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Selective Integration: An Attentional Theory of Choice Biases and Adaptive Choice

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Abstract

Human choice behavior shows a range of puzzling anomalies. Even simple binary choices are modified by accept/reject framing and by the presence of decoy options, and they can exhibit circular (i.e., intransitive) patterns of preferences. Each of these phenomena is incompatible with many standard models of choice but may provide crucial clues concerning the elementary mental processes underpinning our choices. One promising theoretical account proposes that choice-related information is selectively gathered through an attentionally limited window favoring goal-consistent information. We review research showing attentional-mediated choice biases and present a computationally explicit model—selective integration—that accounts for these biases.

Keywords

adaptivity, choice biases, decision making, decoy effects, framing, noise, selective attention, transitivity violation

Suppose that you face a decision among three French holiday destinations, Avignon, Biarritz, and Cannes (A, B, and C). When you are asked to select one of A or B, you choose A. Now suppose you have been asked to reject one of A or B (keeping the nonrejected item) and now choose to reject A (*framing effect*). Or consider you choose A from A or B but choose B from among A, B, and C (*decoy effects*). Or, third, suppose you choose A over B, B over C, and yet C over A (*intransitivity*). Each of these patterns seems mystifying, and some may seem downright irrational (Savage, 1954; von Neumann & Morgenstern, 1947), yet they are routinely and systematically observed in the right experimental circumstances (Tversky & Kahneman, 1981). These three puzzling phenomena—framing, decoy effects, and intransitivity—provide crucial clues to the nature of human decision making.

Our proposed explanation for these phenomena is that people sample and accumulate values of choice options via multiple, sequential comparisons. That means that the value of an option, or whether one option is "better" than another, is not ascertained in a single holistic step but rather is formed gradually by attending to features of the options one by one. Moreover, the process of selectively attending to and integrating the outcome of those value comparisons may be partial, imperfect, and dependent on details of the task framing that are rationally irrelevant. In this article, we argue that such processes of selective integration provide an adaptive explanation of irrational behavior as well as a microfoundation for psychological and neural theories of human decision making.

Puzzling Preferences

Risk biases, framing, and violations of invariance

In 1947, von Neumann and Morgenstern proved that any individual whose preferences satisfy four "rationality" axioms has a utility function (see also Savage, 1954). Any individual whose preferences violate these axioms

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would agree to a *Dutch book*, which is a set of bets that necessarily leads to a loss and therefore is, arguably, irrational. Risk preferences (i.e., whether people seek or are averse to risk) are observed in a variety of choice tasks, both when the potential rewards of the alternatives are described and when they are experienced. Rational-choice theory attempts to account for such risk preferences by assuming a nonlinear mapping of objective rewards to internal (subjective) values and of objective to subjective probabilities, as is the case in normative (subjective expected utility; Savage, 1954) or descriptive (e.g., prospect theory and its extensions; Fox & Poldrack, 2009; Tversky & Kahneman, 1992; but see Rabin & Thaler, 2001) theories. More challenging, however, is a pattern of results that indicates that risk preferences can reverse as a result of task framing. For example, Shafir (1993) first reported a reversal effect when he contrasted the preferences of participants asked to select one out of a pair of alternatives (*select framing*) with those of participants asked to reject one of the same alternatives (*reject framing*). Critically, when the pairs (A, B) were created so that A had more extreme properties (both good and bad) than B, participants tended to choose A (from the A-B pair). But a similar group of participants rejected A from the same pair, in striking contradiction to the rational principle of invariance (Kahneman & Tversky, 1986). More recently, such a framing reversal of risk preference was reported by Tsetsos, Chater, and Usher (2012) in a selection between rapid sequences of payoffs (see also Erev, Ert, Plonsky, Cohen, & Cohen, 2017). A similar effect was recently reported by Vanunu, Pachur, and Usher (2019), who showed a modulation of risk biases by the evaluation format: one by one versus in groups.

