Separating the Influence of Budget and Numeric Priming on Willingness to Pay

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Abstract

Many choices consumers make are impulsive, and numerous behavioral economics models propose stimuli that contribute to these choices. Our study looks at whether the size of one's budget can affect purchasing behavior in the same vein as, for example, a good's placement next to a more expensive item or the discounting of a price from $20 to $19.99. Seventy-one participants mostly from the Duke community were incentivized to buy goods at different budgets via a Becker-DeGroot-Marschak (BDM) paradigm, and we found they were indeed significantly more likely to purchase an item when their budget was $40 rather than $20 or $10—even if they could afford the good in all three cases. Our study also employed eye-tracking data, which led us to analyze attentional patterns correlated with this form of impulsive choice. Finally, we ran a follow-up control study, in which 50 of 60 participants' data have been collected, that measures the extent that the larger budget affected behavior due to priming—that just by seeing a larger number on the screen regardless of its meaning, participants were more likely to buy an item. Our results shed light on both another stimulus that contributes to impulsive choice and the ongoing debate regarding irrelevant information's effect on decision-making.

Keywords: impulsive choice, budget, numeric priming, eye tracking, scanpaths

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Impulsive decision-making is pervasive. According to Amos, Holmes, and Keneson (2014), 40% to 80% of all purchases are impulsive and younger populations are particularly likely to buy impulsively, even at a time when there is a record number of student debt borrowers in default (The Institute for College Access & Success, 2016) and the younger generation is "at a pronounced disadvantage on nearly all measures of financial capability" (FINRA Investor Education Foundation, 2013, p. 32). From a consumer perspective, the very definition of impulsive means people making unplanned purchases that often lead to negative affect (Rook & Gardner, 1993), and in layman's terms, they are not necessarily thinking in their best interests. There have been many studies in the field of behavioral economics that have looked at influences of impulsive decision-making—store environment (Donovan, Rossiter, Marcoolyn, & Nesdale, 1994), personality (Weun, Jones, & Betty, 1998), and availability of a credit card (Dittmar & Drury, 2000) are just some examples.

We ran an exploratory study looking at another possible contribution to impulsive decision-making—budget. In theory, we expect that if people are not close to insolvency, if they initially value a certain consumer good at a given price, and if they suddenly receive an additional $10 to $40, they should still value that good at approximately that given price. In other words, we would assume that people's economic preferences are homothetic, or constant, over such a small change in the total money they have (Nechyba, 2015). The results of our study indicated that participants were significantly more willing to pay for consumer goods at higher budgets: the average proportion of products bought across the 71 participants was 24.7% for the third of the trials involving a 10-dollar budget, 36.5% for trials with a 20-dollar budget, and

49.2% with a 40-dollar budget. Those results highlight work from Kahneman and Tversky (1979) on prospect theory, which predicts that change in income—in this case the new budget they have during the study—matter more for valuing products than one's total income.

Numeric Priming

One potential interpretation of our study is the possibility that budget had an impact on consumer behavior not because of what budget represented—how much money participants were given to spend—but rather due to seeing a large number on the computer screen when they were making a decision. This question falls under the topic of numeric priming that has emerged in literature in the past 25 years and which is still debated. Numeric priming is an incidental type of anchoring effect in which seeing a number can influence the judgment one makes when asked an unrelated question. Whereas the field of anchoring as a whole addresses how a first piece of information affects subsequent decisions, in numeric priming when one is formulating that subsequent decision they are not asked to recall the first piece of information.

Logically, one can see why numeric priming might influence decision-making. As Mussweiler and Englich (2005) point out, when people make judgments they often do so in some sort of comparison, like using egocentric information to judge another person (Dunning & Hayes, 1996). People draw those comparisons based on whatever information they have available, and when the only thing that comes to mind is a random number they just saw, participants might use that number in making a decision. There is some evidence supporting numeric priming, like a between-subject study by Critcher and Gilovich (2008) in which judging how many sacks a football player recorded was influenced by incidentally noticing that the player's jersey number was either 94 or 54. However, Newell and Shanks (2014) argued the results were not robust enough to be evidence of numeric priming. They concluded in what is the most comprehensive literature review to date on the topic that “further studies of incidental anchoring are much needed” (Newell & Shanks, 2014, p. 96). Moreover, of the limited numeric priming studies that exist (e.g. Brewer & Chapman, 2002; Cheek, 2016; Critcher & Gilovich, 2008; Dogerlioglu-Demir & Koçaş, 2015; Frederick & Mochon, 2012; Mussweiler & Englich, 2005), none have involved multiple numbers present at the same. Thus, the literature does not predict how, in our first study, participants might use the numeric prime when there is already a useful number on the screen, price.

Eye Tracking Analysis

Another question worth exploring about budget’s relationship with willingness to pay (WTP) is whether attentional patterns play a predictive role. The approach in similar studies (Krajbich, Lu, Camerer, & Rangel, 2012) to ours—using a Becker-DeGroot-Marschak (BDM) paradigm, which encourages participants to make decisions that reflect their true preferences—measure attentional processes with several particular metrics. Those metrics, which we have also employed, are total time looking at each part of the screen—in our case price, budget, item, and anywhere else; likelihood that a participant will look at certain parts of the screen next after previously looking at one part of the screen, which is known as a transition matrix or Markov model; and which percent of trials participants look at each part of the screen first, as well as last. However, only the last of these metrics measures the order in which participants view the screen, and this metric just accounts for the beginning and end of the trial, not everything in between as well. A likely reason there has not been more breakthrough for measuring order is the difficulty of comparing trials that differ in length. For example, it is not initially clear whether one should compare the second fixation in a trial of three fixations to the second fixation in a trial of seven fixations, or to the fourth, which would be the corresponding middle point.

