CONTEXT DEPENDENCE IN PERCEPTUAL AND PREFERENTIAL CHOICE

A Dissertation Presented

by

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ABSTRACT

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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 of 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 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 understand how and why these the attraction and repulsion effects occur, 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 choice for an option varies systematically with 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

To begin, I formally define the *attraction effect*. 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. I intentionally give these dimensions generic names 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.

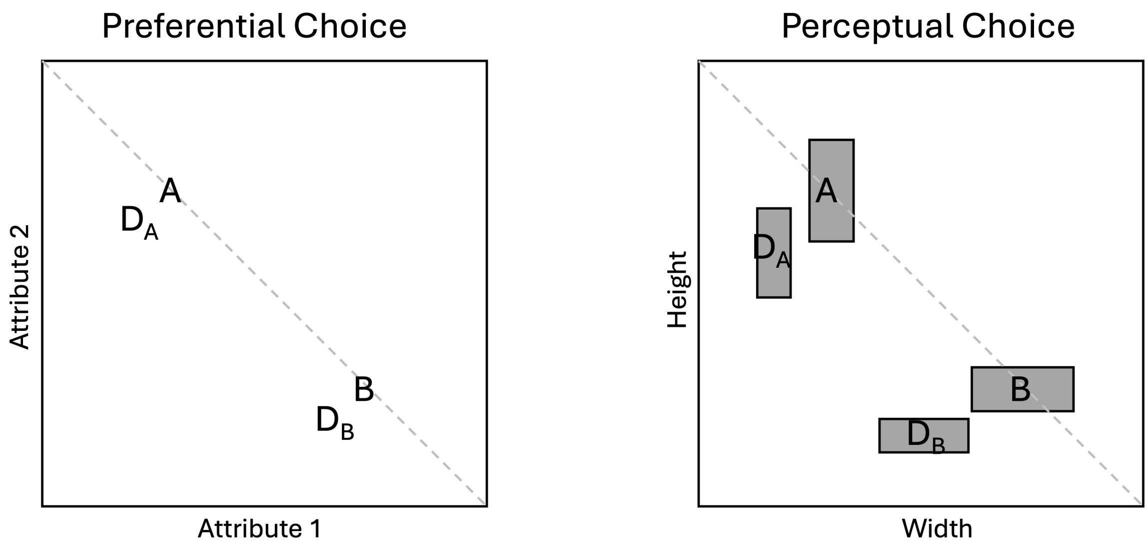

Figure 2.1. A graphical depiction of choice options in the attraction/repulsion effect. Left panel: preferential choice. Right panel: perceptual choice.

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. 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 then given set A, B, D_B[1].

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).

According to IIA:

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[1]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.

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

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

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

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. I adopt this terminology through this dissertation.

The decoy is dominated by the target, so no rational agent who perceives this dominance relationship should intentionally select the decoy over the target.

The attraction effect was first demonstrated by Huber et al. (1982) [2], 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:

$$P(A|[A,B]) \geq P(A|[A,B,D_A]) \tag{2.3}$$

Huber et al. (1982)'s finding that $P(A|[A,B]) \leq P(A|A,B,D_A)$ 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

[2] These authors referred to this finding as the asymmetric dominance effect. To stay consistent with contemporary research, I use the term attraction effect throughout this dissertation.

target. This result suggests that the relative positioning of the decoy to the target 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. Researchers have demonstrated other context effects, such as the similarity effect, where a similar but equally valuable decoy *decreases* the choice share of a target option (Tversky, 1972), and the compromise effect, where an intermediate option decreases the choice share of two relatively extreme options (Simonson, 1989).

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 choice experiment the participant samples 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). As will be the focus of much of this dissertation, the probit model assumes Gaussian distributed utilities (Bolduc, 1999). Often (though not necessarily) RUMs assume IIA (c.f,. Paetz and Steiner (2018)), though this assumption can 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). If IIA is assumed, RUMs are unable to account for context effects (Berkowitsch et al., 2014).

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. Indeed, other researchers have performed such analyses (Berkowitsch et al., 2014; Cataldo & Cohen, 2021; Cohen et al., 2017; Hotaling et al., 2010; Molloy et al., 2019; Tsetsos et al., 2010; Turner et al., 2018), arriving at varying conclusions.

