The Role of Visual Attention in Opportunity Cost Neglect and Consideration

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Abstract

Choices necessitate opportunity costs: choosing one option means foregoing another. Despite their critical role in decision making, consumers often neglect opportunity costs and are less likely to make purchases when reminded of them. Here, we seek to understand whether/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 (~30,000 choices), we find lower purchase rates when opportunity costs are explicit. More importantly, we show that the contribution of attention to 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 consumers are more likely to purchase when explicit opportunity cost reminders are absent.

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

Consumers 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, consumers often spend in ways that suggest they ignore the opportunity costs they face (Frederick et al. 2009). Internal and external factors that prompt consumers to consider opportunity costs cause consumers to be less likely to make purchases and to be more sensitive to the value of those opportunity costs (Spiller 2011). Why? Prior research has proposed attention, but to our knowledge not directly tested that proposition. In this research, we assess the role of visual attention. In particular, we measure visual attention and test whether and how attention to outside options accounts 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 affects 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 supports (b); to our knowledge, no prior research has addressed or quantified (a) or (c).

To preview our key results, when opportunity costs are implicit (relative to when there is an explicit reminder), consumers spend less time attending to the non-buy option. Time spent

attending to the non-buy option predicts the decision to not buy. Moreover, the time that consumers spend attending to the non-buy option is less predictive of not buying when the opportunity costs are implicit rather than explicit, at least under some framings. Together, these two mechanisms, spending less time attending to the non-buy option and the lesser impact of that time, induce the greater purchase rates that characterize opportunity cost neglect.

OPPORTUNITY COST NEGLECT

Consumers 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 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.

Although opportunity costs are equally relevant in both types of decisions, people treat them very differently. 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: why are consumers more likely to purchase when opportunity costs are left implicit?

Understanding the role of attention may help to explain why consumers are more likely to purchase when opportunity costs are neither made explicit by the environment nor spontaneously prompted by the choice context. To our knowledge, prior research has proposed but not directly tested the ways in which attention to opportunity costs affects choice and has not explicitly addressed the multiple ways in which it might matter. 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 incidence 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). 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). 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; Smith and Krajbich 2018; Amasino et al. 2019; Yang and Krajbich 2021).

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;

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).

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). 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, these studies regarding the role of attention largely have not considered the effects of these frames[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 way the choice is framed.

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, incoming support for the looked-at option is amplified relative to when individuals look elsewhere (Smith and Krajbich 2019). 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. This amplifying role of attention in choice is consistent with the attentional drift diffusion model (aDDM; Krajbich et al. 2010).

[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 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; 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 consumer 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. Moreover, attention has not been tested as a moderator of the more general distinction between "which one" choices (i.e., choices among a well-defined set of distinct options) and "whether or not" choices (i.e., choices of whether to

accept a focal option or not, as in purchase decisions). 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.

Based on previous research, we tested two candidate hypotheses. First, as described above, attention can play a causal role in influencing choice. If consumers 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, yet to our knowledge it has not been directly tested.

H1: Opportunity cost salience decreases purchase incidence by increasing 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). 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.

H2: Opportunity cost salience decreases purchase incidence by increasing the relative strength of the relationship between attention and choice when attending to the outside option.

There are multiple ways in which the framing of the choice may influence the decision process. It is possible that the framing simply leads consumers to “think through” the options to different degrees. On the other hand, it is also possible that the explicit framing of opportunity costs leads consumers to ask themselves (and subsequently answer) fundamentally different

questions. These two psychological pathways correspond nicely to our hypothesized attention pathways: if the framing influences the degree of option consideration, we will find support for the "amount" hypothesis. If the framing influences the considered evidence (e.g., questions and answers asked to oneself while deciding), then we will find support for the "impact" hypothesis.

Either way, looking time (which we will refer to as attention) to explicit opportunity costs should result in lower purchase rates. We tested these hypotheses with two incentive-compatible eye-tracking experiments.

STUDY 1 METHODS

Participants

Fifty-one university students participated in this preregistered study.[2] 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[3]. This study was approved by the relevant Internal Review Board and all participants gave informed written consent before participating.

Materials

[2] 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.
[3] 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.

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) 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” (figure 1a). 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 (figure 1b). 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; figure 1c). In the other block of trials, the options were labeled "Buy Food for $X" and "Keep $X" (the *explicit* opportunity cost condition; figure 1d).

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.

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.

