

From Pixels to Preferences: Visual Saliency Shapes Economic Choices Beyond Gaze Alone

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From Pixels to Preferences: Visual Saliency Shapes Economic Choices Beyond Gaze Alone

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Abstract

Visually salient information often sways economic choice, an effect typically attributed to gaze bias. By combining eye-tracking with computer vision, we show that visual saliency alters risky choice largely independent of gaze. People were more likely to accept a 50/50 monetary gamble when its potential gain, rather than its potential loss, was made more visually salient. Saliency induced a pronounced gaze bias toward the salient attribute. Yet multiple complementary analyses converged to show that gaze accounted for less than 20% of the saliency effect on choice, with most of the effect operating independently of gaze. To formalize these pathways, we introduce an image-computable attentional Visual Accumulator Model (aVAM): a convolutional neural network converts stimulus images into value representations that feed a gaze-modulated Linear Ballistic Accumulator. This dual-pathway framework reproduces the saliency

effect on gain-loss trade-offs and highlights the often-overlooked gaze-independent influence of visual salience on economic choice.

1 Introduction

Making rational economic choices is fundamental to navigating everyday life. From selecting consumer goods to making investment decisions, we routinely evaluate options by gathering and processing visual information about the available alternatives [1]. These choices are often susceptible to visual salience—the extent to which an element stands out from its surroundings [2, 3]—despite its irrelevance to economic outcomes. Visually salient features such as brightness or physical size can change preferences in a range of decisions [4, 5]. For instance, people are more likely to choose a risky option when its best possible outcome is displayed in a larger font size [6]. Similarly, individuals discount future reward more steeply when delay information is visually prominent [7]. Relatedly, consumers are more likely to choose visually salient items over alternatives [8, 5, 9]. Beyond laboratory settings, the salience effect on choice has been broadly observed in real-world settings such as shopping [10, 11, 12], saving [13, 14] and stock trading [15].

The leading explanation for these widespread salience effects centers on visual attention, typically measured through gaze. Formally, gaze is assumed to bridge two successive processes [9]. First, visually salient information, by definition, preferentially attracts gaze [2, 3]. Second, gaze is believed to amplify the weight of the fixated item or attribute during evidence accumulation (or down-weight the unattended ones), thereby increasing the probability of choosing the fixated item or the impact of the fixated attribute on choice. This idea is supported by empirical findings linking gaze patterns to choice bias [16, 17, 18, 19], and is formalized in influential computational frameworks like the attentional Drift Diffusion Model (aDDM) [18]. Under this framework, visual salience biases choice because it biases gaze.

47 However, this gaze-dependent pathway may not be the sole mechanism through which
48 visual salience shapes economic decisions. Visually salient attributes have been shown to
49 exert strong influence on consumer choice even when they have not been directly fixated
50 [20]. This finding suggests that other cognitive processes, more implicit than gaze allocation,
51 mediate the salience effect. One mechanism that could account for these effects is that visual
52 salience directly alters the value representation of choice option attributes, independently of
53 how gaze later modulates their weights during value construction. This potential mechanism
54 is consistent with findings on numerical cognition showing that numerical values can appear
55 larger when they visually stand out [21, 22, 23]—an effect that persists even when gaze
56 is controlled [24]. These findings suggest that visual salience may operate not only by
57 redirecting gaze, but also by altering how value is encoded during the process of making a
58 decision.

59 Recent computational studies support this possibility by formalizing the direct influence
60 of visual features on economic choice. Computer-vision salience algorithms have been suc-
61 cessfully used to predict economic choices, demonstrating that low-level visual processing
62 can capture decision-relevant information without explicit gaze information [5]. More re-
63 cently, convolutional neural networks (CNNs) that process raw pixel-level visual input have
64 been shown to extract decision-relevant features and generate behavioral responses that
65 closely match human performance [25], suggesting that visual representations formed early
66 in processing can directly influence choice outcomes. Together, these observations point
67 to a dual-pathway account of the salience effect on economic choice: one pathway medi-
68 ated by gaze-dependent attentional weighting, and another arising from gaze-independent
69 transformations of visual inputs to internal value representations.

70 Here, we dissociate these pathways by coupling eye-tracking with computational model-
71 ing. In a webcam-based eye-tracking experiment ($N = 139$), we examined decisions to accept
72 or reject gambles with equal chance of winning and losing money while gaze allocation was
73 monitored. Crucially, we manipulated the relative visual salience of potential gains and losses

via brightness (Fig. 1A). We observed that manipulating visual salience systematically shifted gain-loss tradeoffs. Although salience reliably altered gaze allocation, causal mediation analysis showed that gaze accounted for only a small fraction of the salience effect on choice. To formalize the underlying mechanisms, we developed an attentional Visual Accumulator Model (aVAM) that integrates a deep CNN for visual representations with gaze-modulated evidence accumulation. This model revealed that visual salience systematically reshaped the value representation of the gamble itself, irrespective of gaze shifts, while gaze contributed an additional attentional amplification effect. Together, these findings demonstrate that visual salience influences economic choices via two pathways: a gaze-dependent attentional amplification pathway and a gaze-independent value representation pathway. This dual-pathway framework clarifies when and how visual design properties shape decision behavior and highlights the importance of modeling the perceptual origins of value.

2 Results

2.1 Visual Salience Biases Risky Choice

We first investigated how the salience manipulation influenced choices to accept or reject gambles. As shown in Fig. 1B, the probability of accepting a gamble generally increased with the magnitude difference of the potential gain versus loss in a sigmoidal fashion (also see Supplementary Fig. 1). Hereafter, we refer to this magnitude difference as the value difference. Critically, choice probability was systematically biased by the brightness manipulation: participants were generally more likely to accept a given gamble when the potential gain was salient compared to when the potential loss was salient (Fig. 1C).