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) demonstrated the attraction effects in perceptual similarity judgments. 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) 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. [3].

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

[3] Trueblood et al. (2013) also demonstrated the similarity and compromise effects.

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 (Ashby & Townsend, 1986).

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

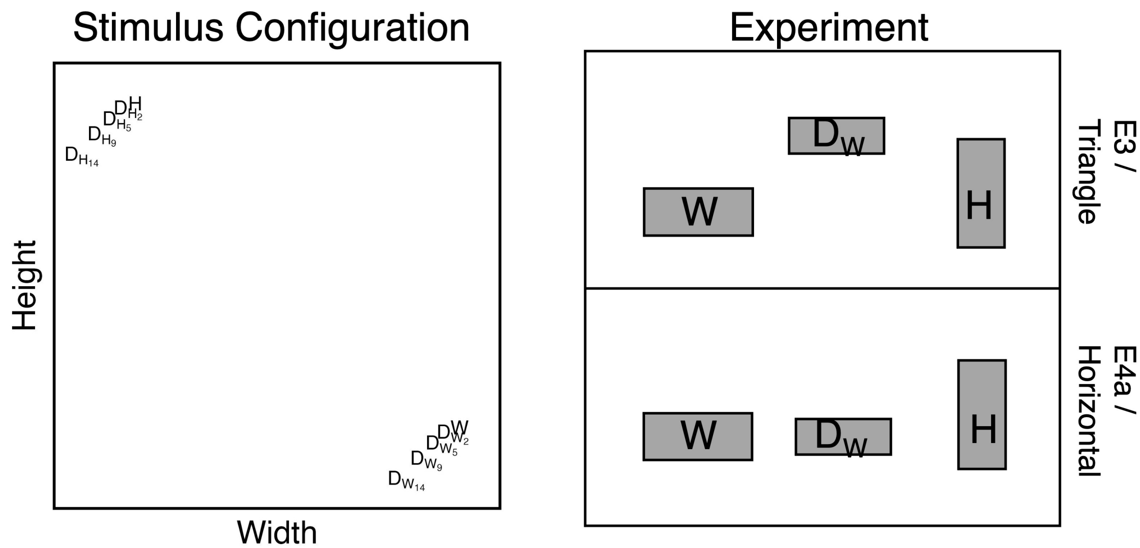

Figure 2.2. Stimulus configuration and example trials from Spektor et al. (2018), Experiments 3 and 4a. Note that the stimulus in the righthand plot were not shown in the experiment; these are solely for the benefit of the reader.

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 trianglular display on the screen (see Figure 2.2, Experiment 3), in contrast to Trueblood et al. (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 diplay 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.

