The Role of Salience in Multialternative Multiattribute Choice

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Abstract

Attention plays a central role in multi-alternative multiattribute decision-making but the cognitive mechanisms for it are elusive (Yang & Krajbich, 2023; Molter, Thomas, Huettel, Heekeren, & Mohr, 2022; Trueblood, 2022). In this project, we explored the role of bottom-up attention by manipulating the salience of different options in a multi-alternative, multi-attribute choice display. Behaviorally, we observed that salience interacts with choice, where the salient option is selected more often, especially in quick decisions. Using computational modeling, we tested two different hypotheses for how salience impacts decision-making for different individuals. We tested (i) if salience created an initial bias in the decision-making process, and (ii) if salience impacted the comparisons that are made during the decision-making process. We find that there are large individual differences in the mechanism through which salience impacts choice. For many individuals, there was no impact of salience. However, for a sizable minority, salience created an initial boost in selecting the salient option. We do not find strong evidence for the impact of salience in the comparison process. In exploratory analyses, we observe that the impact of salience in decision-making is correlated with thinking styles. Our results indicate that salience-driven attention might impact decision-making in different ways for individuals.

Keywords: Salience, Attention, Multiattribute Choice, Cognitive Modeling, Bayesian, Sequential Sampling Model

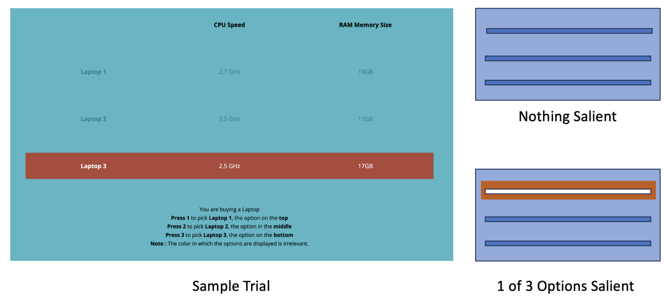

Figure 1: The left panel shows a sample trial. The right panel depicts the different conditions in the experiment.

Introduction

Decision-making often involves integrating several pieces of information about the different options before making a choice. For example, a decision between three computers (such as the one shown in Figure 1) might require one to integrate information about their speed and memory size before deciding which one to buy. Prominent theories of multi-alternative choice hypothesize that a decision maker sequentially attends to the different attributes and integrates them before making a decision (Trueblood, Liu, Murrow, Hayes, & Holmes, 2022; Noguchi & Stewart, 2018; Roe, Busemeyer, & Townsend, 2001; Bhatia, 2013; Yang & Krajbich, 2023; Krajbich & Rangel, 2011). This type of sequential sampling process suggests that attention likely plays a critical role in multi-alternative decisions (Trueblood, 2022; Smith & Krajbich, 2019). Given the importance of attention on decision-making, we study how attention being drawn to one of the choice options impacts the final decision.

Attention is deployed by a complex interaction between bottom-up factors (stimulus-driven) (Itti & Koch, 2000) and top-down factors (task-features) (Wolfe, 1994, 2021). (Chen, Mihalas, Niebur, & Stuphorn, 2013; Towal, Mormann, & Koch, 2013; Orquin, Lahm, & Stojić, 2021; Peschel, Orquin, & Loose, 2019)For example, in the display presented in Figure 1, bottom-up attention processes might be engaged in a primarily blue-colored display by the more salient option presented in a contrasting bright orange color (Itti & Koch, 2000). In this paper, we focus on saliency as a bottom-up driver of attention and study its impact on choice.

One prominent line of work has suggested that increased visual attention boosts the preference for the attended-to choice option (Shimojo, Simion, Shimojo, & Scheier, 2003; Yang & Krajbich, 2023; Krajbich & Rangel, 2011; Smith & Krajbich, 2019). Previous research has found that salience increased the choice share of the salient option (Chen et al., 2013; Towal et al., 2013; Orquin et al., 2021; Peschel et al., 2019). Since, bottom-up factors such as salience potentially direct initial visual attention to the salient option (Itti & Koch, 2000), we hypothesized that the salient option receives an initial boost in preference.

