

# **CONTEXT DEPENDENCE IN PERCEPTUAL AND PREFERENTIAL CHOICE**

A Dissertation Presented

by

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Psychological and Brain Sciences

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## **ABSTRACT**

# **CONTEXT DEPENDENCE IN PERCEPTUAL AND PREFERENTIAL CHOICE**

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A large body of research in psychology has shown that context can systematically affect choice. These *context effects* are in violation of rational choice theory and are both practically and theoretically interesting. Recent work has demonstrated context effects in simple perceptual choice, interesting findings that suggest that these results are not restricted to high-level (e.g., consumer) choice. This dissertation explores the attraction and repulsion effects, two related context effects, with a particular emphasis on perceptual choice. Chapter 1 introduces the attraction and repulsion effects and reviews the empirical and theoretical literature surrounding them. Chapter 2 tests the ability of perceptual and decisional processes to account for these effects through the introduction of a Thurstonian choice model. Chapter 3 uses this model to make predictions about best-worst choice and test them empirically. Chapter 4 generalizes the model and paradigm from Chapter 2 to consumer choice. Chapter 5 tests the idea

that the repulsion effect can be generated through ease of comparability. Chapter 6 discusses and summarizes these results.

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# CHAPTER 1

## INTRODUCTION

### 1.1 Overview

Decades of decision-making research have shown that context can systematically affect choice. In decision-making experiments, researchers present participants with a finite set of options on each trial and ask them to select a single option based on either an internal (e.g., most preferable) or external (e.g., largest shape) criterion. Decision-making research spans multiple fields, including psychology, neuroscience, economics, marketing, and political science. In economics, for example, researchers have developed models based on the idea that, while preferences may vary from moment to moment, people generally make rational choices in any given choice setting. In psychology and marketing, however, researchers have identified a set of phenomena that violate such assumptions, by showing that choices can vary with the *choice set*, or the menu of available options. This class of phenomena is known as *context effects*.

Context effects are interesting to decision-making researchers because they violate properties exhibited by large classes of choice models, such as Independence of Irrelevant Alternatives (IIA) (Ray, 1973) and regularity (MacKay & Zinnes, 1995; Marley, 1989). IIA states that the likelihood of selecting one option over another is invariant of other options available. Regularity states that the probability an option is chosen cannot increase upon the addition of new options to a choice set. IIA and regularity are also properties of Luce's Choice Axiom, a highly influential model of stochastic choice (Luce, 1959, 1977).

One notable context effect, the attraction effect, occurs when the choice share of a *target* option increases upon the inclusion of a similar but inferior *decoy* option (Huber et al., 1982). Another finding, the repulsion effect, occurs when a decoy boosts the choice share of a dissimilar *competitor* option rather than the target (Simonson, 2014). The repulsion effect is an empirical reversal of the attraction effect.

Context effects, originally studied in preferential choice, have been recently demonstrated simple perceptual choice (Evans et al., 2021; Liao et al., 2021; Spektor et al., 2018, 2022; Trueblood & Pettibone, 2017; Trueblood et al., 2013; Turner et al., 2018; Yearsley et al., 2022). This idea is theoretically interesting because it suggests that context effects are a theoretical primitive rather than simply a feature of high-level consumer choice (Trueblood et al., 2013).

As suggested by the title, this dissertation explores various forms of context dependence in both perceptual and preferential choice. In particular, I explore the attraction and repulsion effects. The goal of this dissertation is to further understand why these effects occur in perceptual choice, by employing well-studied statistical models from the psychology literature. Additionally, this dissertation sets out to differentiate perceptual processes from decision-making processes in context effects (specifically, the attraction and repulsion effects).

As I will discuss throughout this dissertation but particularly in Chapter 2, recent work has demonstrated inconsistency in context effects, particularly in perceptual choice. I use behavioral experiments and statistical modeling in an attempt to reconcile these inconsistencies.

This dissertation is structured as follows. In Chapter 2, I develop and test a statistical model of perceptual variability when applied to context effects. In Experiment 1, I first show that the types of stimuli used in perceptual choice context effects experiments are easily confusable and vary systematically with theoretically relevant properties of the stimuli. In Experiment 2, I use the results of a high-powered

psychophysics experiment to show that the repulsion effect, but not the attraction effect, is naturally predicted by this statistical model. In Chapter 3, I further test the statistical model by applying it to best-worst choice. In Chapter 4, I generalize the paradigm and model to preferential choice. Finally, in Chapter 5, I use a perceptual choice experiment to show that stimulus comparability affects choice, even when the decoy is equally similar to both focal options. In Chapter 6, I summarize the findings of the dissertation, their implications, and discuss future directions for research in this domain.

# CHAPTER 2

## PARSING THE ROLES OF PERCEPTION AND DECISION IN CONTEXT-DEPENDENT CHOICE

### 2.1 Introduction

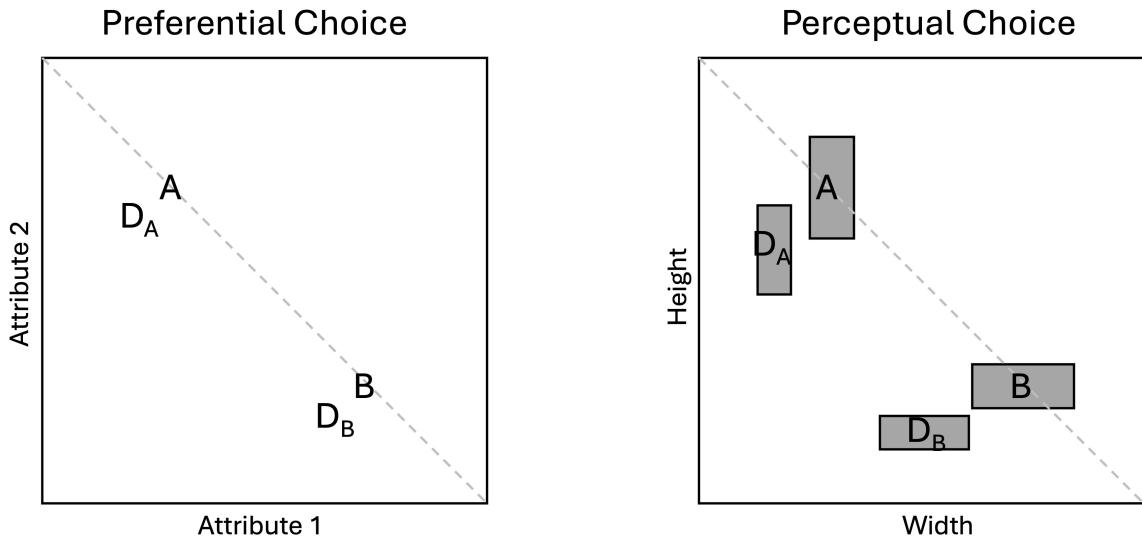
As discussed in Chapter 1, the attraction effect is a well-studied choice phenomenon where an asymmetrically dominated decoy option increases the choice share of a similar, but superior, target option (Huber et al., 1982). The attraction effect is an example of a context effect, where the relative choice share of an option varies systematically with the choice set.

Though context effects originally were originally demonstrated in preferential choice, recent work has generalized these results to simple, perceptual choice. This result has important theoretical and practical implications for decision-making research. I introduce and review this research below.

#### 2.1.1 Introducing the Attraction Effect

First, the attraction effect is formally defined. See Figure 2.1 (left panel), which shows a graphical configuration of various choice options. These options vary on two dimensions (or attributes), where higher values of an attribute are always preferred. These dimensions are named generically to emphasize the generality of the attraction effect.

Let  $A$ ,  $B$ ,  $D_A$ , and  $D_B$  be discrete choice options,  $[]$  denote the options in a choice set, and  $P(A|[A, B])$  denote the probability of choosing option  $A$  from a set consisting of  $A$  and  $B$ , for example.



**Figure 2.1.** A graphical depiction of choice options in the attraction/repulsion effect. Left panel: preferential choice. Right panel: perceptual choice.

In Figure 2.1 (left panel), options  $A$  and  $B$  trade off on attributes.  $A$  is high on dimension 2 but low on dimension 1, while  $B$  is high on dimension 1 but low on dimension 2. A decision-maker who assigns equal importance to both dimensions should be indifferent between both options when presented with choice set  $[A, B]$ . Now, however, consider option  $D_A$ , which is inferior to  $A$  and  $B$ , but more similar to  $A$  than to  $B$ . This *decoy* option is dominated by  $A$ , so no rational agent who perceives this dominance relationship should intentionally select the decoy over the target.. Similarly,  $D_B$  is inferior to both  $A$  and  $B$  but more similar to  $B$ . The attraction effect is the finding that choice for  $A$  over  $B$  is greater given set  $A, B, D_A$  than given set  $A, B, D_B$ <sup>1</sup>(Huber et al., 1982).

Choice models often, though not necessarily, assume the *Independence of Irrelevant Alternatives*(IIA) principle. IIA states that the relative likelihood of choosing a particular option over another is invariant of the choice set (Ray, 1973).

---

<sup>1</sup>This is the weak version of the attraction effect. A strong version requires the ordering of  $P(A)$  and  $P(B)$  to change with choice set. See Davis-Stober et al. (2023) for a discussion of similar issues.

According to IIA:

$$\frac{P(A|[A, B, D_A])}{P(B|[A, B, D_A])} = \frac{P(A|[A, B, D_B])}{P(B|[A, B, D_B])} \quad (2.1)$$

However, in the attraction effect, this equality is violated:

$$\frac{P(A|[A, B, D_A])}{P(B|[A, B, D_A])} > \frac{P(A|[A, B, D_B])}{P(B|[A, B, D_B])} \quad (2.2)$$

Thus, IIA is violated by the attraction effect.

In the context effects literature, it is common to refer to the similar, dominated option as the *decoy*, the similar dominating option as the *target*, and the dissimilar dominating option as the *competitor*. For example, in the choice set  $[A, B, D_A]$ ,  $A$  is the target,  $B$  is the competitor, and  $D_A$  is the decoy.

The attraction effect was first demonstrated by Huber et al. (1982)<sup>2</sup>, who tested participants with duples and triples of choice options, using products such as cars, beers, and TV sets. The authors showed that the introduction of an asymmetrically dominated decoy tended to increase the choice share of a similar, target option. These results violate IIA but also a principle known as regularity, which states that the introduction of another option to a choice set cannot increase the probability of choosing any given option. Put in the above context, regularity implies that:

$$P(A|[A, B]) \geq P(A|[A, B, D_A]) \quad (2.3)$$

Huber et al. (1982)'s finding that  $P(A|[A, B, D_A]) > P(A|[A, B])$  therefore violates regularity. Huber and Puto (1983) replicated these results and also showed that if the decoy has a relatively high value, it can actually take choice shares away from the target. This result suggests that the relative positioning of the decoy to the target

<sup>2</sup>These authors referred to this finding as the asymmetric dominance effect. Contemporary researchers have adopted the term attraction effect.

can greatly affect patterns of choice, a finding explored by numerous other researchers which has strong theoretical consequences.

Numerous researchers have since demonstrated the attraction effect in preferential choice, including in real-world scenarios. Doyle et al. (1999) found an attraction effect in real world supermarket choices by adding a decoy option to an existing product set, where the decoy option was the same brand and price as the target, but of a lower volume. van den Enden and Geyskens (2021) showed that the attraction effect can be used to induce people to choose healthier food items. Slaughter et al. (1999) showed that the attraction effect can be found even without the explicit attribute descriptions commonly used in laboratory experiments, when participants must infer option attributes.

Context effects have strong theoretical implications. Traditional models of choice, as used in economics and marketing research (McFadden, 2001), treat the *utility*, or value, of each option as a random variable whose parameters are estimated from choice data. According to these models, on each trial of a decision-making experiment, the participant samples option values from these distributions and deterministically chooses the option with the highest sampled value. These models are known as *Random Utility Models* (RUMs). When utilities are assumed to follow a Type 1 Generalized Extreme Value distribution, the logit or softmax model is used (Gensch & Recker, 1979). The probit model, another popular model, assumes Gaussian distributed utilities (Bolduc, 1999). Typically, though not necessarily, these models assume independently distributed errors, which typically implies IIA. Typically, these models are used to estimate the inherently unobservable utility values for each option.

RUMs often have difficulty accounting for context effects. For example, Berkowitzsch et al. (2014) tested the independent logit and independent probit models against Roe et al. (2001)'s Multialternative Decision Field Theory (MDFT), a cognitive process model of decision-making. According to MDFT, choice is the end result of

a stochastic evidence accumulation process, where preferences for each option in a choice set accumulate value through a series of comparisons on each dimension. In Berkowitz et al. (2014)'s experiment participants chose between digital cameras from choice sets designed to elicit context effects. Berkowitz et al. (2014) found that MDFT, but not the logit or probit models, could account for the attraction effect (and other related context effects). Furthermore, according to model comparison measures, the majority of participants were best described by MDFT. Participants whose data were best described by MDFT were also more likely to exhibit context effects. Independent RUMs, such as the logit and probit model, assume each option's utility is independently sampled, so these models cannot account for context effects.

Often, though not necessarily, RUMs assume IIA. This assumption can be relaxed, however. Paetz and Steiner (2018) showed, via simulations, that the probit model can violate IIA by allowing non-zero off-diagonal elements in the variance-covariance matrix. IIA can also be relaxed by estimating choice set or alternative specific coefficients (Rooderkerk et al., 2011) or allowing correlations between options and/or attributes (Haaijer et al., 1998). Without such modifications, RUMs are unable to account for context effects.

In cognitive psychology, researchers have developed process models that attempt to explain the mental processes that lead to context effects (Bergner et al., 2019; Bhatia, 2013; Busemeyer et al., 2019; Noguchi & Stewart, 2018; Roe et al., 2001; Trueblood et al., 2014; Tversky, 1972; Tversky & Simonson, 1993; Usher & McClelland, 2004; Wollschläger & Diederich, 2012). These models differ, to varying degrees, in their explanations for the attraction effect. Many, however, rely on comparisons between the target and the similar, but inferior, decoy, which boost an internal preference state for the target. Roe et al. (2001)'s Multialternative Decision Field Theory (MDFT) model proposes that the similarity between target and decoy causes frequent target-decoy comparisons, and through lateral inhibition, the negative valence

for the decoy causes a boost to the preference state of the target at the expense of the competitor. Trueblood et al. (2014)'s Multiattribute Linear Ballistic Accumulator (MLBA) model proposes that pairwise attention weights, which are a function of the similarity between options, increase the importance of target-decoy comparisons and thus boost preference for the target.

This chapter does not explore the predictive success of these models, nor does it incorporate model fitting to compare these models. The goal of this chapter is to test the mechanisms that produce the attraction and repulsion effect in perceptual choice.

The attraction effect is not solely limited to consumer choice. Researchers have also demonstrated the attraction effect in risky choice (Mohr et al., 2017), policy choice (Herne, 1997), intertemporal choice (Marini et al., 2020), probability judgment (Cai & Pleskac, 2023), medical decision-making (Schwartz & Chapman, 1999), episodic memory judgment (Maylor & Roberts, 2007), charitable donation (Pittarello et al., 2020), inference (Trueblood, 2012), job candidate selection (Highhouse, 1996), political choice (Pan et al., 1995), sports prediction (Fang et al., 2024), and, as will be the focus of much of this dissertation, perceptual choice (Evans et al., 2021; Liao et al., 2021; Spektor et al., 2018, 2022; Trueblood et al., 2013, 2015; Turner et al., 2018; Yearsley et al., 2022).

### 2.1.2 From Preferential to Perceptual Choice

Choplin and Hummel (2005) and Yearsley et al. (2022) first demonstrated the attraction effects in perceptual choice. In these experiments, participants saw various perceptual stimuli (i.e., ovals, swirled lines, vertical lines) and chose the option most similar to a reference option. The researchers showed that participants were more likely to choose the option paired with a similar (but less similar to the reference stimulus) decoy option.

Trueblood et al. (2013) also demonstrated the attraction effect in perceptual choice. In their experiments, participants saw three rectangles on each trial, arranged in a horizontal array, and selected the option they perceived to have the largest area. For an example stimulus set, see Figure 2.1 (right panel). Note that options *A* and *B* have equal area but trade off in height and width. The decoy options ( $D_A$  and  $D_B$ , respectively) are smaller in area but are more similar to their respective targets than to their respective competitor. In Trueblood et al. (2013)'s experiments, participants chose the target option more than the competitor option, on average.

Notably, the title of Trueblood et al. (2013)'s paper was "Not Just for Consumers: Context Effects Are Fundamental to Decision Making", and in their General Discussion, Trueblood et al. (2013) argued "our experiments suggest that these context effects are a general feature of human choice behavior because they are a fundamental part of decision-making processes. As such, our results challenge explanations of these effects exclusively in terms that are unique to high-level decision making and thus call for a common theoretical explanation that applies across paradigms." (p. 907). According to Trueblood et al. (2013), context effects are not idiosyncratic to high-level decision-making but are a fundamental feature of choice. Trueblood et al. (2013) also used these perceptual results to argue against the context-dependent advantage (CDA) model (Tversky & Simonson, 1993) as well as the Leaky Competing Accumulators (LCA) model (Usher & McClelland, 2004), as these models use loss aversion - the idea that an option's disadvantages on an attribute are weighted more strongly than its advantages on other attributes - to account for context effects. Trueblood (2012) demonstrated context effects in an inference task and argued similarly against loss aversion.

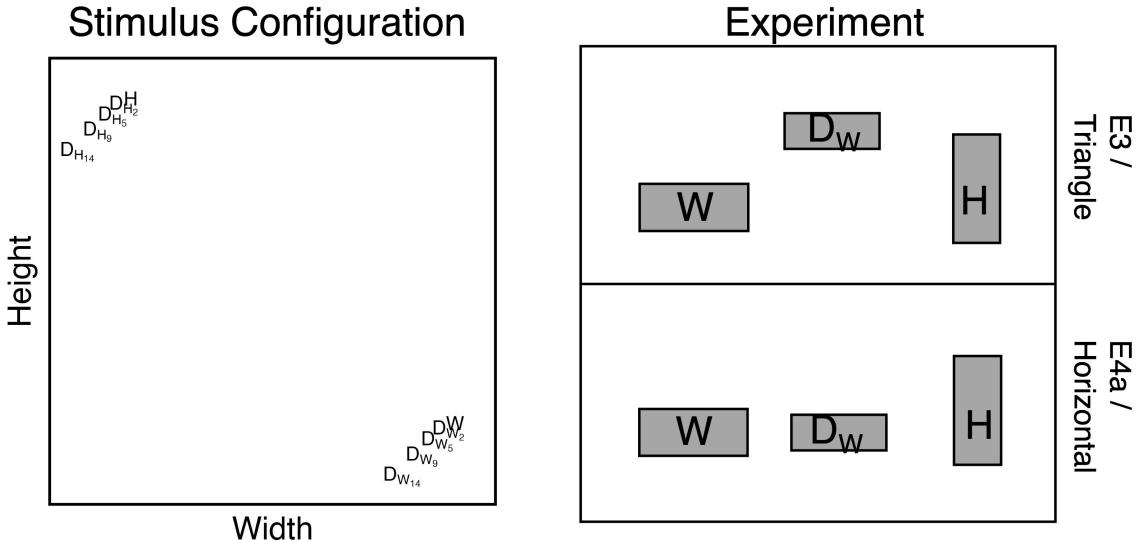
Frederick et al. (2014) failed to replicate Trueblood et al. (2013)'s finding of the attraction effect in perceptual choice. Frederick et al. (2014) collected data online,

which may have resulted in less precision than a laboratory task, potentially leading to the null finding.

Turner et al. (2018) replicated Trueblood et al. (2013)'s results and performed a large scale modeling analysis, comparing the ability of various model mechanisms to account for context effects. For example, Turner et al. (2018) concluded that pairwise comparisons on individual attributes greatly improves models' ability to account for context effects. This may not be appropriate, however, given a perceptual domain where dimensions may not be separable. Specifically, in a consumer choice experiment, participants may very well compare options on a single dimension at a time, e.g. comparing cars on their fuel efficiency. However, in a perceptual choice task, it is unlikely that participants are able to separately compare rectangles on the height dimension and on the width dimension and then arrive at an overall judgment. Rather, it is more plausible that participants compare these stimuli holistically.

Spektor et al. (2018) followed up on this work and demonstrated the *repulsion effect* in a similar perceptual choice experiment. In the repulsion effect, the competitor's choice share is higher than the target's choice share. In Spektor et al. (2018)'s experiments, the target and competitor options varied in area, such that one option was always larger, though on average they were the same size. The researchers also varied the *target-decoy attribute distance* (TDD), the percentage difference between the target and decoy areas. For example, if TDD is 2%, the decoy is 2% smaller than the target.

Spektor et al. (2018) ran a total of five experiments. All experiments showed similar results, so I focus on their experiments 3 and 4a, which are the most representative of the article's conclusions. In Experiment 3, the authors varied TDD at four levels: 2%, 5%, 9%, and 14%. The rectangles were arranged in a triangular display on the screen (see Figure 2.2, Experiment 3), in contrast to Trueblood et al.



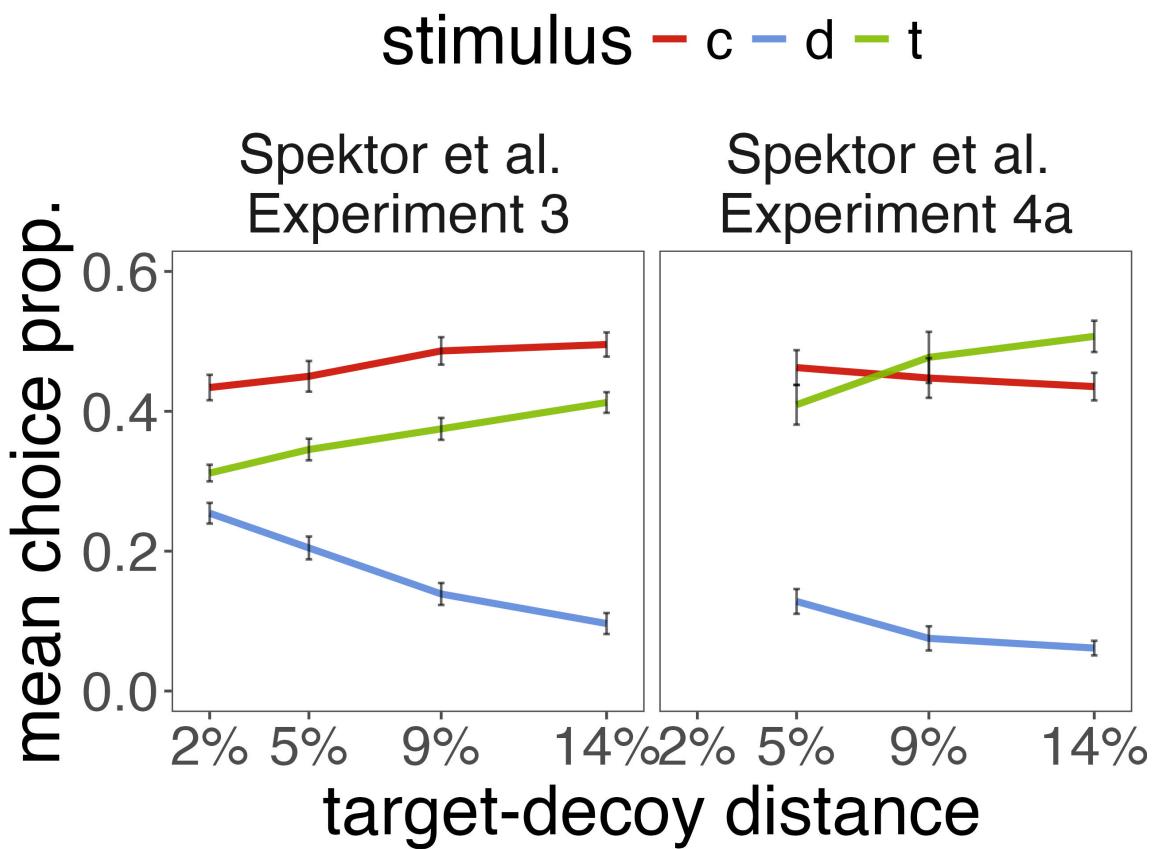
**Figure 2.2.** Stimulus configuration and example trials from Spektor et al. (2018), Experiments 3 and 4a. Decoy subscripts indicate TDD. Note that the stimulus in the righthand plot were not shown in the experiment; these are solely for the benefit of the reader.

(2013)'s horizontal display. Spektor et al. (2018) found a repulsion effect, such that the competitor was selected more than the target at all levels of TDD (see Figure 2.3).

Spektor et al. (2018)'s Experiment 4a, however, used the horizontal display of Trueblood et al. (2013) (see Figure 2.2, Experiment 4a). Here, they varied TDD at 5%, 9%, and 14%. In Experiment 4a, the data show a slight repulsion effect at low TDD levels that eventually becomes an attraction effect at high TDD levels.

Trueblood and Pettibone (2017) demonstrated a "phantom decoy" effect in perceptual choice. Phantom decoys are options that are similar to the target, but also superior in value, and are initially presented but made unavailable at the time of choice. They showed that participants chose the target less than the competitor, a result at odds with phantom decoy effects in preferential choice (Pettibone & Wedell, 2000; Pratkanis & Farquhar, 1992).

Liao et al. (2021) also replicated the general pattern of Spektor et al. (2018)'s results and also found a an inverse U-shaped relationship between TDD and the



**Figure 2.3.** Data from Spektor et al. (2018), collapsed across choice set. Error bars are 95% CIs of the mean, computed using the within-participants error correction from Morey et al. (2008). Dashed lines are drawn at .5 and .33.

attraction effect. Low and high TDD values created a repulsion effect, while intermediate TDD values created an attraction effect.

Spektor et al. (2022) demonstrated the repulsion effect in both preferential and perceptual choice, using similar stimuli and a similar display configuration to Spektor et al. (2018) and Liao et al. (2021). Here, the stimuli were squares containing two bars filled to varying degrees with color. In perceptual choice, participants were to select the stimulus with the largest cumulative filled area. In the preferential choice scenario, participants were told that each filled bar represented one possible outcome of a 50-50 gamble, and they were to select the gamble with the highest expected value. Their results were similar to those of Spektor et al. (2018), however, where both target and competitor choices increased with TDD.

Researchers are clearly using perceptual experiments to demonstrate context effects and test theories of choice. These results are clearly informative and theoretically interesting. However, there are distinct differences between these perceptual choice experiments and the preferential choice experiments in which the attraction effect was originally demonstrated. In preferential choice tasks, participants are typically shown a set of options (e.g., laptops, apartments, washing machines), along with the attribute values associated with each option (e.g., 10 GB RAM, 1500 square feet, 2.7 cubic feet capacity). These attributes are typically represented numerically (Banerjee et al., 2024; Hayes et al., 2024) or with easily discriminable graphical representations (Cataldo & Cohen, 2019). The decoy option, therefore, is rarely selected (e.g., < 5% of all trials in many studies), and these selections are assumed to be the result of inattention or accidental responses. Though participants' preferences may be noisy, researchers can generally assume that participants are able to detect the dominance relationship between target and decoy. Perceptual choice tasks, on the other hand, complicate participants' ability to detect this dominance relationship.

In Spektor et al. (2018)'s experiments, the decoy is selected as often as 25% of all trials in some conditions (see Figure 2.3), far more often than is common in preferential context effect experiments. The decoy is also selected less often in experiment 4a (triangle display) than in experiment 3 (horizontal display). Decoy selections also decrease as TDD increases. Finally, though both target and competitor increase in choice share as TDD increases, the target choice share increases at a higher rate than does the competitor, suggesting a strong trade-off between target and decoy choices; stronger, indeed, than the competitor-decoy trade-off. That is, the mean *Relative Choice Share of the Target*, or RST (Berkowitzsch et al., 2014) increases with TDD in both experiments.

Spektor et al. (2018) found that a relatively small change in stimulus display (arranging stimuli in a triangle rather than a horizontal line) reverses the attraction effect. Why is it that a relatively subtle change in stimulus display led to a qualitative shift in the data? To answer this question, it is worth considering the differences between Spektor et al. (2018)'s data and previous context effect experiments.

Clearly, perceptual discriminability plays a role in Spektor et al. (2018)'s results. Participants clearly are better able to discriminate the target and competitor from the decoy as TDD increases. Any reasonable account of these data should parse value discriminability from genuine context effects.

