The Role of Visual Attention in Opportunity Cost Neglect and Consideration

Stephanie M. Smith

Stephen A. Spiller

Ian Krajbich

Abstract

Choices necessitate opportunity costs: choosing one option means foregoing another. Despite their critical role in decision making, people often neglect opportunity costs and are less likely to make purchases when reminded of them. Here, we seek to understand whether and how opportunity-cost neglect can be explained by attention, a relationship that has been proposed but not explicitly tested. Participants made eye-tracked, incentivized purchase decisions in two conditions: one with implicit opportunity costs (e.g., “Buy” vs. “Do Not Buy”) and one with explicit opportunity costs (e.g., “Buy” vs. “Keep Money”). Across two studies (approximately 30,000 choices), we find lower purchase rates when opportunity costs are explicit. More importantly, we show that the relationship between attention and opportunity cost considerations is two-fold. First, the *amount* of attention to the outside option is greater when opportunity costs are explicit, which partly accounts for the effect of opportunity cost salience on choice. Second, for some framings, the *predictive power* of attention to opportunity costs is greater when opportunity costs are explicit. Using the attentional drift-diffusion model, we model the effect of opportunity cost salience on choice via attention. These findings help explain why people are more likely to purchase when explicit opportunity cost reminders are absent.

Keywords: decision making, visual attention, opportunity cost, drift-diffusion model

The Role of Visual Attention in Opportunity Cost Neglect and Consideration

Humans face scarce resources: their limited means are typically insufficient to pursue every desirable alternative. Limited income precludes making every desirable purchase and limited time precludes engaging in every desirable activity. They must make tradeoffs. Choosing one option necessitates foregoing another, thereby incurring an opportunity cost. Yet when making purchases, people often spend in ways that suggest they ignore the opportunity costs they face (Frederick et al. 2009). When people are prompted to consider opportunity costs (via internal and/or external factors), they are less likely to make purchases and are more sensitive to the value of those opportunity costs (Spiller 2011). Why? Prior research (e.g., Frederick et al. 2009) has proposed attention as a mechanism, but has stopped there, without measuring attention or identifying the possible ways attentional effects might manifest in opportunity cost consideration. Opportunity costs are always present in decision making, but the salience of these opportunity costs may differ from one decision to the next. In this research, we manipulate opportunity cost salience, and then measure visual attention and choices to investigate not just if – but also precisely how – attention to outside options can account for opportunity cost neglect and consideration.

Using eye-tracking data, we measure visual attention to the target product as well as visual attention to a non-buy option in which the opportunity cost is left implicit (in half of the trials), or to a non-buy option in which the opportunity cost is made explicit (in the remaining trials). This enables us to directly assess what role, if any, visual attention plays in the effect of opportunity cost reminders on choice. Specifically, this allows us to assess: (a) how relative attention to the non-buy option varies with the implicit / explicit framing of the non-buy option; (b) how relative attention to the non-buy option relates to purchase decisions; and (c) how the implicit / explicit framing affects the strength of the predictive relationship between relative attention and purchase decisions. Prior research on visual attention (e.g., Shimojo et al. 2003; Armel et al. 2008; Krajbich et al. 2010; Mormann et al. 2010) supports (b); no prior research has addressed or quantified (a) or (c).

Opportunity Cost Neglect

People sometimes encounter straightforward choices between two or more alternatives. When using a free movie voucher, using the voucher on an action thriller clearly means foregoing using it on the next best movie, e.g., a noir drama. In such cases, the opportunity cost of seeing the action thriller (i.e., not seeing the noir drama) is highly salient. In other cases, opportunity costs may only be implied, though no less real. When buying a ticket to that same action thriller with cash, the next best use of that money is at least as valuable as the noir drama, even if it is not specified. Thus, implicit opportunity costs should be at least as effective as explicit opportunity costs at encouraging people to avoid expenditures.

Instead, when opportunity costs are merely implied, as in the second case, people often neglect them altogether and spend resources as though there were no other options (Frederick et al. 2009; Legrenzi, Girotto, and Johnson-Laird 1993; Jones et al. 1998; Northcraft and Neale 1986). For example, people are more likely to purchase when the decision is framed as buying vs. not buying than when it is framed as buying vs. keeping the money for other purchases (Frederick et al. 2009).

This research implies that simply reminding people that opportunity costs exist (i.e., that they could use their time or money for other purposes) can keep them from neglecting opportunity costs. More specifically, reminders heighten sensitivity to the attractiveness of outside options (Bartels and Urminsky 2015; Spiller, 2011) and thus tend to decrease choice of the target option. This result is robust; it has been found across consumer choice (Frederick et al., 2009; Greenberg and Spiller 2016; Plantinga et al. 2016; Spiller 2011; Jones et al. 1998), managerial decision-making (Northcraft and Neale 1986), accounting (Becker, Ronen, and Sorter 1974; Friedman and Neumann, 1980), time use (Legrenzi et al. 1993; Jones et al. 1998; Chatterjee, Rai, and Heath 2016; Zhao et al. 2015), and intertemporal choice (Bartels and Urminsky 2015; Magen, Dweck, and Gross 2008; Read, Olivola, and Hardisty 2016).

Research on opportunity cost neglect and consideration has focused on factors that enhance consideration and the consequences of such consideration. Reminders in the choice environment are one important driver of opportunity cost consideration, though not the only one. Accessibility in memory (Frederick et al. 2009; Spiller 2011) and immediately binding resource constraints can increase the probability of considering opportunity costs (Spiller 2011). But an important question remains: what is the mechanism by which this additional consideration translates into choices? How does additional consideration of opportunity costs result in lower purchase rates?

Understanding the role of attention may help to answer this question. Prior research (e.g., Frederick et al., 2009) has proposed attention as a mechanism, but has not directly tested the ways in which attention to opportunity costs affects choice, nor has it explicitly addressed the multiple ways in which it might matter. The very label of opportuninty cost “neglect” implies that attention matters, but that implication has not actually been tested using measures of attention. Does the salience of an opportunity cost shift the amount of attention given to these opportunity costs? And/or does it also shift the relationship between attention and choices? Measuring overt visual attention, i.e., where the decision maker is looking throughout the course of the decision process, can aid our understanding of how and why opportunity cost reminders reduce purchase rates.

The Role of Visual Attention in Choice

Over the past few decades, there has been extensive research into the relationship between visual attention and choice. This stream of research began with the study of hand-coded eye movements and their relationship to the choice process (Russo and Leclerc 1994). Naturally, research in this area has evolved over time. Many of the prominent early papers focused on choices between two alternatives (two-alternative-forced-choice, or 2AFC: Shimojo et al. 2003; Armel et al. 2008; Krajbich et al. 2010; Mormann et al. 2010). However, others investigated the attention-choice relationship in scenarios with more than two alternatives (Lohse and Johnson 1996; Pieters and Warlop 1999; Chandon et al. 2009; Krajbich and Rangel 2011; Atalay et al. 2012; Folke et al. 2016; Gluth et al. 2019; Reutskaja et al. 2011; Thomas, Molter, Krajbich 2021; Towal et al. 2013). More recently, the research has expanded to focus on multi-attribute decisions, as well (Kim, Seligman, and Kable 2012; Venkatraman, Payne, and Huettel 2014; Fisher 2017; Reeck, Wall, and Johnson 2017; Bhatia 2017; Bhatia and Stewart 2018; Zhao and Bhatia 2018; Smith and Krajbich 2018; Amasino et al. 2019; Fisher 2021a; Yang and Krajbich 2023).

A common finding in all of these papers is that the more attention an option receives, the more likely it is to be chosen (as long as the options have goal-consistent values; see Armel et al. 2008 for insight into choices between aversive options and Sepulveda et al. 2020 for insight into accept/reject framing). This is an uncontroversial relationship, the robustness of which has been demonstrated in a variety of domains (e.g., consumer goods, risky gambles, social preferences, perceptual judgments, intertemporal preferences). Recent research has directly addressed whether the relationship between attention and choice is causal, providing evidence that attention drives choices (Armel, Beaumel, and Rangel 2008; Fisher 2021; Gwinn, Leber, and Krajbich

2019; Lim, O'Doherty, and Rangel 2011; Milosavljevic et al. 2012; Pärnamets et al. 2015; Fisher 2021b; Towal, Mormann, and Koch 2013; see Bhatnagar and Orquin 2022 for a review). There is also evidence that that this causal relationship may be bidirectional (Shimojo et al. 2003; Ghaffari and Fiedler 2018; Newell and Le Pelley 2018; Mormann and Russo 2021).

Most attention-choice research has focused entirely on "which-one" decisions (i.e., decisions between outcomes). Far fewer papers have investigated attention's role in "whether-or-not" decisions (e.g., Krajbich et al. 2012; Fisher 2017), which is what the present paper seeks to address. When the outside set is sufficiently limited, or one of the options is sufficiently broad, these are formally equivalent, as in the studies of opportunity cost neglect described above. However, studies regarding the role of attention largely have not considered the effects of how opportunity cost salience is represented/framed[1]. In addition to understanding the ways in which attention accounts for the effect of opportunity cost salience on choice, the present paper also contributes to our understanding of how the impact of attention on choice varies depending on the framing of the choice.

The relationship between attention and choice can be accounted for by a process in which individuals noisily gather support for each alternative, and they gather support faster for the looked-at alternative than the non-looked-at alternative (Krajbich et al. 2010). Specifically, this framework suggests that incoming support for the looked-at option is amplified relative to when individuals look elsewhere (Smith and Krajbich 2019). In the aDDM, the amplifying nature of attention implies that the same amount of attention, when devoted to different options, may have different downstream effects on choice. More concretely, attention is more predictive of choice for some options than it is for others, and the degree of predictability is related to the features of

[1] Sepulveda et al. 2020 investigate the interaction of attention and decision frame in a different scenario: the authors manipulate accept/reject framing in "which one" choices.

the options themselves. This amplifying role of attention in choice is consistent with the attentional drift diffusion model (aDDM; Krajbich et al. 2010).

The aDDM is an extension of the drift diffusion model (DDM; Ratcliff 1978), which is part of a larger class of decision models known as sequential sampling models (SSMs; Aschenbrenner, Albert, and Schmalhofer 1984; Bhatia 2013; Bhatia and Pleskac 2019; Bhui 2019; Busemeyer 1982; Busemeyer and Diederich 2002; Laming 1968; Link 1975; Petrusic and Jamieson 1978; Pleskac and Busemeyer 2010; Stewart, Chater, and Brown 2006; Stone 1960; see Bogacz 2007; Ratcliff and Smith 2004; Shadlen and Shohamy 2016 for comprehensive reviews). These models assume that decision makers noisily accumulate support for each option over the course of the choice process and make their choice as soon as support for one option has surpassed a predefined threshold. The aDDM adds an additional assumption to the decision-making process: more information is gathered for the looked at (vs. non-looked at) option, such that the non-looked at option is discounted by a multiplicative constant in comparison. Attention to a stimulus is thought to amplify associated reward signals (McGinty, Rangel, and Newsome 2016; Purcell et al. 2021) or relevant information from memory (Barron, Dolan, and Behrens, 2013; Shadlen and Shohamy, 2016; Weber et al., 2007). In this paper, we extend the aDDM to allow for different attentional discounts depending on the type of option (i.e., money or consumer good) in a manner similar to Fisher's (2017) binary-attribute aDDM. We use this new model to parameterize the magnitude of attention's role in decision making under different framings.

Although attention has been shown to be predictive of purchase decisions in the past (e.g., Krajbich et al. 2012), opportunity cost salience has never been tested as a potential moderator for the role of attention in this choice domain. Therefore, we integrate these two literatures (opportunity cost consideration and the link between attention and choice) in order to test a process-driven explanation for the decline in purchase rates observed when opportunity costs are made explicit.

Framework and Hypotheses

Based on previous research, we anticipate that the opportunity cost salience could affect purchase rates through two possible attentional pathways (Fig. 1). We tested two candidate hypotheses for how attention may operate in situations with differing levels of opportunity cost salience.

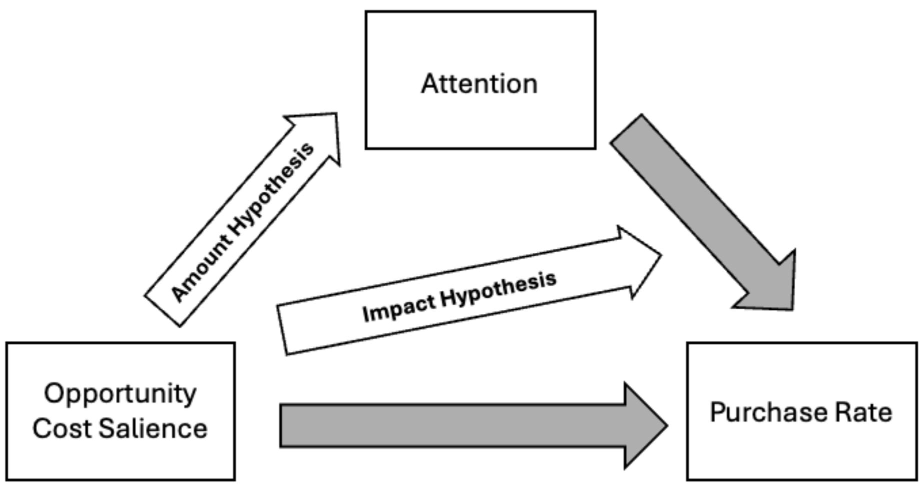

Figure 1. Conceptual framework. Previous work has demonstrated that opportunity cost salience affects purchase rates (bottom gray arrow; Frederick et al., 2009; Spiller 2011) and that attention affects choices (right gray arrow; Armel et al. 2008; Fisher 2021; Gwinn et al. 2019; Lim et al. 2011; Mormann et al. 2012; Pärnamets et al. 2015; Towal et al. 2013; Bhatnagar & Orquin 2022). The current paper tests for two additional pathways in this framework, both of which operate via visual attention.

