The Impact of Presentation Order on Attraction and Repulsion Effects in Decision-making

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Abstract

One of the most interesting findings in multi-alternative, multi-attribute choice is the occurrence of "context effects", where the relative preference between two alternatives is influenced by a third, decoy alternative. Although context effects have been well documented, the circumstances necessary for them to occur is a puzzle. Sometimes, the effects disappear or reverse, suggesting they are fragile. We hypothesize this fragility is partly due to a sequential comparison process where subsets of options are compared and evaluated during deliberation. Thus, manipulating the comparison of options (by manipulating presentation order of options) should influence the manifestation of these effect. We test this hypothesis in two ways for the attraction effect. First, we develop a temporally sequential version of a well-established perceptual context effects paradigm, where participants only see one alternative at a time. Results show that presentation order strongly influences choices. In some orders, a standard attraction effect occurs and in others, a reversal (or "repulsion") effect occurs. A piecewise extension of the Multi-attribute Linear Ballistic Accumulator model explains our results by showing how forgetting (due to the sequential presentation) influences the comparison of options. Quantitative fitting demonstrates that the model explains well the data, outperforming alternative heuristic models. Second, we reanalyze attraction effect data from Trueblood, Brown, and Heathcote (2015) where the spatial order of options was manipulated. Similar to the sequential task, results show a complex pattern of attraction and repulsion effects. Taken together, these results indicate that a malleable comparison process contributes to the fragility of context effects.

Keywords:

Multi-attribute choice; Context effects; Memory; Evidence accumulation models; Perceptual decision-making

Introduction

One of the most interesting findings in the multi-alternative, multi-attribute choice literature is the effect of introducing a new alternative on preferences for existing alternatives. Decades of research have shown that people's choices are sensitive to the context created by the set of options. The majority of this work has focused on understanding three classic context effects (the attraction, Huber, Payne, & Puto, 1982, compromise, Simonson, 1989, and similarity effects, Tversky, 1977), which describe how choices between two alternatives can change with the introduction of a third new alternative. These effects are important because they challenge classical utility models of decision-making (Luce, 1959) by showing that people's choices between two options often depends on the utility of another ("decoy") option.

The present work is focused on arguably the most widely studied context effect, the attraction effect (Huber et al., 1982), which occurs when the addition of a dominated "decoy" option increases choices for the option dominating it. For example, in a decision among cars to buy, if Car 1 has a high price with low mileage, and Car 2 has a low price with high mileage, the attraction effect involves Car 3 (the "decoy") having the same mileage as Car 1 (the "target"), but having a higher price, which would result in an increased preference for Car 1 over Car 2 (the "competitor"). More generally, consider the binary choice set $\{X, Y\}$, where individuals are roughly indifferent between the two options, and the decoys D_X and D_Y, where D_X (respectively D_Y) is similar but inferior to X (respectively Y). The attraction effect occurs when the addition of D_X (respectively D_Y) increases choices for X (respectively Y). This effect violates simple scalability, which is a property of most utility models used to study choice behavior, including Luce's (1959) ratio of strengths model.

An interesting but puzzling feature of the attraction effect is that it is both ubiquitous and fragile. Past research has shown that it occurs in different domains including perception (Trueblood, 2015; Trueblood et al., 2015; Trueblood, Brown, Heathcote, & Busemeyer, 2013), inference (Trueblood, 2012), risky decision-making (Farmer, Warren, El-Deredy, & Howes, 2016), and consumer choice (Huber et al., 1982; Berkowitsch, Scheibehenne, & Rieskamp, 2014; Evangelidis, Levav, & Simonson, 2018). In addition, research in developmental psychology and behavioral ecology has found that it occurs in children (Zhen & Yu, 2016), monkeys (Parrish, Evans, & Beran, 2015), honeybees (Shafir, Waite, & Smith, 2002), hummingbirds (Bateson, Healy, & Hurly, 2003), and even slime molds (Latty & Beekman, 2011). Thus, there is a sense that contextual sensitivity (and the attraction effect in particular) is a universal property of multi-alternative choice behavior.

Despite its ubiquity, the attraction effect is also very fragile. First, there are large individual differences in its strength (Liew, Howe, & Little, 2016; Trueblood et al., 2015). Second, there is evidence that the attraction effect is much stronger in abstract, stylized stimuli as opposed to natural stimuli (Frederick, Lee, & Baskin, 2014). Third, it is easy to reverse with simple changes to display layout, leading to a repulsion effect (Spektor, Kellen, & Hotaling, 2018).

Understanding this paradox involves understanding the factors that influence people's choices. In multi-alternative, multi-attribute decision problems, people are faced with processing many different pieces of information in order to make a choice. Because it is unlikely that people can process all information simultaneously, we hypothesize that information is processed sequentially through shifts in attention where subsets of options are compared and evaluated over the course of deliberation. This hypothesis is supported by decades of research on sequential sampling models of multi-alternative, multi-attribute choice (Roe, Busemeyer, & Townsend, 2001; Usher & McClelland, 2004; Trueblood, Brown, & Heathcote, 2014; Noguchi & Stewart, 2018) as well as eye-tracking studies (Noguchi &

Stewart, 2014).

One important consequence of sequential information processing is that task specific features likely bias which subsets of options are compared during deliberation. We test this hypothesis in two ways using a well-established perceptual context effects paradigm where participants are asked to judge the area of rectangles that differ on the attributes of height and width (Trueblood et al., 2015, 2013; Parrish et al., 2015; Turner, Schley, Muller, & Tsetsos, 2018; Farmer et al., 2016). First, we develop a sequential version of a this task where participants only see one alternative at a time, thereby directly manipulating shifts in attention and consequently the comparison process. Results show that the order in which alternatives are presented has a large impact on subsequent choices, where some orders lead to behavior showing an attraction effect and other orders lead to behavior showing a repulsion effect. To explain our results, we develop a mechanistic model, specifically an extension to the Multi-attribute Linear Ballistic Accumulator (MLBA; Trueblood et al., 2014), to illustrate how forgetting (a consequence of sequential information processing) coupled with a pairwise comparison process leads to the complex pattern of behavior we observe. We compare our model to several alternatives including simple heuristic models, ultimately showing that the extended MLBA model provides the best accounting of the sequential task data.

Second, we reanalyze attraction effect data reported in Trueblood et al. (2015) where options were presented simultaneously, but the spatial order of options was manipulated. As in the sequential task, results show that the order in which alternatives are presented has a large impact on subsequent choices, where some orders result in an attraction effect and other orders result in a repulsion effect. Critically, in both paradigms (sequential and simultaneous) choice patterns result only from the ordering (either temporal or spatial) of the stimuli, not changes in the rectangles themselves. In sum, this collection of results sheds new light on the seemingly fragile nature of the attraction effect, where choices sometimes appear consistent with the effect and other times they do not.

All data are available on the Open Science Framework at https://osf.io/w8ndp/.

Experiment 1: Asymmetrically Dominated Decoys

The goal of the first experiment is directly manipulating shifts in attention, and consequently the comparison process, by presenting options sequentially. In this experiment, we manipulate the presentation order of ternary choice sets containing an asymmetrically dominated decoy, i.e., an option similar to but inferior to the target.

Method

Participants. 50 undergraduate students from Vanderbilt University – collected in accordance with the ethics policy – participated in this computer-based, in-lab experiment, and received course credit for their participation. The sample size was determined prior to data collection and is based off of the sample size in Trueblood et al. (2013). One participant's data was removed due to a computer error.

Task and procedure. Our study used a perceptual multi-alternative choice task, with stimuli similar to Trueblood et al. (2013) and used in Trueblood et al. (2015); Parrish et al. (2015); Turner et al. (2018); Farmer et al. (2016), which have been shown to robustly display an attraction effect. Each alternative was presented as a rectangle, with the height and width dimensions (in pixels) of the rectangles forming the two attributes. Participants were asked to pick the rectangle with the largest area, though in all trials that assessed the attraction effect, the target and competitor rectangles contained equal area.