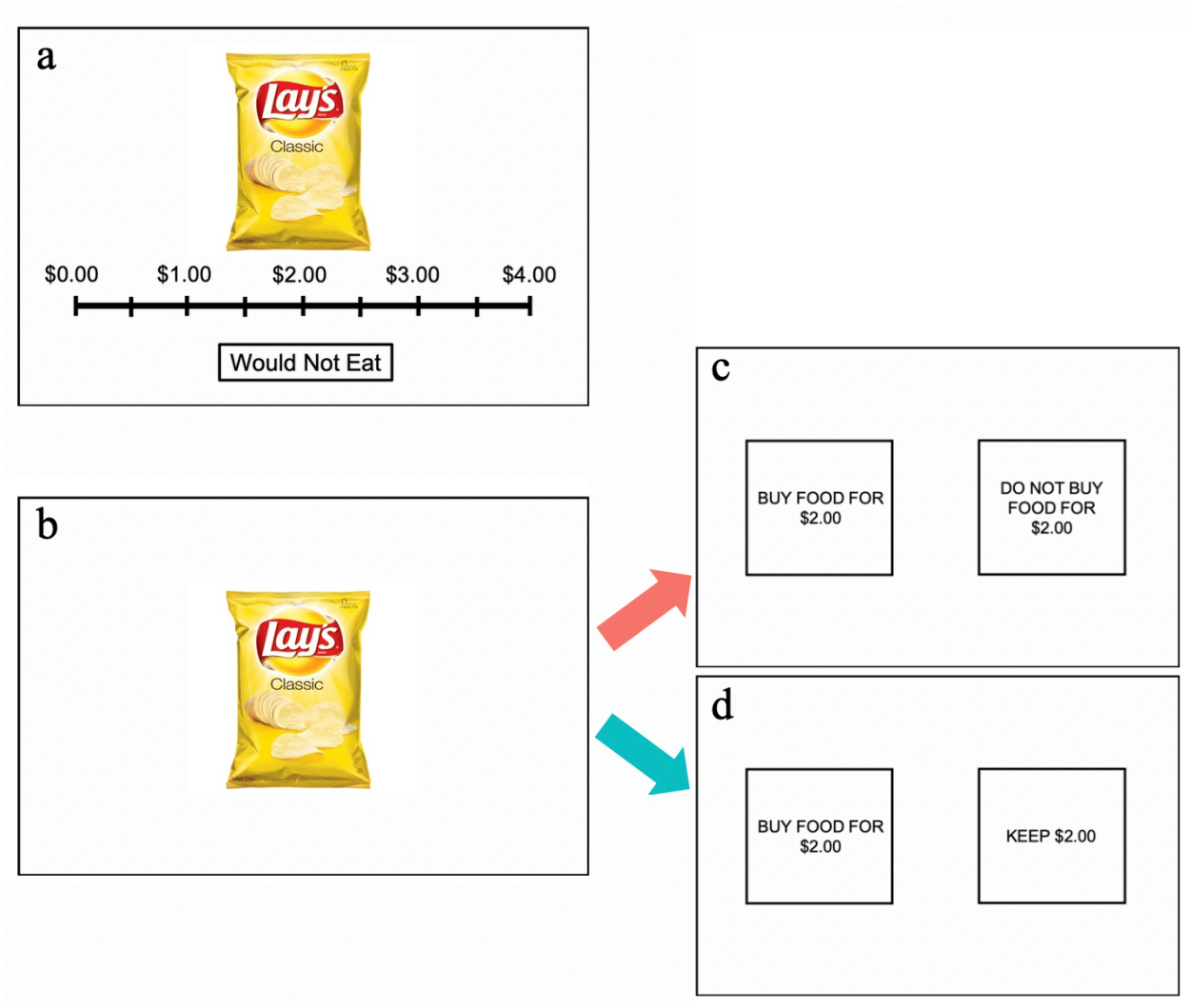

Figure 1.
Experimental setup. Participants first rated their willingness-to-pay (WTP) for 144 snack food items (a). If they would not eat the food, they could click the "Would Not Eat" button. On each choice trial, participants first saw a previously rated food item (b) on the screen for 1 second. After 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").

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.

STUDY 1 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. We conclude the results across studies by fitting a formal model of evidence accumulation. 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 trials for which opportunity costs were implicit and trials for which

opportunity costs were explicit.[4] We 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).[5]

Consistent with prior research, 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. 2). 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.

Given the order effect, which could indicate either position and/or carryover effects, we ran an online posttest with a 2x2 design (first block: explicit or implicit; second block: explicit or implicit). In this online study, we measured choice but not attention. We found evidence consistent with a carryover effect, rather than a position effect ($p = .03$): the second-block purchase rate was lower when the second block opportunity costs were explicit rather than implicit, but this effect was larger when the first block opportunity costs were implicit rather than explicit. For additional details on the posttest, see the supplementary material.

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[4] 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 ($p > .4$).

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

Given the high likelihood of a carryover effect, we examined the effect of condition using a between-subject analysis separately in the first and second blocks. When examining the first block, the mean purchase rate was 11 percentage points lower in the explicit condition (0.404) than in the implicit condition (0.516; $t(48) = -2.63$, $p = 0.011$). When examining the second block, the mean purchase rate was only 4 percentage points lower in the explicit condition (0.372) than in the implicit condition (0.417; $t(48) = -0.82$, $p = 0.416$), though the purchase rates averaged across blocks did not significantly differ by order ($t(48) = -0.74$, $p > .4$)[6].

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 opportunity cost neglect more precisely by using repeated choices, enabling a more fine-grained search for moderators.

Disaggregate Analyses. We repeated this analysis using disaggregate trial-level data to account for the role of surplus (WTP – price). Specifically, we used a logistic regression of purchase as a function of opportunity 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.[7]

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[6] This test, representing a test of differential carryover, is not precisely estimated as it depends on a between-subject analysis with 25 subjects per group. Instead, we consider the posttest a better approach to disambiguate.

