects sensory evidence accumulating faster for one response than the other.

We define perception as the process by which sensory inputs are transformed into internal representations that support experience and behavioral responses. This includes sensory encoding and the integration of sensory evidence, but excludes non-sensory choice processes or memory distortions that shape retrospective judgments. If motivation alters perception, we expect to see specific patterns across behavioral, computational, and neural analyses. Behaviorally, motivation should bias perceptual reports even in situations when there is no benefit to reporting the desirable outcome. Computationally, a **perceptual bias** should manifest in processes associated with sensory encoding and integration. Neurally, motivation should modulate activity in sensory areas, which in turn predict behavior on a trial-by-trial basis. A neurocomputational approach that assesses convergence across behavioral outcomes, computational analyses, and neural measures would thus enable stronger inferences about the nature of motivated seeing.

Evidence supporting motivational effects on both perception and response

Motivated seeing can be understood as a specific instance of perceptual decision-making, where individuals are biased toward selecting the more desirable interpretation of a visual stimulus. Thus, the DDM provides a quantitative framework for inferring the computational processes that support motivated seeing. Specifically, a response bias predicts shifts in the starting point of evidence accumulation, while a perceptual bias predicts differences in the drift rate. The DDM, however, is agnostic about how parameter changes relate to participants' subjective perception, and convergent neural measurements from sensory regions encoding stimulus features can help validate interpretations.

Of particular relevance to motivated seeing are studies that manipulate the reward probability or magnitude associated with perceptual responses [26–30]. In these studies, subjects choose between competing responses based on perceptual information, with one response offering a greater potential reward. Consistent with a reward maximization strategy, subjects tend to bias their choices toward the response associated with greater reward [28,31]. This reward manipulation, however, had no effect on the encoding of sensory evidence in sensory regions [27]. Furthermore, analyses using DDMs in these studies have consistently found that reward shifted the starting point of evidence accumulation, but had little to no effect on the drift rate. Taken together, these results suggest that reward induces a response bias, but did not affect moment-to-moment sensory processing.

Reward manipulations in these earlier studies, however, confound motivation (“wanting to see”) and optimal task performance (“reward maximization”), which may explain why biases in these tasks were driven by a rational shift in response strategy [28]. A subsequent behavioral study employed an alternative incentive scheme, where one category in a visual categorization task was associated with a monetary bonus independent of participants' responses [32]. This is akin to real-world situations where wanting to see an outcome does not have direct effects on reality. As participants were also rewarded for correct categorizations, they should categorize the images accurately to maximize their earnings. Thus, the motivation to see a desirable percept was dissociated from strategic task performance. In contrast to the earlier studies, motivation biased both the starting point and rate of evidence accumulation. While this result suggests that motivation influenced both response tendencies as well as the accumulation of perceptual evidence, the study did not measure sensory representations in the brain and its conclusion relied heavily on the interpretation of the DDM parameters.

A recent study by our research group sought to directly test the effects of wanting to see a percept on sensory representations in the brain during perceptual decision-making [33]. We took advantage of the well-established finding that the perception of faces and scenes elicits distinct neural patterns in the ventral temporal cortex (VTC) [34]. These patterns can be decoded and quantified using multivoxel pattern analysis as a measure of sensory encoding [35]. During fMRI, participants were presented with composite images created by blending a face and scene in varying proportions (Fig. 1A). Participants were rewarded for correctly categorizing whether the face or scene was of higher intensity. On each trial, we motivated participants to see the face (or scene) by instructing them that they would earn or lose an additional amount if the face (or scene) was of higher intensity in the upcoming image. The additional bonus was contingent on the objective category of the image and not on participants' responses (Fig. 1B).

Replicating earlier results, motivation biased both the starting point and the rate of evidence accumulation in favor of the desirable category. Crucially, face-selective and scene-selective neural activity was higher on trials where participants were motivated to see the face or scene, respectively, suggesting that motivation enhanced perceptual processing. The magnitude of motivational enhancement in sensory cortex activity was associated with the drift rate but not the starting point, consistent with the interpretation that the drift bias reflects effects on sensory processing, while the starting point bias reflects response tendencies.

An alternative interpretation of the bias in drift rate is that motivation acted upon evidence accumulation without affecting sensory encoding. This account would predict motivational modulation primarily in regions associated with evidence integration, such as the frontoparietal cortex, while having no effect on sensory regions (e.g., [36,37]). In contrast, we observed motivational enhancement of face- and scene-selective activity in the VTC, where electrical stimulation has been shown to evoke face and scene perception [38,39]. These findings are consistent with the hypothesis that motivation influences not only the integration of evidence during decision-making but also the sensory information that feeds into the accumulation process. We note that this interpretation assumes VTC activity reflects sensory encoding and relies on reverse inference. Converging evidence from methods that probe sensory encoding (e.g., near-threshold detection or perceptual facilitation effects) will help strengthen this interpretation.

Together, these studies provide convergent evidence that motivation biases both perception and responses. They are also consistent with a recent EEG study showing value-driven biases in motor preparation and evidence accumulation, with the latter unfolding in distinct phases [40]. However, as that study did not decode sensory representations, it remains unclear whether these effects reflect changes in sensory encoding. Future work using EEG or MEG to decode sensory representations [41,42] offer a promising approach to clarify the temporal dynamics of motivated seeing, including distinguishing between pre-choice (e.g., sensory enhancement leading up to a decision) and post-choice (e.g., sensory enhancement after committing to a percept) effects. More broadly, considering the computational and neural processes offers a new perspective - instead of asking *whether* motivation biases perception or responses, we can examine *how* motivation shapes both processes.

Mechanisms of Perceptual Bias

Stimuli repeatedly paired with reward or those signaling potential future reward are known to engage attentional mechanisms that enhance processing [43–46]. Here, we refer to attentional mechanisms as processes that bias the competition among sensory inputs by enhancing some representations while suppressing others [47] (Box 2). The amygdala, a brain region critical for affective processing, projects directly into the visual cortex and is well-positioned to mediate motivational effects on sensory activity [48]. This structure is often implicated in “affective attention”, where affectively salient stimuli receive prioritized processing [49]. For example, amygdala activation is associated with enhanced perception of emotional words, pictures and faces [50–52], while lesions to the amygdala impair these

effects [53,54]. In the context of motivated seeing, the desire to perceive a specific percept might imbue related perceptual features with affective value, with the amygdala amplifying the corresponding neural representation in the visual cortex.