First, as described above, attention can play a causal role in influencing choice. If participants attend more to explicit opportunity costs than implicit opportunity costs, attention could mediate the effect of opportunity cost salience on choice. This is the process implied by prior work on opportunity cost neglect (e.g., Frederick et al. 2009), yet it has not been directly tested.

Amount Hypothesis:

> An increase in opportunity cost salience decreases purchase incidence by increasing the amount of attention to the outside option.

Second, the nature of the alternatives can influence the strength of the relationship between attention and choice (Smith and Krajbich 2019, Ting and Gluth 2023). Independently of whether opportunity cost salience causes a shift in the amount of attention to opportunity costs, opportunity cost salience could cause a shift in the relationship between attention and choice. Thus, if attention is differentially related to choice when opportunity costs are explicit rather than implicit, this might provide an additional mechanism by which attention could account for the relationship between opportunity cost salience and choice.

Strength Hypothesis:

> An increase in opportunity cost salience decreases purchase incidence by increasing the strength of the relationship between attention (to the outside outcome) and choice.

It is important to note that while the results of previous research support a positive (and causal) relationship between attention and choice, these two hypotheses document different ways that attention might manifest in the decision process when opportunity costs are involved. It would be possible to find support in the data for (1) either hypothesis, (2) neither hypothesis, or (3) both hypotheses, while still finding an effect of opportunity cost salience on behavior (bottom arrow in Fig. 1) and a relationship between attention and choice (right arrow in Fig. 1).[2]

---

[2] Moreoever, we could find support for any combination (either, neither, or both) of these hypotheses, regardless of the causal direction of attention and choice.

Furthermore, the computational modeling (using the aDDM) will provide additional evidence regarding this framework: the attentional discount parameter in the aDDM reflects the strength of the relationship between attention and choice. Therefore, fits from the aDDM have the potential to provide additional insight into the Strength Hypothesis, as described above.

We tested these hypotheses with two incentive-compatible eye-tracking experiments. Our preregistrations, data, and code are available at: https://researchbox.org/1627&PEER_REVIEW_passcode=PCHWIG.

Study 1

Methods

Participants

Fifty-one university students participated in this preregistered study.[3] We determined the sample size a priori with a power analysis: with 50 participants and 100 trials per condition, we anticipated 90% power to detect meaningful behavioral and attention-based effects[4]. This study was approved by the relevant Internal Review Board and all participants gave informed written consent before participating.

Materials

Stimuli were presented using the MATLAB (Mathworks 2014) Psychophysics Toolbox (Brainard 1997; Kleiner et al. 2007; Pelli 1997). An EyeLink 1000 Plus (SR Research, Canada)

[3] The preregistration may be found at https://aspredicted.org/LCY_DNM. The methods and exclusion criteria were carried out as preregistered. Analyses largely followed the preregistered plan, with some slight changes for consistent reporting and model convergence.
[4] This calculation was based on a 3 percentage-point difference in choice between conditions, and a 35ms difference in buy-dwell advantage with a 500ms within-person standard deviation across trials.

was used to collect eye-tracking data. Attentional areas of interest (AOIs) were defined a priori, each containing an option on the screen. Participants responded using a standard computer mouse and keyboard.

Procedure

In addition to a show-up fee of $8, we endowed participants with $4 that they could use for purchases, and informed them that one of their choices would be implemented at the conclusion of the study.

First, participants used the mouse to indicate how much they would be willing to pay for each of 144 food items on a continuous scale from $0.01 to $4.00. There was also an opt-out button labeled “Would Not Eat” (Fig. 2a). Unbeknownst to participants, clicking this button would ensure that the disliked food would not appear in the subsequent choice task. This willingness-to-pay (WTP) task was incentivized using the Becker-DeGroot-Marschak (BDM) method, in which participants are incentivized to state their true WTP (Becker, DeGroot and Marschak 1964). Specifically, if a trial from this task was selected for payment, then we randomly selected a target price between $0.00 and $4.00. If the participant’s stated WTP for the food was equal to or greater than the target price, then they purchased the food at the target price and took home any remaining funds from the $4.00 endowment. If the participant’s stated WTP for the food was less than the target price, then they did not purchase the food and instead took home the entire endowment. The details of this method were explained to participants before starting the task.

After completing the WTP task, we calibrated participants to the eye-tracker using the built-in 9-point calibration procedure. Participants’ eye movements were tracked for the remainder of the experiment.

Next, participants made 200 incentivized purchase choices (separated in two blocks of 100 trials each) about these food items. Specifically, on each trial, participants saw a picture of one food item on the screen (Fig. 2b). After 1 second, the food disappeared automatically, and two options appeared on the screen: a buy option and a non-buy option. Crucially, we manipulated the framing of the non-buy option. For one block of trials, the options were labeled "Buy Food for $X" and "Do Not Buy Food for $X" (the *implicit* opportunity cost condition; Fig. 2c). In the other block of trials, the options were labeled "Buy Food for $X" and "Keep $X" (the *explicit* opportunity cost condition; Fig. 2d).

The order of the blocks was counterbalanced across participants, and the positioning (left vs. right) of the options was randomly assigned on each trial. Each price was randomized to take on a value between +/-$0.50 of the participant's WTP for that item. The price was uniformly sampled from this range, with a minimum price of $0.01 and a maximum price of $4.00 (so as not to exceed the endowment amount). This participant-level personalization ensured that each participant's trials comprised a comparable range of difficulties.

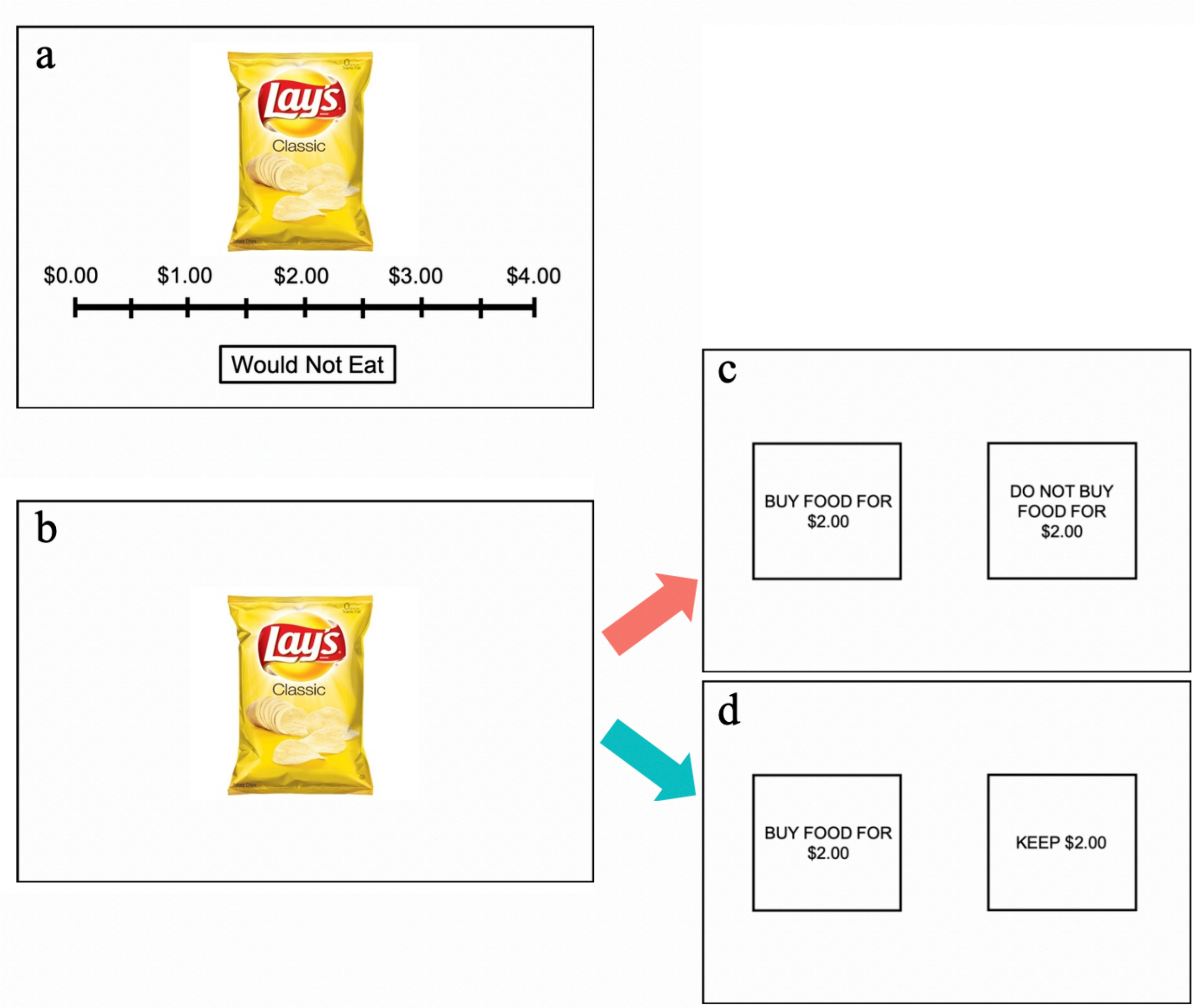

Figure 2. Experimental Setup. Participants first rated their willingness-to-pay (WTP) for 144 snack food items (a). If they would not eat the food, they could click the "Would Not Eat" button. On each choice trial, participants first saw a previously rated food item (b) on the screen for 1 second. After 1 second, the food item disappeared, and the participant was confronted with a purchase decision with buy and non-buy options. For half (100) of the trials, participants saw an implicit opportunity cost framing (c) for the non-buy option (i.e., "Do Not Buy Food for $X"). For the other half (100) of trials, participants saw an explicit opportunity cost framing (d) for the non-buy option (i.e., "Keep $X").

If a trial from this task was selected for payment, then the action chosen by the participant was carried out. If they chose to purchase the food on that trial, then they would receive the food and the endowment minus the price of the food. If they chose not to purchase the food, they did not receive a food, but received the entire endowment ($4). Participants were informed of this payoff structure before beginning the purchase task.

Data Exclusions

As determined in advance, we excluded one participant (N = 1) who chose against their stated WTPs. Among the remaining participants (N = 50), we excluded exceedingly fast or slow decisions (i.e., faster than 250 ms or slower than two standard deviations above the participant-level mean, after taking the logarithm; 4% of trials). We also excluded data from trials in which participants did not fixate on either option (fewer than 2% of trials) and one trial in which the eye-tracker reported a negative dwell time. Including these data does not change our findings; see Appendix B in the supplements for tests of our main results.

Results

The two non-buy options ("Keep" and "Do Not Buy") lead to identical outcomes: the participant chooses not to buy the food at the given price. However, we predicted that participants would not treat them as identical options. We begin by focusing on the choice results before discussing the results for visual attention. Where possible, we examine both aggregate subject-level analyses as well as disaggregate trial-level analyses.

Choice Results

Aggregate Analyses. To test the effect of opportunity cost salience on purchase probability, we calculated the purchase rate (i.e., proportion of trials in which participants chose to buy) separately for implicit-opportunity-cost trials and explicit-opportunity-cost trials.[5] We

---

[5] This analysis is formally equivalent to a 2 × 2 mixed ANOVA with opportunity cost salience as a within-subject factor and counterbalanced order as a between-subject factor. The main effect of order is not statistically significant ($p > .4$).

then calculated the purchase rate difference as the purchase rate in the explicit condition minus the purchase rate in the implicit condition. Regressing the purchase rate difference on a contrast coded variable for order (1 = explicit first; -1 = implicit first) allows us to test whether opportunity cost salience affects the purchase rate averaged across orders (as given by the intercept), and how the purchase rate varies with the interaction of order and condition (as given by the coefficient on order; this effect represents the confounded effects of carryover and position effects averaged across conditions).[6]

Consistent with prior research (Frederick et al., 2009; Spiller, 2011), opportunity cost salience decreased purchase rate, as indicated by the intercept ($b_0 = -0.078$, SE = 0.017, $t(48) = -4.58$, $p < 0.001$). Averaged across participants, the proportion of trials on which participants purchased was about 8 percentage points lower when opportunity costs were explicit (0.388) rather than implicit (0.466; see Fig. 3). This effect was weaker for people who saw the explicit condition first (1% vs. 14%; $b_1 = 0.065$, SE = 0.017, $t(48) = 3.81$, $p < 0.001$), consistent with a carryover effect.[7]

Together, these results replicate prior evidence of opportunity cost neglect and sensitivity to making opportunity costs explicit. Moreover, the fact that we observe strong evidence of opportunity cost neglect using a battery of intensive repeated choices suggests a potential for methodological improvements: researchers may measure moderators more precisely using repeated opportunity cost decisions.