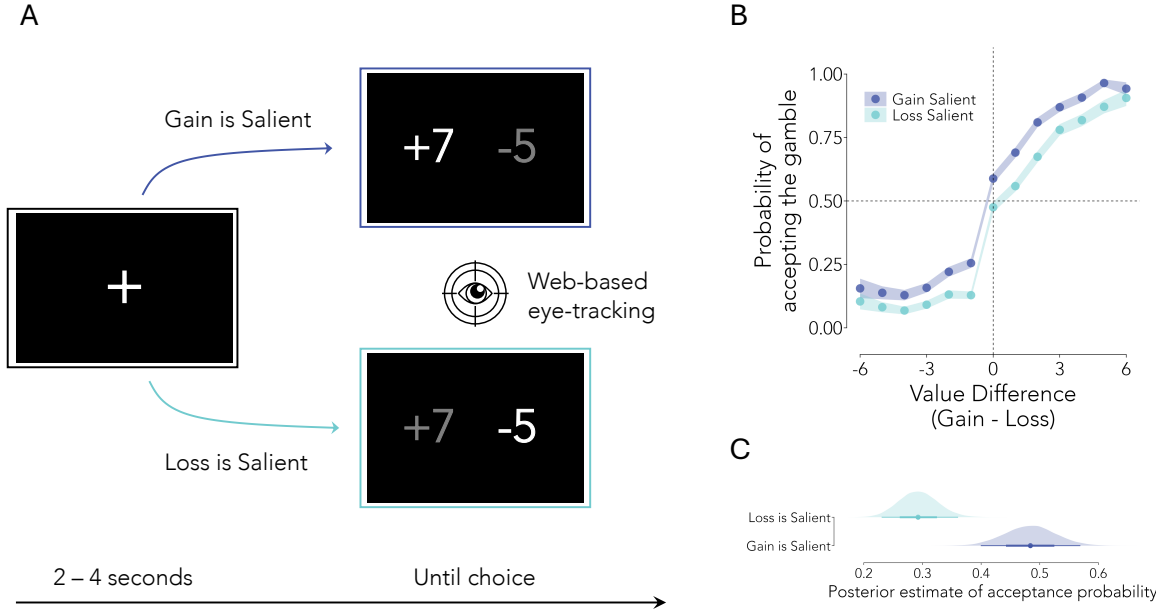


Figure 1: **Experimental paradigm and salience effects on risky choice.** (A) Task design: Participants viewed gambles displaying potential gains and losses with equal probability (50/50). Visual salience was manipulated by making either the gain or loss brighter than the other. Eye movements were recorded using webcam-based gaze tracking throughout the decision process. (B) Probability of accepting gambles as a function of value difference (gain - loss). Participants were more likely to accept gambles when the potential gain was salient (dark blue) compared to when the potential loss was salient (light blue). Shaded areas indicate the $\pm$ standard error of the mean. (C) Posterior estimates of acceptance probability from a Bayesian multilevel logistic regression accounting for participant-level variation. Error bars represent 95% credible intervals.

To quantify the impact of the salience manipulation and the numerical impact of gains and losses, we regressed choice simultaneously on visual salience (1=gain salient, 0=loss salient) and gain-loss value difference. We found significant effects of both value difference ($\beta = 3.182$, $SD = 0.225$, 95% CrI[2.758, 3.634]) and visual salience ($\beta = 0.820$, $SD = 0.155$, 95% CrI[0.515, 1.122]), with the impact of making the gain salient (versus loss salient) equivalent to increasing the value difference approximately by \$0.736 ($\beta = 0.368$, $SD = 0.078$, 95% CrI[0.220, 0.528]). To further distinguish the impacts of gains and losses, we ran a mixed-effects model that regressed choices on gain magnitude, loss magnitude, and visual salience. We found that gamble acceptance increased with gains ($\beta = 2.217$, $SD =$

0.164, 95% CrI[1.904, 2.548]) and decreased with losses ($\beta = -2.322$, SD = 0.163, 95% CrI[-2.653, -2.010]), with the impact of losses slightly larger than gains. The salience effect ($\beta = 0.843$, SD = 0.159, 95% CrI[0.534, 1.159]) was comparable to increasing gains by approximately \$1.09 ($\beta = 1.087$, SD = 0.232, 95% CrI[0.654, 1.567]) or decreasing losses by \$1.04 ($\beta = -1.037$, SD = 0.219, 95% CrI[-1.488, -0.627]). Together, these results demonstrate that while choices were primarily driven by the numerical magnitudes of gains and losses, visual salience exerted a significant and economically meaningful influence on decision-making.

2.2 Visual Salience Biases Gaze Allocation

We next examined how the salience manipulation influenced participants' gaze patterns (Fig. 2), beginning with analysis of first fixation. We found participants were more likely to first fixate on the salient attribute ($\beta = 0.540$, SD = 0.078, 95% CrI[0.388, 0.694], Fig. 2A and Supplementary Fig. 2A). Importantly, beyond salience, first fixations were also influenced by numerical magnitudes: participants were more likely to first look at gains when the value difference was larger ($\beta = 0.096$, SD = 0.033, 95% CrI[0.032, 0.160]). Splitting value difference into gains and losses, we found participants were less likely to first look at gains when facing larger losses ($\beta = -0.093$, SD = 0.023, 95% CrI[-0.138, -0.047]), while gain magnitude had a smaller, more variable effect ($\beta = 0.043$, SD = 0.025, 95% CrI[-0.005, 0.091]; Supplementary Fig. 2B).