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

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).[8] Explicit framing decreased probability of purchase (b_1 = -0.21, SE = 0.045, z = -4.72, p < .001; see fig. 2). 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 0.454, 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 0.349, significantly less than 0.5 (z = -4.12, p < .001). In other words, when participants have not been reminded of opportunity costs, they are approximately as likely to buy as they are to not buy when the item is priced at their WTP, suggesting WTP is appropriately calibrated. When opportunity costs are explicit, participants are less likely to buy (vs. not buy) when surplus is 0, suggesting WTP is not properly calibrated (e.g., if a consumer 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 properly calibrated). Since choice corresponds to WTP only when opportunity costs are not

[8] 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} = –3.43, SE = 0.29, z = –11.89, p < .001; b_{Rating} = 3.26, SE = 0.25, z = 13.18, 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.

explicit, this suggests that perhaps consumers neglect opportunity costs when reporting WTP using standard WTP elicitation methods. We do not have specific process evidence support for this explanation, but it may be fruitful for future research to pursue this finding.

*Discussion***.** Together, these results replicate and extend prior work on opportunity cost neglect. First, they replicate opportunity cost neglect with incentivized choices. Second, they indicate an effect of opportunity cost salience in intensive repeated choices. Third, coupled with the results from the posttest, 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.

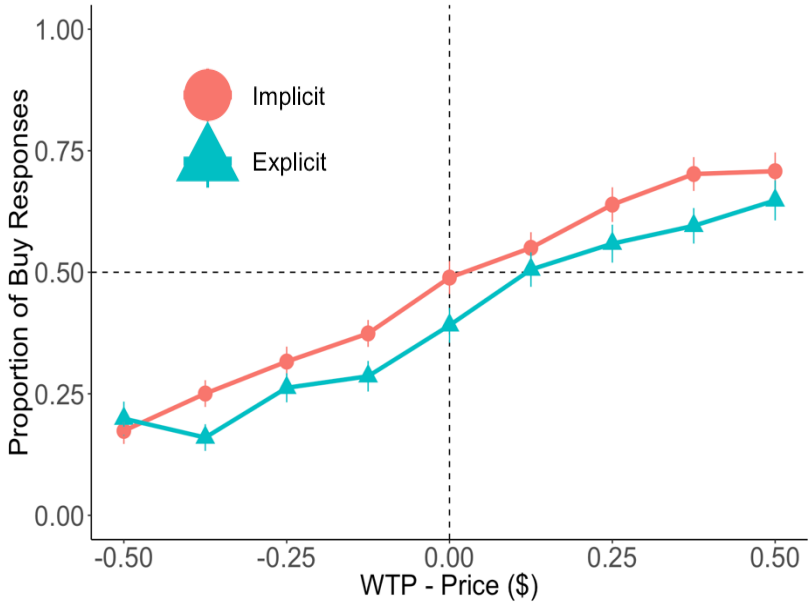

Figure 2.
Purchase behavior as a function of surplus (WTP – Price) and condition. Participants (N = 50) were significantly less likely to purchase in the explicit condition. Bars indicate standard error of the mean, clustered by participant. For display purposes, the surplus is binned into intervals 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.

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 attention (i.e., how many seconds did participants spend looking at an option) and, when appropriate, a standardized measure of attention: proportion of trial-level attention 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.[9] We hypothesized that participants would devote more relative attention to "Keep" than "Do Not Buy" (in comparison to "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 results, the effect of condition significantly differed by order (raw: b_1 = 0.084, SE = 0.023, $t(48)$

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

= 3.70, $p < .001$; standardized: $b_1 = 0.045$, SE = 0.011, $t(48) = 4.25$, $p < .001$). The dwell-time advantage for the buy option in the first block was directionally larger for the implicit condition than for the explicit condition (raw: 0.081 vs. 0.006 seconds; $t(48) = 1.66$, $p = .10$; standardized: 53% vs. 49%; $t(48) = 2.15$, $p = .04$). The dwell-time advantage for the buy option in the second block was directionally larger (though not significantly so) for the implicit condition than for the explicit condition (raw: –0.027 vs. –0.053 seconds; $t(48) = 0.57$, $p = .57$; standardized: 48% vs. 45%; $t(48) = 0.94$, $p = .36$).[10] 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.[11]

Surplus was 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, $t(50) = 9.17$, $p < .001$; all degrees of freedom for mixed models are approximate), indicating participants attended relatively more to

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[10] 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.

[11] 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: $BuyDwellProportion_{it} = \beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \epsilon_{it}; \beta_{0i} = \beta_0 + \eta_{0i};\ \beta_{1i} = \beta_1 + \eta_{1i};\ \beta_{3i} = \beta_3 + \eta_{3i}; \eta \sim N(0, \Sigma)$

buy when surplus was higher. 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 = -0.046, SE = 0.011, $t(48)$ = -4.05, p < .001; standardized: b_2 = –0.024, SE = 0.005, $t(50)$ = –4.83, p < .001), such that the buy dwell advantage (and buy dwell proportion) was larger in the first task than the second task.

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).[12]

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

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

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).

