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High Overall Values Mitigate Gaze-Related Effects in Perceptual and Preferential Choices

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A growing literature has shown that people tend to make faster decisions when choosing between two high-intensity or high-utility options than when choosing between two less-intensity or low-utility options. However, the underlying cognitive mechanisms of this effect of overall value (OV) on response times (RT) remains controversial, partially due to inconsistent findings of OV effects on accuracy but also due to the lack of process-tracing studies testing this effect. Here, we set out to fill this gap by testing and modeling the influence of OV on choices, RT, and eye movements in both perceptual and preferential decisions in a preregistered eye-tracking experiment ($N = 61$). Across perceptual and preferential tasks, we observed significant and consistently negative correlations between OV and RT, replicating previous work. Accuracy tended to increase with OV, reaching significance in preferential choices only. Eye-tracking analyses revealed a reduction of different gaze-related effects under high OV: a reduced tendency to choose the longer fixated option in perceptual choice and a reduced tendency to choose the last fixated option in preferential choice. Modeling these data with the attentional drift-diffusion model showed that the nonfixated option value was discounted least in the high-OV condition, confirming that higher OV might mitigate the impact of gaze on choices. Our results suggest that OV jointly affects behavior and gaze influences and offer a mechanistic account for the puzzling phenomenon that decisions between options of higher OV tend to be faster, but not less accurate.

Public Significance Statement

Overall value (OV) refers to the attractiveness or salience of all available options. For instance, the OV of two appealing snacks is higher than that of two disliked snacks. Previous studies often found that people make faster, but not less accurate, decisions when OV increases. The present work links these findings to attention, showing that our decisions are less influenced by how much we look at one option versus another when the OV of options is high. This reduction in the link between gaze patterns and decisions highlights that the influence of attention on information processing is sensitive to the presented options, as it appears to diminish in the presence of higher OV.

Keywords: overall value, eye tracking, gaze-related bias, decision making, computational modeling

Supplemental materials: https://doi.org/10.1037/xge0001723.supp

Decades of research in psychology, neuroscience, and economics have shown that the accuracy and speed with which humans and other animals make decisions are strongly influenced by how much choice options differ with respect to the relevant criterion (e.g., the utility difference of consumer products or the intensity of different light sources). In addition to the difference between options, however, the role of the overall value (OV) of the entire set of available choice options is receiving growing attention (Frömer et

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The experiments and analysis plans were preregistered on the Open Science Framework at https://osf.io/acse9. A preprint of this article is publicly available on the Open Science Framework at https://osf.io/preprints/psyarxiv/dvj7z. The data and ideas of this article have been presented at the Society for Neuroeconomics conference (SNE, 2022), the Subjective Probability, Utility, and Decision-Making conference (SPDUM, 2023), and the Society for Mathematical Psychology conference (SMP, 2023).

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al., 2019; Mormann & Russo, 2021; Pirrone et al., 2022). Consistent empirical evidence from these recent studies showed that OV also affects response times (RTs), and the effect can be generalized over various decision types, such as perceptual and preferential decisions (Frömer et al., 2019; Gluth et al., 2018, 2020; Polanía et al., 2014; Sepulveda et al., 2020; Shevlin et al., 2022; Smith & Krajbich, 2019; Teodorescu et al., 2016) as well as choices made in reinforcement learning tasks (Fontanesi, Gluth, et al., 2019; Lebreton et al., 2019; Ting et al., 2020). Specifically, when faced with a choice between two high-intensity or highly attractive options, individuals tend to make faster decisions compared with choosing between two low-intensity or less attractive options.

Not only the speed of decisions might be affected by OV, as RTs are intricately linked to other choice outputs, in particular choice accuracy and confidence. For example, quicker decisions are often linked to a lower probability of choosing the better option, reflecting a trade-off between speed and accuracy (Bogacz et al., 2010). Sequential sampling models, which model decisions as a noisy process of accumulating evidence for choosing among the available options, allow to account for this speed–accuracy trade-off by assuming that the required amount of evidence is either reduced or increased. However, previous studies investigating OV often focused on RT only by minimizing (and thus controlling for) value differences (see Mormann & Russo, 2021; Pirrone et al., 2022 for review). Some studies have tested OV effects on accuracy but found inconsistent results between and within choice domains (Brus et al., 2021; Pirrone et al., 2018; Polanía et al., 2014, 2019; Ratcliff et al., 2018; Teodorescu et al., 2016). These inconsistent findings suggest that the underlying mechanism of OV effects on information processing might be task or domain dependent. A solution to this conundrum is to gain deeper insights into the role of OV by examining the role of gaze patterns and their interaction with value on choices (Smith & Krajbich, 2019) and to jointly model eye-movement, choice, and RT data. To the best of our knowledge, however, no study has so far investigated the effect of OV on all these decision processes together and tested for common and dissociable effects in perceptual and preferential decisions.

To fill this gap, we conducted a within-subject experiment, in which OV and value difference (VD) were systematically manipulated in two decision domains (i.e., perceptual decision: brightness-discrimination task and preferential decision: snack-choice task). We recorded eye movements and applied computational modeling to better understand the cognitive mechanisms underlying the OV effects on the interplay of attention and choice. In particular, the behavioral and eye-movement data were fitted to the attentional drift-diffusion model (aDDM; Krajbich et al., 2010; Smith & Krajbich, 2019), which has previously been used to account for the effect of OV on RT. Based on previous literature and by simulating the aDDM prior to data collection, we formulated and preregistered hypotheses regarding the effect of OV on choice accuracy, RT, and confidence. Specifically, we hypothesized that OV would negatively correlate with choice accuracy and RTs while positively correlate with confidence ratings.

Overall, our results suggest a robust and significantly negative association between OV and RT across both perceptual and preferential domains. Furthermore, we observed higher accuracy rates in the high-OV condition across task domains. However, the positive association between OV and choice accuracy was only significant in preferential choices. Importantly, analysis of eye movements indicated a reduction of associations between gaze and choice as OV increased in both choice domains, although these changed associations mapped onto different metrics in perceptual versus preferential choices. In particular, the well-established tendencies to choose options that have been looked at longer or fixated on last diminished under high OV in perceptual and preferential choices, respectively. Modeling the interplay of attention and choice dynamics revealed that the reduced role of gaze on choice in high-OV conditions mapped onto a reduced discounting of the nonfixated option as OV increases. Taken together, our work sheds light onto the puzzle that humans make faster decisions under high OV while maintaining and sometimes even increasing choice accuracy.

Results

Task Overview

Participants came to the lab after fasting for at least 3 hr and were asked to first familiarize themselves with the stimulus material (i.e., brightness patches for the perceptual task, snacks for the preferential task) by passively viewing them (Polanía et al., 2019). Then, they rated all stimuli in terms of brightness (perceptual) or liking (preferential) twice (Figure 1A). Afterward, the (objective) brightness values and the (subjective) liking ratings were used to create nine sets of binary choice options that systematically and orthogonally varied with respect to OV and VD in a 3-by-3 (low, medium, high) within-subjects design (Figure 1B). In the main perceptual task, participants were asked to choose the brighter patch, and the main preferential task required participants to choose their preferred snack (the order of task was counterbalanced). After deciding, participants were asked to state their confidence about their choice. The rating, choice tasks, and confidence ratings were completed without time constraints. Eye movements were recorded in the choice task only (see the Materials and Method section).

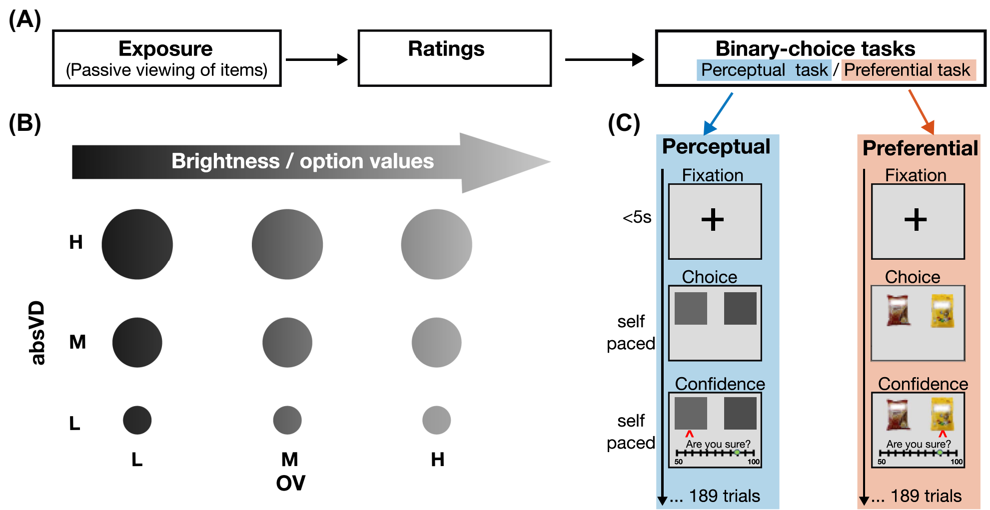
General Task Performance

Overall, our participants ($N = 61$) performed above chance (50%) as they were able to recognize the brighter patch in the perceptual task ($M \pm SE = 77.09 \pm 0.97$; $t_{60} = 27.90$, $p < .0001$) and the snack associated with a higher subjective rating in the preferential task ($M \pm SE = 70.09 \pm 0.68$; $t_{60} = 30.34$, $p < .0001$; Supplemental Table S1). The subjective rating for each snack was computed as the average of two ratings for the same snack measured before the choice tasks (see the Materials and Method section). Two ratings for the same set of snacks were highly correlated ($r = 0.90 \pm 0.01$; min–max: 0.66–0.97), indicating consistent valuation. It is worth noting that we did not mention the same snack set would be rated twice, so the high correlation between the two ratings is not due to the use of a particular mnemonic strategy (Brus et al., 2021; Polanía et al., 2019).

