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Attentional Selection Mediates Framing and Risk-Bias Effects

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Abstract
Humans display a number of puzzling choice patterns that contradict basic principles of rationality. For example, they show preferences that change as a result of task framing or of adding irrelevant alternatives into the choice set. A recent theory has proposed that such choice and risk biases arise from an attentional mechanism that increases the relative weighting of goal-consistent information and protects the decision from noise after the sensory stage. Here, using a divided-attention method based on the dot-probe technique, we showed that attentional selection toward values congruent with the task goal takes place while participants make choices between alternatives that consist of payoff sequences. Moreover, we demonstrated that the magnitude of this attentional selection predicts risk attitudes, indicating a common underlying cognitive process. The results highlight the dynamic interplay between attention and choice mechanisms in producing framing effects and risk biases.

Keywords
selective attention, decision making, computational models, framing effects, risk attitudes, open data, open materials

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According to the normative-decision theory (Luce, 1959; Von Neumann & Morgenstern, 1947), humans should have stable preferences that do not vary with context (i.e., the relative preference between A and B should not change when a new option C is made available) or with task framing (the preference between A and B should not depend on whether the decision maker is asked to select or reject one of them). Nevertheless, a variety of such choice-bias effects was reported in decision-making studies that used multiattribute alternatives (Berkowitsch, Scheibehenne, & Rieskamp, 2014; Simonson, 1989; Tversky, 1972) or choices between sequences of differently framed or temporally correlated payoffs (Pachur & Scheibehenne, 2012; Shafir, 1993; Tsetsos, Chater, & Usher, 2012).

Choices between sequences of payoffs or evidence samples are encountered in many real-life situations, such as selecting a stock on the basis of fluctuating returns or deciding on the culpability of a defendant in a legal case on the basis of sequential pieces of evidence. Moreover, a number of prominent decision theories have suggested that even for decisions between static alternatives (in the domain of risk or multiattribute decisions), the decision mechanism operates by dynamically integrating sequences of internally generated samples (decision field theory: Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001; associative-accumulation model: Bhatia, 2013; leaky competing accumulators: Usher & McClelland, 2004). Here, we focus on choices between externally controlled potential payoff sequences, which allow us to control the objective properties of the alternatives and measure their impact on risk preferences (Tsetsos et al., 2012; Zeigenfuse, Pleskac, & Liu, 2014). Do people prefer an alternative that is characterized by a broader (riskier) distribution of payoffs over a narrower (safer) one, or the other way

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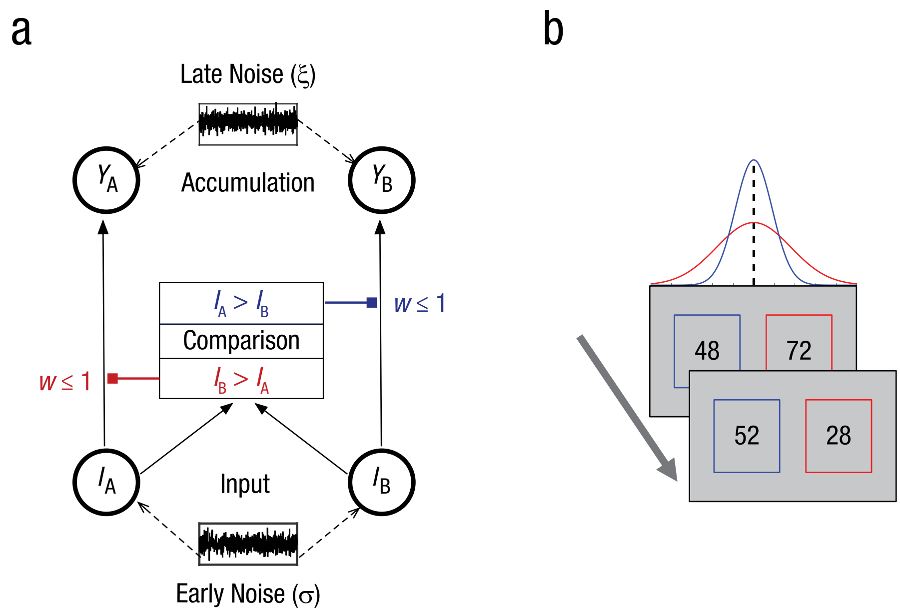

Fig. 1. Schematic illustration of the binary selective-integration model (a; taken from Tsetsos et al., 2016) and an illustration of the risk-seeking effect (b). According to the binary selective-integration model, when individuals choose between two alternatives (A and B), they sample two payoffs (I_A and I_B) on each time step. These payoffs are integrated in two accumulators (Y_A and Y_B), subject to selective gating (w), which discounts the payoff with the lower value. Noise may arise in the input stage (σ) as well as in the accumulation stage (ξ). For the risk-seeking effect, two pairs of payoffs are shown: The broad (red-framed) alternative (i.e., the alternative with the higher variance) is preferred over the narrow (blue-framed) one.

around? Furthermore, do such preferences vary as a function of choice framing?