Disaggregate Analyses. We repeated this analysis using disaggregate trial-level data to account for the role of surplus (WTP – price). Specifically, we regressed purchase on opportunity

---

[6] We used equation 1: $\Delta PurchaseRate_i = \beta_0 + \beta_1 Order_i + \epsilon_i;\ \epsilon_i \sim N(0, \sigma)$

[7] We ran an online posttest to determine whether the order effect was due to carryover and/or position effects; results were consistent with a carryover effect. For additional details, see Appendix A in the supplements.

cost salience (1 = explicit, -1 = implicit), controlling for position (-1 = first block, 1 = second block) and trial-level surplus. We account for nonindependence through inclusion of participant-level random intercepts and random slopes on surplus and condition.[8]

As expected (and as imposed by our a priori exclusion criteria which excluded one subject as described above), surplus was a strong positive predictor of purchase such that participants were more likely to purchase as WTP increased relative to price ($b_3 = 3.29$, SE = 0.26, $z = 12.69$, $p < .001$).[9] Explicit framing decreased probability of purchase ($b_1 = -0.21$, SE = 0.045, $z = -4.72$, $p < .001$; see Fig. 3). There was also an effect of position ($b_2 = -0.22$, SE = 0.046, $z = -4.82$, $p < .001$) such that purchase rates were lower in the second block than the first. The disaggregate analysis permits an additional insight. By including surplus in the model, we can examine the estimated purchase probability in each condition when surplus is equal to 0 (i.e., when price is equal to WTP and one would expect participants to be indifferent between buying and not buying). In the implicit condition, the estimated purchase probability when there was no surplus was 0.45, which did not statistically significantly differ from 0.5 ($z = -1.49$, $p = .136$). In the explicit condition, the estimated purchase probability when there was no surplus was 0.35, significantly less than 0.5 ($z = -4.12$, $p < .001$). In other words, when participants were not reminded of opportunity costs, WTPs appeared to be appropriately calibrated. When opportunity costs were explicit, WTPs appeared to be miscalibrated (e.g., if a participant claims to be willing to pay $3.00, but is only 35% likely to purchase at a price of $3.00, that WTP report is not

[8] We used equation 2: $P(Buy_{it}) = logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it})$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}; \eta \sim \mathrm{N}(0, \Sigma)$

[9] We also estimated equation 2 with separate coefficients on the price and WTP (instead of combining them into the surplus variable. As expected, the coefficients are opposite in direction and nearly identical in size: $b_{Price} = –3.58$, SE = 0.29, $z = –12.22$, $p < .001$; $b_{Rating} = 3.24$, SE = 0.26, $z = 12.30$, $p < .001$. Including both variables leads to convergence issues in more complicated mixed models. Because they are correlated but have (roughly) equal and opposite effects on choice, we simplify the models by using the difference instead.

properly calibrated). Since choice aligns with WTP only when opportunity costs are implicit, this suggests that participants may neglect opportunity costs when reporting WTPs. We do not have specific process evidence to support this explanation, but it may be fruitful for future research to pursue this finding.

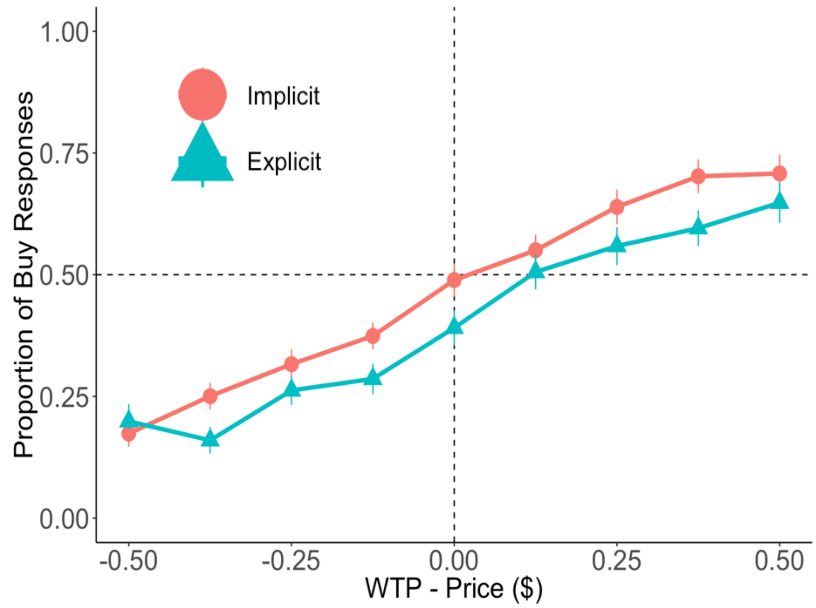

Figure 3. Purchase Behavior as a Function of Surplus (WTP – Price) and Condition. Participants (N = 50) were significantly less likely to purchase in the explicit condition. Bars indicate standard error of the mean, clustered by participant. For display purposes, the surplus is binned into intervals of $0.125. We do not find evidence of a significant interaction across conditions; b = -0.09, SE = 0.22, t = -0.40, p = .69.

Discussion. Together, these results replicate and extend prior work on opportunity cost neglect (e.g., Frederick et al., 2009; Spiller, 2001). First, they replicate opportunity cost neglect with incentivized choices. Second, they indicate an effect of opportunity cost salience in repeated choices. Third, coupled with the results from the posttest (noted in footnote 7), they suggest that explicit frame has a carryover effect on implicit frame but no such carryover of implicit frame, suggesting that the equivalence is evident after one has considered the explicit frame. Fourth, they are consistent with the interpretation that not only choices, but also WTP judgments are made while neglecting opportunity costs.

Attention Results

To investigate visual attention as a potential mechanism underlying opportunity cost neglect, we examined the eye-tracking data, both as a mediator and as a moderator of choice. We looked at our results using raw overt attention (i.e., how many seconds did participants spend looking at an option) and, when appropriate, a standardized measure of overt attention: proportion ([0,1]) of trial-level gaze devoted to an option.

Effect on Attention: Aggregate. Using the same approach that we used for the choice results, we computed the average dwell time advantage for the buy option (total dwell time spent on the buy option minus total dwell time spent on the non-buy option) for each participant. We computed this measure for each condition and then took the difference between them. For the standardized attention version, for each participant we computed the difference between conditions in the average dwell proportion on the buy option. We then regressed these differences on the contrast-coded variable for order.[10] We hypothesized that participants would devote more relative attention to the explicit version of the non-buy option ("Keep") than the implicit version ("Do Not Buy"), as tested by the intercept.

Indeed, the intercept was significantly negative (raw: b_0 = -0.050, SE = 0.023, $t(48)$ = –2.22, p = .031; standardized: b_0 = -0.034, SE = 0.011, $t(48)$ = -3.22, p = 0.002), indicating that subjects looked more at the explicit "Keep" than the implicit "Do Not Buy." As with the choice

[10] We used equation 3a: $\Delta BuyDwellAdv_i = \beta_0 + \beta_1 Order_i + \epsilon_i$ and 3b: $\Delta BuyProportion_i = \beta_0 + \beta_1 Order_i + \epsilon_i$

results, the effect of condition significantly differed by order (raw: $b_1 = 0.084$, SE = 0.023, $t(48) = 3.70$, $p < .001$; standardized: $b_1 = 0.045$, SE = 0.011, $t(48) = 4.25$, $p < .001$).

In both blocks separately, just like the collapsed analysis, the dwell-time advantage for the buy option was directionally larger for the implicit condition than for the explicit condition (1st block: raw: 0.081 vs. 0.006 seconds; $t(48) = 1.66$, $p = .10$; standardized: 53% vs. 49%; $t(48) = 2.15$, $p = .04$; 2nd block: raw: –0.027 vs. –0.053 seconds; $t(48) = 0.57$, $p = .57$; standardized: 48% vs. 45%; $t(48) = 0.94$, $p = .36$).[11] Overall, this evidence indicates that relative to the implicit condition, participants focused relatively more attention on the non-buy option in the explicit condition.

Effect on Attention: Disaggregate. To examine the distribution of attention across conditions with greater control, we regressed trial-level dwell advantage (and trial-level dwell proportion) for the buy option on contrast-coded condition (1 = explicit, -1 = implicit), controlling for position (-1 = first block, 1 = second block) and trial-level surplus, allowing random participant intercepts and slopes on condition and surplus.[12]

As in the between-subject analysis, condition was a significant negative predictor (raw: $b_1 = -0.025$, SE = 0.011, $t(48) = -2.19$, $p = .03$; standardized: $b_1 = –0.017$, SE = 0.005, $t(46) = –3.34$, $p = .002$), indicating that the dwell advantage in favor of buy was stronger in the explicit condition than the implicit condition. There was again a significant effect of position (raw: $b_2 =$ -

[11] Note that we find a significant difference in buy dwell advantage across conditions when including both blocks but not a significant difference for either block separately. This is because the former is a within-subject measurement, while the latter is a between-subjects measurement estimated with less precision, and therefore less statistical power to detect an effect of similar size.

[12] We used the equations 4a: $BuyDwellAdv_{it} = \beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \epsilon_{it}$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\eta \sim N(0, \Sigma)$ and 4b: $BuyDwellProportion_{it} = \beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \epsilon_{it}$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\eta \sim N(0, \Sigma)$

0.046, SE = 0.011, $t(48) = -4.05$, $p < .001$; standardized: $b_2 = -0.025$, SE = 0.005, $t(46) = -4.83$, $p < .001$), such that the buy dwell advantage (and buy dwell proportion) was larger in the first block than the second block. Surplus was also a strong positive predictor of dwell advantage (raw: $b_3 = 0.34$, SE = 0.040, $t(50) = 8.34$, $p < .001$; standardized: $b_3 = 0.17$, SE = 0.018, $t(48) = 9.17$, $p < .001$; all degrees of freedom for mixed models are approximate), indicating that participants attended relatively more to buy when surplus was higher.

Attention Predicts Choice: Aggregate. The analysis above suggests that the amount of attention to the non-buy option differs depending on the condition. To test whether relative amount of attention predicts choice, we regressed each participant's difference in purchase rates between conditions on their difference in average dwell-time advantage between the conditions (or difference in average dwell proportions, in the standardized model), with order (contrast-coded) and mean-centered sum of average dwell time advantage across conditions as covariates (as recommended in Montoya and Hayes 2017).[13]

The coefficient on difference in average dwell time advantage predicting purchase rate difference was significant (raw: $b_2 = 0.40$ per second, SE = 0.10, $t(46) = 3.97$, $p < .001$; standardized: $b_2 = 1.27$, SE = 0.16, $t(46) = 7.92$, $p < .001$); the coefficient on sum of average dwell time advantage/proportion was not (raw: $b_3 = 0.05$, SE = 0.06, $t(46) = 0.90$, $p > .3$; standardized: $b_3 = 0.06$, SE = 0.08, $t(46) = 0.78$, $p > .3$). This means that a 1 second increase in average relative dwell time for the buy option (between conditions) predicts a 40% increase in purchase rate; the more relative attention to buy in one condition (vs. the other), the higher the purchase rate in that condition (relative to the other).

[13] We used equations 5a: $\Delta PurchaseRate_i = \beta_0 + \beta_1 Order_i + \beta_2 \Delta BuyDwellAdv_i + \beta_3 \mathrm{MC}\Sigma BuyDwellAdv_i + \epsilon_i;\ \epsilon_i \sim N(0, \sigma)$ and 5b: $\Delta PurchaseRate_i = \beta_0 + \beta_1 Order_i + \beta_2 \Delta BuyDwellProportion_i + \beta_3 \mathrm{MC}\Sigma BuyDwellProportion_i + \epsilon_i;\ \epsilon_i \sim N(0, \sigma)$

On average, the dwell time advantage for buy was lower in the explicit condition, as was the purchase rate. If the dwell time advantage were equal in the implicit and explicit conditions, we would expect to find a small effect of order (raw: $b_1 = 0.032$, SE = 0.018, $t(46) = 1.81$, $p = .08$; standardized: $b_1 = 0.007$, SE = 0.01, $t(46) = 0.60$, $p > .3$) and a smaller (though still significant) difference in the purchase rate (as given by the intercept: raw: $b_0 = -0.058$, SE = 0.016, $t(46) = -3.59$, $p < .001$; standardized: $b_0 = -0.035$, SE = 0.013, $t(46) = –2.72$, $p = .009$; compare to total effect of -.078 above;). This indicates that the difference in purchase rates is not eliminated when equating attention in the two conditions (although measurement error in visual attention could contribute). However, it is substantially and significantly reduced, as the bootstrapped 95% confidence interval of the reduction excludes 0 (raw: -0.038, -0.002; standardized: -0.071, -0.016), providing evidence for complementary mediation (Montoya and Hayes 2017; Zhao, Lynch, and Chen 2010).