Below results from a two-alternative forced-choice experiment show that these stimuli are easily confusable and that the triangle display of Spektor et al. (2018) decreases discriminability relative to the horizontal display.

## 2.2 Experiment 1

The goal of Experiment 1 was to test participants' ability to discriminate between rectangles in the perceptual choice tasks of Trueblood et al. (2013) and Spektor et al. (2018). On each trial, participants saw three options (target, competitor, and

decoy). After a short delay, two of the rectangles were highlighted and participants chose which of the two rectangles was larger. This experiment also included a within-participants manipulation to compare discriminability in both the triangle display of Spektor et al. (2018), Experiment 3, and the horizontal display of Spektor et al. (2018) Experiment 4a and Trueblood et al. (2013). Otherwise, with a few exceptions discussed below, the experiment followed the stimulus construction and experimental design of Spektor et al. (2018), Experiments 3 and 4a.

### 2.2.1 Methods

#### 2.2.1.1 Participants.

Data collection took place at the University of Massachusetts Amherst. 86 undergraduate students participated in exchange for course credit. 1 participant who achieved less than 80% accuracy on catch trials (see below) was excluded from all analyses. 1,280 and 1,296 trials from the triangle and horizontal conditions, respectively, with response times (RTs) < 100ms or > 10000ms were also excluded from all analyses, leaving 18,069 and 18,054 trials remaining in the triangle and horizontal conditions, respectively.

#### 2.2.1.2 Stimuli.

Stimuli were gray scale rectangles based on Trueblood et al. (2013) and Spektor et al. (2018).

Stimuli varied based on trial type. The experiment had two types of trials: critical trials and catch trials.

On each critical trial, the target and competitor had the same area<sup>3</sup> but differed on orientation, with one stimulus being wide and the other tall. The decoy always had the same orientation as the target. TDD was varied so that the decoy was always

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<sup>3</sup>Here Spektor et al. (2018)'s design was simplified as both focal stimuli had the same area.

0%, 2%, 5%, 9%, or 14% of the target area. Because the target and competitor always had the same area, this means that the decoy was also 0%, 2%, 5%, 9%, or 14% of the competitor area. These are the TDD values from Spektor et al. (2018), plus a 0% level which acted as a baseline<sup>4</sup>.

On each catch trial, there was one large rectangle and two much smaller rectangles. The large rectangle was  $260 \pm U(-40, 40) \times 200 \pm U(-40, 40) \text{px}^2$ , with a random orientation. The smaller rectangles were  $180 \pm U(-40, 40) \times 120 \pm U(-40, 40) \text{px}^2$ , one wide and one tall.

#### 2.2.1.3 Design.

There were 5 blocks of trials. In each block there were 60 critical trials, 12 at each TDD level, and 30 catch trials. Of the 12 critical trials at each TDD level, 6 trials were presented in the triangle display and 6 trials were presented in the horizontal display. Finally, 3 of the 6 targets in each display condition at each TDD level were wide and 3 were tall. Of each of these 3 trials, one trial was a target-decoy comparison, one trial was a target-competitor comparison, and one trial was a competitor-decoy comparison. Trial order and rectangle order within each trial were randomized. Thus, this was a 5 (TDD: 0%, 2%, 5%, 9%, 14%) x 2 (display: triangle, horizontal) x 2 (target-decoy orientation: wide, tall) x 3 (comparison: target-decoy, target-competitor, competitor-decoy) within-participants design.

#### 2.2.1.4 Procedure.

On each trial, participants saw three rectangles, labeled 1, 2, and 3 (from left to right). The horizontal distance between all rectangles was constant, but 25 pixels of jitter was added to each rectangle's vertical location. The rectangles appeared for 1825ms total, but after 500ms, two of the rectangles changed to a darker shade. Next,

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<sup>4</sup>When TDD=0%, the target and decoy are identical, so labeling is arbitrary.

all three rectangles disappeared from the screen, and participants were asked to select which of the two darker rectangles had the larger area. The procedure was identical for critical trials and catch trials.

Stimuli were presented on computer monitors with a resolution of 1920 x 1080 pixels. The experiment was programmed in jsPsych (De Leeuw, 2015).

## 2.2.2 Results

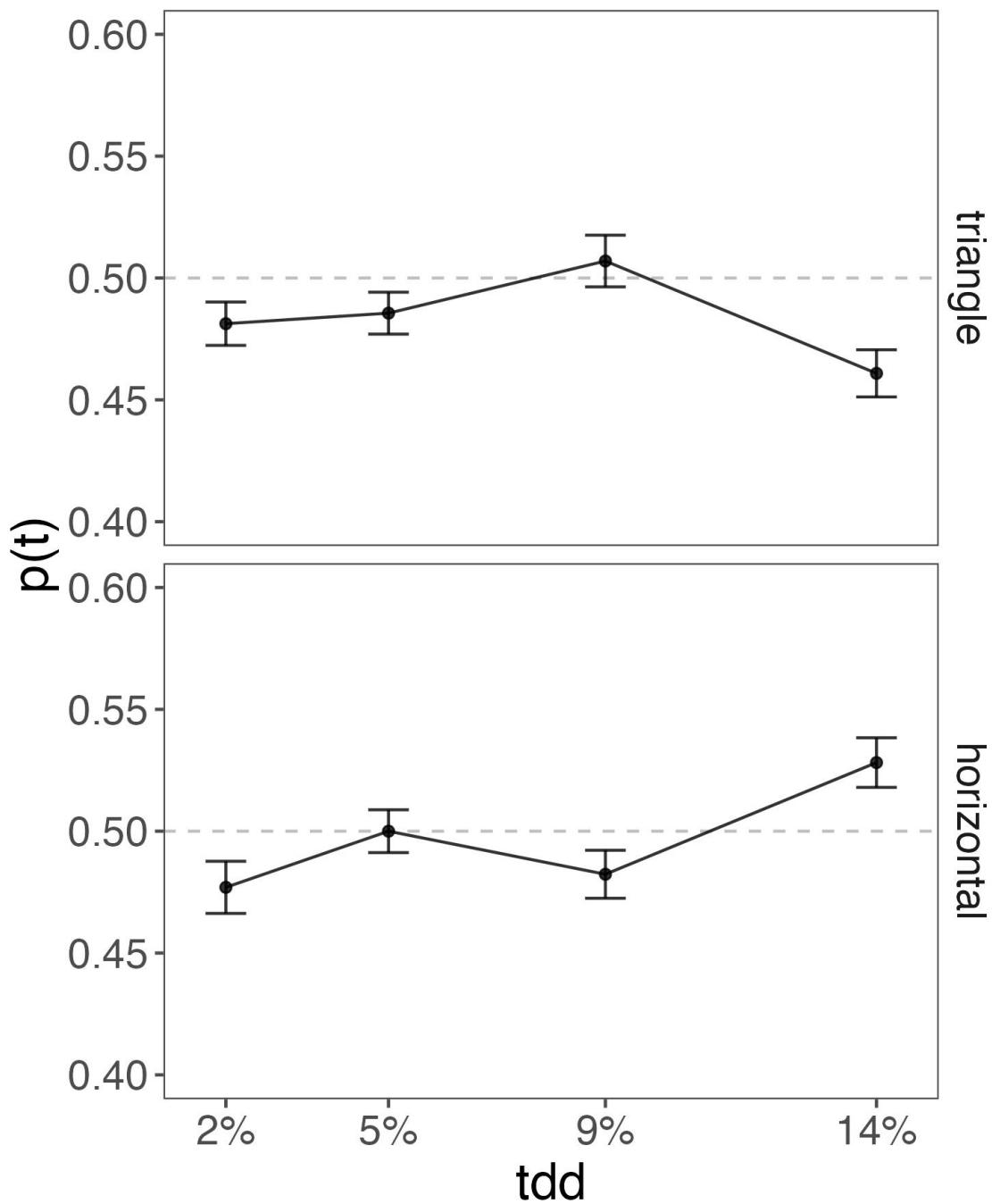
### 2.2.2.1 Catch Trials.

Participants performed well on the catch trials. The mean percentage correct in the triangle display was 92.6% ( $SD = 3.77$ ), and the mean percentage correct in the horizontal display was 93.2% ( $SD = 3.52$ ).

### 2.2.2.2 Critical Trials.

First the baseline TDD level data (TDD=0%) are presented to demonstrate that participants were indifferent between pairs of options when they had identical area. The mean percentage of target choices in target-competitor trials was 48.99% ( $SD=10.18$ , 95% CI [46.80, 51.20]). The mean percentage of competitor choices in competitor-decoy trials was 49.80% ( $SD=11.30$ , 95% CI [47.40, 52.20]). The mean percentage of target choices in target-decoy trials was 49.47% ( $SD=12.06$ , 95% CI [46.90, 52.10]). Participants were indifferent between all pairs of options in the TDD = 0% trials, so these are not considered further.

Next, the target-competitor trials are presented. Note that in these trials, because both stimuli had the same area, there is no correct response. The results are plotted in Figure 2.4, with the y axis (arbitrarily) showing the mean proportion of target selections. Though participants were occasionally biased to select either the target or competitor, there was no systematic pattern to their choices, and these data are not discussed further.



**Figure 2.4.** Experiment 1, mean target choice proportions by stimulus display and TDD for all target-competitor trials. Dashed line is shown at .5.

The primary analysis was performed on the target-decoy and competitor-decoy trials, excluding all TDD=0% trials and the target-competitor trials. Note that participants were to select the option with the largest area. Because the target and competitor were always equal in size, and larger than the decoy, a correct response was one in which the decoy was not chosen.

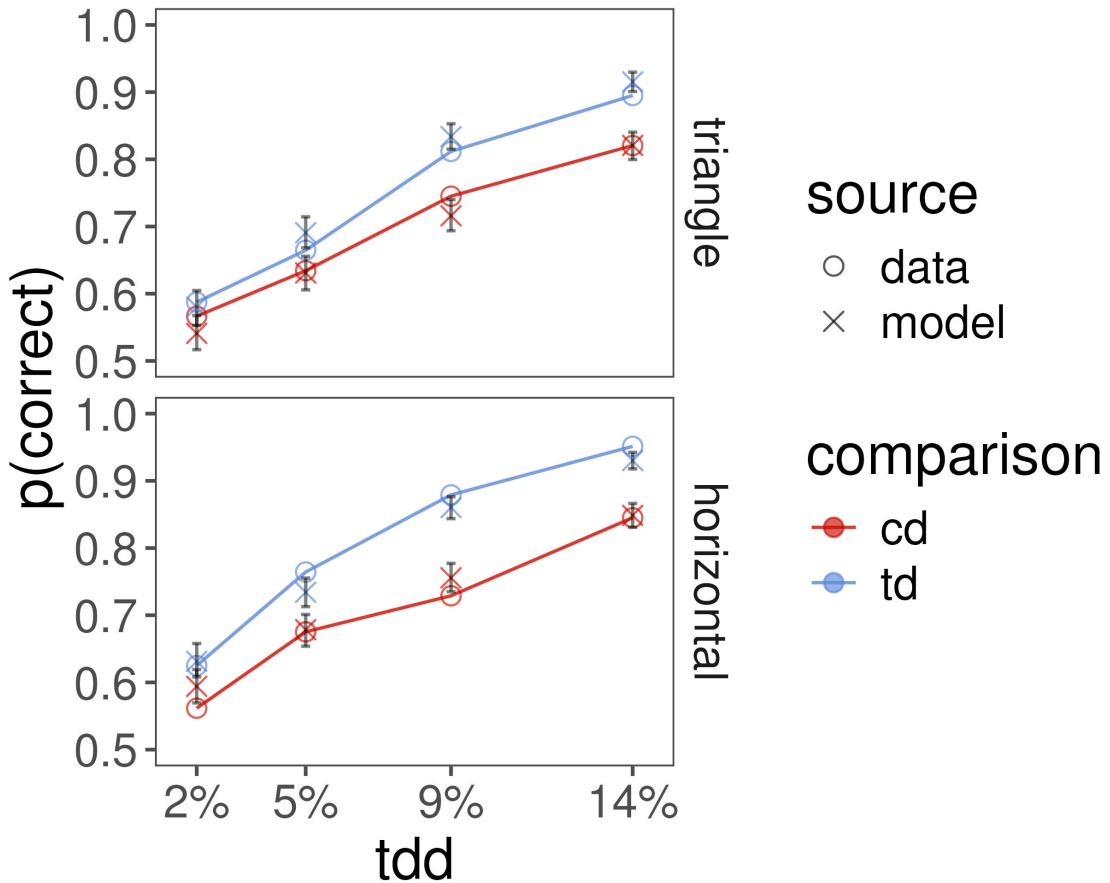
Mean choice proportions across conditions are shown in Figure 2.5. Participants' performance indeed improves with TDD. Furthermore, their performance is better when stimuli are displayed in the horizontal configuration than in the triangle configuration, and it is also better in target-decoy trials compared to competitor-decoy trials. Finally, there is an interaction, such that as TDD increases, the target-decoy performance is even better than the competitor-decoy performance. See the Appendix for inferential statistics which support these conclusions.

### 2.2.3 Discussion

The goal of Experiment 1 was to test participants' ability discriminate between target-decoy and competitor-decoy stimuli in binary perceptual choice. Though participants choose the decoy at non-trivial rates in ternary choice (see Figure 2.3), previous researchers have not tested participants' binary discriminability.

Experiment 1 showed that participants are not always able to discriminate between target-decoy and competitor-decoy stimuli. Additionally, this discriminability increases with TDD and that overall discriminability is better in the horizontal compared to the triangle display. Finally, through the interaction of comparison and TDD, I show that target-decoy discriminability increases with TDD at a higher rate than competitor-decoy discriminability.

These results are important because they show that target-decoy (and indeed, competitor-decoy) discriminability cannot be taken as a given in perceptual context effect experiments. Researchers must carefully consider how perception of the decoy



**Figure 2.5.** Experiment 1, mean choice proportions by stimulus display, TDD, and comparison. td=target-decoy trials, cd=competitor-decoy trials. Model predictions come from the Bayesian hierarchical logistic regression presented in the Appendix and are presented to demonstrate that the model used for inference adequately fits the data. Error bars are 95% HDIs on the mean.

affects choice. The role of perception is theoretically important because any conclusions about context effects being fundamental to choice (Trueblood et al., 2013) rely on the assumption that context effects are qualitatively similar across choice domains.

In the next section, a Thurstonian perceptual choice model is introduced, with the goal of using it to understand the attraction and repulsion effect.

### 2.3 Modeling Context-Dependent Perceptual Choice

Spektor et al. (2018) argued that their work provides partial evidence in favor of the tainting hypothesis, the idea that decoys sometimes "taint" the value of nearby targets, leading to a repulsion effect. They argued that this is supported by the decrease in competitor choice share as TDD increases. They did note that this high level explanation seems implausible for a perceptual rectangle task.

Another plausible account of Spektor et al. (2018)'s data is that participants occasionally perceive the decoy to be at least as large as, or larger than, the target. Indeed, the target and decoy are perceptually similar, more so than the decoy and competitor. Their results may be another form of the similarity effect (Tversky, 1972), where a similar decoy causes a decrease in the choice share of a target option. Simply put, participants may occasionally select the decoy over target, and they do so more often than they select it over the competitor. This account is consistent with the data shown in Figure 2.3. As TDD increases, decoy choices decrease while target choices increase. Though competitor choices also increases with TDD, the target choice shares increase at a higher rate. There appears to be a strong tradeoff between target choices and decoy choices. This explanation is, however, distinct from theoretical accounts of the attraction effect. Spektor et al. (2018) dismiss such an account because the target was always chosen more often than the decoy. This does not, however, rule out that possibility that, on the trials where the decoy was chosen, it was more likely to be chosen over the target than the competitor. In other words,

participants do not always select the decoy; however, when they do, they more often select it over the similar target than the dissimilar competitor.

One goal of this work is to separate the role of perceptual and decisional processes in context effects. To do so, we begin with an extreme stance - that such experiments are solely perceptual experiments rather than decision-making experiments and that no high level decision processes are occurring. This extreme assumption is quite likely incorrect, but it may be helpful in understanding existing data. For example, if a perceptual model can account for the repulsion effect without incorporating higher level decision processes, (such as loss aversion or attribute weighting, as invoked by some cognitive models of context effects), this provides evidence that the repulsion effect is not a decision-making phenomenon, but a perceptual one. On the other hand, if perceptual processes explain part, but not all, of the repulsion effect, this provides evidence that higher-level decision processes must be invoked in a complete theoretical account of these data.

There is a large body of psychological research, beginning with the work of Thurstone (1927), which treats the stimulus perception as a random variable. In his famous "Law of Comparative Judgment" paper, Thurstone (1927) showed that researchers can use binary choice proportions to estimate the psychological distance between stimuli, by treating perceptual intensity as a Gaussian random variable. According to Thurstone's models, given a proportion of the trials on which participants were able to discriminate between two stimuli, researchers can estimate the average psychological distance between these perceptions, scaled by their standard deviations. Thurstone considered multiple forms of this model, but the most relevant model is his Case *II* model, which allows for correlations between perceptions. Models of this class are often called *Thurstonian*.

Thurstone's work has been particularly influential on the choice modeling literature. In marketing and economics, researchers treat the utilities of choice options

as random variables, which are often assumed to be Gaussian or Extreme Value Distributed and estimate choice models known as Random Utility Models (RUMs) (Hausman & Wise, 1978; McFadden, 2001; Train, 2009). Often, though not necessarily, these models share the common property that value - be it the utility of a consumer product, the perception of magnitude in a perceptual task, or memory signal in a recognition task - is stochastic while choice is deterministic (c.f. Benjamin et al. (2009)).

Based on this research, we consider the Thurstonian choice model which will be applied to perceptual choice. This model treats the experiments of Trueblood et al. (2013) and Spektor et al. (2018) as perceptual tasks, rather than decision tasks. This assumption may be incorrect, but the extent to which it can explain existing data can still be highly informative. According to this model, the perceived areas of each rectangle on each trial are sampled from an underlying multivariate probability distribution. Participants then deterministically choose the option with the largest perceived area. Thus, while perception is stochastic, choice is deterministic.

### 2.3.1 A Thurstonian Choice Model

In a perceptual choice task such as that of Spektor et al. (2018), the value/utility of each option is its perceived area. According to the model, on each trial  $i$  with choice set  $K$ , the perception  $\mathbf{X}_i$  of all 3 stimuli is sampled from a multivariate Gaussian distribution:

$$\mathbf{X}_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \quad (2.4)$$

where  $\boldsymbol{\mu}$  is the column vector:

$$\begin{pmatrix} \mu_T \\ \mu_C \\ \mu_D \end{pmatrix} \quad (2.5)$$

where the subscripts  $T$ ,  $C$ , and  $D$  indicate target, competitor, and decoy, respectively.

$\Sigma$  is a positive semi-definite 3x3 covariance matrix computed by:

$$\Sigma = S\Omega S \quad (2.6)$$

where  $S$  is a diagonal matrix consisting of:

$$\begin{pmatrix} \sigma_T & 0 & 0 \\ 0 & \sigma_C & 0 \\ 0 & 0 & \sigma_D \end{pmatrix} \quad (2.7)$$

with  $\sigma_T$ ,  $\sigma_C$ ,  $\sigma_D$  denoting the standard deviations for target, competitor, and decoy, respectively. These parameters reflect the extent to which area perception varies from trial to trial for each stimulus type.  $\Omega$  is a 3x3 correlation matrix:

$$\begin{pmatrix} 1 & \rho_{TC} & \rho_{TD} \\ \rho_{TC} & 1 & \rho_{CD} \\ \rho_{TD} & \rho_{CD} & 1 \end{pmatrix} \quad (2.8)$$

with  $\rho_{TD}$ , for example, denoting correlation between target and decoy perception. These parameters measure the extent to which area perceptions "move" together for

certain pairs of stimuli. For example, as will be shown below, the target and decoy perceptions are strongly positively correlated, meaning that on trials where the target is perceived to be relatively large, the decoy will also tend to be perceived relatively large.

As mentioned above, the model assumes that value is stochastic while choice is deterministic<sup>5</sup>. The model always chooses the option perceived as largest, regardless of the magnitude of the difference between the "winner" and "runners-up". That is, given a vector  $\mathbf{X}_i$  of perceived areas on trial  $i$  with set  $K$ , the probability a participant selects stimulus  $j$  as largest is:

$$P(j|i, K) = P(\mathbf{X}_{ij} > \mathbf{X}_{ik}), \forall k \in K, j \neq k \quad (2.9)$$

If all correlations = 0 and  $\sigma_T = \sigma_C = \sigma_D$ , the model collapses to a trivariate version of the standard Thurstonian Case V model (Thurstone, 1927) often used by cognitive psychology researchers. Models of this form have closed form solutions and their predictions are easy to compute.

On the other hand, if any correlations are non-zero, the closed form solution of this model does not exist, and to compute predictions and estimate model parameters, researchers must use simulation or numerical integration methods (Train, 2009).

This model is easily capable of generating a(n) attraction (repulsion) effect by assuming  $\mu_T > \mu_C$  ( $\mu_C > \mu_T$ ), i.e., that on average target and competitor stimuli differ in their perceived areas. This is an ad hoc assumption that may describe the data well but will generate limited theoretical insight.

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<sup>5</sup>This also assumes ties are not possible, which is true if and only if perceived area is absolutely continuous.

On the other hand, the correlations between perceived area, may allow the model to predict context effects. Other researchers have considered correlations in RUMs as a mechanism for context effects. Kamakura and Srivastava (1984) argued that the correlation between a pair of options in the multinomial probit model reflect their similarity, or substitutability. They implemented a model where the correlation between options is parameterized as a decreasing function of their distance in attribute space. They showed, via simulations, that this model is able to successfully predict the similarity effect. They also fitted the data to risky choice data, which were collected using stimuli designed to elicit the similarity effect, and found that the fitted model could successfully account for the data.

Natenzon (2019) implemented a Bayesian probit model, in which participants are assumed to sample from a multivariate normal distribution on each trial, with the correlation between options being related to their similarity in multiattribute space. Natenzon (2019) also suggested that similarity is related to ease of comparability. They fitted the model to frog mating choice data and showed that not only can the model explain choice reversals (i.e., context effects), but the estimated correlations between pairs of options were greater for options closer in multiattribute space.

It is worthwhile considering then, the role of correlations (i.e.,  $\rho_{TC}$ ,  $\rho_{TD}$ , and  $\rho_{CD}$ ) in predicting the attraction and repulsion effects in perceptual choice.

$\rho_{TD}$  and  $\rho_{TC}$  were varied from -1 to 1; in other words, all rectangles oriented the same way (i.e., target and decoy) shared one correlation and those oriented differently (i.e., target and competitor, decoy and competitor) shared another correlation. These model predictions are shown in Figure 2.6. It was assumed that  $\mu_T = \mu_C > \mu_D$  and that  $\sigma_T = \sigma_C = \sigma_D$ <sup>6</sup>. It is difficult to assess how all parameters may interact if these assumptions are incorrect.

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<sup>6</sup>In Experiment 2 I present evidence supporting these assumptions.

Figure 2.6 shows model predictions in the form of RST<sup>7</sup>, where RST values above .5 indicate an attraction effect and values below .5 indicate a repulsion effect. The model can, depending on the relationship between  $\rho_{TD}$  and  $\rho_{TC}$ , predict a repulsion, attraction, or a null context effect.

First, if  $\rho_{TD} = \rho_{TC} = \rho_{CD}$ , the model predicts a null effect. In this case, no pair of stimuli are more correlated than any other pair, so the predictions are identical to a model where  $\rho_{TD} = \rho_{TC} = \rho_{CD} = 0$ . The decoy will still be chosen occasionally (depending on the relative difference between  $\mu_D$  and  $\mu_T / \mu_C$ ), it does not differentially take choice shares away from the target or competitor.

If  $\rho_{TD} > \rho_{TC}$ , the model predicts a repulsion effect. The correlation between target and decoy causes them to "move" together. If, on a particular trial, the perceived target area is relatively high, the perceived decoy area will also be relatively high. Though the decoy is chosen at a lower rate than target or competitor, the  $\rho_{TD}$  parameter causes it to be chosen over the target more often than it is chosen over the competitor.

Lastly If  $\rho_{TC} > \rho_{TD}$ , the model predicts an attraction effect. The logic here is the similar to the above logic; the decoy and competitor tend to move together, and the decoy is more likely to exceed the competitor than the target.

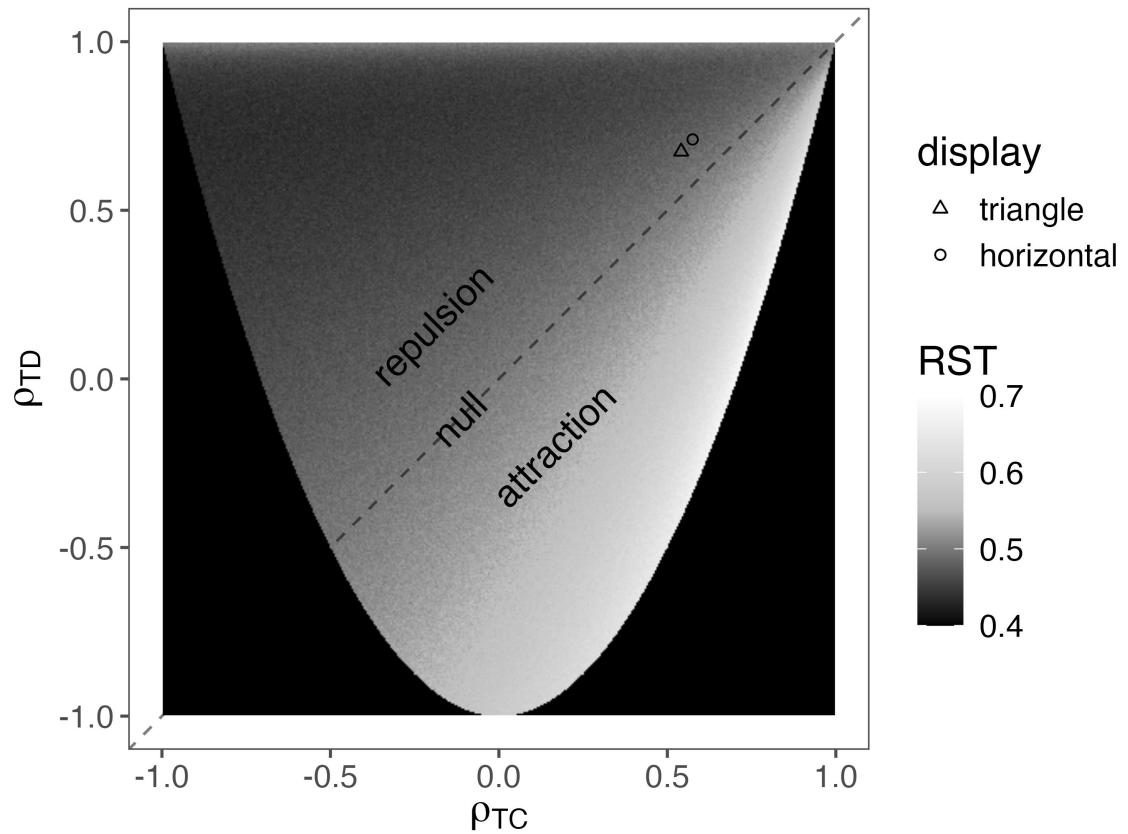
### 2.3.2 Perceptual Correlations as Mechanism for the Repulsion Effect

These perceptual correlations, which cause the decoy to occasionally exceed the target in perceived area, may be, at least partially, driving the repulsion effect in Spektor et al. (2018)'s data.

Experiment 1 demonstrated that participants do not always discriminate between the target and decoy (or indeed, competitor and decoy). Experiment 1 also demon-

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<sup>7</sup>Recall that RST is *Relative Share of the Target*, reflecting the proportion of trials in which the target is chosen over the target, conditional on not having selected the decoy.



**Figure 2.6.** Model simulations for the attraction and repulsion effects based on the variation of  $\rho_{TD}$  and  $\rho_{TC}$ . "Regions" of the plot are labeled based on their qualitative predictions for attraction, null, and repulsion effects. The black region is the area where, due to extreme correlations, a positive semi-definite variance-covariance matrix could not be formed and predictions are unavailable. The triangle and circle mark the estimated mean correlations from the Experiment 2 triangle and horizontal conditions, respectively (see below for details).

strated the triangle display decreases discriminability relative to the horizontal display.