Consistent with this hypothesis, the motivational enhancement of desirable sensory representations closely tracked trial-by-trial fluctuations in amygdala activity [55]. Specifically, higher amygdala activity on a given trial corresponded to stronger motivational enhancement of sensory representations. In contrast, on trials with low amygdala activity, sensory-related activity was driven by objective stimulus features and was unaffected by what participants were motivated to see (Fig. 2A). Analyses using the DDM revealed that amygdala activity was specifically associated with biases in the drift rate, but not the starting point of evidence accumulation, suggesting that the amygdala's influence was specific to the perceptual component of the bias.

How does the amygdala enhance the neural representations of desirable percepts? One putative mechanism involves the recruitment of the locus coeruleus (LC) [56], a cluster of neurons in the brainstem that serves as the primary source of the neuromodulator norepinephrine (NE) (Fig. 2B). NE release increases the gain of neurons, such that they become more sensitive to target inputs [57,58]. The LC projects widely throughout the brain, and the effects of NE neurons were historically thought to be diffuse and non-specific [59]. However, there is growing recognition that NE neurons can exert precise, stimulus-specific effects on sensory representations [60]. According to the Glutamate Amplifies Noradrenergic Effects (GANE) model [61], high glutamate release in response to a prioritized stimulus creates a localized NE hotspot that selectively amplifies the neural response to the stimulus. The amygdala may enhance the neural representations of desirable percepts by activating the LC to modulate NE release and by providing a saliency signal to prioritize the processing of desirable stimuli in the visual cortex.

In support of the role of LC-NE system in motivated seeing, pupil dilation, a correlate of LC activity and NE release [62,63], is associated with a bias towards reporting motivationally desirable percepts [64]. Incorporating trial-by-trial changes in pupil dilation into a DDM revealed that, similar to the amygdala, pupil dilation was specifically linked to biases in the drift rate, but not to biases in the starting point. While these findings implicate the LC-NE system in motivated seeing, direct evidence of its involvement remains an open question, highlighting an important avenue for future research.

Mechanisms of Response Bias

Motivation can bias response responses for preferred stimuli independently of perceptual processing. This bias appears to depend on action selection circuits in the striatum. The striatum is thought to gate the appropriate selection of actions via a polysynaptic loop that disinhibits action representations in cortex [65]. This gating mechanism is implemented by the relative activity of striatal direct pathway neurons, which facilitates action selection, and striatal indirect pathway neurons, which inhibit actions. The gating of actions is determined in part by reward history, with rewards driving dopamine release that enhance the activity of direct pathway striatal neurons, and punishments causing dopamine pauses that enhance the

activity of indirect pathway neurons. Biologically realistic neural networks models of perceptual decision-making suggest that dopamine-dependent learning in the striatum could drive response biases [66].

Electrophysiological recordings in non-human primates have identified “choice-bias” neurons whose pre-stimulus firing rates predict choices in the neuron’s preferred direction [67,68]. As reward value is unknown before the stimulus appears, this anticipatory activity did not reflect encoding of stimulus value, and is consistent with an *a priori* response bias. In a study where monkeys were rewarded for correct detection of targets in one hemifield, increased pre-stimulus activity in choice-bias neurons predicted faster target detection in the rewarded hemifield [69]. When the rewarded hemifield was reversed, choice bias activity rapidly remapped to neurons favoring the alternative hemifield.

While this study suggests that striatal neurons encode preferences for responses, this paradigm confounds the response and the spatial location of perceptual stimuli, leaving open the possibility that these striatal neurons facilitate perceptual processing of the preferred location rather than response biases. To dissociate these two possibilities, a recent study in mice optogenetically stimulated direct pathway striatal neurons during a change detection task where the same motor response was used for both visual hemifields [70]. Stimulation shifted decision criterion toward reporting a change in the contralateral hemifield, without influencing perceptual sensitivity, indicating that these neurons selectively implement a response bias in a context-appropriate manner, without influencing perceptual processing.

Consistent with these findings, in a motivated seeing paradigm, participants' response bias towards selecting the rewarded stimulus was correlated with activation in the nucleus accumbens [33]. Relatedly, activation in the striatum has been linked to flexible changes in response biases according to task demands [71]. Together, the reviewed findings suggest a critical role of the striatum in integrating outcome-related information to bias action selection towards actions associated with desirable outcomes. However, an important distinction is that in human motivated seeing paradigms, motivation is based on instruction about future rewards, whereas in the paradigms used in animal models, motivation is informed by a history of rewards linked to specific stimuli or responses. An open question remains as to how the striatum flexibly modulates response biases based on motivational cues. Addressing this requires an understanding of how contextual information is represented and dynamically updated to guide these biases.

Mechanisms of Context Representation

What is deemed desirable changes depending on reward contingencies, physiological states, and other contextual factors, which we term **motivational context**. Indeed, studies using the motivated seeing paradigm reveal that perceptual and response biases adapt flexibly when the motivationally desirable category changes from trial to trial [33,55]. How does the brain encode and update information about what is desirable to bias perceptual processing and action selection?

While the representation of contextual information has not been specifically investigated in motivated seeing paradigms, insights can be drawn from recent investigations of context representation in learning and decision-making. The lateral prefrontal cortex (IPFC) encodes goals, beliefs, and plans that determine which outcomes are motivationally relevant [72–75], making it a likely source of motivational context. Motivational contexts, however, can be decoupled from task goals. For example, in the motivated seeing task, the adaptive goal is to respond correctly, regardless of what one is motivated to see. How is motivational context represented alongside task-relevant representations in the IPFC?

Recent evidence suggests that multiple task context representations co-exist in an orthogonal code in the IPFC. Prefrontal neurons represent motivational context alongside cognitive task context and other task-relevant variables [76–78]. Mixed selectivity to task features enables the IPFC to flexibly guide behavior according to changing task demands [79,80]. Accordingly, the IPFC could guide behavior in the service of ongoing behavioral goals while simultaneously representing motivational context. This may explain why IPFC is engaged during motivated seeing paradigms, but its overall activity does not correlate with variation in motivational biases [55]. Nonetheless, latent representations of motivational context in the IPFC could indirectly influence motivated behavior via their influence on other brain regions.