Attention Predicts Choice: Disaggregate. To examine the relationship between attention and choice on a trial-by-trial basis, we regressed purchase decisions on condition, buy dwell advantage (buy dwell proportion in the standardized model), and mean-centered total dwell time (excluded in the standardized model), controlling for position and surplus. We include participant random intercepts and slopes on condition, buy dwell advantage (or proportion), and mean-centered total dwell time.[14]

Once again, buy dwell advantage (and proportion) was a strong predictor of choice (raw: $b_4 = 2.40$, SE = 0.16, $z = 14.66$, $p < .001$; standardized: $b_4 = 5.59$, SE = 0.32, $z = 17.51$, $p <$

---

[14] We used equations 6a: $P(Buy_{it}) = logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \beta_{4i}BuyDwellAdv_{it} + \beta_{5i}MCTotalDwell_{it})$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\beta_{4i} = \beta_4 + \eta_{4i}$; $\beta_{5i} = \beta_5 + \eta_{5i}$; $\eta \sim N(0, \Sigma)$ and 6b: $P(Buy_{it}) = logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \beta_{4i}BuyDwellProportion_{it})$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\beta_{4i} = \beta_4 + \eta_{4i}$; $\eta \sim N(0, \Sigma)$

.001); total dwell time was not (b_5 = -0.09, SE = 0.08, z = -1.17, p = .24). Using trial-level data, the indirect effect was negative (raw: -1.3%, 95% CI = [-2.7%, 0.1%]; standardized: -2.3%, 95% CI: [-3.9%, -.8%] Tingley et al. 2014).

Differential Relationship with Attention: Disaggregate. The analyses above suggest that the relative *amount* of attention devoted to the non-buy option is larger in the explicit condition, and that this difference contributes to the observed purchase rate differences (since attention to an option correlates with it being chosen). In addition, a difference in the *strength* of the attention-choice link may help to account for differences between the two conditions. We consider this possibility next.

The disaggregate data allows us to examine how relative attention to buy versus non-buy predicts choice *differentially* across conditions. To test this, we added to the base models above (equations 6a and 6b) the interaction of condition with buy dwell advantage/proportion and the interaction of condition with total dwell time.[15] Buy dwell advantage and proportion were more positively related to purchase in the explicit condition than the implicit condition (raw: b_6 = 0.14, SE = 0.09, z = 1.62, p = .10; standardized: b_5 = 0.43, SE = 0.22, z = 1.97, p = .05). This indicates that relative attention was more strongly predictive of choice when opportunity costs were explicit rather than implicit.[16]

[15] We used equations 7a: $P(Buy_{it}) = logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \beta_{4i}BuyDwellAdv_{it} + \beta_{5i}MCTotalDwell_{it} + \beta_{6i}OppCost_{it}BuyDwellAdv_{it} + \beta_{7i}OppCost_{it}MCTotalDwell_{it})$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\beta_{4i} = \beta_4 + \eta_{4i}$; $\beta_{5i} = \beta_5 + \eta_{5i}$; $\beta_{6i} = \beta_6 + \eta_{6i}$; $\beta_{7i} = \beta_7 + \eta_{7i}$; $\eta \sim N(0, \Sigma)$ and 7b: $P(Buy_{it}) = logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \beta_{4i}BuyDwellProportion_{it} + \beta_{5i}OppCost_{it}BuyDwellProportion_{it}$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\beta_{4i} = \beta_4 + \eta_{4i}$; $\beta_{5i} = \beta_5 + \eta_{5i}$; $\eta \sim N(0, \Sigma)$

[16] We do see an interaction between Total Dwell Time and condition (b_7 = -0.11, SE = 0.05, z = -2.17, p = .03), which suggests that spending more time looking at the two alternatives was associated with not buying in the explicit condition, but unrelated to choice in the implicit condition. This is unrelated to our hypotheses, so we do not discuss it further.

To better understand these results, we reparameterized the model to examine the roles of dwell time on the buy option and dwell time on the non-buy option rather than the roles of relative and total dwell times.[17] In this reparameterized model, we observed that the coefficient for dwell time on the buy option was strongly positive ($b_4 = 2.30$, SE = 0.16, z = 14.55, $p < .001$) but did not vary by condition ($b_6 = 0.03$, SE = 0.10, $z = 0.33$, $p > .5$). In contrast, the coefficient for dwell time on the non-buy option was strongly negative ($b_5 = -2.59$, SE = 0.19, $z = -13.75$, $p < .001$) and varied by condition ($b_7 = -0.26$, SE = 0.11, $z = -2.52$, $p = .01$) such that it was more-strongly negative when opportunity costs were explicit than when they were implicit. In other words, the more that participants looked at the buy option, the more likely they were to buy. The more that participants looked at the non-buy option, the less likely they were to buy, and that relationship was stronger in the explicit condition than the implicit condition (Fig. 4).

We use this final model to decompose the total effect of opportunity cost condition. Using the fitted model, we generate predicted probability of purchase for each participant under each of four scenarios, and then average across participants to calculate the predicted probability of purchase for each scenario. In each scenario, we average across first vs. second position and hold surplus constant at 0. In the implicit scenario, we estimate purchase probability given implicit opportunity costs, with amount of attention to each option estimated from the implicit condition, and weight on attention set to estimates from the implicit condition, leading to a purchase probability of 47%. In the explicit scenario, we estimate purchase probability given explicit opportunity costs, explicit attention amount, and explicit attention weight, leading to a

[17] We used equation 8: $P(Buy_{it}) = logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \beta_{4i}BuyDwell_{it} + \beta_{5i}NonBuyDwell_{it} + \beta_{6i}OppCost_{it}BuyDwell_{it} + \beta_{7i}OppCost_{it}NonBuyDwell_{it})$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\beta_{4i} = \beta_4 + \eta_{4i}$; $\beta_{5i} = \beta_5 + \eta_{5i}$; $\beta_{6i} = \beta_6 + \eta_{6i}$; $\beta_{7i} = \beta_7 + \eta_{7i}$; $\eta \sim N(0, \Sigma)$. We cannot use dwell proportion in this model because two of the coefficients would not be estimable.

purchase probability of 34%. In the amount scenario, we use implicit opportunity costs, implicit attention weight, but explicit attention amount, leading to a purchase probability of 44%, suggesting amount explains approximately 22% of the difference between conditions. In the weight scenario, we use implicit opportunity costs, implicit attention amount, but explicit attention weight, leading to a purchase probability of 41%, suggesting weight explains approximately 47% of the difference between conditions. (Given the uncertainty in parameter estimates and curvature of the logit function, these should be considered rough approximations.)

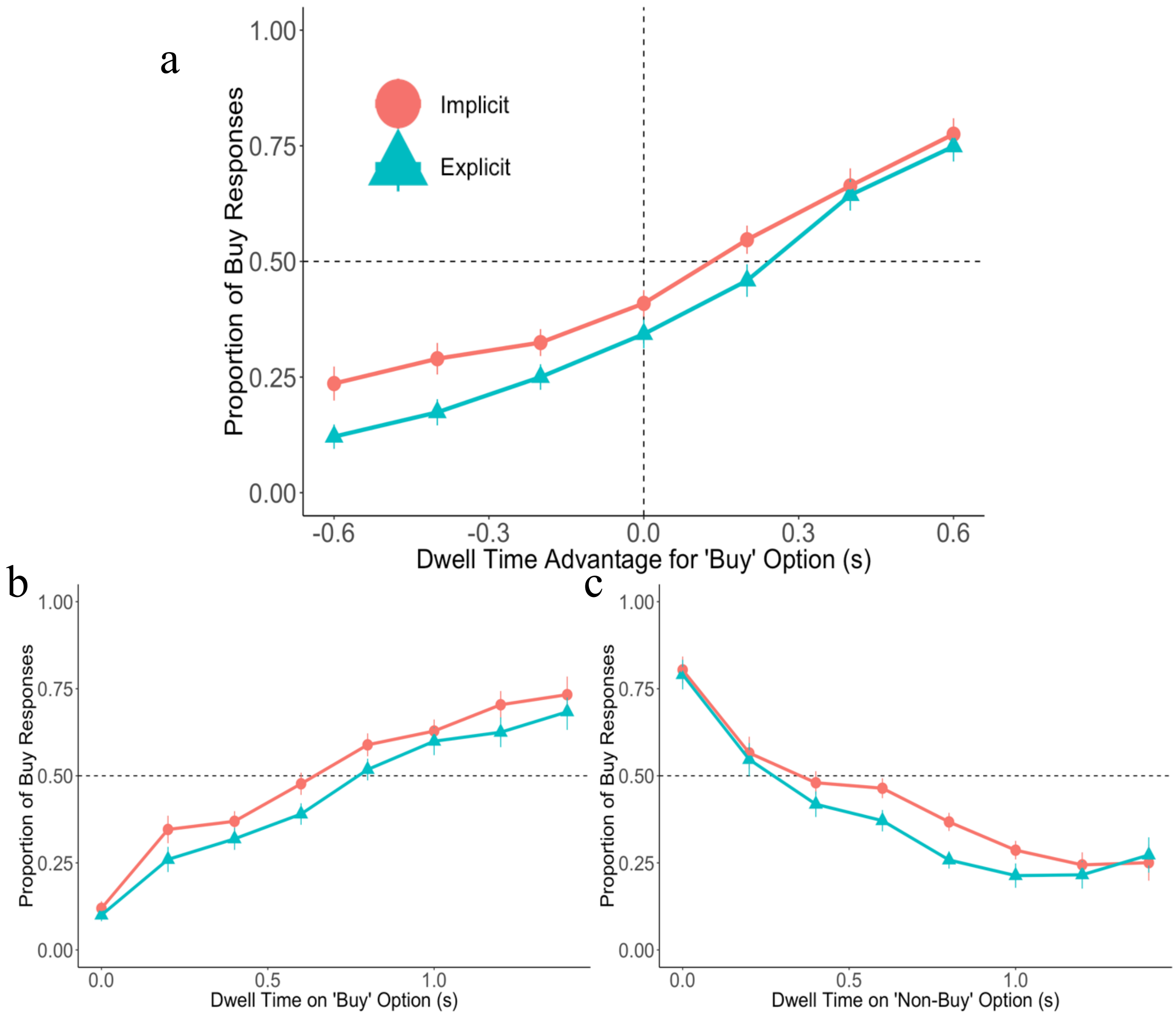

Figure 4. Relationship between attention and choice. As total relative dwell time for the buy option increases (a), the probability of purchase increases; these slopes are marginally different (p = .1). As raw dwell time on the buy option increases (b), the probability of purchase increases;

these slopes are not significantly different ($p > .5$). As raw dwell time on the non-buy option increases (c), the probability of purchase decreases; these slopes are significantly different ($p = .01$). Bars indicate standard error of the mean, clustered by participant ($N = 50$). For display purposes, the dwell times are binned into intervals of 0.2s.

Discussion. Overall, these eye-tracking results provide key evidence for two attentional mechanisms underlying opportunity cost neglect. First, these data demonstrate a shift in the *amount* of attention devoted to the non-buy option when opportunity costs are explicit, and that this shift in the *amount* of attention is predictive of purchasing decisions. Second, these data provide evidence for a difference in the *predictive power* of attention across conditions. Specifically, an extra second spent looking at "Keep $X" is more predictive of choice than an extra second spent looking at "Do Not Buy." Together, these two results illustrate the multiple ways in which attention contributes to purchase rate differences across different levels of opportunity cost salience.

Study 2

Methods

Study 2 serves as both a replication and extension of Study 1. We replicate the original findings in a new sample, and we also demonstrate convergent evidence using different wording for our non-buy options: "Save $X For Later" (explicit) and "Skip $X Purchase" (implicit). These phrases are the same length and have a very similar structure.

Participants

One-hundred and ten university students participated in this preregistered (https://aspredicted.org/7R1_ZMM) study. We determined the sample size a priori. This study was approved by the relevant Internal Review Board and all participants gave informed written consent before participating.

Materials and Procedure

The materials and procedure were identical to Study 1, with the following small changes. First, instead of an EyeLink 1000 Plus (SR Research, Canada), these data were collected using an EyeLink Portable Duo (SR Research, Canada).

During the study, participants were divided into four (rather than two) conditions. In addition to an order manipulation (whether they saw explicit-implicit vs. implicit-explicit), we also manipulated whether participants saw the same non-buy wording in Study 1 ("Don't Buy Food For $X" vs. "Keep $X") or a new set of wording designed to be equivalent in length for both the explicit and implicit conditions ("Skip $X Purchase" vs. "Save $X For Later").

Data Exclusions

As determined in advance, we excluded two participants (N = 2) who chose against their stated WTPs. Among the remaining participants (N = 108), we excluded exceedingly fast or slow decisions (i.e., faster than 250 ms or slower than two standard deviations above the participant-level mean, after taking the logarithm; 4% of trials). We also excluded data from trials in which participants did not fixate on either option (less than 1% of trials). Including these data does not change our findings; see Appendix B in the supplements for tests of our main results.