The target and decoy, however, are quite perceptually similar and easier to compare. Simultaneously, however, the fact that target and decoy share an orientation (i.e., both wide or both tall) makes the comparison of these two options easier. At lower levels of TDD, when discriminability is quite difficult (i.e., the difference between  $\mu_D$  and  $\mu_T/\mu_C$  is small), the similarity of target and decoy makes it more likely the decoy is occasionally perceived as larger than the target, than the competitor. I

In statistical terms, the perception of the decoy is more strongly correlated with the perception of the target than with perception of the competitor. These correlations are measured with the  $\rho_{TD}$  and  $\rho_{CD}$  parameters. According to this account, if  $\rho_{TD} > \rho_{CD}$ , the perceived areas of target and decoy "move" together, allowing the competitor to exceed the target at a higher rate than the target exceeds the competitor, particularly if perceptual discriminability is low. This account explains the repulsion effect as a perceptual phenomenon rather than a decision-making phenomenon.

Experiment 2, shown below, combined a psychophysics task with a choice task to estimate the parameters of the Thurstonian perceptual model outlined in the beginning of this chapter. In the first phase of the experiment, participants estimated the size of target, decoy, and competitor rectangles on each trial. In the second phase of the experiment, I conducted a standard choice experiment, replicating Spektor et al. (2018)'s results. I used the data from the first phase of Experiment 2 to obtain stable estimates of  $\boldsymbol{\mu}$  and  $\boldsymbol{\Sigma}$  for the Thurstonian perceptual model. Finally, I show that the model, conditioned on these parameter estimates, naturally predicts a repulsion effect but not an attraction effect.

## 2.4 Experiment 2

The goal of this experiment was to estimate the parameters of the model presented above and to clarify the role of perception and decision in producing the repulsion and attraction effects. The Thurstonian model introduced above can predict the repulsion effect and the attraction effect through the perceptual correlation parameters. However, this model can produce many different data patterns (as shown in Figure 2.6), some of which may be consistent with existing choice data but many others which are not. Thus this experiment allows us to estimate the model parameters using a non-decision task.

Furthermore, participants also separately completed a choice task, replicating Spektor et al. (2018). This allows us to estimate the parameters of the model using the judgment task and then test the model's ability to predict the results of the choice task.

Experiment 2 utilized the *method of cross-modal matching* (Stevens & Marks, 1965), where participants estimate the intensity of a stimulus presented in one modality using a different response modality (e.g., estimating the loudness of a tone by adjusting the brightness of a light). Participants adjusted the size of a circle to match the perceived area for each rectangle.

The experiment Spektor et al. (2018)'s choice data in the second phase of the experiment. In both phases, there was between-participants manipulation to display the rectangle stimuli in either the horizontal or triangle displays of Spektor et al. (2018).

### 2.4.1 Methods

#### 2.4.1.1 Participants.

Data collection took place at the University of Massachusetts Amherst. 521 undergraduate students participated in exchange for course credit. 68 participants did

not complete the full experiment within the 1 hour time limit and were removed from all analyses. 10 additional participants were failing at least 2/8 catch trials from the circle adjustment phase (see below).

After removing participants, this left 218 participants in the horizontal display condition and 225 participants in the triangle display condition.

Choice trials with RTs < 100ms or > 10,000ms were removed from analysis.

#### 2.4.1.2 Stimuli.

Stimuli were gray-scale rectangles, based on the experiments of Spektor et al. (2018) and Trueblood et al. (2013).

Both the circle adjustment phase and the choice phase (see below) had critical trials, the main focus of the experiment. On each critical trial, there was a target, competitor, and decoy rectangle. The target and competitor rectangles were always oriented differently (i.e., one wider than tall and the other taller than wide), while the decoy was oriented the same as the target. Target-decoy distance (TDD) also varied, with the decoy being either 2%, 5%, 9%, and 14% smaller than the target and competitor. For example, if TDD=2%, then the decoy's area is  $\approx 98\%$  the area of the target and competitor. Decoys were created by reducing both the height and width. For example, on the lowest diagonal (see below), the target and competitor had dimension values of 60 and 135 px, and the TDD=2% decoy had dimension values of 59 and 134 px. Decoys where both dimension values are lower than that of the target are known as range-frequency decoys in the context effects literature (Wedell, n.d.).

To introduce variation in the stimuli, the absolute area of the target and competitor also varied. The target and competitor were either 8100, 14850, or 23400 px<sup>2</sup> (with the decoy area changing proportionally based on TDD), falling along one of three diagonals when plotted. See Figure 2.7 for a plot of all critical stimuli. In

pixels, the smaller/larger dimension values on the lower, middle, and upper diagonals were 60/135, 90/165, and 120/195, respectively.

Participants were randomly assigned to either the triangle or horizontal display condition, where, on each trial both rectangles and circles were either arranged in a triangle or in a horizontal array.

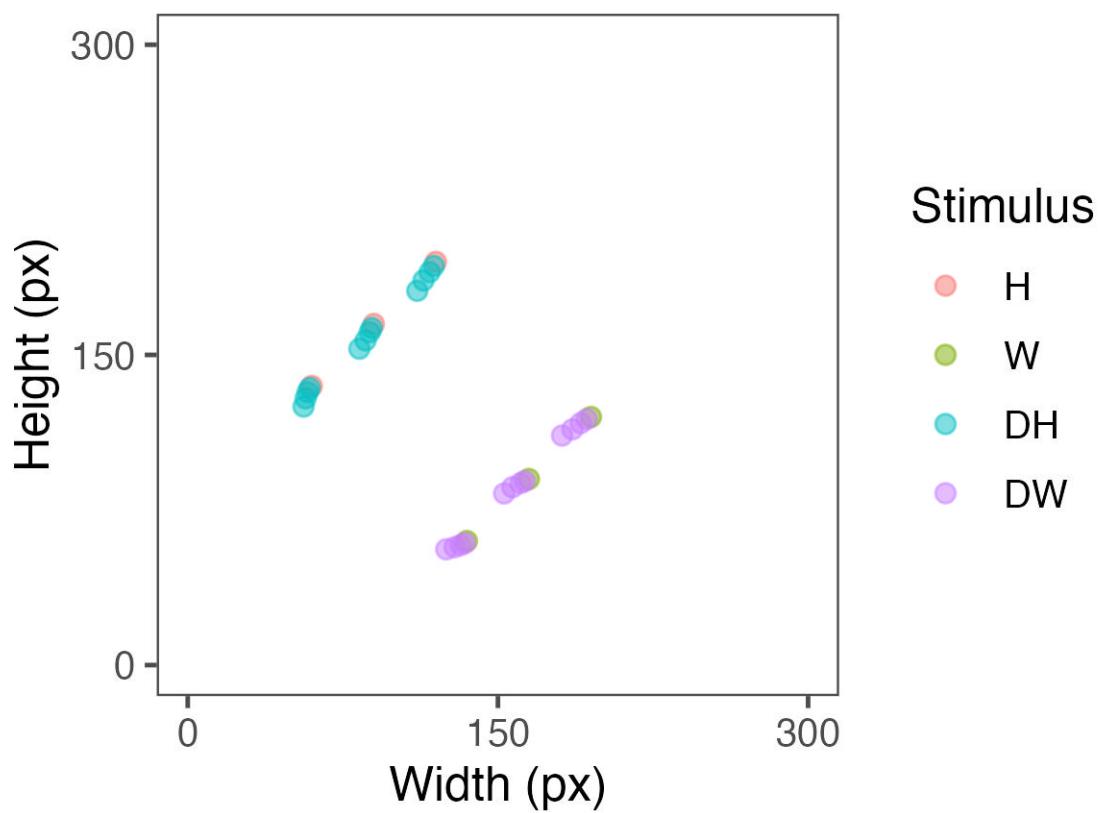
The experiment also contained filler trials (see below). On filler trials, stimuli were randomly generated by independently sampling three rectangles' dimension values from the distribution  $U(56, 195)px$ , the full range of dimension values from the critical trials, where 56px is the smallest decoy dimension value and 195 is the largest target/competitor dimension value.

On the catch trials, one larger stimulus was generated by sampling uniformly from the upper diagonal line from the critical trials (see Figure 2.7). Two additional smaller stimuli were generated by sampling uniformly from the lower diagonal line from the critical trials (see Figure 2.7). This ensured that one rectangle was always larger than the other two rectangles and allowed for the removal of participants who could not complete the task. Specifically, on a given trial, a participant who did not judge the larger rectangle to be greater in area than the other two rectangles was considered to have "failed" this trial. Only participants who passed 6/8 judgment catch trials were retained in the analysis (see above).

The choice phase had identical stimuli with the exception that there were no catch trials, only critical and filler trials. Additionally, there were no circles in this phase (see below).

#### 2.4.1.3 Design.

Across both phases, display condition (triangle, horizontal) varied between-participants and TDD (2%, 5%, 9%, 14%), diagonal (lower, middle, upper), and target-decoy orientation (wide, tall) varied within-participants.



**Figure 2.7.** Stimulus configuration for Experiment 2.

In the circle adjustment phase, there were 4 blocks, each with 40 trials. Each block consisted of 24 critical trials, 14 filler trials, and 2 catch trials. Within the critical trials, there were 6 trials at each level of TDD. In 3 of these 6 trials the target and decoy were oriented wide (choice set  $[W, H, D_W]$ ), and in the other 3 target and decoy were oriented tall (choice set  $[W, H, D_H]$ ).

In the choice phase, there were 4 blocks, each with 34 trials. 24 of these trials were critical trials and 10 were filler trials. Of these 24 critical trials, there were 6 trials at each level of TDD. Within each 6, there were 3 trials where target and decoy were oriented wide and 3 were target and decoy were oriented tall.

#### 2.4.1.4 Procedure.

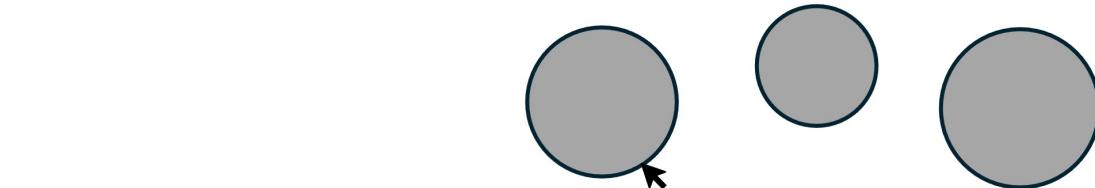
The experiment was presented on computer monitors with a resolution of 1920 x 1080 pixels and programmed with GNU Octave (Eaton et al., 2021) and PsychoPhysics Toolbox (Brainard, 1997).

The experiment took place in two phases: a circle adjustment phase, followed by a choice phase:

On each circle adjustment trial, participants saw three rectangles and three circles, each labeled 1, 2, and 3. The rectangles appeared in the lower left corner of the screen, either in a triangle or horizontal display, depending on the condition to which the participant was assigned. The circles appeared in the upper right of the screen, in the same display as the rectangles (see Figure 2.8 for a sample trial). Stimuli were positioned this way to ensure that participants could not easily compare the circles to the rectangles. A small amount of jitter ( $U(-15, 15)\text{px}^2$ ) was also added to the vertical position of each rectangle and the corresponding circle. Each circle appeared with an area of  $78\text{px}^2$ , the minimum size allowed in the experiment.

Participants were told to adjust the size of each circle until it had the same area as the rectangle with the corresponding label. They used the mouse to adjust the circles.

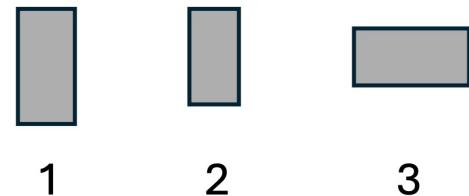
A



1

2

3



1

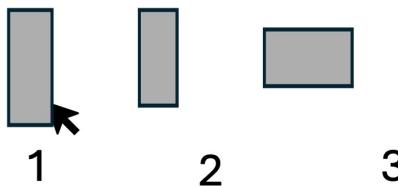
2

3

SUBMIT

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B



1

2

3

Click on the rectangle with the  
largest area.

**Figure 2.8.** Example trials from Experiment 2. A: Circle adjustment phase. B: Choice phase. This is an example from the horizontal display condition.

They were not given instructions on the order they should adjust the circles in or the time they were to spend on the adjustments. The maximum circle area allowed was  $65144\text{px}^2$ <sup>28</sup>, and the minimum area was  $78\text{px}^2$ . When a participant finished adjusting the circles on a trial, they clicked the "Submit" button located on the lower right hand corner of the screen and advanced to the next trial.

The circle adjustment phase began with three calibration trials. Calibration trials were identical to filler trials, with the caveat that participants received feedback after their responses. After participants submitted their responses on a calibration trial, a red circle appeared around each adjusted circle, showing the true area of the corresponding rectangle.

After the calibration trials, the experimental circle adjustment trials began. There were 4 blocks of experimental trials. At the beginning of each block, participants completed 3 calibration trials.

At the end of each block, participants were told that they were either over or under-adjusting, on average, based on the current mean deviation of their responses from the true areas. They were not told the magnitude of their over/under-estimation.

After the circle adjustment phase, the choice phase began. During the choice phase, participants were shown three rectangles on each trial and asked to select the rectangle with the largest area. They were told that they would know their percentage of correct choices at the conclusion of the experiment.

The choice phase began with 3 practice trials, which were identical to the filler trials but separate from the experiment. Participants did not receive feedback during choice practice trials.

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<sup>28</sup>This was the maximum area the circles could be while only appearing on the right half of the screen and maintaining the same horizontal distance from each other as the corresponding rectangles. The minimum possible rectangle area in the experiment was  $3136\text{px}^2$ , while the maximum possible area was  $38025\text{px}^2$ . Thus the range of possible responses was well within the true area of all rectangles.

At the end of the choice phase, participants were told their percentage of correct choices. Note that in a critical trial, a correct response is simply one where the participant did not select the decoy, given that the target and competitor rectangles always had the same area.

## 2.4.2 Results

### 2.4.2.1 Data Processing

These data required processing to ensure that no outliers influenced estimates of  $\mu$  or  $\Omega$ , as it is widely known that outliers can detrimentally influence correlation estimates.

The most substantial data processing occurred in the circle phase data, so these are discussed first.

First, all trials where at least one circle was not adjusted (i.e., at least one circle was left at the starting size) were removed. Given the discrepancy between the starting circle area ( $78\text{px}^2$ ) and the smallest rectangle area shown in the experiment ( $3,136\text{px}^2$ ), these are unlikely to be representative of any participant's true perception of rectangle area.

Next, outlier participants were removed, followed by outlier trials from the remaining participants. An outlier participant is a participant whose responses are substantially different from most other participants, while an outlier trial is a trial from a valid participant, which differs substantially from the rest of a given participant's trials. Outlier participants were first removed, and then outlier trials were removed from the remaining participants.

Outlier participants were identified and removed using the following procedure:

Each individual participant's data were log-transformed<sup>9</sup>. Each participant's data were then fit to a linear regression, regressing each log circle area on each correspond-

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<sup>9</sup>This was done to reduce the skewness observed in the raw data.

ing log rectangle area. Participants whose corresponding  $R^2$  value fell below the 5% quantile for all  $R^2$ 's (.3975 in this case) were removed from all analysis. The 5% quantile was chosen arbitrarily as a conservative threshold to ensure maximum participant retention while removing outliers.

This procedure removed 23 participants, leaving  $N = 420$  participants, 213 in the triangle display condition and 207 in the horizontal display condition. Of the remaining participants,  $R^2$  values were high ( $M = .67, SD = .12$ ), indicating that participants could generally perform the task.

Next, outlier trials were identified and removed using the following procedure:

From the 420 participants whose data were analyzed, outlier trials were removed from the critical trial data. All data points were then z-transformed within each participant and diagonal<sup>10</sup>. All critical trials with at least one z-score with an absolute value above 3.5 were dropped, removing a total of 102 trials. This removed 0, 1, 2, and 4 critical trials from 339, 62, 18, and 1 participants, respectively. This left 20371 data points in the triangle display condition and 19809 data points in the horizontal display condition, where a data point is a vector of the participant's estimated target, competitor, and decoy areas on a given trial.

Only those participants whose data were retained in the circle adjustment phase were retained in the choice phase.

#### 2.4.2.2 Circle Adjustment Phase Results

First, it is important to show that participants could adequately perform the adjustment task. The mean difference between actual log area and estimated log area was computed for each participant, stimulus pair (i.e., target-competitor, target-decoy, competitor-decoy), and actual difference. These results are plotted in Figure 2.9. The x axis shows the actual difference between areas, while the y axis shows

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<sup>10</sup>This was done solely for the removal of outliers, not for the substantive analysis that followed.

the estimated difference in areas according to participants' judgments. Participants' judgments varied considerably along the y axis, but on average, the estimated difference increased with the actual difference.

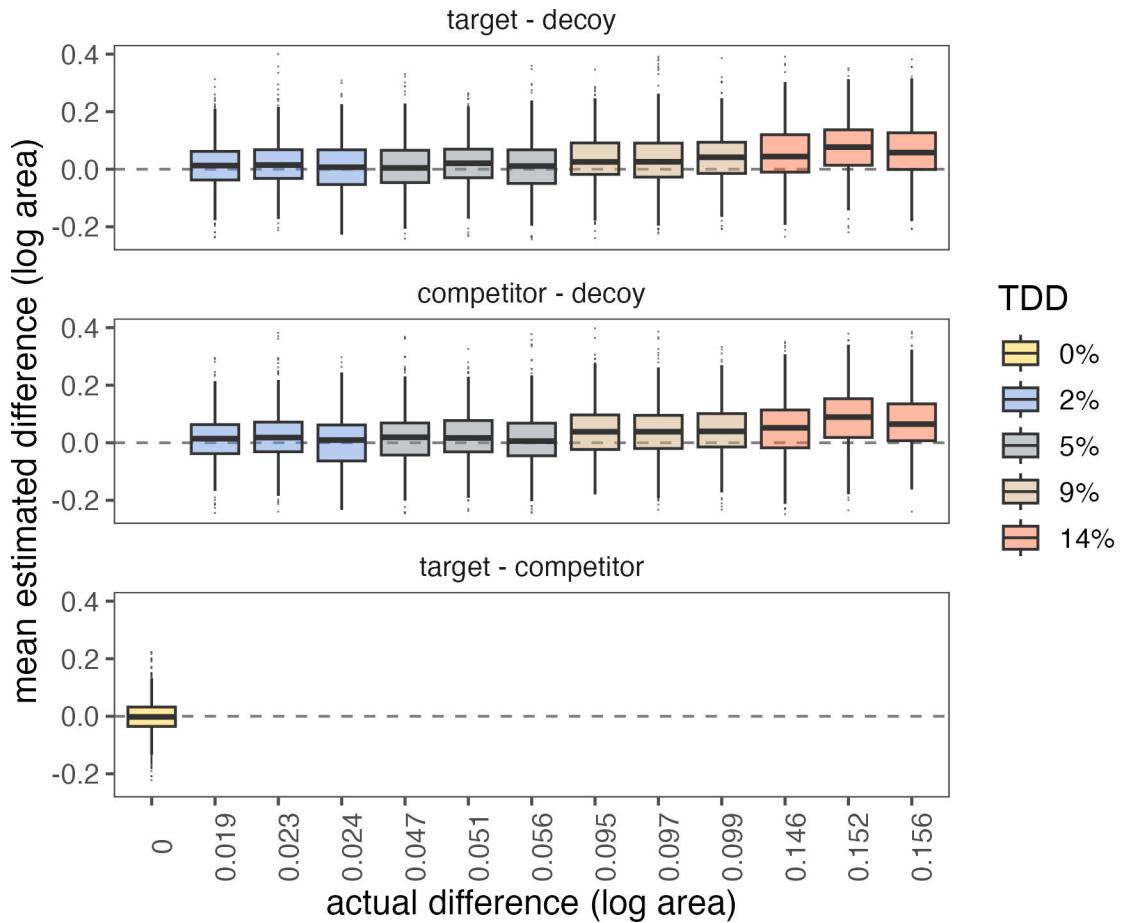
Next scatterplots of all pairwise circle area estimations are shown in Figure 2.10.

I also computed correlation coefficients in each display condition. For the triangle condition,  $r_{td} = .61$ ,  $r_{cd} = .54$ , and  $r_{tc} = .55$ . For the horizontal condition,  $r_{td} = .66$ ,  $r_{cd} = .56$ , and  $r_{tc} = .57$ . In both conditions, the target-decoy correlation is stronger than both the competitor-decoy and the target-decoy correlations.

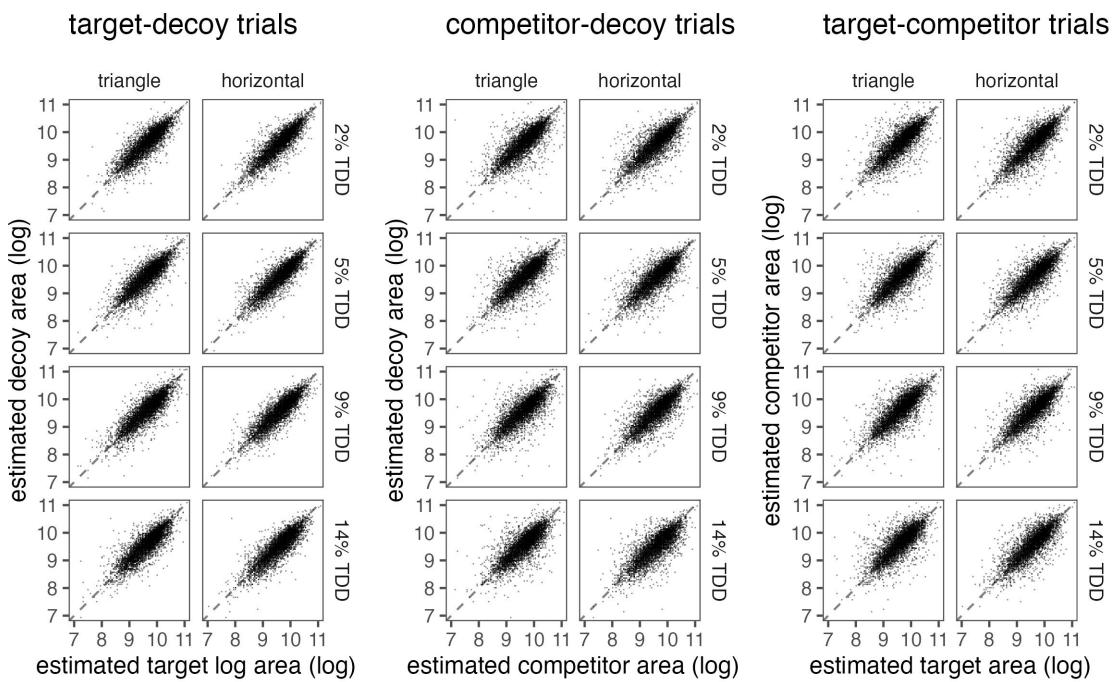
Bayesian hierarchical modeling was used to estimate the parameters of the Thurstonian perceptual model introduced earlier, as well as perform inference on the means and correlations. Though the descriptive parameter estimates are also reported, the Bayesian analysis allows estimating the posterior distributions on each relevant parameter and comparing the range of plausible values across parameters and conditions. Furthermore, the Bayesian hierarchical modeling also takes into account participant-level differences in area estimation.

As an alternative to simply computing descriptive statistics for the relevant components of a multivariate Gaussian (i.e., computing raw means, variances, and correlations), the Bayesian analysis allows us to model the obtained trial-level area judgments as coming from a single joint Gaussian distribution of estimated areas. Additionally, this is also a novel application of the multinomial probit (MNP) model, whose parameters are usually estimated by inferring utilities from choice data (Train, 2009). In the current application, the parameters are estimated using Bayesian modeling and used to predict choices collected from the same participants.

The main text contains estimates of  $\mu$  and  $\Sigma$  (the vector of means and the variance-covariance, respectively), while the details of the estimation procedure are found in the Appendix. As discussed above  $\Sigma$  is a positive semi-definite variance-



**Figure 2.9.** Experiment 2 plots of subject-level mean error in log-transformed area estimations, split by stimulus pair (e.g., target-decoy), TDD, and actual difference in rectangle area. Because the difference in physical area at a given TDD differed across the three diagonals, there are three plots per each TDD level. Note that because the target and competitor rectangles always had equal areas, the true difference is always 0.



**Figure 2.10.** Scatterplots of target-decoy (left), competitor-decoy (middle), and target-competitor (right) log estimated areas, split by display condition (columns) and TDD (rows).

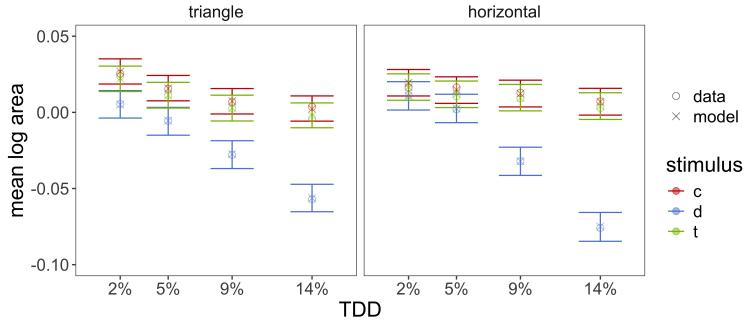
covariance matrix, computed as  $\Sigma = S\Omega S$ , where  $S$  is a vector of standard deviations and  $\Omega$  is a 3x3 correlation matrix.

The estimates of  $S$  suggest no systematic differences in area judgment variance across stimulus type. In the triangle condition, the parameters were as follows:  $\sigma_T: M = 0.34, SD = 0.002, 95\% \text{ HDI } [0.332, 0.338]$ ,  $\sigma_C: M = 0.34, SD = 0.002, 95\% \text{ HDI } [0.335, 0.341]$ ,  $\sigma_D: M = 0.34, SD = 0.002, 95\% \text{ HDI } [0.331, 0.338]$ . In the horizontal condition, the parameters were as follows:  $\sigma_T: M = 0.34, SD = 0.002, 95\% \text{ HDI } [0.334, 0.340]$ ,  $\sigma_C: M = 0.34, SD = 0.002, 95\% \text{ HDI } [0.338, 0.345]$ ,  $\sigma_D: M = 0.34, SD = 0.002, 95\% \text{ HDI } [0.333, 0.340]$ .

Estimates of the  $\mu$  components (averaged across participants) are plotted in Figure 2.11. First, note that the decoy mean is always lower than that of the target and competitor. Furthermore, as TDD increases, the decoy mean decreases, indicating that participants were sensitive to decreases in absolute area, judging smaller rectangles as having smaller areas. Both target and competitor mean areas also decrease with TDD, suggesting that participants somewhat adjusted these areas relative to the decoy.

Focusing solely on the target and competitor means, an interesting pattern emerges. The competitor mean is always larger than the target mean, albeit only slightly. This pattern is somewhat consistent with the tainting hypothesis, the idea that nearby decoys can taint the value of target option (Simonson, 2014). However, the tainting hypothesis predicts that tainting is a decreasing function of distance in attribute space, and the current observed difference between target and competitor means appears to be constant. There is also limited statistical evidence for this difference, as the 95% HDIs overlap considerably at each TDD level in both display conditions (see Figure 2.11).