OV Effect on Behavior

We first evaluated the OV effect on RTs by performing multiple linear regression analyses for each participant in each task. In each regression model, the sum of two options' value/brightness (OV) and the absolute difference between two options' value/brightness (absVD) were standardized within participants. Replicating previous findings (Frömer et al., 2019; Gluth et al., 2018, 2020; Polanía et al., 2014; Sepulveda et al., 2020; Shevlin et al., 2022; Smith &

Figure 1
Experimental Design



Note. (A) General workflow of the experiment. (B) Orthogonalized 3 absVD by 3 OV within-subjects design for each choice task. The stimuli were ordered by gray patches' brightness intensities for the perceptual task and by the snacks' ratings in the preferential task. The options were then equally divided into low, medium to high-value categories. The stimuli for each absVD × OV condition were selected and paired within each value category. Consequently, 21 pairs of stimuli were prepared for each absVD × OV combination and resulted in 189 trials for each choice task. The size of circles refers to the size of absolute value difference. (C) An example trial of the perceptual and preferential task. The options were displayed on the screen after the participant looked at the fixation cross for 1 s. After deciding between two options, the red arrow was displayed under the chosen option. Simultaneously, the participant was asked to state their confidence in his/her choice. absVD = absolute value difference; OV = overall value; H = high; M = medium; L = low. See the online article for the color version of this figure.

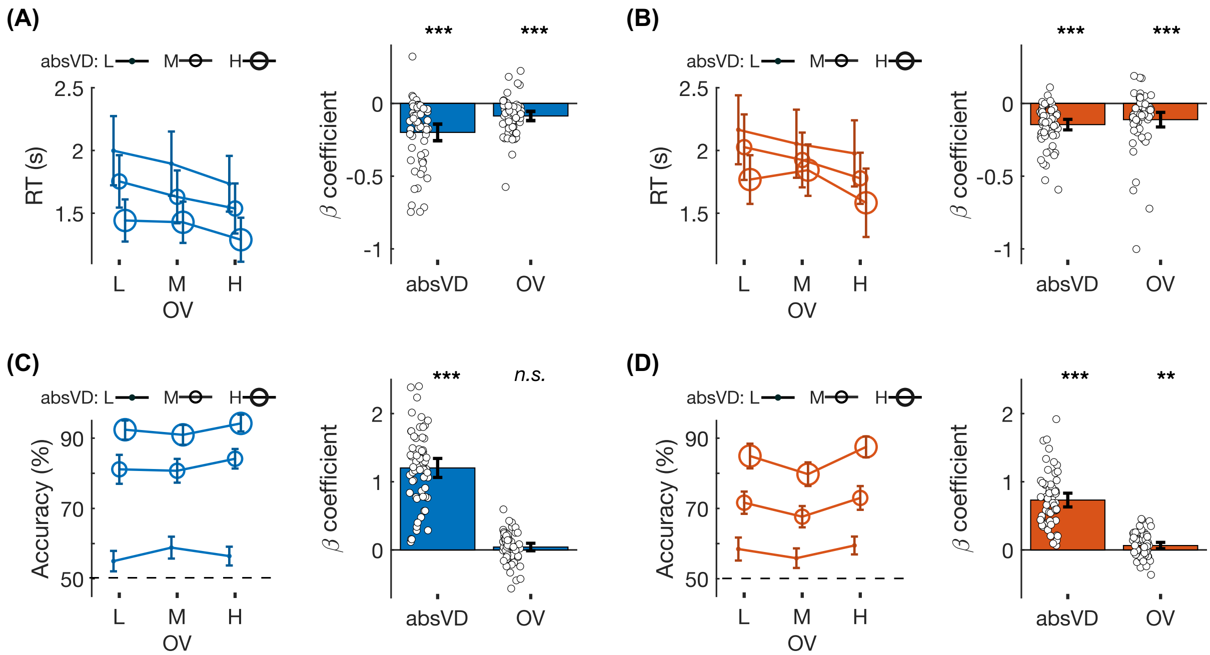
Krajbich, 2019; Teodorescu et al., 2016), we confirmed that RT was negatively associated with absVD (perceptual: $\beta = -0.20$, $SE = 0.02$, $t_{60} = -6.96$, $p < .0001$; preferential: $\beta = -0.14$, $SE = 0.01$, $t_{60} = -8.04$, $p < .0001$) and OV (perceptual: $\beta = -0.08$, $SE = 0.01$, $t_{60} = -5.41$, $p < .0001$; preferential: $\beta = -0.11$, $SE = 0.02$, $t_{60} = -4.44$, $p < .0001$) in both task domains (Figure 2A and 2B, Supplemental Tables S1 and S2).

We then applied logistic regression with the same predictors (OV and absVD) to analyze trial-by-trial accuracy. Note that choice accuracy was defined as choosing the brighter patch in the perceptual task and choosing the snack associated with a higher rating (i.e., choice consistency) in the preferential task. The results revealed that accuracy was positively related to absVD (perceptual: $\beta = 1.20$, $SE = 0.06$, $t_{60} = 17.25$, $p < .0001$; preferential: $\beta = 0.73$, $SE = 0.05$, $t_{60} = 14.51$, $p < .0001$) and OV (perceptual: $\beta = 0.04$, $SE = 0.02$, $t_{60} = 1.52$, $p = .1314$; preferential: $\beta = 0.04$, $SE = 0.02$, $t_{60} = 2.76$, $p = .0075$), suggesting that participants performed better when absVD and OV were higher. However, the OV effect was significant in the preferential task only (Figure 2C and 2D, Supplemental Tables S1 and S2). To address the potential nonlinear relationship between OV and choice accuracy in the preferential task, we also conducted an analysis using contrast coding. Similar to Shevlin et al. (2022), we treated the medium OV condition as the baseline and tested for differences in high and low OV conditions relative to this baseline separately. In this analysis, choice accuracy was significantly higher in the high compared with the medium OV condition ($\beta = 0.32$, $SE = 0.07$, $t_{60} = 4.57$, $p < .0001$). Meanwhile, the coefficient for the low OV condition was positive, but not significant ($\beta = 0.12$, $SE = 0.08$, $t_{60} = 1.52$, $p = .1329$). These results align with the other regression analyses and further suggest that the positive effect of OV on choice accuracy observed in the preferential task was mainly driven by the medium and high-OV conditions. Regarding our third hypothesis, the regression model revealed that confidence ratings were positively related to both VD (perceptual: $\beta = 3.43$, $SE = 0.31$, $t_{60} = 11.01$, $p < .0001$; preferential: $\beta = 2.95$, $SE = 0.72$, $t_{60} = 10.70$, $p < .0001$) and OVs (perceptual: $\beta = 2.58$, $SE = 0.28$, $t_{60} = 9.05$, $p < .0001$; preferential: $\beta = 4.47$, $SE = 0.37$, $t_{60} = 11.95$, $p < .0001$); see Supplemental Figure S1. The observed OV effects hold when we conducted the same analyses without standardizing independent variables for each participant.