In trials that assessed the attraction effect, the two non-decoy rectangles consisted of one that was superior on the attribute height (denoted 'H'), and one that was superior on the attribute of width (denoted 'W'). The exact attribute values of the H rectangle were randomly drawn trial-to-trial from normal distributions with means of 80 and 50 for the height and width attributes, respectively, and a variance of 2. The width of the W rectangle was given by the height of the H rectangle plus some added uniform noise ($[-2, 2]$), with the height of the W rectangle then being constrained to ensure that the rectangles had equal area. For this task, we chose to use the range decoy, which is a decoy that is identical to the target on the target's largest attribute value and smaller on its smallest attribute, with half of the trials having a decoy with equal height as the H rectangle (denoted 'D_H'), and half of the trials having a decoy with equal width as the W rectangle (denoted 'D_W'). The small attribute for the decoy was given by the target's value minus 8, with some added uniform noise ($[-1, 1]$). Within the trials the rectangles were presented sequentially, rather than the standard method of simultaneous presentation, though the rectangles were still presented in different locations to one another. The order of presentation for the rectangles was randomized, creating 6 possible combinations of the target (T), competitor (C), and decoy (D) rectangle orderings that all had an equal number of associated trials: CDT, CTD, DTC, DCT, TCD, TDC.

Each trial began with a fixation cross, which was presented for 250ms in the centre of a white background. The numbers 1, 2, and 3 were then presented at the top of the screen to the left, middle, and right, respectively, which corresponded to the different positions that the rectangles would be presented in, and the associated response key for each rectangle. The rectangles were then presented one at a time in their associated position for 1,000ms each. Participants could respond at any time during the trial, and did so using the 1, 2, and 3 keys at the top of the keyboard. An example of the structure of a trial can be seen at the top of Figure 1.

Participants completed 720 trials in total, which were split into 8 blocks of 90 trials each. Each block consisted of 30 “filler” trials, which did not assess the attraction effect and contained one rectangle that had an objectively greater area than the others. The remaining 60 trials consisted of 10 trials of each of the 6 ordering combinations listed above, with these 10 trials then equally sub-divided into 5 trials each with the D_H and D_W decoy.

Behavioural Results

We treated our study as a 6 (Ordering: CDT, CTD, DTC, DCT, TCD, TDC) by 2 (Decoy: D_H, D_W) repeated-measures design, with the dependent variables of interest being response proportions for each alternative. From these dependent variables, we calculated the *relative choice share of the target* (RST given by $\frac{T}{T+C}$; Berkowitsch et al., 2014) for each sequence (Figure 2 and Table 1).

Initial analysis of filler trials showed performance was greatly above chance accuracy of 33.3% (66.7% accuracy, $BF_{10} = 1.1 \times 10^{25}$), indicating that participants understood the task. Performance on the filler trials was similar, but a little worse than performance on similar (simultaneously presented) filler trials in Trueblood et al. (2015) where the average accuracy was 72.9%. The difference in accuracy between the two studies is likely due to the differences in stimuli presentation between the two studies (i.e., sequential versus simultaneous). Note that the mean response time across all trials was 2,758 milliseconds, indicating most responses occurred after the presentation of the third rectangle. For further analysis, only trials with a response time of at least 2,150 milliseconds were included to ensure participants had adequate time to perceive the final rectangle (including all trials did not qualitatively change these results, see Supplementary Materials). The number of trials with responses before this cutoff was relatively small (7.2%) and did not differ between orderings ($BF_{01} = 117.7$).

To assess whether choices were generally consistent with an attraction effect, we initially performed a one-sample Bayesian t-test to contrast the measured RST, averaged over all conditions (orderings and decoys), to the value of 0.5 (the expected result if the decoy has no influence). Results showed only minor evidence in favor of the attraction effect ($BF_{10} = 2.3$, see Figure 2). We next performed a one-way Bayesian ANOVA on RST using the variable of ordering to determine whether choice patterns differed across orderings, with follow-up one-sample Bayesian t-tests to see which orderings resembled an attraction effect versus a repulsion effect. This analysis showed decisive evidence that choice patterns differed over response orderings ($BF_{10} = 7.5 \times 10^{15}$). The follow-up one-sample Bayesian t-tests found 2 orderings showing decisive evidence in favor of an attraction effect ($RST > 0.5$; $CDT : BF_{10} = 30134$; $CTD : BF_{10} = 7508$), 2 orderings showing decisive evidence in favor of a repulsion effect ($RST < 0.5$; $TCD : BF_{10} = 8235$; $TDC : BF_{10} = 127$), 1 ordering to show moderate evidence for an attraction effect ($DTC : BF_{10} = 5.2$), and 1 ordering with minor evidence in favor of no effect ($DCT : BF_{01} = 2.8$). Thus some orderings result in choice patterns consistent with an attraction effect and other orderings result in choice patterns resembling a repulsion effect, suggesting that 1) the relatively small aggregate effect was the result of averaging these opposing effects and 2) presentation order substantially alters choices. Table 1 provides the RST for each order condition, along with the RST for each order condition in Experiment 2, and the position order conditions (ordered from left to right) in Trueblood et al. (2015), which used very similar stimuli values and a simultaneous presentation format.

Conclusion

The results of Experiment 1 show a complex pattern of choices across different presentation orders. In some orders, choices are consistent with an attraction effect, but in other orders choices are consistent with a repulsion effect. When combining across all presentation orders, behavior is best described as resembling a very small attraction ef-

Table 1: The RST values for each order condition from Experiments 1 and 2 as well as for the attraction effect condition in Trueblood et al. (2015) using a simultaneous presentation format.

Order	Mean RST (%)		
	Exp. 1 sequential	Exp. 2 sequential	Trueblood et al. (2015) simultaneous
CDT	62.18**	63.59**	51.98
CTD	58.67**	59.19**	58.61**
DTC	55.95*	49.05	65.65**
DCT	47.5	51.49	36.54++
TCD	40.77++	41.32++	43.28++
TDC	40.29++	39.00++	62.13**
all orders combined	50.99*	50.59	53.08**

**indicates a strong to decisive attraction effect, *indicates a small to modest attraction effect, ++ indicates a strong to decisive repulsion effect, based on the Bayes factors for each order condition.

fect. We believe this small global effect arises because different orders lead to opposing choice patterns, some orders produce attraction-like behavior and other orders produce repulsion-like behavior. Thus, when combining across all conditions, these effects mostly cancel out, leaving only anecdotal evidence for a global attraction effect. Since our main interest is understanding the effect of order on choice behavior, our focus going forward will be primarily on the individual order conditions, not the presence or absence of a global attraction effect.

Experiment 2: Symmetrically Dominated Decoys

The results of Experiment 1 suggest that information processing order has a strong impact on behavior, sometimes leading to choices consistent with an attraction effect and other times not. One possible explanation for this complex pattern of behavior is that the dominance relationship between the target and decoy is easier to detect in some orders. In these cases, a standard attraction effect occurs. Other times, the dominance relationship is more difficult to detect, leading to competition between the target and decoy to the benefit of the competitor (akin to a similarity effect). This leads to an important question: is the influence of presentation order simply in altering a person's ability to detect dominance? In Experiment 2, we answer this question by replacing the asymmetrically dominated decoys in the previous experiment with symmetrically dominated decoys (i.e., decoys that equally favor both core options). If we observe similar choice patterns as in Experiment 1, we can conclude that presentation order influences information processing mechanisms beyond merely obscuring dominance.

Method

Participants. 50 undergraduate students from Vanderbilt University participated in this computer-based, in-lab experiment, and received course credit for their participation. The sample size was determined prior to data collection and set to be identical to Experiment 1.