There is, however, evidence from the Bayesian Hierarchical Regression (see Appendix), via the competitor-specific regression coefficient  $\beta_{comp}$ , that the competitor



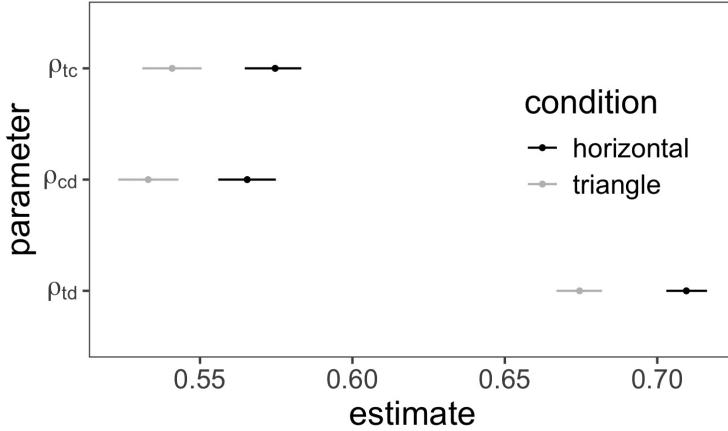
**Figure 2.11.** Experiment 2  $\mu$  estimates. Model values are means, and the error bars are 95% HDIs.

is rated higher than the target, at least in the triangle condition. The  $\beta_{comp}$  parameter captures the tendency for participants to rate the competitor higher than the target, regardless of the TDD or target orientation. In the triangle condition, this parameter was reliably above 0,  $M = 0.005$ ,  $SD = 0.0023$ , 95%HDI [0.0001, 0.009]. Note that this effect is quite small. Given that the data were transformed via the natural logarithm, this corresponds to a  $e^{0.005} = 1.005\text{px}^2$  difference in mean judged area, a considerably small effect size. In the horizontal condition, this parameter was not reliably above or below zero,  $M = 0.003$ ,  $SD = 0.002$ , 95%HDI [-0.002, 0.007]

The estimates of  $\Omega$  components (the correlations) are plotted in Figure 2.12. First, it is worth noting that all correlations are positive. As predicted, in both conditions,  $\rho_{TD}$  is larger than both  $\rho_{CD}$  and  $\rho_{TC}$ , while  $\rho_{CD}$  and  $\rho_{TC}$  do not differ from each other. Interestingly, all  $\rho$  parameters from the horizontal condition are larger than the corresponding parameters from the triangle condition. These inferences should, however, be taken cautiously given that the model was fit separately to each condition.

#### 2.4.2.3 Choice Phase Results

In each trial of the choice phase, participants saw three rectangles and selected the rectangle with the largest area. This was a replication of Spektor et al. (2018).



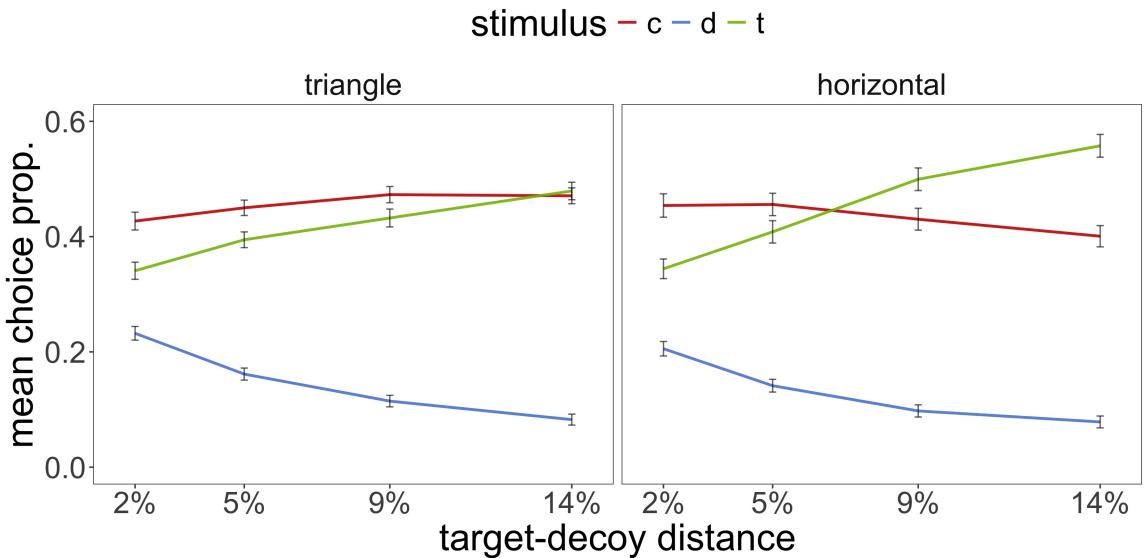
**Figure 2.12.** Experiment 2 posterior estimates of  $\Omega$  off-diagonal parameters across display conditions. Lines show 95% HDIs. Dots indicate means.

Mean choice proportions across display condition and TDD are plotted in Figure 2.13.

At low levels of TDD, the data show a repulsion effect in both display conditions, where participants reliably choose the competitor more than the target. At higher levels of TDD, there was either a small repulsion effect (triangle condition) or an attraction effect (horizontal condition). See the Appendix for inferential statistics that support these conclusions. These data replicate the qualitative results of Spektor et al. (2018).

I also present the mean choice proportions for the current experiment plotted against mean target-decoy discriminability from Experiment 2 in Figure 2.14. These results strongly indicate that the attraction and repulsion effects are related to the perceptual relationship between target and decoy.

Furthermore, when comparing across display conditions, the results show that the point at which the repulsion effect becomes a null effect is strongly related to discriminability. Note that this crossover point occurs at lower TDD levels for the horizontal condition. In other words, the ease of inter-stimulus comparability in the horizontal condition, which facilitates better discriminability in the 2afc discrimina-



**Figure 2.13.** Experiment 2 mean choice proportions for target, competitor, and decoy options, by TDD and display condition. Error bars are 95% CIs on the means.

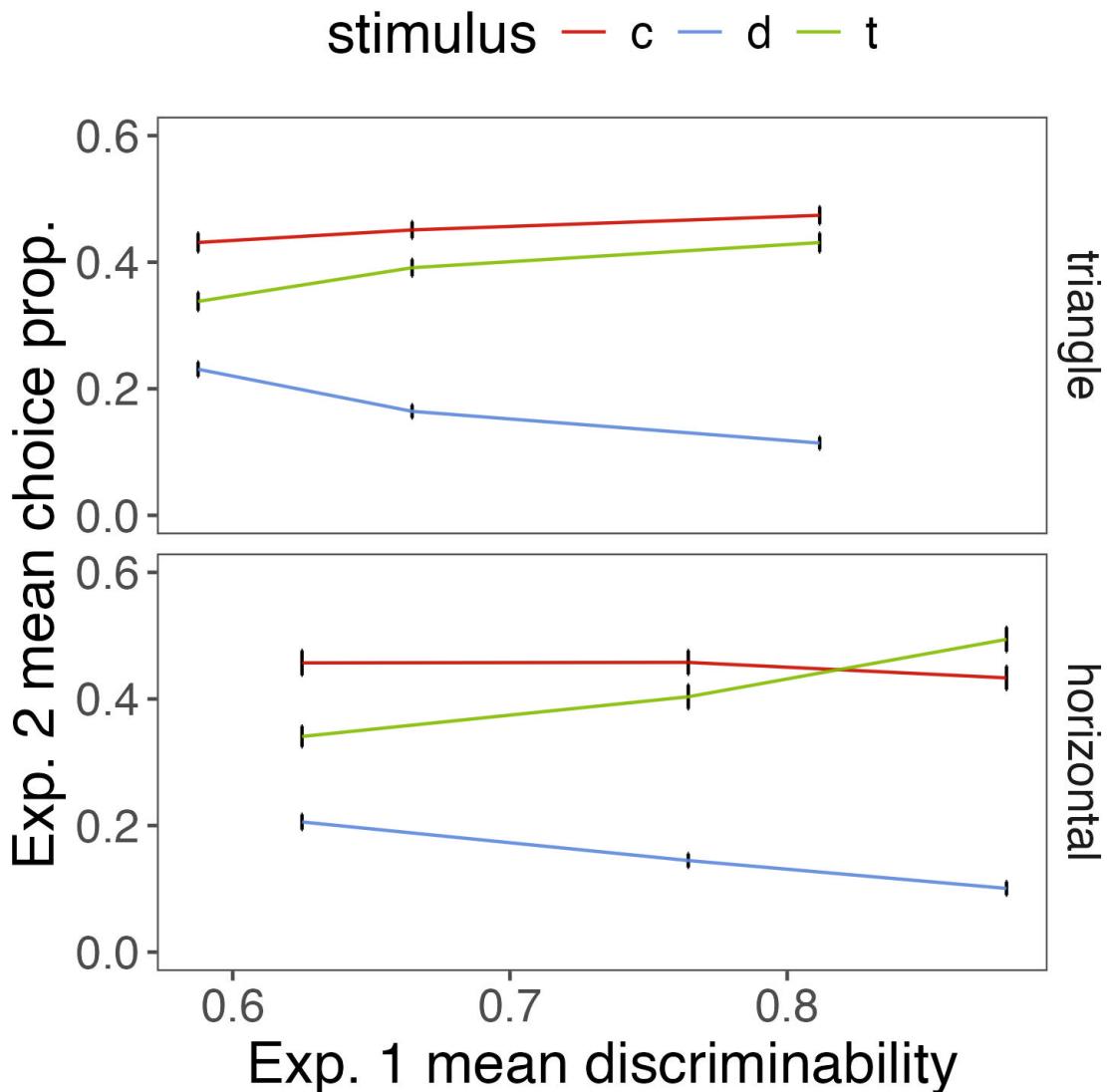
tion task, also requires less discrepancy between target and decoy size in order for the attraction effect to emerge in the ternary choice task.

#### 2.4.3 Model Simulations

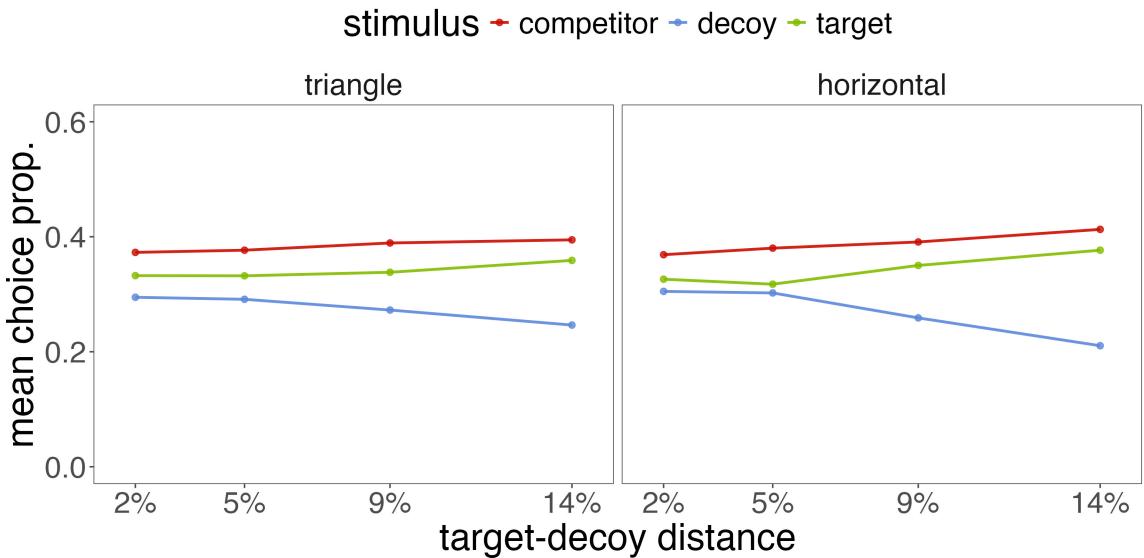
After estimating the parameters of the Thurstonian perceptual choice model and analyzing the choice data, I tested the model’s ability to predict the repulsion and attraction effects. It was an open question whether the parameters estimated from actual data would produce qualitatively accurate predictions.

I used the mean estimates of  $\mu$  and  $\Sigma$  to generate predictions at each level of TDD in each display condition. I present the predicted mean choice proportions in Figure 2.15.

Conditioned on the estimated parameters, the model is able to produce a repulsion effect. This aligns with our predictions from the introduction; the repulsion effect, at least in some forms, can be generated by a higher correlation between target and decoy stimuli compared to target-competitor and competitor-decoy pairs.



**Figure 2.14.** Mean target, competitor, and decoy choice proportions (y axis) for each TDD level in Experiment 2, plotted against mean target-decoy discriminability for each TDD level from Experiment 1. The x axis error bars are 95% HDIs on the mean, computed via the Bayesian hierarchical logistic regression from Experiment 1, and the y axis error bars are 95% CIs on the mean.

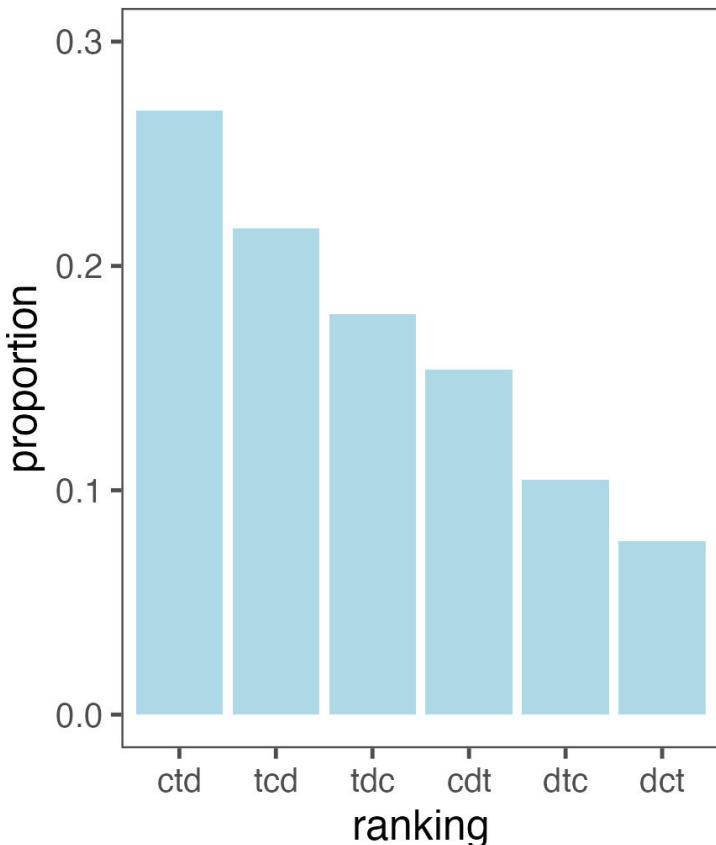


**Figure 2.15.** Model predictions for the choice data, conditioned on the mean estimated parameters from Experiment 2.

The model fails in predicting the null effect found at high TDD levels in the triangle condition, and it also fails completely in predicting the attraction effect. This is unsurprising, as to produce the attraction effect the model requires either  $\mu_T > \mu_C$  or  $\rho_{CD} > \rho_{TD}$ , patterns not shown in the current parameter estimates. The model can produce the repulsion effect from perceptual factors alone, but the attraction effect likely occurs due to higher level decision factors.

## 2.5 Discussion

The results of Experiments 1 and 2 show that participants are not always able to discriminate the decoy from the target and the competitor, and, that target-decoy perceptions appeared to be correlated. The observed correlations can, when embedded in a Thurstonian perceptual choice model, naturally produce the repulsion effect but not the attraction effect. This result is highly informative for decision-making research, as it shows to what extent the effects reported by Trueblood et al. (2013)



**Figure 2.16.** Model-simulated ranking proportions, in the order of largest to smallest.

and Spektor et al. (2018) can be explained by perception alone, and to what extent researchers must invoke higher level decision processes to explain them.

To understand how the model produces the repulsion effect, consider the following simple simulation. Using a multivariate normal model with parameters  $\mu_T = \mu_C = 0$ ,  $\mu_D = -0.1$ ,  $\sigma_T = \sigma_C = \sigma_D = \frac{1}{3}$ ,  $\rho_{TC} = \rho_{CD} = .65$ , and  $\rho_{TD} = .75$  (all comparable values to those estimated in Experiment 2), I simulated 1,000,000 trials of a perceptual choice experiment. On each trial, I computed the *ranking* of all perceived areas; for example, an ranking of "TCD" indicates that the target was perceived as largest, the competitor as second-largest, and the decoy as smallest. The results are plotted in Figure 2.16.

The results show that  $P(CTD) > P(TCD)$ , because the target and decoy tend to move together, making it easier for the competitor to exceed both options. Furthermore,  $P(DTC) > P(DCT)$ , because the relatively large  $\rho_{TD}$  also allows the decoy to be "pulled up" with the target. These correlations also cause  $P(TDC) > P(CDT)$ . In simple terms, if the decoy is in the middle, it is more likely that the target is the largest than it is that the competitor is largest. Note that if we sum up these orderings we can obtain the marginal choice proportions for  $T$ ,  $C$ , and  $D$  which will show a repulsion effect.

Thus far the research provides a statistical account of these data, but a process account is (one) ultimate goal of cognitive psychology research. I argue that the target and decoy, which are inherently more similar to one another than either is to the competitor, are more likely to be compared to one another. This ease of comparison leads to correlated valuations which in turn affects choice. This account is plausible based both on this research and on prior decision-making research.

Cataldo and Cohen (2019) showed that, in preferential choice, context effects can be reversed or eliminated simply by altering stimulus presentation format. For example, they showed that if participants can easily compare pairs of options (e.g., target and decoy) on each dimension, the attraction effect occurs quite strongly, but without this ease of comparison the attraction effect becomes negligible. Hasan et al. (2025) failed to replicate this effect, albeit with different decoys than those of Cataldo and Cohen (2019).

Chang and Liu (2008) also varied option display, in either a by-alternative format, where option names are listed as columns while attribute values are listed as rows, or a by-attribute format, where option attributes are columns while option names are rows. The former display makes it more difficult to compare options on a single attribute, while the latter makes it easier. They found that listing options by-attribute increased the choice share of the compromise option, relative to a by-alternative display.

Hayes et al. (2024) manipulated attribute commensurability in a context effects experiment. When two dimensions are commensurable, they vary on a common unit (e.g., user ratings from 0-10), while incommensurable units exist on incomparable units (e.g., RAM and CPU speed in laptops). They found that when dimensions are commensurable, the attraction effect vanishes, while it still exists strongly when dimensions are incommensurable. This suggests that the attraction effect occurs more strongly when the representation of options encourages between-option comparisons on a single attribute.

Furthermore, modern psychological models of context effects often assume an attribute-wise comparison process (Bhatia, 2013; Roe et al., 2001; Trueblood et al., 2013; Usher & McClelland, 2004). Under this class of models, participants arrive at a decision by comparing pairs of options on a single attribute, where the modeller assumes attribute values are veridical. This assumption is quite reasonable when modeling choices where each attribute is presented separately and discriminability issues are minimal or non-existent. In perceptual choice experiments like those presented here or in Spektor et al. (2018) and Trueblood et al. (2013), these assumptions are likely incorrect. However, the general modeling framework, where inter-stimulus comparison leads to preference, which then leads to choice, is still plausible.

Other researchers have suggested that correlated valuations as a measure of similarity (Kamakura & Srivastava, 1984; Natenzon, 2019). Multialternative Decision Field Theory (MDFT) (Roe et al., 2001) relies on within-trial correlations between similar options to produce the similarity effect, though this mechanism is distinct from the current model, which relies on *across-trial* correlated valuations.

Bhui and Xiang (2021) showed that target and decoy valuations may be correlated, and they further argued that the repulsion effect is rational given a consumer's belief that the target and decoy come from the same distribution (e.g., two products from

the same brand). Bhui and Dubey (2024) similarly argued that context effects can be rational given limited information about options in a choice set.

The results of Experiments 1 and 2 have important methodological implications. Trueblood et al. (2013) and Spektor et al. (2018) designed their studies to test the interesting hypothesis that context effects occur even in low-level, perceptual decision-making. They designed experiments similar to other attraction effect experiments, with two equally viable focal options and an inferior decoy option which is similar to a focal target option. They did not fully consider, however, issues in perceptual variability. While acknowledging that participants may occasionally fail to perceive the dominance relationship, they assumed that this would not affect the overall results. They did not consider the possibility, however, that the target-decoy comparability could cause perceptual correlations which manifest themselves in the choice data. Spektor et al. (2018) even discussed the possibility that their repulsion effect may be a form of the *similarity effect*, where two similar options split choice shares, but they dismissed this hypothesis out of hand because participants chose the target more often than they chose the decoy. I showed in Experiment 2 that despite the fact that  $P(T) > P(D)$ , the decoy is systematically chosen over the target more than it is chosen over the competitor.

Researchers have also argued in favor of the "tainting hypothesis" (Simonson, 2014; Spektor et al., 2018), where the inferior decoy "taints" similar options (i.e., the target). On average, participants did generally rate the competitor as larger than the target in Experiment 2. These results were, however, quite small and not always statistically apparent. Moreover, the model does not require this tainting to produce the repulsion effect.

The existence of context effects in perceptual choice is an interesting phenomenon and one that should be studied further. Still, researchers should be careful in assuming

that an empirical context effect is generated solely by decision processes whenever the choice environment precludes full stimulus discriminability.

There are some limitations to the current experiment. Due to the large amount of data required to estimate a variance-covariance matrix (Martin, 2021; Merkle et al., 2023), I collapsed across participants when estimating  $\Omega$ . This may obscure individual differences, an area of increasing concern in context effect research (Davis-Stober et al., 2023; Liew et al., 2016; Trueblood et al., 2015). Future research should collect enough participant-level data (perhaps by asking participants to return for multiple experimental sessions) to allow participant-level variation in  $\Omega$  estimates. It would be of great theoretical interest if individual differences in  $\Omega$  could explain individual variation in the attraction and repulsion effects.

As discussed in the Appendix, participants were biased to choose wide rectangles as larger than tall rectangles, but they tended to rate tall rectangles as being larger than wide (at least in the triangle condition). The latter effect is quite small (i.e., smaller than that of the difference between the target and the smallest decoy), but it is nonetheless present in the data. I currently have no strong explanation for this result. Gronau et al. (2023) compared participants' ability to perform a perceptual discrimination task based on whether they responded via an ordinal rating scale or a choice. The authors concluded that participants relied on the same representation in both cases, but the participants were more sensitive to stimulus-level differences when choice responses were collected. It may be that, in Experiment 2, the relative lack of perceptual sensitivity caused participants to slightly underestimate their reported responses to stimuli they actually *perceived* as larger. This bias reversal may also be idiosyncratic statistical variation which may not appear in future samples. It is also not particularly theoretically important. We are mainly interested in target, decoy, and competitor ratings (collapsed across orientation), rather than perception of area

*per se.* Nonetheless, this result may be of interest to perceptual (e.g., vision science) researchers.

In the next chapter, I test a prediction of the perceptual model in best-worst choice. I also use these results to test a well-studied theoretical model of the best-worst choice experimental paradigm.

# CHAPTER 3

## EXTENDING A PERCEPTUAL MODEL TO BEST-WORST CHOICE

### 3.1 Introduction

In Chapters 1 and 2, I presented a model of perceptual choice and showed how, conditioned on estimated parameters, it can systematically predict the repulsion effect, but not the attraction effect. In this chapter, I test another prediction of the model while demonstrating an important empirical result in another choice domain: best-worst choice.

#### 3.1.1 Introducing Best-Worst Choice

Best-worst choice is an experimental paradigm where participants select their most and least preferred options from a choice set. Originally proposed by Finn and Louviere (1992), best-worst choice is widely used in a number of applied fields, such as transportation (Beck & Rose, 2016) and healthcare economics (Cheung et al., 2016; Flynn et al., 2007a; Mühlbacher et al., 2016). One key advantage, when compared to discrete choice research, is that researchers can use best-worst choices to gain information about participants' ranking of options while never requiring them to complete a full ranking task (Flynn & Marley, 2014).

Researchers have developed theoretical models to account for best-worst choice data. These models relate best-worst choices to an underlying utility function (or functions). Marley and Louviere (2005) developed a class of models known as the

*maxdiff* (maximum difference) models of best-worst choice<sup>1</sup>. According to the maxdiff model, given choice set  $K$ , the probability of selecting option  $x$  as best and option  $y$  as worst (denoted  $BW(x, y)$ ), where  $x \neq y$ , is defined computed as:

$$BW_K(x, y) = \frac{e^{u_x - u_y}}{\sum_{\substack{p,q \in K \\ p \neq q}} e^{u_p - u_q}} \quad (3.1)$$

where  $u_i$  is the utility of option  $i$ . This model proposes that a single utility scale determines the selection of both the best option and the worst option in a choice set. It assumes that best-choice probabilities are an increasing function of  $u$ , while worst-choice probabilities are a decreasing function of  $u$ . The use of the exponential function means that the maxdiff model is another form of the widely used multinomial logit (MNL) choice model (Hausman & McFadden, 1984). Utilities are also assumed to be independent of each other.

There are several variants of this model along with other best-worst choice models (Flynn & Marley, 2014; Flynn et al., 2007b; Marley & Louviere, 2005; Marley & Pihlens, 2012; Marley et al., 2008), though the maxdiff model from Equation 3.1 remains the dominant model for analyzing best-worst choice data.

The maxdiff model predicts a decreasing monotonic relationship between best-choice probabilities and worst-choice probabilities (Hawkins et al., 2014a). Researchers have explored whether this monotonicity holds empirically. Hawkins et al. (2014b) tested both preferential and perceptual best-worst choice data using response time modeling. They used the linear ballistic accumulator model (LBA) (Brown & Heathcote, 2008), which casts the decision process as a race between "accumulators" towards a threshold, where the average accumulation across trials is captured by the drift rate parameter. Modeling both preferential and perceptual best-worst choice

<sup>1</sup>Note that the term maxdiff is sometimes erroneously used to refer to best-worst experiments in the generic sense. Following Marley and Louviere (2005), I use maxdiff to refer to a specific class and parameterization of a best-worst choice model.

data, they were able to successfully account for choice data by assuming a parallel race between best and worst accumulators for each option. Furthermore, they showed that the utility values estimated for each option using a MNL model were positively linearly related to the log drift rate values from the LBA, suggesting an underlying utility representation that explains both best and worst choices.

In a follow-up article, Hawkins et al. (2014a) found that, collapsing across choice sets, best-choice probabilities are monotonically related to worst-choice probabilities. Options that were most likely to be selected as best were least likely to be selected as worst, and vice versa. This finding held for perceptual choice and consumer choice. They also showed that, using the parallel best-worst LBA as a model, the drift rate parameter for worst choice can be parameterized as the reciprocal of the best choice drift rate.

Both the parallel best-worst LBA and the maxdiff model assume that the utilities of all options presented are independent. However, as I show below, the Thurstonian perceptual model from Chapters 1 and 2 predicts, under certain conditions, a dissociation between best and worst choices inconsistent with this assumption.

### 3.1.2 Model-Based Dissociations in Best-Worst Choice

Below, the Thurstonian perceptual model from Chapter 2 is used to make a prediction regarding a dissociation between best choices and worst choices.

Let  $K$  be a choice set consisting of options  $T$ ,  $C$ , and  $D$  (i.e., target, competitor, and decoy). As in Experiments 1 and 2, the options are rectangles in a perceptual choice experiment. As in Chapter 2, I assume that on each trial  $i$  with choice set  $K$ , the vector  $\mathbf{X}_i$  of perceived areas is sampled from a multivariate Gaussian distribution with a mean vector  $\boldsymbol{\mu}$  and variance-covariance matrix  $\boldsymbol{\Sigma}$ .

Following conventions in the literature, I use  $B(j)$  to denote the probability of selecting option  $j$  as best and  $W(k)$  to denote the probability of selecting option  $k$  as

worst. I also require the model (and participants in the experiment) to never select the same option as best and as worst.

I assume that, given a vector  $\mathbf{X}_i$  of perceived areas on trial  $i$  with set  $K$ , the probability a participant selects stimulus  $j$  as best is:

$$B(j|i, K) = P(\mathbf{X}_{ij} > \mathbf{X}_{ik}), \forall k \in K, j \neq k \quad (3.2)$$

while the probability of selecting stimulus  $j$  as worst is:

$$W(j|i, K) = P(\mathbf{X}_{ij} < \mathbf{X}_{ik}), \forall k \in K, j \neq k \quad (3.3)$$

Simply put, the option with the largest perceived area is always selected as best, while the option with the smallest perceived area is always selected as worst.