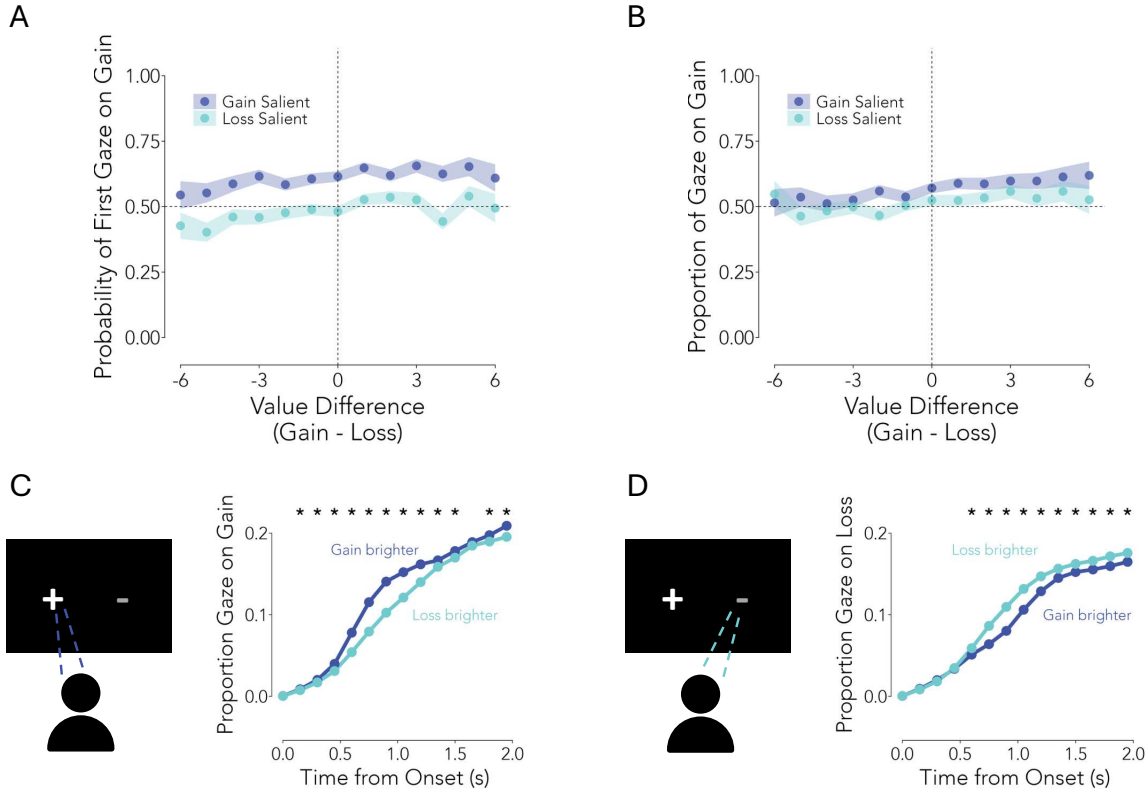


Figure 2: Gaze allocation patterns across salience conditions. (A) Probability of first gaze on gain as a function of value difference (gain - loss), with dark blue representing gain-salient trials and light blue representing loss-salient trials. (B) Proportion of gaze on gain as a function of value difference (gain - loss), separated by salience condition. Shaded areas indicate the $\pm$ standard error of the mean. (C,D) Temporal dynamics of gaze allocation from trial onset. The proportion of gaze directed toward gains (C) and losses (D) over time, separated by salience condition. Asterisks indicate significant differences between conditions at each time point.

To understand how this initial gaze bias evolved during the decision process, we examined the temporal dynamics of gaze allocation from trial onset. This analysis revealed that the gaze bias toward the salient attribute emerged early in the trial (around 0.5s) and persisted over time (Figs. 2C and 2D). This temporal pattern demonstrates that salience effects on gaze are not merely due to initial capture but reflect sustained attentional prioritization throughout the decision-making process.

This temporal pattern resulted in systematic differences in overall gaze allocation. Participants spent a greater proportion of overall time looking at the salient attribute through-

out the trial ($\beta = 0.271$, $SD = 0.081$, 95% CrI[0.110, 0.430], Fig. 2B and Supplementary Fig. 3A). Similarly, sustained viewing was sensitive to numerical magnitudes, with the proportion of time spent looking at gains increasing with the value difference of gain and loss ($\beta = 0.081$, $SD = 0.024$, 95% CrI[0.034, 0.128]). Dividing the value difference into gains and losses, we found that proportion of time viewing gains did not significantly increase with gain magnitude ($\beta = 0.044$, $SD = 0.026$, 95% CrI[-0.007, 0.097]), while it did decrease with loss magnitude ($\beta = -0.069$, $SD = 0.020$, 95% CrI[-0.107, -0.031]; Supplementary Fig. 3B). Thus, while numerical content influenced gaze allocation, the salience manipulation exerted a robust and consistent effect on gaze allocation from the very onset through the entire decision process.

Taken together, these results demonstrate that visual salience robustly captures and sustains attention, influencing both initial orienting and sustained allocation of attention throughout the decision process.

2.3 Gaze Modestly Mediates the Effect of Salience on Choice

Visual salience biases both participants' choices (Fig. 1B,C) and their gaze allocation patterns (Fig. 2). A critical question is how these effects are interconnected. Next we sought to determine whether the influence of salience on choice operates exclusively by shifting gaze patterns, or if salience also exerts an influence on choice through other mechanisms independent of gaze. To disentangle these possibilities, we employed a causal mediation framework (Fig. 3). Within this framework, we considered three main scenarios. First, salience might influence choice solely by altering gaze allocation; here, the entire effect of salience would be explained by changes in looking patterns via the indirect pathway mediated by gaze (Hypothesis 1; Fig. 3A, H1). Second, salience might influence choice through mechanisms entirely separate from the measured gaze behavior (Hypothesis 2; Fig. 3A); this direct pathway represents the portion of salience's influence not accounted for by gaze mediation, suggesting effects channeled through routes other than the measured gaze pat-

156 terns. Finally, salience could influence choice through both routes: partly by altering gaze
 157 patterns and partly through other mechanisms independent of gaze (Hypothesis 3; Fig. 3A).
 158 Mediation analysis quantifies these pathways, estimating the Average Causal Mediation Ef-
 159 fect (ACME) for the indirect pathway via gaze, and the Average Direct Effect (ADE) for
 160 the pathway independent of gaze. Thus, finding only a significant ACME would support
 161 Hypothesis 1, only a significant ADE would support Hypothesis 2, and significant effects for
 162 both ACME and ADE would support Hypothesis 3.

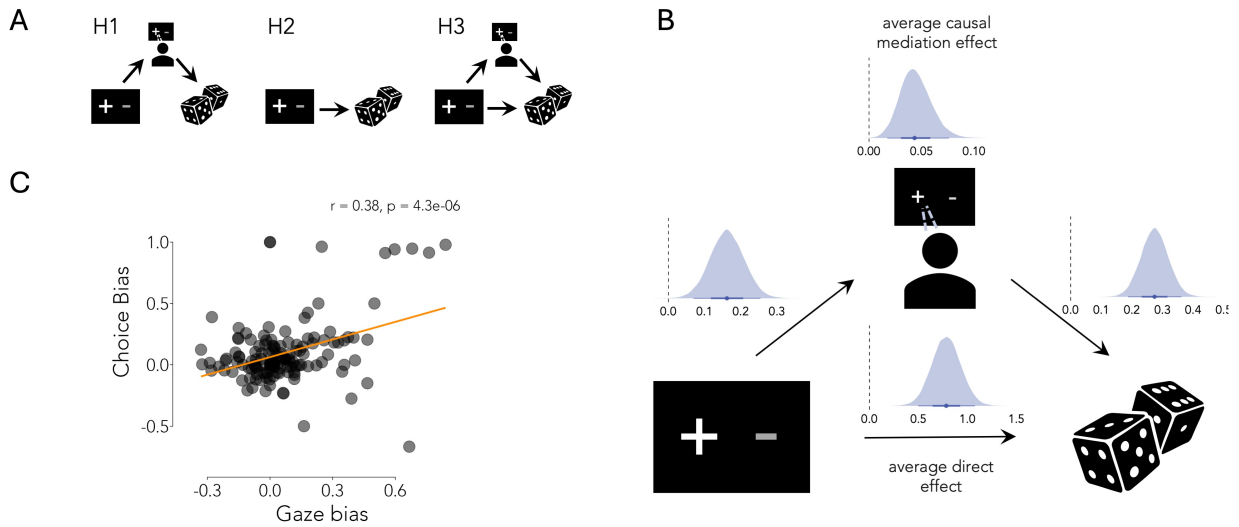


Figure 3: **Mediation analysis of salience effects on choice.** (A) Three hypotheses about pathways through which salience influences choice: H1 (indirect pathway only, mediated by gaze), H2 (direct pathway only, independent of gaze), and H3 (both indirect and direct pathways). (B) Posterior distributions for the Average Causal Mediation Effect (ACME, indirect pathway via gaze) and Average Direct Effect (ADE, direct pathway independent of gaze). Vertical dashed lines indicate zero effect. (C) Correlation between individual differences in gaze bias and choice bias. Each point represents one participant. The orange line shows the linear regression fit.