There are currently two approaches to measuring order that could be implemented for our and other decision-making studies. The first has been used in eye tracking studies for more than 40 years and measures the similarity or dissimilarity between one trial's set of fixations—known as a scanpath—and another set of fixations. For example, the standard similarity measure, the Levenshtein Distance algorithm (Levenshtein, 1966), is like a pairwise string alignment, in that it calculates the minimum number of insertions, deletions, or substitutions needed to turn one scanpath—in the form of a string—into another scanpath. The Needleman-Wunsch algorithm (Needleman & Wunsch, 1970) is essentially the same measure, except rather than each insertion, deletion, or substitution costing the same, one can weigh certain changes more than others, like deemphasizing gap-penalties if two scan paths are mostly interchangeable but one has additional fixations at its head and tail.

The second method for measuring order is finding common patterns among numerous scanpaths. Eraslan, Yesilada and Harper (2016a) found that all existing techniques reduce scanpaths like a common denominator, such that an element has to be present in every trial to be included in the generated pattern. The methods therefore do not accommodate much variance and result in patterns that are oftentimes too short to be representative. Eraslan, Yesilada, and Harper (2016b) introduced the Scanpath Trend Analysis (STA) algorithm, which for every element calculates a sum weighted by its position in each scanpath and the duration the participant viewed it. If an element is present in all trials, it is included in the pattern. If an element is not in all the trials but has a weighted sum greater than any element present for all trials, it too is included in the pattern. Finally, the elements that remain form a new, generalized scanpath in order of greatest to least weighted sum. Since the authors developed STA for webpage viewing, they used gaze data of 40 participants viewing webpages to test STA against existing methods, and they found that STA was more accurate than any of the existing techniques. It appears, therefore, that this method is the most promising way to date of measuring scanpath patterns.

Current Study

This study looked at whether a random number on a computer screen can influence how likely participants are to purchase consumer goods in a BDM paradigm, even if that random number is labeled as “irrelevant” and there is another number—price of the consumer good—also on the screen. By figuring out whether greater anchors induce more purchasing, we can identify the extent to which our results from the exploratory study were influenced by budget and the extent to which, if at all, they were influenced by numeric priming. It was hypothesized that there will be a positive correlation between size of the anchor and average number of items bought per participant. Either way, the results will also shed light on the to-date debated effects of numeric priming.

Method

Participants

Based on a power analysis, which we calculated *a priori* by plugging the results of our exploratory study into R’s power.prop.test function, we are running 60 participants for our control study, and we have already collected data for 50 participants. Participants were recruited from the Duke Center for Cognitive Neuroscience Research Participant Site for this study, which was approved by the Duke University Campus Institutional Review Board. All participants were between the ages of 18 and 25 and had a Social Security number so we could pay them if they earned more than $50 during the study. They also had to have sufficient visual acuity to be able to read and interpret the decision stimuli, sufficient motor capabilities to press a button to indicate a response, sufficient understanding of the English language to comprehend the experimental instructions, and the means to show up to the second part of the study in person at Duke University. Finally, participants had to pass an online part to participate in the in-person part of the study.

To pass the online part, participants needed to correctly answer at least one of two comprehension questions about the study's payment set-up. We chose these criteria because the usefulness of the BDM hinges upon its external validity, which in turn relies on participants' ability to understand it. In addition, participants who passed the comprehension questions correctly needed to be willing to pay more than $0 for at least 30 of 90 items presented. These criteria helped make the BDM paradigm meaningful, otherwise participants might have just chosen to pass on each trial without real consideration of the "Price" and "Other" labels on the screen. 84 participants partook in Part 1, and of those 24 failed the comprehension questions and five did not have a WTP greater than $0 for at least 30 items. Additionally, two participants who passed Part 1 did not show up for Part 2, one participants' eye-tracking data was incomplete for half the trials, and one participant took the study more than 10 days after completing the online part.

Although we did not collect demographic data on the participants who only completed the online portion, among those who also completed the in-person part, the average age was 21.2, 36% were male and 64% female, 92% were Duke students or employees, and 50% identified as white, 4% percent as black or African American, and 40% percent as Asian.

Materials

When participants completed the in-person part of the study, they were informed in advance the computer screen was connected to an eye-tracker. Specifically, we used a Tobii desktop-mounted eye-tracker with recordings at 60 Hz, and the data was outputted via an I-VT fixation filter. The code used to download the eye tracking data from participants, organize the data, and analyze it both in terms of standard metrics as well as more tailored ones like Levenshtein distance and STA can be accessed at https://github.com/jackdolgin/Scanpath-Analyses. In addition, all significance tests in this paper were calculated using a maximum likelihood mixed effects linear model.

Procedure

To control for extraneous variables, the method for the control study was nearly identical to the exploratory study. The first part of the study took place online 5-10 days before participants' in-person follow-up. In part one, they saw 90 top-selling items from Amazon.com and for each said how much they valued them monetarily. For part 2, we selected the 60 items with the greatest WTP for that participant, and in person, participants completed 120 trials with a minute-long break after the first 60 trials. The 60 trials before the break, like the 60 trials after, featured each item once in randomized order from participant to participant. On each trial, participants saw three stimuli—an irrelevant number labeled "Other," the price of the item, and a picture of the item. The difference between the control and exploratory study was just that in the exploratory study the number labeled "Other" was labeled "Budget," and it meant that when participants chose to buy an object they would receive the object and the difference of "Budget" and "Price" in the form of an Amazon gift card. Conversely, passing on the object meant receiving all the money in "Budget." To ensure that control participants looked at "Other," we switched its position on the screen with “Price” from trial to trial. One of the two regions of interest (ROI’s) occupied the top-left of the screen and the other the top right, as seen in Figure 1, but in half the cases the sides were swapped. In contrast, during the exploratory study “Budget” and Price did not switch sides.