Decoy effects

A decoy (or contextual-preference-reversal) effect occurs when the preference between two alternatives, A and B, is reversed because of the introduction of another (irrelevant) alternative into the choice set. Three such decoy effects (attraction, similarity, and compromise) have been extensively reported in the decision-making literature, usually in studies using multiattribute decision designs (see Busemeyer, Gluth, Rieskamp, & Turner, 2019, for a recent review of data and computational theories on decoy effects) or decisions between sequences of temporally correlated payoffs (Pachur & Scheibehenne, 2012; Tsetsos et al., 2012). Among these contextual effects, the attraction effect (Huber, Payne, & Puto, 1982)—in which the introduction of a dominated alternative (that is not chosen) increases the probability of one of the other alternatives in the choice set being chosen—is puzzling, in particular because it contradicts the principle of regularity, which is satisfied by a wide class of (random-utility) choice models (Luce, 1959).

Violation of transitivity

Violations of transitivity, in which people prefer A over B and B over C but C over A, are not reported often. Yet they can reliably be elicited using specially constructed alternatives. For example, such a pattern was reported by Tversky (1969), who constructed pairs of alternatives based on a lexicographic order (but see Regenwetter, Dana, & Davis-Stober, 2011). More recently, a similar pattern was reported by Tsetsos et al. (2016) for alternatives that correspond to rapid numerical sequences presented in pairs.

The Selective-Integration Model: Accounting for Violations of Choice Rationality

The role of selective attention in preference formation

Decoy effects, framing effects, and transitivity violations, contrary to idiosyncratic risk attitudes, cannot be captured by nonlinear value functions or distorted representations of probability. Instead, a number of process models have been developed to explain choice biases and violations of rationality as arising from the dynamics of information processing during preference formation. The first model is the decision-field theory (DFT; Roe, Busemeyer, & Townsend, 2001), which relies on the sequential-sampling framework (Gold & Shadlen, 2007; Ratcliff & McKoon, 2008; Teodorescu & Usher, 2013). In the DFT model, the values of the alternatives are constructed on-line by sampling from the available payoffs, subject to internal fluctuations in attention between the decision attributes. Similar models, which share some of the same assumptions, are the leaky competing accumulator (LCA; Tsetsos et al., 2012; Usher & McClelland, 2004), the associative-accumulation model (AAM; Bhatia, 2013), and the multialternative-decision-by-sampling (MDbS) model (Noguchi & Stewart, 2018; see Turner, Schley, Muller, & Tsetsos, 2018, for a recent review).

These and other models differ in some auxiliary processing and representational assumptions. For example, the DFT model assumes a distance-dependent inhibition, whereas the LCA assumes a loss-averse value function (as in prospect theory), and the MDbS model assumes that the frequency of pairwise comparisons depends on the similarity between the alternatives. These models employ a relatively large number of parameters to explain violations of rationality. Thus, it has been difficult to compare these theoretical models with each other (but see Turner et al., 2018) and test their underlying psychological and neural mechanisms. Here, we focus on a single key component that explains violations of rationality: an internal process that allocates attention to (and prioritizes the processing and weighting of) some aspects of the alternatives. On the basis of this selective-attention mechanism, we have proposed a simple decision-making model—selective integration—in which auxiliary assumptions are minimized (e.g., linear value functions and no distance-dependent inhibition).

Whereas attention is well known to affect memory (Chun & Turk-Browne, 2007), recently, the role of selective attention in preference formation has also been experimentally supported. For example, Krajbich and Rangel carried out a set of studies in which the eye positions of participants were tracked while they were making decisions between food items and perceptual alternatives (Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011; Tavares, Perona, & Rangel, 2017). The results showed that the more one looks (i.e., attends) to an alternative, the more likely he or she is to choose it. Moreover, using computational modeling, Krajbich and Rangel showed that that eye locations modulate the weight assigned to the sampled values. More recently, Gluth, Spektor, and Rieskamp (2018) used a three-alternative choice task and demonstrated that value-based attentional capture—the tendency to look more at high-value alternatives—impacts choice behavior. Furthermore, a number of studies directly manipulated (in a bottom-up manner) the attention given to various alternatives (or aspects of them), showing that by biasing attentional selection, one can influence the choice (Kunar, Watson, Tsetsos, & Chater, 2017; Tavares et al., 2017). These studies allude to the interplay between attention and decision making, which we explicitly formalize in the selective-integration model, presented next.