Specifically, motivational context representations in the IPFC may influence how the ventromedial prefrontal cortex (vmPFC) assigns value to actions and stimuli. The vmPFC has a well-established role in the subjective appraisal of stimuli [81,82] and the computation of value representations for choice options [73,83]. Evidence for motivation influencing vmPFC valuation comes from perceptual decision-making tasks in which a single perceptual feature is associated with reward. In such tasks, humans accumulate sensory evidence preferentially for reward-predictive features, and the vmPFC reflects this bias by showing an amplified representation of evidence for reward-predictive features [84,85]. Supporting the role of the IPFC in shaping valuation, studies on dieters making food-related judgments have found that IPFC transiently influences how the vmPFC represents the value of food items [74,86].

Anatomical projections from vmPFC to the amygdala and striatum could in turn provide the motivational signal underlying perceptual and response biases in these regions. Evidence for such a IPFC-vmPFC-amygdala pathway has been observed in the affective No/Go task, in which implicit emotional cues bias the performance of task rules [87]. The study found that emotional context representations in IPFC influenced amygdala task representations indirectly via the vmPFC. In parallel, in a motivational Go/NoGo task where correct behavior could either earn rewards or avoid punishments, early vmPFC activation was sensitive to motivational cues and predicted trial-by-trial fluctuations in motivational bias. In contrast, later striatal activation was linked to response bias [88]. Together, these results suggest that the vmPFC uses motivational context information to shape processes in subcortical regions linked to perceptual and response biases (Fig. 3).

Motivated Seeing in Aversive Contexts

Thus far, we have not distinguished between contexts involving desirable versus undesirable stimuli. However, motivation may influence perceptual decisions differently in aversive

contexts, where the stimuli are associated with threat, loss, or other undesirable outcomes. Indeed, prior work had found that reward and aversive motivation recruit distinct neural and computational mechanisms during learning and decision-making [89–91]. In the context of motivated seeing, the (un)**desirability** and **motivational salience** of aversive stimuli may exert opposing influences on perceptual decisions.

On one hand, aversive stimuli are undesirable, and people are often motivated to avoid perceiving them. For example, when encountering a spider, people may divert their attention away or retreat from it to minimize the discomfort associated with its presence. Consistent with this notion, a study on motivated seeing [32] demonstrated that, relative to a neutral category, both the starting point and drift rate were biased away from the category associated with financial loss. Similarly, just as individuals may suppress and avoid aversive stimuli, categories linked to financial loss were less effective as distractors during visual search and elicited weaker representations in the visual cortex compared to neutral distractors [92]. Individual differences play a role in these biases; participants with higher punishment sensitivity, as measured by the Behavioral Inhibition Scale (BIS), exhibit stronger biases in perceptual decisions away from aversive stimuli [93].

On the other hand, aversive stimuli are motivationally salient because they signal potential danger or loss, requiring rapid detection and response to minimize harm. For example, encountering a spider may capture attention automatically, ensuring that the potential threat is processed and dealt with effectively. A substantial body of evidence shows that aversive stimuli are detected more quickly than neutral stimuli and elicit stronger representations in the sensory cortex [94–98]. Thus, perceptual decisions can also be biased toward aversive stimuli, even though individuals might prefer to avoid seeing them. At present, it remains underexplored under what conditions perceptual decisions are biased toward aversive stimuli and when they are biased away (Box 3).

Concluding Remarks

We present a neurocomputational account of motivated seeing describing how motivation biases perception and response through distinct mechanisms (Fig. 3). Our framework reframes the longstanding debate about whether motivation biases perception or responses. Instead of treating perception and response biases as mutually exclusive explanations, we propose a shift toward examining the specific mechanisms by which motivation shapes both. This perspective not only unifies existing findings but also provides a mechanistic basis for generating testable predictions, relating motivated seeing to psychopathology [99], and advancing our understanding of how motivational states influence perception and action (see *Outstanding Questions*).

The phenomenon of motivated seeing suggests that motivation can shape what individuals perceive, pointing to the inherently subjective nature of visual experience [100,101]. Despite current progress, we emphasize that the reviewed findings do not provide definitive proof that motivation alters perceptual experience. As subjective experience is inherently inaccessible, our inferences rest on converging indirect evidence across measures. A promising next step is to use near-threshold detection paradigms. Prior work shows that performance-contingent

reward can improve sensitivity to visual targets [102,103]. Near-threshold detection tasks that decouple motivation from accuracy, combined with modeling and neuroimaging, could offer converging evidence of motivational effects on perception.

We note that our current neurocomputational account is primarily descriptive, fitting DDMs to existing behavioral data to infer how latent cognitive processes are affected by motivation. Future work can build on this framework to develop generative accounts that predict motivated seeing outcomes in novel contexts, including varying levels of motivation or stimulus ambiguity. Such models would offer a stronger basis for inference and support richer, testable predictions about the conditions under which motivation shapes perception and action.

Motivated seeing is an example of **motivated cognition**, where individuals are biased to arrive at conclusions that align with their desires or goals [104,105]. While this review focuses on motivated seeing, the general principles outlined here - particularly the decomposition of motivational biases into evidence accumulation (i.e., how information is integrated) and action selection (i.e., what to do about it) - apply broadly to other forms of motivated cognition. Recent studies, for example, have used the DDM to examine how partisans form biased impressions of political candidates [106], as well as how individuals decide whether they are in a high-reward or low-reward environment [107]. Integrating findings from such studies with neural data could reveal shared and distinct neural mechanisms supporting different forms of motivated cognition.

For more than 50 years, motivated seeing has been a phenomenon of interest to cognitive scientists, social psychologists, affective scientists, and neuroscientists. One reason it has garnered such broad interest is because, at its core, it challenges the objectivity of our senses. The phrase “seeing is believing” reflects our lay belief in the veracity of our visual experiences, yet motivated seeing demonstrates that what we perceive can be shaped by internal states such as goals, desires, and emotions. Advancing neurocomputational approaches to motivated seeing represents an exciting opportunity to develop a unified framework for understanding how we decide what we see, and the extent to which our visual experiences reflect our internal motivations rather than the external environment.

Acknowledgments

We would like to acknowledge the members of the University of Chicago Computational and Social Affective Neuroscience Laboratory for helpful discussion.