Results

We ran the same analyses as Study 1, wherever appropriate. We present the results collapsed across wordings and note differences between them at the end of the results section. To preview our findings, we find high similarity in the results between the two studies, especially when looking at the results using proportion (vs. raw amount) of attention. There are some differences between the two wordings; the *amount* hypothesis receives consistent support across wordings (perhaps indicative of a more primitive pathway), whereas support for the *strength* hypothesis depends on the context. For a high-level overview of the results of these two studies, see Table 1. For clarity of exposition, we limit our in-text discussion to hypothesis-relevant coefficients.

Choice Results

Aggregate Analyses. Consistent with Study 1, opportunity cost salience decreased purchase rate (equation 1: $b_0 = -0.072$, $SE = 0.011$, $t(106) = -6.55$, $p < .001$). Averaged across participants, the proportion of trials on which participants purchased was about 7 percentage points lower when opportunity costs were explicit (0.414) rather than implicit (0.489; see Fig. 5). This effect was weaker for people who saw the explicit condition first (1% vs. 14%; $b_1 = 0.067$, $SE = 0.011$, $t(106) = 6.09$, $p < .001$), which is consistent with the finding from Study 1 and the carryover effect detailed in the supplemental posttest (Appendix A).

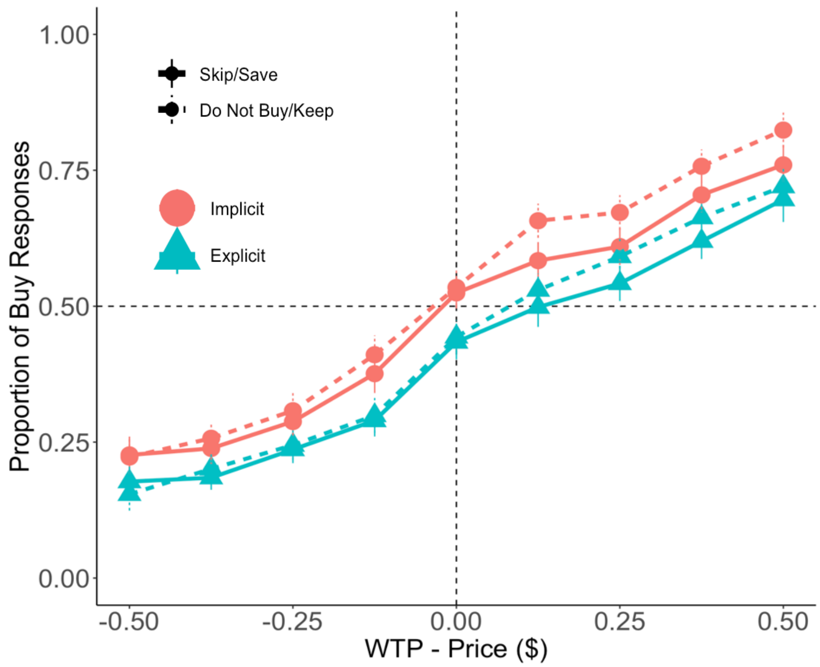

Figure 5. Purchase Behavior as a Function of Surplus (WTP – Price), Condition, and Wording. Participants ($N = 50$) were significantly less likely to purchase in the explicit condition. Bars indicate standard error of the mean, clustered by participant. For display purposes, the surplus is binned into intervals of $0.125. As in Study 1, we do not find evidence for an interaction between surplus and condition; b = -0.10, SE = 0.07, $t = -1.48$, $p = 0.14$.

Disaggregate Analyses. As expected, explicit framing decreased probability of purchase (equation 2: $b_1 = -0.21$, SE = 0.03, $z = -6.76$, $p < .001$; see Fig. 5). Participants were more likely to purchase as WTP increased relative to price ($b_3 = 3.46$, SE = 0.18, $z = 18.96$, $p < .001$).[18] There was also an effect of position ($b_2 = -0.18$, SE = 0.03, $z = -5.82$, $p < .001$) such that purchase rates were lower in the second block than the first. Estimated purchase rate when surplus = 0 was close to chance when opportunity costs were implicit ($m = 0.49$, $z = –0.56$, $p =$

[18] We also estimated equation 2 with separate coefficients on the price and WTP (instead of combining them into the surplus variable). As expected, the coefficients are opposite in direction and nearly identical in size: $b_{Price} = –3.63$, SE = 0.20, $z = –18.50$, $p < .001$; $b_{WTP} = 3.44$, SE = 0.16, $z = 21.05$, $p < .001$. Including both variables leads to convergence issues in more complicated mixed models. Because they are correlated but have (roughly) equal and opposite effects on choice, we simplify the models by using the difference instead.

.58) but below chance when opportunity costs were explicit (m = 0.38, z = –5.16, p < .001), consistent with Study 1.

Discussion. These results replicate the behavioral findings of Study 1: (1) they replicate opportunity cost neglect with incentivized choices, (2) they indicate an effect of opportunity cost salience in repeated choices, and (3) they are consistent with the interpretation that not only choices, but also WTP judgments neglect opportunity costs.

Attention Results

Effect on Attention: Aggregate. As in Study 1, we hypothesized that participants would devote more relative attention to “Keep”/ “Save” than “Do Not Buy”/ “Skip” (in comparison to “Buy”), as tested by the intercept in equations 3a and 3b.

The intercept was not significant in the raw overt attention model (b_0 = –0.016, SE = 0.015, t(106) = –1.06, p = .29), but is directionally in line with participants looking more at the explicit “Keep”/“Save” than the implicit “Do Not Buy”/ “Skip.” When we used standardized overt attention, the intercept was significant (b_0 = –0.015, SE = 0.006, t(106) = –2.45, p = .02), suggesting that participants spent relatively more time looking at the explicit (vs. implicit) non-buy options. The effect did not significantly differ by order in the raw overt attention model (b_1 = –0.017, SE = 0.015, t(106) = –1.17, p = .24), though was in the expected direction, but did differ in the standardized overt attention model (b_1 = –0.018, SE = 0.006, t(106) = –3.01, p = .003).

Effect on Attention: Disaggregate. To examine the distribution of attention across conditions with disaggregate data, we used equations 4a and 4b.

As in the Study 1, the dwell advantage in favor of buy was stronger in the implicit condition than the explicit condition (raw: b_1 = -0.009, SE = 0.007, t(107) = -1.24, p = .22; standardized: b_1 = –0.008, SE = 0.003, t(106) = –2.59, p = .01).

Attention Predicts Choice: Aggregate. As in Study 1, the difference in average dwell time (or proportion) advantage predicting purchase rate difference was significant (raw: $b_2 = 0.38$ per second, $t(104) = 5.83$, $p < .001$; standardized: $b_2 = 1.02$, $t(104) = 6.80$, $p < .001$). If the dwell time advantage were equal in the implicit and explicit conditions, we would expect to find a small difference in the purchase rate (as given by the intercept, raw: $b_0 = -0.068$, SE = 0.010, $t(104) = -7.06$, $p < .001$; standardized: $b_0 = -0.058$, SE = 0.010, $t(104) = -6.20$, $p < .001$; compare to total effect of -.072 above). This indicates that the difference in purchase rates is not eliminated when equating dwell time in the two conditions.

Attention Predicts Choice: Disaggregate. At the trial level (i.e., in equations 6a and 6b), buy dwell advantage was a strong predictor of choice (raw: $b_4 = 2.07$, SE = 0.11, $z = 17.98$, $p < .001$; standardized: $b_4 = 6.11$, SE = 0.29, $z = 20.93$, $p < .001$); total dwell time was marginally significant (raw: $b_5 = -0.08$, SE = 0.05, $z = -1.79$, $p = .07$; not estimable in standardized model).

Differential Relationship with Attention: Disaggregate. As in Study 1, the analyses above suggest that the relative *amount* of attention devoted to the non-buy option is directionally larger in the explicit condition, and that this difference contributes to the observed purchase rate differences. Next, we look at the other hypothesized pathway: the *strength* of attention.

In equations 7a and 7b, buy dwell advantage was more positively related to purchase in the explicit condition than the implicit condition (raw: $b_6 = 0.13$, SE = 0.05, $z = 2.44$, $p = .01$; standardized: $b_5 = 0.24$, SE = 0.15, $z = 1.62$, $p = .11$; Fig. 6a), as in Study 1.

In equation 8, we observe that the coefficient for dwell time on the buy option is strongly positive ($b_4 = 1.99$, SE = 0.11, z = 17.24, $p < .001$) but does not vary by opportunity cost condition ($b_6 = 0.08$, SE = 0.06, $z = 1.31$, $p = .19$; Fig. 6b). In contrast, the coefficient for dwell time on the non-buy option is strongly negative ($b_5 = -2.23$, SE = 0.13, $z = -17.41$, $p < .001$) and varies by opportunity cost condition (b_7 = -0.18 SE = 0.07, z = -2.72, p = .006) such that it is more-strongly negative when opportunity costs are explicit than when they are implicit (Fig. 6c). These findings are consistent with Study 1.

We use this final model to decompose the total effect of opportunity cost condition using the same approach as in Study 1. In the *implicit* scenario, we estimate purchase probability given implicit opportunity costs, implicit attention amount, and implicit attention weight, leading to a purchase probability of 49%. In the *explicit* scenario, we estimate purchase probability given explicit opportunity costs, explicit attention amount, and explicit attention weight, leading to a purchase probability of 38%. In the *amount* scenario, we use implicit opportunity costs, implicit attention weight, but explicit attention amount, leading to a purchase probability of 48%, suggesting amount explains approximately 7% of the difference between conditions. In the *weight* scenario, we use implicit opportunity costs, implicit attention amount, but explicit attention weight, leading to a purchase probability of 46%, suggesting weight explains approximately 28% of the difference between conditions. (As in Study 1, these should be considered rough approximations.)

Discussion. Overall, these eye-tracking results provide additional evidence for the two attentional mechanisms identified in Study 1: *amount* and *strength* of attention.

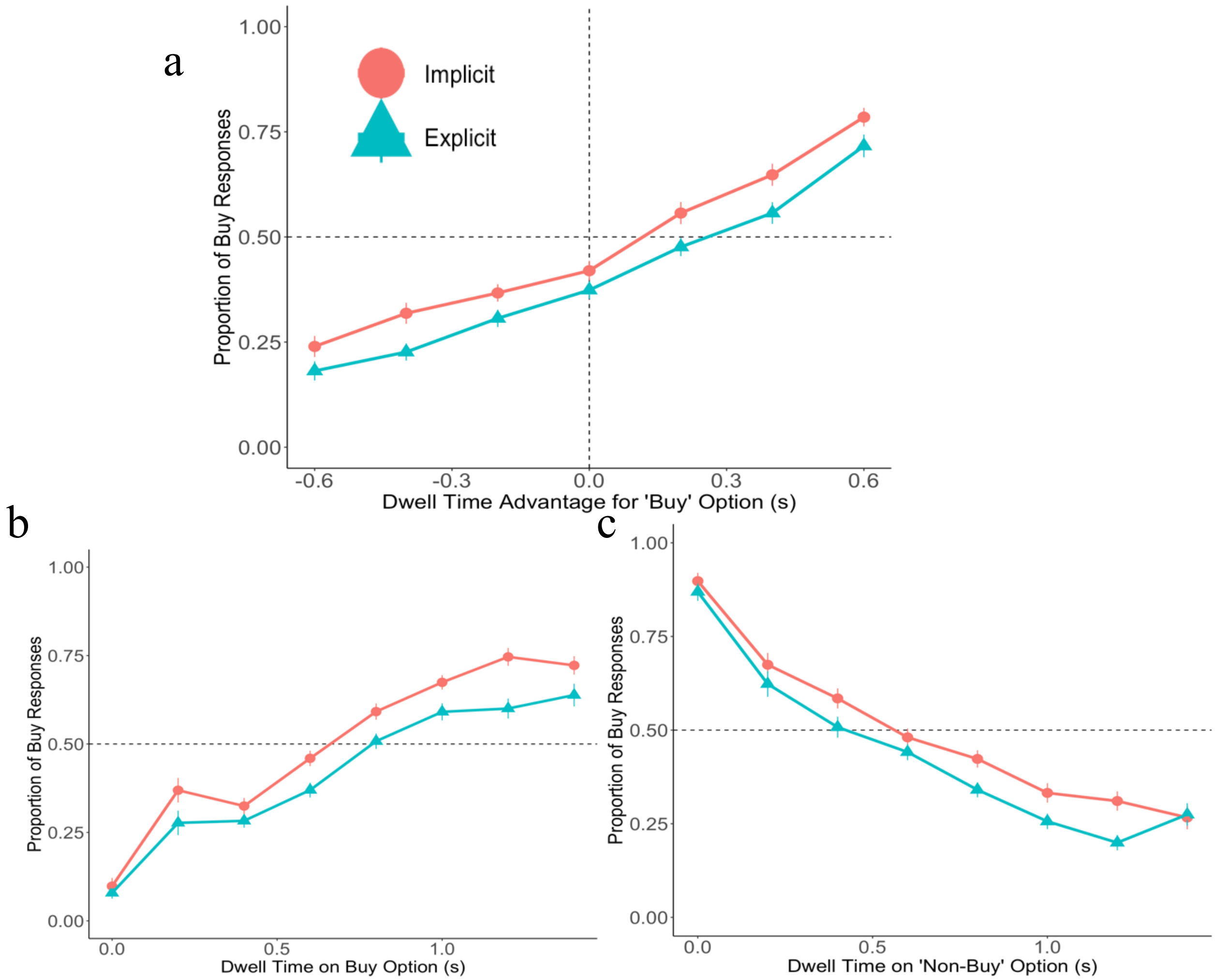

Figure 6. Relationship Between Attention and Choice. As total relative dwell time for the buy option increases (a), the probability of purchase increases; these slopes are significantly different (p = .01) such that dwell time advantage is more predictive of choice in the explicit condition. As raw dwell time on the buy option increases (b), the probability of purchase increases; these slopes do not statistically differ (p = .19). As raw dwell time on the non-buy option increases (c), the probability of purchase decreases; these slopes are significantly different (p = .006) such that dwell time on the non-buy option is more predictive of choice in the explicit condition. Bars indicate standard error of the mean, clustered by participant (N = 108). For display purposes, the dwell times are binned into intervals of 0.2s.