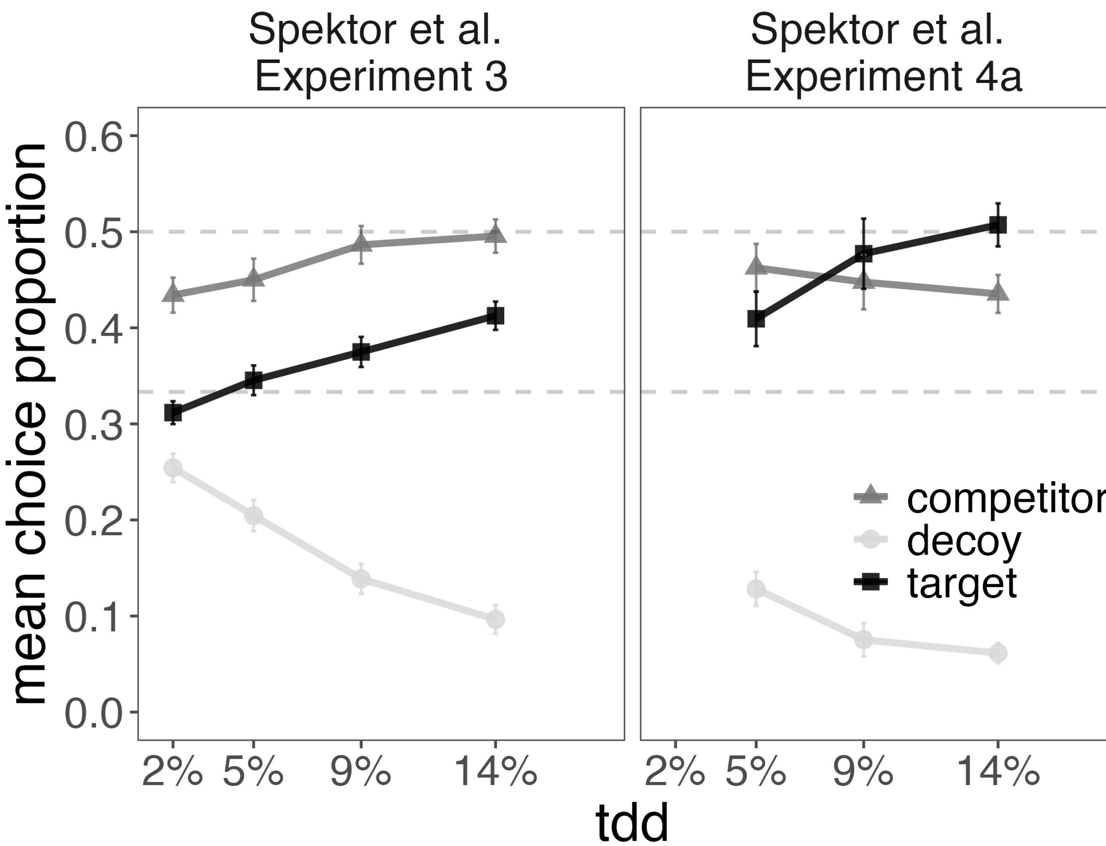

Figure 2.3. Data from Spektor et al. (2018), collapsed across choice set. Error bars are 95% CIs of the mean, computed using the within-participants error correction from Morey et al. (2008). Dashed lines are drawn at .5 and .33.

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 presented but made unavailable at the time of choice. They showed that participants chose the target less than the competitor, i.e., a repulsion effect, 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

Relative Share of the Target RST[4]. 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. I argue, however, that researchers should be cautious in assuming that decision-makers receive perceptual input with the same accuracy that they do in preferential choice experiments. Researchers should seek to separate the role of perceptual discriminability from decisional processes when understanding participants' responses. I elaborate on these ideas below and in Chapter 2, with a demonstration using the results of Spektor et al. (2018).

2.1.3 Understanding Perceptual Choice Experiments

Crucially, many researchers who study context effects in perceptual choice assume that the perceptual difficulty of the experimental task does not impact conclusions. Researchers often assume that the chocie data in perceptual choice experiments can be analyzed identically to that of preferential choice experiments. In these experiments

[4] $RST = \frac{P(T|[T,C,D])}{P(T|[T,C,D])+P(C|[T,C,D])}$. $RST > .5$ indicates an attraction effect, while $RST < .5$ indicates a repulsion effect.

participants often fail to perceive that the decoy is the smallest stimulus in the choice set. Researchers tend to assume that, to the extent that the dominance relationship is misperceived, the decoy is equally likely to be seen as larger than the target than larger than the competitor.

One plausible account of Spektor et al. (2018)'s data is that participants occasionally misperceive the dominance relationship, and due to the difficulty of the task and the similarity of target and decoy, they are more likely to choose the decoy over the target than over the competitor. Such a process creates an *empirical* repulsion effect but is qualitatively different than a reversal of the traditional attraction effect. Spektor et al. (2018) dismiss such an account because the target is chosen more often the decoy; however, this fact does not rule out the above explanation of the data.

One goal of this dissertation is to separate the role of perceptual and decisonal processes in context effects. To do so, I 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.

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, I highlight the differences between Spektor et al. (2018)'s data and previous context effect experiments.

In preferential choice tasks, participants are given a set of options on each trial (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. Researchers can reliably assume that participants are able to detect the dominance relationship between target and decoy. Perceptual choice tasks 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. 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* (RST) (Berkowitsch et al., 2014) increases with TDD in both 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 the decoy decreases in size. Any reasonable account of these data should parse the out discriminability from genuine context effects. To do so, I turn to a well-studied class of models within the psychology literature.

2.1.4 Modeling Context-Dependent Perceptual Choice

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. Models of this class are often called *Thurstonian*, a term I use throughout this dissertation.