To make the study incentive-compatible, we used the Becker De-Groot paradigm. We informed participants we would randomly select one trial from either the online or in-person part and give a payout based on that decision. For example, if someone was willing to pay $8 for a beach ball and we randomly selected a price of $6, they would receive the beach ball for $6 and keep the rest of their randomly determined budget. Whereas participants in the exploratory condition knew their budget because it was on the screen, we informed control participants we would also be calculating a budget from which we would subtract their payment for the item, but we did not tell the participants the value of their budget until the end of the study. To control for temporal discounting (Fisher, 1930) and people’s preference for goods that are in-person (Bushong, King, Camerer, & Rangel, 2010), we informed participants that they would receive their gift in two days either way—we shipped the gifts the day of the study via Amazon Prime if they purchased an item and waited two days to send them a gift card for Amazon. After the 120 trials, participants rated how much they thought items actually cost, thereby accounting for a confound to their reported WTP. Finally, participants answered the Abbreviated Impulsiveness scale (Coutlee, Politzer, Hoyle, & Huettel, 2014) and Consideration of Future Consequences scale (Strathman, Gleicher, Boninger, & Edwards, 1994) and reported their age, gender, affiliation to Duke (student, employee, neither), and ethnicity.

Results

Based on inconclusive existing research on numeric priming, we hypothesized that in our exploratory study, numeric priming explained some of budget's influence on purchasing behavior. However, our follow-up control indicates that numeric priming had negligible effects on how many items consumers purchased. In trials in which they viewed anchor, price, and item, participants purchased an average of 38.0% of items when a \$10 anchor appeared, 39.9% with a \$20 anchor (β = .019, *SE*= .03, *p*= .57), and 42.0% with a \$40 anchor (β = .037, *SE*= .03, *p*= .27) (See Table 1 and Figure 2). In contrast, we observed large effect sizes in the exploratory condition, in which participants purchased almost twice as many items at a budget of \$40 compared to \$20 (see Table 1 and Figure 3). Therefore, we can look at our second hypothesis in the context of solely budget—and not numeric priming—influencing WTP.

Still, a *post-hoc* analysis reveals there may still be a significant effect of numeric priming. In theory, viewing an irrelevant number in the context of the task means that number could have been associated with either price or the item, and that could lead to effects that cancel each other out when all trials are aggregated. To account for this possibility, we isolated the data to trials in which participants looked at item as the first fixation and anchor as the second fixation—indicating that in these cases, participants would associate the anchor's number with the value of the item rather than the price. The results were insignificant across all trials, but they were significant during the first 20 trials of each of the two runs, trials that perhaps are more meaningful than the other 80 because participants were more likely to have been attentive at the start of runs (see Table 2). We also looked at trials at the start of runs in which participants viewed anchor and item back-to-back to end the trial, with the possibility participants paired anchor with item like they appear to have at the start of trials. Instead, the results at the end of trials were insignificant (see Table 3). Thus, this evidence appears to support anchoring as needing to occur at the beginning of a scanpath rather than the end of it if one is to associate the anchor with a particular stimulus.

The second hypothesis predicted that scanpath analyses would correlate with purchasing behavior, and therefore one's susceptibility to budget's influence. The results for this hypothesis were mostly significant. The STA algorithm, which summarizes participants' scanpaths over 120 trials, proposes that the most significant correlates of susceptibility to budget's influence were viewing budget as the second fixation and item as the last fixation (see Figure 4). Indeed, trial-by-trial data spread across all participants represents a similar pattern—viewing budget second was the strongest correlate among the three ROI's with $p<.001$ as either the first or second fixation (see Table 4) and viewing item last was a stronger correlate than viewing price last (see Table 5). The algorithm did not predict the stronger association between susceptibility to budget and price than susceptibility to budget and item, but that is beyond the algorithm's scope as opposed to an error—price was not a popular last fixation point, so the model did not generalize about it in either direction. An informal comparison of Tables 4 and 5 with Figure 4 and its more detailed counterpart, Figure 5, reveals the STA algorithm's general accuracy.

Our results also show the limits of the STA algorithm, which is the most up-to-date scanpath algorithm but was designed primarily for longer scanpaths than those seen in our study. Our results reveal that the most popular first three fixations for each participant aligned with the STA algorithm's output only 18.3% of the time (see Table 6). These results are still better than chance, but if the goal of the algorithm is to replace more traditional eye-pattern measurements, it is not clear whether it realizes that goal. However, exploratory analyses revealed that among several potential candidates, changing one particular line of code increased the algorithm's success in predicting the most popular first-three fixations. Changing the way the STA algorithm ranked repeat fixations in the same scanpath from duration-based to order-based doubled the accuracy for the most common first-three fixations. These results suggest perhaps a different way for researchers to analyze scanpaths when there are only several fixations.