Leading models of multiattribute choice describe choice resulting from a comparative process between choice options (Trueblood et al., 2022; Noguchi & Stewart, 2018; Roe et al., 2001; Bhatia, 2013). For example, in the attraction effect trial presented in Figure 1, the choice share of the top option (target) relative to the middle option -(competitor) increases in the presence of the bottom option - *attraction decoy*, since the target (but not the competitor) dominates the decoy, making the target appear superior. Visual attention is theorized to play an important role in the comparative process between the

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choice options (Noguchi & Stewart, 2018). For instance, gaze transitions between the attraction decoy and the target predicted the selection of the target (Noguchi & Stewart, 2014). Since salience potentially draws visual attention toward the salient option, we hypothesize that it increases the probability with which the salient option is compared to other options.

We designed an experiment where we made one of the options salient by coloring it in a contrasting color as presented in Figure 1. Using this data, we tested both of our hypotheses separately and jointly using computational modeling. To understand individual differences, we fit our models at an individual level. To better characterize the differences across individuals, we included the 4 comprehensive thinking styles questionnaire (Newton, Feeney, & Pennycook, 2023) and examined their relation to salience model parameters.

Methods

The goal of the experiment was to study the role of salience-driven attention on multi-alternative choice. The sample size, experimental procedure and analysis were pre-registered on `https://aspredicted.org/3x9hk.pdf`.

Participants

The study was approved by the Institutional Review Board at Indiana University (#16178). A total of 100 participants were recruited from MTurk using CloudResearch. Ninety-six participants completed the study. The demographics were as follows - Gender: 53 Women, 43 Men; Race: 74 White, 19 Black, 3 Asian; Age: Mean=39.6 years, SD= 10.4, IQR = 32-46.

Materials

The experiment was coded using JSPsych (De Leeuw, 2015). The stimuli and attribute values were adapted from (Hayes, Holmes, & Trueblood, 2023). As shown in Figure 1, the text of the non-salient options was presented in the same hue as the background. The salience was manipulated by selecting a background color for the salient option that was complementary to the text of the non-salient options (Green, 2011). To add contrast, the text of the salient option was made white. The colors for each trial were different from the previous trial.

Procedure

In each trial, participants made hypothetical choices between three different products (e.g., three different laptops) with two attributes (e.g., CPU speed and RAM). There were three different types of trials: attraction effect trials, dominant option trials, and filler trials. In the attraction effect trials, a decoy option was added such that one of the two options called the target dominated it but the other option called the competitor did not. In the dominant option trials, one of the three options was dominant on all attributes. Each participant completed a total of 232 trials. The order of the trials was fully randomized.

Participants completed 96 attraction effect trials. Each choice involved two core options, X and Y, and a decoy that was dominated by either X or Y. In 48 trials, X dominated the decoy. In the remaining 48 trials, Y dominated the decoy. For the attraction trials, there were four within-subject saliency conditions. In three of these conditions, one of the three options - the target, competitor, and decoy was made salient through manipulations of font and background color. In the fourth condition, none of the options were salient.

Participants did 96 dominant option trials. Each choice involved two core options, X and Y, and a third option that was superior to both X and Y on both attributes. In the dominant option trials, there were four within-subject saliency conditions. Similar to the attraction trials, in three conditions, one of the three options was made salient through manipulations of font and background color. Finally, in the fourth condition, none of the four options were salient.

The attraction and dominant option trials used the same product category - laptops. Participants also encountered 40 filler trials. The filler trials involved a choice between three choice options from a different product category - phones - than the attraction and dominant option trials which varied on two attributes camera quality and battery life. At the end of the experiment, participants responded to the Comprehensive Thinking Styles Questionnaire (CTSQ) (Newton et al., 2023) and Cognitive Reflection Test (CRT) (Thomson & Oppenheimer, 2016; Frederick, 2005).

Behavioral Results

We find that compared to the condition where none of the options were salient, individuals selected the salient option at a higher rate as shown in Figure 2. We plot the relationship between choice proportion and response time in Figure 3. As shown by the black dotted circle, we observe a bias in picking the salient option in each condition for decisions with fast response times. Since this analysis was done at the aggregate level, we developed the following modeling methods to study individual-level data.

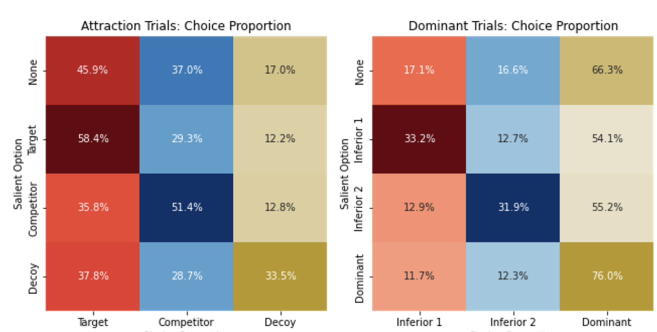


Figure 2: Choice proportions across different conditions. The magnitude of the choice proportion for each option is represented using a different color in the heatmap, where darker colors indicate larger numbers.