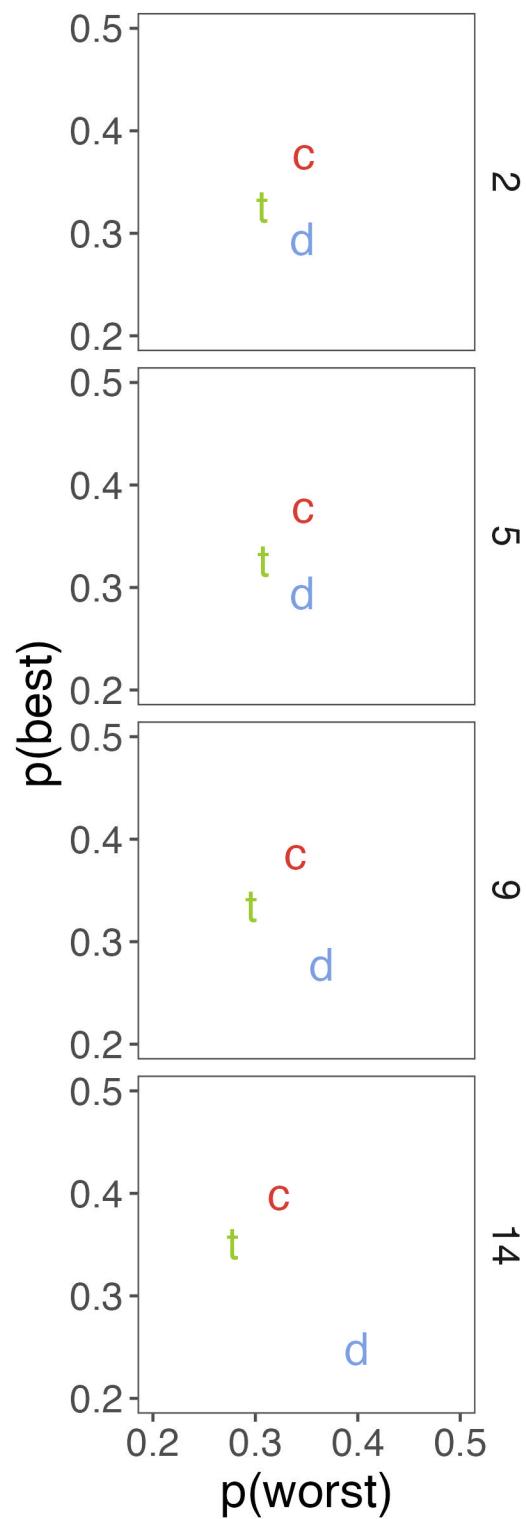
As it happens, the correlations (i.e.,  $\Omega$ ) estimated from Experiment 2 predict that, in a best-worst choice paradigm, best and worst-choice probabilities are non-monotonically related.

I computed predictions for best-worst choice by simulating the model using the mean parameters ( $\boldsymbol{\mu}$  and  $\boldsymbol{\Sigma}$ ) estimated from Experiment 2<sup>2</sup> and simulated a large number of trials ( $N = 1,000,000$ ). As in previous simulations, I collapsed over choice set (i.e., whether the target is wide or tall) and focused on target, competitor, and decoy choice proportions at each level of TDD. I present these results in Figure 3.1, in a series of state-trace plots (Ashby & Bamber, 2022; Bamber, 1979). In a state-trace plot, the analyst plots two dependent variables against one another in each experimental condition.

The model, conditioned on the estimated parameters, predicts an interesting result. Although the competitor is most frequently chosen as best, due to the repulsion effect from Experiment 2 and from Spektor et al. (2018) Experiment 3, it is

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<sup>2</sup>I used only those estimated from the triangle condition (See Experiment 2).



**Figure 3.1.** Simulated best-worst predictions per the Thurstonian perceptual model. Each row is a different TDD value from Experiment 2.

not, however, least frequently chosen as worst. Specifically,  $B(C) > B(T)$ , while  $W(T) < W(C)$ . At lower levels of  $TDD$ , the model even predicts that competitor and decoy are chosen at similar rates. As we will see, this prediction does not bear out empirically, and this prediction is likely due to the fact that participants are generally less sensitive to perceptual differences when providing ratings than when making choices (Gronau et al., 2023).

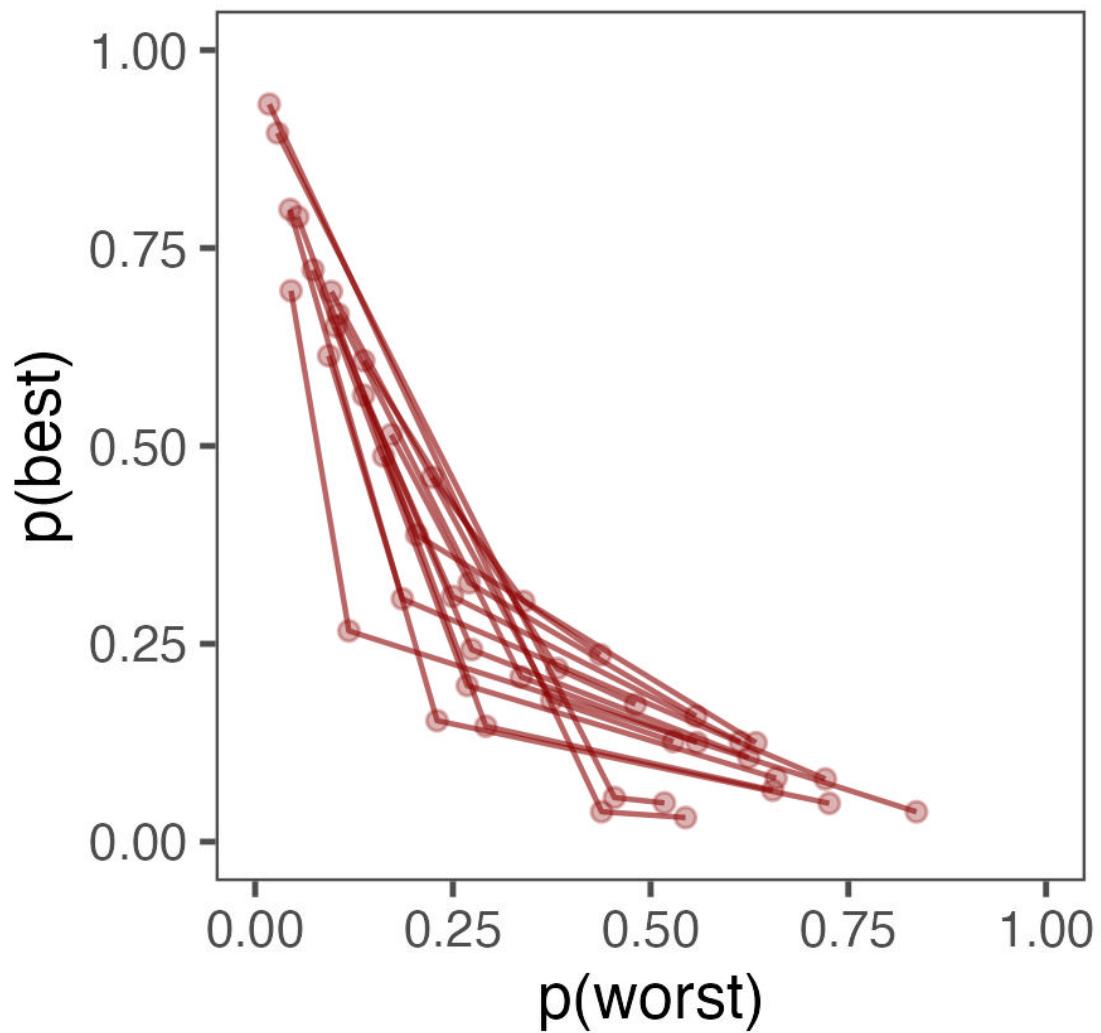
The Thurstonian perceptual model predicts this because  $\rho_{TD} > \rho_{CD} \approx \rho_{TC}$ . On the (relatively few) trials where  $X_{iD}$  is largest, it is more likely that  $X_{iD} > X_{iT} > X_{iC}$  than  $X_{iD} > X_{iC} > X_{iT}$ . In other words, the high  $\rho_{TD}$  value "pulls up" the target more than the competitor. The similarity, and comparability, of target and decoy thus entail that the repulsion effect at the best-choice level (Experiment 2) does not necessarily show up at the worst-choice level.

This effect is subtle, and the predicted effect size is small. Indeed, all differences in predicted  $W(C) - W(T)$  values were  $< .05$ . In Experiment 3, I show the empirical and modeling results from a best-worst choice experiment designed to test this prediction. I show that the dissociation between best and worst choices does indeed occur. I also show that the assumption of monotonicity required by the maxdiff model can fail empirically.

The maxdiff model, on the other hand, necessarily predicts a monotonic state-trace plot. That is, if we assume all options' utilities are independent, the model predicts that best-choice probabilities are negatively related to worst-choice probabilities. To demonstrate this, I simulated the maxdiff model using randomly generated independent utilities and plot results in Figure ??.

## 3.2 Experiment 3

The goal of Experiment 3 was to test the predictions of the Thurstonian perceptual choice model. Specifically, the perceptual model predicts that  $B(C) > B(T)$  but



**Figure 3.2.** Best-worst choice simulations using the maxdiff model. Each curve is a separate simulation. The model predicts a negative, monotonic relationship between best-choice and worst-choice.

$W(T) < W(C)$ . To test this prediction, I used stimuli identical to those of Experiment 2 and presented stimuli in the triangle display. I show that this prediction holds empirically and the maxdiff model cannot account for these results.

### 3.2.1 Methods

#### 3.2.1.1 Participants.

Data collection took place at the University of Massachusetts Amherst. 392 undergraduate students participated in exchange for course credit. 23 participants who achieved less than 80% accuracy on catch trials (see below) were excluded from all analyses. Trials with response times (RTs)  $< 100\text{ms}$  or  $> 10000\text{ms}$  were also excluded from all analyses.

#### 3.2.1.2 Stimuli.

The experiment had three types of trials: critical trials, filler trials, and catch trials.

Stimuli on critical trials were identical to those of Experiment 2. On each critical trial, the target and competitor had the same area but differed on orientation, with one stimulus being wide and the other tall. The decoy always had the same orientation as the target. I varied TDD at 2%, 5%, 9%, and 14%. I also varied the target, competitor, and decoy rectangles along three diagonals, as in Experiment 2.

On each filler trial, three stimuli were uniformly sampled from the space between the largest and smallest diagonals.

On each catch trial, one stimulus was sampled from the largest diagonal, while two stimuli were sampled from the smallest diagonal.

### **3.2.1.3 Design.**

There were 8 blocks of trials. In each block there were 24 critical trials, 6 at each TDD level. There were 8 trials per diagonal. In addition to the critical trials, there were 10 filler trials and 3 catch trials per block.

Participants were randomly assigned into one of two conditions: best-worst or worst-best. On each trial, participants in the best-worst condition first chose the largest rectangle and then chose the smallest rectangle. Participants in the worst-best condition chose in the opposite order. The condition factor was included to account for the possibility that best-worst choice order impacts choice. Results were consistent regardless of condition, so I collapsed over this factor in the analyses reported below.

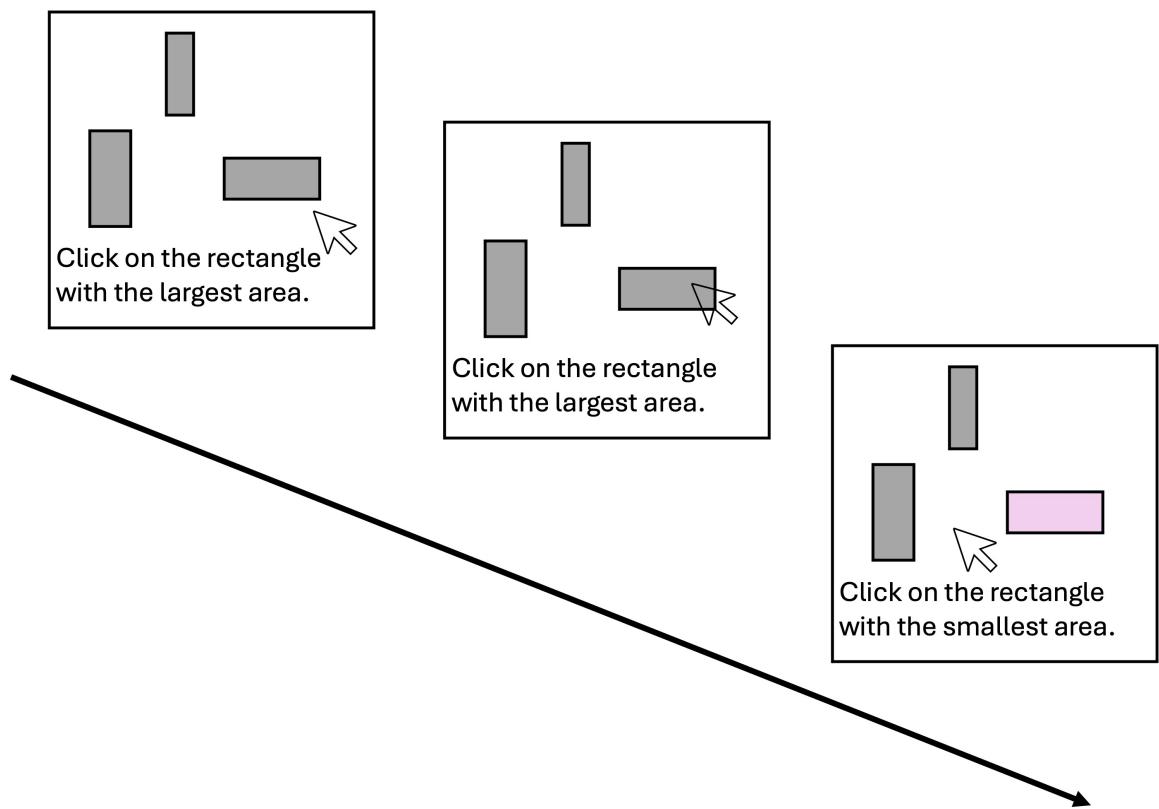
After removing participants, there were 185 participants in the best-worst condition and 184 participants in the worst-best condition.

Stimuli were presented on computer monitors with a resolution of 1920 x 1080 pixels. The experiment was programmed with GNU Octave and Psychtoolbox (Brainard, 1997; Eaton et al., 2021).

### **3.2.1.4 Procedure.**

The experiment began with three practice trials, which were identical to the filler trials.

On each trial, participants saw three rectangles, labeled 1, 2, and 3 (from left to right), arranged in a triangle display. Participants in the best-worst (worst-best) condition saw a prompt asking them to select the largest (smallest) rectangle on screen. Participants used the mouse to click their choice. After they made their choice, this rectangle changed color to indicate that it was no longer available as an option. Next, participants in the best-worst (worst-best) condition selected the smallest (largest) rectangle, at which point the trial ended. See Figure 3.3 for an example trial.



**Figure 3.3.** A sample experimental trial from Experiment 3. Note that this is a trial in the best-worst condition.

Stimulus order was randomized on each trial.

Participants were told their percentage correct of best choices, worst choices, and overall choices at the end of the experiment.

### 3.2.2 Results

#### 3.2.2.1 Catch Trials.

Participants performed well on the catch trials. The mean percentage correct for best choices was 97.97%( $SD = 14.09$ ), and the mean percentage correct for worst choices was 98.26%( $SD = 13.09$ ). The mean percentage correct for both best and worst choices (i.e., the mean percentage of the trials on which participants were able to correctly identify the largest and smallest rectangles) was 96.98%( $SD = 17.12$ ).

#### 3.2.2.2 Filler Trials.

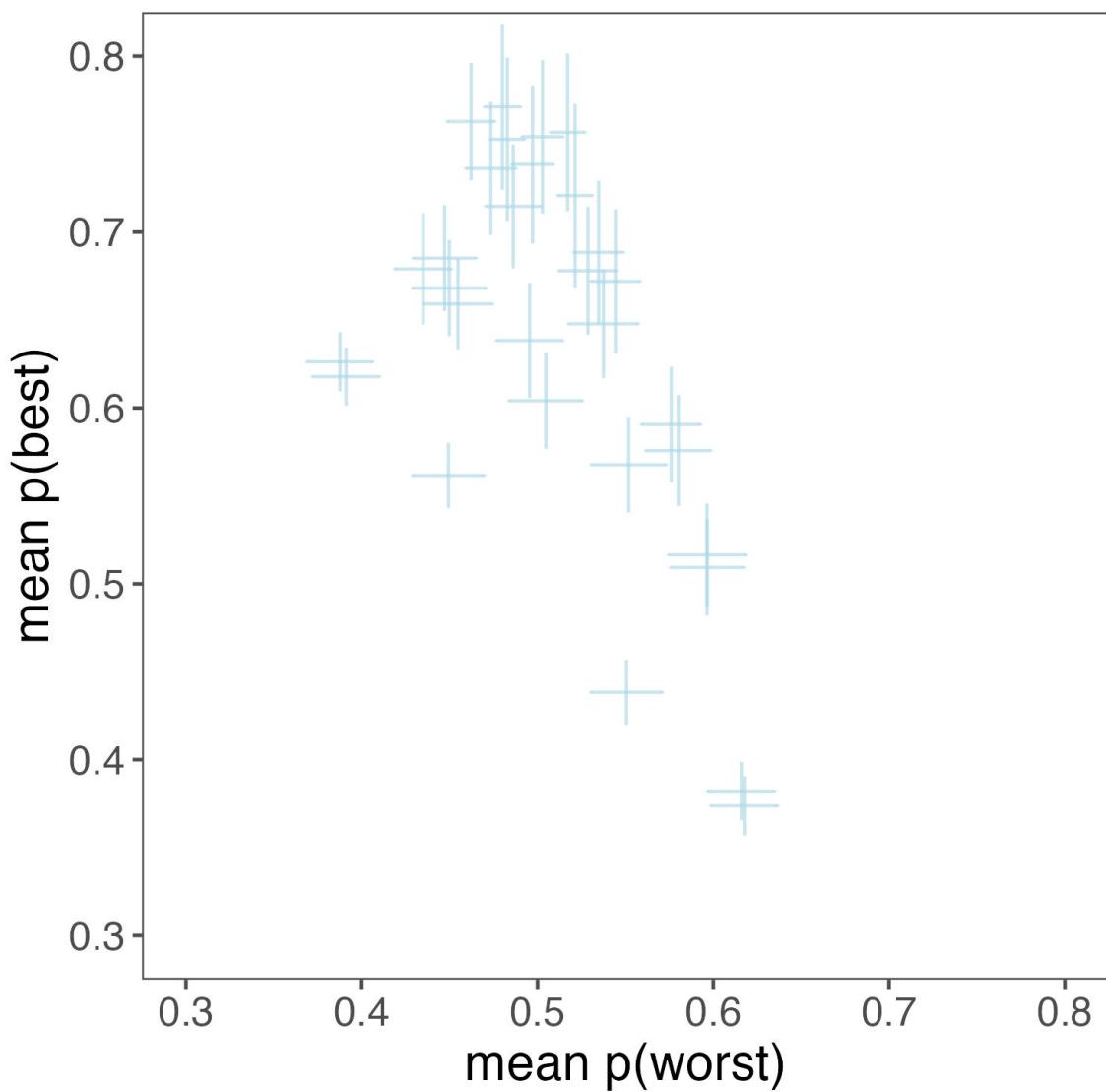
Participants performed worse on the filler trials compared to the catch trials, but still well above chance. The mean percentage correct for best choices was 89.83%( $SD = 30.23$ ), and the mean percentage correct for worst choices was 88.95%( $SD = 41.35$ ). The mean percentage correct for both best and worst choices was 80.95%( $SD = 39.37$ ).

#### 3.2.2.3 Critical Trials.

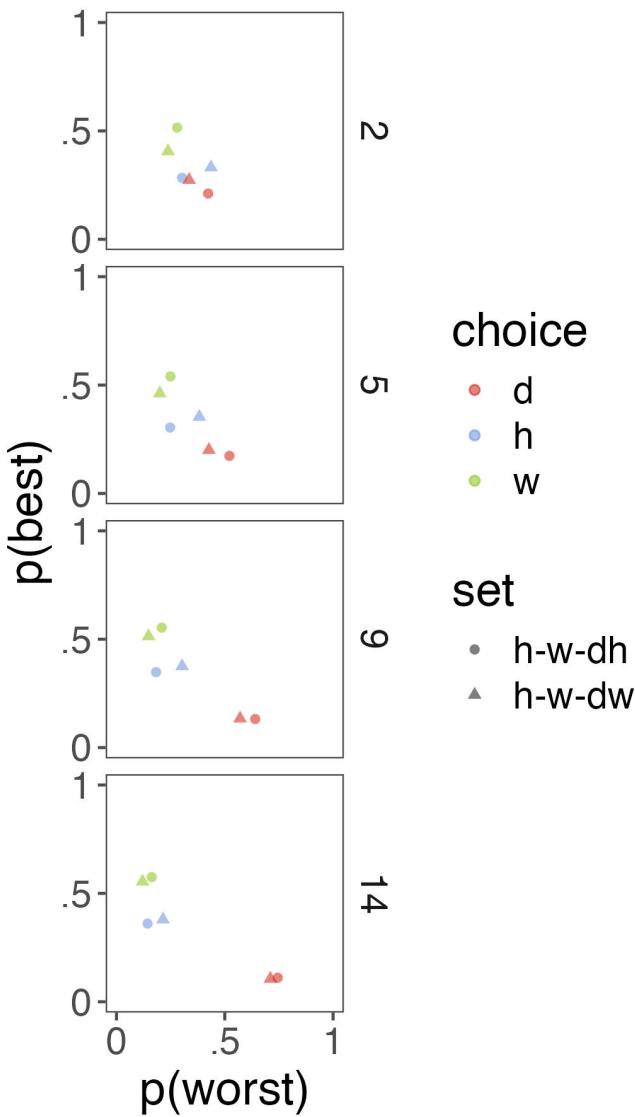
First, I computed the mean choice proportions for each distinct rectangle, collapsed across choice set. Here, I replicated the findings of Hawkins et al. (2014a), that, when ignoring the effect of context, best choices and worst choices are monotonically related. These data are plotted in Figure 3.4.

Next, I analyzed choice proportions by conditioning on TDD and choice set. Mean choice proportions for these data are plotted in Figure 3.5.

Participants showed a consistent bias to choose  $w$  (the wider rectangle) as largest, a finding also shown in Experiments 1 and 2. Participants also (on average) regularly



**Figure 3.4.** Experiment 3 marginal mean best and worst-choice proportions for all unique rectangles, collapsed across choice set. X and Y axis error bars are 95% CIs.



**Figure 3.5.** Experiment 3 mean best and worst-choice proportions for the  $h$ ,  $w$ , and  $d$  rectangles, conditioned on TDD (rows) and choice set (shapes).

choose the decoy rectangle as smallest, with the exception of the choice set  $h, w, d_w$  and  $TDD = 2\%$ , where they selected the  $h$  rectangle as smallest, on average. This can be attributed to the difficulty of the  $TDD = 2\%$  condition and the overall wide rectangle bias. However, consistent with the predictions of the model, the target was still less likely to be chosen as worst than the competitor,  $W(h|h, w, d_h) < W(h|h, w, d_w)$  and  $W(w|h, w, d_w) < W(w|h, w, d_h)$ , while the competitor option was more likely to be chosen as best,  $B(h|h, w, d_w) > B(h|h, w, d_h)$  and  $B(w|h, w, d_h) > B(w|h, w, d_w)$ .

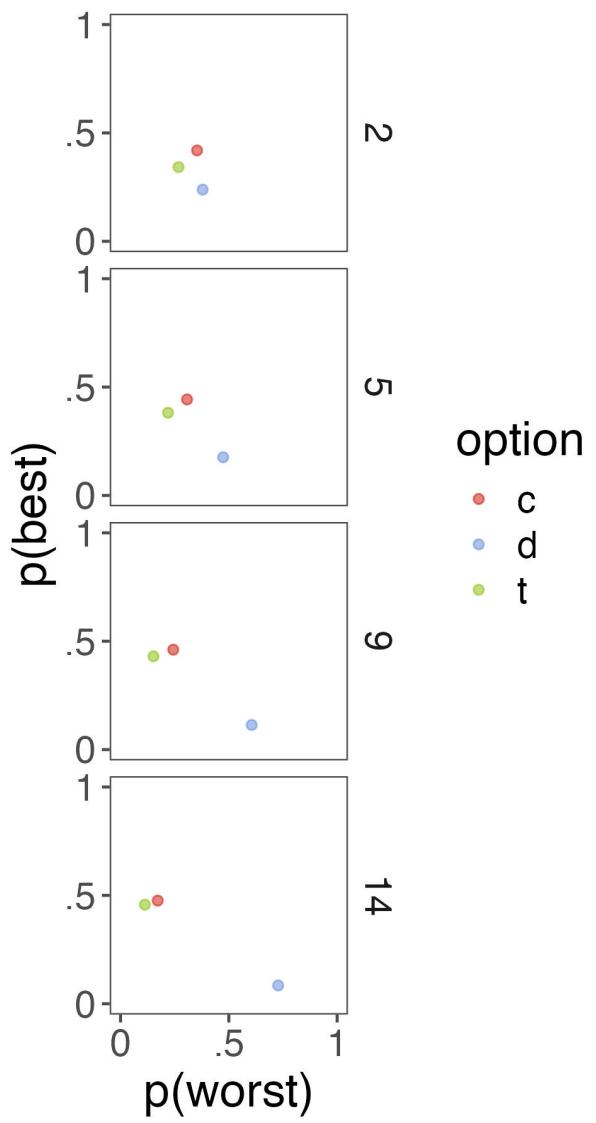
These results are more easily understood by plotting mean target, competitor, and decoy choice proportions across TDD levels, collapsed over choice set. See Figure 3.6 for these data.

The best-choice proportions replicated the repulsion effect initially found by Spektor et al. (2018) and replicated in Experiment 2, where the competitor was more likely to be chosen as best at low TDD levels, while the target and competitor were chosen equally often at high TDD levels. Decoy best-choice proportions also decrease systematically with TDD.

Furthermore, the target is always more likely to be chosen as worst, compared to the competitor and decoy, at all TDD levels,  $W(T) < W(C)$ , as predicted by the perceptual model outlined in Chapter 2. This model still cannot predict the null best-choice repulsion effect when  $TDD = 14\%$ , as discussed in Chapter 2, which suggests that this effect may be due to higher level decision processes.

### 3.2.2.4 Maxdiff Modeling

I now turn to the maxdiff model (Marley & Louviere, 2005), which was outlined in the introduction to this chapter. This model predicts that the probability of choosing options  $x$  as best and  $y$  as worst,  $x \neq y$ , increases monotonically with the difference in their estimated utilities (see Equation 3.1). This model is the most commonly used analysis technique for best-worst choice data. I applied this model to the current



**Figure 3.6.** Experiment 3 mean best and worst-choice proportions for the target, competitor and decoy rectangles, conditioned on TDD (rows).

experiment and show that it is unable to predict the observed dissociations in best-worst choices, even with its best fitting parameters.

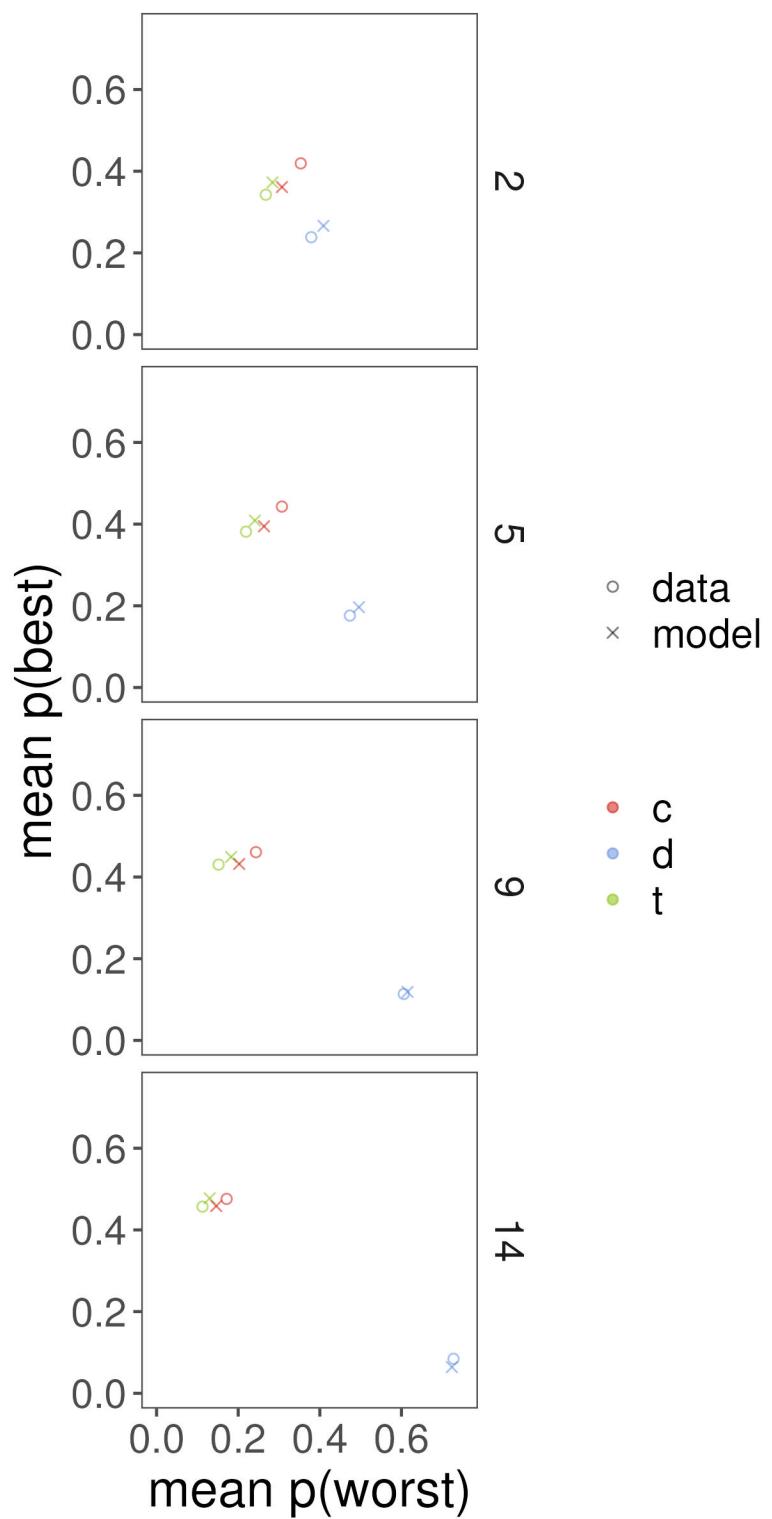
I implemented this model as a Bayesian hierarchical model. I show the details of the model fitting procedure, including parameterization, parameter estimates, and all priors in the Appendix and focus on the model predictions in the main text. The model predictions for the mean best and worst choices are shown in Figure 3.7.