The selective-integration model

We start by presenting an experimental paradigm that quantifies choice-bias effects in a way that allows detailed computational modeling (Glickman, Tsetsos, & Usher, 2018; Tsetsos et al., 2012; Tsetsos et al., 2016; see also Zeigenfuse, Pleskac, and Liu, 2014, for a similar experimental paradigm). In each experimental trial, rapid (2–4 per second) sequences of payoffs (pairs or trios) are presented, and participants are asked to select the sequence with the higher mean or, alternatively, the sequence from which they would like to receive an extra sample as a reward (Fig. 1a).

First, when pairs of alternatives are sampled from normal (and overlapping) distributions with different means and equal variance (Fig. 1a), participants are accurate at selecting the sequence with the higher mean. Critically, choice accuracy increases with the number of samples, indicating a value-integration process that averages out encoding or decision noise (Fig. 1b). Second, when pairs of alternatives are sampled from payoff distributions with the same mean but with different variance (Fig. 1c), participants are risk seeking: They prefer the high-variance alternative (see also Zeigenfuse et al., 2014). Crucially, this bias reverses to risk aversion under a reject framing (Fig. 1c; Tsetsos et al., 2012). Finally, when trios of alternatives were presented, so that the values shown in each frame were temporally correlated to create an analog of the attraction and similarity effects, participants showed the corresponding choice biases (see Fig. 4d in Tsetsos et al., 2012).

The selective-integration model accounts for all these effects (see Zeigenfuse et al., 2014, for a similar model, called *rank-dependent sequential sampling*). The selective-integration model assumes that the preference of each alternative is represented by a leaky accumulator, which integrates the value samples that are observed. Critically, however, these samples are weighted by their goal congruence. In a select framing, one attends more and thus gives higher weight to (momentarily) higher values (blue area in Fig. 1d). This results in risk-seeking choices and accounts for memory biases in a similar paradigm (Madan, Ludvig, & Spetch, 2014). In a reject framing, however, attention is attracted to the (momentarily) lower payoffs (more attention to the purple area in Fig. 1d), resulting in risk aversion. Finally, the model accounts for the decoy effects by assuming that when three payoffs are presented together, attention is attracted to the two higher payoffs and thus that the lowest one (in each frame) is downweighted. To summarize, the selective-integration model accounts for the effects by postulating a top-down attentional selection that shifts attention on a given pair or trio of samples to those samples that are congruent with the participant's goal (looking more to the higher or lower values).

Testing the Selective-Integration Model

To test this top-down attentional selection mechanism, we deployed a dual-task design in which participants chose between rapid sequences of payoffs (as before) but in addition monitored the presence of a probe (a red dot), which randomly appeared on one of the payoffs on about half of the trials (Glickman et al., 2018; Fig. 2a). Critically, the probe could appear either on the higher or on the lower of the two payoffs.