163 To formally test these competing hypotheses, we performed a Bayesian multilevel me-
 164 diation analysis, modeling the effect of salience (1=gain salient) on choice (1=accept) as
 165 mediated by the proportion of total gaze time on the gain attribute, with the gain magni-
 166 tude and the loss magnitude as control variables. We included gain and loss as covariates
 167 in both the mediator and outcome models to isolate the effect of salience from the variables

that should guide choice from an optimal perspective. Consistent with Hypothesis 3, the results revealed significant effects for both pathways (Fig. 3B and Supplementary Fig. 4). We found a significant indirect effect ($ACME = 0.043, SD = 0.015, 95\%CrI [0.017, 0.076]$), replicating the conventional gaze-dependent mechanism. Crucially, the analysis also revealed a substantial direct effect ($ADE = 0.784, SD = 0.147, 95\%CrI [0.498, 1.076]$), supporting the existence of gaze-independent mechanisms underpinning the salience effect.

To quantify the relative contributions of these pathways, we calculated the proportion of the total salience effect operating through each route. The gaze-mediated pathway accounted for only 5.2% of the total effect ($ACME / [ACME + ADE]$), while the gaze-independent pathway accounted for 94.8%, approximately 18 times larger. This finding demonstrates that while gaze partially mediates the influence of salience on choice, the predominant effect operates through mechanisms independent of measured gaze allocation. To complement this effect decomposition with a variance-based perspective, we compared hierarchical models that progressively added predictors. A baseline model including only gain and loss magnitudes (the attributes that should rationally determine choice) explained 57.4% (Bayesian R^2) of variance in choice ($95\% CrI [0.566, 0.582]$). Adding salience to this baseline increased explained variance to 60.2% ($95\% CrI [0.594, 0.610]$; $\Delta R^2 = 2.8$ percentage points), quantifying the extent to which this normatively irrelevant visual feature systematically biases decisions. Including gaze as a mediator further increased explained variance to 60.7% ($95\% CrI [0.599, 0.615]$; $\Delta R^2 = 0.5$ percentage points). From a variance perspective, gaze accounted for 18.5% of the contribution of salience to explaining choice ($0.5/2.8$), while 81.5% (2.3 percentage points) operated independently of measured gaze patterns. Both analytical approaches converge on the key conclusion that gaze mediates only a modest fraction of the influence of salience on choice, with the majority operating through gaze-independent mechanisms.

To further examine the relationship between gaze and choice biases, we investigated whether individual differences in gaze bias could account for individual differences in choice

bias. We calculated each participant’s gaze bias as the difference in gaze allocation toward gains when gains were salient versus when losses were salient, and their choice bias as the corresponding difference in acceptance rates. We found a significant positive correlation between these individual difference measures ($r = 0.38$, $p < 0.001$, Fig. 3C), indicating that participants who showed stronger gaze biases toward salient attributes also exhibited stronger choice biases. However, this correlation, while significant, was moderate in magnitude, suggesting that gaze bias accounts for only a limited portion of the individual variation in choice bias ($R^2 = 14\%$). This finding complements the mediation analysis by demonstrating that while gaze patterns partially explain both trial-level and individual-level variation in salience effects, substantial variation remains unexplained by measured gaze behavior alone.

Together, these converging lines of evidence, effect decomposition (5.2% vs. 94.8%), variance decomposition (18.5% vs. 81.5%), and individual differences (14% shared variance), provide strong support for Hypothesis 3 and demonstrate that visual salience biases risky choice through dual pathways: a minor gaze-mediated route and a predominant gaze-independent route.

2.4 Salience Modulates Internal Value Representations Independent of Gaze

Our mediation analysis revealed that a substantial portion of the influence of salience on choice occurs independently of measured gaze patterns (Fig. 3B). This raises the question of what cognitive mechanism underlies this gaze-independent effect. One hypothesis is that visual salience might directly bias the internal representation of the magnitudes associated with gains and losses. This aligns with growing evidence suggesting that economic choices are sensitive to how numerical magnitudes are perceived and neurally encoded, potentially involving biases or noise in these representations [26]. To test this idea, we explored whether visual salience could be one factor that directly modulates these internal magnitude representations independently of gaze.

221 We employed a computational modeling approach that simulates the decision process
 222 directly from visual input (Fig. 4A). Specifically, we adapted the Visual Accumulator Model
 223 (VAM) framework [25], which uses a Convolutional Neural Network (CNN) to extract decision-
 224 relevant features directly from raw pixel input, passing these features as drift rates to a Linear
 225 Ballistic Accumulator (LBA) model. To account for gaze effects, we modified this framework
 226 by incorporating gaze-dependent discounting of the evidence derived from the CNN output,
 227 conceptually similar to the Gaze-weighted Linear Accumulator Model (GLAM) [27], where
 228 the effective drift rate depends on the gaze proportion towards an item and a fitted gaze-bias
 229 parameter λ . In other words, this model has two key components. First, a visual processing
 230 module (a CNN) that acts like an artificial visual system. It takes the raw pixels of the
 231 gamble image as input and learns to extract decision-relevant features, similar to how the
 232 human brain processes visual scenes to identify numbers and their visual properties. Sec-
 233 ond, a gaze-modulated accumulation module (based on the Linear Ballistic Accumulator,
 234 LBA) that simulates the process of accumulating evidence for accepting or rejecting the
 235 gamble over time. Crucially, the rate of evidence accumulation is influenced by the features
 236 extracted by the CNN and by the participant’s measured gaze patterns. We refer to this
 237 modified framework as the attentional Visual Accumulator Model (aVAM).