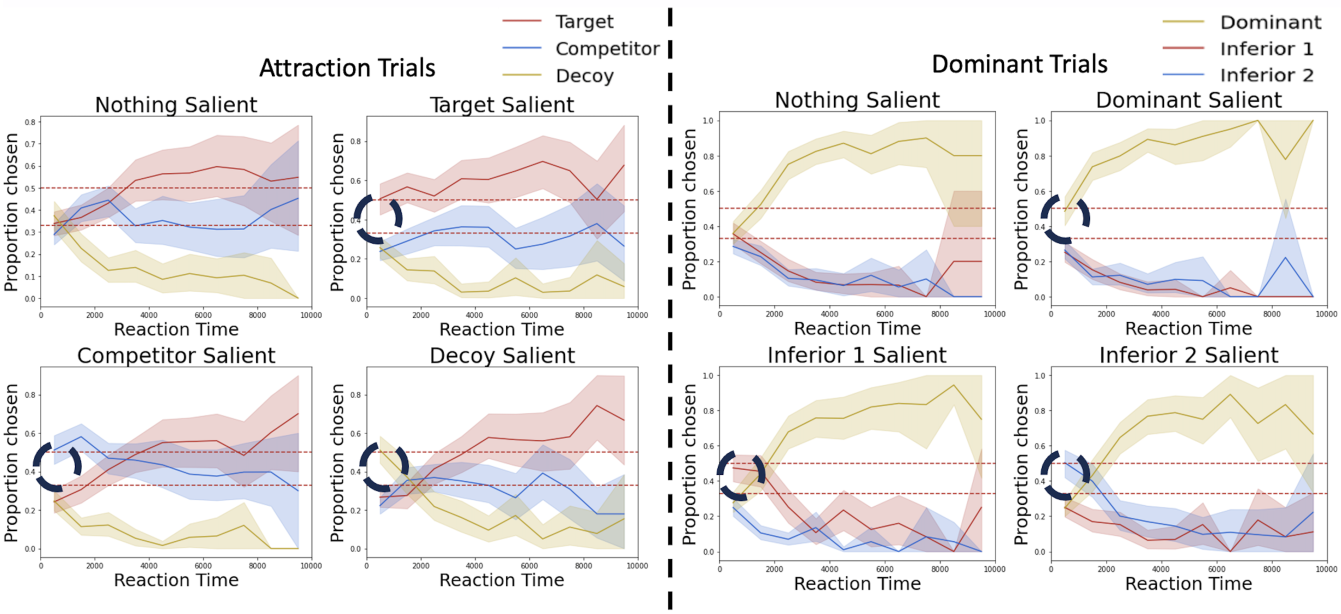


Figure 3: Response time and choice. In all the panels, we observe an initial bias to pick the salient option.

Modeling Methods

We used a sequential sampling model framework, called the comparison sampling framework, to model the decision-making process in our task (Trueblood et al., 2022). As shown in Figure 4, this framework delineates a preference accumulation process and an attentional process, making it suitable for modeling our hypotheses. We specify the details of the model fitting procedure in the following sections.

Base Model Description

As shown in Figure 4, this model consists of two components (i) a Markov attention process and (ii) a preference accumulation process. The Markov attention process defines the probabilities for selecting a pairwise comparison, involving two options along a single attribute. This comparison is used to update the preference accumulation process, which assumes that each option is associated with an accumulator. The rate of accumulation is determined by the difference in the attribute values of the two options being compared. The option with the higher attribute value results in positive preference accumulation for that option. The option with the lower attribute value results in negative preference accumulation for that option. If an option is not being compared, there is no change in preference accumulation for that option. The first accumulator to reach a decision threshold determines which option is selected.

The model has five parameters that determine choice and response times. The *drift scale* (ν) controls the rate at which preference is accumulated for each option. The *threshold* (a) controls the amount of preference that is accumulated before making a decision. The *weight* (w) allows for differential weighting of the two attributes during decision-making. The Markov process probabilities are defined in terms of option similarity using Shepard's Law (Shepard, 1987; Trueblood, Brown, & Heathcote, 2014). Specifically, a pair of options, i and j, are chosen to be compared on attribute a with a probability proportional to $\exp(-\lambda|x_i^a - x_j^a|)$ where x_i^a is the value of alternative i on attribute a and λ is a free parameter. The *non-decision time* was quantified using a parameter tnd. To account for decisions that are made randomly, we add an extra component according to which a random decision is made at a random time which is captured using an additional *guess* parameter (g).