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.[13]

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[13] 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: $P(Buy_{it}) =$

Once again, buy dwell advantage (and proportion) was a strong predictor of choice (raw: $b_4 = 2.38$, SE = 0.16, $z = 14.97$, $p < .001$; standardized: $b_4 = 5.59$, SE = 0.32, $z = 17.51$, $p < .001$); total dwell time was not ($b_5 = -0.10$, SE = 0.08, $z = -1.27$, $p = .20$). Using trial-level data, the indirect effect was marginally significantly 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 *impact* of attention 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 interactions of condition with buy dwell advantage/proportion and condition with total dwell time.[14] 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 = .09, $z = 1.62$, $p = .10$; standardized: $b_5 = 0.43$, SE = .22, $z = 1.97$, $p = .05$). This indicates that relative

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$logit^{-1}(\beta_{0i} + \beta_{1i}OppCost_{it} + \beta_2 Position_{it} + \beta_{3i}Surplus_{it} + \beta_{4i}BuyDwellProportion_{it})$; $\beta_{0i} = \beta_0 + \eta_{0i}$; $\beta_{1i} = \beta_1 + \eta_{1i}$; $\beta_{3i} = \beta_3 + \eta_{3i}$; $\beta_{4i} = \beta_4 + \eta_{4i}$; $\eta \sim N(0, \Sigma)$

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

attention was more strongly predictive of choice when opportunity costs were explicit rather than implicit. Total dwell time was significantly more negatively related to purchase in the explicit condition than the implicit condition (b_7 = -0.105, SE = .048, z = -2.17, p = .03). This indicates 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.

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.[15] 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 = 14.07, p < .001) but did not vary by condition (b_6 = 0.06, SE = 0.09, z = 0.61, p > .5). In contrast, the coefficient for dwell time on the non-buy option was strongly negative (b_5 = -2.53, SE = 0.19, z = -13.31, p < .001) and varied by condition (b_7 = -0.27, SE = 0.11, z = -2.47, p = .014) 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. See figure 3.

[15] 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.