Thurstone's work led to similar research using Signal Detection Theory (SDT) (Hautus et al., 2021), which also treats psychological constructs (e.g., memory, perception), as random variables (typically Gaussian). Ashby and colleagues' General Recognition Theory (GRT) models the perception of a single stimulus as a multivariate normal random variable, where each dimension of the model is the perceived intensity on that dimension (Ashby & Gott, 1988; Ashby & Perrin, 1988; Ashby & Townsend, 1986; Maddox & Ashby, 1993). 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 Model (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, I now introduce the Thurstonian model I explore throughout the dissertation. This model is simplistic, as it treats the experiments of Trueblood et al. (2013) and Spektor et al. (2018) as perceptual tasks, rather than decision tasks. This completely eschews the possibility of higher level decision processes. I use this model to differentiate perceptual from decision-making processes in the repulsion and attraction effects. The model treats value (perceived area) as stochastic and choice as deterministic. Furthermore, I do not treat height and width as independent attributes but rather consider perceived area to be unidimensional.

2.1.5 A Thurstonian Choice Model

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:

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

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

$$\begin{pmatrix} \mu_T \\ \mu_C \\ \mu_D \end{pmatrix} \tag{2.5}$$

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

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

$$\boldsymbol{\Sigma} = S\boldsymbol{\Omega}S \tag{2.6}$$

where S is a diagonal matrix consisting of:

$$\begin{pmatrix} \sigma_T & 0 & 0 \\ 0 & \sigma_C & 0 \\ 0 & 0 & \sigma_D \end{pmatrix} \tag{2.7}$$

with σ_T, σ_C, σ_D denoting the standard deviations for target, competitor, and decoy, respectively. $\boldsymbol{\Omega}$ is a 3x3 correlation matrix:

$$\begin{pmatrix} 1 & \rho_{TC} & \rho_{TD} \\ \rho_{TC} & 1 & \rho_{CD} \\ \rho_{TD} & \rho_{CD} & 1 \end{pmatrix} \tag{2.8}$$

with ρ_{TD}, for example, denoting correlation between target and decoy perception.

As mentioned above, the model assumes that value is stochastic while choice is deterministic[5]. 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:

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

If all off-diagonal elements of $\mathbf{\Omega}$ are 0 and $\sigma_T = \sigma_C = \sigma_D$, the model collapses to 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 elements of $\mathbf{\Omega}$ 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). In all applications of these model through this dissertation, I use simulation to generatepredictions.

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. Moreover, I wil later present empirical data that suggest, generally speaking, $\mu_T \approx \mu_C$.

[5]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. Indeed, other researchers have explored such a mechanism (Haaijer et al., 1998; Kamakura & Srivastava, 1984).

To test this, I used model simulations to assess the effect of correlations (.e., ρ_{TC}, ρ_{TD}, and ρ_{CD}) on predictions for the attraction and repulsion effects.

I varied both ρ_{TD} and ρ_{TC} from -1 to 1; in other words, all rectangles oriented the same way share one correlation and those oriented differently share another correlation. I show model predictions that result from varying these correlations in Figure 2.4. Here, I assume that $\mu_T = \mu_C > \mu_D$ and that $\sigma_T = \sigma_C = \sigma_D$[6].

Figure 2.4 shows model predictions in the form of RST (Relative Share of the Target), 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 ρ_{TD} and ρ_{TC}, predict a repulsion, attraction, or a null context effect. If $\rho_{TD} > \rho_{TC}$, the model predicts a repulsion effect. If the target and decoy are correlated more strongly than competitor and decoy, it is more likely that if on a particular trial the target perception is large, that the decoy is even *larger*, causing the decoy to "steal" choice shares from the target more than the competitor, i.e., a repulsion effect.

If $\rho_{TD} < \rho_{TC}$, the model predicts an attraction effect. This is because $\rho_{TC} = \rho_{CD} > \rho_{TD}$, so the decoy "steals" choice shares from the competitor more than the target.

Finally, 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 $\rho_{TD} = \rho_{TC} = \rho_{CD} = 0$.

[6] In Experiment 2 I present evidence supporting these assumptions.

