Dynamic Gaze Effects on Cost-Benefit Decisions: from Value Modulation to Additive Influences

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Abstract:

Gaze biases choice during value-based decision-making. The attention drift diffusion model describes this bias as a multiplicative interaction whereby gaze amplifies the value of the attended relative to the unattended option. Another account proposes that the direction of gaze effects on choice might be reversed, such that a latent decision to choose an option causes participants to dwell on that option, resulting in additive rather than interactive effects of value and gaze. Here, we tracked dynamic gaze patterns while participants chose between two options, the costs and benefits of which are spatially separated on the screen. Influences of gaze on choice evolved over time: Early gaze at benefits versus costs biases choices toward high-cost / high-benefit options, consistent with the attention drift diffusion model. Conversely, later gaze increasingly reflects the upcoming choice, so that gaze at both high benefits and high costs accompany choice of high-cost / high-benefit options. Formally, early gaze predicts drift rates via a multiplicative interaction with value, while late gaze is additive with value, consistent with a reversal of the direction of influence. Our results help reconcile competing models by applying drift diffusion modeling to the domain of multi-attribute decisions.

Keywords: gaze; value; decision-making; drift diffusion; dopamine; motivation

Introduction

Decision-makers tend to choose options to which they devote more of their gaze. This may reflect a causal role of visual attention in amplifying the value difference between attended and unattended options. The attention drift diffusion model (aDDM; Krajbich, Armel, & Rangel, 2010) formalizes the potentially causal interaction between gaze and value. According to the aDDM, instantaneous evidence for item A is given by the value difference between items (r_A versus r_B), where the unattended item value is discounted. Thus, the effective drift rate on that trial v is the product of the difference in values and the difference in gaze at A versus B (g_A versus g_B).

$$v \sim \beta_0 + \beta_1(g_A r_A - g_B r_B) + \beta_2(g_B r_A - g_A r_B) + \varepsilon \quad \text{Eqn. 1}$$

An alternative account posits that putative influences of gaze on choice might instead reflect a window into the decision-maker's latent choice prior to responding (Cavanagh, Wiecki, Kochar, & Frank, 2014). Perhaps, for example, participants identify their preference and then fixate that preference before responding. Just like the aDDM, such an account would predict both that gaze predicts choice and that effective drift rates would be higher for larger differences in value and proportion gaze. However, under this account, drift rates are predicted by an additive rather than a multiplicative combination of gaze and value (Cavanagh et al., 2014).

$$v \sim \beta_0 + \beta_1(r_A - r_B) + \beta_2(g_A - g_B) + \varepsilon \qquad \text{Eqn. 2}$$

Qualitative mimicry between the two models makes adjudicating between them a challenge – particularly if decisions involve purely appetitive offers: under both

accounts, the more one looks at an option the more likely they are to choose it. By contrast, the models make starkly different predictions about the effects of gaze on choice if there are both appetitive and aversive choice dimensions. Consider a choice between high-cost / high-benefit, and a low-cost / low-benefit options. Here, a multiplicative model predicts that the more a decision-maker attends to the cost of the high-cost option, the less likely they should be to choose it. An additive model, however, predicts that regardless of cost differences, more gaze at the cost of the high-cost option should still increase the likelihood of choosing it.

Here, we test diverging predictions about gaze effects on choice in a cost-benefit decision task. By separating attributes, we can test how gaze influences choice when participants gaze at appetitive benefit, or aversive cost information. This approach also allows us to test whether evidence accumulation is best explained by value differences between options (the standard approach in aDDM), or attributes, as articulated in attribute-wise decision models (e.g. (Roe, Busemeyer, & Townsend, 2001)). Finally, our study was part of a larger study of the influence of striatal dopamine on decision-making. Thus we further tested the specific predictions that striatal dopamine increases sensitivity to benefits versus costs (Collins & Frank, 2014), thus increasing high-cost, high-benefit selection rates.