Recent research has proposed a mechanism of *selective integration*—increased relative weighting of the momentarily larger payoff on each pair—as a possible source of such choice biases in decisions between sequences of payoffs (see Fig. 1a). Selective integration is motivated by recent research that has indicated an important role for attentional processes as an input into the decision (Diederich, 1997; Krajbich & Rangel, 2011; Shimojo, Simion, Shimojo, & Scheier, 2003; Towal, Mormann, & Koch, 2013). For example, eye-tracking studies of decisions between consumer products have shown that the evidence-accumulation process is modulated by eye fixations: The value of a fixated alternative is enhanced compared with a nonfixated one (Krajbich, Armel, & Rangel, 2010). In contrast to these important results, however, selective integration focuses on the inverse causal process, from semantic (goal-dependent) values to attentional selection. In particular, selective integration assumes that when people are viewing two sequences of payoffs (see the example in Fig. 1b) and asked to select the one they prefer, attentional resources (overt or covert) are attracted toward the higher (i.e., goal-consistent) values within each frame (72 and 52 in the cases shown in Fig. 1b), and thus the lower values (48 and 28) are filtered out from contributing to the accumulated value of the corresponding alternative (and vice versa in a task of rejecting one of the alternatives). Therefore, when facing a choice of selecting between a broad and a narrow distribution of payoffs, the selective-integration mechanism generates risk seeking, whereas when facing a choice of rejecting between the same alternatives, it generates risk aversion (Tsetsos et al., 2012).

Although selective integration accounts for a variety of choice biases and provides an adaptive account of their cost-benefit calculus (Tsetsos et al., 2016), its basic assumption—an attentional selection—has not been directly tested. Here, we set out to do so by relying on a dot-probe technique (MacLeod, Mathews, & Tata, 1986; Mathews & MacLeod, 1994) to measure attentional selection during task performance; we chose this measure (instead of measuring eye fixations) because it allows the detection of covert (and not only overt) attention. Furthermore, we extended the selective-integration model from its simplified binary original formulation, in which attention is attracted to the largest number in a pair, to a more graded formulation, in which attentional allocation is a function of the value difference. As we will show, goal-consistent attentional selection, as predicted by the graded selective-integration model, takes place while participants observe rapid sequences of pairs of payoffs (see Fig. 1b), and furthermore, it is correlated with risk biases.

We start with a computational simulation that extended and tested the selective-integration model on previous data. We then use the extended selective-integration model to make quantitative predictions for two behavioral experiments that probed attentional selection during preference formation and its association with choice biases. Finally, we present the experimental results that tested our predictions and discuss the adaptive properties of the model.

Computational Study: Selective-Integration Model Generalization (Binary vs. Graded Attentional Selection)

Method

The selective-integration model assumes that the binary preference between two alternatives, A and B, is the result of a comparison between two leaky accumulators that integrate sampled values of A and B, respectively. The input to this (leaky) integration is subject to an attentional modulation, which gives more relative weight to the higher of two values in each time frame (see Fig. 1a). Whereas the original (binary) selective-integration model is characterized by a selective-integration parameter, w, whose value is the same for all payoffs that satisfy the binary criterion (for further details, see Computational Models in the Supplemental Material available online), in the graded selective-integration model, we assumed that weight (w) assigned to each sample is a gradual function of the salience of each payoff, which depends on the payoff difference, as follows:

$$w\left(\text{goal-consistent payoff}\right) = \frac{1}{1+e^{-\beta(x-y)}}$$

$$w\left(\text{goal-inconsistent payoff}\right) = 1 - w\left(\text{goal-consistent payoff}\right),$$

in which x and y are the values of the goal-consistent and goal-inconsistent payoffs within each frame, respectively. The goal consistency depends on task framing, so that for selection tasks, the higher payoff is goal consistent and the lower one is goal inconsistent (and vice versa for rejection tasks). This is motivated by the idea that values generate a top-down type of salience that may be subject to an attentional selection, similar to bottom-up visual salience (Wolfe & Horowitz, 2017), and by independent research using rapid serial visual presentation of payoff sequences that show higher decision weights for larger payoffs (Spitzer, Waschke, & Summerfield, 2017; Zeigenfuse et al., 2014). Note that the graded and the binary selective-integration versions of the model have the same number of degrees of freedom: The selective gating parameter (w) of the binary model is replaced by the logistic slope of the graded selective integration (β).

Results

We tested the binary and the graded models on data from a previous study (Tsetsos et al., 2012, Experiment 2) and carried out a model comparison of the two versions of the selective integration. We found that the graded selective-integration model provided a better fit to the data, as indicated by lower deviance scores (−2 log likelihood) in 15 of 16 participants (see Fig. 2a) and by decisive support at the group level (see Computational Study in the Supplemental Material). Furthermore, the graded selective-integration model provided a better fit compared with a nonselective leaky-accumulators model in 12 of 16 participants and by decisive support at the group level (Akaike information criterion, or AIC, scores; for the individual data and for a cross-validation-based comparison, see Computational Study in the Supplemental Material). Moreover, we also compared the graded and the binary selective-integration models with regard to their robustness to processing noise. To do so, for each level of noise, we selected the selective-integration parameter (w for the binary selective-integration model and slope for the graded selective-integration model), which maximizes accuracy. The results favor the graded selective-integration model over the binary selective-integration model (see Fig. 2b and Discussion section). Therefore, we relied on this graded selective-integration model to make predictions for attentional selection.