Task and procedure. The stimuli, task, and procedures were identical to Experiment 1 except for the attribute values of the decoy D. In this experiment, D was a symmetrically dominated decoy meaning that it equally favored both of the core options. In our task, the two non-decoy rectangles consisted of one that was superior on height (H) and one that was superior on width (W). The decoy D was defined as having the width of H and height of W. That is, the decoy's attributes were the minimum attribute values from the two core options. Because the decoy D was symmetrically dominated in this experiment, there are technically no "target" and "competitor" options. However, to allow for comparisons with Experiment 1, we continue to use this terminology. In Experiment 2, "target" options refer to options that were "target" alternatives in Experiment 1 (and likewise for "competitor" options).

Behavioral Results

Initial analysis of filler trials again showed performance was greatly above chance accuracy of 33.3% (61.2% accuracy, $BF_{10} = 6.3 \times 10^{13}$), suggesting that most participants were performing the task properly. As with Experiment 1, the following analyses only used trials with a response time of at least 2,150 milliseconds. It should be noted that this led to the exclusion of four entire participants – all of whom had accuracy close to chance – as they had no responses above 2,150 milliseconds. This made the number of trials with responses before this cutoff much larger than in Experiment 1 (16.2%), though the number of trials excluded did not differ between orderings ($BF_{01} = 185.3$).

An initial one-sample Bayesian t-test showed moderate evidence against either an attraction or a repulsion effect (i.e., evidence in favor of a null effect) when RST was averaged overall all conditions ($BF_{01} = 3.2$). However, a one-way Bayesian ANOVA showed that RST differed between orderings ($BF_{10} = 3.3 \times 10^{10}$). Follow-up one-sample Bayesian t-tests found 2 orderings showing decisive evidence in favor of an attraction effect ($RST > 0.5$; $CDT : BF_{10} = 232$; $CTD : BF_{10} = 45965$), 2 orderings showing decisive evidence in favor of a repulsion effect ($RST < 0.5$; $TCD : BF_{10} = 294$; $TDC : BF_{10} = 249$), and 2 orderings showing moderate evidence in favor of no effect ($RST = 0.5$; $DTC : BF_{01} = 5.8$; $DCT : BF_{01} = 5.4$). The pattern of the results are very similar to those in Experiment 1 (Table 1), with the exception of the DTC ordering, which in Experiment 1 showed moderate evidence for an attraction effect, and in Experiment 2 showed moderate evidence for no effect. A two-way Bayesian ANOVA – using the factors of ordering and experiment – supported this assessment, with the best model only having the main effect of ordering ($BF = 10.8$ vs the model with both the main effects ordering and experiment), showing strong evidence for no difference between experiments.

Conclusion

The choice patterns observed in Experiment 2 are almost identical to those observed in Experiment 1. In some orders, choices are consistent with an attraction effect, whereas in other orders choices are consistent with a repulsion effect. Importantly, Experiment 2 used symmetrically dominated decoys. Thus, the results of Experiment 1 cannot be attributed to simple changes in dominance detection due to changes in presentation order. Rather, order appears to exert a strong influence on information processing and subsequent choice. Note, however, the difference between Experiments 1 and 2 for the *DTC* ordering suggest that presentation order may have some influence on dominance detection, though this effect is minor in comparison to the overall influence of order observed in both experiments. In the "Computational Modeling" section below, we show how forgetting (due to the sequential presentation of options) impacts the comparison process, explaining the complex pattern of choices we observe in Experiments 1 and 2.

Computational Modeling

The behavioral results of Experiments 1 and 2 show that temporal presentation order leads to a complex pattern of choices, sometimes resembling an attraction effect and other times resembling a repulsion effect. An important question is why does manipulating temporal order produce these complex behavioral patterns? We answer this question using computational modeling, building off of a previously established model called the Multi-attribute Linear Ballistic Accumulator (MLBA) model. In addition, we compare this model to three heuristic models, encoding alternative hypotheses for how order impacts choices.

Piecewise Multi-attribute Linear Ballistic Accumulator

We hypothesize that the complex pattern of attraction-like and repulsion-like effects in Experiments 1 and 2 are at least in part due to the interaction of memory and decision processes during deliberation[1]. To model these interactions, we draw on computational modeling work in multi-alternative, multi-attribute choice as well as in memory. Many computational models of context effects are Evidence Accumulation Models (EAMs), which propose that decisions are made through a process where evidence accumulates for each alternative at some rate (the "drift rate") until the amount of evidence for one of the alternatives crosses some threshold level of evidence (the "decision threshold"), triggering a decision. One example of such a model is the Multi-attribute Linear Ballistic Accumulator (MLBA; Trueblood et al., 2014), an extension of an EAM called the linear ballistic accumulator (LBA, Brown & Heathcote, 2008). The MLBA hypothesizes that context effects in multi-alternative, multi-attribute choice arise through a dynamic, similarity-based process of comparing the different features of options. Specifically, the MLBA proposes that drift rates are formed by a series of pairwise comparisons between alternatives on each attribute, with people paying more attention to more similar attribute values. Mathematically, the drift rates for the model are determined by the following pairwise comparison function:

$$V_{i,j} = W_{P,i,j} \times (u_{P,i} - u_{P,j}) + W_{Q,i,j} \times (u_{Q,i} - u_{Q,j}) \tag{1}$$

where i is the alternative being accumulated for, j is the alternative that it is being compared to, and P and Q are the attributes. The notation $u_{P,i}$ indicates the valuation of option i on attribute P. The quantities $W_{P,i,j}$ and $W_{Q,i,j}$ are the similarity-based attention weights, which are calculated based on the similarity of the two options being compared. Psychologically, these weights capture the idea that a decision-maker might spend more time or effort on options that are difficult to discriminate. The exact details of the MLBA can be found in the Supplementary Materials, or in Trueblood et al. (2014) or Evans,

[1]Note that we only display modeling results for Experiment 1, though fitting to Experiment 2 produced a very similar pattern of results, which can be seen in the supplementary materials.

Holmes, and Trueblood (2019).

The MLBA produces an attraction effect through its similarity-based attention weighting mechanism. When two options are very similar to one another (i.e., close together in attribute space), the comparisons between those options receive greater weight. Because the target and decoy options are very close in attribute space, target-decoy comparisons receive more weight to the benefit of the target (since it is superior to the decoy). Note that the original version of the MLBA does not take into account presentation order (either spatial or temporal). In order to apply the model to our sequential task used in Experiments 1 and 2, we extend it by drawing on recent ideas about the interaction of memory and decision-making (Gluth, Sommer, Rieskamp, & Büchel, 2015) as well as the piecewise evidence accumulation model literature (Holmes, Trueblood, & Heathcote, 2016; Holmes, 2015; Holmes & Trueblood, 2017; Krajbich & Rangel, 2011).

Recent research by Gluth et al. (2015) found that people often show a memory bias (i.e., people prefer items they remember better), which can be explained by EAMs constrained by forgetting. Building on this idea, we constructed a piecewise extension (Holmes et al., 2016; Holmes, 2015; Holmes & Trueblood, 2017; Krajbich & Rangel, 2011) of the MLBA (Trueblood et al., 2014) that incorporates forgetting. Piecewise extensions have recently been suggested as a simple method of generalizing decision-making models to account for systematic changes in information during a trial (e.g., the pLBA; Holmes et al., 2016), making them a natural choice for our sequential task. Our piecewise extension of the MLBA (denoted pMLBA) involves a change in the drift rate after each option is presented (see Figure 1). Specifically, we subdivided the trial length into five intervals, each one second in length (trials time out at five seconds). During each interval, the drift rate associated with an alternative was determined as follows. The drift rate for any alternative that has not yet appeared on the screen is governed by a "baseline" drift (d_{base}). The drift rate for the option that appears during the first interval is determined by comparison against an internal "reference point". In all subsequent intervals, alternatives are compared against those that have appeared previously as described in equation 1. Once an alternative has disappeared from the screen, it is assumed its drift rate decreases according to $\alpha^n * d_i$ where $0 < \alpha < 1$ and n is the number of seconds after the presentation of option i. This accounts for potential effects of forgetting (Gluth et al., 2015). In all cases, comparisons are carried out as defined in the MLBA, specifically using its similarity-based attention weights which are critical for producing the attraction effect (see equation 1 and the supplement).