Modeling Salience Mechanisms

We modeled our hypotheses by incorporating additional parameters to capture the two ways salience-driven attention might impact decision processes as described in the introduction.

Specifically, we add a *salience initial* parameter (β) for the *initial boost hypothesis*. Specifically, we set the preference at time $t = 0$ for the salient option to βa, which is a fraction of the threshold a. As described below in the model fitting section, we allow for this parameter to be negative to allow for suppression of the initial preference for the salient option.

We added a *salience comparison* parameter (ω) for the *salience comparison hypothesis*. This parameter changes the Markov process probabilities and thus the comparisons that are made during the deliberation process. Let the original Markov transition matrix that determines the probability of making the next comparison be M_i. We created a new transition matrix M_i' where the comparisons involving the salient option are made e^{ω} more often ($M_{i'}' = e^{\omega} M_i$), where i' is a comparison involving a salient option. We allow it to be a boost (i.e., positive) and also suppressive (i.e., negative).

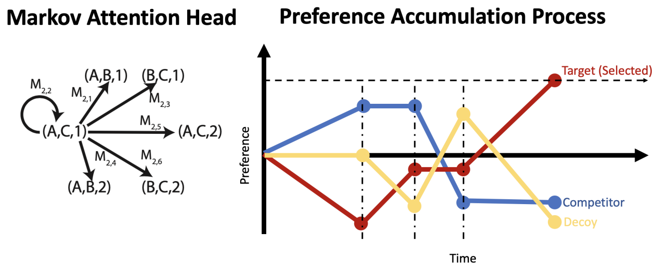


Figure 4: The comparison sampling modeling framework (Trueblood et al., 2022) has two components (i) Markov attention process that determines which comparisons are being made at each moment in time and (ii) a preference accumulation process that integrates these comparisons until a decision threshold is crossed.

	Parameter $\sim$ Distribution
1	Threshold (a) $\sim$ Unif(0,10)
2	Non-Decision Time (tnd) $\sim$ Half Normal(0.5)
3	Drift Scale (ν) $\sim$ Unif(-1,20)
4	Similarity Parameter (λ) $\sim$ Unif(0,10)
5	Weight (w) $\sim$ Unif(0.1,0.9)
6	Guessing Rate (g) $\sim$ Half Normal(0.05)
7	Initial Boost/Suppression (β) $\sim$ Unif(-1,1)
8	Comparison Boost/Suppression (ω) $\sim$ Unif(-3,3)

Table 1: Priors used for Bayesian model fitting.

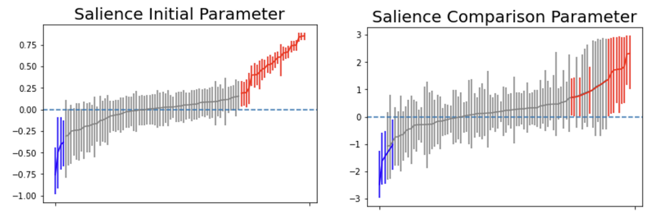
Model Fitting

To make the model fitting procedure tractable, we derived a continuous approximation to the model (Trueblood et al., 2022). We calculated the stationary matrix of the attentional Markov matrix (Ross, 2014). The stationary matrix uses the transition probability matrix to estimate the average amount of time spent in making any comparison. This is then used to estimate the mean and standard deviation of the drift rate for each choice accumulator separately. Using the mean and standard deviation of the drift rates, we estimated the choice and response time distribution likelihood. A parameter recovery exercise showed that our parameters were identifiable.

We fit each individual independently. We used relatively uninformative uniform priors as shown in Table 1. We fit the models using the Differential Evolution Markov Chain Monte Carlo method described in Turner and Sederberg (2012). We tested for convergence with $\widehat{R}$. The mean Rhat for all participants was less than 1.05, indicating convergence. (For two variables, for two different participants, the $\widehat{R}$ was slightly higher at 1.07.)

Results

We first present the results from the full model and then present the results from a nested model comparison.