Experiment 1: Attentional Capture by Goal-Congruent Stimuli via Dot-Probe Detection

In this experiment, we examined the feasibility of the dot-probe technique (used as a secondary task) while participants viewed rapid sequences (800 ms per item) of payoffs and reported which of them had a higher mean (Experiment 1a, $N = 15$) or lower mean (Experiment 1b, $N = 15$). In two thirds of the trials, a small red dot (the dimness of which was calibrated individually using a staircase procedure; see Fig. 3b and the staircase procedure in the Supplemental Material) appeared superimposed on one of the payoffs (see Fig. 3a). The participants were asked to report the dot's presence, after first entering their choice for the high-mean sequence. The critical manipulation involved the payoff that the dot appeared with, which was based on two orthogonal factors: (a) *target payoff magnitude*—the probe could appear on the highest or lowest value

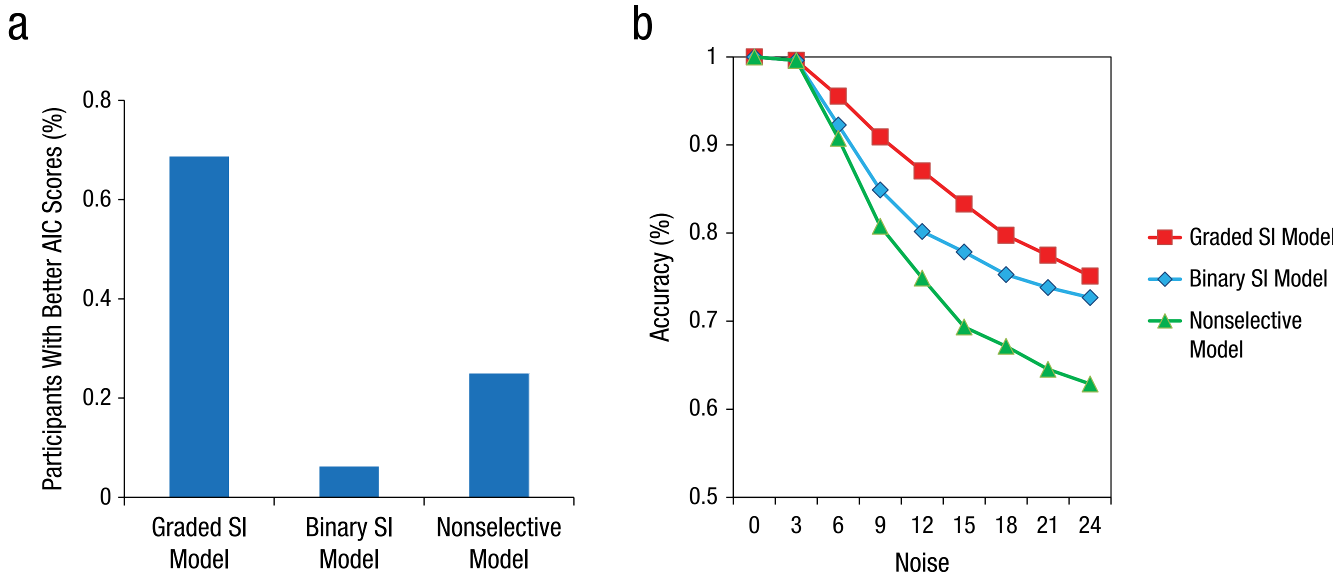

Fig. 2. Comparison of the graded selective-integration (SI), binary SI, and nonselective models. The bar graph (a) shows the percentage of participants for which each model obtained the best Akaike information criterion (AIC) scores. The line graph (b) shows accuracy (i.e., robustness to noise) as a function of noise, separately for each of the three models.

within a frame—and (b) *pair difference*—the difference in values between the numbers in the probed frame was either large or small. According to selective integration, attention should be attracted toward large values in Experiment 1a and toward small values in Experiment 1b; therefore, the detection rate of the probe should be higher when located on goal-consistent payoffs. Moreover, on the basis of the graded selective-integration model (but not the binary selective-integration model), we expected this difference to be higher for the large pair-difference frames (in which the payoff difference was more salient).

Method

Participants. Fifteen undergraduates from Tel Aviv University (11 female students; age: M = 23 years, range = 18–36 years) participated in Experiment 1a, and 15 undergraduates participated in Experiment 1b (13 female students; age: M = 22 years, range = 19–27 years); all of them reported having normal or corrected-to-normal vision. Our sample size was based on the effect sizes obtained in previous studies that used a similar paradigm (η_p^2 = .66; Tsetsos et al., 2012, Experiment 2, balanced condition) and on a pilot study we conducted (η_p^2 = .38). The participants received course credit in exchange for taking part in the experiment as well as a bonus fee ranging from 15 to 25 ILS, which was determined by their task performance. The experiment was approved by the ethics committee at Tel Aviv University.