We also fit two other MLBA model variants that make different assumptions about the memory process and are described in the supplementary materials, but are qualitatively unable to account for observations. These variants are also based on the MLBA framework, but alter the effects of forgetting and how pairwise comparisons are made.

Alternative Models

An alternative explanation for the results of Experiments 1 and 2 is that participants are using a simple heuristic or order-based method for deciding among the different options, rather than behavior arising from a complex interaction between the memory and decision processes as hypothesized in the pMLBA model described above. Here, we consider three potential alternative models and compare these to the pMLBA. These models are all forms of linear-weight models, where the evaluation of each alternative was determined by the area of the stimulus multiplied by a weight parameter, W. Choice probabilities were calculated by applying a logistic soft-max function to these evaluations. The first model was a *temporal order model*, where a weight was estimated for each presentation position, fixed across all orderings. Formally, this meant that the weight, W, for each alternative was simply $W_i = w_i$, where i is the order (either 1, 2, or 3) that the stimulus appeared in the sequence. This temporal order model was designed to reflect the possibility that participants were deciding purely based on order and stimulus area. The second model was a *mixture model*, which contained a mixture of the temporal order model and a model where participants ignore the decoy. The model for ignoring the decoy was also a temporal order model, though with the decoy being skipped, meaning that only the first two sequential weights were used. This model was designed to reflect the possibility that participants were deciding purely based on order and stimulus area, but on some proportion of trials they also ignored the decoy. The third model was a *heuristic-based model*, where two weights were estimated and fixed across all orderings: a weight for the stimulus presented temporally closest to the decoy (in the case of the decoy being in the middle, this was the stimulus presented after the decoy), and a weight for the stimulus presented further from the decoy. This heuristic-model was designed to reflect the possibility that participants were simply picking the option temporally closest to the decoy. Additional details about these models are available in the supplement.

Results

A summary of all models is provided in Tables 2 and 3. To fit the models we minimized the root mean squared error (RMSE) between the observed and predicted response proportions of the model. Minimization was performed using a differential evolution algorithm (Ter Braak, 2006; Turner, Sederberg, Brown, & Steyvers, 2013) with 100 particles run for 500 iterations. To prevent over-fitting (see Evans, Howard, Heathcote, & Brown, 2017 for an explanation) we used a generalization approach (Busemeyer & Wang, 2000), where the model was fit 6 times. In each case, one condition was removed, the model was fit to the remaining five, and then model predictions for the removed sequence were generated and compared to observations. Results for the pMLBA, temporal order model, mixture model, and heuristic-based model are shown in Figures 3, 4, 5, and 6, respectively.

Overall, the pMLBA model captures all of the key behavioral trends (i.e., the ordering of response proportions), and provides a good account of the trends for each individual. An important question is how does pMLBA explain the choice patterns we observed? Recall that there are two orderings, CDT and CTD, that show decisive evidence in favor of an attraction effect and two orderings, TCD and TDC, that show decisive evidence in favor of a repulsion effect. In the orderings CDT and CTD, the competitor receives an initial advantage because it appears first in the sequence, however comparisons between the competitor and the other options are subject to increasing forgetting over the course of the trial (i.e., $\alpha^n * d_C$). This means that comparisons favoring the competitor, see equation 1, have less impact as the trial progresses. On the other hand, comparisons favoring the target are subject to less forgetting because they occur later in the sequence. Ultimately, this leads to an advantage for the target and behavior that appears consistent with an attraction effect. Figure 1 illustrates this process for the CDT order. For the orderings TCD and TDC, which show a repulsion effect, the opposite occurs. In these orderings, the target has an initial advantage, but this advantage diminishes over the trial because of forgetting. This allows comparisons favoring the competitor to ultimately win out, leading to a repulsion-like effect.

We note that the pMLBA can likely predict other patterns of RST values across the orderings in our task. These predictions would be a trade-off between the regular MLBA parameters and the forgetting parameters. If there is little forgetting (e.g., $\alpha = 1$), this would lead to preference for early stimuli whereas increased forgetting (e.g., α near 0) would lead to preference for late stimuli. Forgetting parameters with intermediate values would likely balance out the extra time that the early options have to accumulate and the resulting behavior would resemble that of the regular MLBA. This flexibility allows the model to capture individual differences in our task. However, model flexibility can also lead to problems of over-fitting. We take this into consideration by using a generalization approach to the model fitting where we focus on out-of-sample predictions.

Although the temporal order model, mixture model, and heuristic-based model capture some trends in the data well, there are also substantial misfits. Specifically, the heuristic-based model does an extremely poor job of capturing the individual variability in response proportions, and the temporal order model provides a poor account of orderings where the decoy is presented first (i.e., DCT and DTC). While the mixture model improves upon the temporal order, as it is able to account for some of these trends through ignoring the decoy on some portion of trials, the generalization is still poorer than the pMLBA. Therefore, it does not appear that our pattern of results can be explained by a simpler model based upon temporal ordering or heuristics alone. However, it should be noted that there are some individual and between condition differences in the preferred model (Table 3). While the MLBA is the preferred model for the largest share of participants in all conditions, the MLBA is not the preferred model for the vast majority of participants in any condition, suggesting that the performance of some participants may be described well by simpler, heuristic or order-based strategies. In conclusion, we found that a piecewise extension of the MLBA, where comparisons between options are constrained by forgetting, generates the best predictions of our data.

Table 2: The different models fit to the data within the main text. The first column provides the model, and the second and third columns display the root mean squared error value (averaged over subjects) for the generalization analyses in Experiments 1 and 2, where smaller values indicate a better model fit.

Model	RMSE Exp. 1	RMSE Exp. 2
pMLBA	0.113	0.094
temporal order model	0.134	0.145
heuristic-based model	0.158	0.207
mixture model	0.13	0.134

Combined, these results indicate that modification of the comparison process due to

Table 3: The different models fit to the data within the main text. The first column provides the model, columns two to seven display the number of participants in Experiment 1 that were preferred by each model from the generalization analysis (via root mean squared error) separate for each condition, with column eight displaying the average over all conditions.

Model	CDT	CTD	DCT	DTC	TCD	TDC	Mean
pMLBA	20	29	27	23	25	23	24.5
temporal order model	8	9	8	7	4	12	8
heuristic-based model	15	6	4	7	12	8	8.67
mixture model	6	5	10	12	8	6	7.83

memory impairment / forgetting substantially alters people's preferences. This can lead to choice patterns consistent with a reversal of the attraction effect (i.e., a repulsion effect) simply by changing the sequential presentation of stimuli (but not the stimuli themselves). Importantly, these observations are washed out if only aggregate data (averaged over presentation orders) is considered. Furthermore no existing models of multi-attribute choice can account for our results because they make no distinction between different presentation orders and could not account for sequential or memory effects that alter comparisons.

Reanalysis of Trueblood et al. (2015)

Results from Experiments 1 and 2 show that order has a large impact on choice behavior. In some cases, presentation order leads to behavior that resembles an attraction effect and in other cases it leads to behavior that resembles a repulsion effect. This occurs regardless of whether the decoy is dominated or not. Cognitive modeling suggests that the features of this task (specifically, sequential presentation) biases the comparison process by making some options easier to remember and compare. Here we investigate whether the spatial configuration of options leads to similar effects by similarly biasing the comparison process.

Traditionally, context effects are studied using simultaneous presentation formats, which require the experimenter to choose a spatial arrangement of options. The spatial order of options has the potential to bias the comparison process by making some comparisons easier than others, similar to temporal manipulations in Experiments 1 and 2. The stimuli used in Experiments 1 and 2 were based on Trueblood et al. (2015), which used a simultaneous presentation format. In that study, the three rectangles were presented in a row with the order of the options randomized on each trial. Thus, there were 6 spatial order conditions in that experiment, similar to the 6 temporal order conditions analyzed in Experiments 1 and 2. In this section, we reanalyze the Trueblood et al. (2015) data based on the 6 spatial orders.