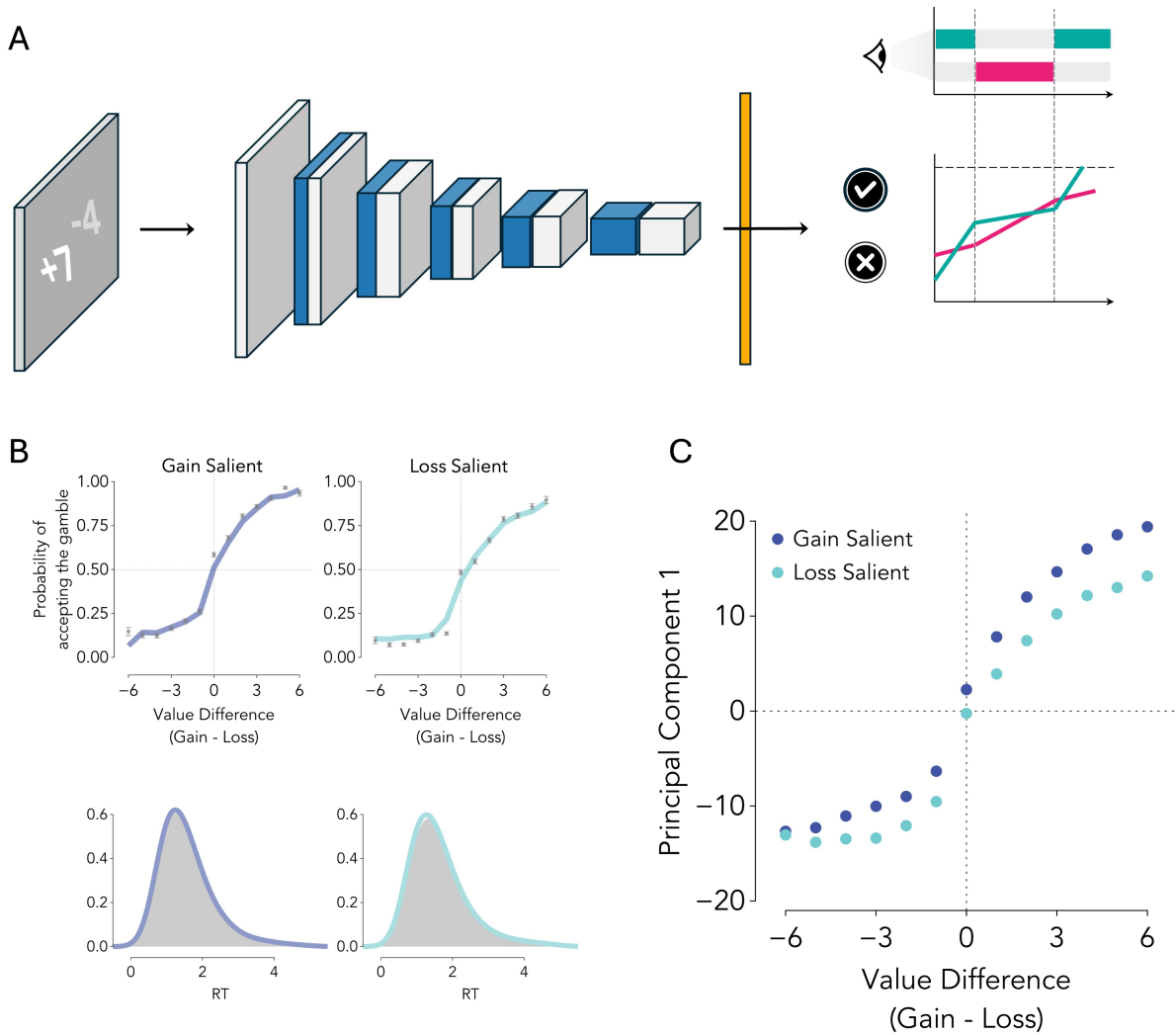


Figure 4: **Computational modeling of salience effects using the attentional Visual Accumulator Model (aVAM).** (A) Model architecture showing the visual processing pathway from raw pixel input through convolutional neural network layers to evidence accumulation and choice output. The CNN extracts decision-relevant features from gamble images, which are then processed by a gaze-modulated Linear Ballistic Accumulator (LBA) to generate accept/reject decisions and reaction times. (B) Model predictions compared to actual behavioral data for choice probabilities (upper panels) and response times (RTs; lower panels) across different value differences (gain - loss), separated by salience conditions. Left panels show gain-salient trials, and right panels show loss-salient trials. Grey points and error bars (upper panels) represent actual choice data with standard error, and grey areas (lower panels) represent actual RT data. Colored lines show model predictions. (C) Internal representation analysis showing the first principal component (PC1) of CNN activations as a function of value difference, with dark blue points representing gain-salient trials and light blue points representing loss-salient trials. Vertical and horizontal dashed lines indicate zero reference points.

We trained the aVAM to reproduce participants’ choices and reaction times. The model accurately captured both the choice patterns and reaction time distributions across different value differences and salience conditions (Fig. 4B). The power of this approach is that, once trained, we can examine the model’s internal representation to understand how it processes the visual information. Specifically, we inspected the information represented within the CNN just before it feeds into the final evidence accumulation stage, to provide insight into the model’s internal representation of the gamble’s value, prior to gaze-dependent modulation in the accumulation stage.

We found that the best-fitting gaze-bias parameter λ in the accumulation module was less than 1 ($\lambda = 0.73$, 95% CrI [0.66, 0.80]). This confirms that the model captured the attentional discounting effect, where participants down-weighted information they were not looking at, consistent with the gaze-mediated pathway identified earlier.

To probe the internal value representations learned by the model, we extracted the activations from the penultimate layer of the trained CNN (i.e., the input to the final drift-rate mapping layer) for each trial. This layer was chosen because, analogous to higher stages in cortical processing hierarchies, it is expected to contain the most abstract, integrated representation of task-relevant variables before the final output transformation. For each trial, this layer produced a high-dimensional vector (1024 dimensions) representing the network’s internal encoding of the visual information before it gets translated into drift rates for the decision process. To understand what information was captured in these internal representations, we applied Principal Component Analysis (PCA) across all trials. The logic underlying this approach is that neural networks, like biological brains, use distributed representations where information is encoded across patterns of activity distributed over many neurons, rather than being localized to individual units. While we cannot directly interpret what each individual neuron represents, PCA allows us to uncover the underlying structure of these distributed representations by identifying the principal dimensions along which the network’s internal state varies most across different inputs.

This analysis revealed that the first principal component (PC1), capturing the largest proportion of variance in the network’s internal representations (45.4%), strongly correlated with the objective value difference between gain and loss ($r = 0.84$, $p < 0.001$), suggesting it captures the model’s internal assessment of the overall value of the gamble. Most importantly, we found that internal value representation (PC1 score) was affected by visual salience (Fig. 4C). For any given objective value difference, the PC1 score was systematically higher when the gain was salient compared to when the loss was salient.

This finding provides computational evidence supporting the hypothesis that visual salience directly modulates the internal representation of value within the visual processing stage itself (as captured by PC1). In the model, this modulation is dissociable from the influence of gaze, which is implemented separately through the accumulation-stage parameter λ . These results suggest that the gaze-independent pathway identified in the mediation analysis may operate, at least in part, by altering how the subjective magnitudes of potential gains and losses are encoded on the basis of their visual presentation, over and above the effect of gaze allocation. This offers a deeper mechanistic insight into how seemingly irrelevant visual features can alter the valuation process itself, biasing choices beyond their influence on overt attention.