Methods

Fifty healthy young adults were recruited for a larger, multi-session pharmaco-imaging study of the effects of dopamine on decision-making about cognitive effort. In each drug session, participants decided between offers to complete a harder (high-cost) N-back task for more money, or an easier (low-cost) N-back task for less money, while we monitored gaze. Previously, we have shown that the N-back task is subjectively effortful, and that subjective costs increase parametrically with N-back load (Westbrook, Kester, & Braver, 2013).

In our paradigm, participants experience multiple N-back load levels. Next, following drug administration, a discounting procedure is used to estimate the subjective value (SV) of offers to repeat each N-back level for money. Finally, participants decide between pairs of offers to repeat higher levels for more money or lower load levels for less while we monitored their gaze. Offers are tailored to participants' SVs such that the high effort option is preferred on half of trials and to ensure a balanced mix of trials in which offer pairs are close and far apart in terms of their SV. To study dopamine, we measured individual differences in

striatal dopamine synthesis capacity using [18]FDOPA PET. Moreover, all decisions were made either under the influence of the catecholamine transporter blocker, methylphenidate, the selective dopamine receptor antagonist sulpiride, or placebo.
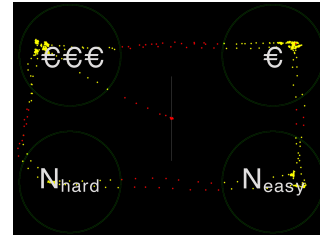

Figure 1: Gaze data from a trial with costs (N-back load) and benefits (€) separated in space. Yellow dots indicate gaze at two attributes across two options.

Results

As anticipated, higher load was more subjectively costly. In a multi-level regression, offers were discounted proportionally more: subjective values (SVs) decreased as N-back load increased ($b_{placebo}$ = -0.15; p = 1.4×10^{-14}), controlling for offer amount. This result confirmed that load was subjectively costly and thus an aversive attribute. Also, SVs were stable across a session, reliably predicting subsequent choices between high- and low-effort offers, while we monitored gaze. In a multi-level logistic regression, high- versus low-effort offer SV robustly predicted more high-effort choice ($b_{placebo}$ = 1.67, p < 2.2×10^{-16}).

Gaze Patterns

Gaze at Options Predicts Choice Consistent with prior studies, participants gazed more at the options they chose. Across participants, the average proportion of gaze at the high-effort option was reliably higher on trials in which the high-effort option was chosen (51.3% versus 44.0%; p < 2.2×10^{-16}). Moreover, we found that selection of the high-effort option increased as a function of gaze at both the benefits and the costs of that option. In a multi-level logistic regression, controlling for SV differences, the probability of a high-effort choice increased, on placebo, when participants spent more time looking at the benefits (b = 0.87; p < 2.2×10^{-16}), and also when they spent more time looking at the costs (b = 0.58; p < 2.2×10^{-16}) of the high-effort option. Notably, while the signs of both terms are positive, the effect of increasing gaze at costs is smaller than gaze at benefits (p = 5.0×10^{-4}) suggesting both additivity and multiplicativity with attribute values.

Early Gaze at Attributes Predicts Choice Participants were more likely to fixate on benefits rather than costs early in a trial. Interestingly, this effect was larger on trials in which the high effort option was selected (Fig. 3). This effect suggests that greater attention to benefits versus costs increased motivation for high-cost, high-benefit offers, and thus that gaze is multiplicative with value in biasing choice. Moreover, this suggests that gaze interacts with attribute rather option values.
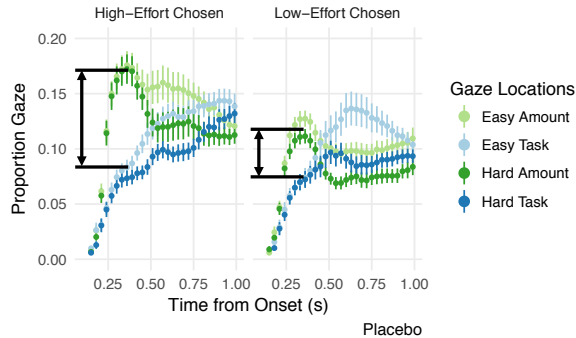

Figure 3: Gaze data time-locked to offer. Participants gazed more at benefit than cost information early in trials, and even more so on trials in which they chose the high-effort option.