Stimuli. Displays were generated by an Intel i3 personal computer attached to a 19-in. ViewSonic Graphics Series G90fB CRT monitor with a 60-Hz refresh rate, using 1,024 × 768 resolution graphics mode. Responses were collected via the computer keyboard. Viewing distance was approximately 60 cm from the monitor. The stimulus consisted of eight pairs of numerical values, which were presented sequentially and described as past outcomes of casino slot machines (for an illustration, see Fig. 3a). The sequences were normally distributed, with a presentation rate of 1.25 Hz. In two thirds of the sequences, a small dim red dot, with a diameter of 0.1°, briefly appeared (50 ms) within the center of one of the numerical values.

Task and design. Each trial began with a fixation display that consisted of a black 0.2° × 0.2° fixation cross (+) that remained on the screen for 1 s. Then, pairs of numerical values were presented sequentially to the participants. Once a response cue was presented, the participants were asked to decide which of the sequences had the higher (Experiment 1a) or lower (Experiment 1b) mean. Additionally, the participants were asked, as a secondary task, to indicate whether they had seen the red dot. Responses to the integration task were given by pressing the arrow keys (left/right arrow keys for the left/right sequences, respectively). Responses for the dot-detection task were given by pressing the "x" key (if the participants reported seeing the dot) or "z" key (if the participants reported not seeing the dot). Feedback was given