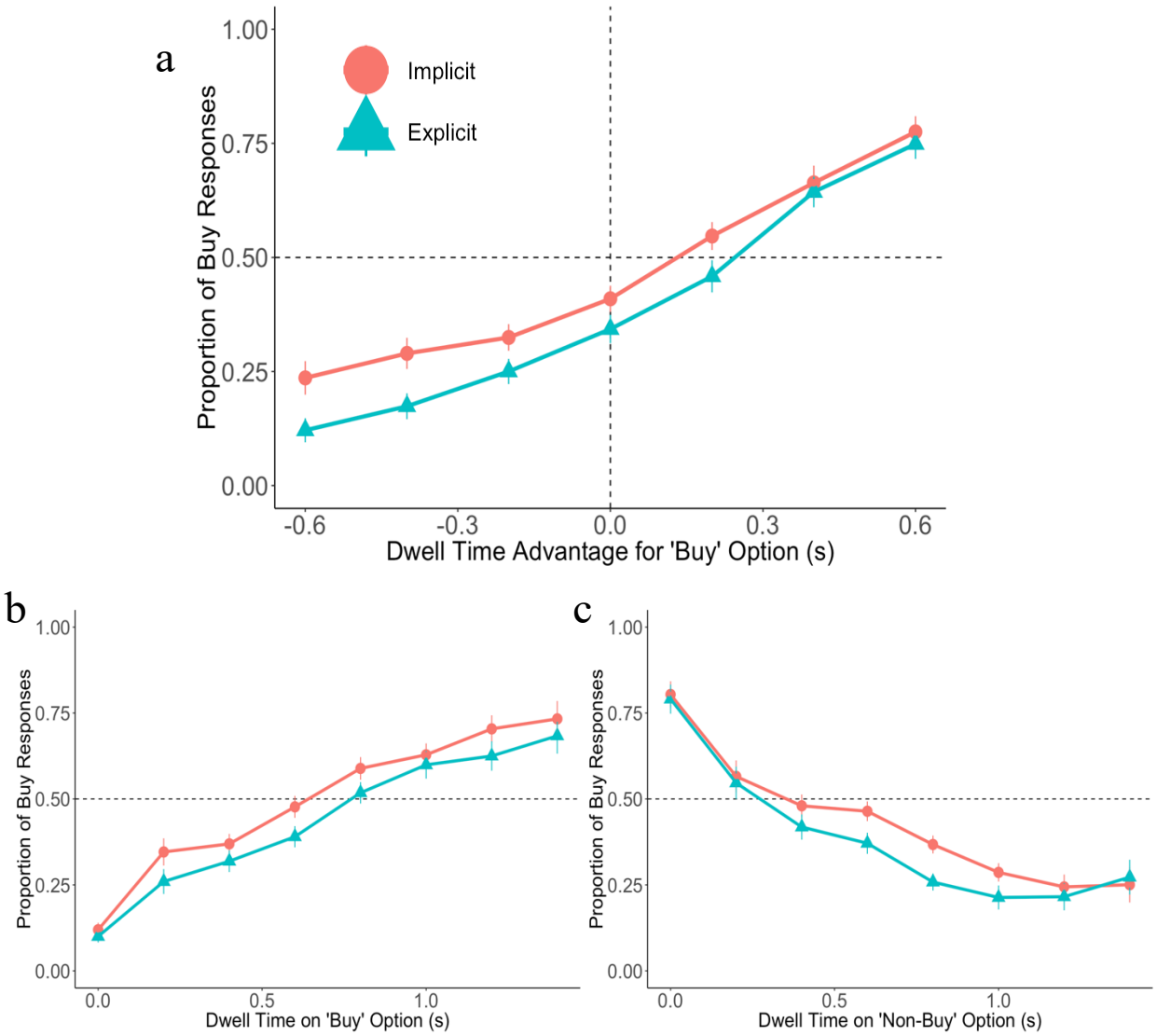


Figure 3.
Relationship between attention and choice. As total relative dwell time for the buy option increases (a), the probability of purchase increases. As raw dwell time on the buy option increases (b), the probability of purchase increases. As raw dwell time on the non-buy option increases (c), the probability of purchase decreases. 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). This new wording has a useful characteristic suggested by a reviewer: the 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).

STUDY 2 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 *impact* hypothesis depends on the context. For a high-level overview of the results of these two studies, see Table 1.

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. 4). 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.

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. 4). Participants were more likely to purchase as WTP increased relative to price ($b_3 = 3.46$, SE = 0.18, $z = 18.96$, $p < .001$).[16] There was also an effect of position ($b_2 = -0.18$, SE = 0.03, $z = -5.82$, $p < .001$) such that

[16] 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, $z = –18.51$, $p < .001$; $b_{WTP} = 3.44$, SE = 0.16, $z = 21.06$, $p < .001$. 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.

purchase rates were lower in the second block than the first. Estimated purchase rate when there was no surplus was close to chance when opportunity costs were implicit (m = 0.49, z = –0.55, p = .58) but below chance when opportunity costs were explicit (m = 0.38, z = –4.12, 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 intensive repeated choices, and (3) they are consistent with the interpretation that not only choices, but also WTP judgments are made while neglecting opportunity costs.

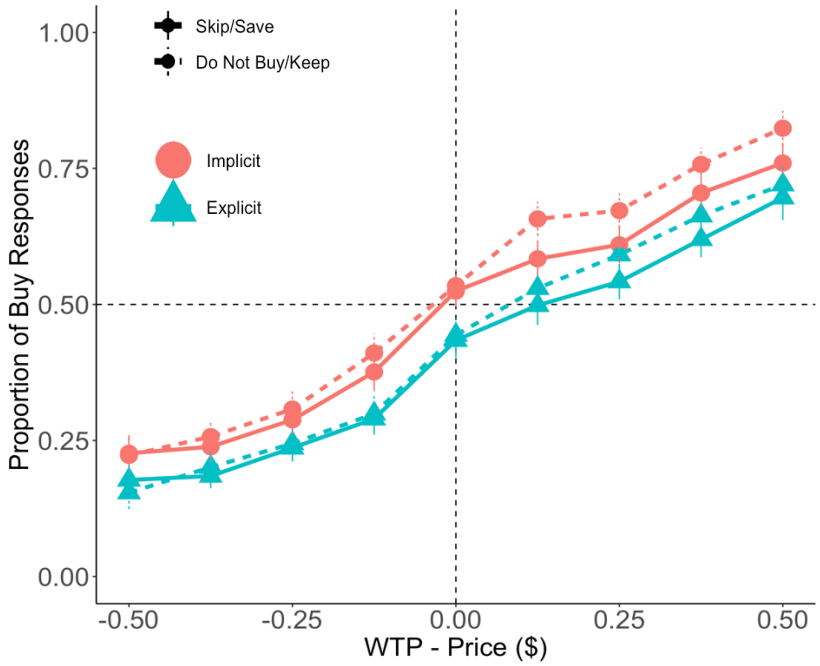


Figure 4.
Purchase behavior as a function of surplus (WTP – Price), condition, and wording. Participants (N = 50) were significantly less likely to purchase in the explicit condition. Bars indicate standard error of the mean, clustered by participant. For display purposes, the surplus is binned into 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.

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 attention model (b_0 = –0.016, SE = 0.015, $t(106) = -1.06$, $p = .29$), but is in directionally in line with participants looking more at the explicit "Keep"/"Save" than the implicit "Do Not Buy"/ "Skip." When we used standardized 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 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 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 Study 1, surplus was a strong positive predictor of dwell advantage for "Buy" (raw: b_3 = 0.38, SE = 0.03, $t(107) = 13.31$, $p < .001$; standardized: b_3 = 0.14, SE = 0.01, $t(105) = 15.57$, $p < .001$). As in the between-subject analysis, the coefficient on condition was in the expected (negative) direction (raw: b_1 = -0.009, SE = 0.007, $t(107) = -1.24$, $p = .22$; standardized: b_1 = –0.008, SE = 0.003, $t(106) = -2.59$, $p = .01$), indicating that the dwell advantage in favor of buy was stronger in the implicit condition than the explicit condition. There was again a nonsignificant effect of position in the raw attention model (b_2 = -0.010, SE = 0.007, $t(106)$ = -

1.39, p = .17), but a significant effect of position in the standardized attention model (b_2 = -0.009, SE = 0.003, t(107) = -3.02, p = .003).