3 Discussion

Visual salience effects are pervasive in economic decision-making, with seemingly irrelevant features systematically biasing choices across diverse domains from consumer goods to financial investments [4, 5]. Understanding the mechanisms underlying these effects is crucial both for advancing our understanding of human decision making and for practical applications in helping people make better economic decisions. Our study reveals that visual salience influences risky choice through dissociable pathways. While we confirmed that salience influences gaze allocation and that gaze patterns modestly mediate the effect on

choice [18], three converging lines of evidence demonstrate that the majority of salience’s influence operates independently of measured gaze behavior. First, causal mediation analysis revealed that only 5.2% of the total salience effect operates through the gaze-mediated pathway, while 94.8% operates directly. Second, hierarchical model comparison showed that adding gaze as a mediator increased explained variance by 0.5 percentage points beyond what salience and numerical magnitudes already explain, representing 18.5% of salience’s variance contribution. Third, individual differences in gaze bias explained only 14% of the variance in choice bias across participants, indicating that gaze patterns alone cannot account for the substantial individual differences in salience susceptibility. Critically, these converging estimates, ranging from 5% to 19% across different analytical approaches, provide robust evidence for a dual-pathway model where salience operates through both attentional amplification and a separate mechanism that directly modulates the internal representation of choice attributes. This aligns with emerging evidence that economic choices are sensitive to how numerical magnitudes are perceived and neurally encoded, potentially involving biases or noise in these representations. [26].

To probe the mechanism underlying the gaze-independent pathway, we extended a recently developed computational modeling approach that simulates the entire decision process from raw pixel input to choice and reaction time outputs [25], by incorporating an attentional component [27]. Critically, analysis of the model’s internal representations revealed that visual salience systematically biased the encoding of gamble value in a manner dissociable from gaze-dependent modulation within the model architecture, providing computational evidence for magnitude amplification as a mechanism distinct from attentional amplification.

Our computational findings align with recent neuroscientific evidence demonstrating that economic choices causally depend on the precision of numerical magnitude representations in parietal cortex. Using combined transcranial magnetic stimulation and fMRI, de Hollander et al. (2025) showed that perturbing the parietal region implicated in encoding numerical magnitudes, directly affected risk preferences by making magnitude representations noisier

[26]. The CNN’s internal representations in our model may thus be analogous to these parietal magnitude representations, with salience acting as a factor that systematically biases how numerical values are encoded at this early processing stage. This perspective suggests that the gaze-independent pathway we identified may operate through what we term "magnitude amplification", a process where visual salience directly affects the subjective representation of numerical magnitudes upstream of the evidence accumulation stage in the model. This mechanism is distinct from but complementary to attentional amplification, offering a more complete account of how seemingly irrelevant visual features can systematically bias economic choices [26]. This interpretation also converges with recent primate electrophysiological research showing that, within orbitofrontal cortex, the neural representation of value is dominated by reward salience rather than by spatial attention [28], pointing to a general role for visual salience in shaping the neural representation of value. One possibility is that magnitude amplification arises from covert attentional shifts—orienting mechanisms that enhance processing at salient locations without overt eye movements [2, 3]. Such covert attention could modulate early magnitude encoding in a way that is not captured by gaze tracking, thereby producing observed gaze-independent effects. This possibility would align with evidence that covert attention can alter perceptual precision [20, 29, 30] and bias numerical judgments [31] even in the absence of measurable fixation changes.

Our modeling approach represents a significant methodological advance in understanding choice mechanisms. By directly modeling the pixel-to-choice pathway, we can examine how visual information is transformed into decision-relevant representations without relying on a priori assumptions about which visual features matter. The current model architecture assumes that gaze affects evidence accumulation after initial representation formation, which is supported by evidence that value signals in orbitofrontal cortex depend on fixation location during free viewing [32]. However, future work could explore more dynamic models where gaze influences the CNN representations themselves, perhaps through sequential processing with attentional spotlights that modify the visual input based on fixation patterns.

In conclusion, our study demonstrates that visual salience influences economic choice through dual pathways: directly by modulating internal value representations, and indirectly through gaze. This multi-pathway account provides a more complete understanding of how visual features impact economic decisions and suggests that both magnitude amplification and attentional amplification mechanisms contribute to the pervasive influence of visual salience on choice. These findings challenge purely attentional accounts of salience effects and highlight the importance of considering perceptual and representational processes in models of economic decision-making.

4 Methods

Participants. A total of 171 participants were recruited for the online eye-tracking study. We excluded 32 participants given the quality of the eye-tracking data (see Preprocessing of Gaze Data below) and analyzed data from 139 participants (67 females; 18–80 y old, $M \pm SD = 48.03 \pm 17.60$). All participants provided informed consent before the start of the experiment. All participants had normal or corrected-to-normal vision. The study was approved by the ethical committee of Zhejiang University.

Procedure. In the gambling task, participants decided whether to accept or reject gambles of equal chance of winning and losing money on a computer (Fig. 1A). We used the JavaScript library jsPsych to code the task. Each trial started with a 2-4s fixation period, followed by a gamble with the amounts of potential gain and loss displayed on the left and right sides of the screen. In 50% of the trials the potential gain was salient, while in the remaining 50% the potential loss was salient. We used brightness as the salience manipulation: The salient attribute was brighter than the non-salient attribute. Participants were given unlimited time to make the decision by pressing one of two keys. The gambles were not immediately resolved after the decision. The amounts of potential gain and loss ranged from \$3 to \$9, with \$1 increment. Each gamble of a specific gain-loss combination was presented twice, once in

which the potential gain was salient and once in which the potential loss was salient, for a total of 98 trials. The presentation order of the trials was randomized across participants. The left-right positions of gain and loss were randomized across trials.

Participants received a fixed endowment of \$4 for their participation. Moreover, they had an additional \$1 as an endowment for the gambling task, and they were instructed that at the end of the experiment, one trial (out of 98) would be randomly selected, and a payment would be made according to their actual decision. If the selected gamble was rejected, participants were left with the original \$4 + \$1. If the gamble was accepted and they won it, the amount of gain was divided by 10 and added to the tally. If instead they lost, the amount of loss was divided by 10 and subtracted from it. Thus, decisions directly impacted payments, making the task incentive-compatible.

Online Eye Tracking Using Web Cameras. We recorded gaze fixations using WebGazer.js, a JavaScript library that uses common webcams to infer eye-gaze locations in real time. WebGazer.js runs entirely in the client browser, and only the coordinates of the gaze position were transmitted and saved on our online server. For the software to predict the gaze position on the screen, a thirteen-points calibration-validation scheme was used. Participants had up to three attempts to reach 70% accuracy. After the third attempt, the gambling task started regardless of the validation outcome. The task paused after 24, 48 and 72 trials to allow participants to rest their eyes. After each break, participants repeated the calibration and validation procedure only once, and they went on with the task regardless of the validation accuracy.