Declaration of generative AI and AI-assisted technologies in the writing process:

During the preparation of this work the author(s) used chatGPT-4o and Grammarly to improve language and readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

References

1. Firestone, C. and Scholl, B.J. (2016) Cognition does not affect perception: Evaluating the evidence for “top-down” effects. *Behav. Brain Sci.* 39
2. Niedenthal, P.M. and Wood, A. (2019) Does emotion influence visual perception? Depends on how you look at it. *Cogn. Emot.* 33, 77–84
3. Erdelyi, M.H. (1974) A new look at the new look: Perceptual defense and vigilance. *Psychol. Rev.* 81, 1–25
4. Ogilvie, R. and Carruthers, P. (2016) Opening Up Vision: The Case Against Encapsulation. *Rev. Philos. Psychol.* 7, 721–742
5. Bruner, J.S. (1957) On perceptual readiness. *Psychol. Rev.* 64, 123–152
6. Bruner, J.S. and Goodman, C.C. (1947) Value and need as organizing factors in perception. *J. Abnorm. Soc. Psychol.* 42, 33–44
7. Carter, L.F. and Schooler, K. (1949) Value, need, and other factors in perception. *Psychol. Rev.* 56, 200–207
8. Klein, G.S. *et al.* (1951) The effect of personal values on perception: an experimental critique. *Psychol. Rev.* 58, 96–112
9. McCurdy, H.G. (1956) Coin perception studies and the concept of schemata. *Psychol. Rev.* 63, 160–168
10. Balcetis, E. *et al.* (2012) Subjective value determines initial dominance in binocular rivalry. *J. Exp. Soc. Psychol.* 48, 122–129
11. Balcetis, E. and Dunning, D. (2006) See what you want to see: Motivational influences on visual perception. *J. Pers. Soc. Psychol.* 91, 612–625
12. Balcetis, E. and Dunning, D. (2010) Wishful Seeing: More Desired Objects Are Seen as Closer. *Psychol. Sci.* 21, 147–152
13. Aarts, H. *et al.* (2001) On the psychology of drinking: Being thirsty and perceptually ready. *Br. J. Psychol.* 92, 631–642
14. Radel, R. and Clément-Guillotin, C. (2012) Evidence of Motivational Influences in Early Visual Perception: Hunger Modulates Conscious Access. *Psychol. Sci.* 23, 232–234
15. Heekeren, H.R. *et al.* (2008) The neural systems that mediate human perceptual decision making. *Nat. Rev. Neurosci.* 9, 467–479
16. O’Connell, R.G. and Kelly, S.P. (2021) Neurophysiology of Human Perceptual Decision-Making. *Annu. Rev. Neurosci.* 44, 495–516
17. Summerfield, C. and Blangero, A. (2017) Chapter 12 - Perceptual Decision-Making: What Do We Know, and What Do We Not Know? In *Decision Neuroscience* (Dreher, J.-C. and Tremblay, L., eds), pp. 149–162, Academic Press
18. Heekeren, H.R. *et al.* (2004) A general mechanism for perceptual decision-making in the human brain. *Nature* 431, 859–862
19. Shadlen, M.N. and Newsome, W.T. (2001) Neural Basis of a Perceptual Decision in the Parietal Cortex (Area LIP) of the Rhesus Monkey. *J. Neurophysiol.* 86, 1916–1936
20. Kim, J.-N. and Shadlen, M.N. (1999) Neural correlates of a decision in the dorsolateral prefrontal cortex of the macaque. *Nat. Neurosci.* 2, 176–185
21. O’Connell, R.G. *et al.* (2018) Bridging Neural and Computational Viewpoints on Perceptual Decision-Making. *Trends Neurosci.* 41, 838–852
22. Hanks, T.D. and Summerfield, C. (2017) Perceptual Decision Making in Rodents, Monkeys, and Humans. *Neuron* 93, 15–31
23. Forstmann, B.U. *et al.* (2016) Sequential Sampling Models in Cognitive Neuroscience: Advantages, Applications, and Extensions. *Annu. Rev. Psychol.* 67, 641–666
24. Ratcliff, R. *et al.* (2016) Diffusion Decision Model: Current Issues and History. *Trends*

- Cogn. Sci.* 20, 260–281
25. White, C.N. and Poldrack, R.A. (2014) Decomposing bias in different types of simple decisions. *J. Exp. Psychol. Learn. Mem. Cogn.* 40, 385–398
 26. Mulder, M.J. *et al.* (2012) Bias in the Brain: A Diffusion Model Analysis of Prior Probability and Potential Payoff. *J. Neurosci.* 32, 2335–2343
 27. Summerfield, C. and Koechlin, E. (2010) Economic Value Biases Uncertain Perceptual Choices in the Parietal and Prefrontal Cortices. *Front. Hum. Neurosci.* 4
 28. Feng, S. *et al.* (2009) Can Monkeys Choose Optimally When Faced with Noisy Stimuli and Unequal Rewards? *PLOS Comput. Biol.* 5, e1000284
 29. Platt, M.L. and Glimcher, P.W. (1999) Neural correlates of decision variables in parietal cortex. *Nature* 400, 233–238
 30. Doi, T. *et al.* (2020) The caudate nucleus contributes causally to decisions that balance reward and uncertain visual information. *eLife* 9, e56694
 31. Bogacz, R. *et al.* (2006) The physics of optimal decision making: A formal analysis of models of performance in two-alternative forced-choice tasks. *Psychol. Rev.* 113, 700–765
 32. Voss, A. *et al.* (2008) Interpreting ambiguous stimuli: Separating perceptual and judgmental biases. *J. Exp. Soc. Psychol.* 44, 1048–1056
 33. Leong, Y.C. *et al.* (2019) Neurocomputational mechanisms underlying motivated seeing. *Nat. Hum. Behav.* 3, 962–973
 34. Grill-Spector, K. (2003) The neural basis of object perception. *Curr. Opin. Neurobiol.* 13, 159–166
 35. Norman, K.A. *et al.* (2006) Beyond mind-reading: multi-voxel pattern analysis of fMRI data. *Trends Cogn. Sci.* 10, 424–430
 36. Rahnev, D. *et al.* (2011) Prior Expectation Modulates the Interaction between Sensory and Prefrontal Regions in the Human Brain. *J. Neurosci.* 31, 10741–10748
 37. Rao, V. *et al.* (2012) Neural Correlates of Prior Expectations of Motion in the Lateral Intraparietal and Middle Temporal Areas. *J. Neurosci.* 32, 10063–10074
 38. Mégevand, P. *et al.* (2014) Seeing Scenes: Topographic Visual Hallucinations Evoked by Direct Electrical Stimulation of the Parahippocampal Place Area. *J. Neurosci.* 34, 5399–5405
 39. Jonas, J. *et al.* (2018) A face identity hallucination (palinopsia) generated by intracerebral stimulation of the face-selective right lateral fusiform cortex. *Cortex* 99, 296–310
 40. Corbett, E.A. *et al.* (2023) Multiphasic value biases in fast-paced decisions. *eLife* 12, e67711
 41. Aitken, F. *et al.* (2020) Prior Expectations of Motion Direction Modulate Early Sensory Processing. *J. Neurosci.* 40, 6389–6397
 42. Bae, G.-Y. and Luck, S.J. (2019) Decoding motion direction using the topography of sustained ERPs and alpha oscillations. *NeuroImage* 184, 242–255
 43. Anderson, B.A. (2017) Reward processing in the value-driven attention network: reward signals tracking cue identity and location. *Soc. Cogn. Affect. Neurosci.* 12, 461–467
 44. Hickey, C. and Peelen, M.V. (2015) Neural Mechanisms of Incentive Salience in Naturalistic Human Vision. *Neuron* 85, 512–518
 45. Serences, J.T. (2008) Value-Based Modulations in Human Visual Cortex. *Neuron* 60, 1169–1181
 46. Grahek, I. *et al.* (2021) Dynamic Interplay between Reward and Voluntary Attention