Attention Predicts Choice: Aggregate. In equations 5a and 5b, the coefficient on difference in average dwell time (or proportion) advantage predicting purchase rate difference was significant (raw: b_2 = 0.38 per second, SE = 0.06, t(104) = 5.83, p < .001; standardized: b_2 = 1.02, SE = 0.15, t(104) = 6.80, p < .001); the coefficient on sum of average dwell time (or proportion) advantage was not (raw: b_3 = –0.055, SE = 0.041, t(104) = –1.33, p = .19; standardized: b_3 = -0.13, SE = 0.10, t(104) = -1.41, p = .16). 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 = –0.060, SE = 0.010, t(104) = –6.08, p < .001; standardized: b_1 = -0.048, SE = 0.010, t(104) = -4.93, p < .001) and a smaller 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 attention in the two conditions.

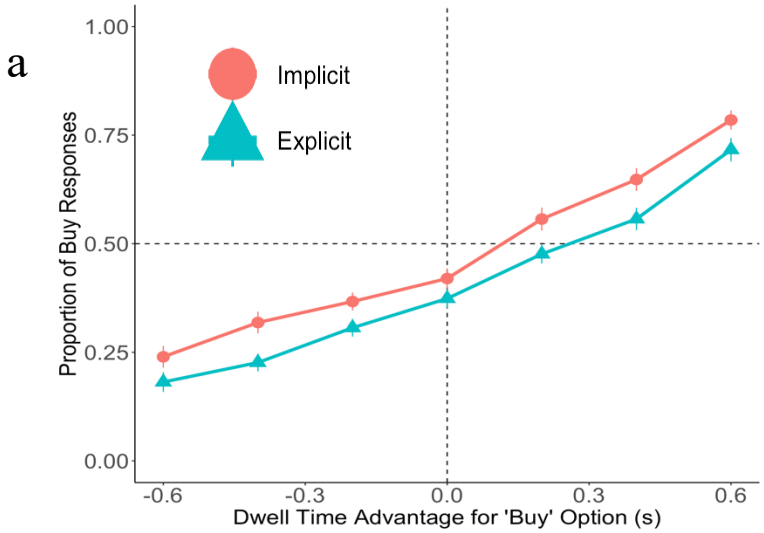
Attention Predicts Choice: Disaggregate. At the trial level (i.e., in equations 6a and 6b), buy dwell advantage was a strong predictor of choice (raw: b_4 = 2.07, SE = 0.11, z = 17.98, p < .001; standardized: b_4 = 6.11, SE = 0.29, z = 20.92, p < .001); total dwell time was marginally significant (raw: 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 *impact* 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, $z = 1.63$, $p = .10$; fig. 5a), as in Study 1. Total dwell time was not significantly more related to purchase in either opportunity cost condition (raw: $b_7 = -0.05$, SE = 0.03, $z = -1.49$, $p = .14$; not included in standardized model).

In equation 8, we observe that the coefficient for dwell time on the buy option is strongly positive ($b_4 = 1.98$, SE = 0.11, z = 17.26, $p < .001$) but does not vary by opportunity cost condition ($b_6 = 0.08$, SE = 0.06, $z = 1.32$, $p = .19$; fig. 5b). In contrast, the coefficient for dwell time on the non-buy option is strongly negative ($b_5 = -2.23$, SE = 0.13, $z = -17.43$, $p < .001$) and varies by opportunity cost condition ($b_7 = -0.18$ SE = 0.07, $z = -2.75$, $p = .006$) such that it is more-strongly negative when opportunity costs are explicit than when they are implicit (fig. 5c). These findings are consistent with Study 1.



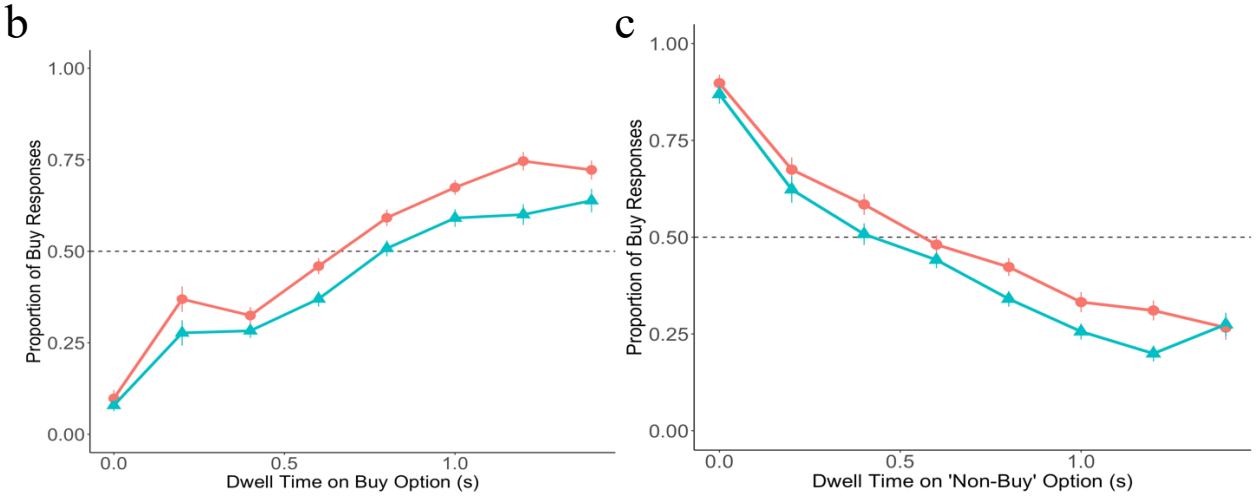


Figure 5.
Relationship between attention and choice. As total relative dwell time for the buy option increases (a), the probability of purchase increases. As raw dwell time on the buy option increases (b), the probability of purchase increases. As raw dwell time on the non-buy option increases (c), the probability of purchase decreases. 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.