The model clearly mispredicts the data. The model predicts that the target and competitor are chosen at roughly equal amounts for both best and worst choice. This misprediction stems from the fact that the model choices are a function of the utility of each option, in this case calculated through a linear combination of experimental factors multiplied by model coefficients, including target/competitor/decoy status. The model could, if the data suggest it, predict that the target has greater utility than the competitor or vice versa. However, because best-choice proportions are positively related to utility and worst-choice proportions are negatively related to utility, the model cannot simultaneously predict  $B(C) > B(T)$  and  $W(T) < W(C)$ . Instead, the mostly likely parameter set is that which predicts  $B(C) \approx B(T)$  and  $W(T) \approx W(C)$ .

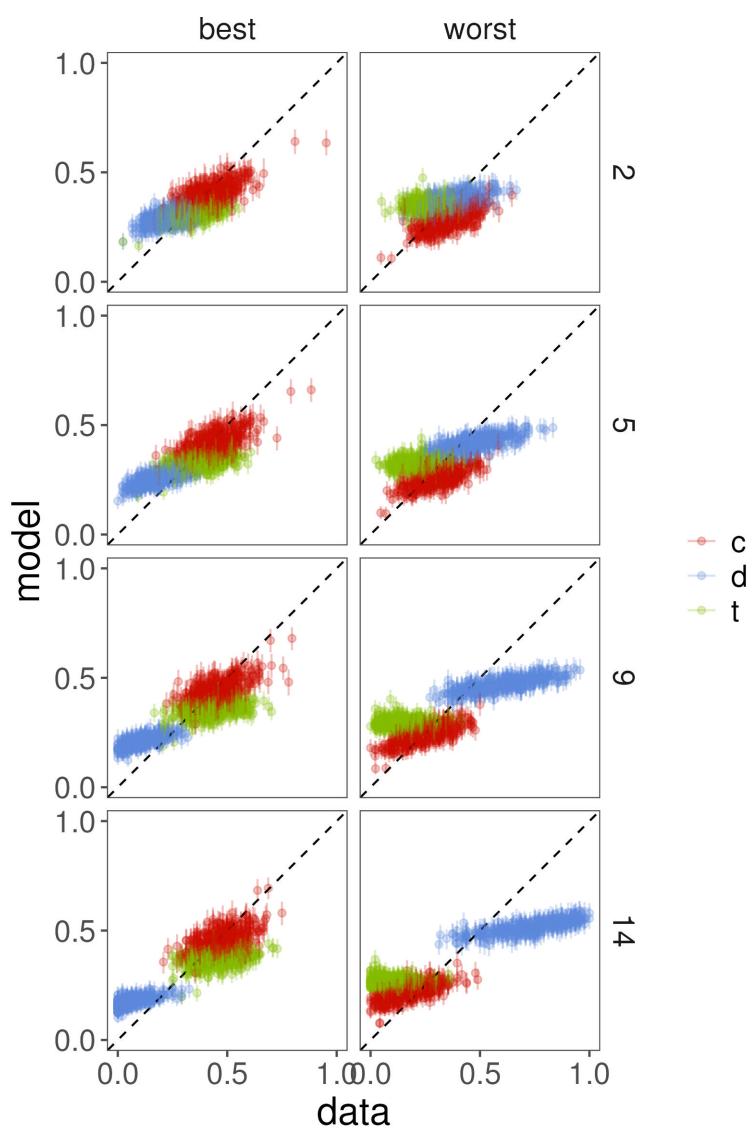
I also show participant-level data and model predictions in Figure 3.8. The model generally does a poor job at accounting for participant worst-choice proportions.

### 3.3 Discussion

In Experiment 3, I showed that correlated valuations can induce dissociations in best-worst choice. Specifically, given a target, competitor, and decoy option (borrowing the terminology of the attraction effect), the competitor is more likely than the target to be selected as best ( $B(C) > B(T)$ ), but the competitor is also more likely than the target to be selected as worst ( $W(C) > W(T)$ ). This prediction was made using the Thurstonian perceptual choice model of Chapter 2, conditioned on



**Figure 3.7.** Experiment 3 maxdiff model predictions for the mean target, competitor, and decoy best-worst choice proportions.



**Figure 3.8.** Experiment 3 maxdiff model predictions for the mean target, competitor, and decoy best-worst participant-level choice proportions, conditioned on TDD (rows) and choice type, i.e. best v. worst (columns). Vertical error bars are 95% HDIs.

the parameters estimated from Experiment 3. Furthermore, the prediction was made with different set of participants and a completely different experimental task. This level of predictive success is atypical in psychology and even relatively uncommon in the cognitive modeling literature.

The maxdiff model, the most common model for best-worst choice analysis cannot predict these results.

The maxdiff model assumes that, when selecting the best and worst option, the decision-maker picks the option with the highest and lowest utility, respectively. The utilities of each option are independently distributed, and the decision-maker uses the same utility for both best and worst choices. The use of a single utility scale is to some extent a convenience assumption. Marley and Louviere (2005) explored several theoretical models, including the case where best and worst utilities exist on independent ratio scales, though such a model does not seem to have been adopted by substantive researchers. Marley et al. (2008) introduced set-dependent best-worst choice models, which allow for context dependence based on choice set, albeit with best and worst choices still a function on a common underlying utility scale.

Hawkins et al. (2019) also argued that best and worst choices rely on a common utility representation. They fit the maxdiff model to 5 best-worst datasets and showed, via Bayesian mixture modeling, that the overwhelming majority of participants were best fit by a model with a single utility representation.

Geržinič et al. (2021) argued (and provided evidence for) the claim that while best and worst choices rely on a common utility scale, people use two distinct decision rules for best choices and worst choices. They argued that the former is compensatory (i.e., allowing tradeoffs between attributes), while the latter is non-compensatory (i.e., disallowing tradeoffs to minimize future regret).

The Thurstonian perceptual model, used for the current predictions, also employs a common utility scale for both best and worst choices. However, the model does not

assume independently distributed utilities, as assumed by the maxdiff model. Thus, the claims of Hawkins et al. (2014a) and Hawkins et al. (2019) are not necessarily falsified; rather, they are amended to account for correlations between option utilities. I also replicated the main findings of Hawkins et al. (2014a), that *marginal* best and worst choice probabilities are monotonically related.

Due to the small effect size, I required a large amount of data to estimate these dissociations. Most best-worst choice research is applied (for example in transportation and healthcare economics), where researchers do not typically have access a large amount of data, at least at the individual participant level. Thus, researchers are unlikely to observe the dissociations in best-worst choice and will analyze the data using the maxdiff model. They may then arrive at incorrect conclusions regarding participants' preferences.

I did not fit the Thurstonian perceptual model to Experiment 3. In Experiment 2, I asked participants estimate the size of the stimuli and used these direct size ratings to estimate the model parameters. It also seems unreasonable to expect researchers to fit a multivariate Thurstonian model to most best-worst choice studies, given limitations in data and potential issues with parameter identifiability.

The central purpose for conducting best-worst choice studies is to identify participants' preference distributions on a set of options. Best-worst choice is less cognitively demanding on participants than asking them to rank all options and far more efficient than pairwise forced choices on all combinations of options (Louviere et al., 2008). In many cases, analyzing best-worst data with the maxdiff model may be the best approach, especially if researchers have no reason to believe that options are strongly correlated, or if all pairs of options have equally strong correlations. It is an open question, left for future research, whether correlations between options in applied choice research can create similar dissociations in best-worst choice.

The current study only considered Case 3 best-worst choice (Marley & Pihlens, 2012), where the attributes of options (in this case, height/width, TDD, diagonal) are systematically manipulated. I ignored Case 1 best-worst choice, where researchers are interested in preference for each option as a whole (e.g., a consumer's preference for cars over bicycles) or Case 2 best-worst choice, where researchers ask participants to select their preferred attribute from a set (e.g., a consumer's preference for short waiting times over physician experience in an urgent care clinic). Future research should consider ways to generalize the current paradigm and results to the other best-worst choice types.

For the time being, I have identified a discrepancy between theory and data, in a prominent area of decision-making research. This gap is both theoretically and practically interesting. It is up to future researchers, myself included, to continue theoretical development in this line of study.

# CHAPTER 4

## VALUATIONS AND CORRELATIONS IN PREFERENTIAL CHOICE

### 4.1 Introduction

Thus far, the dissertation has focused on perceptual choice. This allowed me to reconcile conflicting findings from other researchers (Spektor et al., 2018; Trueblood et al., 2013). It also allowed me to develop a Thurstonian choice model from the ground up in a simplified choice environment.

However, many decision theorists, in particular those who study context effects, are interested in a wide variety of choice environments. For example, the original demonstration of the attraction effect came from the marketing literature (Huber et al., 1982), where participants selected amongst hypothetical consumer products. In this chapter, I generalize the paradigm and model from Chapter 2 to preferential choice. Below, I demonstrate results similar to Chapter 2.

#### 4.1.1 Expanding the Paradigm to Preferential Choice

In Experiment 2, I collected psychophysical ratings and used them to estimate the parameters of a Thurstonian choice model, which I then applied to make predictions for choices in the same experiment. To test this approach in preferential choice, it was necessary to collect continuous preference ratings from participants. In Experiment 4, I collected both pricing data (the best continuous measure for consumer stimuli) and choices.

In most studies of consumer preference, researchers collect choice data rather than ratings. There are good reasons for this. The literature on willingness to pay (WTP;

the largest amount a given consumer would be willing to pay for a particular product) has shown that, when responding to hypothetical survey questions, participants tend to over-estimate their WTP by a sizeable amount (Breidert et al., 2006; Schmidt & Bijmolt, 2020), (Miller et al., 2011, c.f. ). It is generally more advisable to collect discrete choices, rather than ordinal or continuous ratings, when attempting to measure preferences.

These concerns, while crucial to applied researchers, are not relevant to the current study, as I am interested in participants' relative rather than absolute valuations. In other words, if participants over (or under) estimate their preferences by a constant, but generally rate higher valued options more highly than lower valued options, I can obtain reliable estimates of the  $\rho$  parameters. As in Experiment 2, where I was concerned with whether participants' estimates of perceived size increased with absolute size (regardless of how it deviated from actual size), here I am interested in a measure that increases monotonically with the value participants place on each option.

Other researchers have studied context effects with ratings measures. Wedell and Pettibone (1996) collected Likert scale attractiveness ratings for attraction effect stimuli, generally finding that the presence of a decoy increased mean ratings for a target option. Windschitl and Chambers (2004) asked participants to judge the likelihood of various events (also on a Likert scale). They found that the presence of a "dud" (highly unlikely) alternative increased participants' ratings of focal options. Cai and Pleskac (2023) and Fang et al. (2024) demonstrated similar effects with continuous probability judgments.

To my knowledge, however, there has been no research systematically connecting valuations and choices in a single experiment through application of a choice model. Thus, I collected ratings to estimate the multivariate normal parameters  $\mu$  and  $\Sigma$

for the choice model from Chapter 2 and used these to predict consumer choice data collected from the same group of participants.

#### 4.1.2 Correlations in Preferential Choice

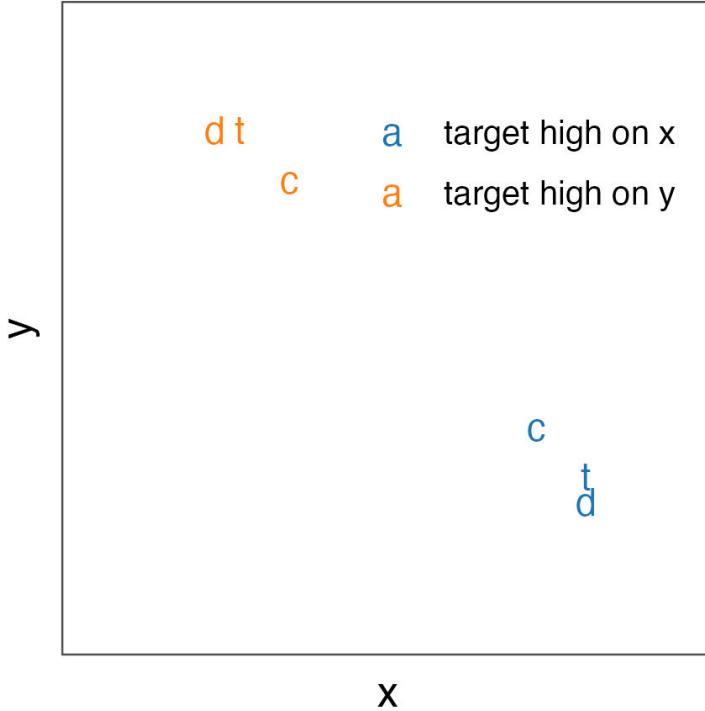
In Chapter 2, I showed that the model could capture the repulsion effect in perceptual choice (Spektor et al., 2018) through target-decoy correlations, estimated via the parameter  $\rho_{TD}$ . I am now interested in whether 1) preferential stimuli also elicit these correlations and 2) the model can capture the repulsion effect in preferential choice.

The literature on the repulsion effect in preferential choice is relatively sparse. Liao et al. (2021) varied TDD in preferential choice and found a U-shaped relationship between TDD and RST (Relative Share of the Target), with the attraction effect occurring at low and high TDD levels but the repulsion effect occurring at more intermediate TDD levels.

Spektor et al. (2022) demonstrated the repulsion effect in (risky) preferential choice, displaying stimuli graphically but in the same triangle display as Spektor et al. (2018).

Banerjee et al. (2024) demonstrated a binary-ternary form of the repulsion effect using the stimuli depicted in Figure 4.1, across multiple experiment. Participants saw either two or three options on each trial, each varying on two dimensions. The options were consumer choice products from a number of categories (e.g., cameras, coffee makers, laptops), and the dimension names varied by product category (e.g., coffee makers' dimensions were brew speed and features). Attribute values were always displayed numerically using ratings of 1-100.

In each set, the target was always the most extreme option - particularly high on one dimension and particularly low on the other dimension. The competitor was a more intermediate option. For example, consider the blue-colored stimuli in



**Figure 4.1.** Graphical depiction of a subset of the stimuli used in Banerjee et al. (2024), Experiment 5. Target, competitor, and decoy are labeled  $t$ ,  $c$ , and  $d$ , respectively. Dimensions are (generically) labeled X and Y.

. The choice sets vary based on whether the target is higher on the X or Y dimension.

Figure 4.1.  $t$  is very high on  $X$  and very low on  $Y$ . Compared to  $t$ ,  $c$  is slightly worse on  $X$  but slightly better on  $Y$ .  $d$ , however, is as high as  $t$  on  $X$  but even worse on  $Y$ .

Using these stimuli, Banerjee et al. (2024) showed that the competitor's choice share increased from binary to ternary choice sets,  $P(C|[T, C, D]) > P(C|[T, C])$ , in violation of the regularity principle (Marley, 1989). They also showed that the repulsion effect decreased with  $TDD$ .

Banerjee et al. (2024)'s experiments compared binary to ternary choice rather than ternary to ternary choice, as in Spektor et al. (2018). To do a ternary-ternary comparison, one would "flip" the target and competitor labels, such that the target is the intermediate option, the competitor is the extreme option, and the decoy is nearby

the new, intermediate target. It is in one sense, quite interesting, that Banerjee et al. (2024) were able to generate violations of regularity in this binary-ternary comparison. However, the results are somewhat limited by the fact that the target was always more extreme than the competitor.

Banerjee et al. (2024) argued that their results are consistent with the "tainting hypothesis" (Simonson, 2014) because the repulsion effect is strongest when the target and decoy are similar. They also argued that the decoy may have caused participants to focus more attention on the competitor's superior dimension. For example, in the blue choice set of Figure 4.1, the decoy is quite poor on  $Y$  while being equally good as the target on  $X$ , so participants may have focused more attention on  $Y$ , leading to a preference for the competitor.

Banerjee et al. (2024)'s results are interesting and worth exploring further. The authors are also remarkably transparent about their stimulus generation procedure, in addition to posting their data online, so their stimuli were a perfect candidate for the Experiment 4.

## 4.2 Experiment 4

With Experiment 4, I sought to collect ratings and choice data in a preferential choice setting using (a subset of) Banerjee et al. (2024)'s Experiment 5 stimuli. I used these data to estimate the parameters of the choice model from Chapter 2.

For a ratings measure, I asked participants to assign prices to each option. Though people often overestimate prices (Breidert et al., 2006), pricing measures are approximately continuous and monotonic with value and are thus comparable to estimated area, the value measure in Experiment 2.

## 4.2.1 Methods

### 4.2.1.1 Participants

137 U.S. adults participated in the experiment. Participants were recruited from Prolific, an online platform for research studies, and they were paid \$5 for their participation. 24 participants were removed from all analyses for failing catch trials (see below), leaving a final sample size of  $N = 113$ .

### 4.2.1.2 Stimuli

The stimuli were borrowed from Banerjee et al. (2024)'s Experiment 1. The stimuli were hypothetical consumer choice products. All stimuli varied on two attributes, each of which ranged from 0-100. The products came from four different categories: televisions, washing machines, laptops, and microwave ovens.

The attributes varied by category. Televisions varied on screen size and average lifespan. Washing machines varied on average lifespan and energy savings. Laptops varied on processing speed and memory (RAM). Microwave ovens varied on warranty and cooking power.

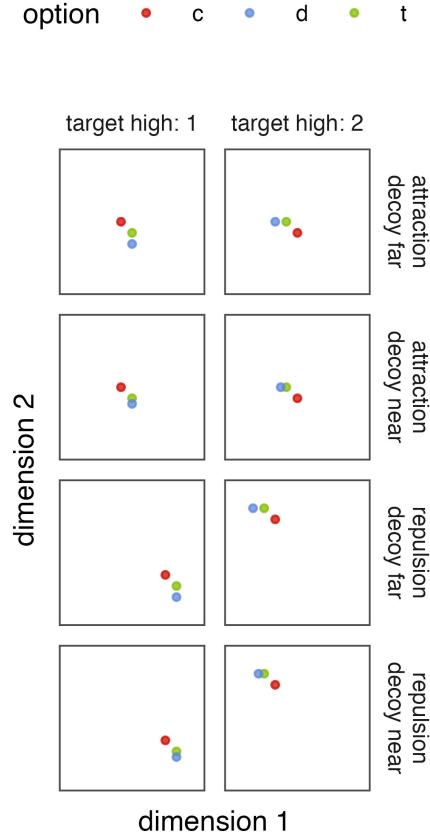
Within each category, one attribute was arbitrarily designated as dimension 1 and another as dimension 2 (see below).

### 4.2.1.3 Design

The experiment took place in two phases: pricing and choice. The trial types were identical for both phases.

In each phase, there were two types of trials: critical trials and catch trials. The critical trial stimuli are shown in Figure 4.2.

There were two types of critical trials: those designed to elicit the repulsion effect (a replication of Banerjee et al.), and those designed to elicit the attraction effect. Within both the attraction and repulsion trials, I varied which dimension the target was higher on (1 or 2), *TDD* (designated near or far from the target), and product



**Figure 4.2.** Graphical depiction of the critical stimuli from Experiment 4. Rows show the different choice sets designed to elicit the attraction/repulsion effect, with the label also specifying whether the decoy is near or far from the target in attribute space. The columns indicate which dimension the target is high on (1 or 2). Dimensions are labelled generically because their names vary with product category.

category (microwaves, washing machines, laptops, and televisions). Note that to create the attraction trials, I simply "shifted" the target and competitor towards the center of the attribute space. That is, target and competitor are equally similar in both repulsion and attraction trials, but they are both more extreme in the repulsion trials.

The catch trials were designed such that one option was clearly superior to the other two. On each catch trial, the superior option's dimension values were each independently sampled from the vector [50, 55, 60, 65, 70, 75, 80, 85, 90, 95], while the

two inferior options' dimension values were independently sampled from the vector [5, 10, 15, 20, 25, 30, 35, 40, 45, 50].

In both the rating phase and the choice phase, there were 32 critical trials (16 designed to elicit the repulsion effect and 16 designed to elicit the attraction effect) and 8 catch trials.

I did not test binary repulsion effect trials, as in Banerjee et al. (2024)'s experiments, so I cannot assess the repulsion effect to the same degree as those authors. The goal of this experiment was to measure valuation correlations in consumer preference and attempt to relate them to choice.

#### 4.2.1.4 Procedure

The experiment took place in two phases: a pricing phase and a choice phase.

Prior to the pricing phase, participants were provided with a cover story. According to the cover story, they were told to imagine that they run an online consumer goods resale business. On each trial, they would see three products, and they needed to determine which price to sell each product for. Participants were also told that they should determine a price that maximizes both profit and the likelihood the product is purchased.

During the pricing trials, the three options were presented in a table, with the options in rows and the attributes in columns. All attributes were represented numerically. The options were labeled A, B, and C. The last column of the table contained three boxes, which participants used to type in their selling price for each option. Participants typed in their selling price, and then clicked a button on the screen to advance to the next trial. Both option order and dimension order was randomized on each trial. See Figure 4.3 (left panel) for an example trial. Participants were only allowed to enter in whole numbers (e.g., dollars not cents).

### Microwave ovens



Please enter the price you want to sell each product for.

Product	Cooking power (1=worst, 100=best)	Warranty (1=worst, 100=best)	Your Selling Price
Product A	60	75	\$ <input type="text" value="0"/>
Product B	5	30	\$ <input type="text" value="0"/>
Product C	45	25	\$ <input type="text" value="0"/>

### Televisions



Please select one of the following products::

Product	Average lifespan (1=worst, 100=best)	Screen size (1=worst, 100=best)	
Product A	25	30	<input type="radio"/>
Product B	35	10	<input type="radio"/>
Product C	70	85	<input type="radio"/>

**Figure 4.3.** Sample trials from the pricing phase (top) and choice phase (bottom) in Experiment 4.

After completing all pricing trials, participants moved onto the choice phase. Prior to this phase, participants were told to imagine that they were purchasing consumer goods in bulk. On each trial, they were to select the option they wanted to purchase.

As in the pricing phase, options were presented in a table, where option order and dimension order was randomized. See Figure 4.3 (bottom) for an example trial.

Trial order was randomized in both phases.

After the choice phase, participants completed a short demographics form before ending the experiment.

## 4.2.2 Results

### 4.2.2.1 Data Processing

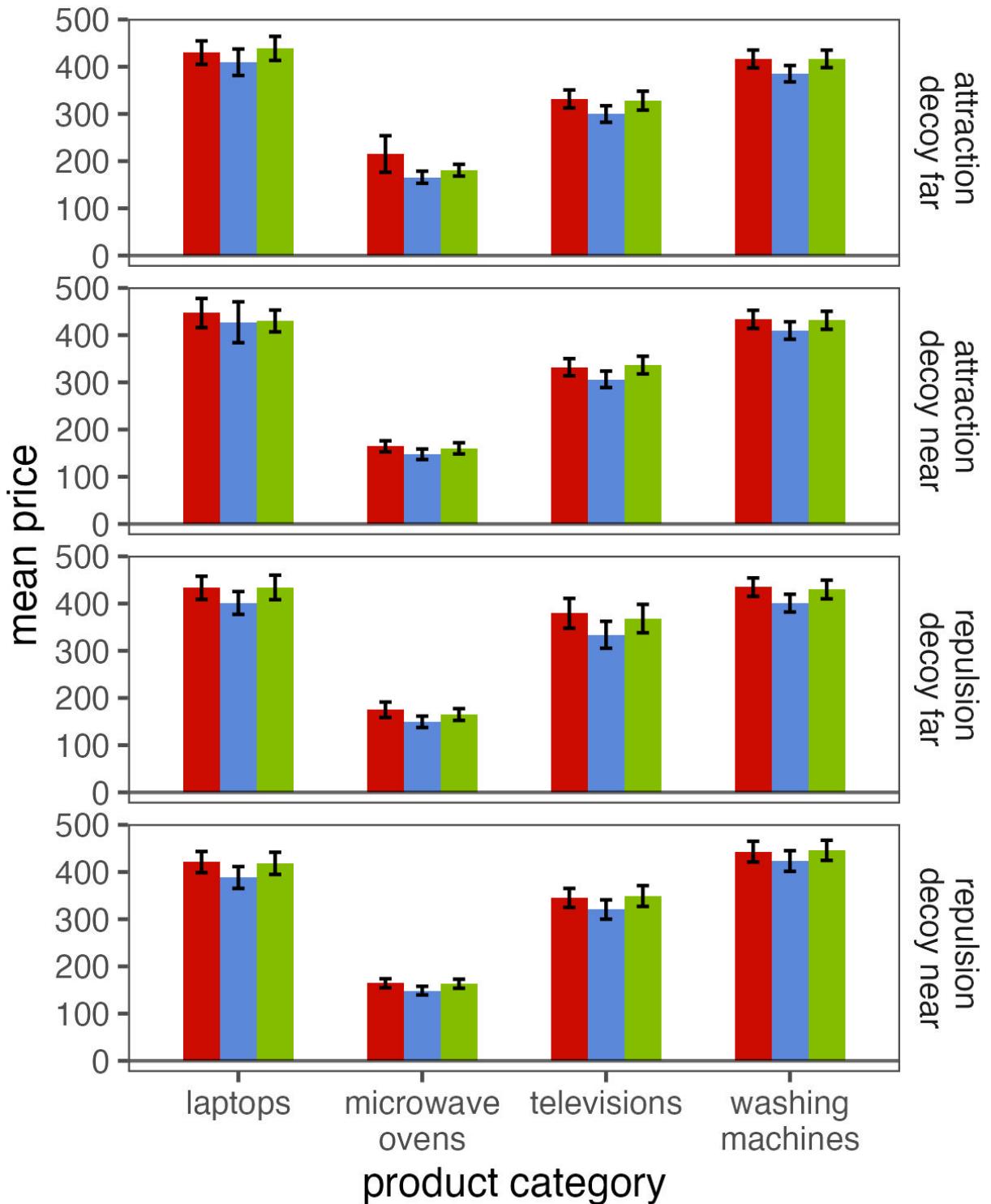
First, I removed 24 participants who did not pass at least 5/8 catch trials in both the pricing phase and the choice phase. To pass a pricing catch trial, the participant needed to price the superior option at least as high as the other two inferior options. To pass a choice catch trial, the participant needed to select the superior option.

### 4.2.2.2 Pricing Trials

First, I computed mean prices for the target, competitor, and decoy option within each trial type and product category. These means are shown in Figure 4.4.

On average, participants priced the target and competitor higher than the decoy. They also assigned higher prices to products that are typically more expensive (e.g., washing machines are more expensive than microwave ovens). This suggests that participants were engaged with the task and, in a relative sense, performed the task well.