Method

75 undergraduate students at the University of California, Irvine participated in the experiment reported in Trueblood et al. (2015). The stimuli and task were similar to Experiments 1 and 2 except that the rectangles were presented simultaneously on the screen in a row, numbered from left to right. The location of the different rectangles was randomized across trials. The experiment consisted of a total of 720 trials with 160 testing the attraction effect. The remainder of the trials tested the similarity and compromise effects or were catch trials used to gauge engagement in the task. Full details about the experiment can be found in Trueblood et al. (2015).

Behavioral Results

In Trueblood et al. (2015), 20 participants were removed from the data analysis because they answered more than one third of the catch trials incorrectly. We applied the same exclusion criterion for the analyses reported here. We focus our analysis on the 160 attraction effect trials, analyzing the RST for each spatial order condition (CDT, CTD, DTC, DCT, TCD, TDC), determined by the ordering of the options from left to right on the screen. An initial one-sample Bayesian t-test showed strong evidence in favour of an attraction effect when RST was averaged over all conditions ($BF_{10} = 42$), and a one-way Bayesian ANOVA showed decisive evidence that RST differed between orderings ($BF_{10} = 4.2 \times 10^{20}$). Follow-up one-sample Bayesian t-tests found 3 orderings showing decisive evidence in favor of an attraction effect ($RST > 0.5$; $CTD : BF_{10} = 340$; $DTC : BF_{10} = 2489157$; $TDC : BF_{10} = 7656$), 1 ordering showing decisive evidence and 1 ordering showing strong evidence in favor of a repulsion effect ($RST < 0.5$; $DCT : BF_{10} = 1284813$; $TCD : BF_{10} = 14.3$), and 1 ordering showing moderate evidence in favor of no effect ($RST = 0.5$; $CDT : BF_{01} = 4.6$). The pattern of the results are similar to those in Experiments 1 and 2 (Table 1), with a few exceptions. First, while the CDT condition still trends in the same direction as Experiments 1 and 2, the evidence is in favour of the null instead of an attraction effect. Second, the TDC shows decisive evidence in favour of an attraction effect, rather than decisive evidence in favour of a repulsion effect as in Experiments 1 and 2. Finally, the trends in the conditions where the decoy was presented first (DTC and DCT) are much stronger than in Experiments 1 and 2, suggesting that the presentation of all stimuli simultaneously may make comparisons between the decoy and the stimulus in close proximity (in this case, visually rather than temporally) even stronger.

Conclusion

The reanalysis of the attraction effect data in Trueblood et al. (2015) shows that spatial presentation order has a large impact on choices, where some orders lead to an attraction effect and others lead to a repulsion effect. This finding is similar to the results of Experiments 1 and 2, which manipulate the temporal ordering of options. Our key hypothesis about why order (both spatial and temporal) influences the manifestation of context effects is that people cannot process all information simultaneously in multi-alternative, multi-attribute decision problems (even when all information is available on the screen at the same time). Rather, information is processed through a series of shifts in attention where subsets of options are compared and evaluated. Experiments 1 and 2 directly manipulate shifts in attention, and consequently the comparison process, by presenting options sequentially. In Trueblood et al. (2015), spatial proximity likely facilitates the comparison and evaluation of options near one another, resulting in those comparisons having greater impact on final decisions. Indeed, we observe that the attraction effect occurs when the target and decoy are spatially close (presented next to one another on the screen). However, when the competitor comes between the target and decoy (i.e., the middle option on the screen), the attraction effect reverses, leading to a repulsion effect. While there are similarities in the choice patterns for the sequential and simultaneous tasks, there are also clear differences (e.g., the TDC order). These differences likely arise because spatial and temporal orders manipulate attention and the comparison process in different ways.

General Discussion

Decades of research into context effects has led to an apparent paradox: they are general but fragile. That is, they appear in a wide array of decision domains but can be easily altered in any one of those domains (e.g. turning an attraction effect into a repulsion effect; Frederick et al., 2014; Spektor et al., 2018). Our results suggest a potential explanation of this paradox. In multi-alternative, multi-attribute decision problems, it is unlikely people can process all information simultaneously (even when it is presented that way). As such, we hypothesize that information is processed sequentially where different subsets of options are compared and evaluated over the course of deliberation, consistent with decades of research on sequential sampling models of multi-alternative, multi-attribute choice (Usher & McClelland, 2004; Roe et al., 2001; Trueblood et al., 2014; Noguchi &

Stewart, 2018). Because comparisons and evaluations are likely performed on subsets of options (rather than on all options simultaneously), task features can bias which subsets are compared during deliberation. In the case of temporal order manipulations, temporally proximal options are likely easier to remember and compare. In the case of spatial order manipulations, it is likely easier to attend and evaluate spatially proximal options, thus biasing the comparison process towards these options.

To test this hypothesis, we directly manipulated shifts in attention, and consequently the comparison process, by sequentially presenting options in Experiments 1 and 2. Our basic idea was that forgetting (either through memory decay or interference; Sadeh, Ozubko, Winocur, & Moscovitch, 2016; Farrell et al., 2016) will lead to different decisions in different sequences due to the difficulty of comparing items retrieved from memory with items currently visible. Empirical results showed a complex pattern of attraction and repulsion effects in different sequences as predicted, with no obvious heuristic pattern of responding (e.g. choosing the last alternative). Critically, these effects arise only from the sequencing of stimuli and not the stimuli themselves; the same stimuli presented in different orders yield different effects.

To determine whether the interaction of decision processes with memory can explain these complex observations, we developed a piecewise version of the MLBA model. The piecewise specification of drift rates, which are determined by the standard MLBA comparison process, automatically accounts for the sequential ordering of alternatives. Effects of forgetting were further encoded by assuming drift rates are discounted after an alternative disappeared from the screen. Leave-one-condition-out cross-validation (i.e., a generalization approach; Busemeyer & Wang, 2000) of the proposed model, which was performed to ensure it was not over-fitting, demonstrated that it predicts well the complex pattern of choice proportions and out performs alternative heuristic models. These empirical and model based results show that manipulating the processing order of alternatives can dramatically alter context effects by either nullifying or fully reversing them.

To further examine the hypothesis that the comparison and evaluation process is sensitive to task specific features, we reanalyzed the attraction effect data in Trueblood et al. (2015) where the spatial ordering of options was manipulated. Results showed that some spatial orders lead to an attraction effect whereas other spatial orders lead to a repulsion effect. This is consistent with recent research that shows that the attraction effect only occurs for some spatial orders in consumer choice tasks (He & Sternthal, 2018) as well as other research showing that context effects can be eliminated and even reversed by changing the grouping of the options and attributes (Cataldo & Cohen, 2018, 2019). Spatial ordering likely influences context effects because it is easier to attend to and compare spatially proximal options. Taken together, the results from the temporal and spatial order tasks point to the ease at which the comparison process can be manipulated to influence context effects.

Our results also have real world consequences. Rather than being presented with all alternatives simultaneously at the start of a decision, people are often presented alternatives sequentially, as they come across them. For example, when online shopping, consumers sequentially visit different webpages for different products they are considering to purchase. To date, we are unaware of any research on context effects in these sequential decision scenarios. More generally, all multi-alternative, multi-attribute choice tasks (whether they be experimental tasks or real world shopping tasks) involve some level of temporal or spatial manipulation of the options. As our results show, context effects are highly sensitive to these task features.

Our study also presents several avenues for future research. A natural next step would be to assess the other main context effects – the compromise and similarity. Another natural extension would be to apply the sequential paradigm to other types of stimuli (beyond perceptual) commonly used within multi-attribute choice, such as "consumer choice" stimuli used in many context effects experiments. On the theoretical side, we do not know of any computational models that can explain the impact of spatial order on context effects in simultaneous tasks. In this paper, we develop an extension of the MLBA model to explain choices in our sequential task. In that model, it is the interaction of forgetting with a pairwise comparison process that explains our results. However, forgetting likely plays less of a role in simultaneous tasks. Instead spatial proximity likely facilities the comparison of options near one another. In MLBA, this could be captured through spatial attention weights, in addition to the similarity-based attention weights already included in the model. Lastly, an interesting piece of future research would be investigating the use of presentation order as a debiasing strategy. Our results suggest that the strength of context effects can be manipulated by presentation order, suggesting that it is possible to debias these decisions.