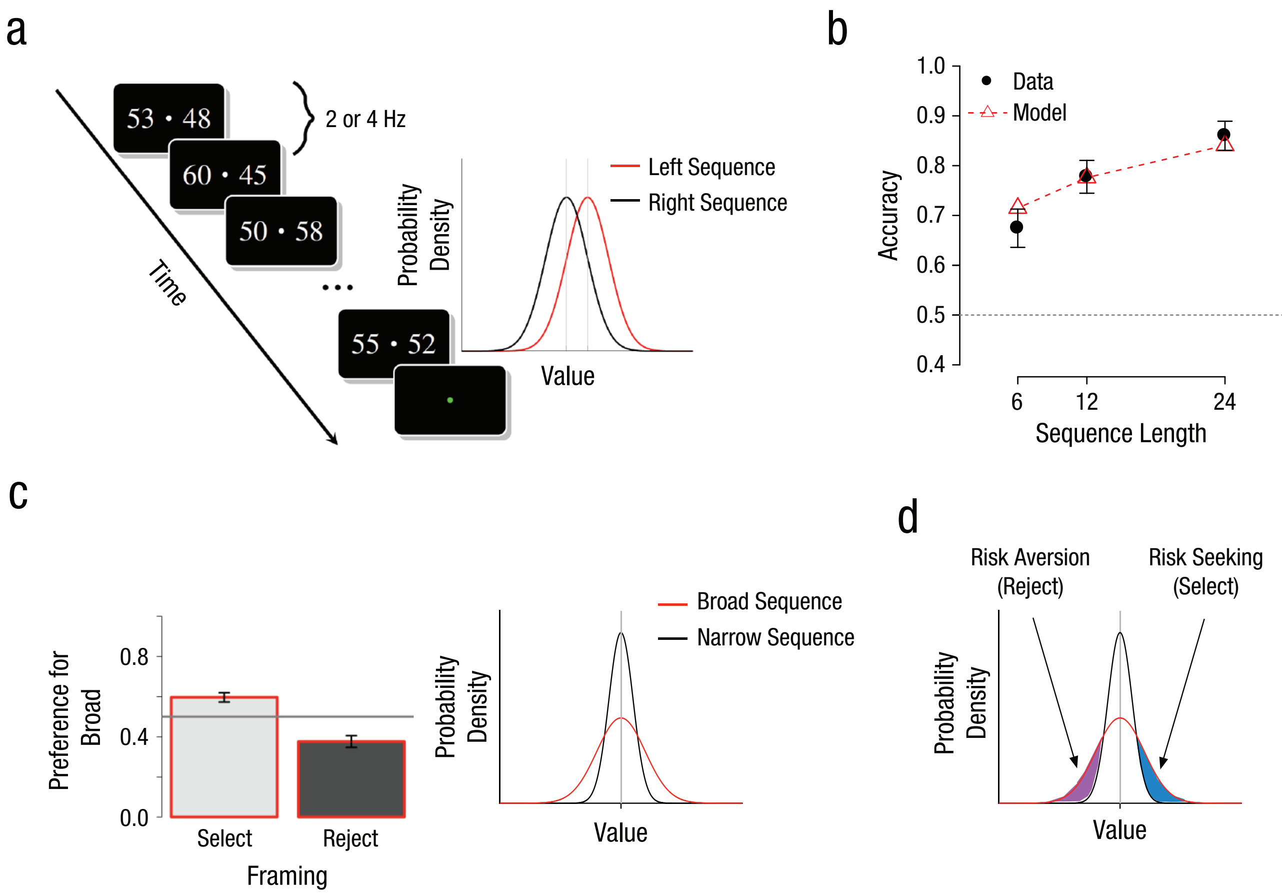

Fig. 1. Task outline and risk attitudes in a value-accumulation experiment. In each trial (a), rapid sequences of payoffs are presented (at either 2 or 4 Hz, depending on the trial), and participants are asked to select the sequence with the higher mean or, alternatively, the sequence from which they would like to receive an extra sample as a reward. The graph to the right shows the probability distributions from which the values of the left- and right-hand sequences were sampled. The proportion of correct responses (accuracy; b) is shown as a function of the length of sequences (i.e., number of pairs) with different means. Observed data and model predictions are shown separately. Error bars indicate ±2 *SEM*. Risk seeking (in a select framing) and risk aversion (in a reject framing) are shown (c) for broad and narrow sequences. Error bars indicate ±2 *SEM*. The graph to the right shows the probability distributions from which the values of the broad and narrow sequences were sampled. The schematic (d) shows how selective weighting accounts for risk bias, framing, and decoy effects. In a select framing, one attends more and thus gives higher weight to higher values (effectively paying more attention to the blue area), resulting in risk-seeking choices. In a reject framing, attention is attracted to the lower payoffs (more attention to the purple area), resulting in risk aversion. Curves are shown in different colors (black and red) for ease of visualization. Figure based on the work of Tsetsos, Chater, and Usher (2012).