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

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) p = .28
Eq. 2: Buy ~ b0 + b1*Position + b2*OppCost + b3*Surplus	b2 = –0.21 (0.05)***	b2 = –0.24 (0.04)***	b2 = –0.18 (0.04)***	b2 = –0.21 (0.03)***	b = –0.070 (0.062) p = .26
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)* p = .03
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) p = .94
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)* p = .04

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) p = .90
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) p = .06
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) p = .12
Eq. 6a: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwellAdvantage + b5*MCTotalDwell	b4 = 2.38 (0.16)***	b4 = 2.25 (0.16)***	b4 = 1.89 (0.16)***	b4 = 2.06 (0.11)***	b = 0.36 (0.23) p = .11
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 = 0.36 (0.66) p = .59
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 (0.078)	b6 = 0.13 (0.05)*	b = 0.25 (0.11)* p = .02
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 = 0.67 (0.31)* p = .03
Eq. 8: Buy ~ b0 + b1*OppCost + b2*Position + b3*Surplus + b4*BuyDwell + b5*NonBuyDwell + b6*OppCost*BuyDwell + b7*OppCost*NonBuyDwell	b6 = 0.055 (0.063) b7 = –0.16 (0.06)*	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)* p = .04 b = –0.30 (0.14)* p = .03

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 *impact* 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 (Smith and Krajbich 2015).

In the current paper, we focus on 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 alter 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 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 subjective utilities 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[17]), 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[18]. 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.

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[17] 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*).

[18] One could parameterize this by boosting the option that is being looked at rather than discounting the option that is not being looked at. If one were to take that approach, the boosting parameter for attending to the buy option would be equal to $1/\theta_B$ and the boosting parameter for attending to the non-buy option would be equal to $1/\theta_N$.

Model Derivation and 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 as follows:

The drift rates during dwells to the buy and non-buy options are specified in equations 9 and 10. Consequently, the total net evidence gained for the buy option within a trial is:

(11) $$A_B(d_B X_B - \theta_N d_N X_N) + A_N(\theta_B d_B X_B - d_N X_N) + \varepsilon$$

Here, A_B and A_N are the proportion of trial dwell time spent on the buy and non-buy options, respectively, and ε is an error term to represent the noise in the accumulation process. After rearranging terms, we obtain the following:

$$d_B A_B X_B - d_N \theta_N A_B X_N + d_B \theta_B A_N X_B - d_N A_N X_N + \varepsilon$$

$$\downarrow$$

(12) $$d_B Z_1 + d_N Z_2 + d_B \theta_B Z_3 + d_N \theta_N Z_4 + \varepsilon$$

$$\downarrow$$

$$\beta_1 Z_1 + \beta_2 Z_2 + \beta_3 Z_3 + \beta_4 Z_4 + \varepsilon$$

Where

$$Z_1 = A_B X_B$$

$$Z_2 = -A_N X_N$$

$$Z_3 = A_N X_B$$

$$Z_4 = -A_B X_N$$

And

$$\frac{\beta_3}{\beta_1} = \frac{d_B \theta_B}{d_B} = \theta_B$$

$$\frac{\beta_4}{\beta_2} = \frac{d_N \theta_N}{d_N} = \theta_N$$

Thus, since the Z_i comprise measured variables in our study (i.e., the values of the options, X_i, and the proportion of attention devoted to each option, A_i), we can estimate the β_i (and ultimately, 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, 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).[19]

Table 2.
Estimates of θ

	Explicit	Implicit
θ_B	0.12	0.36
θ_N	0.89	0.68

Note. 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. 2010; Krajbich and Rangel 2011). Moreover, the weak discount on "Keep" (0.89, table 2) implies that substantial evidence is gathered for "Keep," even when it is not the currently looked-at option.

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

In this project, we were particularly interested in the differences in θ_i across conditions (i.e., explicit vs. implicit). The lower point estimate for θ_B in the explicit condition implies that on average, the buy option was discounted more when participants were looking at "Keep" than "Do Not Buy." The lower point estimate for θ_N in the implicit condition implies that on average, "Keep" was not discounted as much as "Do Not Buy" when the participants were looking at "Buy." We also used an alternative strategy to estimate these parameters. This second analysis permitted estimation of confidence intervals around the parameter estimates. 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. 6). The details on the computation of these confidence intervals are 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.