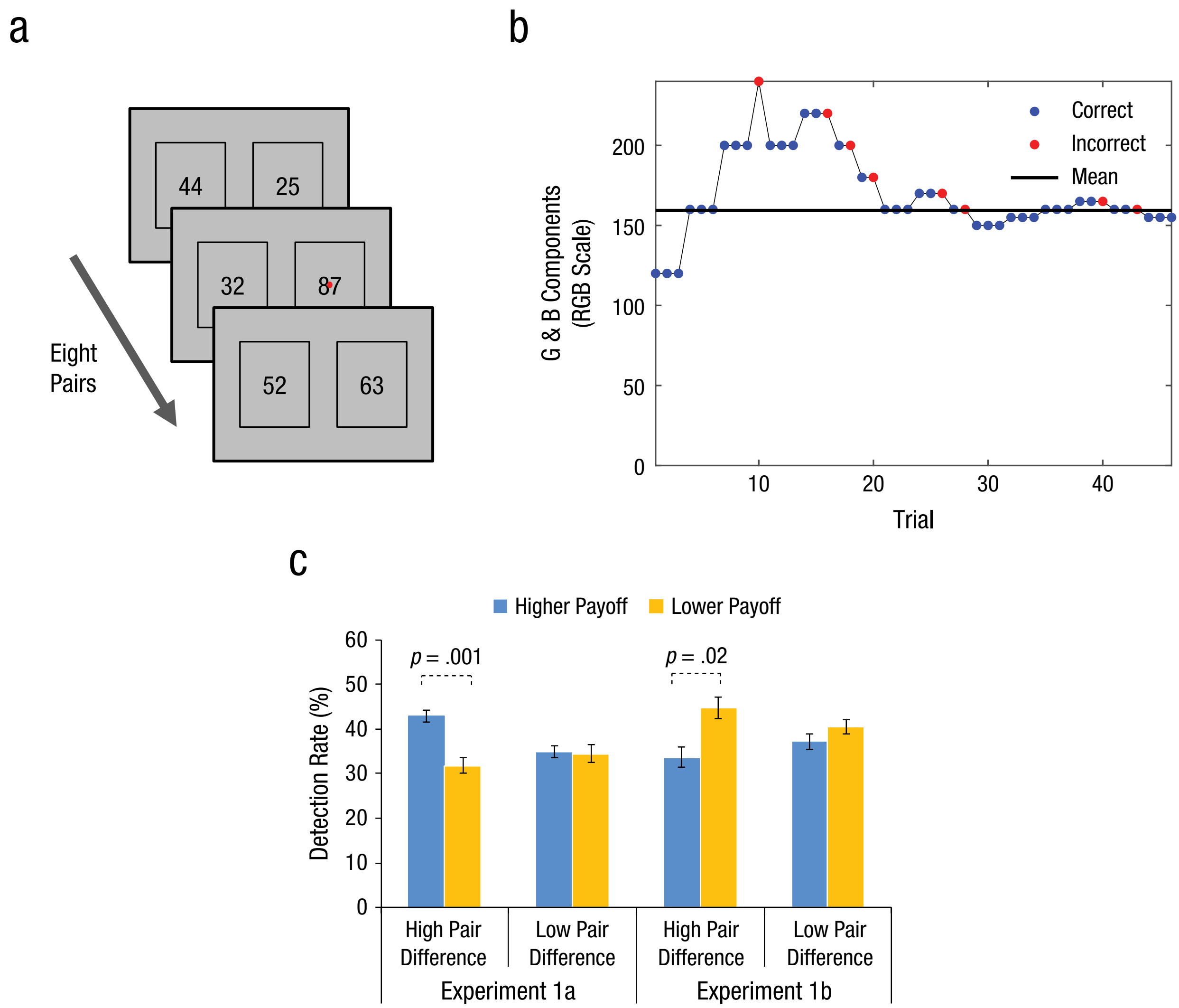

Fig. 3. Design and results of Experiments 1a and 1b. As shown in (a), participants (N = 15 in each experiment) viewed two synchronized streams of numbers and had to choose which stream had a higher mean (Experiment 1a) or lower mean (Experiment 1b). In two thirds of the trials, a small red dot appeared superimposed on one of the payoffs, and participants were asked to report whether the dot was present. An example of the staircase procedure preceding the main experiment is shown in (b). On each trial, a small red dot appeared superimposed on one of two payoffs. The contrast between the color of the dot and the color of the gray background was reduced following three successive correct identifications of the location of the dot (making the task more difficult) and enhanced following an incorrect identification. The contrast was adapted by varying the green and blue color component of the dot (lower values correspond to easier probes). Probe-detection rates (c) are shown for each combination of pair difference (high vs. low) and payoff (higher vs. lower) in Experiment 1a and Experiment 1b. Error bars correspond to within-subjects standard errors of the mean.

only for the primary task. In all experiments, the trials were randomly presented across conditions in blocks of 50 trials each. Participants were allowed a short rest after each block.

Both experiments (1a and 1b) consisted of 240 trials, in each of which two synchronized streams of eight numbers were presented to the participants. The numbers were drawn from the following Gaussians: $X \sim N(45 + k, 15)$ and $Y \sim N(55 + k, 15)$, $k \sim U(-10, 10)$. The probe appeared in two thirds of the trials and was always located between Frames 3 and 6 (inclusive). In the high-pair-difference condition, the probe was placed within the frame that had the largest difference among those four frames, whereas in the low-pair-difference condition, the probe was placed within the frame that had the lowest difference. This resulted in an average mean difference between the numbers of 35.1 (SD = 9.5) for the high-pair-difference condition and 6.1 (SD = 4.5) for the low-pair-difference condition. The probe was placed equiprobably within the higher or lower number of the frame. In all of the experiments, for each participant, the contrast between the dot and the color of the screen was determined using a staircase procedure preceding the main experiment (see staircase procedure in the Supplemental Material).

Results

Experiment 1a. The results demonstrate that although participants were highly accurate in identifying the sequence with the higher mean in the primary choice task (87%), they detected the dot probe at an average rate of 36% (false alarm rate < 5%; d' = 1.55; 95% confidence interval, or CI = [1.16, 1.93]; for individual participants' data, see Fig. S1a in the Supplemental Material). Critically, we found an interaction between the target payoff magnitude and the pair difference, $F(1, 14) = 5.90$, $p = .03$, $\eta_p^2 = .30$ (see Fig. 3c). Post hoc analyses confirmed that, consistent with the graded selective-integration model, the detection rate of the probe was higher when it appeared on the higher payoffs compared with the lower ones for the high-pair-difference condition, $F(1, 14) = 16.24$, $p = .001$, $\eta_p^2 = .54$. This dot-probe bias effect disappeared, however, for the low-pair-difference condition, $F(1, 14) < 1$, $\eta_p^2 = .01$.

Experiment 1b. Here, we replicated the results of Experiment 1a with a single modification that involved the task framing: A new group of participants (N = 15) was instructed to report which of the alternatives had a lower (rather than higher) mean. Again, the participants were able to detect the probes at an average rate of 39% (false alarm rate < 5%; d' = 1.62; 95% CI = [1.33, 1.93]; for individual participants' data, see Fig. S1b in the Supplemental Material). As in Experiment 1a, there was a significant interaction between the target payoff magnitude and the pair difference, $F(1, 14) = 5.08$, $p = .04$, $\eta_p^2 = .27$. Critically, the detection rate shows a total reflection of the pattern found in Experiment 1a (see Fig. 3c): The participants were more accurate in detecting the probes that were presented on the lower of two values for the high-pair-difference condition, $F(1, 14) = 7.08$, $p = .02$, $\eta_p^2 = .34$, whereas for the low-pair-difference condition, no significant effect was obtained, $F(1, 14) = 2.04$, $p = .17$, $\eta_p^2 = .13$ (for a full three-way analysis of variance that includes the task framing as a between-subjects factor, see Experiment 1 in the Supplemental Material).

Discussion

The results of Experiment 1 indicate that the attentional allocation (as measured using the dot-probe technique) is influenced by the goal determined by the payoff framing (looking for higher vs. lower payoffs). Whereas participants carried out the primary task with high accuracy, they also showed an attentional bias that was predicted by the graded selective-integration model. In the high-mean framing (Experiment 1a), participants attended more to the higher of the two payoffs in each pair, whereas in the low-mean framing (Experiment 1b), they attended more to the lower of the two (see Fig. 3c). This is consistent with previous results that demonstrated that task framing reverses risk preferences (Tsetsos et al., 2012, Experiment 2). When participants attended more to higher values, they overestimated risky (broadly distributed) alternatives, resulting in risk seeking, whereas when they attended to lower values, they underestimated the same alternatives, resulting in risk aversion (Tsetsos et al., 2012).