95% HPDI	Salience Initial	Salience Comparison
Positive	25	13
Negative	4	4
Includes 0	67	79

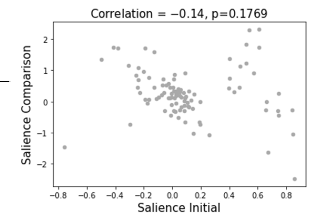


Figure 5: The top panel shows the Bayesian parameter estimates for the salience initial and salience comparison parameters estimated from the Full Model. The bottom left panel lists the number of individuals with 95% Highest Posterior Density Intervals above, below, and including 0 for each of the two parameters. The bottom right panel shows the correlation between the two parameters.

Full Model Fits

We focus on the two salience parameters in our model. In the top panels of Figure 5, we order each participant based on the mean of their estimated salience initial and salience comparison parameters. The bands around these are the 95% highest posterior density intervals (HDI). The bottom left panel shows the correlation between these parameters ($r(94) = -0.14$; $p = 0.1769$).

For the salience initial parameter, we observed that for most (67) participants, the 95% HDI for the salience initial parameter included 0. This implies no initial boost or suppression due to salience for these participants. For 25 participants, the 95% HDI for the salience initial parameter was above 0, indicating an an initial boost due to salience. For only 4 there was initial suppression due to the salience of the option as seen by the 95% HDI for the salience initial parameter being below 0. Hence, we find that for most individuals, salience did not change the initial starting point of preference of the evidence. However, for a substantial set of participants, we find a positive starting point for the salient option.

For the salience comparison parameter, we also observed that for most participants (79), we found no impact of salience on the comparison process (i.e., 95% HDI includes 0). For about 13 participants, we see that the 95% HDI is entirely positive. For 4 participants, we see that the 95% HDI is entirely negative. Hence, we see that for most participants, we did not infer a change in the comparison process. However, for some participants, we did find evidence for a change in the comparison process.

	Model	Mean DIC
1	Base	670.7
2	**Initial Boost only**	**635.2**
3	Comparison Boost only	659.2
4	Full	635.3

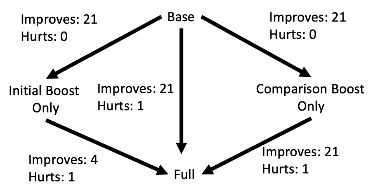


Figure 6: In the left panel, we show the mean Deviance Information Criterion. In the right panel, we show a nested model comparison.

Nested Model Comparison

We conducted a nested model comparison and present our results in Figure 6. We fit the base model with no mechanism for salience, the initial-only model, the salience comparison-only model, and the full model with both parameters.

Our model comparison was based on the deviance information criterion (DIC). The DIC measures the likelihood of the data based on the Bayesian model fit and penalizes the model flexibility. A lower score indicates a better fit and a difference of around 10/20 points is considered significant. From the left panel of Figure 6, we find that both the parameters provide better accounts for our data compared to the base model. However, the full model does not improve the fit of the initial boost-only model. This indicates that on average, the salience comparison parameter does not improve the likelihood of the data in the full model compared to the initial boost-only model when accounting for additional model complexity.

We focus on the individual level fits in the right panel of Figure 6. We used a DIC difference of at least 20 for significance. Compared to the base model, the full model improved the fit for 21 people but hurt it for 1 person. When we add parameters one-by-one, we see that adding the initial parameter and the comparison parameter improved fit for 21 people and did not hurt performance for anyone. Adding the comparison parameter to the model with only the salience initial parameter, improved the fit for 4 individuals and hurt it for 1 person. Adding the salience initial parameter to the model with only the salience comparison parameter improved the fit for 21 and hurt it for one person. Overall, we find that both the parameters improve the fit for the data. However, when compared against each other, the salience initial model has a lower DIC than the comparison boost model and adding the comparison boost parameter to the salience initial model results in little improvement.

Exploratory Analysis

As a further test of the individual differences, we wanted to see if individual thinking styles correlated with behavior and model parameters. We present our results in Figure 7. Since we did not have the power to necessarily detect moderate-sized effect sizes of correlations around 0.2 (Bujang & Baharum, 2016), we did not pre-register this analysis and treat our results as exploratory.

We focused our attention on the salience selection rate (i.e., the proportion of trials where an individual selected the salient option when one of the options was salient). From Figures 7 and 8, we observed that it is negatively associated with actively open-minded thinking ($r(94) = -0.22, p < 0.05$), preference for effortful thought ($r(94) = -0.27, p < 0.01$) and positively associated with preference for intuitive thought ($r(94) = 0.21, p < 0.01$). We see a similar relationship between the magnitude of the salience initial and salience comparison parameters, indicating that thinking styles potentially impact the role of salience in decision-making.