Discussion

This study looked at whether anchoring explained the positive relationship between budget and consumer spending as well as the eye-tracking patterns that corresponded with different purchasing behaviors. Our results suggest that numeric priming—anchors that are not explicitly associated with the decision-making context—was not responsible for budget's positive relationship with purchasing behavior. Nevertheless, there are hints that scanpath analysis patterns predict susceptibility to budget's influence, particularly the viewing of budget as the second fixation and item as the last fixation, in ways that ordinary ROI patterns may not unearth on their own. The results offer a window into consumer's decision-making process, highlighting why people make impulsive choices and how they can avoid doing so.

The first of the study's two main findings focused on numeric priming. Numeric priming research has been inconclusive so far, and our results raise further doubts about its effects. Participants bought items at a greater rate when they viewed a larger anchor, but this increase was statistically insignificant. The most supportive evidence for numeric priming in our study came from the significant effect of viewing the anchor as the second fixation during earlier trials. In fact, no other combination of ROI's in the first two fixations was significant beyond the $p<.01$ threshold, and in line with the significance of budget as the second fixation in the exploratory study, there is reason to think viewing any number—budget or anchor—as the second fixation may maximize their use. However, this finding on numeric priming came during *post hoc* analysis and should be considered with caution. A replication study with positive results is needed before stronger conclusions can be drawn. Such a finding would increase the influence we attribute to unconscious encoding in our everyday lives. Assuming numeric priming does not have significant effects and that our results are due solely to budget's size, we can still see how unconscious processes affect our decision-making—these types of effects lay at the heart of behavioral economics work on why people make impulsive choices, choices that are unplanned and lead to negative affect (Rook & Gardner, 1993).

Second, the many participants and their 120 trials during the experiment were promising testing ground for the STA algorithm, the most robust scanpath synthesizer to date, and the algorithm returned results that seem to signify its validity. A few modifications to the code in terms of what it prioritizes and its rigidity for including certain fixations were shown to improve its performance in our study, which involves shorter scanpaths than those on which the model was originally tested. However, any future modifications would only add to the success of the model, which already detected many of the relationships between budget's influence and specific ROI's. The potential for a successful scanpath model is so promising because it can predict eye-tracking patterns without the need for unnecessary exploratory analyses, and because it can make hundreds of scanpaths more understandable. The recent introduction of the STA algorithm hints that there is only more to come in reaching this analytical goal.

It is worth noting there were several more eye-tracking patterns not based on scanpaths that predicted purchasing patterns. In the exploratory and control studies, the recency effect contributed in that it seemed whatever was last on people's minds during each trial most heavily influenced their choices. When participants saw the item last—and therefore were reminded of the value of the good rather than its price—they were significantly more likely to buy the item than if they viewed the anchor or price last. However, whether the last item was a larger or smaller anchor made no difference in purchasing behavior, implying limitations to the power of the recency effect.

One of the greatest drawbacks of this study was the demographics of the sample. Since we were looking at the financial choices of people age 18-25, it is not clear whether their spending habits can be applied to older individuals because most of our participants were still in school. We did not know how much disposable income participants had, so there is a question of whether some participants were so desperate for money that they did not seriously consider the consumer goods. We tried to control for that confound by requiring participants to be willing to pay more than $0 for at least a third of the goods they saw, but participants may still have been less interested in buying items than an average adult. It also is unclear whether the eye-tracking patterns we found caused purchasing behavior, or whether the two were just correlated. Our study design did not force people to look at the screen in a certain order, so we do not know if controlling for gaze path would have led participants to be more or less responsive to budget size.

Still, that attentional patterns were associated with choice raises hope for how people can learn to act less impulsively, especially through the lens of dual process theories. Ideally, if people know the unconscious traps they are susceptible to, they can overcome them by making different choices about how they attend to information. Unfortunately, though, budget size is just one of many stimuli that can influence impulsive behavior. Perhaps similar attentional processes underlie different forms of impulsive behavior. Otherwise, people will need to an active working memory to remember the vast attentional processes that contribute to unplanned and ill-advised purchases.

References

Amos, C., Holmes, G. R., & Keneson, W. C. (2014). A meta-analysis of consumer impulse buying. *Journal of Retailing and Consumer Services*, *21*(2), 86-97. doi: 10.1016/j.jretconser.2013.11.004

Brewer, N. T., & Chapman, G. B. (2002). The fragile basic anchoring effect. *Journal of Behavioral Decision Making*, *15*(1), 65-77. doi: 10.1002/bdm.403

Bushong, B., King, L. M., Camerer, C. F., & Rangel, A. (2010). Pavlovian processes in consumer choice: The physical presence of a good increases willingness-to-pay. *American Economic Review*, *100*(4), 1556–1571. doi: 10.1257/aer.100.4.1556

Cheek, N. N. (2016). Semantic versus numeric priming and the consider-the-opposite strategy: Comment on Adame. *Learning and Motivation*, *53*, 49-51. doi: 10.1016/j.lmot.2016.03.001

Coutlee, C. G., Politzer, C. S., Hoyle, R. H., & Huettel, S. A. (2014). An Abbreviated Impulsiveness scale (ABIS) constructed through confirmatory factor analysis of the BIS-11. *Archives of Scientific Psychology*, *2*(1), 1-12. doi: 10.1037/arc0000005

Critcher, C. R., & Gilovich, T. (2008). Incidental environmental anchors. J*ournal of Behavioral Decision Making*, *21*(3), 241-251. doi: 10.1002/bdm.586

Dittmar, H., & Drury, J. (2000). Self-image – is it in the bag? A qualitative comparison between “ordinary” and “excessive” consumers. *Journal of Economic Psychology*, *21*(2), 109-142. doi: 10.1016/S0167-4870(99)00039-2