Late Gaze at Options Predicts Choice Just before a response, gaze was increasingly committed to either attribute (cost or benefit) of the option the participant was about to select (Fig. 4).
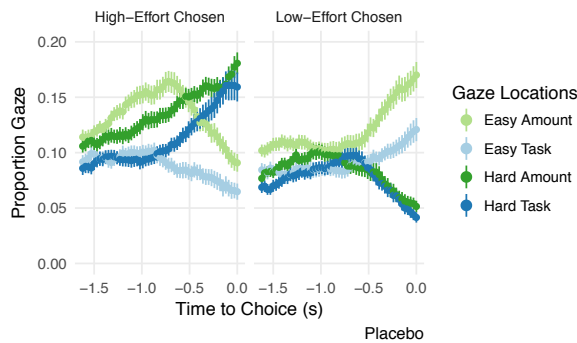

Figure 4: Gaze data time-locked to response. Participants increasingly fixated either attribute of the to-be selected option prior to choice.

Commitment began well before a response. Indeed, when locked to responses, we found a clear bifurcation in looking patterns – identified as the time of peak proportion gaze at the unchosen option – occurring ~800 ms prior to choice. This dynamic implies a protracted post-choice (yet pre-response) commitment of gaze to the chosen option and suggests that, post-choice (but pre-response), gaze is additive to value.

Drift Diffusion Modeling

Qualitative gaze patterns imply both multiplicative and additive contributions of gaze and value during evidence accumulation. Moreover, the early effect of gaze at benefits-versus-costs implies an interaction with attributes rather than options. To test these possibilities, we estimated the effect of gaze and value differences on effective drift rates using hierarchical, Bayesian estimation of drift diffusion models (HDDM; Wiecki, Sofer, & Frank, 2013). Namely, in different models, we estimated whether drift rate varied with 1) value differences between options or attributes, 2) gaze differences at options or at attributes, and 3) additive or multiplicative combinations of gaze and value terms. We used Deviance Information Criteria (DIC) for primary model selection, and posterior predictive checks to ensure good model fit.

We found that the best fitting model featured both multiplicative interactions of gaze with the value of attributes rather than options as well as additive contributions of gaze. Namely, trial-wise drift rate was best predicted by a multiplicative interaction between proportion gaze at benefits g_{ben}, versus costs g_{cost}, and differences in benefits BenD and costs CostD, as well as additive contributions of the difference in gaze at the benefits of option A versus B, given by $g_{benA} - g_{benB}$ and differences in gaze at the costs $g_{costA} - g_{costB}$.

$$v \sim \beta_0 + \beta_1(g_{ben} \times \mathrm{BenD}) + \beta_2(g_{cost} \times \mathrm{BenD}) + \cdots$$
$$\beta_3(g_{cost} \times \mathrm{CostD}) + \beta_4(g_{ben} \times \mathrm{CostD}) + \cdots$$
$$\beta_5(g_{benA} - g_{benB}) + \beta_6(g_{costA} - g_{costB}) \quad \text{Eqn. 3}$$