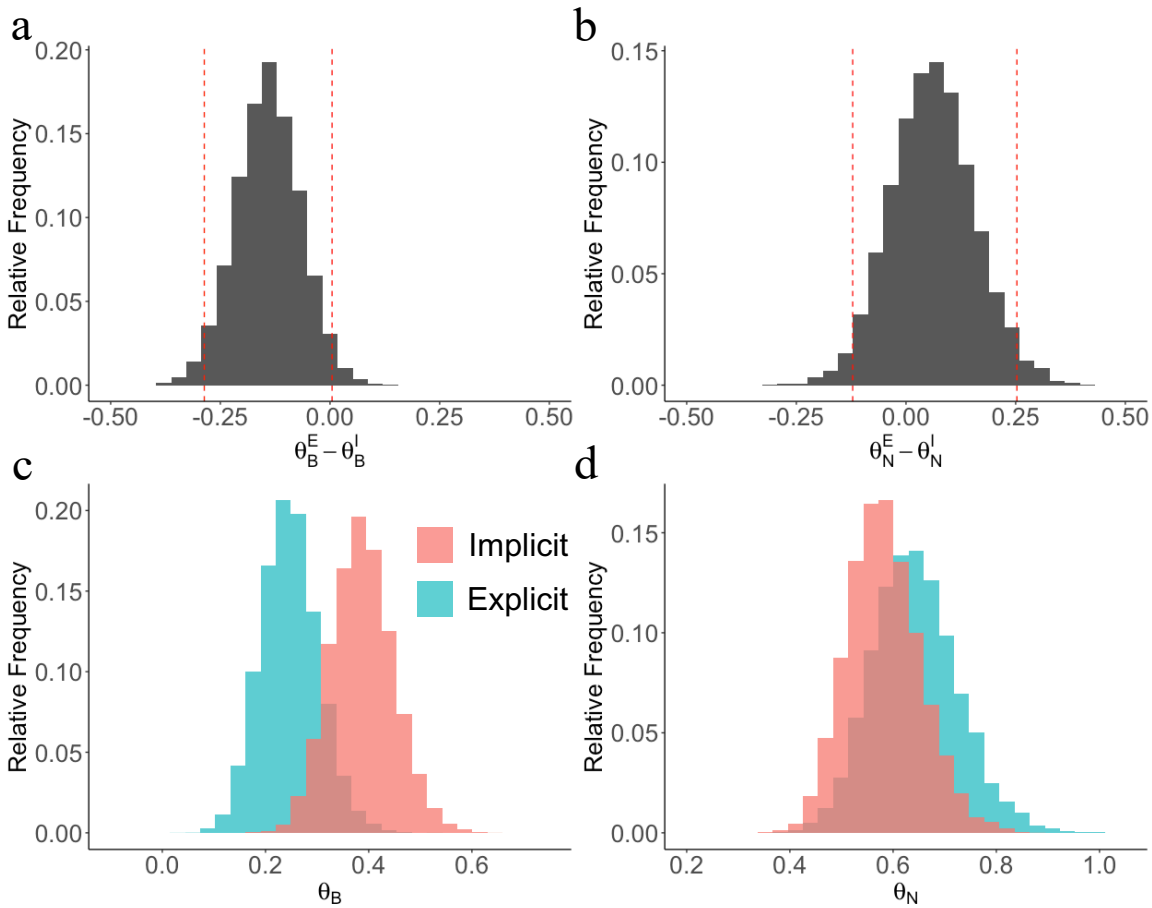

Figure 6.
Approximate distributions of parameters. The discount on the buy option is stronger in the explicit (vs. implicit) condition (a, c). The 95% confidence interval (red dashed lines) on the difference in θ_B between the conditions (a) is [–0.29, 0.005]. The 95% confidence intervals for θ_B (c) are: explicit = [0.14, 0.36]; implicit = [0.27, 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 = [0.45, 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 effects on choice. Overall, the computational modeling results (stronger attentional discounting of "Buy" in the explicit condition) provide a process-driven explanation for the decline in purchase rates when opportunity costs are made explicit. 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 under the "Keep" vs. "Do Not Buy" wording and weaker evidence under the "Save" vs. "Skip" wording.

GENERAL DISCUSSION

Overall, we provide evidence for the previously hypothesized, but yet to be tested, role of attention in opportunity cost neglect and consideration. In particular, we demonstrate that purchase choices and attention are strongly linked. 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 *impact* of their attention is also greater when they are looking at "Keep" compared to "Do Not Buy." Together, these two factors (*amount* and *impact* 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). Consumers 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 the distinction between formally equivalent "which one" decisions between two alternatives and "whether or not" decisions of 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 consumer behavior. For example, despite its prominence in decision science, we were unable to find any use of the phrase "drift diffusion model" in *Journal of Consumer Research*. Beyond opportunity costs, more formal process modeling has the potential to enhance our understanding of other tradeoffs consumers regularly make (between hedonic and utilitarian goods, quality and price, experiential and material goods, 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; cf. Ghaffari and Fiedler 2018; Newell and Le Pelley 2018). Second, there are some key differences between this experimental setup and the situation experienced by

consumers 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 to the consumer. 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. 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 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.

Ultimately, this research enhances the important connection between research in consumer behavior and research on visual attention in decision science (Russo and Leclerc 1994; Pieters and Wedel 2004; Pieters and Wedel 2017; Mormann et al. 2020). 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.

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