Negative OV Effect on Fixation Times and Allocations

We applied the same logistic regression model to analyze the influence of OV and absVD on eye-movement data, specifically focusing on fixation times (i.e., duration of first, middle, and final fixations) and fixation allocations (i.e., the number of fixations, the probability of looking at the better option) as dependent variables. Consistent with the effect on RT, OV was negatively related to the duration of middle fixations (perceptual: $\beta = -6.66$, $SE = 3.24$, $t_{60} =$

Figure 2
OV Effects on Response Times and Accuracy



Note. (A and B) Left panels refer to average response times (RTs) in the low, medium, and high-OV conditions of the perceptual (A) and preferential task (B). (C and D) Left panels refer to the percentage of accuracy in the low, medium, and high-OV conditions of the perceptual (C) and preferential task (D). The right panels represent the regression coefficient of OV for RT (A and B) and accuracy (C and D). Dots correspond to individual regression coefficients for absolute value difference and overall value. The circles and error bars represent mean and 95% confidence interval, respectively. The larger circles represent the higher absVD level. The dashed lines represent the guessing level. absVD = absolute value difference; OV = overall value; L = low; M = medium; H = high; n.s. = non-significant. See the online article for the color version of this figure.
$^{**}p < .01$. $^{***}p < .001$.

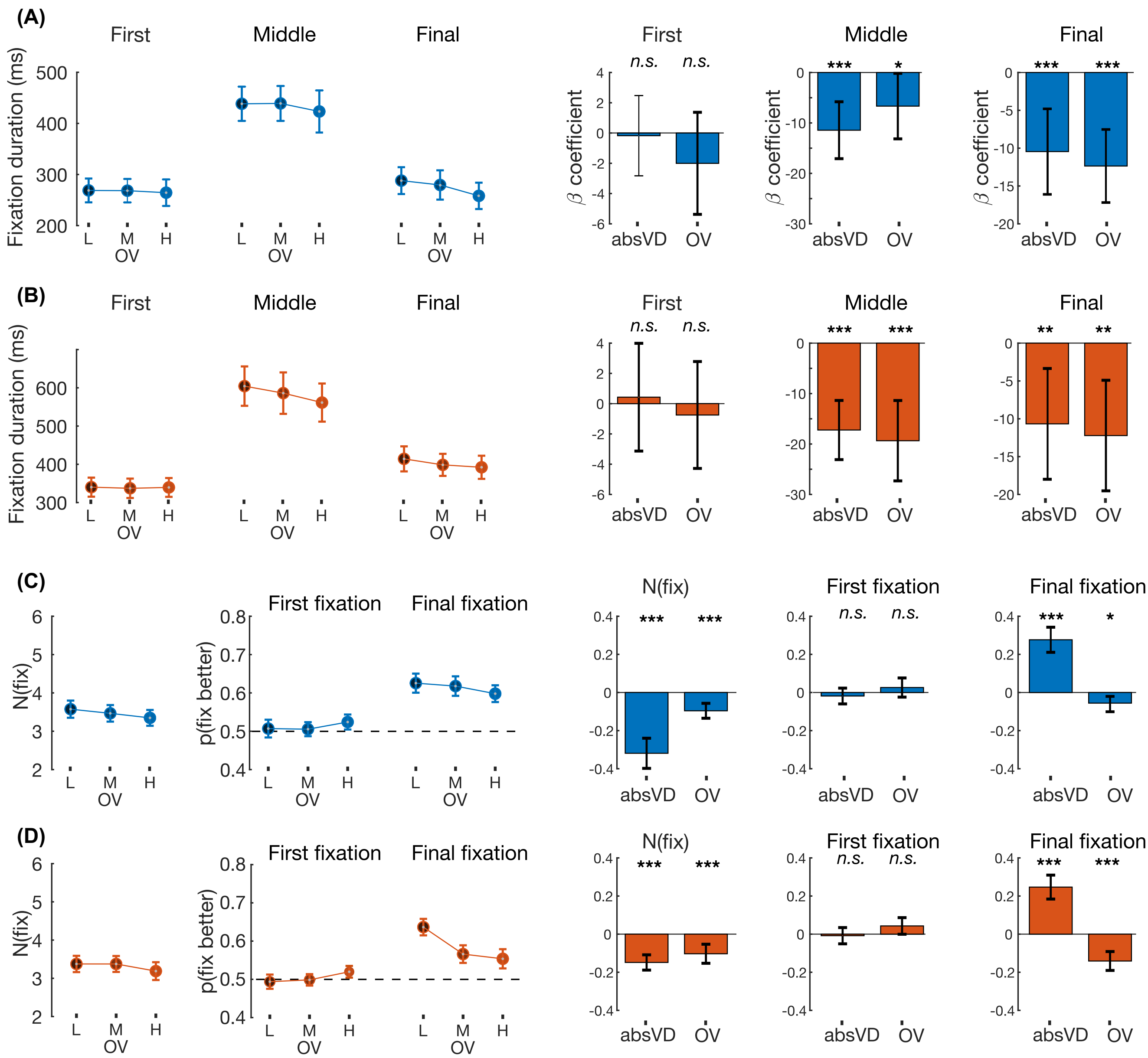
−2.05, $p = .0446$; preferential: $\beta = -19.34$, $SE = 3.98$, $t_{60} = -4.85$, $p < .0001$), as well as to the duration of the final fixation (perceptual: $\beta = -12.35$, $SE = 2.41$, $t_{60} = -5.11$, $p < .0001$; preferential: $\beta = -12.21$, $SE = 3.65$, $t_{60} = -3.34$, $p < .0001$; Figure 3A and 3B, Supplemental Table S3). The first fixation durations were independent of OV ($p > .2396$), indicating that the reduced RT in high OV was only related to middle and last fixations. Similar to the effect on fixation durations, the number of fixations was negatively correlated with OV in both tasks (perceptual: $\beta = -0.09$, $SE = 0.02$, $t_{60} = -4.89$, $p < .0001$; preferential: $\beta = -0.10$, $SE = 0.02$, $t_{60} = -4.41$, $p < .0001$) (Figure 3C and 3D). Moreover, the first fixation was independent of OV as the probability of looking at the better option first was not significantly related to OV ($p > .0533$). Remarkably, however, we found the probability of looking at the better option last to be significantly and negatively related to OV (perceptual: $\beta = -0.05$, $SE = 0.02$, $t_{60} = -2.47$, $p = .0163$; preferential: $\beta = -0.14$, $SE = 0.02$, $t_{60} = -5.69$, $p < .0001$; Figure 3C and 3D, Supplemental Table S3), indicating that we were more likely to look at the better option at the end of the decision when OV was lower. These findings remained consistent when the dependent variables were not standardized. Altogether, our eye-movement data suggested that, when confronted with options of higher OV, participants were able to maintain their performance while reducing the number of fixations and time spent on evaluating options and the probability of fixating on the better option before making decisions.

Assessing the Role of Gaze

Next, we examined the role of dwell-time advantage and final fixation. Dwell-time advantage, which measures how much longer one option is looked at compared to another, has been robustly related to the final choice: The option is more likely to be chosen when it is looked at longer (Krajbich, 2019). On the other hand, the role of the final fixation refers to the fact that an option is more likely to be chosen if it is looked at last given the same VD. The regression results confirmed these robust associations between gaze and choice across two task domains. In particular, participants tended to choose the option they looked at longer (perceptual: $\beta = 1.07$, $SE = 0.22$, $t_{59} = 4.74$, $p < .0001$; preferential: $\beta = 0.60$, $SE = 0.10$, $t_{58} = 5.79$, $p < .0001$) and they looked at last (perceptual: $\beta = 2.64$, $SE = 0.28$, $t_{59} = 9.20$, $p < .0001$; preferential: $\beta = 3.85$, $SE = 0.28$, $t_{58} = 13.73$, $p < .0001$; Figure 4A and 4B, Supplemental Table S4). Nevertheless, the interaction between dwell-time advantage and OV level was significant in the perceptual task only (perceptual: $\beta = -0.16$, $SE = 0.08$, $t_{59} = -2.11$, $p = .0391$; preferential: $\beta = 0.01$, $SE = 0.05$, $t_{58} = 0.21$, $p = .8290$), suggesting that the association between dwell-time advantage and choice was weaker in the higher

Figure 3

OV Effects on Fixation Duration and Fixation Allocation



Note. (A and B) Left panels: the first, middle, and final fixation duration in the perceptual task (A) and preferential task (B). (C and D) Left panels: The fixation allocation is evaluated as the number of fixation, and the percentage of the first and final fixation is the better option. The right panels represent the regression coefficient of OV and absVD. The results were separately plotted for the low, medium, and high OV levels. The error bars represent the mean ± 95% confidence interval. OV = overall value; absVD = absolute value difference; *N*(fix) = number of fixations; L = low; M = medium; H = high; n.s. = non-significant. See the online article for the color version of this figure.
* $p < .05$. ** $p < .01$. *** $p < .001$.