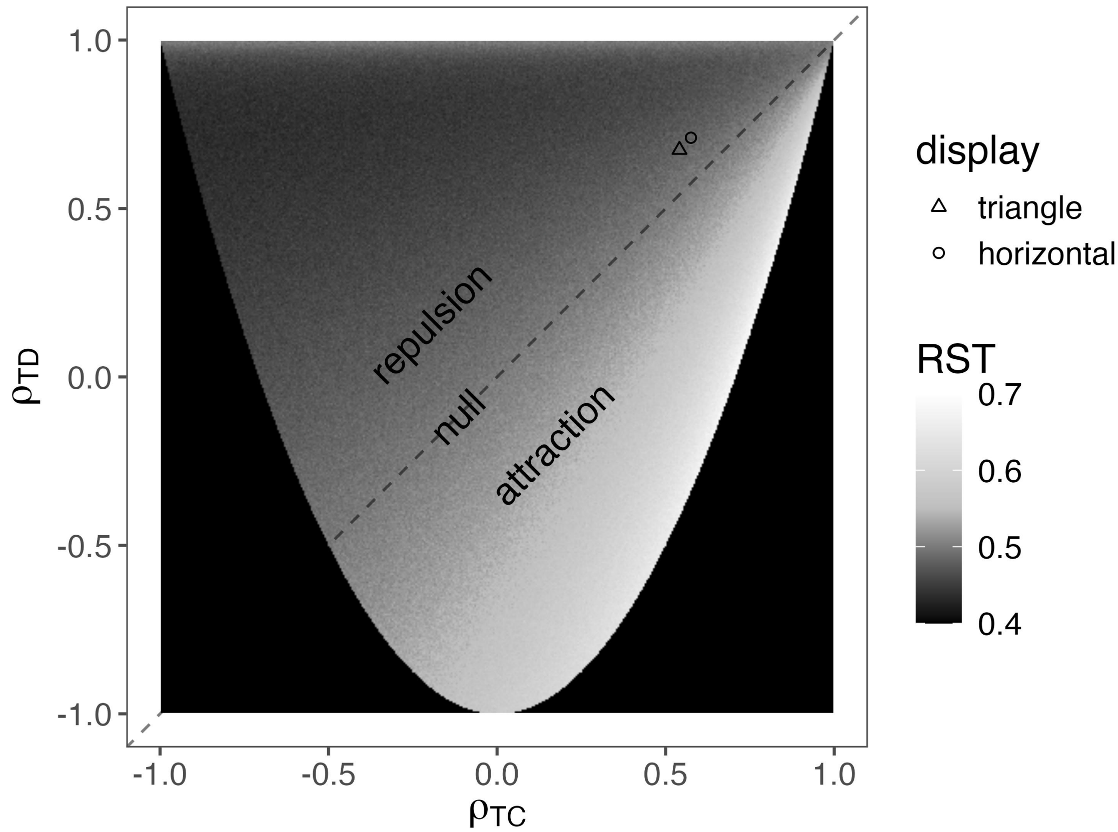

Figure 2.4. Model simulations for the attraction and repulsion effects based on the variation of ρ_{TD} and ρ_{TC}. "Regions" of the plot are labeled based on their qualitative predictions for attraction, null, and repulsion effects. The black region is the area where, due to extreme correlations, a 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.

2.1.6 Perceptual Correlations as Mechanism for the Repulsion Effect

I propose that these perceptual correlations may be driving the repulsion effect in Spektor et al. (2018)'s data. The decoy option is smaller than the the target and competitor options and is thus not always discriminated. The triangle configuration makes discriminability particularly difficult for participants (as I show below in Experiment 1). 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. When TDD is low, the ease of target-decoy comparison will increase the likelihood that the decoy is perceived to be larger than the target. 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 ρ_{TD} and ρ_{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. The repulsion effect may thus be driven by perceptual processes rather than decision processes.

In Experiment 1, I first present results from a two-alternative forced-choice experiment to show that these stimuli are easily confusable and that the triangle display of Spektor et al. (2018) decreases discriminability relative to the horizontal display. I also show that, consistent with the predictions of a Thurstonian perceptual model where $\rho_{TD} > \rho_{TC} = \rho_{CD}$, target-decoy discriminability is in fact greater than competitor-decoy discriminability in binary choice and that target-decoy discriminability increases with TDD.

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[7]. Otherwise, with a few exceptions discussed below, I follow 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. Trials with response times (RTs) $<$ 100ms or $>$ 10000ms were also excluded from all analyses.