As shown in Figure 2b, participants had a higher detection rate when the probe was placed on the value that was consistent with their goal (i.e., monitoring for high values). Moreover, this attentional bias reversed in a reject framing (Fig. 3 in Glickman et al., 2018). Critically, we reasoned that if as assumed by the selective-integration model, the risk-seeking bias is due to selective attending to high payoffs, we should find that the magnitude of the two effects correlates among participants. As shown in Figure 2c, we indeed found that attending to higher payoffs correlates with preferring sequences with larger variance. Moreover, the greater this attentional bias, the higher the choice accuracy (i.e., the probability of selecting the sequence with the higher mean; Fig. 2d).

Finally, Tsetsos et al. (2016) tested a striking prediction of the selective-integration model: The lower of two simultaneously presented payoffs is discounted, resulting in a frequent-winner preference. This allows the construction of sequences with the same mean but temporally correlated, for which the model predicts a transitivity violation. To illustrate, consider the following three sequences: A = (1, 2, 3), B = (2, 3, 1), C = (3, 1, 2), which are cyclic permutations of each other. Assume that pairs of these sequences are presented to participants as three frames of payoffs. Discounting the lower values in each frame results in a frequent-winner preference. Thus, the selective-integration model predicts that in binary choice between these sequences, one should prefer B to A (B wins twice over A) and C to B

