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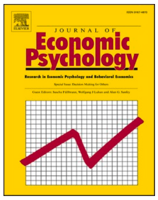

Eyes on the account size: Interactions between attention and budget in consumer choice☆

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ABSTRACT

The context surrounding a consumer decision, such as one's overall budget available for purchases, can exert a strong effect on the subjective value of a product. Across three eye-tracking studies, we explore the attentional processes through which budget size influences consumers' purchasing behavior. Higher budgets increased and sped up purchasing even when items were affordable at all budget sizes. Moreover, attention interacted with budget size to promote purchasing at higher budgets. Finally, individual differences in the magnitude of the budget effect related to attentional patterns: those whose decisions depended more on budget exhibited more budget-price transitions and less variability in search patterns compared to those whose decisions were less dependent on budget. These findings indicate that attention moderates the effect of budgets on purchasing decisions, allowing low budgets to serve as self-control devices and large budgets to generate impulse purchases.

1. Introduction

Budgeting can be a useful and intuitive tool for keeping track of spending and saving, but how budgets shape the *processes* of decision making remains poorly understood. Revealing how budget information influences consumer choices is key to understanding why budgets can reduce purchasing in some contexts and increase it in others—each of which been observed in prior work (Larson & Hamilton, 2012; Thaler, 1985; Zhang & Sussman, 2018)—and thus for identifying what behavioral nudges might improve economic well-being. In understanding consumer decision-making, budgets are particularly relevant because they can be used by the consumer to promote their own financial goals; other contextual factors that impact purchasing (e.g., store layouts, promotions) are controlled entirely by the seller. While wealth-based budgets can provide inflexible constraints, consumers also establish artificial and temporary

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budgets that impact spending and savings decisions (Thaler, 1985). Such "mental accounts" may increase savings by creating artificially low budgets for purchases, or earmarking money for savings accounts, but they can also lead to overspending because of leftover in a budget category, loopholes in category definitions, temporal distance between purchase and consumption, or windfalls (e.g., gift cards) that lead to more hedonic spending (Arkes et al., 1994; Chambers & Spencer, 2008; Cheema & Soman, 2006; Cheng & Cryder, 2018; Heath & Soll, 1996; Helion & Gilovich, 2014; Milkman & Beshears, 2009; Shafir & Thaler, 2006; Soman & Cheema, 2011; Sussman & Alter, 2012; Thaler, 1985, 1999; Ülkümen & Cheema, 2011). In some cases, coupons created for marketing purposes or externally-provided savings benchmarks can have similar effects to self-generated budgets, suggesting that even externally-imposed budgets can influence valuation and choice (Helion & Gilovich, 2014; Milkman & Beshears, 2009; Soman & Cheema, 2011).

Despite the well-documented impact of budget constraints on consumer choice, the mechanisms that impact the strength of budget constraints remain incompletely understood. The literature on mental accounting suggests that budgets may have differential impacts depending on the source of money being spent, how well the purchase matches a budget category, the salience or mental accessibility of a given budget category, or other factors that influence consumers' integration of budget information into the decision process (Heath & Soll, 1996; Morewedge et al., 2007; Mrkva & Boven, 2017). The impact of each of these factors, in turn, may be moderated by the attention allocated to a given budget. In this paper, we explore the impact of attention through two main questions: How does attention to budget information shift the valuation of items to potentiate or discourage purchasing? And, what aspects of the information-gathering process lead some individuals to be more sensitive to budget information? We use eye-tracking to explore how attention to budget information affects its use in decisions compared to price and item information and to characterize the patterns of information-gathering that distinguish budget-sensitive and budget-insensitive individuals.

1.1. *Information-processing and attention*

Eye tracking allows researchers to identify the location of a participant's gaze, providing a naturalistic measure of overt attention (Meißner & Oll, 2019; Orquin & Mueller Loose, 2013). It can be used to quantify which information is processed (fixations), for how long (dwell time), and what comparisons are made between pieces of information (saccades), as well as the order of information processing as revealed through more complex scanning paths. Behavioral decision research has used eye-tracking—and related methods that measure the order in which visual information is sampled—to reveal the processes underlying information gathering and choice (Amasino et al., 2019; Arieli et al., 2011; Ashby et al., 2015; Barrafrem & Hausfeld, 2020; Bettman & Kakkar, 1977; Fiedler et al., 2013; Glockner & Herbold, 2011; Johnson et al., 1988; Pachur et al., 2018; Payne et al., 1992, 1988; Reeck et al., 2017; Venkatraman et al., 2014).

Process tracing approaches have been particularly important for understanding how people simplify multi-attribute and multi-alternative decision problems, making complex decision problems more tractable. Decision-makers cannot process all information simultaneously, so to reduce working memory load, they typically attend to the specific information they are considering, especially for complex and difficult choices. Therefore, examining where they look can indicate which information is prioritized and compared (Droll & Hayhoe, 2007; Hayhoe & Ballard, 2005; Meißner et al., 2016; Meißner & Oll, 2019; Orquin & Mueller Loose, 2013; Pärnamets et al., 2016). This allows researchers to identify the variations in the decision process that explain individual differences in choice (Amasino et al., 2019; Fiedler et al., 2013; Reeck et al., 2017).

More generally, how the interaction between attention and attributes in consumer choice relates to budget information remains largely unexplored. One potential mechanism has been identified through process-tracing research: highly valued options attract attention and gaze, while attention-grabbing stimuli or random fluctuations in attention lead to increased subjective value (Armel et al., 2008; Bird et al., 2012; Ghaffari & Fiedler, 2018; Gluth et al., 2018, 2020; Krajbich et al., 2010; Milosavljevic et al., 2012; Mullett & Stewart, 2016; Orquin et al., 2021; Reutskaja et al., 2011; Shimojo et al., 2003; Smith & Krajbich, 2019). We focus on the latter part of the bi-directional attention and value interaction whereby attention impacts subjective value. Only a few papers have quantified the role of gaze in consumer decisions about whether to buy an item for a given price or in budget use. Krajbich et al. showed that that longer dwell times on items increase purchasing likelihood relative to longer dwell times on prices—a finding consistent with laboratory studies showing that gaze increases the subjective value of the attended information during evidence accumulation (Krajbich et al., 2012). In addition, Imai et al. find that longer gaze durations to both item and price reflect more consideration and predict purchasing in both mouse-tracking and eye-tracking (Imai et al., 2019). Finally, in the domain of mental accounting and budgets, Mrkva and Van Boven find that drawing attention using an independent spatial cueing task leads to increased prioritization of the mental account presented near the cue (Mrkva & Boven, 2017). All of these studies show that attention increases consideration of the attended options or attributes, but do not directly address whether attention interacts with subjective value of an option or attribute to influence choice.

More recent work bringing attention into sequential sampling models, such as the aDDM, further suggests that attention exerts more influence with increasing value of an option or attribute, suggesting a multiplicative relationship (Fisher, 2021; Krajbich, 2019; Pirrone & Gobet, 2021; Shevlin & Krajbich, 2021; Smith & Krajbich, 2019). Other studies emphasize a more nuanced relationship between attention and value: attention may not simply amplify value, but instead increase the impact of goal-relevant evidence, which can lead to different effects on behavior depending on the choice goal (e.g., choosing the least- or most-preferred option; Sepulveda et al., 2020). For purchasing decisions, a common goal is to gather evidence about whether an option is worth buying. In this context, higher budgets are higher-value and push toward purchasing, so attention should amplify these higher-magnitude budgets. In contrast, higher prices represent a higher cost and push away from purchasing, so attention would not be expected to amplify them but should instead amplify the relatively more appealing lower prices that support purchasing decisions. In our study, we build on this work to examine how budget information interacts with attention and, in turn, shapes choice processes during purchasing decisions.