Dogerlioglu-Demir, K., & Koçaş, C. (2015). Seemingly incidental anchoring: The effect of incidental environmental anchors on consumers’ willingness to pay. *Marketing Letters,* *26*(4), 607-618. doi: 10.1007/s11002-014-9295-0

Donovan, R. J., Rossiter, J. R., Marcoolyn, G., & Nesdale, A. (1994). Store atmosphere and purchasing behavior. *Journal of Retailing*, *70*(3), 283–294. doi: 10.1016/0022-4359(94)90037-X

Dunning, D., & Hayes, A. F. (1996). Evidence for egocentric comparison in social judgment. *Journal of Personality and Social Psychology, 71*(2), 213-229. doi: 10.1037/0022-3514.71.2.213

Eraslan, S., Yesilada, Y., & Harper, S. (2016a). Eye tracking scanpath analysis techniques on web pages: A survey, evaluation and comparison. *Journal of Eye Movement Research*, *9*(1), 1-19. doi: 10.16910/jemr.9.1.2

Eraslan, S., Yesilada, Y., & Harper, S. (2016b). Scanpath trend analysis on web pages: Clustering eye tracking scanpaths. *ACM Transactions on the Web*, *10*(4), 20-35. doi: 10.1145/2970818

FINRA Investor Education Foundation. (2013). *Financial capability in the United States: Report of findings from the 2012 National Financial Capability Study*. Retrieved from http://www.usfinancialcapability.org/downloads/NFCS_2012_Report_Natl_Findings.pdf

Fisher, I. (1930). *The theory of interest: As determined by impatience to spend income and opportunity to invest it.* New York: Macmillan.

Frederick, S. M., & Mochon, D. (2012). A scale distortion theory of anchoring. *Journal of Experimental Psychology: General*, *141*(1), 124-133. doi: 10.1037/a0024006

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), 263-291. doi: 10.2307/1914185

Krajbich, I., Lu, D., Camerer, C., & Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in Psychology, 3*. doi: 10.3389/fpsyg.2012.00193

Levenshtein, V. I. 1966. Binary codes capable of correcting deletions, insertions and reversals. *Soviet Physics Doklady*, *10*(8), 707- 710.

Mussweiler, T., & Englich, B. (2005). Subliminal anchoring: Judgmental consequences and underlying mechanisms. *Organizational Behavior and Human Decision Processes*, *98*(2), 133-143. doi: 10.1016/j.obhdp.2004.12.002

Nechyba, T. J. (2015). *Microeconomics: An intuitive approach with calculus*. Boston, MA: CENGAGE Learning.

Needleman, S. B., & Wunsch, C. D. (1970). A general method applicable to the search for similarities in the amino acid sequence of two proteins. *Journal of Molecular Biology*, *48*(3), 443-453. doi: 10.1016/0022-2836(70)90057-4

Rook, D. W., & Gardner, M. (1993). In the mood: Impulse buying's affective antecedents. *Research in Consumer Behavior*, *6*(7), 1–28.

Strathman, A., Gleicher, F., Boninger, D. S., & Edwards, C. S. (1994). The consideration of future consequences: Weighing immediate and distant outcomes of behavior. *Journal of Personality and Social Psychology*, *66*(4), 742-752. doi: 10.1037/0022-3514.66.4.742

The Institute for College Access & Success. (2016). *Student debt and the class of 2015*. Retrieved from https://ticas.org/sites/default/files/pub_files/classof2015.pdf

Weun, S., Jones, M. A., & Beatty, S. E. (1998). Development and validation of the Impulse Buying Tendency Scale. *Psychological Reports*, *82*, 1123-1133. doi: 10.2466/pr0.1998.82.3c.1123

Wilson, T. D., Houston, C. E., Etling, K. M., & Brekke, N. (1996). A new look at anchoring effects: Basic anchoring and its antecedents. *Journal of Experimental Psychology: General*, *125*(4), 387-402. doi: 10.1037/0096-3445.125.4.387

Figure 1. An example trial from the exploratory study is on the left. The right image represents the control study, with “Other” replacing “Budget.”