Preprocessing of Webcam-Based Gaze Position Data. To ensure good quality of gaze data for analyses, we used four exclusion criteria. First, we removed all trials whose response time was lower than 300 ms (1.4% trials). Second, we removed all trials in which the sampling rate was less than 8 Hz (19% trials). Third, whenever WebGazer does not classify the eyes from the webcam input, it returns a “NA” rather than an x and y coordinate. We

removed all trials in which the NAs were more than 50% of the total number of samples (0.6% trials). Lastly, we defined two regions of interest (ROIs), one for each attribute. We discarded all trials with a summed fixation time outside of the ROIs greater than 80% of the total decision time (28.8% trials). After applying these four criteria, some participants were excluded because all of their trials were removed, resulting in a final sample of 139 participants, with an average number of trials of 59.7 ± 27.3 ($M \pm SD$). For the remaining trials, we linearly interpolated missing data and denoised gaze positions using a 300-ms-long median filter.

Regression and Mediation Analyses. We used the R package `brms` [33] to perform all Bayesian multilevel regression models. For the causal mediation analysis, we specified a Bayesian multilevel mediation model to examine the extent to which the effect of salience on choice was mediated by gaze allocation. The model consisted of two simultaneous equations. The first equation modeled the mediator, the z-scored proportion of gaze to the gain attribute, as a function of the salience manipulation (gain-salient vs. loss-salient) as well as z-scored gain and loss magnitudes. This model included random intercepts and random slopes for all fixed effects by participant. The second equation modeled the outcome variable, choice (accept/reject), using a Bernoulli distribution with a logit link function. Predictors for choice included the salience manipulation, the mediator proportion of gaze to the gain attribute, and z-scored gain and loss magnitudes. This model also included random intercepts and random slopes for all fixed effects by participant. All models used weakly informative priors with $Normal(0, 2.5)$ distributions for fixed effects coefficients to provide gentle regularization while allowing for a reasonable range of effect sizes [34]. Models were run with 4 chains, each for 20,000 iterations, with the first 10,000 iterations discarded as warmup, and an `adapt_delta` parameter of 0.95 to ensure good sampling [35].

To quantify the economic significance of the salience effect, we calculated the dollar equivalent of the salience manipulation by comparing its impact with the numerical impact

of value difference (VD) on choice. Since both effects operate on the same outcome variable (log-odds of choice), we can determine equivalent magnitudes by finding what change in VD would produce the same change in log-odds as the salience manipulation. Specifically, if β_{salience} represents the coefficient for the salience manipulation and β_{VD} represents the coefficient for z-scored VD, then the ratio $\beta_{\text{salience}}/\beta_{\text{VD}}$ gives the equivalent change in standard deviation units of VD. To convert this to dollar units, we multiply this ratio by the standard deviation of VD in the original data: Dollar equivalent = $(\beta_{\text{salience}}/\beta_{\text{VD}}) \times \text{SD}(\text{VD})$. This approach allows us to express the salience effect in terms of the actual monetary amounts used in the experiment, providing an intuitive measure of the practical significance of visual salience on economic choice.

Computational Modeling. To investigate the mechanisms by which salience influences choice, we employed a Visual Accumulator Model (VAM) adapted from Jaffe et al. (2020). This model (illustrated in Fig. 4A) integrates a visual processing module with a decision module to simulate choices and reaction times directly from raw pixel-level image inputs.

The visual processing module was a Convolutional Neural Network (CNN). The CNN architecture consisted of six convolutional layers with 64, 64, 128, 128, 128, and 256 features respectively, followed by one fully-connected layer with 1024 units. This network culminated in an output layer that produced two mean drift rates for the decision module, corresponding to the 'accept' and 'reject' options of the gamble. To enhance robustness and prevent overfitting to specific pixel configurations, the training dataset was expanded through data augmentation, creating five variations of each original stimulus image. This augmentation involved randomly displacing each numerical attribute (gain and loss) within a circular region and applying a random rotation (between -15 and +15 degrees) to each. To potentially leverage pre-existing visual feature extractors, the initial convolutional layers of the CNN was initialized with weights from a VGG16 model [36] pre-trained on ImageNet [37], with these weights being fine-tuned during training.

The decision module was a Linear Ballistic Accumulator (LBA) model [38] with two accumulators. The LBA component was characterized by parameters for non-decision time t_0 , threshold-related component c , and the upper bound of the uniform distribution for starting point variability a , where the decision threshold b is defined as $b = c + a$. The standard deviation of drift rates was fixed to 1. Crucially, to incorporate attentional effects, the mean drift rates from the CNN were modulated by gaze. If v_k was the mean drift rate for accumulator k (accept or reject) derived from the CNN, and g_k was the proportion of gaze to the choice attribute primarily informing accumulator k , the effective drift rate for that accumulator was calculated as $v_k(g_k + (1 - g_k)\lambda)$, where λ is a fitted gaze-bias parameter. A λ value less than 1 indicates that evidence from the attribute not being looked at is down-weighted.

The entire VAM, including the CNN parameters and the posterior distributions of the LBA parameters (a , c , t_0 , λ), was jointly fitted to each participant’s trial-level data (stimuli, choices, reaction times, and gaze proportions) using a Bayesian framework. This involved variational inference for the LBA parameters and optimization of the CNN parameters to maximize the evidence lower bound (ELBO), effectively learning visual representations and decision parameters that best explained the observed behavior.

References

- [1] Pearson, D., Watson, P., Albertella, L. & Le Pelley, M. E. Attentional economics links value-modulated attentional capture and decision-making. *Nature Reviews Psychology* **1**, 320–333 (2022). URL <https://www.nature.com/articles/s44159-022-00053-z>. Publisher: Nature Publishing Group.
- [2] Itti, L. & Koch, C. Computational modelling of visual attention. *Nature Reviews. Neuroscience* **2**, 194–203 (2001).

- [3] Wolfe, J. M. & Horowitz, T. S. Five factors that guide attention in visual search. *Nature Human Behaviour* **1**, 0058 (2017).
- [4] Bordalo, P., Gennaioli, N. & Shleifer, A. Saliency. *Annual Review of Economics* **14**, 521–544 (2022).
- [5] Li, X. & Camerer, C. Predictable Effects of Visual Saliency in Experimental Decisions and Games. *The Quarterly Journal of Economics* **137**, 1849–1900 (2022).
- [6] Vanunu, Y., Hotaling, J. M., Le Pelley, M. E. & Newell, B. R. How top-down and bottom-up attention modulate risky choice. *Proceedings of the National Academy of Sciences* **118**, e2025646118 (2021).
- [7] Fisher, G. Intertemporal Choices Are Causally Influenced by Fluctuations in Visual Attention. *Management Science* **67**, 4961–4981 (2021). URL <https://pubsonline.informs.org/doi/10.1287/mnsc.2020.3732>.
- [8] Milosavljevic, M., Navalpakkam, V., Koch, C. & Rangel, A. Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology* **22**, 67–74 (2012).
- [9] Towal, R. B., Mormann, M. & Koch, C. Simultaneous modeling of visual saliency and value computation improves predictions of economic choice. *Proceedings of the National Academy of Sciences* **110**, E3858–E3867 (2013). URL <https://www.pnas.org/doi/10.1073/pnas.1304429110>.
- [10] Blake, T., Moshary, S., Sweeney, K. & Tadelis, S. Price Saliency and Product Choice. *Marketing Science* **40**, 619–636 (2021).
- [11] Bollinger, B., Leslie, P. & Sorensen, A. Calorie Posting in Chain Restaurants. *American Economic Journal: Economic Policy* **3**, 91–128 (2011). 41238086.