1.2. Present research

In this paper, we investigate the attentional processes underlying to what extent budgets frame purchasing decisions. Participants viewed a series of non-necessity consumer products and decided whether to purchase each item, based on its price and an experimentally-determined budget. The relatively small budgets (less than $50) in gift card form could be treated as a windfall with a high propensity to consume (Helion & Gilovich, 2014). We collected both participants' purchasing behavior and real-time measures of the decision process (e.g., response time, eye gaze) as they evaluated product, price, and budget information. Our attention data allowed us to examine how looking behavior relates to subsequent choice. We examined how information-gathering differs between purchasing and skipping products, extending previous research to include the role of budget size. Furthermore, we characterized individual differences in gaze patterns to distinguish those who use budget the most from those who use budget the least in their decision making, going beyond just looking at attention to budget and further examining transitions and scanpath consistency to identify potential heuristic patterns.

Across three studies, we establish the effects of budget information upon the decision process, replicate those effects in an independent sample, and eliminate perceptual anchoring effects as a possible explanation of our results. Our results demonstrate that budget size influences item purchasing decisions for non-necessity items and that measures of the attentional process provide new insights into how budgets shape purchasing behavior overall and the patterns that distinguish individuals who rely more or less on budget.

We tested a set of hypotheses about the effects of budgets upon consumer behavior, with Hypotheses 1 and 2 addressing the general impact of budgets on the decision process and Hypotheses 3a and 3b focusing on individual differences in the use of budget information. Hypotheses 1-3a were all generated and pre-registered before completing the replication study, whereas Hypothesis 3b was developed later and is more exploratory.

H1: Larger budgets relative to smaller budgets lead to faster response times for decisions to buy.

This is because larger budgets enable less consideration before buying as purchasing is perceived as less costly. For smaller budgets, there may be a longer consideration of whether the item is truly worth the price.

H2: There is a positive interaction between budget size and attention such that spending relatively more time looking at the budget information increases the likelihood of purchasing at higher budgets.

This hypothesis tests the multiplicative relationship between of attention and value in choice. Prior work on binary choice between two options finds that attention has a greater impact for higher-value options or attributes in the attentional drift diffusion model (aDDM), but this has not been investigated for more indirect attributes of purchasing choices (Pirrone & Gobet, 2021; Smith & Krajbich, 2019).

H3a: Individuals who modulate purchasing more by budget make more transitions between the budget and price AOIs.

Individuals who make more budget-price comparisons are likely interpreting prices with respect to budgets and deciding whether the price is appealing given the budget. This is because budgets can frame spending such that the same price seems lower relative to a higher budget, an effect that might be even more pronounced for this experiment where budgets could be seen as windfall gains or "slack" for buying (Arkes et al., 1994; Shefrin & Thaler, 1988; Stilley et al., 2010). Those who make fewer comparisons between budgets and prices may instead evaluate prices relative to an internal WTP or value for the item and thus be less influenced by budget size.

H3b: People who modulate purchasing more by budget show more consistency in their scanpaths across trials, regardless of whether they purchase or not.

This is a more exploratory hypothesis based in part on qualitative scanpath trends. Those who show higher budget sensitivity may be more likely to look at all information across trials on which they buy or skip as their process may evaluate if an item is worth buying given the full budget and price context. In contrast, those who show less budget sensitivity may have more of a filtering process by which they look at item information and then decide whether to investigate more information depending on whether they are interested which would lead to more differentiation in attention on trials in which they skip or purchase.

2. Material and methods

2.1. Participants

Sample size and characteristics: We chose a target sample size of 70 for our primary and replication samples from a power analysis based on Knutson et al., 2008 (see the Supplementary methods for more information). We based the sample size calculation for our anchoring control sample on a power analysis of our primary sample budget effect, which established a target sample of 55. Our age range of interest was 18–25 years as we were specifically interested in financial decision making by young adults, given the importance of that age range for potential interventions that could shape lifetime financial patterns. All participants were recruited from the local communities and provided informed consent under a protocol approved by the university's Institutional Review Board.

Primary sample: We recruited 139 participants for our pre-survey; of those, 76 passed our eligibility criteria and participated in the laboratory experiment. Following data collection but before analysis, we excluded 5 participants for poor eye-tracking data or calibration (see eye-tracking section below for details of exclusion criteria), leaving a final sample of 71 participants (mean age = 21.4 y, SD = 2.5 y; 48 female).

Replication sample: Before completing our replication, we preregistered our main hypotheses derived from the primary sample: https://osf.io/dnum5. Hypothesis 3b was generated after the preregistration and can be considered more exploratory. We recruited 152 participants for our pre-survey; of those, 86 passed our eligibility criteria and participated in the laboratory experiment. Following data collection but before analysis, we excluded 15 participants for poor eye-tracking data or calibration and one additional participant after they indicated a lack of understanding of the payoff structure upon completing the experiment, leaving a final sample of 70 participants (mean age = 21.8 y, SD = 2.2 y; 53 female).

Anchoring control sample: We recruited 104 participants for our pre-survey; of those, 58 passed our eligibility criteria and participated in the laboratory experiment. Following data collection but before analysis, we excluded 3 participants for poor eye-tracking data or calibration, leaving a final sample of 55 participants (mean age = 21.1 y, SD = 2.2 y; 36 female).

2.2. Procedure and tasks

Participants gave informed consent followed by an online eligibility survey. Those who were eligible came to the laboratory for in-person eye-tracking tasks approximately a week later. After the laboratory task, participants completed surveys including items from the Buying Impulsiveness scale, the Abbreviated Barratt Impulsivity Scale (ABIS), and the Consideration of Future Consequences (CFC) survey (Coutlee et al., 2014; Rook & Fisher, 1995; Strathman et al., 1994). Participants also answered questions about their task strategy.

In an online eligibility pre-survey, participants bid their willingness to pay for 90 non-necessity consumer items through a Becker-DeGroot-Marschak (BDM) procedure (Becker et al., 1964). Participants were informed that the budget range would be $10-$40, but the exact budget was not specified. Participants who passed comprehension questions indicating understanding of the auction procedure and who had at least 30 non-zero bids were eligible for the lab experiment. For each participant, the 30 items with the lowest