- Determines Stimulus Processing in Visual Cortex. *J. Cogn. Neurosci.* 33, 2357–2371
47. Desimone, R. and Duncan, J. (1995) Neural mechanisms of selective visual attention. *Annu. Rev. Neurosci.* 18, 193–222
 48. Freese, J.L. and Amaral, D.G. (2005) The organization of projections from the amygdala to visual cortical areas TE and V1 in the macaque monkey. *J. Comp. Neurol.* 486, 295–317
 49. Pourtois, G. *et al.* (2013) Brain mechanisms for emotional influences on perception and attention: What is magic and what is not. *Biol. Psychol.* 92, 492–512
 50. Herbert, C. *et al.* (2009) Amygdala activation during reading of emotional adjectives—an advantage for pleasant content. *Soc. Cogn. Affect. Neurosci.* 4, 35–49
 51. Sabatinelli, D. *et al.* (2005) Parallel amygdala and inferotemporal activation reflect emotional intensity and fear relevance. *NeuroImage* 24, 1265–1270
 52. Hariri, A.R. *et al.* (2002) The Amygdala Response to Emotional Stimuli: A Comparison of Faces and Scenes. *NeuroImage* 17, 317–323
 53. Vuilleumier, P. *et al.* (2004) Distant influences of amygdala lesion on visual cortical activation during emotional face processing. *Nat. Neurosci.* 7, 1271–1278
 54. Anderson, A.K. and Phelps, E.A. (2001) Lesions of the human amygdala impair enhanced perception of emotionally salient events. *Nature* 411, 305–309
 55. Calabro, R. *et al.* (2023) Trial-by-trial fluctuations in amygdala activity track motivational enhancement of desirable sensory evidence during perceptual decision-making. *Cereb. Cortex* 33, 5690–5703
 56. Markovic, J. *et al.* (2014) Tuning to the significant: Neural and genetic processes underlying affective enhancement of visual perception and memory. *Behav. Brain Res.* 259, 229–241
 57. Berridge, C.W. and Waterhouse, B.D. (2003) The locus coeruleus–noradrenergic system: modulation of behavioral state and state-dependent cognitive processes. *Brain Res. Rev.* 42, 33–84
 58. Aston-Jones, G. and Cohen, J.D. (2005) An integrative theory of locus coeruleus–norepinephrine function: adaptive gain and optimal performance. *Annu. Rev. Neurosci.* 28, 403–450
 59. Poe, G.R. *et al.* (2020) Locus coeruleus: a new look at the blue spot. *Nat. Rev. Neurosci.* 21, 644–659
 60. Ghosh, S. and Maunsell, J.H.R. (2024) Locus coeruleus norepinephrine contributes to visual-spatial attention by selectively enhancing perceptual sensitivity. *Neuron* 112, 2231–2240.e5
 61. Mather, M. *et al.* (2016) Norepinephrine ignites local hotspots of neuronal excitation: How arousal amplifies selectivity in perception and memory. *Behav. Brain Sci.* 39, e200
 62. Joshi, S. *et al.* (2016) Relationships between Pupil Diameter and Neuronal Activity in the Locus Coeruleus, Colliculi, and Cingulate Cortex. *Neuron* 89, 221–234
 63. Reimer, J. *et al.* (2016) Pupil fluctuations track rapid changes in adrenergic and cholinergic activity in cortex. *Nat. Commun.* 7, 13289
 64. Leong, Y.C. *et al.* (2021) Pupil-Linked Arousal Biases Evidence Accumulation Toward Desirable Percepts During Perceptual Decision-Making. *Psychol. Sci.* 32, 1494–1509
 65. Alexander, G.E. and Crutcher, M.D. (1990) Functional architecture of basal ganglia circuits: neural substrates of parallel processing. *Trends Neurosci.* 13, 266–271
 66. Lo, C.-C. and Wang, X.-J. (2006) Cortico–basal ganglia circuit mechanism for a decision threshold in reaction time tasks. *Nat. Neurosci.* 9, 956–963