Considering our qualitative gaze patterns, we further suspected that additive and multiplicative contributions would vary dynamically across the trial. We thus broke up trials into gaze occurring before or after bifurcation defined for each participant in each session separately, as described above. Next, we fit the winning model (Eqn. 3) using either pre- or post-bifurcation gaze. The result confirmed our suspicion: Multiplicative terms are reliably positive pre-bifurcation, and near zero post-bifurcation, whereas additive terms are near zero pre-bifurcation and positive post-bifurcation (Fig. 5). This double-dissociation supports the hypothesis that visual attention shapes value formation early in a trial, while gaze comes to reflect the preferred option late in a trial.
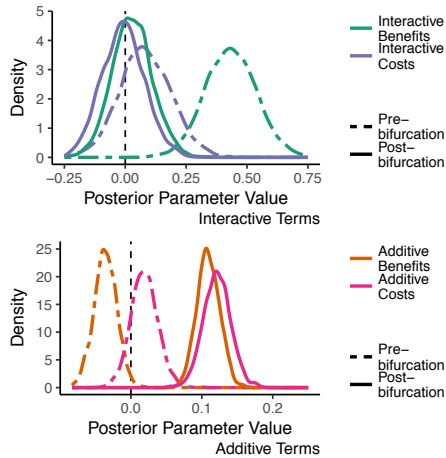
Figure 5: Multiplicative and additive terms are near zero or positive, depending on when gaze occurs. Multiplicative terms are $\beta_1 - \beta_2$ for benefits and $\beta_3 - \beta_4$ for costs. Note that, Eqn. 3 reduces to the additive model in case $\beta_1 = \beta_2$ or $\beta_3 = \beta_4$.

Dopamine Enhances Sensitivity to Benefits
Finally, we found that higher striatal dopamine predicts increased high effort selection, and amplified gaze-value interactions. In a multi-level logistic regression, caudate dopamine synthesis capacity predicted more high effort selection ($b = 0.96$; p = 0.012) and correlated with larger, more positive interactions between gaze at benefits across a trial and benefit value differences (β_1 in Eqn. 3; $r_{Pearson}$ = 0.33; p = 0.029; Fig. 6). Methylphenidate also increased high effort selection versus placebo ($b = 1.66$; p = 0.0053), and amplified the gaze-benefits interaction (t_{paired}= 2.18; p = 0.034). These results highlight the value of trial-level hierarchical drift diffusion modeling by providing evidence for an active role of visual attention in evidence accumulation and moreover implicating caudate dopamine in enhancing the accumulation of benefit information during choice.
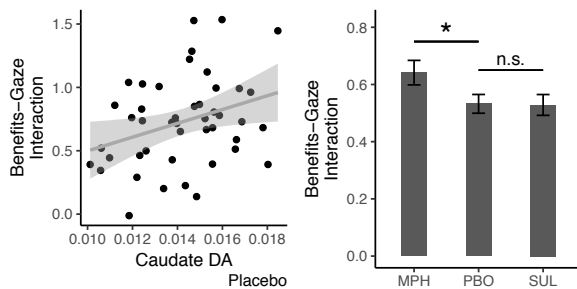

Figure 6: Multiplicative gaze-benefit interaction term is larger for individuals with higher dopamine synthesis

capacity, and on methylphenidate (MPH) but not sulpiride (SUL) versus placebo (PBO).

Summary

Our results show that visual attention, as indexed by gaze, predicts subsequent choice in a dynamic fashion. Namely, early gaze may play more of a causal role in shaping the perception of value while late gaze may reflect post-choice commitment. We also show that striatal dopamine may enhance motivation by increasing sensitivity to benefits during evidence accumulation, biasing high-cost, high-benefit choices.

Acknowledgments

References

Cavanagh, J. F., Wiecki, T. V., Kochar, A., & Frank, M. J. (2014). Eye Tracking and Pupillometry Are Indicators of Dissociable Latent Decision Processes. *Journal of Experimental Psychology*, *143*(4), 1476–1488.

Collins, A. G. E., & Frank, M. J. (2014). Opponent actor learning (OpAL): Modeling interactive effects of striatal dopamine on reinforcement learning and choice incentive. *Psychological Review, 121*(3), 337–366.

Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, *13*(10), 1292–1298.

Roe, R. M., Busemeyer, J. R., & Townsend, J. T. (2001). Multialternative decision field theory: A dynamic connectionst model of decision making. *Psychological Review, 108*(2), 370.

Westbrook, A., Kester, D., & Braver, T. S. (2013). What Is the Subjective Cost of Cognitive Effort? Load, Trait, and Aging Effects Revealed by Economic Preference. *PloS One, 8*(7), e68210.

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. *Frontiers in Neuroinformatics, 7*, 1–10.