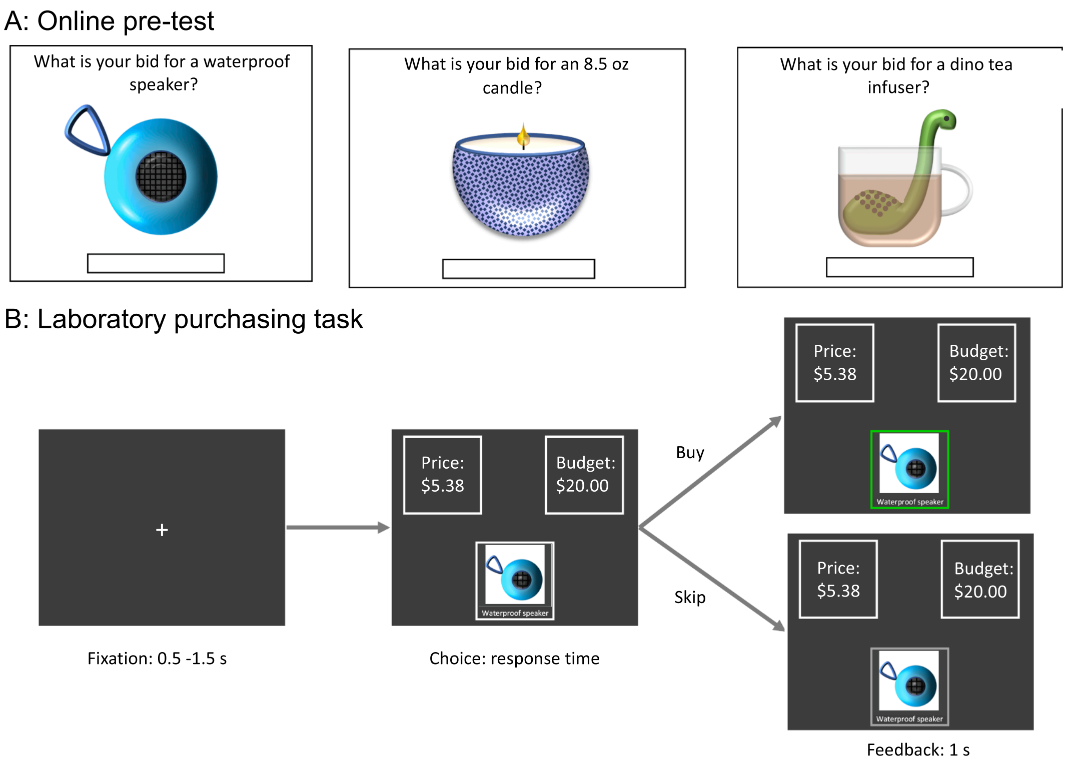

Fig. 1. Online bidding and laboratory purchasing task. A. Sample of three items from the online pre-survey to obtain willingness to pay ratings. Participants gave their WTP for 90 non-necessity items. Participants saw real items in the bidding task. B. Laboratory purchasing task. Participants viewed the item in the lower center of the screen (constant across participants) and viewed price and budget information in the top right and left corners (counterbalanced across participants). Participants could choose whether to buy or skip each item at the given price and budget. For illustrative purposes, the font size of the price and budget information is increased in these images.

bids from the pre-survey were dropped, and their top 60 items were used in the eye-tracking task. Participants who failed comprehension questions or bid $0 for more than 60 of the 90 items offered during the eligibility survey were not eligible for the laboratory study and were excluded prior to data collection. They had to have at least 30 non-zero bids to ensure that participants were motivated to purchase at least half of the products shown to them as budgets are only meaningful if a participant is considering purchasing an item (see Fig. 1).

In the eye-tracking task used in our Primary and Replication experiments, participants completed 120 trials, choosing on each trial whether to buy an item for a given price and a given budget ($10, $20, or $40). Each of the 60 items was presented on two trials at different points in the experiment; we label the second of these as "repeat" trials. On half of the repeat trials the budget changed (half of these increased budget; half decreased), and on the other half the budget remained identical. This enabled us to distinguish changes in purchasing associated with variation in budget size from changes attributable to repeated presentation of the same item. Participants were informed that they might see the same item presented multiple times with different budgets, but prices did not change from the first to the second trial. Most items had subject-specific WTPs between $2 and $10; those items were assigned a price within $1 of the WTP. Items for which the WTP was over $10 were assigned a price between $8–10 because we wanted all prices to be less than the minimal budget (i.e., $10). Items with a WTP under $2 were randomly assigned a price from $1-$10 to ensure that participants saw a variety of prices. Participants were not provided information about these pricing rules. Histograms of the distributions of WTP bids from part 1 and prices in part 2 can be found in Supplementary Fig. 2. Budget and price information were presented at the top right and top left of the screen, with location constant within a participant but randomized across participants. After the task, participants estimated the retail prices of each item and were paid a small bonus for accuracy.

The tasks were incentive compatible, such that a single trial was drawn from either the pre-survey or the lab study and resolved in the following manner. For a pre-survey trial, we selected a random item, a random price from $1–10, and a random budget from $10–40, both uniformly distributed, and performed a modified BDM auction. If the participant's bid was below the random price, they would receive the entire random budget; if their bid was equal to or higher than the price, they received both the item and the monetary amount remaining after subtracting the random experimental price from the random budget. For a laboratory study trial, we selected a random item from all viewed by the participant. If they bought the item on that trial, they would get the item along with the remaining funds in that trial's budget. If they skipped that item, they received the full budget amount.

The anchoring control experiment (Supplementary Fig. 1) followed the same general procedures except that we did not provide trial-specific budgets in the purchasing task; instead, we included a section labeled "Other" that had the same numerical values with a dollar sign (i.e., $10, $20, or $40). Participants were told that these numbers were randomly generated and had no effect on the task. Whereas in the primary and replication samples, budget and price were in stable positions on the screen, in this control experiment, budget and price positions were randomized to the upper left or right of the screen across trials. Participants were also informed that we would randomly generate a budget from $10-$40 and that they would not know this value until the end of the experiment (similarly to the pre-survey with a randomly selected budget). For this control experiment, if the laboratory study was randomly chosen for payment, we selected a random trial that was resolved based on their choice. If they bought the item on that trial, they would get the item along with the remaining funds from the randomly generated budget (unknown at the time of choice). If they skipped that item, they received the full randomly generated budget amount.

Participants were paid $6 for completing only the online eligibility survey, or $9 plus the item, budget, and retail guess bonuses described above for completing the laboratory experiment. All items were delivered within two days. To minimize potential effects of temporal discounting, leftover budget amounts were also sent two days after the experiment. Budget money was paid as an Amazon gift card to reduce the transaction costs of sending the money later and because gift cards are more likely to be viewed as a windfall and used for impulse purchases (Helion & Gilovich, 2014).

2.3. *Eye tracking*

We used a Tobii T60 eye tracker to collect eye gaze data. This eye tracker estimates gaze position at 60 Hz using an unobtrusive infrared camera system; participants can freely move their head during the task, making the experience similar to real-world computer-based interactions (e.g., online shopping). Participants were approximately 65 cm from the eye tracker and were calibrated with a 9-point calibration through the Tobii system. We established areas of interest (AOIs) around the 3 key pieces of information present during choice (item image, budget, and price). Each AOI was 346 by 346 pixels within the 1280 by 1024 total resolution of the screen. The closest edges of the budget and price AOIs were 294 pixels apart, or approximately 7.4 visual angle degrees. The item AOI's closest edge to the budget and price AOIs was 144 pixels vertically or about 3.6 visual angle degrees. Participants were excluded from eye-tracking analyses following data collection if they had limited usable data during the choice screen (25% or more data points outside of AOIs) or overall poor eye tracking throughout the experiment (35% or more data points not identifiable by the Tobii eye tracker).

2.4. *Analysis*

Behavioral analysis: For all models, we excluded bids over $40 because $40 was the maximum budget, so participants could not have paid more than $40 for any item. All models use mean-centered, scaled (divided by standard deviation) explanatory variables to account for multicollinearity (e.g., between price and WTP), and to facilitate model convergence. We used mixed-effects logistic regression with individual intercepts to explore the behavioral effect of budget on purchasing, including price and WTP as control variables. For trial-by-trial analyses including eye-tracking information, we used mixed-effects logistic regression to explore the interactions between the proportion of dwell time on areas of interest (AOIs) including budget and price and their values and looking elsewhere on the screen (null AOI). We exclude the proportion of dwell time on the item AOI in these regressions to avoid perfect multicollinearity. We plotted the interaction effects using the *effects* package in R (Fox, 2003; Fox & Weisberg, 2018, 2019).

Indices of looking behavior: We calculated the dwell time as the total fixation time spent looking in each AOI during a given trial. We calculated the proportion of dwell time on each AOI by dividing dwell time by the total fixation time in a given trial. We also calculated the proportion of gaze transitions between each pair of AOIs relative to the total number of AOI transitions.