2.2.1.2 Stimuli.

The experiment had two types of trials: critical trials and catch trials. On each critical trial, the target and competitor had the same area[8] but differed on orientation, with one stimulus being wide and the other tall. The decoy always had the same orientation as the target. The height and width of the decoy were reduced proportionally so that the decoy area was always 0%, 2%, 5%, 9%, or 14% of the target areas. Because the target and competitor always had the same area, this means that

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[7] see also Trueblood et al. (2013), Experiment 1.

[8] Here I simplify Spektor et al. (2018)'s design by ensuring both focal stimuli had the same area.

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[9].

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 were presented in a triangle and 6 were presented horizontally.. 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, one was a target-decoy comparison, one was a target-competitor comparison, and one was a competitor-decoy comparison. Trial order and rectangle order within each trial were randomized. Thus, this was a 4 (TDD: 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.

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

On every trial, the rectangles were displayed in either a triangle or horizontal display (see Figure 2.2). The horizontal distance between all rectangles was constant, but 25 pixels of jitter was added to each rectangle's vertical location.

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

[9]When TDD=0%, the target and decoy are identical, so labeling is arbitrary.

2.2.1.4 Procedure.

On each trial, participants saw three rectangles, labeled 1, 2, and 3 (from left to right). The rectangles appeared for $1825ms$ total, but after $500ms$, two of the rectangles changed to a darker shade. After all three rectangles disappeared from the screen, participants were asked to select which of the two darker rectangles had the larger area.

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.

I first checked the baseline TDD level data (TDD=0%) across to make sure 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). The mean percentage of competitor choices in competitor-decoy trials was 49.80% (SD=11.30). The mean percentage of target choices in target-decoy trials was 49.47% (SD=12.06). Participants were indifferent between all pairs of options in the TDD = 0% trials, so I do not consider these trials further.

The primary analysis was performed on the target-decoy and competitor-decoy trials, excluding the TDD=0% trials. In these trials participants' task is simply to not select the decoy option on a given trial. I present mean choice proportions across conditions 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