Finally, our results shed new light on the ongoing debate about the robustness of the attraction effect (Frederick et al., 2014; Huber, Payne, & Puto, 2014; Simonson, 2014; Yang & Lynn, 2014; Evangelidis et al., 2018). Importantly, we show that the apparent paradox of a fragile, but ubiquitous effect can be explained by understanding the cognitive mechanisms underlying multi-alternative, multi-attribute decision-making. Through a joint experimental and computational modeling approach, we show that this paradox is well explained by a dynamic and malleable sequential comparison process that is dependent on other cognitive functions, memory in this case. Importantly, our results suggest that determining the "boundary conditions" of the attraction effect (Evangelidis et al., 2018; Huber et al., 2014) will be best accomplished by understanding the "boundary conditions" of the decision process and its interaction with other cognitive processes.

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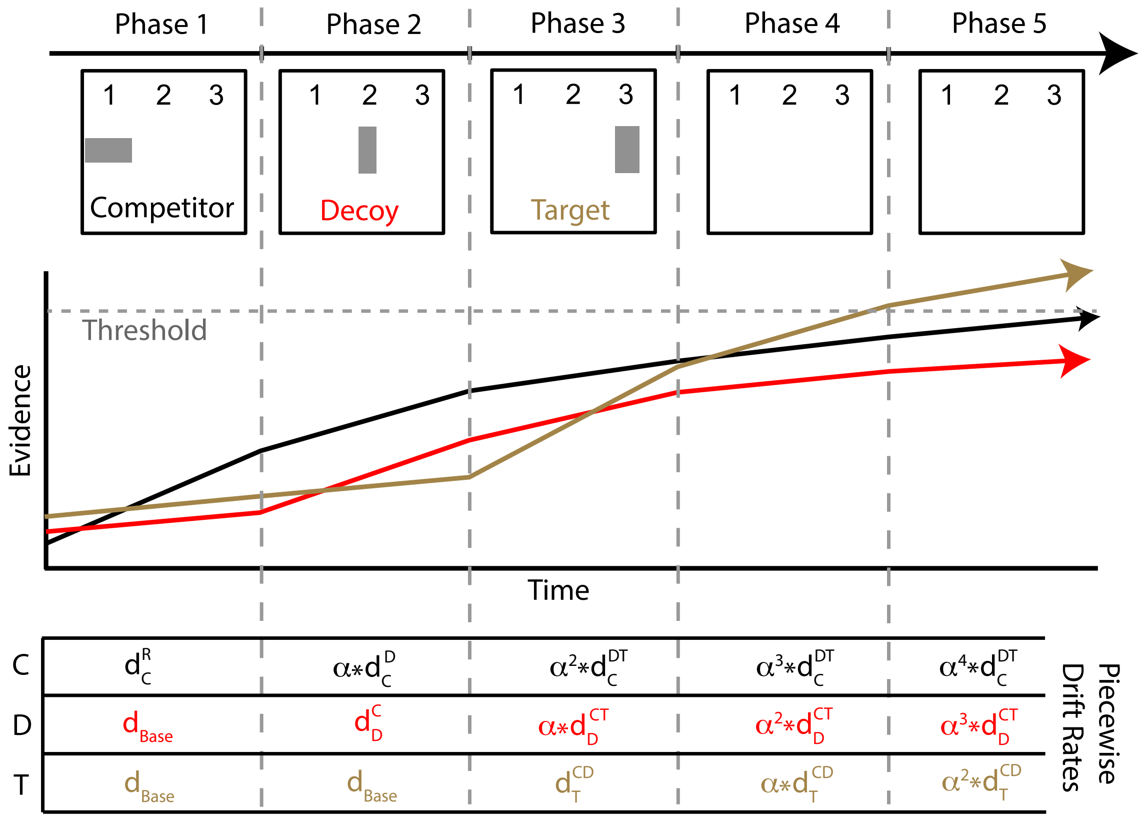

Figure 1. Displays the structure of the sequential rectangle task (top), schematic of the piecewise MLBA (middle), and the drift rates for the piecewise MLBA model (bottom) used to explain the data for a CDT trial with a D_H decoy. Time moves from left to right, beginning at the start of the trial (0 seconds), where the W rectangle is presented until 1 second has elapsed (labeled "Phase 1"). At 1 second from trial onset, the W rectangle disappears, and the D_H rectangle is presented (labeled "Phase 2"), and at 2 seconds from trial onset, the D_H rectangle disappears and the H rectangle is presented (labeled "Phase 3"). From 3 second onwards no alternatives are presented, but participants are still able to make a choice, until the deadline of 5 seconds. In the middle panel, evidence accumulation changes at the start of each phase reflecting the new information available to participants, which is accounted for in the model using piecewise linear shifts. In the bottom panel, the drift rates for the first phase consist of a comparison between C and some internal reference point (R), and D and T having a baseline drift (dBase). Comparisons between alternatives are presented in the format d_1^2, where 1 is the alternative associated with the accumulator, and 2 is/are the alternative(s) it is being contrasted against. α is the memory parameter multiplied to drift rates after an option is no longer visible.

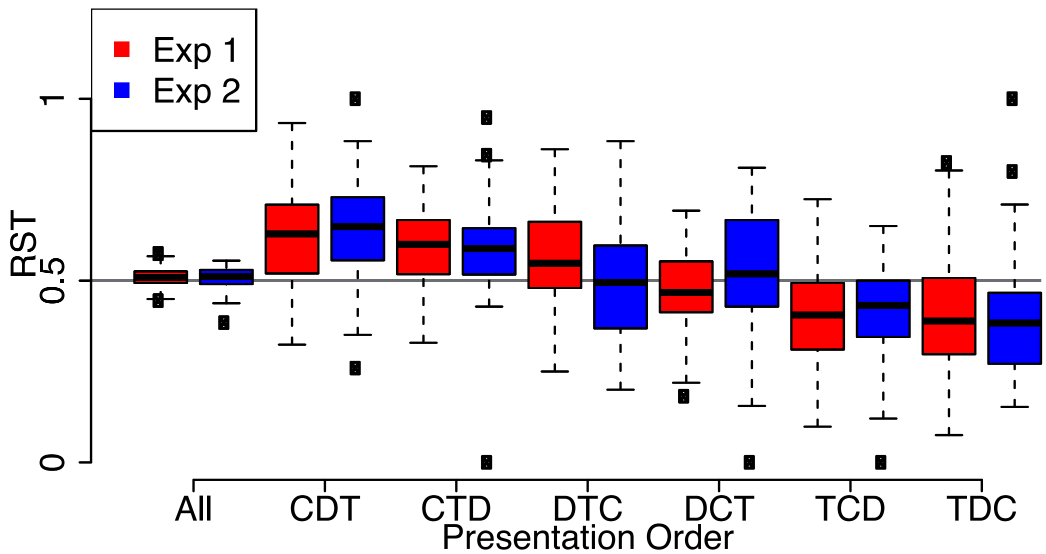

Figure 2. Box plots for the "relative choice share of the target" (RST) for each of the 6 orderings. Results for Experiment 1 are shown in red, and results for Experiment 2 are shown in blue. The left-most bars shows the RST for all orders combined.