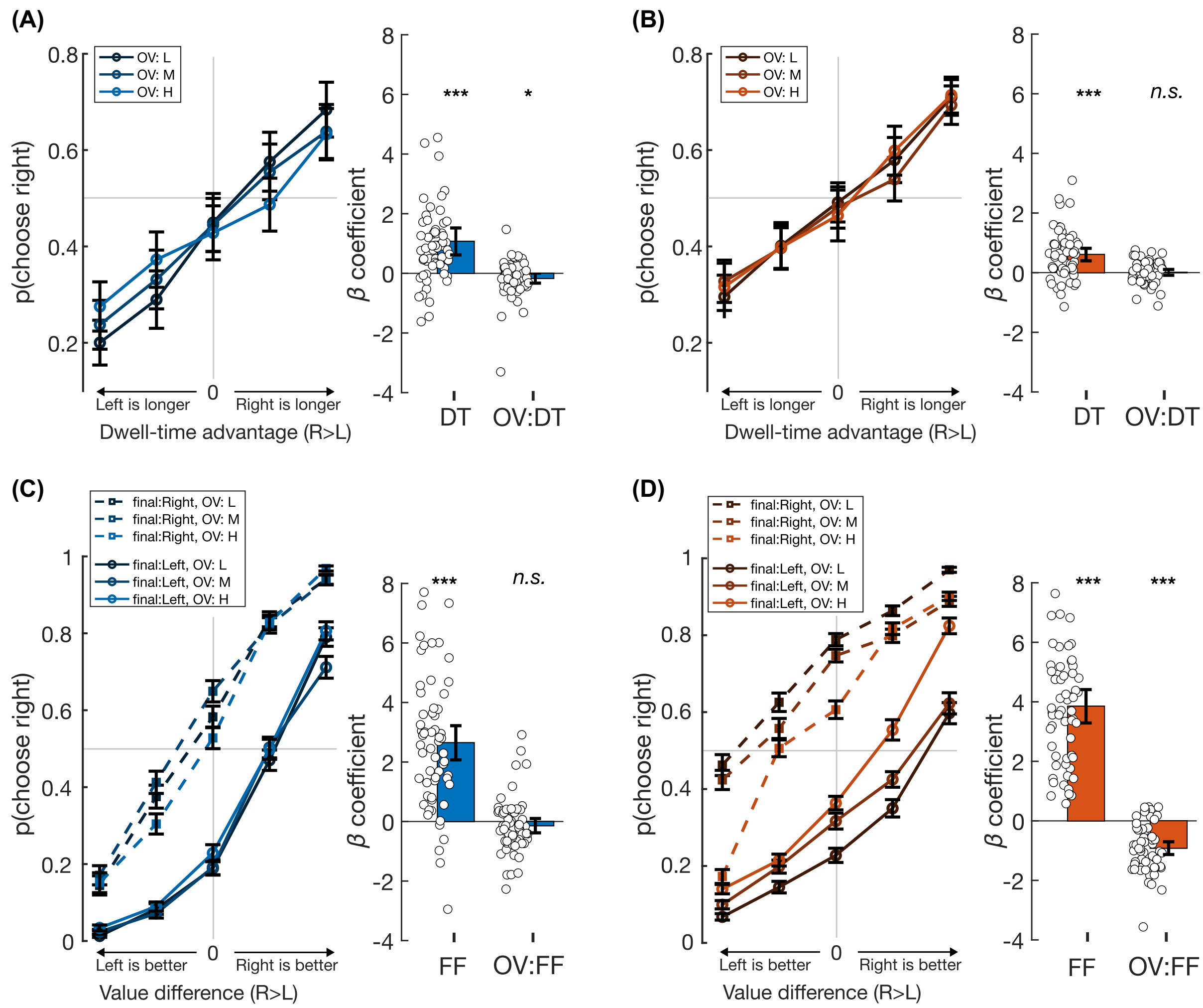
OV conditions. On the other hand, the effect of final fixation was significantly modulated by OV levels in the preferential task only (perceptual: $\beta = -0.14$, $SE = 0.12$, $t_{59} = -1.15$, $p = .2527$; preferential: $\beta = -0.91$, $SE = 0.10$, $t_{58} = -8.53$, $p < .0001$). The (in)significant interactions remained consistent when the dependent variables were not standardized. Notably, the negative sign of the interaction indicates that participants exhibited a reduced tendency of choosing the last-fixated option in the high-OV condition in both tasks (Figure 4C and 4D, Supplemental Table S4).

Computational Modeling of the Impact of OV

To gain a deeper understanding of how OV was involved in information processing, the aDDM (Krajbich et al., 2010) was fitted

Figure 4

Domain-Specific OV Effects on the Association Between Gaze Patterns and Choices



Note. (A and B) The left panels show the impact of dwell-time advantage on choice, which is illustrated as the percentage of choosing the right option as the function of five bins of the dwell-time advantage between right and left options for the perceptual task (A) and preferential task (B). (C and D) The left panels show the impact of final fixation on choice, which is illustrated as the percentage of choosing the right option as the function of five bins of intensity/value difference for the perceptual task (C) and preferential task (D). The dashed and solid lines in (C and D) indicate that the final-fixated option is the right and left options, respectively. The right panels represent the regression coefficient of the interaction between OV and dwell-time advantage (A and B) and final fixation (C and D). Error bars represent 95% confidence interval. DT = dwell-time advantage; OV:DT = interaction between OV and dwell-time advantage; FF = final-fixation effect; OV:FF = interaction between OV and final-fixation effect; L = low; M = medium; H = high; n.s. = non-significant. See the online article for the color version of this figure. $^{*}p < .05$. $^{***}p < .001$.

to both behavioral and eye-movement data for two tasks separately, using hierarchical Bayesian modeling (Wiecki et al., 2013; see also the Computational Modeling section). Note that the aDDM assumes the drift rate to be a linear function of the attention-weighted VD. Thus, the aDDM provides a mechanistic explanation for the negative effect of OV on RT (Smith & Krajbich, 2019). In our implementation of the aDDMs, the models consist of at least five parameters. These parameters include the nondecision time (NDT), which accounts for RT associated with motor and perceptual processing, and threshold (a), which denotes the evidence required to initiate an action. The remaining parameters are three coefficients ($\beta 0$, $\beta 1$, $\beta 2$) in a linear regression used to estimate the drift rate (ν). Specifically, $\beta 0$ represents the intercept, $\beta 1$ represents the impact of the fixated option, and $\beta 2$ represents the impact of the nonfixated option (see the Computational Modeling section). Note that aDDM's discounting factor θ can be rewritten as $\beta 2/\beta 1$ (Cavanagh et al., 2014). Because our preregistered hypotheses were derived from simulating the standard aDDM with parameters held constant across OV conditions, we first estimated the aDDM parameters per choice domain without separating the OV conditions (Model 1). We saw, however, that the resulting model predictions did not fully align with our observed data (Figure 5). Specifically, while the data showed a positive effect of OV on choice accuracy, the simulated data predicted the opposite. Given the crucial role of θ in capturing the effect of OV on RT (Krajbich et al., 2010; Pirrone & Gobet, 2021; Smith & Krajbich, 2019), we then expanded the standard aDDM by incorporating OV-dependent θ-related parameters, denoted as β1 and β2 in Models 2 and 3, respectively, while keeping the other parameters constant across different OV levels. Model comparison results indicated that Model 3, incorporating OV-dependent β2 (and thus OV-dependent θ) provided the best account of the data, as evidenced by its lowest deviance information criterion (DIC) value. Building upon Model 3, we further explored whether the threshold (Model 4) or the NDT also differed for different OV levels (Model 5). Ultimately, the model with OV-dependent β2 and NDT (i.e., Model 5) exhibited the lowest DIC value in both perceptual and preferential tasks (see Table 1). Notably, the parameter estimates of the winning model (Table 2) closely resembled those obtained from fitting the original aDDM separately to different OV conditions (as detailed in Supplemental Tables S5 and S6).

Finally, we performed posterior predictive checks to test whether the aDDM can reproduce the behavioral effects of OV reported above (see the Materials and Method section). Specifically, we assessed the importance of allowing the attentional discounting factor (θ) to differ across OV conditions (see the Materials and Method section). Regression analyses of the posterior predictives with OV-dependent θ (i.e., Model 5 with varied NDTs and θ) successfully reproduced the negative OV effect on RT (perceptual: $\beta = -0.02$, $SE = 0.01$, $t_{60} = -2.02$, $p = .0473$; preferential: $\beta = -0.10$, $SE = 0.08$, $t_{60} = -6.48$, $p < .0001$) and positive OV effect on accuracy (perceptual: $\beta = 0.01$, $SE = 0.02$, $t_{60} = 0.55$, $p = .5831$; preferential: $\beta = 0.03$, $SE = 0.02$, $t_{60} = 1.70$, $p = .0926$) in both task domains (Figure 5). By contrast, when both θ and NDT were not allowed to vary over the three OV levels (i.e., Model 1 with fixed NDT and θ), only the negative association between OV and RT could be reproduced (perceptual: $\beta = -0.04$, $SE = 0.01$, $t_{60} = -2.84$, $p = .0062$; preferential: $\beta = -0.10$, $SE = 0.01$, $t_{60} = -6.60$, $p < .0001$), but the OV effect on accuracy observed in our empirical data was not matched by the simulation result (Figure 5B). Instead, the model with fixed θ and NDT predicted a negative effect of OV on accuracy (perceptual: $\beta = -0.07$, $SE = 0.03$, $t_{60} = -2.40$, $p = .0191$; preferential: $\beta = -0.06$, $SE = 0.02$, $t_{60} = -2.62$, $p = .0110$).