- [12] Taubinsky, D. & Rees-Jones, A. Attention Variation and Welfare: Theory and Evidence from a Tax Salience Experiment. *The Review of Economic Studies* **85**, 2462–2496 (2018).
- [13] Badoer, D. C., Costello, C. P. & James, C. M. I can see clearly now: The impact of disclosure requirements on 401(k) fees. *Journal of Financial Economics* **136**, 471–489 (2020).
- [14] Choi, J. J., Haisley, E., Kurkoski, J. & Massey, C. Small cues change savings choices. *Journal of Economic Behavior & Organization* **142**, 378–395 (2017).
- [15] Frydman, C. & Wang, B. The Impact of Salience on Investor Behavior: Evidence from a Natural Experiment. *The Journal of Finance* **75**, 229–276 (2020).
- [16] Sheng, F., Wang, R., Liang, Z., Wang, X. & Platt, M. L. The art of the deal: Deciphering the endowment effect from traders’ eyes. *Science Advances* **9**, eadf2115 (2023). URL <https://www.science.org/doi/10.1126/sciadv.adf2115>.
- [17] Thomas, A. W., Molter, F., Krajbich, I., Heekeren, H. R. & Mohr, P. N. C. Gaze bias differences capture individual choice behaviour. *Nature Human Behaviour* **3**, 625–635 (2019). URL <https://www.nature.com/articles/s41562-019-0584-8>.
- [18] Krajbich, I., Armel, C. & Rangel, A. Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience* **13**, 1292–1298 (2010).
- [19] Sheng, F. *et al.* Decomposing loss aversion from gaze allocation and pupil dilation. *Proceedings of the National Academy of Sciences* **117**, 11356–11363 (2020).
- [20] Carrasco, M. & McElree, B. Covert attention accelerates the rate of visual information processing. *Proceedings of the National Academy of Sciences* **98**, 5363–5367 (2001). URL <https://www.pnas.org/doi/10.1073/pnas.081074098>.
- [21] Cohen Kadosh, R. *et al.* Are numbers special? The comparison systems of the human brain investigated by fMRI. *Neuropsychologia* **43**, 1238–1248 (2005). 15949508.

- [22] Gebuis, T. & van der Smagt, M. J. Incongruence in number–luminance congruency effects. *Attention, Perception, & Psychophysics* **73**, 259–265 (2011). URL <https://doi.org/10.3758/s13414-010-0002-9>.
- [23] Cohen Kadosh, R., Cohen Kadosh, K. & Henik, A. When brightness counts: The neuronal correlate of numerical-luminance interference. *Cerebral Cortex (New York, N.Y.: 1991)* **18**, 337–343 (2008). 17556772.
- [24] Kunar, M. A., Watson, D. G., Tsetsos, K. & Chater, N. The influence of attention on value integration. *Attention, Perception, & Psychophysics* **79**, 1615–1627 (2017).
- [25] Jaffe, P. I., Santiago-Reyes, G. X., Schafer, R. J., Bissett, P. G. & Poldrack, R. A. An image-computable model of speeded decision-making. *eLife* **13** (2025).
- [26] de Hollander, G., Moisa, M. & Ruff, C. C. Risk preferences causally rely on parietal magnitude representations: Evidence from combined TMS-fMRI. *bioRxiv* 2025–01 (2025).
- [27] Molter, F., Thomas, A. W., Heekeren, H. R. & Mohr, P. N. C. GLAMbox: A Python toolbox for investigating the association between gaze allocation and decision behaviour. *PLOS ONE* **14**, e0226428 (2019).
- [28] Zhang, W., Xie, Y. & Yang, T. Reward salience but not spatial attention dominates the value representation in the orbitofrontal cortex. *Nature Communications* **13**, 6306 (2022).
- [29] Foster, J. J., Thyer, W., Wennberg, J. W. & Awh, E. Covert attention increases the gain of stimulus-evoked population codes. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* **41**, 1802–1815 (2021). 33441434.
- [30] Carrasco, M., Ling, S. & Read, S. Attention alters appearance. *Nature Neuroscience* **7**, 308–313 (2004). URL <https://www.nature.com/articles/nn1194>.

- [31] Hyde, D. C. & Wood, J. N. Spatial attention determines the nature of nonverbal number representation. *Journal of Cognitive Neuroscience* **23**, 2336–2351 (2011). 20961170.
- [32] McGinty, V. B., Rangel, A. & Newsome, W. T. Orbitofrontal Cortex Value Signals Depend on Fixation Location during Free Viewing. *Neuron* **90**, 1299–1311 (2016).
- [33] Bürkner, P.-C. Brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software* **80**, 1–28 (2017).
- [34] Gelman, A., Jakulin, A., Pittau, M. G. & Su, Y.-S. A weakly informative default prior distribution for logistic and other regression models. *The Annals of Applied Statistics* **2** (2008). 0901.4011.
- [35] Hoffman, M. D. & Gelman, A. The No-U-Turn Sampler: Adaptively Setting Path Lengths in Hamiltonian Monte Carlo (2011). 1111.4246.
- [36] Simonyan, K. & Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition (2015). 1409.1556.
- [37] Deng, J. *et al.* ImageNet: A large-scale hierarchical image database. In *2009 IEEE Conference on Computer Vision and Pattern Recognition*, 248–255 (2009).
- [38] Brown, S. D. & Heathcote, A. The simplest complete model of choice response time: Linear ballistic accumulation. *Cognitive Psychology* **57**, 153–178 (2008).

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Author contributions

S.D., M.L.P., and F.S. designed the study; S.D. and F.S. collected the data; S.D., Z.F., M.L.P. and F.S. analysed the data; S.D., Z.F., M.L.P. and F.S. wrote the manuscript; M.L.P. and F.S. supervised the study.

Competing interests

The authors declare no competing interests.

Data availability

All data supporting the findings of this study (including raw and preprocessed behavioral and gaze-tracking data) are publicly available on the Open Science Framework at <https://osf.io/uk46v/>.

Code availability

The code to replicate the analyses and figures is available at <https://github.com/simonedambrogio/Brightness>.

Supplementary Files

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