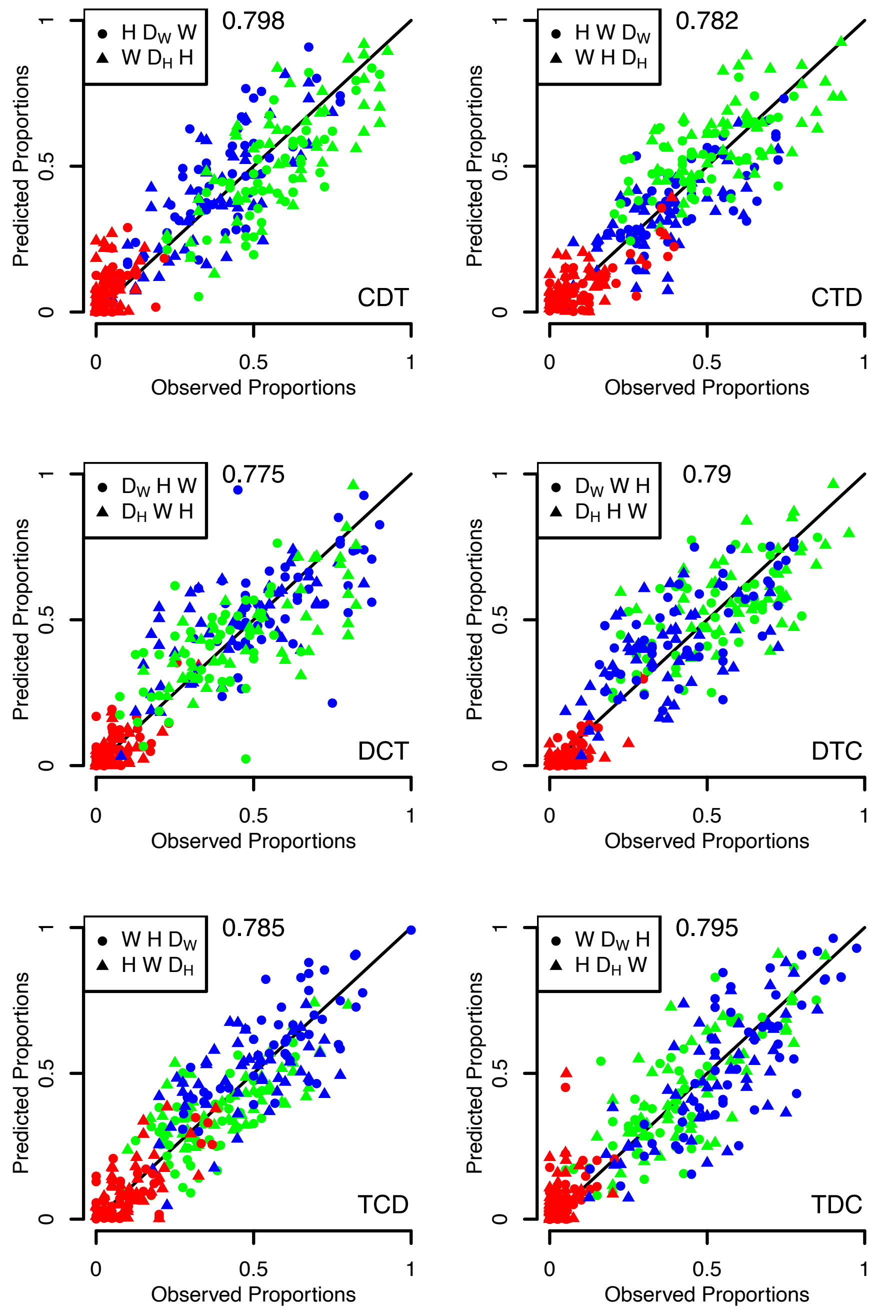

Figure 3. Plots of the 6 generalizations of the pMLBA model to the response proportions from the left-out condition. Within each plot, the x-axis shows the observed response proportions for each individual, and the y-axis shows those predicted by the pMLBA, with different points for different participants and response alternatives. The green points show the target, the blue points show the competitor, and the red points show the decoy. The number at the top of the panel reflects the R^2 of the goodness-of-fit.

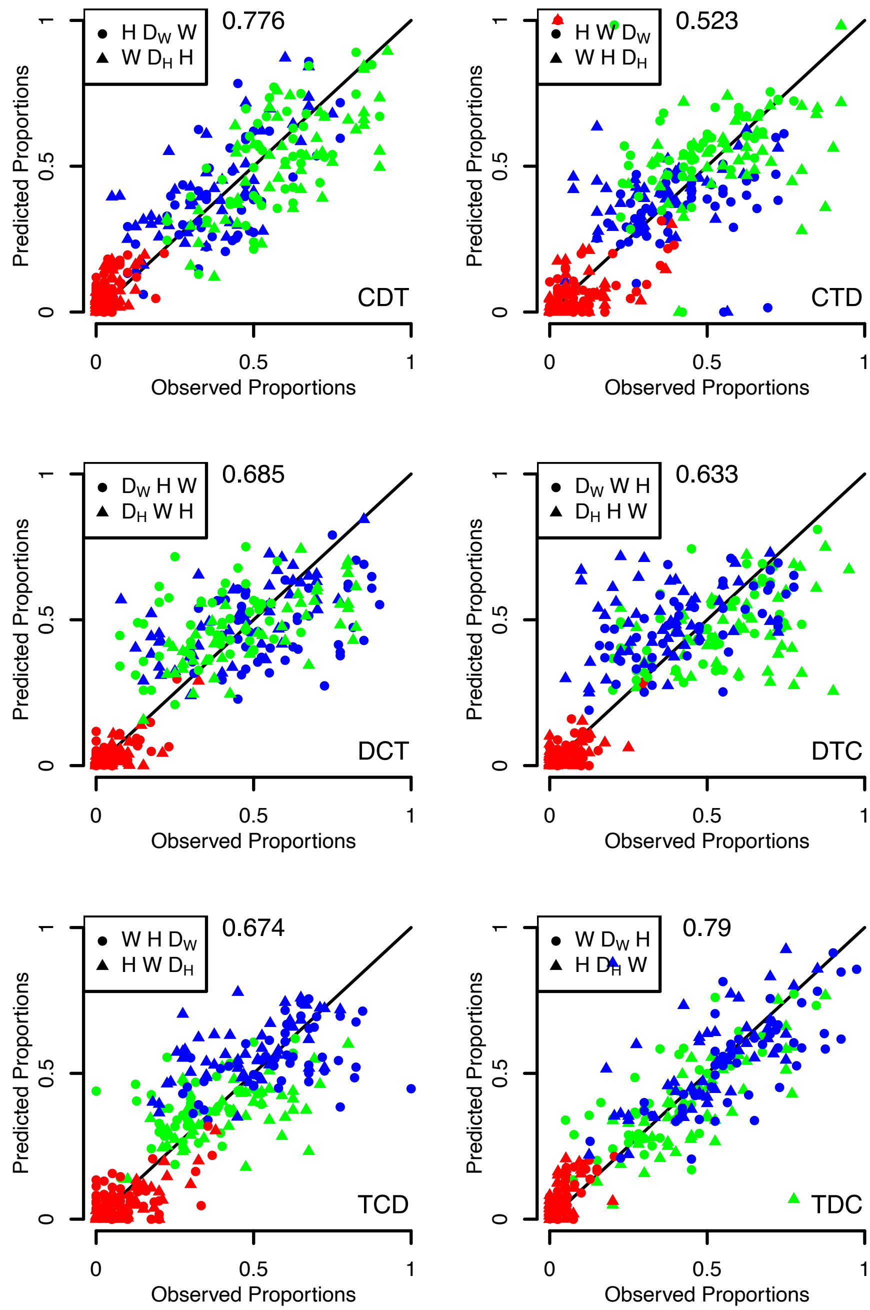

Figure 4. Plots of the 6 generalizations of the temporal order model to the response proportions from the left-out condition. Within each plot, the x-axis shows the observed response proportions for each individual, and the y-axis shows those predicted by the temporal order, with different points for different participants and response alternatives. The green points show the target, the blue points show the competitor, and the red points show the decoy. The number at the top of the panel reflects the R^2 of the goodness-of-fit.