Scanpath consistency analysis: To measure scanpath consistency, we operationalized scanpaths as strings using different letters for each of the three primary AOIs; then, we used the R package "stringdist" to compute the pairwise dissimilarities between strings—where deletions, insertions, substitutions, and transpositions all count toward the dissimilarity quantification. We summed the pairwise dissimilarities divided by the number of comparisons to get an average dissimilarity (van der Loo, 2014). We used the stringdistmatrix command to examine all pairwise dissimilarities between buy and skip trials; the average match between them provides an index of scanpath consistency between trial types.

Programming environments: MATLAB was used to preprocess eye-tracking data and create eye-tracking measures. R using the Rstudio environment was used to run models, calculate statistics, and plot data.

Data and code availability: Data and code are available on the Open Science Framework at this link: https://osf.io/z6f5r/files/osfstorage.

3. Results

3.1. Budgets, but not numerical anchors, affect purchasing rates

We first confirmed the effect of budget size on willingness to purchase consumer items, ruling out numerical anchoring. For both our primary and replication samples, increasing the budget did increase the overall proportion of items bought from ~25% for a \$10 budget up to ~50% for a \$40 budget (Fig. 2A, B), further confirmed in mixed effects logistic regressions controlling for individual purchasing rate, price, and WTP (primary $b = 0.52$, $p < 0.001$; replication $b = 0.49$, $p < 0.001$ in Table 1 columns 1, 2). Further, the impact of budget is robust to allowing the budget to vary across individuals and to subsets of the data including those items for which budget changed across trials and the subset of items for which the price was within \$1 of WTP (Supplementary Tables 1, 3, 4).

Our control experiment tested the alternative hypothesis that budgets act as incidental numerical anchors that signal higher values and thus increased willingness to buy (Critcher & Gilovich, 2008; Dogerlioglu-Demir & Koças, 2015). We found no influence of our numerical anchor on the proportion of items bought ($b = -0.01$, $p = 0.71$; Table 1 column 3); instead, participants exhibited a constant purchasing rate of ~35% for all levels of the anchor (Fig. 2C). Because there was no effect of the anchor, we do not discuss data from that experiment hereafter.

In addition to the overall effect of budget on purchasing, we wanted to investigate whether certain items were more likely to be affected by higher budgets. Higher budgets could be perceived as a general increase in wealth and influence purchasing equally across all items, or a higher budget could exert a value-specific effect by making more highly-valued (and often more expensive) items seem more accessible even though all prices were below all budgets. We observed interactions between budget and WTP (primary $b = 0.06$, $p = 0.027$; replication $b = 0.09$, $p < 0.001$ Table 1 columns 4,5) as well as budget and consumer surplus (Supplementary Table 2). These results supported the second, value-specific possibility: higher budgets increased purchasing more for items with higher consumer surplus and higher WTPs. However, neither of these effects consistently held for the subsets of items in which budget changed or price was within \$1 of WTP (Supplementary Tables 5, 6), so this effect has mixed evidence. We conclude that lower budgets acted as self-control devices that deterred participants from purchasing even desirable items, while higher budgets gave more license to purchase expensive but valued items.

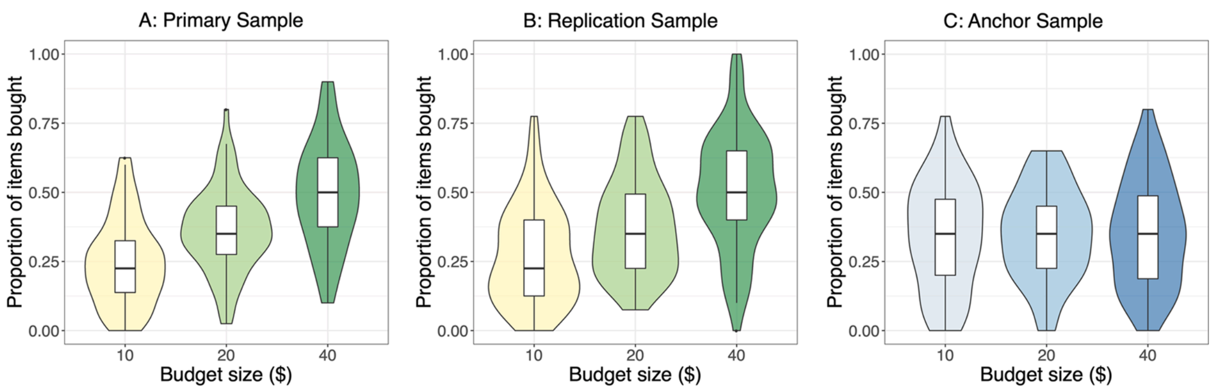

Fig. 2. Purchasing rates change with budget size (A, B) but not anchor size (C). Distributions displayed as violin plots with median and quartiles displayed as boxplots.

Table 1
Budget, price, and WTP in purchasing.

	(1) Baseline: Primary	(2) Baseline: Replication	(3) Baseline: Anchoring	(4) Interaction: Primary	(5) Interaction: Replication
Fixed effects					
Intercept	−0.68***	−0.61***	−0.82***	−0.67***	−0.61***
	(0.10)	(0.11)	(0.15)	(0.10)	(0.11)
WTP	1.07***	0.83***	1.35***	1.09***	0.85***
	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)
Price	−0.30***	−0.04	−0.19***	−0.31***	−0.06
	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)
Budget (Anchor)	0.52***	0.49***	−0.01	0.52***	0.49***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
WTP × Budget				0.06*	0.09***
				(0.03)	(0.03)
Random effects					
Subject: variance (st. dev.)	0.60	0.86	1.18	0.60	0.86
	(0.77)	(0.93)	(1.09)	(0.77)	(0.93)
Obs., Subjects	8442, 71	8314, 70	6566, 55	8442, 71	8314, 70
BIC	9484.4	9564.0	6982.6	9488.5	9562.0
Pseudo-R^2 marginal (conditional)	0.18	0.15	0.21	0.18	0.15
	(0.28)	(0.29)	(0.38)	(0.28)	(0.29)

Standard errors in parentheses. Purchasing is coded as 1, skipping as 0. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

3.2. Low budgets slow the decision to buy

To investigate the effect of budget on the decision process, we examined response time as a function of budget (Fig. 3). Participants were much slower to buy than to skip (Paired *t*-test: buy = 3.57 s, skip = 2.66 s, $t(70) = 8.78$, $p < 0.001$, 95% Cl: [0.22, 0.35]; replication: paired *t*-test: buy = 3.37 s, skip = 2.64 s, $t(69) = 7.35$, $p < 0.001$, 95% Cl: [0.19, 0.33]; mean response times of untransformed RTs, but tests run on natural log-transformed RTs), and lower budgets slowed the decision to purchase even further. A mixed effects linear regression of response time on budget and purchasing, controlling for WTP, price, and individual intercepts confirmed the interaction between budget and buying such that higher budgets decreased response time for buying compared to lower budgets (primary $b = -0.004$, $p < 0.001$; replication $b = -0.005$, $p < 0.001$, Table 2), confirming H1. Moreover, participants looked relatively less at the item AOI (primary $b = -2.01$, $p < 0.001$; replication $b = -2.78$, $p < 0.001$), and more at the budget and price AOIs when purchasing instead of skipping suggesting that they become more likely to seek out budget and price information when considering purchasing (Supplementary Tables 7, 9). Furthermore, all AOIs have longer dwell times on buy compared to skip trials, so all information is explored more thoroughly (Supplementary Table 8, Supplementary Fig. 3). Together, these finding suggest that buying and skipping involve different information-seeking patterns, with buying involving a longer and more comprehensive information gathering process that is also more sensitive to budget information.