An alternative account of these results is that attention is driven toward the chosen alternative rather than to the higher value within a frame. To test this account, we conducted a regression analysis of the dot-detection rate based on two independent factors: (a) the probe location within a frame (high vs. low payoff) and (b) the consistency between the probe location and the chosen alternative. The results provide strong support for the account of attention within a frame (see Experiment 1 in the Supplemental Material).

So far, we have shown that participants attend more to goal-consistent payoffs in accordance with the selective-integration hypothesis. In our second experiment, we asked whether, as predicted by selective integration, the attentional effect observed in Experiment 1 shares a common source with the risk-seeking biases in choices between sequences of payoffs (Erev, Ert, Plonsky, Cohen, & Cohen, 2017; Ludvig & Spetch, 2011; Tsetsos et al., 2012; Zeigenfuse et al., 2014).

Experiment 2: Goal-Dependent Attentional Selection Drives Risk Biases

In Experiment 2, we set out to replicate the attentional-selection effect observed in Experiment 1, but in addition to the equal-variance and different-mean trials, we included trials with equal means and different variances, which allowed us to measure risk biases (Tsetsos et al., 2012). As in Experiment 1, the probe was placed on either the higher or lower payoffs of a frame. If the risk-bias effect and the attentional selection measured by the dot-probe technique have a common source, as the selective-integration explanation postulates, we expected that they would correlate: Participants with a higher detection bias on the dot probe should also show a higher risk-seeking bias in choices (see Experiment 2 in the Supplemental Material).

Method

Participants. Thirty-three undergraduate students from Tel Aviv University (27 females; age: M = 23 years, range =

19–34 years) participated in Experiment 2 (similar to the total number of participants in Experiments 1a and 1b). All of them reported having normal or corrected-to-normal vision. The participants received course credit in exchange for taking part in the experiment as well as a bonus fee ranging from 15 to 25 ILS, which was determined by their task performance. The experiment was approved by the ethics committee at Tel Aviv University.

Stimuli, task, and design. The stimuli, task, and design of Experiment 2 were similar to those of Experiment 1, except for the following changes. The experiment consisted of 400 trials; in half of the trials, the sequences had the same mean ($\mu_1 \sim U(40, 50)$) but different variances ($\sigma_1 = 10$ and $\sigma_2 = 20$), whereas in the other half of the experiment, the sequences had different means ($\mu_1 \sim U(40, 50)$) and ($\mu_2 = \mu_1 + 10$) but equal variances (σ = 10). The choice pattern in the former condition (i.e., the preference rate of the broader distribution over the narrower one) provided a measure of risk attitude, and choice in the later condition (i.e., the difference in the detection rate of the probe when it was placed within higher payoffs compared with lower ones) provided a measure of accuracy. In both conditions, the probe appeared in half of the trials, only within frames in which the difference between the numbers was the maximum in the sequence. This resulted in an average mean difference between the numbers of 35.4 (SD = 11.9) for the different-means (equal-variances) condition and 32.4 (SD = 9.8) for the equal-means (different-variances) condition. As opposed to Experiments 1a and 1b, in which participants were asked to indicate which sequence had a higher or lower mean, in Experiment 2, the participants were asked to choose from which sequence they would like to draw an extra sample and received feedback in the form of an extra reward from the alternative they chose. The sequences were presented at a rate of 2 Hz.

Results

As shown in Figure 4a, the results replicate the risk-bias effect (Tsetsos et al., 2012): The participants preferred the riskier (broader) payoff option over the narrower one, $F(1, 32) = 72.52$, $p < .001$, $\eta_p^2 = .69$; we also replicated the risk-bias effect in an eye-tracking experiment with constrained viewing (see Control Experiment: Constrained Viewing in the Supplemental Material). Additionally, the results replicate the dot-probe effect that we reported in Experiment 1a (see Fig. 2c): higher detection rate when the probe was placed on the larger of two payoffs in the different-mean trials, $F(1, 32) = 18.07$, $p < .001$, $\eta_p^2 = .36$ (see Fig. 4b; for individual differences in the d' of the probe detection, see Fig. S1c in the Supplemental Material).

Moreover, we confirmed the predicted positive correlation between the risk-seeking bias and the dot-probe bias in the different-mean trials ($r = .58$, $p < .001$; see Fig. 4c; for estimation of the dot-probe bias using all trials, see Fig. S2b in the Supplemental Material). The results indicate that while observing streams of payoffs, participants allocate more attention (and therefore give higher weights) to the larger payoffs within a frame, resulting in a risk-seeking bias and, at the same time, enhancing the detection rate of the probes at the attended location. Finally, we fitted the graded selective-integration model (as well as the binary selective-integration model and the nonselective leaky-accumulator model) to the data in Experiment 2. First, we found that the graded selective-integration model was favored, compared with the binary selective-integration and the nonselective models, by both the AIC and cross-validation measures (see Computational Study in the Supplemental Material). Furthermore, we regressed the dot-probe bias against the graded selective-integration parameters (noise, selectivity, and leak, fitted to the choice data of the individual participants). The regression revealed a significant positive effect for the selectivity parameter, $b = 0.39$, $t(29) = 2.1$, $p = .04$. A negative trend was found for the leak parameter, $b = -0.14$, $t(29) = -2.0$, $p = .05$. A possible explanation for this effect is that high levels of leak indicate decay of information presented in the earlier frames in which the probe appeared. The effect of noise did not reach statistical significance, $b = -0.06$, $t(29) = -1.12$, $p = .27$.