67. Ding, L. and Gold, J.I. (2010) Caudate Encodes Multiple Computations for Perceptual Decisions. *J. Neurosci.* 30, 15747–15759
68. Ding, L. and Gold, J.I. (2013) The Basal Ganglia's Contributions to Perceptual Decision Making. *Neuron* 79, 640–649
69. Lauwereyns, J. *et al.* (2002) A neural correlate of response bias in monkey caudate nucleus. *Nature* 418, 413–417
70. Wang, L. *et al.* (2018) Activation of Striatal Neurons Causes a Perceptual Decision Bias during Visual Change Detection in Mice. *Neuron* 97, 1369–1381.e5
71. Forstmann, B.U. *et al.* (2008) Striatum and pre-SMA facilitate decision-making under time pressure. *Proc. Natl. Acad. Sci.* 105, 17538–17542
72. Ballard, I.C. *et al.* (2018) Causal evidence for the dependence of the magnitude effect on dorsolateral prefrontal cortex. *Sci. Rep.* 8, 16545
73. Ballard, I.C. *et al.* (2017) More Is Meaningful: The Magnitude Effect in Intertemporal Choice Depends on Self-Control. *Psychol. Sci.* 28, 1443–1454
74. Hare, T.A. *et al.* (2009) Self-Control in Decision-Making Involves Modulation of the vmPFC Valuation System. *Science* 324, 646–648
75. Sakamoto, K. *et al.* (2020) Dynamic Axis-Tuned Cells in the Monkey Lateral Prefrontal Cortex during a Path-Planning Task. *J. Neurosci.* 40, 203–219
76. Watanabe, M. and Sakagami, M. (2007) Integration of Cognitive and Motivational Context Information in the Primate Prefrontal Cortex. *Cereb. Cortex* 17, i101–i109
77. Abbass, M. *et al.* (2025) Prefrontal cortex neuronal ensembles dynamically encode task features during associative memory and virtual navigation. *Cell Rep.* 44
78. Kounieher, F. *et al.* (2009) Motivation and cognitive control in the human prefrontal cortex. *Nat. Neurosci.* 12, 939–945
79. Rigotti, M. *et al.* (2013) The importance of mixed selectivity in complex cognitive tasks. *Nature* 497, 585–590
80. Chatham, C.H. *et al.* (2014) Corticostriatal Output Gating during Selection from Working Memory. *Neuron* 81, 930–942
81. Hutcherson, C.A. *et al.* (2015) Emotional and Utilitarian Appraisals of Moral Dilemmas Are Encoded in Separate Areas and Integrated in Ventromedial Prefrontal Cortex. *J. Neurosci.* 35, 12593–12605
82. Lyu, Y. *et al.* (2024) Hostile Attribution Bias Shapes Neural Synchrony in the Left Ventromedial Prefrontal Cortex during Ambiguous Social Narratives. *J. Neurosci.* 44
83. McNamee, D. *et al.* (2013) Category-dependent and category-independent goal-value codes in human ventromedial prefrontal cortex. *Nat. Neurosci.* 16, 479–485
84. Ballard, I.C. *et al.* (2024) Reward Reinforcement Creates Enduring Facilitation of Goal-directed Behavior. *J. Cogn. Neurosci.* 36, 2847–2862
85. Shenhav, A. *et al.* (2018) Dissociable neural mechanisms track evidence accumulation for selection of attention versus action. *Nat. Commun.* 9, 2485
86. Wilson, D.J. *et al.* (2023) Recruitment of dlPFC during dietary self-regulation predicts the transience of regulatory effects. *Soc. Cogn. Affect. Neurosci.* 18, nsab088
87. Lapate, R.C. *et al.* (2022) Emotional Context Sculpts Action Goal Representations in the Lateral Frontal Pole. *J. Neurosci.* 42, 1529–1541
88. Algermissen, J. *et al.* (2022) Striatal BOLD and midfrontal theta power express motivation for action. *Cereb. Cortex* 32, 2924–2942
89. Leng, X. *et al.* (2021) Dissociable influences of reward and punishment on adaptive

- cognitive control. *PLOS Comput. Biol.* 17, e1009737
90. Yee, D.M. *et al.* (2022) Aversive motivation and cognitive control. *Neurosci. Biobehav. Rev.* 133, 104493
 91. Palminteri, S. and Pessiglione, M. (2017) Chapter 23 - Opponent Brain Systems for Reward and Punishment Learning: Causal Evidence From Drug and Lesion Studies in Humans. In *Decision Neuroscience* (Dreher, J.-C. and Tremblay, L., eds), pp. 291–303, Academic Press
 92. Barbaro, L. *et al.* (2017) Valence, Not Utility, Underlies Reward-Driven Prioritization in Human Vision. *J. Neurosci.* 37, 10438–10450
 93. Kim, H. *et al.* (2025) Desirability biases perceptual decisions in the aversive domain. *Emotion* DOI: 10.1037/emo0001511
 94. Li, W. and Keil, A. (2023) Sensing fear: fast and precise threat evaluation in human sensory cortex. *Trends Cogn. Sci.* 27, 341–352
 95. Rossi, V. *et al.* (2017) Motivational Salience Modulates Early Visual Cortex Responses across Task Sets. *J. Cogn. Neurosci.* 29, 968–979
 96. Kalhan, S. *et al.* (2022) Neural and computational processes of accelerated perceptual awareness and decisions: A 7T fMRI study. *Hum. Brain Mapp.* 43, 3873–3886
 97. Kim, H. *et al.* (2021) Motivational Salience Guides Attention to Valuable and Threatening Stimuli: Evidence from Behavior and Functional Magnetic Resonance Imaging. *J. Cogn. Neurosci.* 33, 2440–2460
 98. Sussman, T.J. *et al.* (2017) Here Comes Trouble: Prestimulus Brain Activity Predicts Enhanced Perception of Threat. *Cereb. Cortex N. Y. N 1991* 27, 2695–2707
 99. Rossi-Goldthorpe, R.A. *et al.* (2021) Paranoia, self-deception and overconfidence. *PLOS Comput. Biol.* 17, e1009453
 100. Lieberman, M.D. (2022) Seeing minds, matter, and meaning: The CEEing model of pre-reflective subjective construal. *Psychol. Rev.* 129, 830–872
 101. Peters, M.A.K. (2025) Introspective psychophysics for the study of subjective experience. *Cereb. Cortex* 35, 49–57
 102. Engelmann, J.B. *et al.* (2009) Combined effects of attention and motivation on visual task performance: transient and sustained motivational effects. *Front. Hum. Neurosci.* 3
 103. Hughes, G. *et al.* (2013) EEG indices of reward motivation and target detectability in a rapid visual detection task. *NeuroImage* 64, 590–600
 104. Hughes, B.L. and Zaki, J. (2015) The neuroscience of motivated cognition. *Trends Cogn. Sci.* 19, 62–64
 105. Bromberg-Martin, E.S. and Sharot, T. (2020) The Value of Beliefs. *Neuron* 106, 561–565
 106. Derreumaux, Y. *et al.* (2023) Computational underpinnings of partisan information processing biases and associations with depth of cognitive reasoning. *Cognition* 230, 105304
 107. Gesiarz, F. *et al.* (2019) Evidence accumulation is biased by motivation: A computational account. *PLOS Comput. Biol.* 15, e1007089
 108. Ma, D.S. *et al.* (2015) The Chicago face database: A free stimulus set of faces and norming data. *Behav. Res. Methods* 47, 1122–1135
 109. Corbetta, M. and Shulman, G.L. (2002) Control of goal-directed and stimulus-driven attention in the brain. *Nat. Rev. Neurosci.* 3, 201–215
 110. Kincade, J.M. *et al.* (2005) An Event-Related Functional Magnetic Resonance Imaging Study of Voluntary and Stimulus-Driven Orienting of Attention. *J. Neurosci.* 25,