Table 1. Main Results Across Studies

Analysis	Study 1 - Wording 1 (N = 50)	Study 2 - Wording 1 (N = 54)	Study 2 - Wording 2 (N = 54)	Study 2 - Combined (N = 108)	Wording Interaction
Eq. 1: Purchase Rate Difference ~ b0 + b1*Order	b0 = 0.078 (0.017)***	b0 = 0.084 (0.015)***	b0 = 0.060 (0.016)***	b0 = 0.072 (0.011)***	b = 0.024 (0.022)
Eq. 2: Buy ~ b0 + b1*Position + b2*OppCost + b3*Surplus	b2 = –0.21 (0.05)***	b2 = –0.24 (0.04)***	b2 = –0.17 (0.04)***	b2 = –0.21 (0.03)***	b = –0.07 (0.06)
Eq. 3a: Buy Dwell Advantage Difference ~ b0 + b1*Order	b0 = –0.050 (0.023)*	b0 = 0.017 (0.022)	b0 = –0.049 (0.019)*	b0 = –0.016 (0.015)	b = 0.065 (0.029)*
Eq. 3b: Buy Dwell Proportion Difference ~ b0 + b1*Order	b0 = –0.034 (0.011)**	b0 = –0.015 (0.010)	b0 = –0.014 (0.007)*	b0 = –0.015 (0.006)*	b = –0.001 (0.012)
Eq. 4a: Buy Dwell Advantage ~ b0 + b1*OppCost + b2*Position + b3*Surplus	b1 = –0.025 (0.011)*	b1 = 0.008 (0.011)	b1 = –0.027 (0.010)**	b1 = –0.009 (0.007)	b = 0.030 (0.014)*
Eq. 4b: Buy Dwell Proportion ~ b0 + b1*OppCost + b2*Position + b3*Surplus	b1 = –0.017 (0.005)**	b1 = –0.008 (0.005)	b1 = –0.008 (0.003)*	b1 = –0.008 (0.003)*	b = –0.001 (0.006)
Eq. 5a: Purchase Rate Difference ~ b0 + b1*Order + b2*BuyDwellAdvantageDifference + b3*MCBuyDwellAdvantageSum	b2 = 0.40 (0.10)***	b2 = 0.33 (0.09)***	b2 = 0.53 (0.09)***	b2 = 0.38 (0.06)***	b = –0.23 (0.12)
Eq. 5b: Purchase Rate Difference ~ b0 + b1*Order + b2*BuyDwellProportionDifference + b3*MCBuyDwellProportionSum	b2 = 1.27 (0.16)***	b2 = 0.94 (0.18)***	b2 = 1.32 (0.28)***	b2 = 1.02 (0.15)***	b = –0.47 (0.30)
Eq. 6a: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwellAdvantage + b5*MCTotalDwell	b4 = 2.40 (0.16)***	b4 = 2.25 (0.16)***	b4 = 1.89 (0.16)***	b4 = 2.07 (0.11)***	b = 0.36 (0.23)
Eq. 6b: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwellProportion	b4 = 5.59 (0.32)***	b4 = 6.40 (0.41)***	b4 = 5.81 (0.41)***	b4 = 6.11 (0.29)***	b = 0.37 (0.66)
Eq. 7a: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwellAdvantage + b5*MCTotalDwell + b6*OppCost*BuyDwellAdvantage + b7*OppCost*TotalDwell	b6 = 0.14 (0.09)	b6 = 0.28 (0.08)***	b6 = 0.003 (0.08)	b6 = 0.13 (0.05)*	b = 0.25 (0.11)*
Eq. 7b: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwellProportion + b5*OppCost*BuyDwellProportion	b5 = 0.43 (0.22)*	b5 = 0.57 (0.21)**	b5 = –0.03 (0.21)	b5 = 0.24 (0.15)	b = 0.66 (0.31)*
Eq. 8: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwell + b5*NonBuyDwell + b6*OppCost*BuyDwell + b7*OppCost*NonBuyDwell	b6 = 0.03 (0.10) b7 = –0.26 (0.11)*	b6 = 0.21 (0.09)* b7 = –0.35 (0.10)***	b6 = –0.03 (0.08) b7 = –0.04 (0.09)	b6 = 0.08 (0.06) b7 = –0.18 (0.07)**	b = 0.24 (0.12)* b = –0.30 (0.14)*

Effects of Wording

As seen in Table 1, we find some significant interactions in our main analyses of interest, suggesting that some of our results may be sensitive to whether participants saw Wording 1 ("keep"/"do not buy") or Wording 2 ("save"/"skip"). Choice behavior (equations 1 and 2) is not significantly impacted by wording. We do see interactions between wording and opportunity cost frame when predicting attention, though only while using raw (equations 3a and 4a) – but not standardized (equations 3b and 4b) attention. There is not a significant difference between wording conditions in the relationship between attention and choice (equations 5 and 6). Instead, the most consistent difference we see between wording conditions is in the interaction between opportunity cost frame and the attention-choice link (equations 7 and 8). Specifically, we see a significant three-way interaction, such that there is larger interaction between opportunity cost frame and the attention-choice relationship in Wording 1 ("keep"/"do not buy") than in Wording 2 ("save"/"skip"). This supports the notion that the *strength* mechanism might be more sensitive to contextual features than the *amount* mechanism.

Computational Modeling Results

We also analyzed the data from Studies 1 and 2 together in a sequential sampling framework. Sequential sampling models (SSMs) assume that over the course of a decision, the decision maker accumulates evidence in favor of each alternative. Once the decision maker has enough evidence in favor of one alternative, a choice is made. SSMs typically have a number of parameters that capture different facets of the decision process (e.g., response threshold, processing speed, noise). There are a variety of SSMs that have been used to better understand the decision-making process and in particular, how attention and decision-making interact (Krajbich and Smith 2015).

In the current paper, we use the drift diffusion model (DDM; Ratcliff, 1978) and its attention-informed extension, the attentional DDM (aDDM; Krajbich et al. 2010). In the aDDM, more evidence is gathered for the looked-at option than the non-looked-at option. Therefore, as decision makers shift their attention from one option to the other, the net evidence accumulation rate (for one option vs. the other) shifts as well. The degree to which decision makers discount the evidence for the non-looked-at option is characterized by a parameter, θ. This parameter serves as a multiplicative discount on the non-looked at option. As a concrete example, consider a decision maker choosing between options A and B with subjective values of 10 and 5, respectively. While the decision maker looks at option A (with value = 10), the non-looked at option (option B) has an effective value of $5 \cdot \theta$ for the entire duration of the fixation. Alternatively, while the decision maker looks at option B (with value = 5), option A has an effective value of $10 \cdot \theta$. Generally, θ is assumed to take on values between 0 (implying complete discounting of the non-looked at option) and 1 (implying no attentional discounting at all). Thus, decision makers accumulate (multiplicatively) more evidence for options when they are looked at than when they are not looked at. The precise value of θ (which can be fit in multiple ways) quantifies the magnitude of attentional effects in the choice process, with lower values implying a stronger attentional effect.

Adapting the aDDM

Based on the results of the eye-tracking analyses above (which suggest that attention to the non-buy option contributes to the purchase rate effect more than attention to the buy option), we decided to extend the aDDM. Fitting the aDDM with only one attentional parameter (θ) (as is typically done) would constrain the attentional discount to be the same for both options. Thus, in this paper, we introduce an extension of the aDDM that allows for different attentional discounting parameters for each option. The formulation of attention-dependent evidence accumulation rate for purchasing (i.e., a decision to buy) is detailed below:

(9) Look at buy option: $v = d_B X_B - \theta_N d_N X_N$

(10) Look at non-buy option: $v = \theta_B d_B X_B - d_N X_N$

Here, v is the average rate of evidence accumulation in favor of the buy option (i.e., the "drift rate"), d_i is a fitted scaling parameter (to convert values into units of evidence), X_B is the value of the buy option (i.e., the WTP), X_N is the value of the non-buy option (i.e., the price[19]), θ_B is the discount on the buy option when it is not being looked at, and θ_N is the discount on the non-buy option when it is not being looked at. By estimating separate θ_i for each option, we can compare the size of the attentional discount on each option. We can also compare the discount on a given option (e.g., the non-buy option) across conditions.

We hypothesized (pre-registered) that the non-buy option would be discounted less in the explicit condition, because participants would be more focused on the money when peripherally considering "Keep" compared to "Do Not Buy." That is, when participants are looking at "Buy," we expected them to discount "Keep" less than they discount "Do Not Buy." We also compared the attentional discounts on the buy options (between the explicit and implicit conditions). If "Keep" requires and/or attracts more focus than "Do Not Buy," we would expect "Buy" to be discounted more while looking at "Keep" than while looking at "Do Not Buy." We did not explicitly pre-register this second hypothesis, but it follows from the first, given the notion that "Keep" requires more focus than "Do Not Buy," regardless of gaze location.

[19] In the strictest sense, the value of the buy option is equal to *WTP* + *Endowment* – *Price* and the value of the non-buy option is equal to *Endowment*. However, the endowment is present in both options and thus irrelevant to the decision. At its core, the decision is to take the item (*WTP*) or take the money (*Price*).

Model Results

Recent research (Cavanagh et al. 2014; Smith, Krajbich, and Webb 2019) has demonstrated the usefulness and efficiency of a random utility model (RUM) in estimating the attentional discounting parameter θ_i. More specifically, the attentional effect can be estimated using a traditional logistic regression. The derivation of this method for our extension of the aDDM is available in the supplements (Appendix C). We can estimate the θ_i in a mixed-effects logistic regression (with choice as a binary variable, where choosing to buy = 1, and random slopes and intercepts at the participant level). When we estimate this regression separately for the two conditions (collapsed across both studies and wordings), we find what we hypothesized: a lower θ_B in the explicit (vs. implicit) condition and a higher θ_N in the explicit (vs. implicit) condition (Table 2).[20]

Table 2. 95% CI of θ_i

	Explicit	Implicit	Difference (Explicit-Implicit)
θ_B	[0.14, 0.36]	[0.28, 0.51]	[-0.29, 0.004]
θ_N	[0.49, 0.82]	[0.46, 0.73]	[-0.12, 0.25]

Note. These CIs are estimated using all data (Studies 1 and 2, collapsed). Because θ is a multiplicative attentional discount, a lower point estimate implies greater attentional discounting. θ_B is the discount on the buy option when it is not looked at, and θ_N is the discount on the non-buy option when it is not looked at.

Interestingly, the attentional discounts on the buy option were much stronger than those on the non-buy options. This aligns with past work finding less attentional discounting in purchasing decisions (Krajbich et al. 2012) compared to choices between goods (Krajbich et al.

[20] Separate attentional discounting parameters are recoverable with this RUM approach. See Appendix D in the supplementary material for more detail on our recovery exercise.

2010; Krajbich and Rangel 2011). Moreover, the weak discount on “Keep” ([0.49, 0.82], Table 2) implies that substantial evidence is gathered for “Keep,” even when it is not the currently looked-at option.

In this project, we were particularly interested in the differences in θ_i across conditions (i.e., explicit vs. implicit). The 95% confidence interval of the difference in θ_B nearly excludes 0 and the 95% confidence interval of the difference in θ_N does not exclude 0 (Fig. 7). The details on the computation of these confidence intervals are in Appendix E in the supplements.

These patterns are consistent with the regression results (under *Differential Relationship with Attention: Disaggregate*, in particular). The smaller θ_B in the explicit condition indicates that drift rate more strongly favors not purchasing when looking at “Keep” compared to “Do Not Buy.” This implies that choice is more strongly associated with gaze to “Keep” than to “Do Not Buy.” This stronger association is similarly implied by the significant interaction between condition and dwell time on the non-buy option reported earlier. The lack of a significant difference in θ_N between conditions is consistent with the nonsignificant interaction between condition and dwell time on the buy option reported earlier.