General Discussion

Why do decision makers violate basic rationality axioms, as indicated by preference reversals, transitivity violations, and risk biases? One idea suggested in previous investigations is that such violations are caused by an attentional-selection mechanism, which allocates higher weights to values congruent with the decision maker's goals (Spitzer et al., 2017; Tsetsos et al., 2012; Tsetsos et al., 2016; Zeigenfuse et al., 2014). This is consistent with recent work showing that attentional mechanisms play a key role in the development of the preferences (Anderson, Laurent, & Yantis, 2011; Chen, Mihalas, Niebur, & Stuphorn, 2013; Krajbich & Rangel, 2011; Shimojo et al., 2003; Towal et al., 2013) and that manipulating the attentional salience of an item within a sequence of payoffs affects the evaluation of the overall sequence value (Kunar, Watson, Tsetsos, & Chater, 2017; Tavares, Perona, & Rangel, 2017). In particular, a prominent decision model—the attentional-drift-diffusion model (Krajbich et al., 2010; Tavares et al., 2017)—relies on eye fixations to modulate the evidence accumulation. The selective-integration model

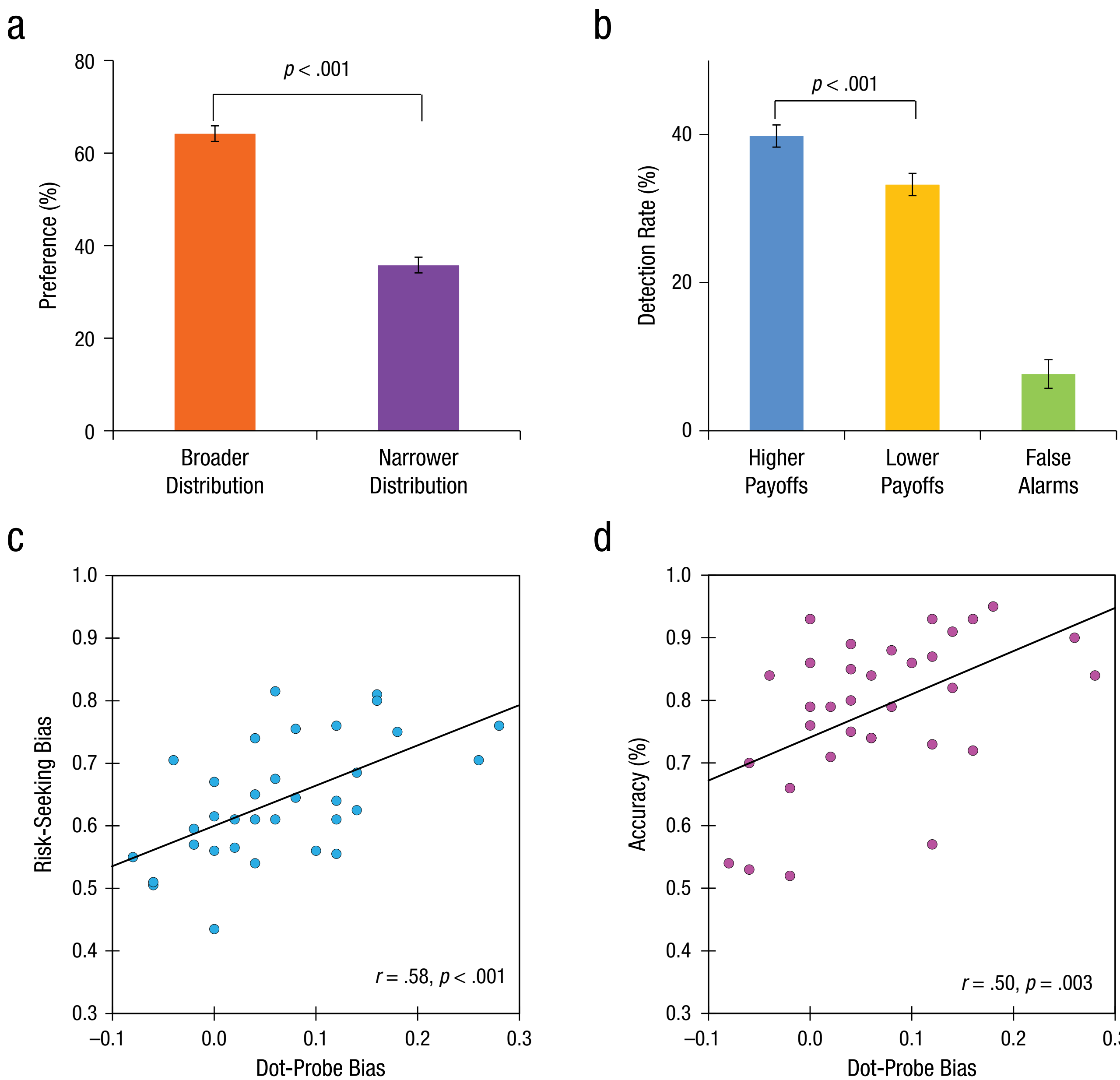

Fig. 4. Results of Experiment 2. The bar graphs show (a) the participants' preference rates for each distribution type and (b) the detection rate of the probe for higher payoffs and lower payoffs, as well as false alarms. Error bars correspond to within-subjects standard errors of the mean. The scatterplots (with best-fitting regression lines) show the relationship between (c) risk-seeking bias and dot-probe bias and (d) accuracy and dot-probe bias.

goes further than previous attentional models of choice, in assuming a causal relation from semantic (goal-congruent) values to attention, in addition to the causal relation between attention and choice. So far, however, this suggestion has been purely theoretical with respect to the actual processes that operate in the type of tasks we examined. Closing the value-attention loop provides an important connection to other prominent decision models, such as transfer of attention exchange (Birnbaum, 2008), rank dependent sequential sampling (Pleskac, Yu, Hopwood, & Liu, 2018), or decision field theory (Busemeyer & Townsend, 1993), which also assume that attention is value dependent in order to account for choice biases.

Here, we demonstrated that while carrying out a decision between alternatives that consist of sequences of payoffs, participants attend more to goal-consistent payoffs. Although our dot-probe task does not distinguish between covert and overt attention (and it remains to be seen whether the attentional selection is reflected in overt eye shifts), on the basis of our control experiment, it seems that overt attention is not necessary for risk biases (see Control Experiment: Constrained Viewing in the Supplemental Material). Critically, we found that individual differences in the magnitude of attentional-selection bias correlate with risk biases (see Fig. 4c), suggesting a causal relation. This inference needs to be qualified in two respects. First, there is a need for further experimental work to fully establish causality via interventions that boost or interfere with attentional selection. Second, the results need to be qualified to decisions between alternatives that are characterized by relatively rapid sequences of payoffs. Note, however, that an internal sequential sampling is often assumed to operate even in decisions between unchanging alternatives (Roe et al., 2001) and that a similar risk-seeking bias effect was obtained with static stimuli (Shafir, 1993).