4593–4604

111. Szczepanski, S.M. and Kastner, S. (2013) Shifting Attentional Priorities: Control of Spatial Attention through Hemispheric Competition. *J. Neurosci.* 33, 5411–5421
112. Sadaghiani, S. and D'Esposito, M. (2015) Functional Characterization of the Cingulo-Opercular Network in the Maintenance of Tonic Alertness. *Cereb. Cortex* 25, 2763–2773
113. Dosenbach, N.U.F. *et al.* (2006) A Core System for the Implementation of Task Sets. *Neuron* 50, 799–812
114. Dosenbach, N.U.F. *et al.* (2008) A dual-networks architecture of top-down control. *Trends Cogn. Sci.* 12, 99–105
115. Vuilleumier, P. and Huang, Y.-M. (2009) Emotional Attention: Uncovering the Mechanisms of Affective Biases in Perception. *Curr. Dir. Psychol. Sci.* 18, 148–152
116. Cole, S. *et al.* (2013) Affective Signals of Threat Increase Perceived Proximity. *Psychol. Sci.* 24, 34–40
117. Krusemark, E.A. and Li, W. (2011) Do All Threats Work the Same Way? Divergent Effects of Fear and Disgust on Sensory Perception and Attention. *J. Neurosci.* 31, 3429–3434
118. Brandtstädter, J. *et al.* (2004) Perception of Danger Signals: The Role of Control. *Exp. Psychol.* 51, 24–32

Outstanding Questions

- When goals or contingencies change, how does the brain rapidly encode and update what is desirable or undesirable to guide perceptual and response biases?
- How does the striatum modulate response biases based on abstract motivational cues, such as task instructions or context? In motivated seeing paradigms, is striatal neuronal activity updated based on top-down inputs from vmPFC?
- What is the time course of motivational enhancement of perceptual and motor processing, as assessed with tools such as EEG or MEG? Are there different roles for pre-decision and post-decision influences of motivation on perceptual processing?
- Are participants better able to detect stimuli that are otherwise calibrated to be below their perceptual threshold when motivated to see them, and is this behavioral enhancement accompanied by increased neural activity encoding the stimulus?
- Under what conditions are perceptual decisions biased toward or away from aversive stimuli, and what neural mechanisms adjudicate between the two?
- What role does motivated seeing play in shaping both healthy cognition and psychopathology? Does anxiety amplify biases toward aversive stimuli, while depression attenuate biases toward desirable stimuli?
- Do different sources of motivation differentially modulate motivated seeing? For example, do social versus non-social motivations or intrinsic versus extrinsic goals produce distinct patterns of perceptual and response bias?
- What features must generative neurocomputational models capture to predict motivated seeing across tasks and contexts?
- What computational and neural mechanisms are shared across different forms of motivated cognition (e.g., motivated seeing, reasoning, and memory), and which mechanisms are specific to perception?

Figure Captions.

Figure 1. Motivated Perceptual Decision-Making Task. (A) Participants are presented with composite images created by blending a face and scene in varying proportions and receive a 10-cent bonus for correctly categorizing whether the face or scene was of higher intensity (i.e., face or scene-dominant). On each trial, additional monetary incentives motivated them to see the face or the scene. (B) Payoff Structure. Participants earn or lose an additional 40 cents depending on the objective category of the image and will thus be motivated to see the category associated with greater earnings. However, the category bonus and loss is independent of participants' responses. To earn the maximum amount, participants should ignore the motivation manipulation and categorize each image accurately. Face stimuli were obtained from the Chicago Face Database [108]

Figure 2. Mechanisms of perceptual bias. (A) Amygdala activity mediates motivational enhancement of sensory representations in the object-selective ventral temporal cortex (VTC). When individuals are motivated to see a particular object category (e.g., scenes), the amygdala enhances the corresponding neural representation in the VTC, which in turn biases perceptual decisions in favor of that category. (B) Motivation also recruits the locus coeruleus-norepinephrine (LC-NE) system, which can be indexed by pupil dilation. Increased LC-NE activity enhances neural gain, amplifying the encoding of motivationally desirable percepts. Enhanced sensory encoding leads to a bias in the drift rate during decision-making, as formalized by drift diffusion models. Face stimuli were obtained from the Chicago Face Database [108].

Figure 3. (Key Figure). Neural model of motivated seeing. Motivational contexts (e.g., which player you root for in a tennis match) are represented in the lateral prefrontal cortex (IPFC). These contexts influence the value attributed to perceptual features and actions in the ventromedial prefrontal cortex (vmPFC), which in turn modulates the function of downstream subcortical regions including the ventral striatum and amygdala. The ventral striatum induces response biases by reducing response thresholds for motivationally-aligned actions (e.g., yelling "out" when motivated to believe it did). The amygdala enhances the representation of desirable sensory information in the VTC while also recruiting the locus coeruleus (LC). LC recruitment triggers norepinephrine release, which further amplifies the encoding of motivationally relevant percepts. Together, the amygdala and LC induce a perceptual bias in favor of desirable interpretations (e.g., seeing the ball as having landed out of bounds).

Figure I. Schematic of starting point and drift bias in a drift diffusion model. Both shifting the starting point and a higher drift rate toward the "dog" threshold increases the probability of responding "dog" but have distinct effects on the response time distributions. A bias in starting point has stronger influences early in the trial, leading to a larger proportion of fast "dog" responses. In contrast, a bias in the drift rate is constant throughout, resulting in an increase in both fast and slow "dog" responses. a : decision threshold, t : non-decision time, z : starting point, v : drift rate.

Figure II. Distinct Brain Regions Supporting Different Types of Attention. The dorsal attention network (left) is associated with voluntary, goal-directed attention, enabling the selection of specific stimuli based on task relevance [109–111]. The cingulo-opercular network (middle) supports sustained attention, maintaining focus on relevant inputs over extended periods [112–114]. The amygdala (right) is implicated in affective attention, prioritizing stimuli with emotional salience [54,115]. Motivated seeing has been specifically linked to heightened amygdala activity, suggesting that similar processes underlying affective attention may also contribute to the amplification of desirable sensory representations.