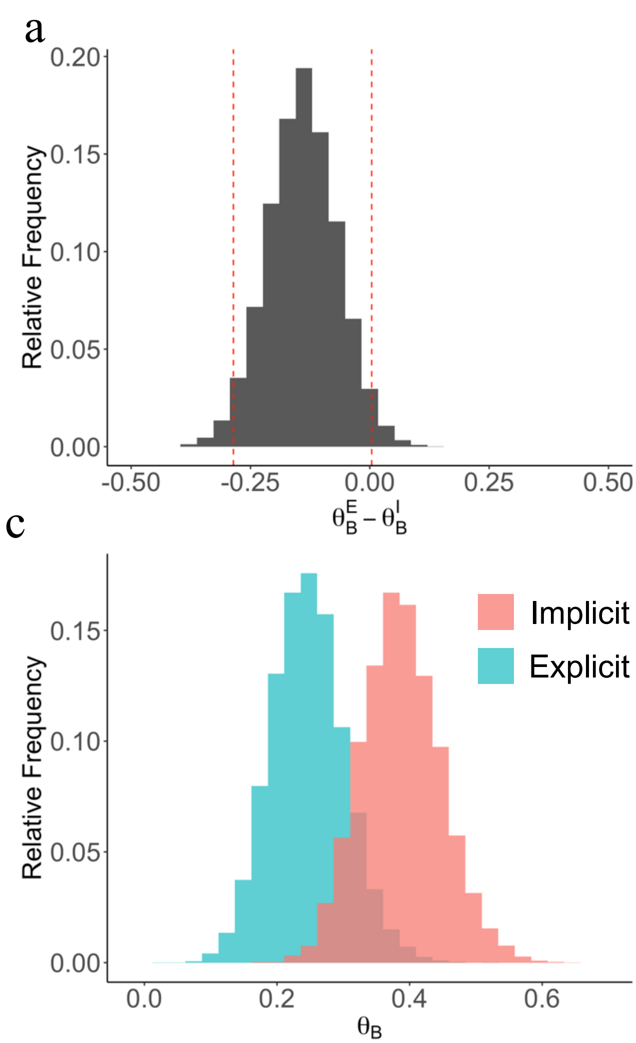

Figure 7. Approximate Distributions of Parameters. The discount on the buy option is stronger in the explicit (vs. implicit) condition (a, c). The 95% confidence interval (red dashed lines) on the difference in θ_B between the conditions (a) is [–0.29, 0.004]. The 95% confidence intervals for θ_B (c) are: explicit = [0.14, 0.36]; implicit = [0.28, 0.51]. The discount on the non-buy option is stronger in the implicit (vs. explicit) condition (b, d). The 95% confidence interval (red dashed lines) on the difference in θ_N between the conditions (b) is [–0.12, 0.25]. The 95% confidence intervals for θ_N (d) are: explicit = [0.49, 0.82]; implicit = [0.4, 0.73].

Discussion

These computational modeling results provide another lens through which to examine the relationship between attention, opportunity cost salience, and choices. The SSM framework (and more specifically, our adaptation of the aDDM) enables magnitude estimates of attention's connection to choice. Overall, the computational modeling results (stronger attentional discounting of "Buy" in the explicit condition) provide evidence consistent with a process-driven explanation for the decline in purchase rates when opportunity costs are made explicit. In Appendices F and G in the supplement, we consider how the model varies across the different slices of the data. Consistent with the regression results presented earlier, we find stronger evidence for different θ (and in particular, θ_B) under the "Keep" vs. "Do Not Buy" wording and weaker evidence under the "Save" vs. "Skip" wording. In Appendix H, we have included hierarchical Bayesian model fits (estimated using HSSM; Fengler et al., in preparation), where we test for parameter differences across conditions in boundary separation and starting point.

General Discussion

Overall, we provide evidence for the precise roles of attention in opportunity cost neglect and consideration. In particular, we demonstrate that purchase choices and attention are strongly linked in multiple ways. Participants devote relatively more dwell time to "Keep" or "Save" than they do to "Do Not Buy" or "Skip" — even though these two options have identical outcomes. In addition to spending *more* time on the explicit option, the marginal *strength* of their attention is also greater when they are looking at "Keep" compared to "Do Not Buy." Together, these two factors (*amount* and *strength* of attention) help to explain the difference in purchase rates observed between situations with implicit vs. explicit opportunity costs.

This work has important implications for decision framing, especially in situations where opportunity costs might be visible and/or attention-grabbing. For instance, highlighting consumers' other options for spending their money as a way to show affordability may backfire, due to the increased salience of — and subsequent attention paid to — the opportunity cost (cf. Gourville 1998). People who spontaneously consider opportunity costs even in the absence of explicit reminders may be more likely to attend to options in a way that is unaffected by opportunity cost frame (Shah et al. 2018; Shah, Shafir, and Mullainathan 2015; but cf. Plantinga et al. 2018). More broadly, this research enhances our understanding of "whether or not" decisions about whether to accept a given target alternative, where not accepting that alternative implies accepting an outside alternative (Jones et al. 1998; Frederick et al. 2009; Spiller 2011; Greenberg and Spiller 2016).

The computational model that we used in this study extends the original model of visual attention in choice, the attentional drift diffusion model (aDDM), in that it allows the attentional discount rate to differ based on the option. Giving the model this added flexibility revealed that money is easier to peripherally evaluate than consumer goods, as conjectured in prior work (Krajbich et al. 2012) and supported by the fact that θ_N was substantially greater than θ_B. Moreover, the modeling confirmed that the explicit opportunity cost framing has a substantial effect on these discount rates, increasing the discount on the buy option and decreasing the discount on the non-buy option. In other words, the explicit opportunity cost holds more focus, regardless of gaze location.

This study exemplifies the potential value for application of computational cognitive models to economic behavior. Beyond opportunity costs, more formal process modeling has the potential to enhance our understanding of other tradeoffs that people regularly make (between time and money, quality and price, etc.).

Naturally, there are several limitations to this study. First, since we did not manipulate attention, we cannot use this data to assert a causal relationship between attention and choice. However, previous research has provided evidence in support of a causal link (e.g., Armel et al. 2008; Gwinn et al. 2019; Lim et al. 2011; Milosavljevic et al. 2012; Pärnamets et al. 2015; Towal et al. 2013; Bhatnagar & Orquin 2022; cf. Ghaffari and Fiedler 2018; Newell and Le Pelley 2018; Mormann & Russo 2021). Second, there are some key differences between this experimental setup and the situation experienced outside of the lab. Specifically, when deciding whether to buy a product, consumers often only have two visual cues: the product and the price. The decision options (purchase vs. don't purchase) are not always presented visually. In our study, however, the decision options were visually presented, which is what allowed us to manipulate the opportunity cost framing. This experimental set-up is commensurate with past research in both areas (opportunity cost consideration: Frederick et al. 2009; Greenberg and Spiller 2016; Plantinga et al. 2018; attention in choice: Ghaffari and Fiedler 2018; Krajbich et al. 2012; Newell and Le Pelley 2018; Pärnamets et al. 2015). However, the field stands to gain additional insight from a more ecologically valid set-up. A related concern is that visual attention is just an ancillary feature that correlates with the actual process involved in these decisions (e.g., Mormann & Russo, 2021). We can not formally rule out this possibility. However, it is important to note that shifts in visual attention are not necessary to make these decisions. A participant could look at one of the options (e.g., Buy Food for $2.00), and know (without shifting their visual attention) exactly what the other option entails (e.g., not buying the food for $2.00). But, in so far as the participants in our study do look at both options, often shifting their attention back and forth multiple times, we can infer that the patterns of attention are (at the very least) a marker of the underlying process. Furthermore, the methods in this paper are limited to a single product type (snack food), with relatively low subjective and objective value. Future research in other product types or with different task set-ups would stand to increase the generalizability of these results.

Future research might also consider looking into the persistence of this type of framing effect. We observe a large (and substantively and statistically significant) effect of opportunity cost salience in the first block but a small (and not statistically significant) effect of opportunity cost salience in the second block. The posttest reported in detail in Appendix A in the supplement finds support for differential carryover, such that explicit opportunity costs at the beginning can induce subsequent opportunity cost consideration, even if the opportunity costs are no longer explicit. The eye-tracking studies were not sufficiently powered to disentangle this explanation from an overall effect of position or average carryover effect. Given that such differential carryover effects appear to hold, it is worth asking whether it is possible to cause a decrease in purchase rates for an extended period of time, and if so, how short and simple an effective intervention could be.

Another avenue for future research is to investigate the applicability of this modeling approach in other scenarios. For example, does the inclusion of separate attentional discounting parameters for different options help explain other choice biases (e.g., context effects, valence-framing effects)? A complementary investigation would be into other SSMs. The aDDM is one model that has been shown to account for the relationships between attention, response times, and choices, but there are other models, as well (e.g., decision field theory {e.g., Busemeyer and Townsend 1993; Busemeyer and Diedrich 2002} linear ballistic accumulator {e.g., Brown and Heathcote 2008; Trueblood, Brown, and Heathcote 2014}, and other related models {e.g., Bhatia 2013; Westbrook et al. 2020; Callaway et al. 2021; Jang et al. 2021; Li and Ma 2021}), and the field stands to gain additional knowledge about the underlying decision process by comparing models of decision making.

Ultimately, this research enhances the important connection between research on choice and research on visual attention (Russo and Leclerc 1994; Pieters and Wedel 2004; Pieters and Wedel 2017; Mormann et al. 2020; Mormann & Russo 2021). We provide evidence for a two-part attentional mechanism in the connection between opportunity cost consideration and purchasing decisions: explicit opportunity costs change not only the amount of attention devoted to the non-buy option, but they can also change the strength of the relationship between visual attention and the decision to purchase.

References

Amasino, D. R., Sullivan, N. J., Kranton, R. E., and Huettel, S. A. (2019). Amount and time exert independent influences on intertemporal choice. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-019-0537-2

Armel, K. C., Beaumel, A., and Rangel, A. (2008). Biasing simple choices by manipulating relative visual attention. *Judgment and Decision Making*, *3*(5), 396–403.

Aschenbrenner, K. M., Albert, D., and Schmalhofer, F. (1984). Stochastic choice heuristics. *Acta Psychologica*, *56*(1-3), 153-166.

Atalay, A. S., Bodur, H. O., and Rasolofoarison, D. (2012). Shining in the center: Central gaze cascade effect on product choice. *Journal of Consumer Research*, *39*(4), 848–866.

Bartels, D. M., and Urminsky, O. (2015). To know and to care: How awareness and valuation of the future jointly shape consumer spending. *Journal of Consumer Research*, *41*(6), 1469-1485.

Becker, G. M., DeGroot, M. H., and Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behavioral Science*, *9*(3), 226.

Becker, S. W., Ronen, J., and Sorter, G. H. (1974). Opportunity costs-an experimental approach. *Journal of Accounting Research*, 317-329.

Bhatia, S. (2013). Associations and the accumulation of preference. *Psychological Review*, *120*(3), 522.

Bhatia, S., and Pleskac, T. J. (2019). Preference accumulation as a process model of desirability ratings. *Cognitive Psychology*, *109*, 47–67. https://doi.org/10.1016/j.cogpsych.2018.12.003

Bhatnagar, R., & Orquin, J. L. (2022). A meta-analysis on the effect of visual attention on choice. *Journal of Experimental Psychology: General*, *151*(10), 2265.

Bhui, R. (2019). Testing optimal timing in value-linked decision making. *Computational Brain & Behavior*, *2*(2), 85-94.

Bogacz, R. (2007). Optimal decision-making theories: Linking neurobiology with behaviour. *Trends in Cognitive Sciences*, *11*(3), 118–125. https://doi.org/10.1016/j.tics.2006.12.006

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, *10*, 433–436.

Busemeyer, J. R. (1982). Choice behavior in a sequential decision-making task. *Organizational Behavior and Human Performance*, *29*(2), 175-207.

Busemeyer, J. R., and Diederich, A. (2002). Survey of decision field theory. *Mathematical Social Sciences*, *43*(3), 345-370.

Callaway, F., Rangel, A., & Griffiths, T. L. (2021). Fixation patterns in simple choice reflect optimal information sampling. *PLoS computational biology*, *17*(3), e1008863.

Cavanagh, J. F., Wiecki, T. V., Kochar, A., and Frank, M. J. (2014). Eye tracking and pupillometry are indicators of dissociable latent decision processes. *Journal of Experimental Psychology: General*, *143*(4), 1476–1488. https://doi.org/10.1037/a0035813

Chandon, P., Hutchinson, J. W., Bradlow, E. T., and Young, S. H. (2020). Does In-Store Marketing Work? Effects of the Number and Position of Shelf Facings on Brand Attention and Evaluation at the Point of Purchase. *Journal of Marketing*, *73*(6), 1–17.