General Discussion

Consistent with previous research, we find that salience increases the choice share of the salient option on average. We find individual differences in the tendency to select the salient option which we test using computational modeling.

We find evidence that for a substantial minority of individuals, salience boosts the initial preference for the salient option. These individuals did not select the dominant option even when there was one, suggesting that they might not have gazed at all of the information. This indicates that salience boosts the initial preference since it potentially directs initial visual attention. This is consistent with theories that argue that visual attention boosts the preference for the option being looked at (Krajbich & Rangel, 2011; Smith & Krajbich, 2019).

We find little impact of salience on the comparison process. Presentation formats that facilitate the comparison between the target and the decoy are theorized to increase the strength of the attraction effect (Spektor, Bhatia, & Gluth, 2021; Cataldo & Cohen, 2019). For instance, when the target and the decoy are presented beside each other on the information display, the attraction effect is strengthened (Evans, Holmes, Dasari, & Trueblood, 2021; Hasan, Liu, Owens, & Trueblood, 2023). Computational modeling has revealed that this might be accounted for by additional comparisons between neighboring options (Trueblood et al., 2022). Thus while visual factors might impact the comparative process, it seems to be independent of bottom-up salience.

Previous research has found large individual differences in the role of gaze on choice (Thomas, Molter, Krajbich, Heekeren, & Mohr, 2019). We find that individuals whose initial preference was impacted by salience displayed increased system 1 thinking (Kahneman, 2011; Thomson & Oppenheimer, 2016; Frederick, 2005). This indicates that including the salience in the decision-making process might be an automatic, fast, intuitive and less effortful response. Practically, this tendency to select the salient option could allow one to nudge specific individuals towards better choices but also makes these individuals susceptible to manipulation due to choice irrelevant factors (Noggle, 2018; Peschel et al., 2019). We note that the salience selection bias might be due to experimenter demand effects and needs testing with real incentives.

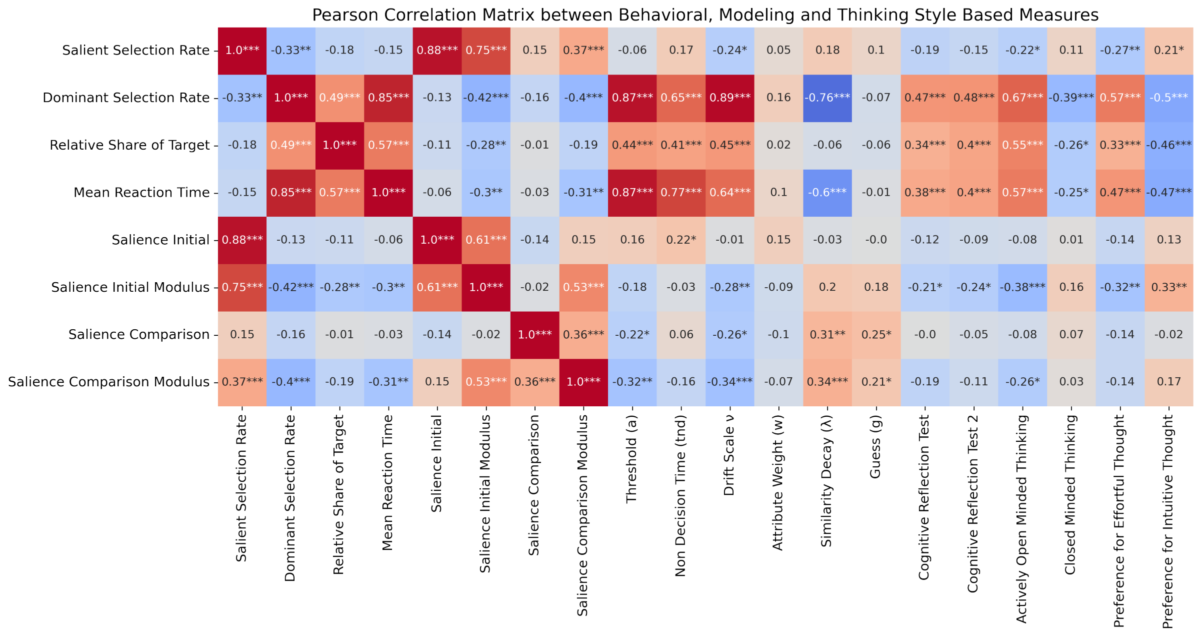


Figure 7: The results of the exploratory analysis examining the correlations between behavioral, modeling, and thinking styles measures. The number of stars indicates the significance. Specifically, * $p < 0.05$, ** $p < 0.001$ and *** $p < 0.0001$.