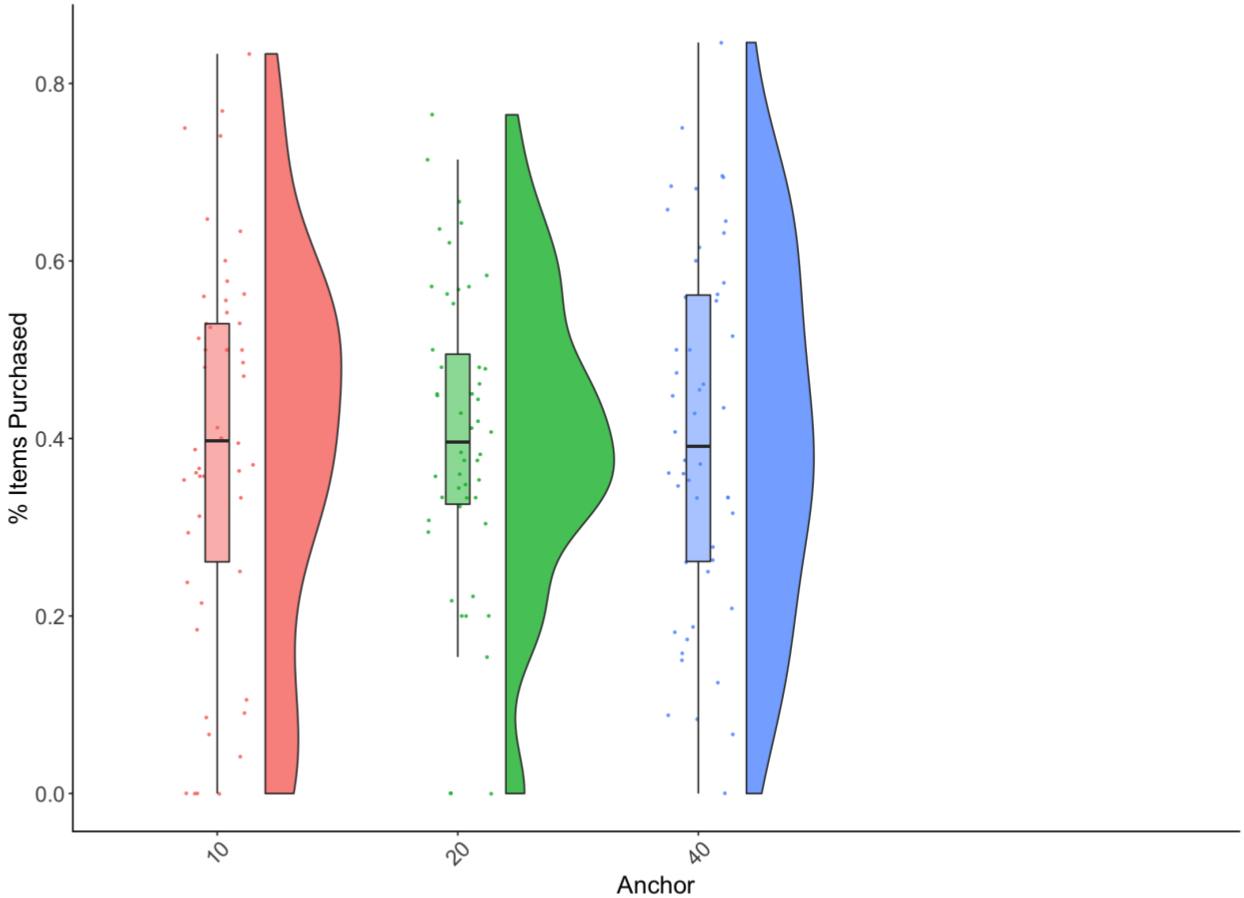

Figure 2. Purchasing Behavior for Each Participant When Viewing Different Anchors The average frequency of purchases for each participant based on which irrelevant number participants viewed. This data only includes trials in which participants viewed item, anchor, and price on the screen at least once each.