Discussion

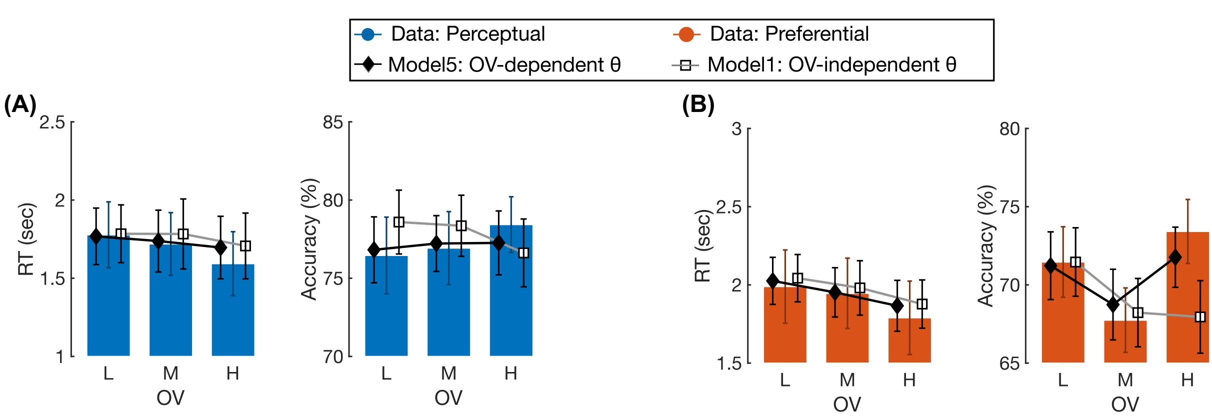
The present study aimed to better understand the role of the OV of available options in perceptual and preferential decision making. Specifically, we investigated whether OV influences choice behaviors and eye movements beyond RT, which has consistently been reported to decrease with higher OV in previous research (Fontanesi, Gluth, et al., 2019; Krajbich et al., 2010; Lebreton et al., 2019; Mormann & Russo, 2021; Pirrone et al., 2018, 2022; Polanía et al., 2014; Smith & Krajbich, 2019; Ting et al., 2020). Given the strong interdependencies of RT, choices, and gaze, which have led to process models of decision making such as the aDDM, our hypothesis was that OV would simultaneously impact all three measures. Furthermore, we sought to include eye movements when modeling choice and RT to shed light on the hitherto elusive phenomenon that RT robustly decreases with OV, but choice accuracy is often unaffected by OV and may even increase (Shevlin et al., 2022).

First, we successfully replicated the negative impact of OV on RT in both perceptual and preferential choice tasks. However, we observed less consistent OV effects on choice accuracy and on gaze-related choice bias across choice domains. Specifically, the association between dwell-time advantage and choice was significantly weaker as OV increased in the perceptual task only, indicating that participants were less likely to choose the option looked at longer when OV was higher. This effect was not significant in preferential choices. Instead, OV exhibited significant associations with accuracy and the impact of the final fixation. In particular, participants tended to choose options linked to higher ratings and options they had not fixated on last in the higher OV condition.

In line with prior studies using perceptual (Ratcliff et al., 2018) and preferential tasks (Frömer et al., 2019; Polanía et al., 2014, 2019; Shevlin et al., 2022), the positive coefficients of OV on choice accuracy suggest that our participants did not sacrifice task performance while

Figure 5

Posterior Predictive Checks for the Attentional Drift-Diffusion Model With OV-Dependent Discount Factors θ and OV-Independent θ to Assess OV Effect on Behaviors in the Perceptual and Preferential Tasks



Note. (A and B) RT (left panels) and accuracy rates (right panels) are plotted as a function of OV levels. Error bars represent 95% confidence interval. RT = response times; L = low; M = medium; H = high; OV = overall value. See the online article for the color version of this figure.

Table 1
Model Comparison Results (Deviance Information Criterion Values)

Model	Fixed parameter	Varied parameter	Perceptual	Preferential
Model 1	NDT, a, β0, β1, β2		26039.55	32373.95
Model 2	NDT, a, β0, β2	β1	26234.92	32347.01
Model 3	NDT, a, β0, β1	β2	26186.40	32287.15
Model 4	NDT, β0, β1	a, β2	26022.06	32091.94
Model 5	a, β0, β1	NDT, β2	**25929.18**	**31669.02**

Note. β2 refers to d^* θ, and values presented in bold indicate the lowest deviance information criteria. NDT = nondecision time.

making quicker decisions. These findings cannot be explained by the notion of a speed–accuracy trade-off, which would suggest that faster decisions are more likely to be wrong. As noted by Shevlin et al. (2022), they are also difficult to reconcile with many traditional psychophysical and economic accounts such as the Weber–Fechner law or marginal utility, which would predict that high OV should be associated with diminished sensitivity and thus greater difficulties to identify the correct option. Importantly, the pattern of accuracy rates observed in the present study (and others) is also inconsistent with the predictions derived from the standard aDDM (with θ being independent of OV), which formed the basis of our preregistered hypotheses and which suggested that both RT and accuracy would be negatively associated with OV (Shevlin & Krajbich, 2021).

Our eye-tracking and modeling results point toward a solution and mechanistic explanation of this conundrum. Thus, our model-free analysis revealed that gaze patterns (including dwell-time advantage and final fixation) are predictive of choices, yet the strength of this association between gaze and choice decreased with higher OV. This result is further substantiated by our model-based analysis. Choice patterns were better explained by the aDDM with OV-dependent θ, in contrast to an aDDM with a constant θ across OV levels. More specifically, we observed that the discounting factor θ for the nonfixated option was larger and closer to 1 (indicating less discounting) as OV increased. Note that as θ approaches 1, the (biasing) influence of attention on preference formation diminishes, so that decisions will be less affected by trial-wise fluctuations in attention and can thus be expected to be more consistent with the indicated preferences from the rating task. Importantly, the positive effect of OV on accuracy can only be explained by the aDDM with OV-dependent θ (Figure 5), whereas the negative relationship between OV and RT was adequately explained by the aDDM, irrespective of whether it utilized an OV-dependent or OV-independent θ.

Why does higher OV lead to less discounting of the nonfixated option? We speculate that the representation of high-OV options might be less affected by fixating on other options due to more efficient peripheral viewing and better memory. This notion is supported by recent studies indicating that the association between gaze and choice becomes stronger (i.e., θ in the aDDM decreases) when the nonfixated option is invisible (Eum et al., 2023) and when options need to be retrieved from memory (Weilbächer et al., 2021).

Table 2
Group Maximum Posterior Estimates of Attentional Drift-Diffusion Model Parameters and Parameter Comparisons Between Overall Value Levels From the Winning Model (Model 5)

Parameter estimate						
	Perceptual task			Preferential task		
Parameter	L	M	H	L	M	H
NDT_{group}	0.53	0.49	0.46	0.70	0.70	0.60
[HDI = 95%]	[0.50, 0.56]	[0.46, 0.52]	[0.43, 0.49]	[0.66, 0.73]	[0.66, 0.74]	[0.57, 0.64]
θ_{group}	0.86	0.94	0.96	0.47	0.59	0.75
[HDI = 95%]	[0.78, 0.95]	[0.88, 0.99]	[0.94, 1.00]	[0.35, 0.60]	[0.52, 0.66]	[0.69, 0.82]
$\beta2_{group}$	0.24	0.26	0.27	0.02	0.03	0.04
[HDI = 95%]	[0.22, 0.26]	[0.25, 0.28]	[0.26, 0.29]	[0.02, 0.03]	[0.03, 0.04]	[0.04, 0.05]
$\beta1_{group}$		0.28			0.06	
[HDI = 95%]		[0.26, 0.30]			[0.05, 0.06]	
$\beta0_{group}$		0.06			0.08	
[HDI = 95%]		[−0.00, 0.12]			[0.03, 0.12]	
a_{group}		2.31			2.20	
[HDI = 95%]		[2.12, 2.52]			[2.05, 2.34]	

Parameter comparison						
	Perceptual task			Preferential task		
Parameter	M-L	H-M	H-L	M-L	H-M	H-L
NDT [HDI = 95%]	[−0.08, 0.00]	[−0.07, 0.01]	**[−0.11, −0.03]**	[−0.04, 0.07]	**[−0.15, −0.03]**	**[−0.14, −0.01]**
θ [HDI = 95%]	**[0.03, 0.13]**	[−0.01, 0.04]	**[0.05, 0.14]**	**[0.02, 0.34]**	**[0.10, 0.31]**	**[0.24, 0.53]**
β2 [HDI = 95%]	**[0.00, 0.03]**	[−0.00, 0.01]	**[0.01, 0.04]**	[−0.00, 0.01]	**[0.00, 0.01]**	**[0.00, 0.02]**

Note. θ refers to (β_2/β_1), and values presented in bold indicate significant differences in the parameter comparison. L = low; M = medium; H = high; NDT = nondecision time; HDI = highest density intervals.