I performed a Bayesian modeling analysis comparable to that of Experiment 2. I estimated the mean prices and the correlations between prices. The details of this modeling analysis can be found in the Appendix.



**Figure 4.4.** Experiment 4 mean prices by product category, option, and trial type. Error bars are  $\pm 1$  SEM.

Below I discuss descriptive statistics, but whenever I claim that one parameter value is greater than another, the reader can see the Appendix to support these conclusions. The ordering of these correlations, however, is the same in both the model-based and the descriptive analysis. I report the descriptive values for all correlations, rather than those based on model estimates, because the latter are biased downward due to limited data (Merkle et al., 2023; Stephens et al., 2020).

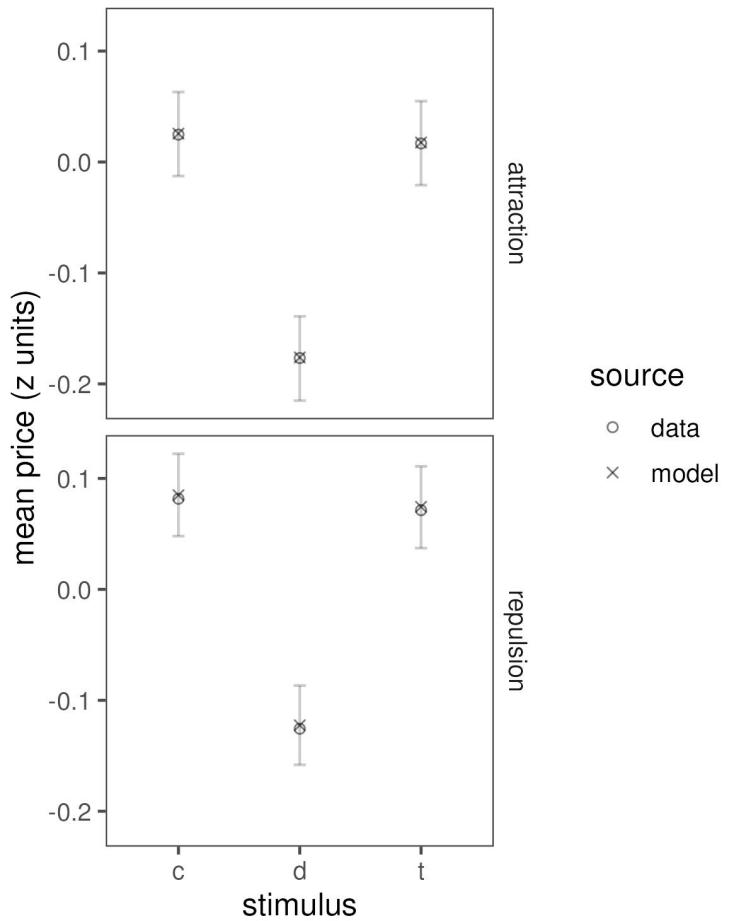
To account for participant-level differences in pricing, I first z-scored all prices within each participant. To avoid the influence of outliers on correlation estimates, I removed trials in which at least one price z-score had an absolute value  $> 3$ .

I computed the mean prices for target, competitor, and decoy options within each trial type, collapsing over product category and TDD, in Figure 4.5. In both repulsion and attraction effect trials, the target and competitor do not differ in mean price, while both are priced higher than the decoy option.

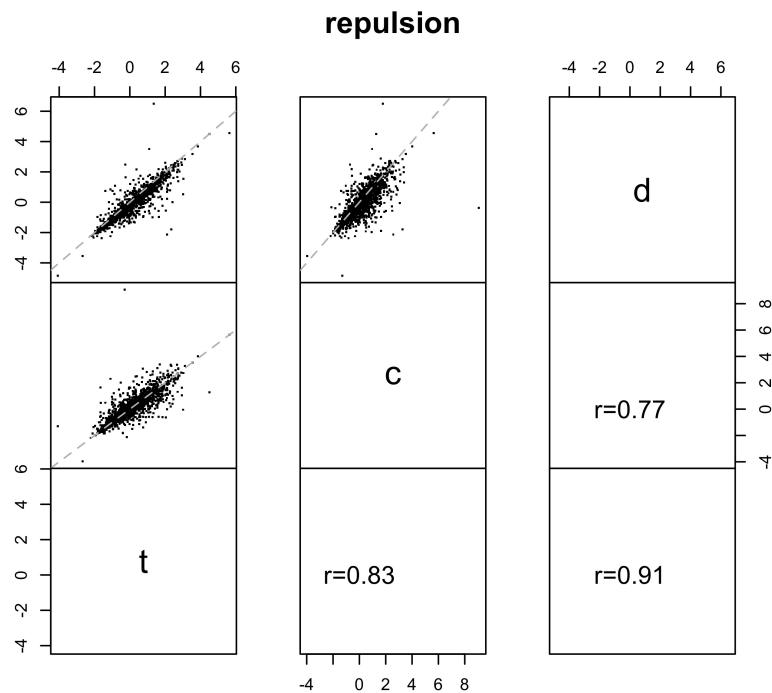
I then computed correlations between the prices assigned to options within each trial type. I plot the z-scored prices in a series of scatterplots, with the Pearson correlations included. See Figure 4.6 for repulsion effect correlations and Figure 4.7 for attraction effect correlations.

In the repulsion trials, I replicated the results of Experiment 2, in that  $\rho_{TD} > \rho_{TC}$  and  $\rho_{TD} > \rho_{CD}$ . Interestingly, I also found that  $\rho_{TC} > \rho_{CD}$ , while in Experiment 2  $\rho_{TC} \approx \rho_{CD}$ .

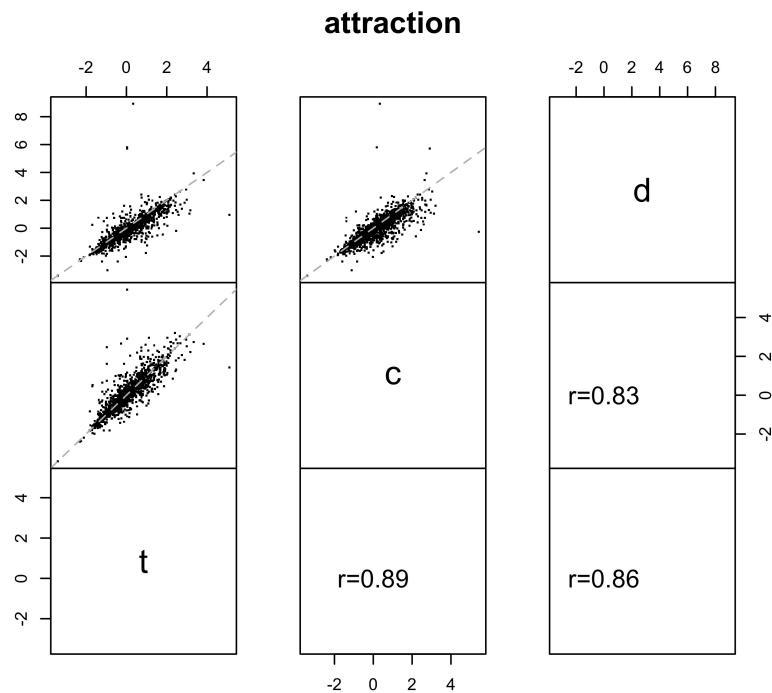
In the attraction trials, I found that  $\rho_{TC} \approx \rho_{TD} > \rho_{CD}$ . In other words, the target and competitor are approximately equally similar as target and decoy, which are in turn more similar than competitor and decoy.



**Figure 4.5.** Experiment 4 mean prices for target, competitor, and decoy options in both repulsion and attraction trials. Model values are the means from the posterior distribution, and error bars are 95% HDIs.



**Figure 4.6.** Experiment 4 correlation plots for all pairs of stimuli, in trials designed to elicit the repulsion effect. t=target, c=competitor, and d=decoy.



**Figure 4.7.** Experiment 4 correlation plots for all pairs of stimuli, in trials designed to elicit the attraction effect. t=target, c=competitor, and d=decoy.

#### 4.2.2.3 Choice Trials

I next computed choice proportions for the critical choice trials. I collapsed across participant (due to the small  $n$  per subject), as well as product category and the target's superior dimension.

These choice proportions are plotted in Figure 4.8. The results clearly show a null attraction effect, regardless of  $TDD$ . Participants chose the target and competitor options at equal rates. This is likely due to the strong similarity of target and competitor, atypical of attraction effect studies.

The results show what appears to be a repulsion effect, where the participants generally prefer the competitor option to the target option. However, because I did not include a ternary-ternary comparison (i.e., varying whether the decoy is located nearer to the extreme option or to the intermediate option), these results may be due to participants simply preferring the less extreme option.

Participants seldom chose the decoy, another indication that they were attentive to the task. This also provides evidence that decoy selection is far more common in perceptual choice than preferential choice.

#### 4.2.2.4 Model Simulations

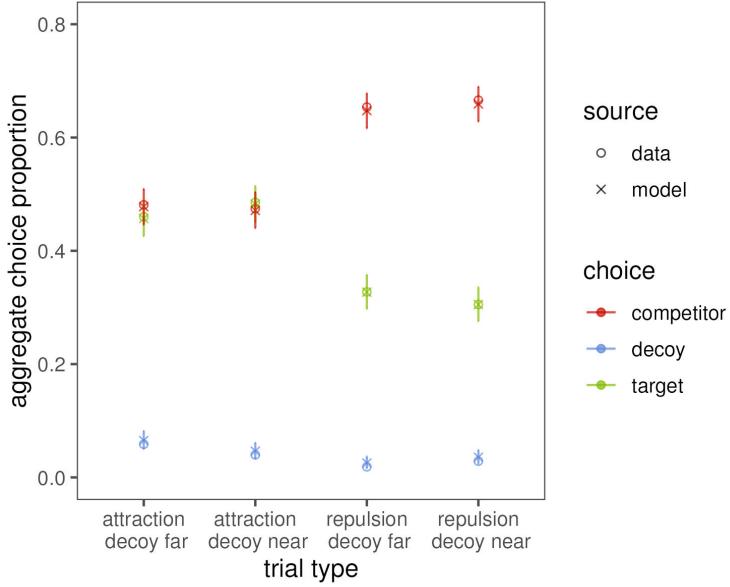
As in Chapter 2, I used the parameter estimates for  $\mu$  and  $\Sigma$  to simulate choice. I use the Thurstonian model from Chapter 2, originally used to simulate perceptual choice.

To simplify this analysis, I only consider attraction and repulsion trials, collapsing over all other factors.

As in Chapter 2, the model assumes that value is stochastic while choice is deterministic<sup>1</sup>. The model always chooses the option perceived as most valuable, regardless

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<sup>1</sup>This also assumes ties are not possible, which is true if and only if perceived area is absolutely continuous.



**Figure 4.8.** Experiment 4 aggregate choice proportions for each trial type, TDD, and option. Data points are aggregate choice proportions, while model points are posterior means computed from the Bayesian Dirichlet-multinomial model presented in the Appendix. Error bars are 95% HDIs.

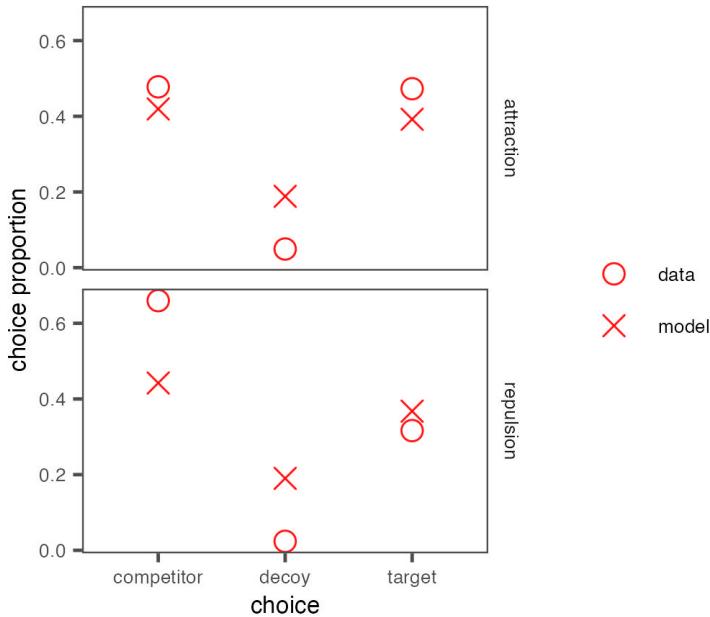
of the magnitude of the difference between the "winner" and "runners-up". That is, given a vector  $\mathbf{X}_i$  of perceived values on trial  $i$  with set  $K$ , the probability a participant selects stimulus  $j$  is:

$$P(j|i, K) = P(\mathbf{X}_{ij} > \mathbf{X}_{ik}), \forall k \in K, j \neq k \quad (4.1)$$

I ran 1,000,000 simulations of the model and plotted the results against the data in Figure 4.9.

The model mispredicts the attraction trials. It predicts a slight repulsion effect when in fact the data suggest a null effect.

The model successfully predicts a qualitative repulsion effect, i.e.,  $P(C) > P(T)$ . However, it strongly overpredicts decoy choice proportions. The model relies on the correlation between target and decoy choice proportions to predict the repulsion ef-



**Figure 4.9.** Experiment 4 data vs. Thurstonian model predictions.

fect. According to the model because the target and decoy are strongly correlated, it is more likely that the utility of the decoy exceeds the target than the competitor. The decoy then "steals" choice shares from the competitor. This prediction makes sense in perceptual choice, where stimulus discriminability is not a given and participants pick the decoy roughly 20-30% of all trials (see Experiment 2). In preferential choice, participants almost never pick the decoy, and researchers assume that any participant with sufficient attention can always discriminate the target and competitor from the decoy. Thus, though the model can qualitatively predict a repulsion effect, the mechanism by which it does so is implausible.

### 4.3 Discussion

This experiment generalizes the paradigm of Chapter 2 to preferential choice. Participants completed two phases; in the first phase, they assigned a selling price to each of three options on each trial. In the second phase, they selected the option they

would most prefer. Option sets were designed to either elicit the attraction effect or the repulsion effect. I used the prices to estimate the mean value of each option as well as the correlations between all pairs of options. In doing so, I extended not only the experimental paradigm of Chapter 2, but also the modeling framework, to a preferential choice setting.

Crucially, when estimating the correlations, I replicated the result of Experiment 2, that, in the repulsion effect  $\rho_{TD} > \rho_{TC}$  and  $\rho_{TD} > \rho_{CD}$ . Interestingly, the inferential statistics also show that  $\rho_{TC} > \rho_{CD}$ . This result was unexpected, but it may be due to the fact that, because both are high on one dimension and low on another, it is easier to compare target and competitor to one another than it is to compare the competitor to the decoy.

Interestingly, in the trials designed to elicit the attraction effect, I found that  $\rho_{TC} \approx \rho_{TD} > \rho_{CD}$ . This is likely due to the similarity of target and competitor on both attributes (i.e., one option's dimension values were [50, 60] while the other's was [60, 50]). The target and competitor are easily comparable to one another, and the tradeoff on attributes is negligible.

The choice results replicated those of Banerjee et al. (2024), in that participants chose the competitor more than the target in each of the repulsion effect choice sets. However, given that I did not vary the decoy location (i.e., the competitor was always less extreme than the target), nor did I include a binary-ternary choice comparison. These results may be due to a bias for the less extreme option, which happens to be the competitor in this case. Future research should include binary-ternary and ternary-ternary trials to generalize these results.

The strong correlation between target and decoy valuations appears to be a robust finding, holding across perceptual and preferential choice. It is worth exploring, in greater detail, what causes these correlations.

In the attraction and repulsion effect, the target and decoy are designed such to be more similar to each other than either option is to the competitor. It may be that, by measuring the correlation in valuations, we are actually measuring the *similarity* between options. Indeed, the similarity of target and decoy was a primary motivation for the original demonstration of the attraction effect (Huber et al., 1982).

These correlations may also be measuring the ease of comparability between pairs of options. Comparability has previously been shown to drive the attraction effect (Cataldo & Cohen, 2019; Noguchi & Stewart, 2014), and several models of context effects rely on comparisons of options on single attributes to generate context effects (Roe et al., 2001; Trueblood et al., 2014). Supporting this hypothesis is the finding that  $\rho_{TC} > \rho_{TD}$  in the trials designed to elicit the attraction effect, when the target and competitor were quite similar on each attribute and thus easier to compare.

Future work could test these hypotheses by systematically manipulating option comparability and assessing whether the correlations vary with comparability. I work towards this in Chapter 5 through testing the effect of comparability on choice, but it would be interesting to directly measure inter-option correlations in choice environments of varying comparability.

# CHAPTER 5

## COMPARABILITY IN PERCEPTUAL CHOICE

### 5.1 Introduction

Thus far in the dissertation, I have explored perceptual and decisional processes in both perceptual and preferential choice. I showed that stimuli which are more similar to one another, and are thus more easily comparable, generate valuations with stronger correlations. This result holds across both perceptual choice (Chapter 2) and preferential choice (Chapter 4). I define the comparison process as a cognitive operation where a participant attends to the relative difference between two options on a choice set, typically (though not necessarily) on a single dimension.

Embedded in a Thurstonian choice model (Thurstone, 1927), these correlations can produce the repulsion effect (Simonson, 2014; Spektor et al., 2018) because the decoy option, whose value is tightly correlated with the target, occasionally exceeds the target in perceived value and thus "steals" choice shares from the target.

In this chapter, I directly manipulate stimulus comparability in a perceptual choice task in an attempt to explicitly test the relationship between comparability and choice. I first review previous literature on comparability and then present the results of a perceptual choice experiment.

#### 5.1.1 Previous Literature on Comparability

Other researchers have studied the comparison process in decision-making, particularly in high-level choice (e.g., preferential). I first discuss the preferential choice work before transitioning to previous research on perceptual choice.

Chang and Liu (2008) tested the compromise effect by varying the presentation of options. In the compromise effect, a “middle” ground option decreases the choice share of two dissimilar, “extreme” options. Chang and Liu (2008) displayed the options either by-alternative format, where option names are listed as columns while attribute values are listed as rows, or by-attribute, where option attributes are columns while option names are rows. The former display makes it more difficult to compare options on a single attribute, while the latter makes it easier. Chang and Liu (2008) found that listing options by-attribute increased the choice share of the compromise option, relative to a by-alternative display.

Cataldo and Cohen (2019) replicated this result, also finding that a by-alternative format nullified the attraction effect. The authors attributed this result to a “flexible comparison process”, where the comparison strategy is influenced by display format. According to this account, the by-attribute format increases the ease of target-decoy comparisons relative to the by-alternative format<sup>1</sup>. Cataldo and Cohen (2018) showed that presenting options in a format that encourages within-dimension comparisons on pairs of options can reverse the well-studied similarity effect.

Noguchi and Stewart (2014) studied context effects using eye-tracking, showing that people tend to compare pairs of options on a single attribute, and that this appears to drive the attraction, similarity, and compromise effect. In their study, participants’ eye movements showed that they were more likely to transition between options on a single dimension than they were to transition between dimensions within a single option. They also found that transitions between two options are negatively related to the choice share of a third option.

Hayes et al. (2024) manipulated attribute comparability, such that the dimensions of each option were either measured in the same unit (high comparability, e.g., 0-

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<sup>1</sup>Hasan et al. (2025) failed to replicate these results, albeit with slightly different decoy types.

10 ratings) or in different units (low comparability, e.g., CPU speed vs. RAM for laptops). They found that the attraction effect only occurred in the low comparability condition.

Hasan et al. (2025) conducted a large scale replication of the attraction effect, systematically varying option order, presentation mode (numerical or graphical), and presentation format (by-attribute or by-alternative). They found that the attraction effect was stronger when the target and decoy options were adjacent to one another, presumably because this allows for easier target-decoy comparison. The attraction effect was stronger when attributes were presented numerically compared to graphically, a result found by other researchers (Frederick et al., 2014; Yang & Lynn, 2014). They did, however, fail to replicate **cataldo**<empty citation>'s finding that the attraction effect varies with by-alternative vs. by-attribute format.

Hsee and colleagues (Hsee et al., 1999; Hsee, 1996, 1998; Hsee & Leclerc, 1998) have also shown that the comparison of options affects consumer behavior. For example, they repeatedly showed that participants' evaluation of a given option can change with the addition of a reference point (i.e., lower valued options improve with a high reference point and vice versa). That is, participants' judgments can reverse when options are evaluated jointly, compared to separately (Hsee et al., 1999).

Several computational models of decision-making also rely on the comparison process. According to Trueblood et al. (2014)'s Multiattribute Linear Ballistic Accumulator Model (MLBA), each option accumulates evidence through pairwise comparisons to all other available options. These comparisons are modulated by several processes, such as distance in attribute space and extremeness aversion. Roe et al. (2001)'s Multialternative Decision Field Theory (MDFT) model also assumes that options accumulate evidence through comparison, and that comparisons between nearby options exhibit greater influence on preference. Other decision models incorporate similar

mechanisms (Landry & Webb, 2021; Noguchi & Stewart, 2018; Usher & McClelland, 2004; Wollschläger & Diederich, 2012) (c.f. Bergner et al. (2019) and Bhatia (2013)).

Trueblood et al. (2022) argued that options that are more similar garner more attention in the comparison process. They presented a simple Markov model where pairwise comparisons on a single attribute determine the accumulation of preference, and the time spent on a comparison is an increasing function of the similarity of options on the attribute. Their model can successfully, and simply, account for the “big three” context effects (attraction, compromise, and similarity).

### 5.1.2 Comparability Effects in Perceptual Choice

There has been other research, albeit relatively limited, on the comparison process in perceptual decision-making. Much of this work has focused on the spatial layout of the options and its effect on perceptual context effects.

Trueblood et al. (2022) re-analyzed previous perceptual choice context effect data (Trueblood et al., 2015) by examining the order of the options on the screen. They found that the attraction effect was strongest when the target and decoy were next to each other, while the effect was weak (or even absent) when the options were separated spatially. Their conclusion, supported by a modeling analysis, was that people tend to compare pairs of options which are spatially closer to one another more often than pairs further away from one another. This result may seem obvious, but previous researchers have largely ignored the order of options in choice, generally collapsing over stimulus order in all analyses.

Evans et al. (2021) found a similar result in perceptual choice, though in their experiment the options were separated both spatially and temporally. In their experiment, participants saw three rectangles, presented sequentially, and selected the largest rectangle after all stimuli were presented. They found that orders in which the target and decoy were presented in the latter two positions elicited an attraction

effect, whereas orders in which the competitor and decoy were presented in the latter two positions tended to elicit a repulsion effect. They interpreted their results as evidence that the comparison process can be altered through spatial and temporal properties of the stimuli.

Another interpretation of their results, and those of Trueblood et al. (2022), is that by altering the location and timing of the stimuli, the researchers are also altering the comparability. In the perceptual model of Chapter 2, increased comparability is represented by an increase in perceptual correlation. As shown previously, this perceptual correlation can create a repulsion effect by allowing the decoy to more easily "steal" choice shares from the target.

The experiments of Evans et al. (2021) and Trueblood et al. (2015) are interesting and have much to tell us about the role of comparability in decision-making. However, I wished to isolate the effect of comparability from context effects. To do so, I conducted a simple perceptual choice experiment where participants saw three rectangles at a time and selected the largest one. On critical trials, two of these rectangles were equally large but oriented differently (i.e., *focal* rectangles, as in Experiments 1, 2, and 3). A third *decoy* option was a square, and thus equally similar to either option. I designated one of the two focal options as the *target* based on its proximity and comparability to the decoy. Based on the results of Chapter 2, this should increase the correlation between the comparable options and result in a *decrease* in the target's choice share. These predictions are generally borne out in the data, albeit with limitations which will be addressed in future work.

## 5.2 Experiment 5

Experiment 5 addresses the effect of comparability in perceptual choice. To do so, I incorporated *symmetrically dominated* decoys. A symmetrically dominated decoy is dominated by both focal options but is also equally similar to both options. Thus,

the terms target and competitor, which have been used throughout this dissertation, take on a different meaning here. Here I define the target as the option that is both adjacent to and easily comparable to the decoy.

### 5.2.1 Methods

#### 5.2.1.1 Participants

231 undergraduate students at the University of Massachusetts Amherst participated in the lab, in exchange for course credit. 17 participants' data were removed from all analyses because they failed to achieve at least 80% correct on catch trials (see below), leaving final sample size of  $N = 214$ .

#### 5.2.1.2 Stimuli

The stimuli were gray-scale rectangles and squares, varying systematically on height and width.

The critical stimuli are depicted in Figure 5.1. The focal stimuli ( $H$  and  $W$ ) are equal in area and fell on two diagonals, the upper diagonal area being 25000 square pixels and the lower diagonal being 7581 square pixels. The decoy options were either 20% or 35% smaller than the focal options.

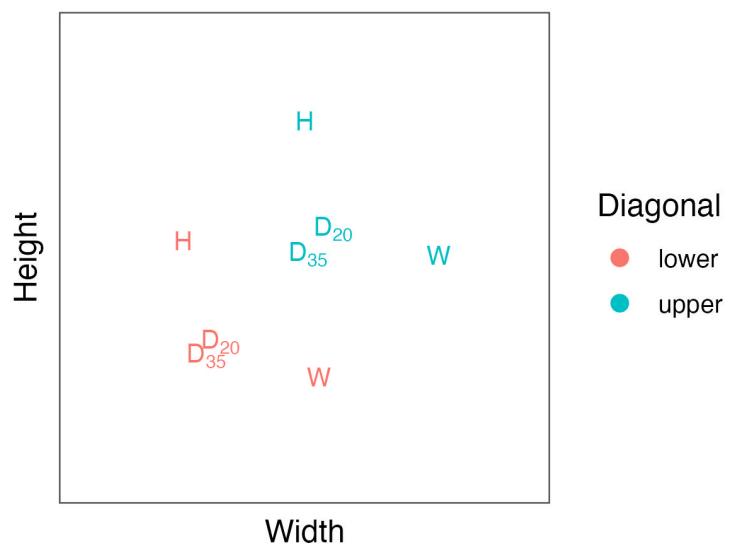
There were other types of stimuli on non-critical trials, which are explained below.

#### 5.2.1.3 Design

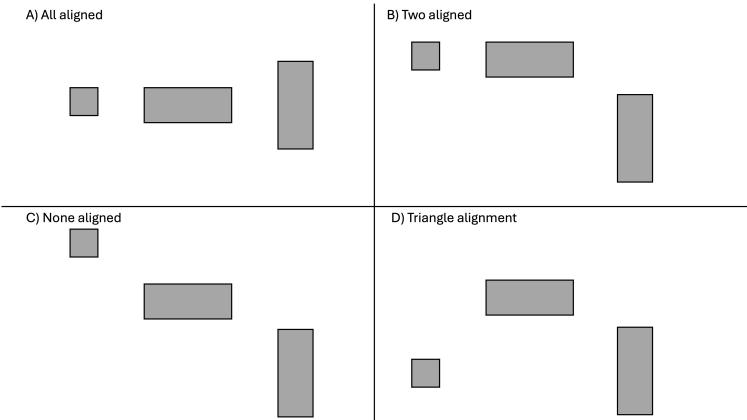
Trials were split into four blocks in the experiment.

There were four types of trials: critical trials, filler-square trials, filler-random trials, and catch trials.

On each critical trial, there were three options: an  $H$  rectangle, a  $W$  rectangle, and a  $D$  rectangle. The focal rectangles fell on two diagonals (upper and lower, see above), while the decoy rectangle varied in  $TDD$  at 20% and 35%.



**Figure 5.1.** Graphical depiction of critical stimuli from Experiment 5. The stimuli fall on two diagonals, labeled as upper and lower. The H rectangles are taller than wide, while the W rectangles are wider than tall. The decoy (D) rectangles are equally wide and tall (i.e., squares). The decoy subscripts indicate the *TDD* %.



**Figure 5.2.** Critical trials from Experiment 5.

The stimuli were arranged in one of four displays: all-aligned, two-aligned, none-aligned, or triangle. See Figure 5.2 for sample trials.

In the all-aligned display, all stimuli were arranged in a horizontal array, as in the experiments of [trueblood2013not](#) and Spektor et al. (2018) (Experiment 4).