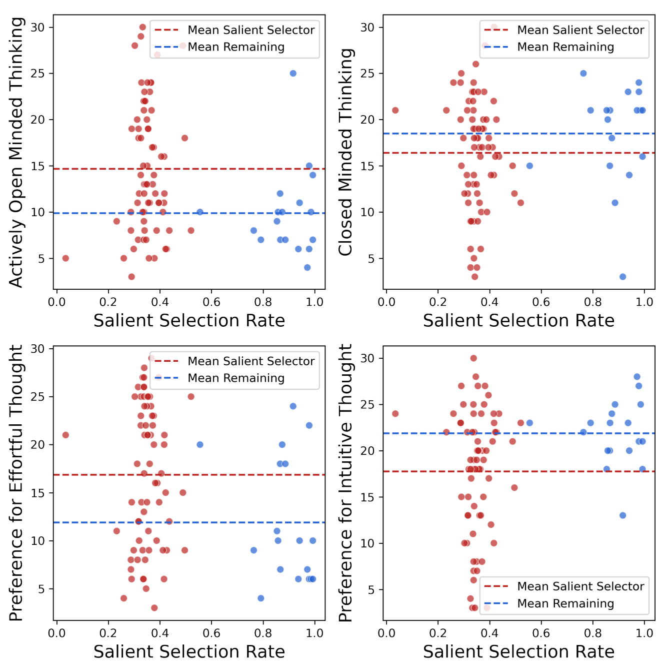


Figure 8: The relationship between thinking styles and the salient selection rate. The blue color indicates the individuals that selected the salient option at a rate higher than chance as determined by the exact binomial test.

Limitations and Future Directions

We were not able to test if salience drew visual attention to the salient option using eye-tracking data and if this changed over time. In our task, visual attention might be driven by top-down processes involving value (Towal et al., 2013; Chen et al., 2013) or spatial arrangement (Orquin et al., 2021). Salience might also only drive the first few fixations and thereby have a smaller impact on later fixations (Milosavljevic, Navalpakkam, Koch, & Rangel, 2012). Our results indicate that even if the gaze is being drawn towards the salient option, it is not being compared more often. We note that our results are based on color based salience and may not generalize to other salience manipulations.

There are many different ways that salience could impact decision processes beyond the two hypotheses we tested (Towal et al., 2013; Thomas et al., 2019; Chen et al., 2013; Rieskamp & Hadian Rasanan, 2023; Molter et al., 2022). Previous research testing these possible mechanisms has found some support for salience creating an initial bias as opposed to a drift rate bias (Chen et al., 2013). Future experiments can be designed to further disambiguate different mechanisms.

Conclusion

We find an increase in choice share for the salient option. This is explained by an initial boost in the preference for the salient option for a substantial minority of participants. We did not find evidence for an impact of salience on the comparison process. The salience boost was associated with system 1 thinking, higher levels of intuitive thinking styles and lower levels of effortful thought and actively open minded thinking.

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References

Bhatia, S. (2013). Associations and the accumulation of preference. *Psychological review*, *120*(3), 522.

Bujang, M. A., & Baharum, N. (2016). Sample size guideline for correlation analysis. *World*, *3*(1), 37–46.

Cataldo, A. M., & Cohen, A. L. (2019). The comparison process as an account of variation in the attraction, compromise, and similarity effects. *Psychonomic Bulletin & Review*, *26*(3), 934–942.

Chen, X., Mihalas, S., Niebur, E., & Stuphorn, V. (2013). Mechanisms underlying the influence of saliency on value-based decisions. *Journal of vision*, *13*(12), 18–18.

De Leeuw, J. R. (2015). jspsych: A javascript library for creating behavioral experiments in a web browser. *Behavior research methods*, *47*, 1–12.

Evans, N. J., Holmes, W. R., Dasari, A., & Trueblood, J. (2021). The impact of presentation order on attraction and repulsion effects in decision-making. *Decision*, *8*(1), 36.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic perspectives*, *19*(4), 25–42.

Green, D. (2011). A colour scheme for the display of astronomical intensity images. *Bulletin of the Astronomical Society of India*, *39*, 289–295.