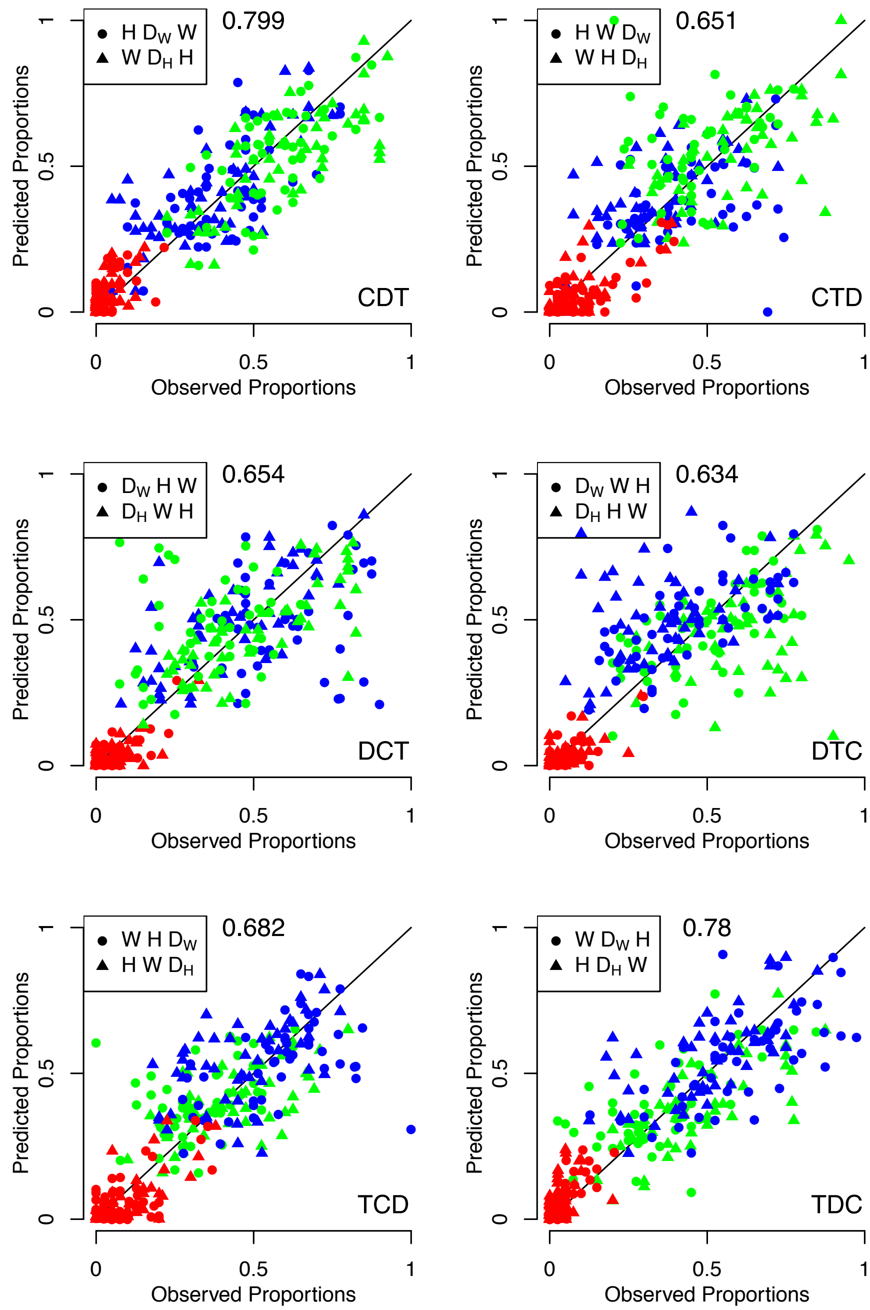

Figure 5. Plots of the 6 generalizations of the mixture model to the response proportions from the left-out condition. Within each plot, the x-axis shows the observed response proportions for each individual, and the y-axis shows those predicted by the mixture, with different points for different participants and response alternatives. The green points show the target, the blue points show the competitor, and the red points show the decoy. The number at the top of the panel reflects the R^2 of the goodness-of-fit.

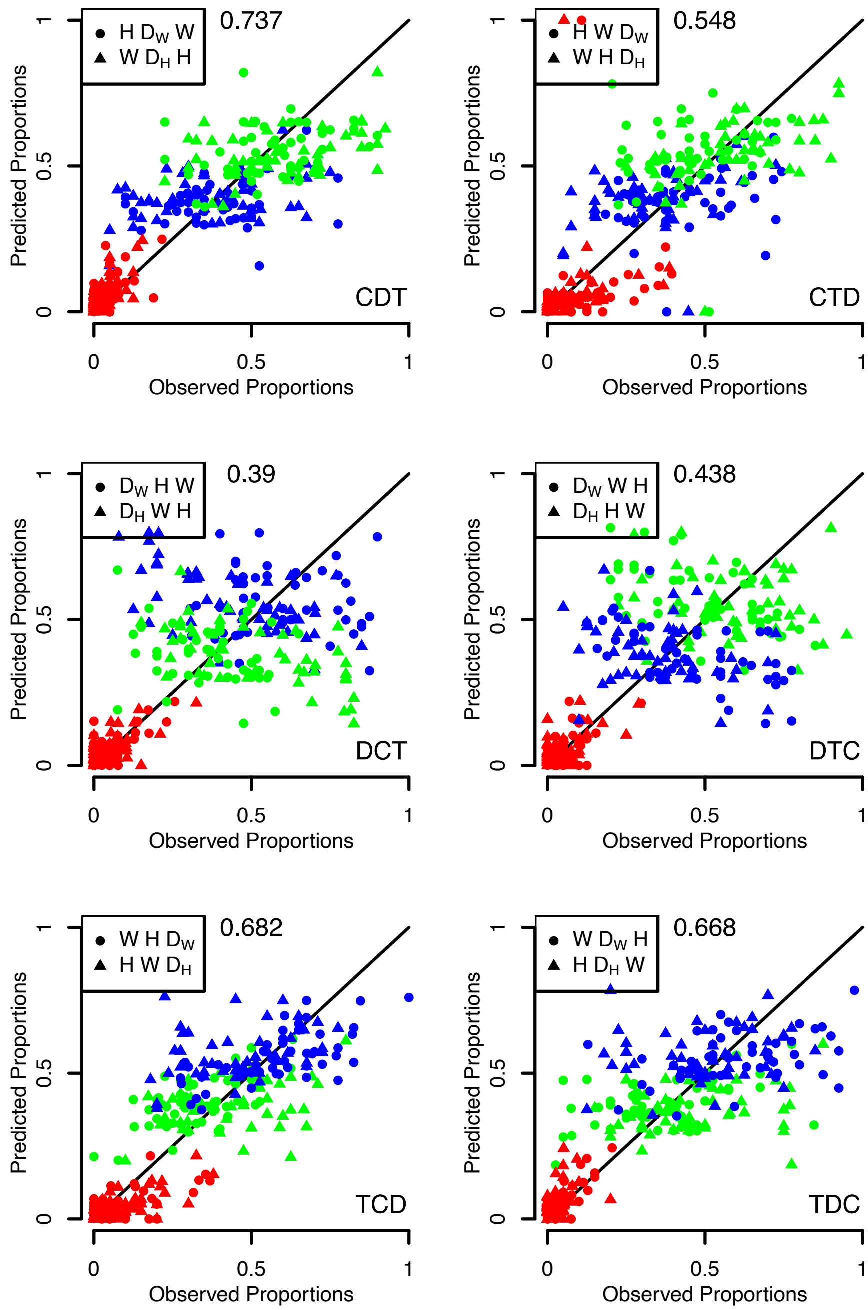

Figure 6. Plots of the 6 generalizations of the heuristic-based model to the response proportions from the left-out condition. Within each plot, the x-axis shows the observed response proportions for each individual, and the y-axis shows those predicted by the heuristic-based, with different points for different participants and response alternatives. The green points show the target, the blue points show the competitor, and the red points show the decoy. The number at the top of the panel reflects the R^2 of the goodness-of-fit.