In the two-aligned display, two options were aligned horizontally in the top-left and top-middle positions, while the third option was placed in the bottom-right position of the screen. This is a crucial condition and an instantiation of the "comparability" hypothesis, in which the comparison of the two aligned options is far easier than all other pairwise comparisons.

In the none-aligned display, all options are located in different vertical and horizontal positions, such that all comparisons should (in principle) be more difficult.

The triangle display is identical to the triangle display of Experiments 1 and 2, with the exception that on half of all triangle display trials, the triangle was inverted. The triangle display condition was collected for future analyses but is not germane to the current research question, and it will be excluded from critical analyses.

In all displays, the horizontal distances between all options was constant.

In addition to varying diagonal, *TDD*, and display, I also varied option order, such that all six orders (*DHW*, *DWH*, *HDW*, *HWD*, *WDH*, and *WHD*) were equally common.

This was a 2 (diagonal: lower, upper)  $\times$  2 (*TDD*: 20%, 35%)  $\times$  4 display: (all-aligned, two-aligned, none-aligned, triangle)  $\times$  6 (order: *DHW*, *DWH*, *HDW*, *HWD*, *WDH*, and *WHD*) within-participants study. Each participant completed 4 trials for all combinations of these factors (1 per each of the four blocks), except for the two-aligned trials, for which they completed 8 trials (2 per each of the four blocks). Thus, there were a total of 480 critical trials ( $(2 * 2 * 3 * 6 * 4) + (2 * 2 * 1 * 6 * 8) = 480$ ).

On filler-random trials, three options were randomly generated by sampling a height and width from the  $U(57, 200)px$  distribution. There were 40 filler-random trials per block for each of four blocks, leading to a total of 160 filler-random trials.

On filler-square trials, a square was randomly generated by sampling a side length from the  $U(57, 200)px$  distribution. Then, two non-square rectangles were generated by sampling a height and width from a the  $U(57, S)px$  distribution, where  $S$  is the side length for the square. This ensured that the square was always the largest option on these trials. These trials were included to ensure that participants did not learn to ignore the squares, as the critical trials rely on participants comparing the squares to the focal options. There were 40 filler-square trials per block for each of four blocks, leading to a total of 160 filler-square trials.

On catch trials, one large option was randomly generated by randomly sampling a stimulus from the upper diagonal (see Figure 5.1). Two smaller options were randomly sampled from the lower diagonal. There were 10 catch trials per block for each of four blocks, leading to a total of 40 catch trials.

On each of the non-critical trials, stimulus order was randomized. Additionally, one of the four displays (all-aligned, two-aligned, none-aligned, triangle) was selected at random.

There were a total of 840 trials in the experiment (480 critical + 160 filler-random + 160 filler-square + 40 catch=840).

#### 5.2.1.4 Procedure

On each trial, participants saw three rectangles, labeled '1', '2', and '3'. They selected the largest rectangle by pressing the corresponding key on the keyboard.

Trials were split into four blocks, with a 15-second break between blocks.

### 5.2.2 Results

#### 5.2.2.1 Data Processing

In addition to removing participants who failed to meet the 80% correct criterion for catch trials, I removed all trials with RTs < 100ms or > 10,000ms.

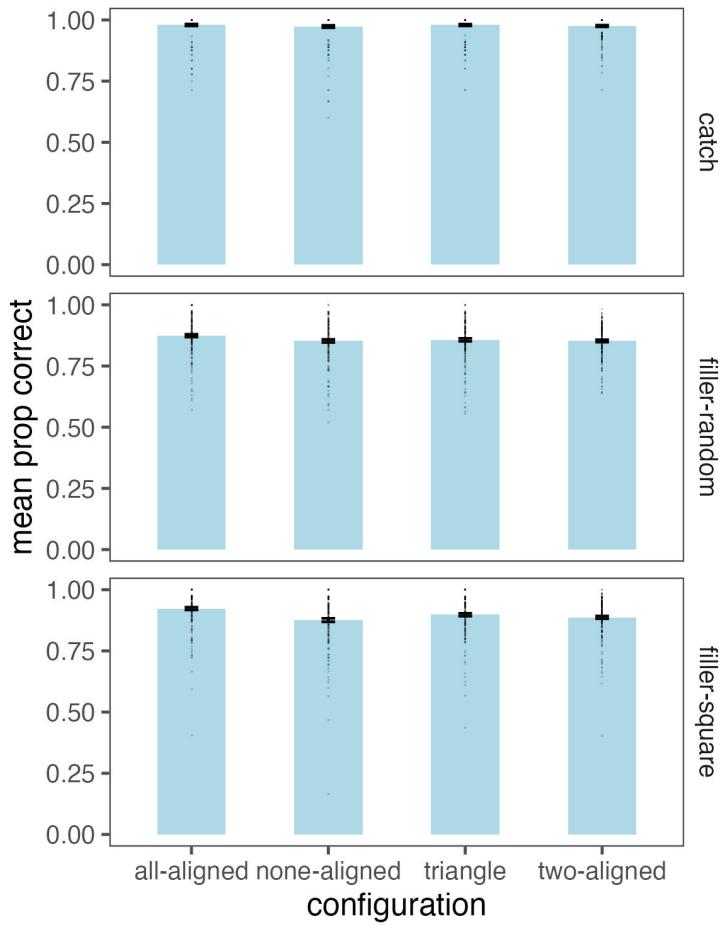
#### 5.2.2.2 Catch and Filler Trials

On average, all participants performed above chance on the catch, filler-random, and filler-square trials, including on all display types. See Figure 5.3 for data.

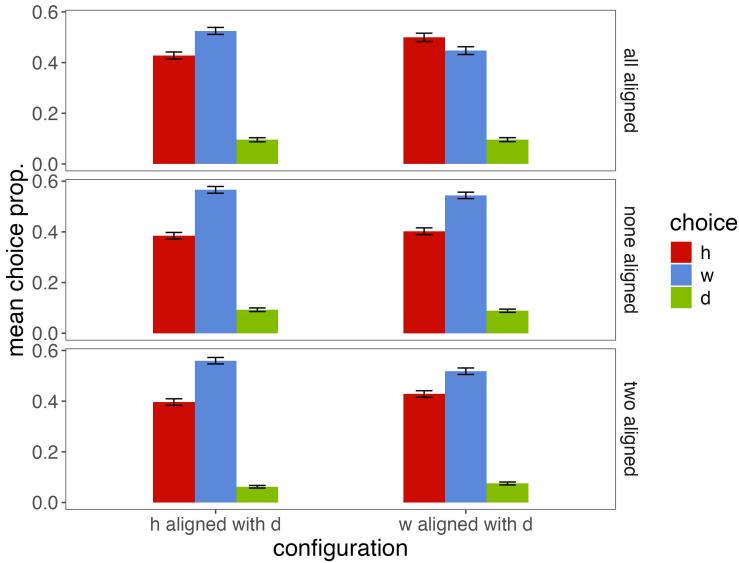
#### 5.2.2.3 Critical Trials

The goal of the critical trial analysis was to determine the rate at which participants selected the comparable and non-comparable focal options based on the configurations. I first removed the triangle condition from all analyses.

Next, I considered the order of options on screen. There were six possible orderings: *DHW*, *DWH*, *HDW*, *HWD*, *WDH*, and *WHD*. I re-classified the ordering into a variable I will call alignment. Because the two-aligned condition is the critical one, I labeled the alignment variable based on the alignment (or comparability) in the two-aligned condition. If the ordering is *DHW* or *HDW*, the alignment is "*H* aligned with *D*". If the ordering is *WDH* or *DWH*, the alignment is "*D* aligned with *W*". I removed the *WHD* and *HWD* trials from further analysis.



**Figure 5.3.** Results from non-critical trials in Experiment 5. Rows show trial types. Bars show mean proportion correct in a given condition, with the error bars showing  $\pm 1\text{SE}$ . Dots show individual participant data.

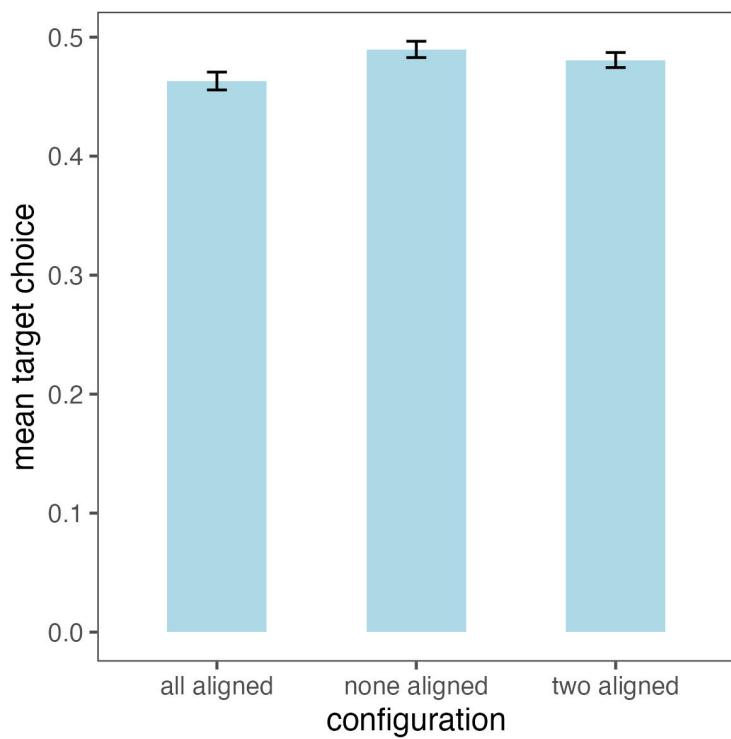


**Figure 5.4.** Results from critical trials in Experiment 5. Mean choice proportions for the  $H$ ,  $W$ , and  $D$  rectangles conditioned on alignment and configuration.

I computed mean choice proportion for the  $H$ ,  $W$ , and  $D$  rectangles based on alignment, which are shown in Figure 5.4. The data show that, in the two-aligned condition, participants were less likely to choose the  $W$  option when it was aligned with  $D$  than when  $H$  was aligned with  $D$ . This effect also appears to occur in the none-aligned and all-aligned conditions, which suggests a position bias.

Next, I removed all trials in which participants chose the decoy. I refer to the option aligned with the decoy as the *target*. I next computed mean target choice proportions by configuration, results which are plotted in Figure 5.5.

On average, participants select the target option on less than  $1/2$  of trials (conditional on not having selected the decoy). This again may suggest a position bias. However, crucially, they select the target less when it is aligned with the decoy in the two-aligned condition than when it is adjacent to the decoy in the none-aligned condition. See the Appendix for inferential statistics which support these conclusions.



**Figure 5.5.** Experiment 5 mean target choice proportions by configuration.

### 5.3 Discussion

In Experiment 5, I showed that comparability can affect choice, in a form similar to the repulsion effect. Given two equally viable, but dissimilar options, when one of these options (i.e., the target) is more easily comparable to a symmetrically dominated decoy option, participants choices are "repulsed" away from the target option and towards the competitor option. This effect is small but nonetheless present even after accounting for participant effects and a position bias.

This result aligns with the predictions from the Thurstonian perceptual choice model from Chapter 2. Increasing the comparability of a focal option and a decoy option increases the perceptual correlations between the two, which in turn decreases the choice share of the comparable *target*, for the benefit of the non-comparable competitor option. This result is also similar to previous results presented by Trueblood et al. (2022) and Evans et al. (2021), who also manipulated the arrangement of options on screen in perceptual choice.

These results are, however, somewhat limited by the positioning of the target and decoy options. In the two-aligned condition, the target and decoy were always presented in the first and second position. The statistical model accounted for this through a position bias effect, though a more thorough design would include a variety of presentation formats to more effectively test this effect.

I assume that increasing comparability decreased target choice share through perceptual correlation; however, given that I did not measure correlations directly, this may not be the case. It would be interesting to use the paradigm from Experiment 2 to directly measure the correlations between options when the decoy is symmetrically dominated and the comparability is systematically manipulated.

Future research should generalize this paradigm to high-level preferential choice. For example, given three consumer products, does the comparability of two of them affect the choice for a third option? I leave this question for future research.

The effect demonstrated is another form of context dependence, the main focus of this dissertation. Here, the context is not the choice set (which remains constant), but rather the presentation of the options. In this sense, the repulsion effect in this experiment is qualitatively similar to the repulsion effect of Spektor et al. (2018) and Experiment 2 of this dissertation.

In the final chapter, I discuss the implications of all experiments, future directions, and limitations of the current research.

# CHAPTER 6

## GENERAL DISCUSSION AND CONCLUSIONS

### 6.1 General Discussion

Decisions, even simple ones, may be impacted by context. Context effects occur when the relative choice for a particular option varies with situational properties. In particular, the set of other available affects choice. The attraction effect occurs when a decoy option "boosts" the choice share of a similar, superior target option. The repulsion effect, a reversal of the attraction effect, occurs when the inclusion of the decoy causes people to select the dissimilar competitor more than the target.

This dissertation has explored context dependence in choice, largely by studying the attraction and repulsion effect (Chapters 2-4) but also through studying context dependence induced by the presentation format of options in simple perceptual choice (Chapter 5).

In Chapter 2, I used a Thurstonian perceptual choice model to measure the correlation between valuations in the attraction and repulsion effect. In Experiment 2, I collected valuations (area estimations for simple rectangles) and choices (where participants selected the largest rectangle from each ternary choice set). I connected valuations to choices using the Thurstonian model. I showed that, through the  $\rho_{TD}$  parameter, this model can parsimoniously account for the repulsion effect without invoking higher-level decision processes (Experiment 2). The model cannot, however, account for the attraction effect, suggesting that higher-level decision processes may be required to explain this effect. I also demonstrated systematic discriminability

issues in a 2AFC task, using the same experimental stimuli, in accordance with the Thurstonian model (Experiment 1).

In Chapter 3, Experiment 3, I showed that the model makes an interesting prediction for best-worst choice experiments. In best-worst choice, participants select their most and least preferred options from a given choice set. Given the stimuli from Experiment 2 (a set of target, competitor, and decoy rectangles in a perceptual choice experiment), the model predicts a non-monotonic relationship between best and worst choice probabilities. Specifically, the model predicts that the target is both less likely to be chosen as worst, compared to the competitor, and also less likely to be chosen as best. This effect is not predicted by the maxdiff model, a highly influential of best-worst choice. Thus, I have identified another form of context dependence: whether participants are selecting the best option or the worst option from a particular choice set.

In Chapter 4, Experiment 4, I generalized the paradigm and model from Chapter 2 to preferential choice. On each experimental trial, participants saw three consumer products (e.g., microwave ovens, laptops) and assigned each one a viable selling price. In later experimental trials, they saw the same three options and selected the option they most preferred. I showed that the similarity, and comparability, of the target and decoy options, appears to generalize across choice types and can be reliably measured using Pearson correlations. I also replicated previous researchers' choice results (Banerjee et al., 2024), albeit with limitations. For example, the experiment did not systematically decoy position nor did it include binary choices to combat this limitation.

The model from Experiment 4 is able to qualitatively account for the repulsion effect, there is one crucial limitation here; the model accounts for the effect through the correlation between target and decoy evaluations, which causes the decoy to take choice shares away from the target. In preferential choice, and unlike perceptual

choice, participants seldom if ever select the decoy. In the absence of these correlations, or if all correlations are equal (i.e.,  $\rho_{TD} = \rho_{TC} = \rho_{CD}$ ), the model will be unable to predict the effect<sup>1</sup>. Thus, this form of the repulsion effect may be due to higher-level decision processes. Nonetheless, the demonstration of target-decoy correlations, and indeed target-competitor correlations, is a novel and interesting result.

Though other researchers have proposed correlations as a measure of the similarity between options in a choice set (Kamakura & Srivastava, 1984; Natenzon, 2019), these studies was the first (to my knowledge) to systematically measure these correlations using valuations, incorporate them into a Thurstonian choice model, and connect this model to choices obtained from the same experimental participants.

In Chapter 5, Experiment 5, I demonstrated a new form of context dependence, where choice systematically varies based on option comparability. Given a *symmetrically dominated decoy* option, placing a focal target option in a nearby position, such that participants can more easily compare it to the decoy, *decreases* the target's choice share. This is similar to the standard repulsion effect, with the important caveat that both focal options are equally perceptually similar to the decoy.

There were limitations to this experiment. In particular, given the critical "two-aligned" condition, the target and decoy were only ever in the first and second positions. Future work should fix this experimental design flaw, while also including different configurations.

The results of this dissertation also have important methodological considerations. In particular, I argue that researchers should carefully consider the assumptions made when designing and analyzing experiments. For example, the experiments of Spektor et al. (2018) contain a crucial assumption: that stimulus discriminability issues do not systematically affect target or competitor choice, and that the repulsion effect

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<sup>1</sup>See the diagonal line from Figure 2.6 for evidence of this result.

observed in these experiments is a qualitative reversal of the attraction effect rather than just an empirical one. I also showed, in Chapter 3, that the independence assumption of the maxdiff choice model is incorrect (at least in some cases) and a failure to consider whether the stimuli of a given experiment can cause these violations may lead to incorrect conclusions about participants' preferences. The results of Chapter 5 show that the comparability, and even order on screen, can systematically affect choice. Previous researchers have also argued in favor of this point (Evans et al., 2021; Hasan et al., 2025; Trueblood et al., 2022).

There are numerous directions that this work could take beyond this dissertation. I could generalize the experimental and modeling paradigm of Experiment 2 to other context effects (e.g., compromise, similarity). I am also interested in measuring correlations between option valuations at the individual participant level, which is currently limited by the quantity of data available.

Regarding best-worst choice, future work should explore models of best-worst choice that can be used when the independence assumption is violated. Exploration, or development is necessary, is beyond the scope of this dissertation. However, given the numerous applied uses for best-worst choice, this avenue of research would be important and fruitful.

In the future, I plan on continuing the line of research begun in Experiment 4. For example, I have already conducted a binary-ternary version of the choice phase from Experiment 4. I also plan on running an experiment collecting both prices and choices in binary and ternary choice sets. This work will significantly add to the preferential choice and context effects literature.

In addition to the experimental modifications discussed earlier, future work in comparability should generalize the paradigm to various choice types. Additionally, the effect observed in Experiment 5 was quite small; practically speaking, this have

limited impact on actual choices. Future work should address the limitations of comparability in affecting choice.

## 6.2 Conclusions

In this dissertation, I have identified various forms of context dependence, in both perceptual and preferential choice. I provided theoretical explanations for these results in the form of a mathematical model of choice. To ensure falsifiability, I tested the model’s predictions on out-of-sample data, to considerable success. This work will further the study of context effects and decision-making in general.

Below I show the prior distributions on all parameters.

### .1 Prior Distributions on Parameters

- $\beta_{or} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD5} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD9} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD14} \sim \mathcal{N}(0, 5)$
- $\beta_{comp} \sim \mathcal{N}(0, 5)$
- $\beta_{decoy} \sim \mathcal{N}(0, 5)$
- $\beta_{S_{comp_i}} \sim \mathcal{N}(0, \sigma_{S_{comp}})$
- $\beta_{S_{decoy_i}} \sim \mathcal{N}(0, \sigma_{S_{decoy}})$
- $\sigma_{S_{comp}} \sim \text{Half-Cauchy}(0, 2.5)$
- $\sigma_{S_{comp}} \sim \text{Half-Cauchy}(0, 2.5)$

## .2 Parameter Estimates

Table 1 shows parameter estimates, including means and 95% credible intervals.

Parameter	M	SD	CI low	CI high
$\beta_{or}$	0.27	0.01	0.26	0.28
$\beta_{TDD5}$	0.27	0.01	0.24	0.29
$\beta_{TDD9}$	0.64	0.01	0.61	0.67
$\beta_{TDD14}$	1.05	0.02	1.02	1.08
$\beta_{comp}$	-0.03	0.01	-0.05	-0.01
$\beta_{decoy}$	-0.25	0.02	-0.28	-0.21
$\sigma_{comp}$	0.14	0.01	0.12	0.16
$\sigma_{decoy}$	0.29	0.01	0.27	0.32

**Table 1.** Parameter estimates for maxdiff modeling from Experiment 3, including means, SDs, and 95% Credible Intervals.

# APPENDIX A

## BAYESIAN MODELING OF PRICE DATA FROM EXPERIMENT 4

I modeled the pricing data from Experiment 4 using a similar Thurstonian model to that of Experiment 2.

### A.1 Thurstonian Price Model

I assumed that on each trial  $i$ , a vector of prices  $\mathbf{X}_i$  is drawn of a multivariate normal distribution:

$$\mathbf{X}_i \sim \mathbf{N}(\boldsymbol{\mu}_{jk}, \boldsymbol{\Sigma}_k) \quad (\text{A.1})$$

where  $j$  is the product category (washing machines, laptops, televisions, microwave ovens) and  $k$  is the trial type (attraction, repulsion).

$\boldsymbol{\mu}_{jk}$  is the column vector:

$$\begin{pmatrix} \mu_{T_j k} \\ \mu_{C_j k} \\ \mu_{D_j k} \end{pmatrix} \quad (\text{A.2})$$

and  $\boldsymbol{\Sigma}_k$  is a 3x3 positive semi-definite variance-covariance matrix:

$$\boldsymbol{\Sigma}_k = S \boldsymbol{\Omega}_k S \quad (\text{A.3})$$

where  $S$  is a diagonal matrix consisting of:

$$\begin{pmatrix} \sigma_T & 0 & 0 \\ 0 & \sigma_C & 0 \\ 0 & 0 & \sigma_D \end{pmatrix} \quad (\text{A.4})$$

with  $\sigma_T$ ,  $\sigma_C$ ,  $\sigma_D$  being the standard deviations for target, competitor, and decoy, respectively.  $\boldsymbol{\Omega}_k$  is a correlation matrix:

$$\begin{pmatrix} 1 & \rho_{TC_k} & \rho_{TD_k} \\ \rho_{TC_k} & 1 & \rho_{CD_k} \\ \rho_{TD_k} & \rho_{CD_k} & 1 \end{pmatrix} \quad (\text{A.5})$$

with  $\rho_{TD_1}$ , for example, indicating the population-level correlation between target and decoy valuations in the attraction condition.

This model has relatively 24 free parameters, relatively few compared to the several hundred from Experiment 2.

I had no a priori predictions about the size or even direction of the price differences here. Given this, I freely estimated all  $\boldsymbol{\mu}$  parameters rather than estimate them through linear regression, as in Experiment 2.

Prior to model estimation, I z-scored all prices within participants.

## A.2 Prior Distributions on all Parameters

- $\boldsymbol{\mu}_{jk} \sim \mathbf{N}(0, 1)$

- $\sigma_T \sim \text{Half-Cauchy}(0, 2.5)$
- $\sigma_C \sim \text{Half-Cauchy}(0, 2.5)$
- $\sigma_D \sim \text{Half-Cauchy}(0, 2.5)$
- $\Omega_k \sim \text{LKJCorr}(\eta = 0.5)$

### A.3 Parameter Estimates

For brevity, I omit  $\mu$  and  $\sigma$  estimates and show only  $\rho$  estimates below.

Trial Type	Parameter	<i>M</i>	<i>SD</i>	HDI lower	HDI upper
<b>Attraction</b>	$\rho_{TC}$	.87	0.005	.86	.88
	$\rho_{TD}$	.87	0.005	.86	.88
	$\rho_{CD}$	.83	0.007	.81	.84
<b>Repulsion</b>	$\rho_{TC}$	.77	0.008	.75	.79
	$\rho_{TD}$	.87	0.005	.86	.88
	$\rho_{CD}$	.69	0.011	.67	.72

**Table A.1.**  $\rho$  Parameter estimates for  $\rho$  parameters from the Bayesian Hierarchical Thurstonian Model from Experiment 4 Pricing Data, including means, standard deviations, and 95% Credible Intervals.

## APPENDIX B

### BAYESIAN MODELING OF CHOICE DATA FROM EXPERIMENT 4

To analyze the choice data of Experiment 4, I used a Dirichlet-Multinomial model. The Dirichlet distribution is a generalization of the Beta distribution to  $> 2$  dimensions. Here the Dirichlet distribution is used to model the variability in ternary choice proportions for the attraction and repulsion trials from Experiment 4.

In this analysis, I collapsed over participants. This is a limitation, particularly given recent concerns about participant-level variability in context effects (Liew et al., 2016; Trueblood et al., 2015). Future modeling work will address this concern. However, given that the main goal of Experiment 4 was to measure correlations in pricing, I performed this analysis on aggregate choice data.

#### B.1 Dirichlet-Multinomial Choice Model

According to the model, the vector  $\mathbf{C}_{ijkl}$  of target, competitor, and decoy counts for trial type (attraction, repulsion)  $i$ , TDD (near, far)  $j$ , product category (laptops, microwave ovens, televisions, wachine machines)  $k$ , target high dimension (1,2)  $l$  is

$$C_{ijkl} \sim \text{Multinomial}(\boldsymbol{\theta}_{ijkl}) \quad (\text{B.1})$$

$\boldsymbol{\theta}_{ijkl}$  is a vector of choice probabilities which is turn distributed:

$$\boldsymbol{\theta}_{ijkl} \sim \text{Dirichlet}(\boldsymbol{\alpha}_{ijkl}) \quad (\text{B.2})$$

where all  $\boldsymbol{\alpha} > 0$ .

For a prior distribution on  $\boldsymbol{\alpha}$ , I assumed:

$$\boldsymbol{\alpha}_{ijkl} \sim \text{LogNormal}(1, 1) \quad (\text{B.3})$$

I performed inference using the mean target, competitor, and decoy choice probabilities, collapsed across product category and the target's high dimension. See Table B.1.

<b>Trial Type</b>	<b>TDD</b>	<b>Option</b>	<i>M</i>	HDI lower	HDI upper
Attraction	Near	Target	.48	.45	.51
		Competitor	.47	.44	.50
		Decoy	.05	.03	.06
	Far	Target	.46	.43	.49
		Competitor	.48	.45	.51
		Decoy	.07	.05	.08
Repulsion	Near	Target	.31	.28	.34
		Competitor	.66	.63	.69
		Decoy	.04	.03	.05
	Far	Target	.33	.30	.36
		Competitor	.65	.62	.68
		Decoy	.03	.02	.04

**Table B.1.** Experiment 4 Mean Posterior Choice Proportions from the Bayesian Dirichlet-Multinomial Model.

On average, participants chose the competitor more than the target in both TDD levels, in the repulsion effect trials. In the attraction effect trials, participants chose the target and competitor at equal rates.

## APPENDIX C

### BAYESIAN HIERARCHICAL LOGISTIC REGRESSION FOR EXPERIMENT 5 DATA

To analyze the comparability data from Experiment 5, I used a Bayesian hierarchical logistic regression model.

As discussed in Chapter 5, I first removed all trials where participants chose the decoy option. I also removed trials where the W and H rectangles were in the first two positions.

I classified the target as the option aligned with the decoy in the two-aligned option. I then predicted choice in the model as a linear function of configuration (none-aligned, two-aligned, all-aligned) and whether the target was in the middle position (1, 0). The reference level for configuration was none-aligned. There were no interactions included in the model. I also included a random effect of participant in the model.

I fit the model as a Bayesian hierarchical logistic regression model using the rstanarm package (Goodrich et al., 2020), using default priors for all parameters. Posterior estimates for all fixed effects are shown in Table C.1.

Parameter	<i>M</i>	<i>SD</i>	HDI lower	HDI upper
$\beta_0$	-0.18	0.03	-0.24	-0.13
$\beta_{\text{two-aligned}}$	-0.03	0.02	-0.08	0.01
$\beta_{\text{all-aligned}}$	-0.11	0.03	-0.16	-0.06
$\beta_{\text{target middle}}$	0.27	0.02	0.24	0.31

**Table C.1.** Experiment 5 Posterior Estimates for all Fixed Effects from the Bayesian Hierarchical Logistic Regression Model.

The main parameter of interest is  $\beta_{\text{two-aligned}}$ , which captures the change in target choice when comparing the none-aligned condition to the two-aligned condition. The posterior mean was below 0 ( $M = -0.03$ ), and while the 95% HDI included 0 ( $[-0.08, 0.01]$ ), 93.23% of all samples were  $< 0$ , which is taken as moderate evidence for an effect.

Interestingly, participants also chosen the target less in the all-aligned condition ( $M = -0.11$ ), suggesting a bias away from the aligned option even when all options were aligned.

There was also a position effect, such that participants chose the target more when it was in the middle of the screen  $M = -.27, 95\%CI[0.24, 0.41]$ .

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