In particular, Eum et al. (2023) found a greater tendency to choose the final-fixated option when the nonfixated option was concealed with a gaze-contingent design, as opposed to when all options were always visible. In a similar vein, Weilbächer et al. (2021) observed a stronger influence of both dwell-time advantage and final fixation on choice when participants had to remember options via associated locations compared with when presenting those options directly. Drawing from these findings, we propose that the strength of representation or availability in memory of the nonfixated option is stronger in the high compared with low OV condition. In the case of perceptual decisions, this could be due to stronger effects of high-intensity stimuli (Constant & Liesefeld, 2021; Klink et al., 2017). In preferential choices, high-value stimuli might be more familiar and easier to keep in memory (Mechera-Ostrovsky & Gluth, 2018). Following the same logic, OV effects could be smaller when selecting between "novel" objects. Indeed, Shevlin et al. (2022) replicated the negative association between OV and RT with novel images, but the changes in RT were not significant when comparing medium and low OV. Fiedler and Glöckner (2012) found a positive effect of OV (quantified as the mean of the expected values of two gambles) on RT and the number of fixations. These findings suggest that the OV effects observed in the present and previous studies might depend on the use of memory and the specific paradigm. Future studies could provide further evidence for this link, for instance, by combining a memory manipulation and gaze-contingent design with a systematic variation of OV and testing for their interaction.

Another alternative explanation for our findings could be that participants are motivated by the attractive options, which may affect the efficiency of information processing and confidence in choosing the better option. Indeed, we found that self-report confidence was positively related to OV (Supplemental Figure S1), which aligns with the results of several recent studies (Lebreton et al., 2018; Salem-Garcia et al., 2023; Ting et al., 2023). Furthermore, we found that not only RT but also the NDT, which is independent of evidence accumulation, was lowest in the high-OV condition (Table 2). The result is consistent with a recent study showing that participants move their eyes more quickly when evaluating options associated with high subjective values (Korbisch et al., 2022). In line with this idea, we found that the number of fixations and fixation durations, particularly for the middle and final fixations, decreased when OV was higher. Both, the reduced NDT and the faster eye movements could be indicative of a higher level of response vigor in case of higher OV levels (Beierholm et al., 2013).

To some extent, our OV results rest on the assumption that the lowest rated snacks have neutral or slightly positive subjective value. However, snacks rated as "do not like at all" in our task could have been perceived as losses or aversive. Interestingly, aversive options are commonly associated with longer decision times (Fontanesi, Palminteri, et al., 2019; Guitart-Masip et al., 2012; Jahfari et al., 2019), lower confidence (Ting et al., 2020), and increased attention (Yechiam & Hochman, 2013), suggesting that some of our findings in the preferential task could be reactions to these aversive options. We tested this potential explanation by focusing exclusively on low-OV trials in the preferential task. This exploratory analysis showed that even within the low OV condition, OV and RTs were still negatively related to each other ($\beta = -2{,}93$, $SE = 0.06$, $t_{60} = -4.81$, $p < .0001$). This is in line with a recent study that excluded any options that participants "would not eat" and still replicated the negative association between OV and RT (Shevlin et al., 2022). Intriguingly, similar to our findings on choice accuracy, Shevlin et al. (2022) also observed the *v*-shaped pattern of accuracy (as a function of OV) in the preferential task, but this pattern disappeared when the familiarity for the options was controlled (Shevlin et al., 2022). Altogether, these findings indicate that the valence of the options may not be the primary driver of the negative OV effect on RT. Because our study did not control for familiarity and lacked access to the 0 point on the rating scale, we cannot completely rule out the possibility that valence or familiarity may contribute to the changes in accuracy from the low to the medium OV condition.

Along this line, it is noteworthy that brightness intensity in our perceptual task was unrelated to reward, as a correct choice always resulted in the same bonus regardless of OV. Therefore, a more plausible interpretation of the OV effects observed in the present study could be that participants were motivated by goal-relevant information (Frömer et al., 2019; Sepulveda et al., 2020). In other words, brighter options and highly rated snacks may be more congruent with the task's goal than darker or less preferred options, leading participants to focus on and possibly enhance their cognitive processing of these particular information sources.

Our research expands the application of sequential sampling models in general and the aDDM in particular to the study of OV effects in significant ways. Previous studies did not take attention into account when modeling OV effects (Shevlin et al., 2022) or focused on trials with no or little VD (e.g., Pirrone & Gobet, 2021; Smith & Krajbich, 2019), whereas we systematically varied and orthogonalized VD and OV in our experimental design. This allowed us to define choice accuracy and test corresponding predictions of the aDDM. Notably, based on model simulations (performed for the preregistration protocol) as well as modeling results (Figure 5), we see that the aDDM predicts decreasing choice accuracy with increasing OV as long as the attentional discounting factor θ is kept constant. Given that most studies do not find this decrease, and some even find an increase (including our own), it can be expected that θ scales positively with OV. Importantly, however, our model-free analyses of the eye-tracking data suggest that the association of attention and choice is indeed reduced under high OV levels, implying that the increased θ does not only reflect the model's need to compensate for its accuracy predictions. Intriguingly, our findings contrast with a recent publication (Pirrone & Gobet, 2021), which reanalyzed previous studies of snack-choice tasks and concluded that the discounting factor θ in the aDDM was independent of OV. This inconsistency could be due to different parameter estimation methods (i.e., simple regression in Pirrone & Gobet's study vs. hierarchical modeling of the full aDDM in our study), or it could be a consequence of the broader and more systematically varied ranges of both VD and OV in our study.

Finally, we note that while the aDDM with OV-dependent θ is quantitatively and qualitatively superior to the standard aDDM with OV-independent θ, neither model can fully reproduce the modulation of OV on gaze-related choice effects in the preferential task (Supplemental Figure S2). In particular, even the winning model (aDDM with OV-dependent θ) predicts that gaze-related choice biases are stronger in the higher OV conditions, which is contrary to what we observed in the actual data. Alongside this discrepancy, we also observed differences between the perceptual and preferential domains, in terms of choice accuracy and gaze-related choice biases, that are difficult to reconcile with a single model. Specifically, the aDDM would predict that the dwell-time and final-fixation biases emerge from the same underlying mechanism, which stands in contrast to our findings that the former was significant in perceptual and the latter in preferential decisions, respectively. Future studies are needed to refine the computational descriptions of OV effects for different task domains by incorporating eye-movement data and exploring additional mechanisms of choice dynamics, like the lateral inhibition, information leakage (Teodorescu & Usher, 2013; Teodorescu et al., 2016; Usher & McClelland, 2001), or collapsing boundaries (Hawkins et al., 2015).

In conclusion, the present study extended the understanding of the impact of OV, suggesting a mechanistic account of the puzzling phenomenon that decisions become faster, but not less accurate, under high OV: Both model-free and model-based analyses indicate that high OVs mitigate gaze-related effects in both perceptual and preferential choices. The similarities and differences in OV effects across choice domains are pivotal for guiding future research on OV effects and for building similar yet distinct mechanisms for evidence accumulation in different task contexts.

Materials and Method

Transparency and Openness

Our research question, hypotheses, task design, sample size, and data collection strategy were preregistered (https://osf.io/acse9) prior to the data collection. The data and the analysis scripts are publicly available on the Open Science Framework at https://osf.io/af6u9/.

Participants

The target sample size was 60 human participants completing the entire experiment (with two main tasks). The sample size was determined by a simulation-based power analysis that simulates the planned experiment in much detail, including the number of participants and number of trials. Specifically, we ran the simulations based on the aDDM (Krajbich et al., 2010) with the following parameters: $\mu\_\theta = [0.2, 0.9]$, $\sigma\_\theta = 0.01$, $\mu\_SD = [0.02, 0.03]$, $\sigma\_SD = 0.001$, $\mu\_d = [0.0002, 0.0004]$, $\sigma\_d = 0.00001$, $\mu\_\text{NDT} = [350, 650]$, and $\sigma\_\text{NDT} = 10$. To quantify the effect of OV on choice, we fit generalized linear mixed models to each simulated data set—generalized linear mixed models: dependent variable ~1 + OV + absVD + (1 + OV + absVD|subjectID), where the dependent variable is choice accuracy/consistency (i.e., choosing the option with higher value) and the predictors are OV (i.e., the summed value of two options) and VD. With 200 data sets, the analysis suggested that with a sample size of 60 participants and 20 trials per condition (nine conditions in total), the statistical power to identify the OV effect on choice accuracy/consistency is .89. Statistical power did not increase dramatically by enlarging the sample size or number of trials.