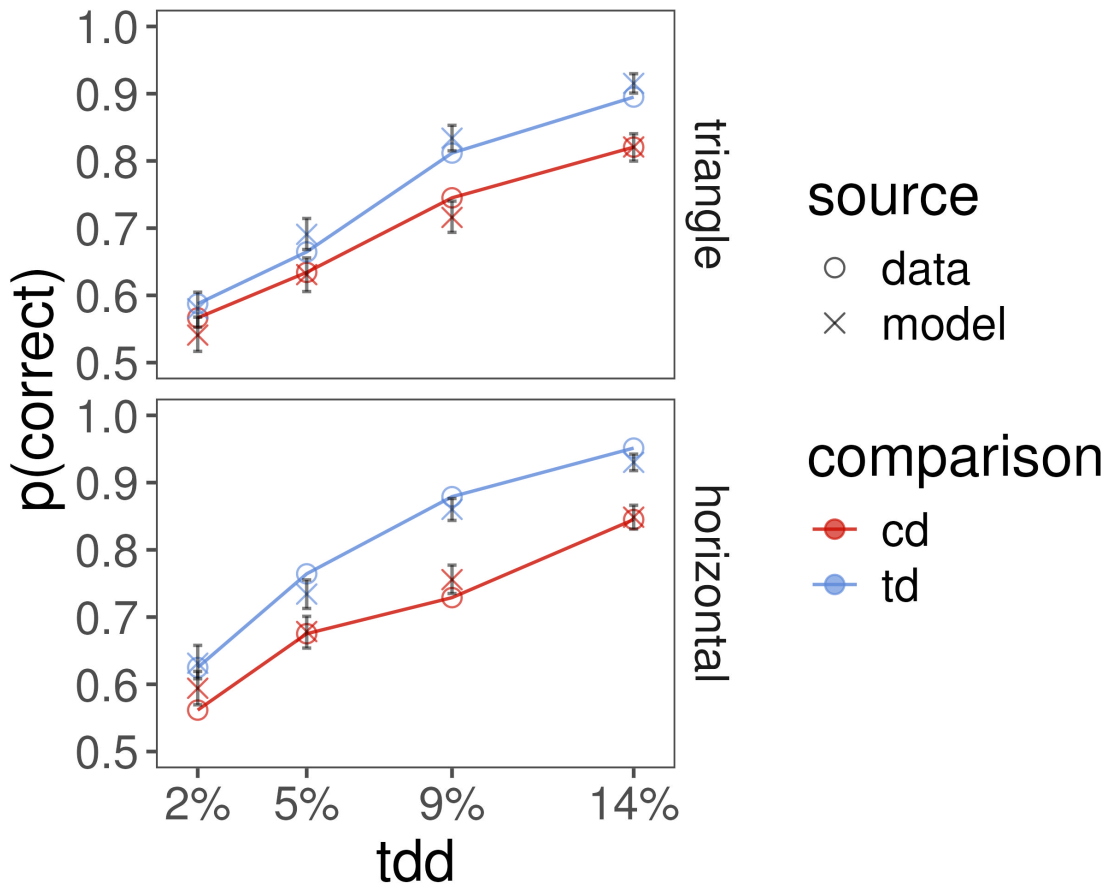

Figure 2.5. Experiment 1, mean choice proportions by stimulus display, TDD, and comparison. td=target-decoy trials, cd=competitor-decoy trials. Model predictions come from the Bayesian hierarchical logistic regression presented in the Appendix. Error bars are 95% HDIs on the mean.

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

In Experiment 1, I showed that participants are not always able to discriminate between target-decoy and competitor-decoy stimuli. I also show that 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-pair

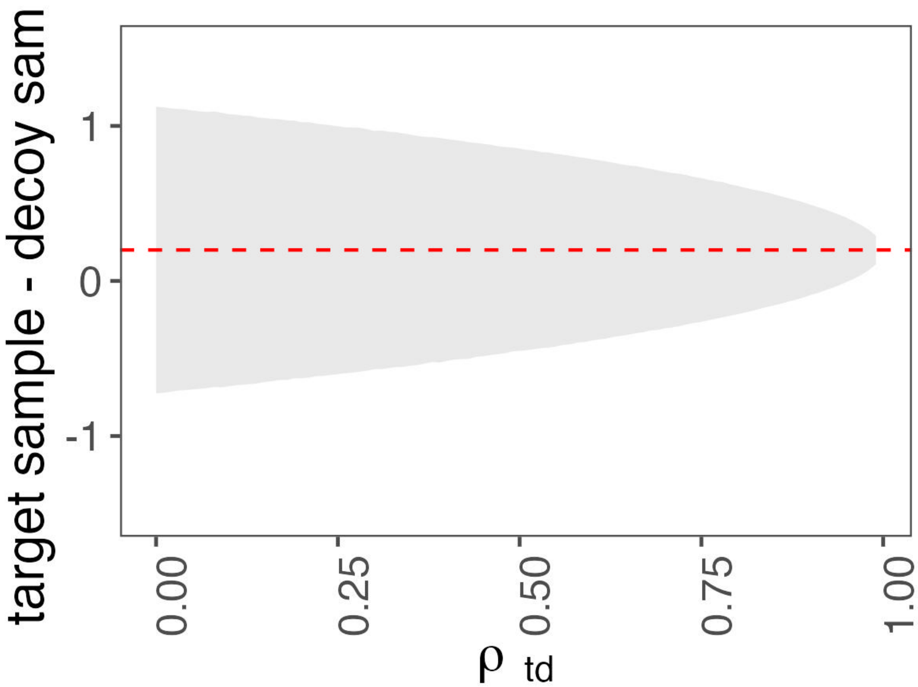

Figure 2.6. Simulated differences in sampled target minus decoy area (i.e., $X_T - X_D$) as an plotted against increasing values of ρ_{TD}. The lower and upper boundaries of the polygon show the lower and upper quantiles (2.5% and 97.5%, respectively) of the difference between sampled target and decoy values. The dotted red line marks the true $\mu_T - \mu_D$ value.

and TDD, I show that target-decoy discriminability increases with TDD at a higher rate than competitor-decoy discriminability.

It may seem counterintuitive that target-decoy correlations can simultaneously create greater discriminability in binary choice while also generating a repulsion effect in ternary choice. To understand this, it may help to express the correlation ρ_{TD} as:

$$\rho_{TD} = \frac{\mathbb{E}[(X_T - \mu_T)(X_D - \mu_D)]}{\sigma_T \sigma_D} \tag{2.10}$$

As ρ_{TD} increases, the difference between sampled target and decoy values converges towards the true difference between μT and μ_D. I also show this by plotting the difference in sampled target and decoy values against increasing values of ρ_{TD}.