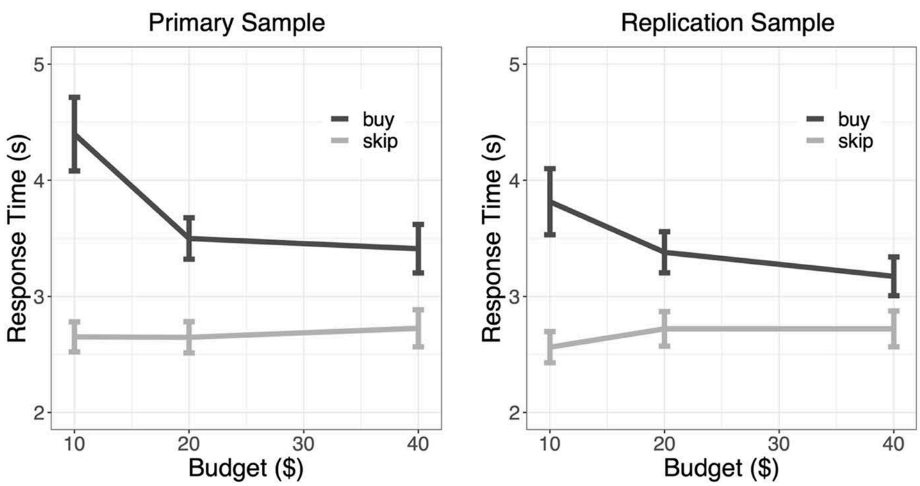

Fig. 3. Response time as a function of purchasing and budget. Lines connect average response times across budget sizes and error bars represent standard errors.

Table 2
Response time relates to WTP, price, budget, and purchasing.

	(1) Response time: Primary	(2) Response time: Replication
Fixed effects		
Intercept	0.61***	0.51***
	(0.05)	(0.05)
WTP	0.010***	0.009***
	(0.002)	(0.002)
Price	0.004	0.02***
	(0.003)	(0.004)
Budget	0.0002	0.0007
	(0.0006)	(0.0006)
Buy	0.54***	0.49***
	(0.03)	(0.03)
WTP X Buy	−0.020***	−0.014***
	(0.002)	(0.002)
Budget X Buy	−0.004***	−0.005***
	(0.001)	(0.001)
Random effects		
Subject variance	0.34	0.34
(st. dev.)	(0.54)	(0.54)
Obs., Subjects	8442, 71	8314, 70
BIC	14024.6	13603.21
Pseudo-R^2 marginal	0.054	0.05
(conditional)	(0.32)	(0.32)

Standard errors in parentheses. Response times are natural log-transformed. Buy is coded as 1, skipping as 0. *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$.

Table 3
Trial by trial influences of gaze to AOI information in purchasing.

	(1) Baseline: Primary	(2) Baseline: Replication	(3) AOI: Primary	(4) AOI: Replication	(5) AOI interactions: Primary	(6) AOI interactions: Replication
Fixed effects						
Intercept	−0.73***	−0.65***	−0.75***	−0.66***	−0.75***	−0.66***
	(0.10)	(0.12)	(0.11)	(0.12)	(0.11)	(0.12)
WTP	1.07***	0.83***	1.05***	0.81***	1.06***	0.81***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Price	−0.32***	−0.09*	−0.33***	−0.11**	−0.33***	−0.11**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Budget	0.54***	0.50***	0.54***	0.51***	0.54***	0.50***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
Budget AOI			0.18***	0.18***	0.16***	0.16***
			(0.03)	(0.03)	(0.03)	(0.03)
Budget × budget AOI					0.20***	0.16***
					(0.03)	(0.03)
Price AOI			0.22***	0.23***	0.21***	0.23***
			(0.03)	(0.03)	(0.03)	(0.03)
Price × price AOI					−0.08**	−0.03
					(0.03)	(0.03)
Null AOI			−0.02	−0.002	−0.03	−0.0004
			(0.03)	(0.03)	(0.03)	(0.03)
Response time	0.58***	0.52***	0.61***	0.56***	0.60***	0.56***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
Random effects						
Subject: variance	0.71	0.89	0.76	0.88	0.76	0.88
(st. dev.)	(0.84)	(0.95)	(0.87)	(0.94)	(0.87)	(0.94)
Obs., subjects	8442, 71	8314, 70	8405, 71	8297, 70	8405, 71	8297, 70
BIC	9127.2	9285.6	9022.7	9185.3	8975.1	9164.8
Pseudo-R^2 marginal	0.23	0.19	0.24	0.21	0.25	0.22
(conditional)	(0.34)	(0.33)	(0.36)	(0.35)	(0.36)	(0.35)

Standard errors in parentheses. Purchasing is coded as 1, skipping as 0. Response times are natural log-transformed *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. AOIs are the proportion of time spent in an AOI compared to total fixation time. Null AOI encompasses fixations on the screen there were not to one of the three pieces of information. The excluded (baseline) AOI is the item AOI.

3.3. Attention amplifies the impact of higher budgets in purchasing

We investigated how attention influences choice via a trial-level logistic regression that predicted purchasing behavior from gaze and response time data. Including eye-tracking improves models of choice behavior above and beyond what can be derived from WTP, price, and budget values, as indicated by lower BIC values and slightly higher pseudo-R^2 values (Table 3). We found that looking relatively longer at the budget or price AOI, relative to the excluded item AOI, related to increased purchasing (Table 3, columns 3, 4). We additionally found a positive interaction between the proportion of time looking at the budget AOI and budget size (Fig. 4; primary: $b = 0.20$, $p < 0.001$; replication: $b = 0.16$, $p < 0.001$; Table 3 columns 5, 6), indicating that looking relatively longer at higher budgets increased the budget's effect on purchasing—supporting H2. This suggests that attention moderates the relationship between budget size and choice, with more attention leading to a stronger relationship. Furthermore, spending a higher proportion of time looking at the price AOI had a positive effect on purchasing, but this seems to be stronger for lower prices, perhaps because cheaper prices make purchasing more appealing. These effects are robust to using overall dwell time instead of the proportion of time spent looking at an AOI, as well as to allowing the budget effect to vary by individual, and to dropping the 10% of trials with the lowest proportion of eye-tracking data during the response time (Supplementary Tables 10–14; Supplementary Fig. 4). The overall positive effects of response time and budget and price AOIs align with the previous result that purchasing trials involved more consideration of information than skip trials. Moreover, the interaction results indicate that dwell times had particularly strong effects on higher budgets, amplifying their impact on purchasing.