Eighty-three healthy participants were recruited from the campus and completed the experiment. Considering one of tasks (i.e., food-choice task) in the present study required participants to make choices between rather high-caloric snack options, only the participants who were not on a diet or vegetarian or suffer from food allergies and/or food intolerances were invited. The recruitment criteria were explicitly described in the advertisement. Following the exclusion criteria described in the preregistered document (https://osf.io/acse9), we excluded 22 participants due to (a) a low correlation between two ratings for the same set of snacks ($n = 1$), (b) a technical issue ($n = 1$), and (c) too many extreme ratings ($n = 19$), which led to difficulties of creating equal numbers of snack pairs for each of OV and absVD level in the food-choice task. In the end, data from 61 participants (age = 26.75 ± 7.33; 40 people reported their gender as female and 21 as male) were analyzed.

Procedure

To enhance participants' motivations for the food-choice task (both ratings and decisions), we asked each participant to fast for at least 3 hr before the study. Once the participants came to the lab and before the start of the experiment, all participants were asked to carefully read the instruction and signed the informed consent. The experiment in the present study consisted of three phases: exposure phase, rating phase, and choice phase (Figure 1A). The experimental setting was the same across three phases, but the eye tracker was turned on in the choice phase only. At the end of the experiment, participants were asked to fill out a State-Trait Anxiety Inventory questionnaire (Spielberger et al., 1983) and three free-response demographic questions (i.e., gender, birth year, and handed). The compensation for each participant was 12 € per hr. On average, the experiment was completed in ~1.5 hr, including reading instructions and filling in the final questionnaires. In addition to the participant fee, participants had the chance to win bonuses: a food snack and 2 €.

Task

Exposure Phase

Participants started with passively viewing a series of gray patches and a series of snacks in two separated blocks. The order of exposure was counterbalanced. The gray patches and snacks were displayed once a time for 500 ms. This was done to ensure participants were familiar with the range of stimuli used in the study.

Rating Phase

After all stimuli were shown once, participants were asked to rate the snacks using a visual analog scale with a sliding bar so that we could compute the subjective value for each snack and use it in the choice phase. In each trial, only one stimulus was displayed above the rating bar and a question "How much do you like this snack?" in German (i.e., *Wie sehr moegen Sie diesen Snack?*). We did not show the numerical values explicitly on the rating bar, so that the participants had less chance to remember the previous location based on the "number" (Polanía et al., 2019). The extreme left point of the rating line (i.e., *not at all*) was encoded as 0, and the extreme right point of the rating line (i.e., *very much*) was encoded as 100. Each snack was rated twice, and the averaged ratings for the same snack were used to determine the subjective value of the snack. It is worth noting that we did not inform participants whether the stimuli would repeat or not, so that they were less likely to implement a memory strategy and rate the same snacks based on the first rating (Brus et al., 2021; Polanía et al., 2019). We also included the ratings for the gray patches used in the brightness-discrimination task. Similar to rating snacks, participants passively viewed 30 gray patches first and then rated each gray patch with respect to the question "How bright is the square?" In German (i.e., *Wie hell ist das Quadrat?*). The brightness of each patch was determined by the gray levels ranging from 0.23 to 0.57 (0 indicates fully dark and 1 indicates fully white). To increase the variance of brightness, a random number selected from the range between 0 and 0.005 was added up to the predetermined gray levels. The inclusion of gray patch ratings ensured that the level of familiarity with these stimuli was comparable with the preferential stimuli. The ratings for the gray patches were not further used in the choice phase, and the main analysis used objective brightness intensity to identify OV effect on RT, similar to previous work (Polanía et al., 2014; Ratcliff & Smith, 2010).

The ratings from each participant were utilized to form multiple pairs of snacks for the three levels of OV (OV: sum of option values) and three levels of absVD in the subsequent choice phase (Figure 1B). This was done in four steps. First, we calculated the subjective value for each snack by taking the average of two ratings given to the same snack. Second, the snacks were divided into three categories (i.e., high, medium, low) based on the values. Specifically, the highest one third (67%–100%) of snack values was categorized as high, the second third (33%–67%) of snack values was categorized as medium, and the remaining snacks were categorized as low. Third, we paired snacks within each category to ensure the OV level of each pair of snacks was either high, medium, or low (i.e., high OV = high-value snack1 + high-value snack2). Fourth, each pair of snacks was further labeled as high, medium, or low absVD, based on 67%–100%, 33%–67%, and 33% of the VD within each OV level. To enhance the task difficulty, the VD between the two snacks in each pair was enforced to be smaller than 30. With this procedure, we customized the snack pairs for each participant based on his/her ratings.

We repeated the same procedure to create pairs of gray patches for the three levels of OV (OV: sum of brightness) and three levels of absolute value difference (absVD: the absolute difference between brightness) in the subsequent choice phase. The only two differences were that (a) we used objective value rather than subjective value of gray patches to generate pairs and (b) the intensity difference between two gray patches was not larger than 0.4.

Choice Phase

Half of the participants started with three blocks of the perceptual task (i.e., brightness discrimination), while the second half of the participants began with the preferential task (snack choice). At the beginning of each trial, participants were asked to look at a fixation cross for 1 s to view the stimuli. A failure to look at a fixation cross for 1 s in 3 s led to an additional eye-movement calibration (see the Eye Movement section). After the fixation cross, participants were asked to choose a brighter gray patch in the perceptual task and to choose a preferred snack in the preferential task (Figure 1C). Before the end of each trial, participants stated confidence in the choice using a visual analog scale ranging from 50 to 100, with a step of five (50 = *not confident at all* and 100 = *very confident*). Given our three-by-three OV and absVD manipulation, participants completed 189 binary choices (i.e., 9 conditions * 21 trials) in three blocks (63 trials/block) for each task. To incentivize participants to follow the instruction and choose their preferred snack, participants were told that they can earn a snack as an extra bonus. The bonus snack was determined by either two trials from the rating phase or one trial from the choice phase. If two trials were selected from the rating phase, then the higher rating will be the bonus snack; otherwise, the bonus is the chosen snack from the random trial from the choice phase. Similarly, participants were incentivized for the brightness-discrimination task as they have a chance to earn a 2 € monetary reward if the choice in the randomly selected trail from the brightness-discrimination task was correct (i.e., choosing the brighter gray patch).

Eye Movement

Setting and Measurement

In addition to the behavioral data, an EyeLink 1000 Plus (SR Research Ltd.) eye tracker was used to record eye-movement data at a sampling rate of 1,000 Hz in the choice phase. Participants sat in front of the eye tracker and screen. The chin rest was used to avoid large head movements. The distance between the chin rest and the screen was approximately 93 cm, which was about 1.5–1.75 *t* the width of the screen (wide × height = 54 × 29 cm). To ensure the quality of measurement, we performed calibrations between the blocks of the decision tasks (i.e., choice phase). In particular, eye movement was calibrated and validated before each session of the task. Within a block, participants were required to look at the fixation cross (with an invisible, 150-pixel diameter area of interest, AOI) on the screen at the beginning of each trial. If participants successfully kept fixating the cross for 1 s, the fixation cross disappeared, and the options were displayed. If this criterion was not reached within 5 s, the calibration was triggered. In each trial, a pair of visual stimuli was displayed on the left and right of the screen. The distance between the two options, the right edge of the left stimuli to the left edge of the right stimuli, was also fixed (i.e., 800 pixels). All tasks were programmed in MATLAB (Version *R*2021a) and MATLAB-based software: Psychtoolbox-3. The screen resolution was set to 1920 × 1080 pixel.