Hasan, E., Liu, Y., Owens, N., & Trueblood, J. (2023). A registered report on presentation factors that influence the attraction effect.

Hayes, W., Holmes, W., & Trueblood, J. (2023). Attribute comparability and context effects in preferential choice.

Itti, L., & Koch, C. (2000). A saliency-based search mechanism for overt and covert shifts of visual attention. *Vision research*, *40*(10-12), 1489–1506.

Kahneman, D. (2011). *Thinking, fast and slow*. macmillan.

Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences*, *108*(33), 13852–13857.

Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of consumer psychology*, *22*(1), 67–74.

Molter, F., Thomas, A. W., Huettel, S. A., Heekeren, H. R., & Mohr, P. N. (2022). Gaze-dependent evidence accumulation predicts multi-alternative risky choice behaviour. *PLoS computational biology*, *18*(7), e1010283.

Newton, C., Feeney, J., & Pennycook, G. (2023). On the disposition to think analytically: Four distinct intuitive-analytic thinking styles. *Personality and Social Psychology Bulletin*, 01461672231154886.

Noggle, R. (2018). Manipulation, salience, and nudges. *Bioethics*, *32*(3), 164–170.

Noguchi, T., & Stewart, N. (2014). In the attraction, compromise, and similarity effects, alternatives are repeatedly compared in pairs on single dimensions. *Cognition*, *132*(1), 44–56.

Noguchi, T., & Stewart, N. (2018). Multialternative decision by sampling: A model of decision making constrained by process data. *Psychological review*, *125*(4), 512.

Orquin, J. L., Lahm, E. S., & Stojić, H. (2021). The visual environment and attention in decision making. *Psychological Bulletin*, *147*(6), 597.

Peschel, A. O., Orquin, J. L., & Loose, S. M. (2019). Increasing consumers' attention capture and food choice through bottom-up effects. *Appetite*, *132*, 1–7.

Rieskamp, J., & Hadian Rasanan, A. (2023, July). Improving decision making models by considering attention processes: The gaze-weighted advantage race diffusion model. In *Mathpsych/iccm/empg 2023.* Retrieved from `http://mathpsych.org/presentation/1164`

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.

Ross, S. M. (2014). *Introduction to probability models*. Academic press.

Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science*, *237*(4820), 1317–1323.

Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature neuroscience*, *6*(12), 1317–1322.

Smith, S. M., & Krajbich, I. (2019). Gaze amplifies value in decision making. *Psychological science*, *30*(1), 116–128.

Spektor, M. S., Bhatia, S., & Gluth, S. (2021). The elusiveness of context effects in decision making. *Trends in Cognitive Sciences*, *25*(10), 843–854.

Thomas, A. W., Molter, F., Krajbich, I., Heekeren, H. R., & Mohr, P. N. (2019). Gaze bias differences capture individual choice behaviour. *Nature Human Behaviour*, *3*(6), 625–635.

Thomson, K. S., & Oppenheimer, D. M. (2016). Investigating an alternate form of the cognitive reflection test. *Judgment and Decision making*, *11*(1), 99–113.

Towal, R. B., Mormann, M., & Koch, C. (2013). Simultaneous modeling of visual saliency and value computation improves predictions of economic choice. *Proceedings of the National Academy of Sciences*, *110*(40), E3858–E3867.

Trueblood, J. (2022). Theories of context effects in multialternative, multiattribute choice. *Current Directions in Psychological Science*, *31*(5), 428–435.

Trueblood, J., Brown, S. D., & Heathcote, A. (2014). The multiattribute linear ballistic accumulator model of context effects in multialternative choice. *Psychological review*, *121*(2), 179.

Trueblood, J., Liu, Y., Murrow, M., Hayes, W., & Holmes, W. (2022). Attentional dynamics explain the elusive nature of context effects.

Turner, B. M., & Sederberg, P. B. (2012). Approximate bayesian computation with differential evolution. *Journal of Mathematical Psychology*, *56*(5), 375–385.

Wolfe, J. M. (1994). Guided search 2.0 a revised model of visual search. *Psychonomic bulletin & review*, *1*, 202–238.

Wolfe, J. M. (2021). Guided search 6.0: An updated model of visual search. *Psychonomic Bulletin & Review*, *28*(4), 1060–1092.

Yang, X., & Krajbich, I. (2023). A dynamic computational model of gaze and choice in multi-attribute decisions. *Psychological Review*, *130*(1), 52.