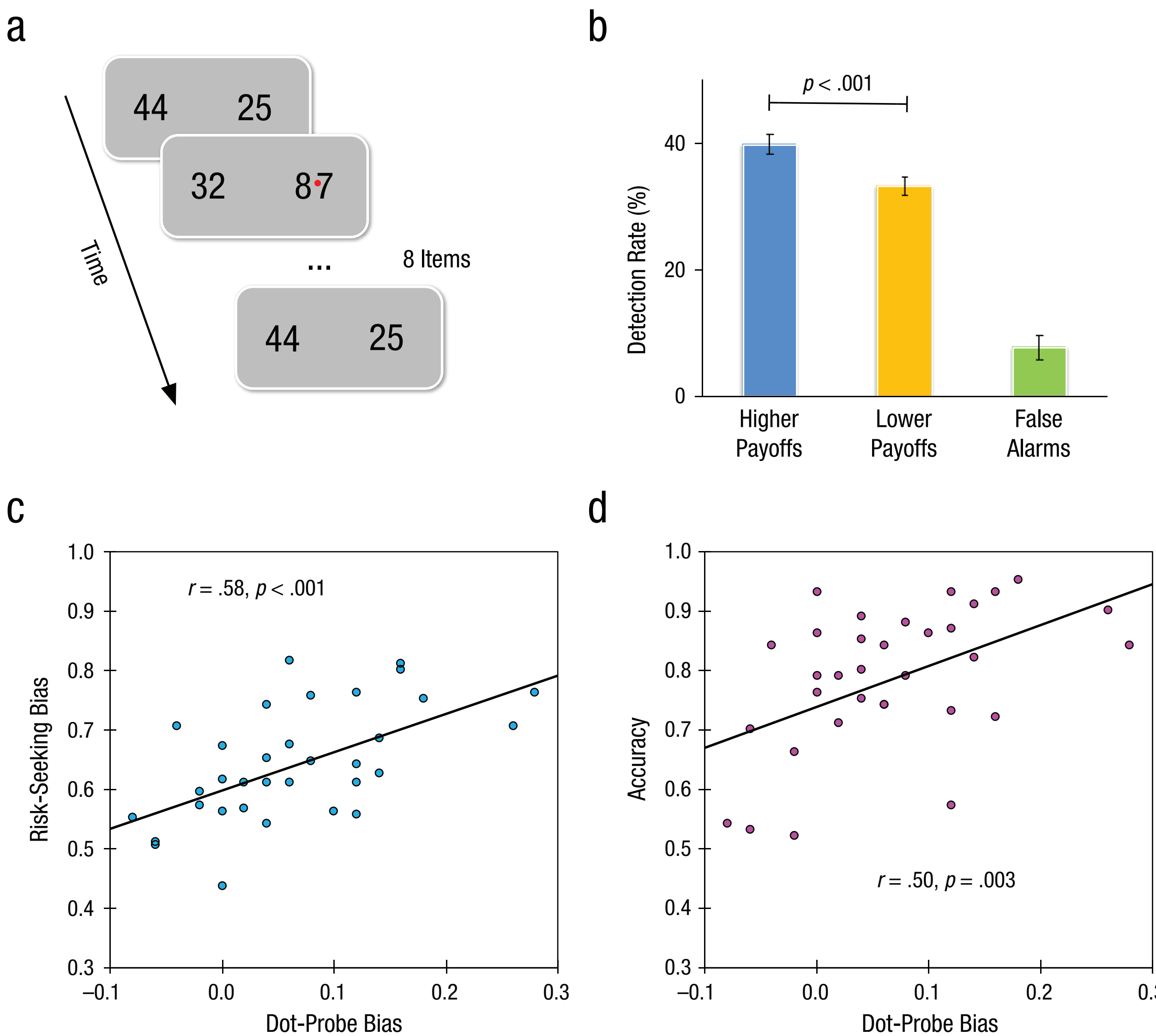

Fig. 2. Testing attentional allocation during preference formation. On each trial (a), participants viewed two rapidly presented payoff sequences; in some of the trials, a red dot was superimposed on one of the payoffs, and participants were asked to report its presence. The intensity of the dot probe was individually calibrated for each participant using a staircase procedure. Participants' mean detection rate of the probe for higher payoffs and lower payoffs, as well as false alarms, is shown in (b). Error bars correspond to within-subjects standard errors of the mean, and the p value indicates a significant difference between the two payoff conditions. The scatterplots (with best-fitting regression lines) show the relationship between (c) risk-seeking bias and dot-probe bias and (d) accuracy and dot-probe bias. Figure based on the work of Glickman, Tsetsos, and Usher (2018).

but A to C (see Tsetsos et al., 2016, for model-simulation details). To test this prediction, Tsetsos et al. presented participants with pairs of alternatives that consisted of sequences of pairs of bars that were generated according to this design. The results showed that participants indeed preferred the frequent-winner alternatives in contradiction to the transitivity principle. Moreover, Tsetsos et al. found that the more a participant discounted the lower of two simultaneously presented values (as indicated by fitting of the selective-integration model), the higher the transitivity violation was.

The Adaptive Role of Selective Integration

A key question is why does the selectiveness of preference formation result in striking violations of rationality, such as intransitivity. The selective-integration model allows us to tackle this question by varying the selective-integration parameter from a value corresponding to completely nonselective integration to a value corresponding to totally selective integration. To quantify the decision quality, we can consider choices between alternatives that correspond to samples from overlapping