An important conceptual question is how one can attend more to goal-congruent values (a potential issue of circularity: attention for explaining attention). One way toward a noncircular theory is to posit that the semantic contents (goal-dependent values) can be registered outside (or with only minimal) attentional focus (Li, VanRullen, Koch, & Perona, 2002), and this serves to deploy attention and to weight evidence toward a decision. Alternatively, it is possible that participants first divide attention over the two numerical payoffs (enough to register them) before focusing further processing on the goal-congruent one.

Another key question is whether this selective-weighting mechanism has an adaptive value (Rieskamp, Busemeyer, & Mellers, 2006; Summerfield & Tsetsos, 2015). An attractive idea has recently been proposed by Tsetsos et al. (2016), according to whom, although selective gating may trigger choice biases, it confers the advantage of increasing the decision robustness to noise. This takes place because while ignoring some of the information, selective integration makes the integrated values more polarized and further away from the decision boundary. In our simulation results, we further determined that the robustness to noise that is achieved by the graded selective-integration model exceeds the one achieved by the binary selective-integration model (see Fig. 2b). This is because the selective-integration model prioritizes value integration on the basis of value differences rather than binary relations. Consistent with the adaptive-decision proposal (Spitzer et al., 2017; Tsetsos et al., 2016), the results of Experiment 2 showed that the accuracy of the participants in the different-mean trials (in which there was an objective-performance criterion) correlated with the magnitude of the dot-probe bias (r = .5, p = .003; see Fig. 4d). Thus, participants who show a higher attentional bias (and are more prone to the prorisk choices in equal mean trials) are more accurate in trials for which there is an objective criterion. This confirms the prediction of selective-integration robustness and indicates that choice biases are the cost that the decision mechanism is sacrificing for the benefit of enhancing overall decision performance.

Action Editor

Timothy J. Pleskac served as action editor for this article.

Author Contributions

All the authors developed the study concept and designed the experiment. M. Glickman and M. Usher conducted Experiments 1 and 2 and analyzed their data. K. Tsetsos conducted the constrained viewing experiment and analyzed its data. M. Glickman and M. Usher wrote the manuscript, with critical feedback from K. Tsetsos. All the authors approved the final manuscript for submission.

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Declaration of Conflicting Interests

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797618803643

Open Practices

All data and materials have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/3hu8m. The design and analysis plans for the experiments were not preregistered. The complete Open Practices Disclosure for this article can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797618803643. This article has received the badges for Open Data and Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

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