Box 1: Decomposing Biases using Drift Diffusion Models

The drift diffusion model (DDM) is a widely used computational model that formalizes the cognitive processes underlying perceptual decision-making [24]. It is a variant of the broader family of sequential sampling models that describe decision-making as a process of accumulating and integrating noisy evidence over time toward a decision threshold.

The DDM is defined by four core parameters that characterize distinct aspects of the decision process. The starting point (z) specifies the initial bias in the accumulation process, which can reflect prior knowledge or preferences that predispose the observer toward one decision. The drift rate (v) reflects the rate of evidence accumulation, with higher drift rates indicating stronger sensory information that favors one decision over the other. The boundary separation (a) captures the distance between decision thresholds, which influences the amount of evidence required before committing to a decision. Finally, the non-decision time (t) accounts for processes outside of evidence accumulation, including the initial encoding of sensory information and motor preparation.

To illustrate, consider a task where an observer has to detect whether an image of a dog or cat is embedded in a noisy background. Prior information that the upcoming image is likely to contain a dog can shift the starting point closer to the corresponding threshold, increasing the likelihood of responding “dog”. On the other hand, changes in the drift rate correspond to the quality of sensory evidence; for instance, seeing a clear image of a dog biases the drift rate toward the “dog” threshold. Both starting point and drift rate biases increase the probability of a “dog” response, but influence response time (RT) distributions differently: starting point bias is most prominent early in a trial, leading to greater bias on short-RT trials (Fig. 1A), while drift rate bias is constant throughout, producing bias on both short- and long-RT trials (Fig. 1B). An increase in boundary separation reflects a greater amount of evidence required to reach a decision (i.e., greater “response caution”), leading to slower but more accurate responses. Lastly, an increase in non-decision time slows responses across the board without affecting accuracy or biasing decisions.

As each parameter uniquely affects choice and response time distributions, biases can be dissociated by fitting the DDM to behavioral data. Furthermore, the parameters estimated from the model can be mapped onto neural activity to identify the neural substrates underlying specific aspects of the decision-making process. It is important to note that the application of the DDM in the reviewed studies are primarily descriptive, aimed at inferring latent processes from observed behavior. Developing generative models that predict motivated seeing under new conditions represents an exciting future direction.

Box 2: The Contentious Role of Attention in Motivated Seeing

In their seminal critique of top-down effects on perception, Firestone and Scholl [1] argue that many purported perceptual effects are mediated by attention rather than directly influencing perception, which they consider a methodological pitfall. We contend, however, that motivational effects on perception, by definition, rely on attentional mechanisms to prioritize sensory input. Rather than viewing attention as a confound, there is value in recognizing attention as the primary process through which motivational states shape perceptual experience. Importantly, attention is not a unitary construct but encompasses a set of related processes, each relying on distinct neural mechanisms (Fig. II).

We adopt a functional definition of attention, where attention is defined as a process that biases the competition among sensory inputs [47]. Different types of attention can serve distinct roles in shaping perception. For example, voluntary attention involves the goal-directed selection of specific stimuli based on task relevance, such as focusing on a particular location or feature to achieve an objective [109–111]. Sustained attention involves maintaining focus over extended periods, ensuring consistent processing of relevant inputs despite distractions [112–114]. Affective attention is driven by emotional information, drawing focus toward affective stimuli, such as emotional faces or words [54,115].

In recent work [55], we show that the enhancement of desirable sensory representations is associated with heightened amygdala activity, a region heavily implicated in affective attention. In contrast, activity in regions typically associated with voluntary and sustained attention did not track motivational enhancement of sensory representations. This dissociation suggests that motivated seeing may be less likely to result from volitional, goal-directed prioritization and more closely resembles the automatic attention capture by stimuli with affective value, as typically observed in affective attention. Neural data can thus provide a framework for linking motivated seeing to related phenomena and reveal the specific attentional mechanisms through which motivation biases sensory processing.

Box 3: Motivated Seeing in Aversive Contexts

Aversive stimuli can differ in the negative emotions they evoke. Even the same stimulus can evoke categorically distinct negative emotions in different individuals resulting in different perceptual and behavioral consequences. For example, in a distance judgment task, individuals who find a spider threatening estimated it as closer than those who find it disgusting [116]. A similar dissociation was observed in an EEG study, where fearful images facilitated visual search and elicited stronger visual event-related potentials, whereas disgusting images had the opposite effect [117]. This pattern may arise because of functional differences between threat and disgust. Threat signals imminent danger, necessitating rapid detection and action, while disgust signals potential contamination to be avoided, promoting withdrawal and suppression to reduce emotional discomfort. This perspective predicts that perceptual decisions may be more likely to be biased toward threatening stimuli away from disgusting stimuli.

A related factor that may influence motivated seeing is the degree of control participants have over aversive outcomes. In a target detection task, participants were better at detecting stimuli associated with an aversive outcome when they had the opportunity to mitigate that outcome, but worse when they had no control over it [118]. Together, these studies highlight the functional dependence of motivational effects on perceptual decisions in aversive contexts. Yet, little is known about how the brain adjudicates between biasing perceptual decisions toward or away from aversive stimuli. Understanding the neurocomputational mechanisms underlying this process represents an exciting avenue for future research, and would provide valuable insights into how perceptual decisions are biased to serve adaptive goals.

Glossary

Desirability: The extent to which a stimulus or outcome is valued or preferred based on an individual's current goals, needs, or emotional state

Drift diffusion model: A computational model of decision-making that describes the process as the accumulation of noisy evidence over time toward a decision threshold

Motivated cognition: A family of cognitive biases where individuals are steered toward conclusions that align with an individual's desires, goals, or preferences.

Motivational context: the set of internal and external factors, including task demands, reward contingencies, and prior experiences, that determine what is currently desirable

Motivational salience: The property of a stimulus that enhances its prominence due to its relevance to an individual's goals or needs, driving attention and action toward it.

Motivated seeing: A phenomenon where individuals are biased toward reporting seeing a visual stimulus as the interpretation they are motivated to see

Perceptual bias: A systematic deviation in how sensory information is processed, resulting in certain stimuli being perceived more readily than others.

Perceptual decision-making: The act of selecting one option from a set of alternatives based on available sensory information

Response bias: A tendency to favor certain response options over others, independent of sensory information