Preprocessing of Eye-Tracking Data

The raw eye-tracking data from the choice phase were preprocessed before data analysis. The preprocessing contained four steps (Eum et al., 2023; Krajbich et al., 2010). First, we extracted the fixation points (as *x*–*y* coordinates) from the beginning to the end of the option presentation. Second, each fixation point was labeled as "LEFT," "RIGHT," or "BLANK" depending on whether the *x*–*y* coordinate fell in the left or right AOIs. AOIs were 450 × 450-pixel square located in the centers of the left and right options. If the fixation was detected but could not be categorized into any AOIs, then the fixation point was labeled as "BLANK." Otherwise, the fixation points were labeled as "MISSING." The missing rates were comparable between perceptual task (M = 1.08%; max: 7.94%) and preferential task (M = 1.58%; max: 8.57%) tasks. Third, the "BLANK" fixation was replaced by "LEFT" or "RIGHT" if the blank fixation took place between two "LEFTs" (e.g., LEFT-BLANK-LEFT becomes LEFT-LEFT-LEFT) or two "RIGHTs" (e.g., RIGHT-BLANK-RIGHT becomes RIGHT-RIGHT-RIGHT). Finally, we discarded trials, which contained more than 30% of MISSING fixation points or with no fixation point. The average (±*sem.*) dropped trials per participant were 10.0 ± 3.3 trials and 3.7 ± 2.4 trials (out of 189 each) in the perceptual and preferential tasks, respectively. The labeled fixation points were eventually used to compute fixation allocation (i.e., the number of fixations and which option was looked at first and last) and fixation duration.

Data Analysis

The trials with RTs lower than 250 ms were excluded. The exclusion criterion was preregistered. The mean percentages of excluded trials were 0.13% for the perceptual task and 0.53% for the preferential task. The rest of the data points were analyzed with individual-level multiple linear regression model, which was written as follows:

$$\text{Dependent variable} \sim \beta_0 + \beta_1 \cdot OV + \beta_2 \cdot absVD, \quad (1)$$

where OV refers to the OV of two options and absVD refers to the absVD between two options. Both OV and absVD were z scored at the individual level.

The impacts of gaze were analyzed with two additional regressions ($\text{Regression}_{\text{DT}}$ and $\text{Regression}_{\text{FF}}$). The structure of each regression is as follows:

$$\begin{aligned}\text{Choice} \sim \beta_0 + \beta_1 \cdot \text{value difference} + \beta_2 \cdot \text{OV level} \\ + \beta_3 \cdot \text{gaze effect} + \beta_4 \cdot \text{OV level} \times \text{gaze effect},\end{aligned} \quad (2)$$

where the choice was the dummy variable (0 for choosing the left option and 1 for choosing the right option) and OV levels referred to three categories of OV (1 = low, 2 = medium, 3 = high; Figure 1B). The impact of gaze (gaze effect) in the analysis was operationalized differently for two separate models. In the $\text{Regression}_{\text{DT}}$, the impact of gaze was quantified as the difference in dwell time between the right and left options (i.e., $\text{Dwell}_{\text{right}}$–$\text{Dwell}_{\text{left}}$). In the $\text{Regression}_{\text{FF}}$, gaze effect was quantified as the final fixation (i.e., 0 = $\text{option}_{\text{left}}$, 1 = $\text{option}_{\text{right}}$). Dwell-time difference and value difference were z scored at the OV and at the individual levels. In both $\text{Regression}_{\text{DT}}$ and $\text{Regression}_{\text{FF}}$, one participant from the perceptual task and two participants from the preferential task were excluded because the parameter estimation did not converge. The estimated coefficients of interest were subsequently assessed using t tests to compare them against 0. All statistical analyses were performed using MATLAB and its built-in functions (i.e., one-sample t test: t test; Pearson's correlation: corr), with a statistical significance level of α 0.05. Two-sided tests were conducted for the t tests.

Computational Modeling

aDDM Fitting

We fitted choice (i.e., correct/incorrect) and reaction time data to aDDM (Krajbich et al., 2010; Smith & Krajbich, 2019) using a hierarchical Bayesian estimation procedure (or hierarchical Bayesian diffusion model; Wiecki et al., 2013). According to the aDDM, evidence in each trial was initiated from the starting point z and started accumulating with the drift rate ν until the evidence touched the threshold (i.e., $a/2$ for the correct choice and $-a/2$ for the incorrect choice). The final estimated RT was determined by the time point of reaching the threshold and NDT. The model estimated the threshold a, NDT, and drift rate ν. Following the suggestion of Cavanagh et al. (2014), the drift rate ν represents the slope of evidence accumulation to the correct or wrong option. By incorporating the proportion of dwell time (Prop.Dwell) and the option value (V), the drift rate ν in each trial was estimated as follows:

$$\begin{aligned}\nu = \beta0 + \beta1 \times (\text{Prop.Dwell}_{\text{corr}} \times V_{\text{corr}} \\ - \text{Prop.Dwell}_{\text{wrong}} \times V_{\text{wrong}}) \\ + \beta2 \times (\text{Prop.Dwell}_{\text{wrong}} \times V_{\text{corr}} \\ - \text{Prop.Dwell}_{\text{corr}} \times V_{\text{wrong}}) + \varepsilon,\end{aligned} \quad (3)$$

where β1 represented the impact of fixated option and β2 represented the impact of nonfixated option. In comparison to the drift rate formula in the standard aDDM (Krajbich et al., 2010; $\nu = d \times (V_{\text{fixated}} - \theta \times V_{\text{non-fixated}}) + \varepsilon$), β1 and β2 in Cavanagh et al.'s (2014) equation are equivalent to d and $d \times \theta$, respectively. Thereto, the discounting factor θ could be written as β2/β1. The parameters were estimated individually for each OV level using maximum posterior estimation. Posterior estimation was conducted via Monte Carlo methods with five chains for a total of 1,000 burn-in samples and 5,000 samples from each of the posterior distributions. To minimize the convergence issue, the starting values to the maximum posterior in each chain were randomized. We first examined the reliability of parameter estimates using the Gelman–Rubin $\hat{R}$ statistic (Gelman & Rubin, 1992), which quantified the similarities of the estimations between and within chains of the models. The Gelman–Rubin $\hat{R}$ value for each parameter (and each participant in each OV condition) was lower than the acceptable threshold of 1.1 (Brooks & Gelman, 1998) within the winning model (i.e., Model 5; perceptual: $\text{Max}_{\text{convergence}} = 1.05$; preferential: $\text{Max}_{\text{convergence}} = 1.04$), indicating that the parameter estimations were reliable. We further tested the difference in posterior distributions between OV levels with 95% highest density intervals. Specifically, the estimated parameter (difference) is significantly different from 0 if the 95% highest density interval of the estimated posterior distribution does not overlap with 0.

We compared different instantiations of the aDDM by fixing and relaxing different parameters in different conditions (Table 1). Specifically, five parameters (i.e., NDT, a, β0, β1, β2) were fixed over OV levels in the Model 1. In Models 2 and 3, either β1 or β2 was estimated separately for each OV condition. In Models 4 and 5, we extended the variation, allowing not only β2 but also the threshold (a) or NDT to differ between OV conditions. To identify which model can explain our data best, Models 1–5 were compared using DIC.

Model Simulation

The estimated parameters from the winning model (Model 5: varied NDTs and θ; Table 2) and the actual pairs of stimuli that our participants experienced were used to stimulate data. One main feature of aDDM is that the fixation (duration) was taken into account. To fulfill this requirement, the initial fixation location was assigned to the left option based on the probability of looking at the left option first (perceptual task: 59%; preferential task: 67%). On the other hand, the first and the final fixation durations were randomly selected from the log-normal distributions estimated by the MATLAB building function *lognfit*. Specifically, the best fitting parameters (mean and sigma) for each distribution were estimated by fitting the actual fixation durations. The mean and sigma for the first fixation duration were 5.48 and 0.50 in the perceptual task and

5.73 and 0.40 in the preferential task. The mean and sigma for the middle fixation duration were 6.02 and 0.41 in the perceptual task and 6.32 and 0.42 in the preferential task. The estimated mean and sigma for the log-norm distribution were similar to the previous report (see Supplemental Table S1 in Krajbich et al., 2010). The interest of simulation results were RT, accuracy, and gaze-related choice biases, which were analyzed with the same multiple linear regression (Equations 1 and 2) to test the OV effect. To better understand the role of θ, we ran the same simulation analysis with the fixed θ value estimated in Model 1 (Model 1: fixed all parameters; Supplemental Table S7).

Constraints on Generality

The present study recruited healthy participants from the University of Hamburg's subject pool. This sample may not fully represent diverse populations, potentially limiting the generalizability of our findings. To generalize the findings to specific populations, future research should investigate this topic within distinct demographic groups. Additionally, individual differences in stimulus perception could affect the observed effects in the perceptual task. Future studies should tailor stimuli to each participant in the perceptual task to enhance comparability with preferential task results. Finally, our model-based analysis focused on the aDDM and targeted its key parameter because the aDDM is commonly used to explain the underlying mechanism of the negative OV effect on RT. Consequently, our modeling results cannot rule out the possibility that OV affects other information-processing mechanisms not captured by the aDDM. For instance, the boundary of the aDDM might decrease over time (Hawkins et al., 2015), and the rate of this decrease could potentially be OV dependent.

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