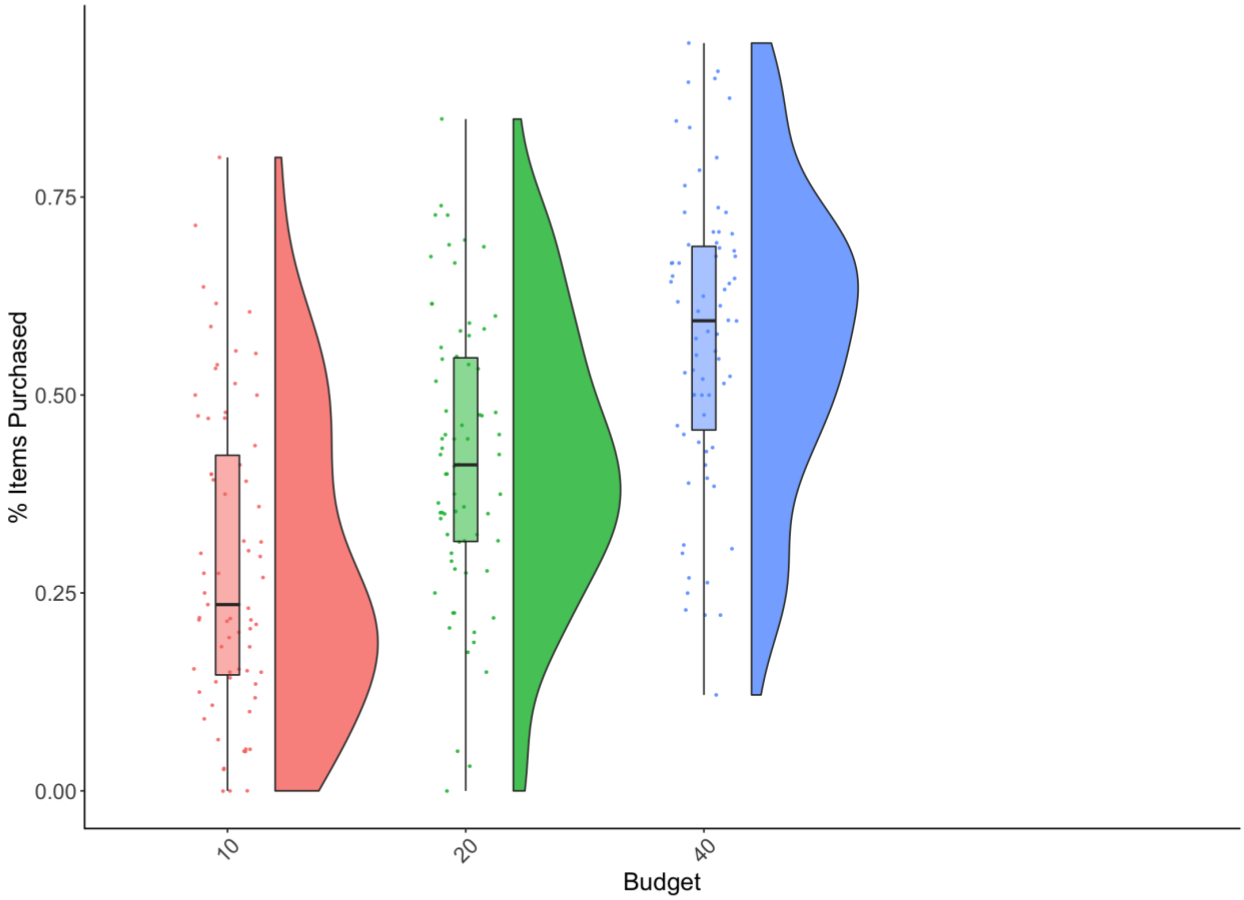

Figure 3. Purchasing Behavior for Each Participant When Viewing Different Budgets. The average frequency of purchases for each participant based on which budget was assigned to that trial. This data only includes trials in which participants viewed item and price on the screen at least once each.

Table 1

Percent of Items Bought by Number on Screen and Significance of Number on Screen

	Number on Screen		
Experimental Condition	\$10	\$20	\$40
Percent of Items Bought in Anchor Condition	38.0	39.9	42.0
Percent of Items Bought in Budget Condition	28.6	42.1**	57.2**

Note. The percent of items bought in each condition represents the proportion of purchases made during each condition as a fraction, multiplied by 100, of the total number of trials that appeared for each condition, excluding any trial in which the participant did not view the item or the price.

**$p < .001$

Table 2

Interaction of First and Second ROI on Susceptibility to Anchor's Influence, *P-Values*

	Second Fixation			
First Fixation	Any ROI	Anchor	Item	Price
Any ROI	.022*	.004**	.99	.71
Anchor	.48	—	.58	.93
Item	.16	.023*	—	.69
Price	.35	.99	.35	—

Note. This data includes only data from the first 20 trials of each run, trials 1-20 and 61-80. The data also only includes trials in which participants viewed all three ROI's—anchor, item, and price.

Table 3

Interaction of Penultimate and Final ROI on Susceptibility to Anchor's Influence, *P-Values*

	Final Fixation			
Penultimate Fixation	Any ROI	Anchor	Item	Price
Any ROI	.022*	.88	.31	.12
Anchor	.28	—	.59	.57
Item	.21	.79	—	.15
Price	.83	.91	.31	—

Note. This data includes only data from the first 20 trials of each run, trials 1-20 and 61-80. The data also only includes trials in which participants viewed all three ROI's—anchor, item, and price.

Table 4

Interaction of First and Final Second on Susceptibility to Budget's Influence, Ratio of Items Bought at $40/ at $10

	Second Fixation			
First Fixation	Any ROI	Budget	Item	Price
Any ROI	2.13**	2.54**	2.38**	1.91**
Budget	2.05*	—	1.82**	2.25**
Item	2.10**	2.42**	—	1.86**
Price	2.36**	2.84*	1.94*	—

Note. *p<.05 ** p< .001

Table 5

Interaction of Penultimate and Final ROI on Susceptibility to Budget's Influence, Ratio of Items Bought at $40/ at $10

	Final Fixation			
Penultimate Fixation	Any ROI	Budget	Item	Price
Any ROI	2.13**	1.95**	2.15**	2.25**
Budget	2.29**	—	2.13**	2.85**
Item	1.91**	2.06*	—	1.73*
Price	2.08**	1.92**	2.21**	—