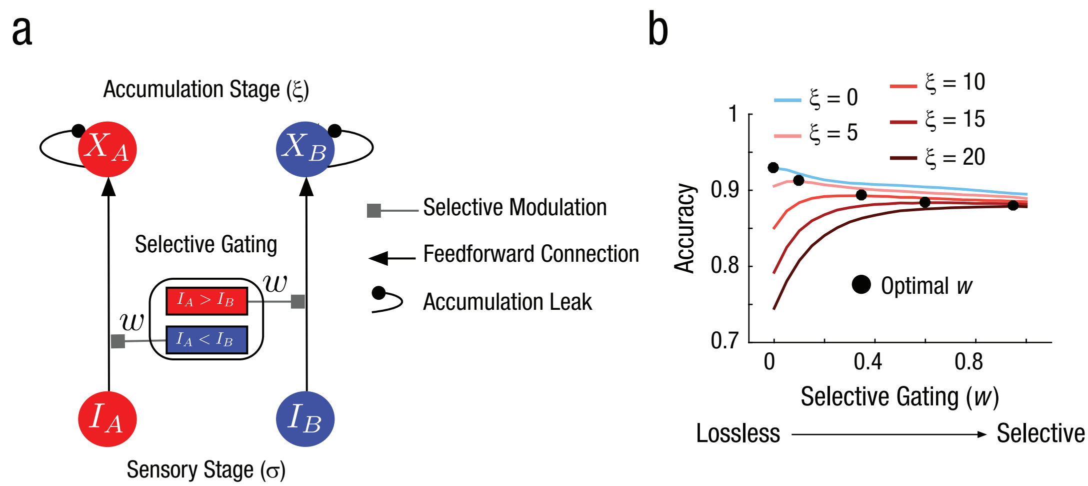

Fig. 3. Selective integration and robustness to late noise. In the selective-integration model (a), noise can corrupt the decision process at the sensory stage (early noise, before the selective-gating stage) or at the accumulation stage (late noise, past the selective-gating stage). In this model, "I" refers to input strength, "A" and "B" are indexes for each choice alternative, and "R" is a response unit that makes a choice on the basis of the state of the "X" accumulators. Accuracy in the selective-integration model (b) is shown as a function of selective gating w (x-axis) and late noise ξ (solid curves). Black circles indicate the point of maximum accuracy for each level of late noise. When late noise is 0 (blue curve), accuracy is maximized when integration is nonselective. When late noise is higher than 0 (red curves), accuracy is maximized via selective integration. Figure based on the work of Tsetsos et al. (2016).

normal distributions that differ in their mean. We further consider two types of noise factors (Tsetsos et al., 2016; Fig. 3a). The first is *encoding* noise that reflects how each sample is registered. The second is *late* noise that does not involve the individual samples but rather distorts the representation of the accumulated values at a postencoding stage. It appears that in the absence of the late-noise component, any selectivity reduces performance. Indeed, the optimal decision strategy is to integrate all values (without any discounting) to average the encoding noise. Remarkably, however, in the presence of late noise, selective integration becomes more efficient than nonselective integration (Fig. 3b). This is because selective integration enhances the value difference, making it more robust to the corrupting effect of the late noise (Tsetsos et al., 2016), consistent with the correlation between attentional bias and choice accuracy (Fig. 2d). A similar conclusion was recently reported with choices between nonsimultaneous sequences of numbers as a result of overweighting the larger magnitudes (Spitzer, Waschke, & Summerfield, 2017).

It is thus possible that choice biases, such as intransitivity, which are typically viewed as irrational, are the cost that the decision system must pay to protect itself from the pervasive impact of late noise. In support of this notion, the selective-integration and the late-noise parameters (fitted to the data) are correlated across participants (Tsetsos et al., 2016), indicating an adaptive mechanism. Importantly, in perceptual tasks, with high sensory or early noise (compared with the late noise), reliance on selective integration is not optimal. Future research will be needed to test the application of the selective-integration model to more standard type of experience-based decisions (Hertwig & Erev, 2009) and to choices between simultaneously presented multiattribute alternatives, for example, by eye tracking. Finally, future research is needed to probe the boundary of the selective-integration adaptive mechanism.

Conclusions

Although it is well established that attention affects choice, we propose that goal-consistent values affect attentional selection in a somewhat similar way as hearing one's own name at a cocktail party (Conway, Cowan, & Bunting, 2001). The selective-integration model explains how the sequential allocation of attention to the features of the available options can significantly affect the choices people make. Indeed, the model provides a simple account of a variety of patterns of choice that seem anomalous from the point of view of rational economic theory. These phenomena emerge naturally from a detailed analysis of the mechanisms through which information is sampled and used. Moreover, as we argued, this selective mechanism offers benefits in term of making decisions robust to noise and provides theoretical support for models of risky choice that assume value-dependent attentional weighting (Zeigenfuse et al., 2014).

Recommended Reading

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