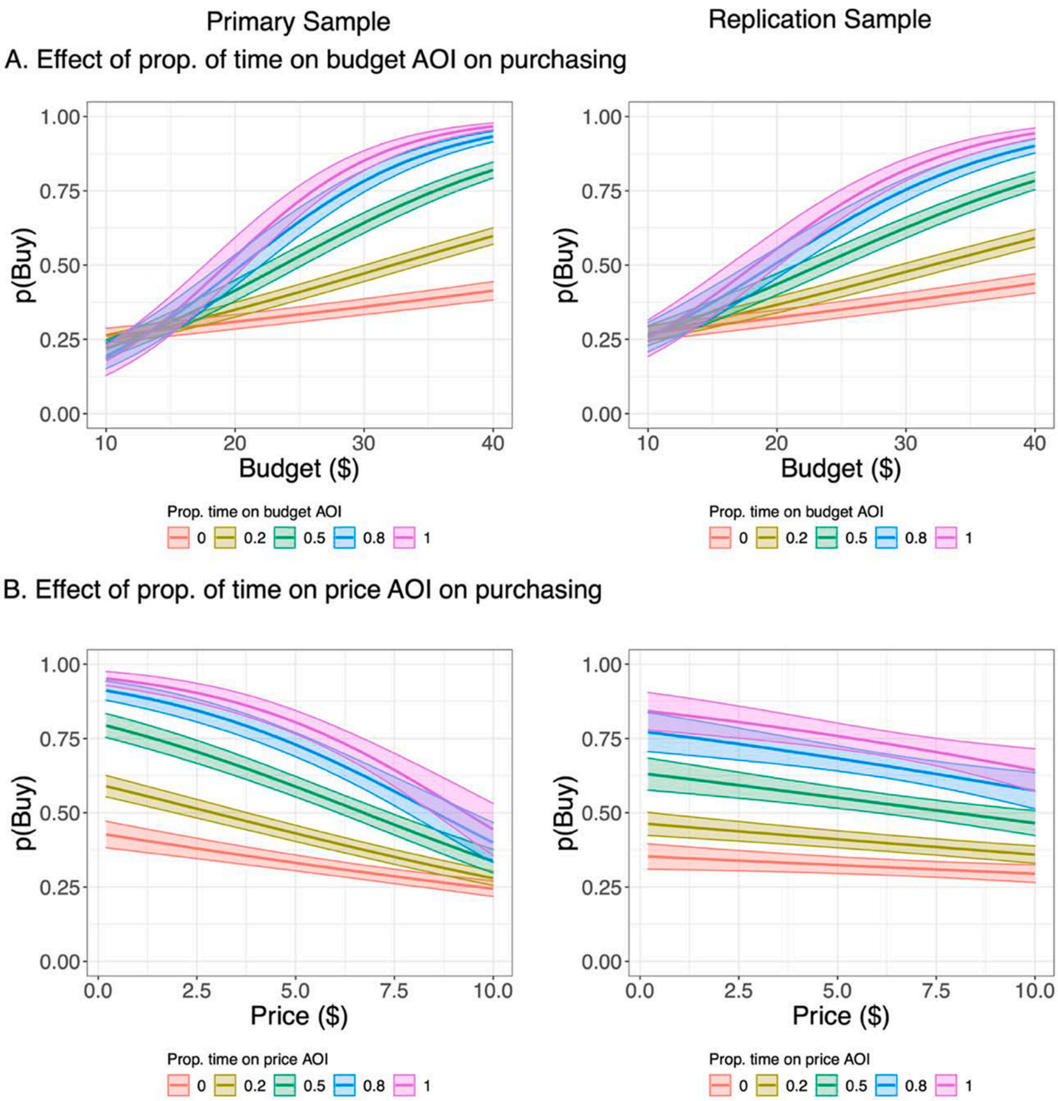

Fig. 4. Illustration of interaction effects between proportion of time spent on AOIs and the budget and price values. Effect plots of the fitted models use mean values for the variables not displayed.

3.4. Individual differences in budget use relate to budget-price transitions and more consistent gaze patterns across choice

We also examined how individual differences in patterns of information gathering might shape the effects of budgets on purchasing. We ran separate logistic regressions for each participant to estimate their individual effect of budget upon purchasing. We then transformed this coefficient into an odds ratio indicating the multiplicative increase in likelihood of purchasing (i.e., 1, no change; > 1, increasing likelihood; < 1, decreasing likelihood). Most participants showed a positive odds ratio (Supplementary Fig. 5), confirming that greater budgets increased the likelihood of purchasing. However, there was also substantial variability, indicating that the strength of this effect varied widely across individuals (see Fig. 5).

We investigated how these individual differences in budget use related to attention. Unsurprisingly, we found a positive correlation between individual's behavioral use of budget and the proportion of time spent looking at budget information (Kendall's rank correlation tau: $z = 3.99$, $tau(69) = 0.32$, $p < 0.001$, 95% CI [0.17, 0.48]; replication: $z = 3.14$, $r(68) = 0.26$, $p = 0.002$, 95% CI [0.11, 0.41]). This effect was driven primarily by price-budget comparisons, where the relative proportion of budget-price transitions (but not budget-item AOI transitions) correlated with the budget odds ratio (Kendall's rank correlation tau: $z = 4.02$, $tau(69) = 0.33$, $p < 0.001$, 95% CI: [0.16, 0.48]; replication: $z = 2.74$, $tau(68) = 0.22$, $p = 0.006$, 95% CI [0.06, 0.39]). This result indicates that those who were more affected by budget size were more likely to acquire information about budget and price in consecutive gaze fixations, whereas others were focused more on the value of the item.

Furthermore, we were interested in whether more budget-sensitive individuals were also more likely to adopt consistent scanpaths that could reflect a heuristic approach to the decision process. We tested this by computing the average dissimilarity in scanpaths across buy and skip trials within an individual (focusing analyses on the first three AOIs fixated) with higher values indicating less