Chatterjee, S., Rai, D., and Heath, T. B. (2016). Tradeoff between time and money: The asymmetric consideration of opportunity costs. *Journal of Business Research*, *69*(7), 2560-2566.

Fengler, A., Xu, Y., Bera, K., Omar, A., and Frank, M.J. (in preparation). HSSM: A generalized toolbox for hierarchical bayesian estimation of computational models in cognitive neuroscience.

Fiedler, S., and Glöckner, A. (2012). The Dynamics of Decision Making in Risky Choice: An Eye-Tracking Analysis. *Frontiers in Psychology*, *3*. https://doi.org/10.3389/fpsyg.2012.00335

Fiedler, S., Glöckner, A., Nicklisch, A., and Dickert, S. (2013). Social Value Orientation and information search in social dilemmas: An eye-tracking analysis. *Organizational Behavior and Human Decision Processes*, *120*(2), 272–284. https://doi.org/10.1016/j.obhdp.2012.07.002

Fisher, G. (2017). An attentional drift diffusion model over binary-attribute choice. *Cognition*, *168*, 34-45.

Fisher, G. (2021). A multiattribute attentional drift diffusion model. *Organizational Behavior and Human Decision Processes*, *165*, 167-182.

Fisher, G. (2021). Intertemporal choices are causally influenced by fluctuations in visual attention. *Management Science*, *67*(8), 4961-4981.

Folke, T., Jacobsen, C., Fleming, S. M., and Martino, B. D. (2016). Explicit representation of confidence informs future value-based decisions. *Nature Human Behaviour*, *1*, 0002. https://doi.org/10.1038/s41562-016-0002

Frederick, S., Novemsky, N., Wang, J., Dhar, R., and Nowlis, S. (2009). Opportunity Cost Neglect. *Journal of Consumer Research*, *36*(4), 553–561. https://doi.org/10.1086/599764

Friedman, L. A., and Neumann, B. R. (1980). The effects of opportunity costs on project investment decisions: A replication and extension. *Journal of Accounting Research*, 407-419.

Ghaffari, M., and Fiedler, S. (2018). The Power of Attention: Using Eye Gaze to Predict Other-Regarding and Moral Choices. *Psychological Science*, *29*(11), 1878–1889. https://doi.org/10.1177/0956797618799301

Glickman, M., Sharoni, O., Levy, D. J., Niebur, E., Stuphorn, V., and Usher, M. (2019). The formation of preference in risky choice. *PLoS: Computational Biology*, *15*(8), e1007201.

Gluth, S., Kern, N., Kortmann, M., and Vitali, C. L. (2020). Value-based attention but not divisive normalization influences decisions with multiple alternatives. *Nature Human Behaviour*. https://doi.org/10.1038/s41562-020-0822-0

Gourville, J. T. (1998). Pennies-a-day: The effect of temporal reframing on transaction evaluation. *Journal of Consumer Research*, *24*(4), 395-408.

Greenberg, A. E., and Spiller, S. A. (2016). Opportunity cost neglect attenuates the effect of choices on preferences. *Psychological Science*, *27*(1), 103-113.

Gwinn, R., Leber, A. B., and Krajbich, I. (2019). The spillover effects of attentional learning on value-based choice. *Cognition*, *182*, 294–306. https://doi.org/10.1016/j.cognition.2018.10.012

Hayes, A. F. (2013). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.

Jang, A. I., Sharma, R., & Drugowitsch, J. (2021). Optimal policy for attention-modulated decisions explains human fixation behavior. *Elife*, *10*, e63436.

Jones, S. K., Frisch, D., Yurak, T. J., and Kim, E. (1998). Choices and opportunities: Another effect of framing on decisions. *Journal of Behavioral Decision Making*, *11*(3), 211-226.

Kim, B., Seligman, D., and Kable, J. W. (2012). Preference reversals in decision making under risk are accompanied by changes in attention to different attributes. *Frontiers in Neuroscience*, *6*, 109.

Kleiner, M., Brainard, D., Pelli, D., Ingling, A., Murray, R., Broussard, C., and others. (2007). What's new in Psychtoolbox-3. *Perception*, *36*(14), 1.

Konovalov, A., and Krajbich, I. (2016). Gaze data reveal distinct choice processes underlying model-based and model-free reinforcement learning. *Nature Communications*, *7*, 12438. https://doi.org/10.1038/ncomms12438

Krajbich, I., Armel, C., and Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298. https://doi.org/10.1038/nn.2635

Krajbich, I., Lu, D., Camerer, C., and Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in Psychology*, *3*. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3374478/

Krajbich, I., and Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences*, *108*(33), 13852–13857. https://doi.org/10.1073/pnas.1101328108

Laming, D. R. J. (1968). *Information theory of choice-reaction times*. Academic Press.

Legrenzi, P., Girotto, V., and Johnson-Laird, P. N. (1993). Focusing in reasoning and decision making. *Cognition*, *49*(1-2), 37-66.

Li, Z. W., & Ma, W. J. (2021). An uncertainty-based model of the effects of fixation on choice. *PLoS computational biology*, *17*(8), e1009190.

Lim, S.-L., O'Doherty, J. P., and Rangel, A. (2011). The decision value computations in the vmPFC and striatum use a relative value code that is guided by visual attention. *The Journal of Neuroscience*, *31*(37), 13214–13223.

Link, S. W. (1975). The relative judgment theory of two choice response time. *Journal of Mathematical Psychology*, *12*(1), 114–135. https://doi.org/10.1016/0022-2496(75)90053-X

MATLAB (Version 8.3). (2014). Natick, MA: The MathWorks Inc.

Magen, E., Dweck, C. S., and Gross, J. J. (2008). The hidden zero effect: Representing a single choice as an extended sequence reduces impulsive choice. *Psychological Science*, *19*(7), 648-649.

Milosavljevic, M. M., Navalpakkam, V., Koch, C., and Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, *22*(1). Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1998433

Montoya, A. K., and Hayes, A. F. (2017). Two-condition within-participant statistical mediation analysis: A path-analytic framework. *Psychological Methods*, *22*(1), 6-27.

Mormann, M., & Russo, J. E. (2021). Does attention increase the value of choice alternatives?. *Trends in cognitive sciences*, *25*(4), 305-315.

Mormann, M., Griffiths, T., Janiszewski, C., Russo, J. E., Aribarg, A., Ashby, N. J. S., Bagchi, R., Bhatia, S., Kovacheva, A., Meissner, M., and Mrkva, K. J. (2020). Time to pay attention to attention: Using attention-based process traces to better understand consumer decision-making. *Marketing Letters*. https://doi.org/10.1007/s11002-020-09520-0

Newell, B. R., and Le Pelley, M. E. (2018). Perceptual but not complex moral judgments can be biased by exploiting the dynamics of eye-gaze. *Journal of Experimental Psychology: General*, *147*(3), 409–417. https://doi.org/10.1037/xge0000386

Northcraft, G. B., and Neale, M. A. (1986). Opportunity costs and the framing of resource allocation decisions. *Organizational Behavior and Human Decision Processes*, *37*(3), 348-356.

Pachur, T., Schulte-Mecklenbeck, M., Murphy, R. O., and Hertwig, R. (2018). Prospect theory reflects selective allocation of attention. *Journal of Experimental Psychology: General*, *147*(2), 147.

Pärnamets, P., Johansson, P., Hall, L., Balkenius, C., Spivey, M. J., and Richardson, D. C. (2015). Biasing moral decisions by exploiting the dynamics of eye gaze. *Proceedings of the National Academy of Sciences*, *112*(13), 4170–4175.

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision*, *10*(4), 437–442. https://doi.org/10.1163/156856897X00366

Petrusic, W. M., and Jamieson, D. G. (1978). Relation between probability of preferential choice and time to choose changes with practice. *Journal of Experimental Psychology: Human Perception and Performance*, *4*(3), 471.

Pieters, R., and Warlop, L. (1999). Visual attention during brand choice: The impact of time pressure and task motivation. *International Journal of Research in Marketing*, *16*(1), 1–16. https://doi.org/10.1016/S0167-8116(98)00022-6

Pieters, R., & Wedel, M. (2004). Attention Capture and Transfer in Advertising: Brand, Pictorial, and Text-Size Effects. *Journal of Marketing*, *68*(2), 36–50. https://doi.org/10.1509/jmkg.68.2.36.27794

Pieters, R., and Wedel, M. (2017). A review of eye-tracking research in marketing. In *Review of marketing research* (pp. 143-167). Routledge.

Plantinga, A., Krijnen, J. M., Zeelenberg, M., and Breugelmans, S. M. (2018). Evidence for opportunity cost neglect in the poor. *Journal of Behavioral Decision Making*, *31*(1), 65-73.

Pleskac, T. J., and Busemeyer, J. R. (2010). Two-stage dynamic signal detection: A theory of choice, decision time, and confidence. *Psychological Review*, *117*(3), 864–901. https://doi.org/10.1037/a0019737

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. https://doi.org/10.1037/0033-295X.85.2.59

Ratcliff, R., and Smith, P. L. (2004). A Comparison of Sequential Sampling Models for Two-Choice Reaction Time. *Psychological Review*, *111*(2), 333–367. https://doi.org/10.1037/0033-295X.111.2.333

Read, D., Olivola, C. Y., and Hardisty, D. J. (2017). The value of nothing: Asymmetric attention to opportunity costs drives intertemporal decision making. *Management Science*, *63*(12), 4277-4297.

Russo, J. E., and Leclerc, F. (1994). An eye-fixation analysis of choice processes for consumer nondurables. *Journal of Consumer Research*, *21*(2), 274–290.

Sepulveda, P., Usher, M., Davies, N., Benson, A. A., Ortoleva, P., & De Martino, B. (2020). Visual attention modulates the integration of goal-relevant evidence and not value. *Elife*, 9, e60705.

Shadlen, M. N., and Shohamy, D. (2016). Decision Making and Sequential Sampling from Memory. *Neuron*, *90*(5), 927–939. https://doi.org/10.1016/j.neuron.2016.04.036

Shah, A. K., Zhao, J., Mullainathan, S., and Shafir, E. (2018). Money in the mental lives of the poor. *Social Cognition*, *36*(1), 4-19.

Shah, A. K., Shafir, E., and Mullainathan, S. (2015). Scarcity frames value. *Psychological Science*, *26*(4), 402-412.

Smith, S. M., and Krajbich, I. (2018). Attention and choice across domains. *Journal of Experimental Psychology: General*, *147*(12), 1810–1826. https://doi.org/10.1037/xge0000482

Smith, S. M., and Krajbich, I. (2019). Gaze amplifies value in decision making. *Psychological Science*, *30*(1), 116–128. https://doi.org/10.1177/0956797618810521

Smith, S. M., Krajbich, I., and Webb, R. (2019). Estimating the dynamic role of attention via random utility. *Journal of the Economic Science Association*. https://doi.org/10.1007/s40881-019-00062-4

Spiller, S. A. (2011). Opportunity Cost Consideration. *Journal of Consumer Research*, *38*(4), 595–610. https://doi.org/10.1086/660045

Stewart, N., Chater, N., and Brown, G. D. (2006). Decision by sampling. *Cognitive Psychology*, *53*(1), 1-26.

Stewart, N., Hermens, F., and Matthews, W. J. (2015). Eye Movements in Risky Choice: Eye Movements in Risky Choice. *Journal of Behavioral Decision Making*. https://doi.org/10.1002/bdm.1854

Stone, M. (1960). Models for choice-reaction time. *Psychometrika*, *25*(3), 251–260. https://doi.org/10.1007/BF02289729

Tavares, G., Perona, P., and Rangel, A. (2017). The Attentional Drift Diffusion Model of Simple Perceptual Decision-Making. *Frontiers in Neuroscience*, *11*. https://doi.org/10.3389/fnins.2017.00468

Ting, C., and Gluth, S. (2023). High overall values mitigate gaze-related effects in perceptual and preferential choice. *PsyArXiv.*

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., and Imai, K. (2014). mediation: R Package for Causal Mediation Analysis. *Journal of Statistical Software*, 59(5), 1-38.

Towal, R. B., Mormann, M., and Koch, C. (2013). Simultaneous modeling of visual saliency and value computation improves predictions of economic choice. *Proceedings of the National Academy of Sciences*, *110*(40), E3858–E3867.

Vaidya, A. R., and Fellows, L. K. (2015). Testing necessary regional frontal contributions to value assessment and fixation-based updating. *Nature Communications*, *6*, 10120. https://doi.org/10.1038/ncomms10120

Westbrook, A., Van Den Bosch, R., Määttä, J. I., Hofmans, L., Papadopetraki, D., Cools, R., & Frank, M. J. (2020). Dopamine promotes cognitive effort by biasing the benefits versus costs of cognitive work. *Science*, *367*(6484), 1362-1366.

Zhao, C. X., Jiang, C. M., Zhou, L., Li, S., Rao, L. L., and Zheng, R. (2015). The hidden opportunity cost of time effect on intertemporal choice. *Frontiers in Psychology*, *6*, 311.

Zhao, X., Lynch Jr, J. G., and Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, *37*(2), 197-206.