Note. *$p<.05$ **$p < .001$

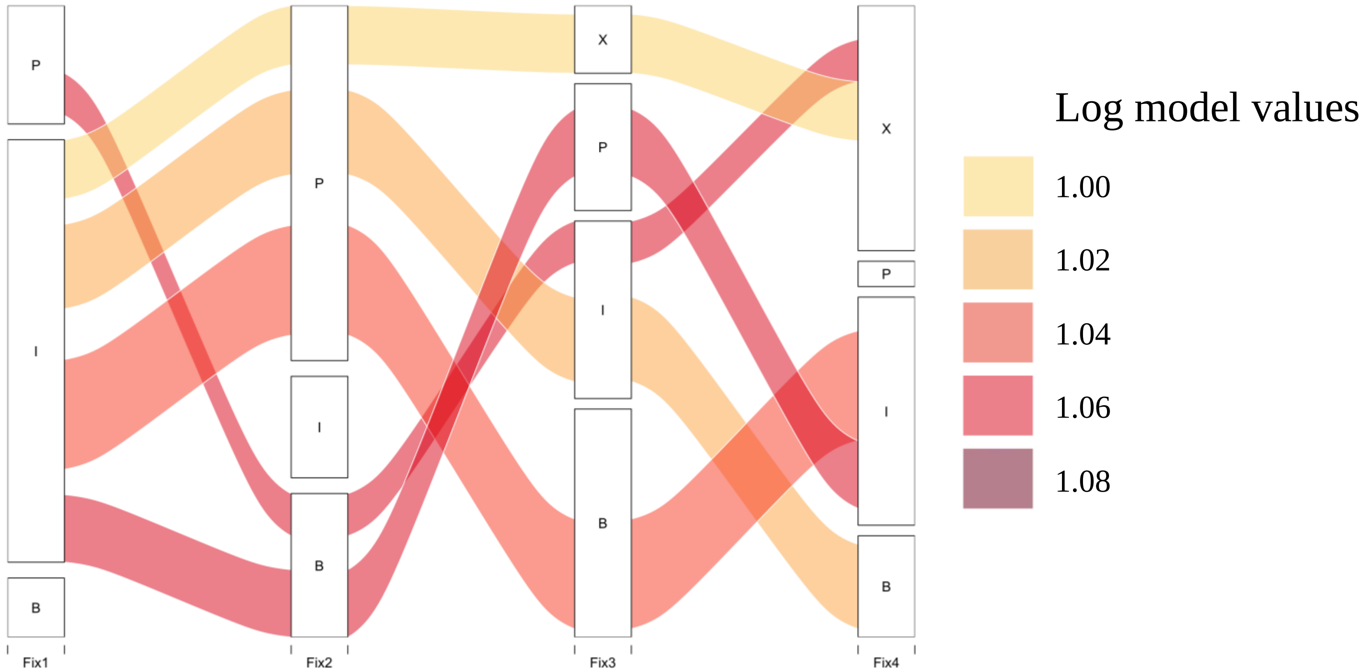

Figure 4. The most popular synthesized scanpaths over 120 trials among all participants, colored by susceptibility to budget. Only scanpaths shared by five or more participants are illustrated. The graph goes from left to right, and the letters indicate the ROI's: "P" for price, "I" for item, "B" for budget, and "X" represents the participant had moved on to the next trial. The data only includes trials in which participants viewed all three ROI's—anchor, item, and price. The lines' thickness indicates how many participants share that scanpath, and darker colors indicate greater susceptibility to budget.

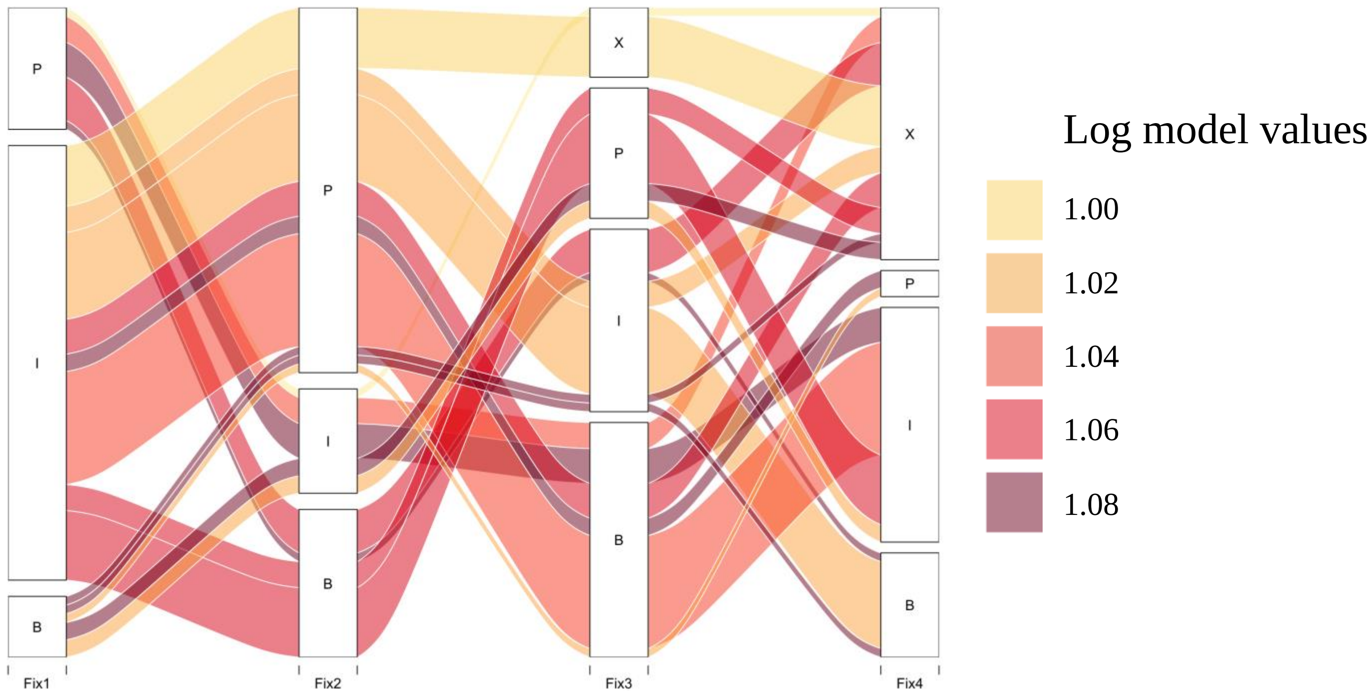

Figure 5. The most popular synthesized scanpaths over 120 trials among all participants, colored by susceptibility to budget's influence. All scanpaths are shown, even if they belonged to just one participant. The graph goes from left to right, and the letters indicate the ROI's: "P" for price, "I" for item, "B" for budget, and "X" represents the participant had moved on to the next trial. The data only includes trials in which participants viewed all three ROI's—anchor, item, and price. The lines' thickness indicates how many participants share that scanpath, and darker colors indicate greater susceptibility to budget.

Table 6

Accuracy of STA Algorithm and Tweaks to It Compared to Most Popular Viewed Scanpaths

	Percent of Matching Scannpaths
Original STA Algorithm	18.3
Reducing Threshold Num. Fixations for Scanpath Element to be Trending	46.4
+ Reducing Threshold Duration for Scanpath Element to be Trending	40.8
+ Ranking Repeat Fixations by Order Instead of Duration	74.6

Note. The percent of matching scanpaths represents the number of participants for whom the STA algorithm's output aligned with their first three fixations as a fraction, multiplied 100, of the total number of participants, excluding any trial in which the participant did not view the item or the price.