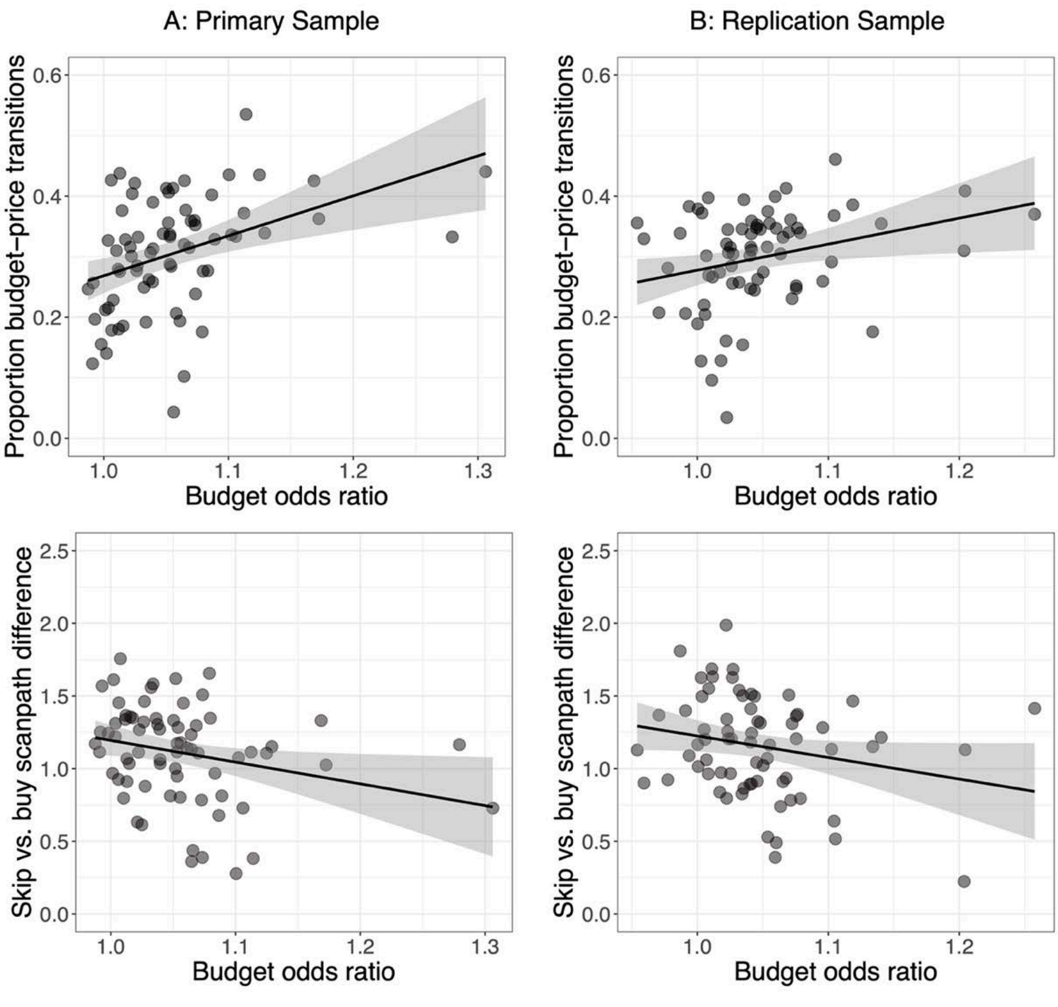

Fig. 5. Correlations between budget use and eye-tracking patterns. A. Proportion of budget-price transitions. B. Scanpath differences across buy and skip trials where higher values indicate less consistency and lower values indicate more consistency. The raw data are displayed with linear trends and shaded 95% confidence bands for illustration, but Kendall's rank-correlations are used to determine significance to minimize the impact of outliers.

consistency. We find that those who used budget more also showed more consistency in their scanpaths across skip and buy trials compared to those who were less influenced by budget information (Kendall's rank correlation tau: $z = -2.56$, $tau(69) = -0.21$, $p = 0.011$, 95% CI: [−0.35, −0.06]; replication: $z = -2.00$, $tau(68) = -0.16$, $p = 0.045$, 95% CI [−0.32, −0.01]). This finding supports the interpretation that consumers who prioritize budget information do so as part of a stereotyped information gathering process that emphasizes price-budget comparisons.

4. Discussion

In this paper, we explore how attention modulates the impact of budgets in consumer choice. We find that higher budgets speed up the decision process for purchases, that increased attention to higher budgets amplifies their impact in choice, and that larger budgets justify higher spending while lower budgets reduce purchasing. Moreover, there were large individual differences in the patterns of information gathering and use of budget. People who made more gaze transitions between budget and price information showed a larger effect of budget size in their decisions. Finally, those with a larger budget effect also used more consistent scanpaths across trials, indicating more of a heuristic pattern. All conclusions were confirmed using a pre-registered replication in an independent sample.

Taken together, our results show that attention to budget information influences purchasing decisions—an effect moderated by individual differences in the patterns of information gathering. Revealing the choice process by examining attention deepens the understanding of how information is weighted and interacts in consumer choice, with implications for how budget information could be emphasized by marketers to promote certain types of spending or by consumers to gain control of their spending habits.

Our results indicate that budget size drives choice through a process that interprets price information in the context of the current budget. For example, because of diminishing marginal utility, spending \$5 from a \$10 budget may be perceived as a larger expense than spending \$5 from a \$40 budget. This may also act in the framework of mental accounting where making the budget size salient leads to more focus on the price and constrains purchasing for small budgets (Morewedge et al., 2007). This effect may be more pronounced with experimental payments that act like small windfalls, a category of money that increases spending even more than gains in income or wealth according to mental accounting research (Arkes et al., 1994; Shefrin & Thaler, 1988). Nevertheless, the budget values used in this experiment are within a range typical for consumer purchases, a context that has been previously shown to evoke mental accounting of budgets (Stilley et al., 2010; Thaler, 1990). Our findings add to the literature suggesting that people can use budgets as a self-control device to shift their valuation of a product.

An alternative interpretation of our results could be that purchasing was constrained by the experimental setting (e.g., participants expected a minimal amount to be earned). Our study design employed four main strategies to minimize this concern. First, participants received a base payment for participation and their purchasing choices were framed as a bonus on top of this guaranteed amount. Second, the price of the item was always below the budget, so lower budgets never limited participants' ability to buy the item. Third, to reduce temporal discounting in the tradeoff between items and money, we paid bonus money two days later so that it was not a more immediate reward and instead would arrive at the same time as an item ordered online. Finally, all money was paid in Amazon gift cards rather than cash to reduce transaction costs and to reduce the immediacy of the ability to use that money. People are more likely to purchase luxury or hedonic items with a gift card compared to cash, so paying in Amazon gift cards may additionally put people in a more purchasing-oriented mindset (Helion & Gilovich, 2014). These approaches made the experimental setting more realistic and particularly well-matched to online shopping, which is an increasingly common setting for consumer behavior.

Our eye tracking findings contribute to a growing body of literature that examines real-time measures of how attention contributes to consumer choice. Attention to one item in a choice set leads to preferential processing of that item—and decreased value for unattended items—which in turn has been shown to shape many types of consumer choice (Fisher, 2017; Krajbich et al., 2010, 2012, 2015; Krajbich & Rangel, 2011). Further research has shown that gaze does not simply boost all value equally, but instead has a greater impact for options of higher value (Smith & Krajbich, 2019). This explains why higher budgets benefit more from attention than lower budgets.

The relationship between attention and price is more nuanced because higher prices may represent more of a cost, but also looking at price indicates more consideration of a purchase. In support of the cost view, previous work on attention in consumer choice suggests that attention to an appealing item increases the likelihood of purchasing, whereas attention to a costly price may decrease it (Krajbich et al., 2012). We similarly found that longer dwell time on items relative to price increased the likelihood of purchasing, especially for choices where the price was higher than WTP (Supplementary Table 15, Supplementary Figure 6). We further find that attention has more of a beneficial effect for lower prices which may be perceived as less costly and therefore increases the subjective-value of purchasing which is the goal-relevant decision (Sepulveda et al., 2020). However, given that prices were often set near WTPs, this finding is not as clear as in studies where they are fully independent. In contrast, longer dwell times on all information including price, relate to increased purchasing likely reflecting more consideration of all information when buying compared to skipping. Longer dwell time on item and price predicting purchasing has been found in other studies and may be attributable to a multi-stage process of consumer choice (Imai et al., 2019; Mormann et al., 2020). This extends work showing that initial attention toward items tends to cause consumers to make liking judgements, whereas initial attention to prices leads to an evaluation of benefits and costs (Karmarkar et al., 2015). Most people in our study looked at the item first, skipped rejected items quickly without gathering more information, and evinced longer dwell times on all information for subsequently purchased items—behaviors all consistent with a rapid liking judgement that shapes subsequent processing (Supplementary Fig. 3). Our findings thus accord with prior studies that examined the interaction of price and budget but extend those findings by describing interaction between attention and budgets in the choice process.

Importantly, we showed that our budget effect did not result from incidental numerical anchoring, which occurs when an arbitrarily-determined number biases subsequent numerical estimates like WTP (Ariely et al., 2003; Chapman & Johnson, 1994; Tversky & Kahneman, 1974; Tymula et al., 2016; Yoon et al., 2019). Some studies explicitly ask participants to compare the anchor value and their WTP or the price on screen, but others also find that the mere presence of numbers near typical prices in the brand or product name may suffice to influence valuation (Ariely et al., 2003; Critcher & Gilovich, 2008; Dogerlioglu-Demir & Koças, 2015; Krishna et al., 2006; Nunes & Boatwright, 2004; Wilson et al., 1996). Our lack of anchoring effect may be due to the fact that our participants were not asked to make direct comparisons between the anchor and the price on screen, but also because incidental anchors may be sensitive to a number of factors including whether they are attended, their proximity to the comparison value, and the familiarity of the items (Brewer & Chapman, 2002; Dogerlioglu-Demir & Koças, 2014, 2015; Tymula & Plassmann, 2016; Wong & Kwong, 2000). Options with very strong prior knowledge or expectations may be less influenced by anchoring or bottom-up attention because preferences and strategies are better defined than for options with weaker internal preferences or expectations (Konovalov & Krajbich, 2016; Orquin & Mueller Loose, 2013; Payne et al., 1992). Therefore, while we do not find evidence of numerical anchoring, such effects might occur in other contexts, such as when consumers make decisions about items with which they only have limited familiarity.

4.1. Implications and extensions

Our findings suggest that more attention to larger budgets relative to other features of the choice increases the chance of purchasing. This means that consumers may inadvertently be swayed by windfalls (e.g., recent gifts) or by marketing actions (e.g., prominent e-gift cards or promotional store credits). However, consumers can also influence their spending by making their own budget goals salient during shopping via explicit reminders, as when writing a target budget on a shopping list or using an online tool that provides budget information when visiting shopping websites. The impact of such budgets depends on context, including the level of attention and perceived budget size. The impact of attention is reduced for budgets that are perceived as smaller, which may act as constraints regardless of the amount of attention they receive. In contrast, more attention to relatively larger budgets leads to even more purchasing, so the extent to which budget information is salient may create a greater sense of ability to purchase and more focus on the appeal of the item (Larson & Hamilton, 2012). Whether a budget is perceived as relatively smaller or larger may have to do with the comparisons between the budget and prices being considered as well as mental accounting that assigns a budget size to a category of purchase or that creates a reference point for how much to spend in a given shopping trip (Stilley et al., 2010; Thaler, 1999). The ability of consumers to shift their attention to change purchasing habits does not negate the importance and prevalence of structural barriers to economic mobility that should be addressed through broader societal action rather than individual shifts in behavior. Nevertheless, in the cases where psychological biases also factor into maladaptive decisions (e.g., impulse purchases) that affect savings over time, such attentional insights can suggest more impactful interventions (Bertrand et al., 2006; Madrian et al., 2017). Indeed, more traditional approaches of pure information campaigns to increase financial literacy often have short-term and minimal effects on behavioral change (Fernandes et al., 2014), so other approaches that work within the decision process, such as increasing or reducing the salience of budget information at the time of decision making, can offer consumers a more impactful tool to shift choice than information alone (Madrian et al., 2017).

Budgeting and mental accounting outside of the lab often occur in more complex environments with multiple competing items and a budget that must last for a set period of time. Therefore, expanding an eye-tracking approach towards more complex paradigms and realistic decisions could prove fruitful for understanding the mechanisms of mental accounting and developing more effective interventions. For example, looking at the effect of budget on purchasing bundles of items, or examining how people keep track of serially buying items within one budget is important for understanding the decision-making process that occurs while shopping or planning spending over the course of a month (Shaddy & Fishbach, 2017; Ülkümen et al., 2008). Another relevant factor is that people may create budgets with others, whether in a multi-person household or as part of a larger organization. This requires a better understanding of how those with different budget sensitivities may adapt their spending when part of a larger group and whether conflicts may arise from how the constraints of budgets are interpreted by different individuals. Moreover, budgets are not the only factor in purchasing. Budgets should be examined in combination with other factors that are relevant in impulse-purchasing particularly, such as time pressure, social context, the physical presence of items, advertising, and promotions (Bushong et al., 2010; Friese et al., 2006; Jeffrey & Hodge, 2007; Kocher & Sutter, 2006; Luo, 2005; Reutskaja et al., 2011; Shukla et al., 2014). Eye tracking can help elucidate how these differing pressures interact and reinforce or compete with each other for attention.

Further extensions could explore the process by which individuals create budget categories. This includes examining individual differences in strict vs. flexible budget categories and how people assign purchases into these categories, as well as looking at how mental accounts for saving and spending interact – as when people take on high interest debt instead of using savings, resulting in higher interest payments than necessary (Cheema & Soman, 2006; Hershfield et al., 2015; Prelec & Loewenstein, 1998; Sussman & O'Brien, 2016; Ülkümen & Cheema, 2011). Examining the processes by which people create and use mental accounts as well as the attention to these mental accounts during decision making could further pinpoint the contexts in which budgets promote or undermine saving and spending goals. Outside of the monetary domain, mental accounting may also play a role in other decisions such as food choices or time allocation (Basil et al., 2009; Duxbury et al., 2005; Morewedge et al., 2007; Rajagopal & Rha, 2009; Soman, 2001). People create budgets for other categories beside money, such as for calorie consumption or time usage, and our process-tracing approach could be applied to investigate whether budgets in these other domains exert influences on decision making in similar or different ways to monetary budgets.

4.2. Limitations

One caveat of our findings is that we did not measure other financial factors such as socio-economic status (SES). Monetary amounts from $10-$40 may have a very different meaning to people depending on their SES or their life stage and responsibilities, and this may drive their use of budget (Bertrand et al., 2004; Shah et al., 2015). Our current study focuses on a young adult sample, including many college students, and as such it has more homogeneity with respect to income and financial responsibilities than a sample across the adult lifespan. However, younger adults are a particularly important target for understanding the financial decision making process, including consumer choice, because financial habits built before and during early adulthood can impact long-term life outcomes (Bucciol & Veronesi, 2014; Greenberg & Hershfield, 2019; Serido et al., 2013). Therefore, this age group is relevant when thinking about designing interventions to aid consumer habits, as they may have the most impact during this important inflection point in the financial lifespan. Future studies should test whether the use of budget is stronger or weaker in a more heterogenous population that varies across socioeconomic status and life stage.

Another caveat is that we measure naturally arising individual differences in the attentional process, but do not *manipulate* attention. Measuring how attention and information gathering influence choice in a more naturalistic setting is important for understanding how consumers make purchasing choices and for developing more effective interventions to shift the evaluation process. However, while the variations in attentional patterns could impact choices, pre-existing preferences could also drive participants' attentional patterns and impact choices. Therefore, future studies should introduce manipulations that alter attentional processes directly to evaluate the interactions of those manipulations with budget. For example, drawing attention to budget by revealing it earlier than other information, by putting it in a more central location, or by facilitating budget-price comparisons could all affect its relevance for consumer choice (Orquin et al., 2018; Reeck et al., 2017). In addition, the information screen was designed to make the decision feel natural and easy to navigate, so the size of the AOIs and font on the screen was quite large to match typical shopping scenarios which may come at a cost to measuring the full extent of the attentional bias for two reasons. First, it has been shown that numbers, which are easier to process than complex visual stimuli such as pictures, may lead to a lower attentional bias (Krajbich et al., 2012). Second the large size of AOIs means that peripheral vision may have played a role, which could also reduce the attention bias (Eum et al., 2022). Both design choices may reduce the impact of attention which would make our results weaker than they otherwise might be, but they should not change the overall patterns. By investigating the attentional patterns underlying choice, our research offers new directions to investigate the salience of budgets and budget-price comparisons and to develop new consumer interventions.

4.3. Conclusions

We find that attention to budget amplifies the impact of budget magnitude in purchasing decisions. Furthermore, we find that individuals who modulate purchasing more by budget make more price-budget comparisons and use show consistent scanpaths regardless of their eventual purchase decision. Effective use of budgets can help people spread consumption more evenly to enjoy the money that they do have, allowing them to avoid both extreme savings and impulse purchasing (Lempert & Phelps, 2015; Rick et al., 2008). Budgets thus provide an important tool that can lead to either maladaptive or adaptive decisions, depending on both the properties and the salience of budget information.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data and analysis code can be found at: https://osf.io/z6f5r/files/osfstorage.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.joep.2023.102632.

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