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 affects choice. This is important theoretically 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 Experiment 2, I 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.

2.3 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. I used the *method of cross-modal matching* (Stevens & Marks, 1965) to do so.

In Experiment 2, participants adjusted the size of a circle to match the perceived area for each rectangle. On each trial, participants saw three rectangles and three circles, each labeled 1, 2, and 3. Participants adjusted the size of the circle corresponding to each rectangle, until they believed the two to have equal area. I also replicated Spektor et al. (2018)'s choice data in the second phase of the experiment.

In both phases, I used a between-participants manipulation to display the rectangle stimuli in either the horizontal or triangle displays of Spektor et al. (2018).

2.3.1 Methods

2.3.1.1 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.

2.3.1.2 Stimuli.

In the circle adjustment phase there were three types of trials: critical trials, filler trials, and catch trials. 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 stimuli to fall on three diagonals. In pixels, the small and larger focal stimulus dimension values on the lower, middle, and upper diagonals were $[60, 135]$, $[90, 165]$, and $[120, 195]$. I reduced the absolute size of the target/competitor stimuli from Experiment 1 to Experiment 2 to accomodate the circle adjustment phase, which required the simultaneous presentation of both circles and rectangles.

On filler trials, I generated stimuli by sampling three heights and widths from the distribution $U(56, 195)$px, the full range of stimuli from the critical trials.

On the catch trials, I randomly sampled one rectangle from the lower diagonal and two from the upper diagonal. This ensured that one stimulus was always larger than the other two and allowed me to remove participants who could not perform the task.

The choice phase had identical trial types with the exception that there were no catch trials, only critical and filler trials.

2.3.1.3 Design.

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

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.

2.3.1.4 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:

On each circle adjustment trial, three gray 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. In the upper right, three gray circles appeared in the upper right of the screen, in the same display as the rectangles (see Figure 2.7). A small amount of jitter ($U(-15, 15)$px) was added to the vertical position of each rectangle and the corresponding circle. Each circle started with an area of 78 square pixels, the minimum size allowed in the experiment.

Participants used the mouse to adjust the size of the circle. Within a single trial, they were free to adjust the circles in any order they liked or to go re-adjust a circle as much as they liked. There was no time limit to each adjustment trial. The maximum circle area allowed was 65144 square pixels[10]. 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 practice trials, followed by the 4 blocks of experimental trials. At the beginning of each experimental block, participants completed 3 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.

Throughout the circle phase, the experiment kept track of the deviations between the true rectangle areas and the participants' adjusted circle areas. At the end of each block, the experiment told participants that they were either over or under-adjusting, on average, based on the current mean deviation of their responses.

The choice phase began with 3 practice trials. Participants did not receive feedback during choice practice trials.

On each choice trial, three rectangles appeared in the center of the screen in a horizontal or triangle display. There was no vertical jitter added in the choice phase. Participants selected the largest rectangle by clicking on it.

[10] I arrived at this value based on 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.

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.

2.3.2 Results

2.3.2.1 Data Processing

Given the difficulty of the circle adjustment task, the data required considerable processing to ensure that outlier trials and participants did not influence estimates of $\mathbf{\Omega}$.

After removing participants who did not complete the experiment there were 223 participants in the horizontal display condition and 230 participants in the triangle display condition.

I then removed 10 participants who did not provide correct responses on 75% (6/8) of the catch trials from the circle phase. To respond correctly, participants needed to estimate the largest rectangle to be larger than the other two rectangles in the trial. This left a total of 443 participants in the experiment.

Next, from the remaining participants, I first natural log-transformed all responses. I then dropped all trials where at least one circle was not adjusted (i.e., at least one circle was left at the starting size).

I then removed outlier participants using the following procedure:

I fit a linear regression to each individual participants' data, regressing each log circle area on each corresponding log rectangle area. I then computed an R^2 for each participant. I then removed all participants whose R^2 fell below the 5% quantile for all R^2s, which in this case was .3975. This removed 23 participants, leaving $N = 420$ participants, 213in the triangle display condition and 207 in the horizontal display

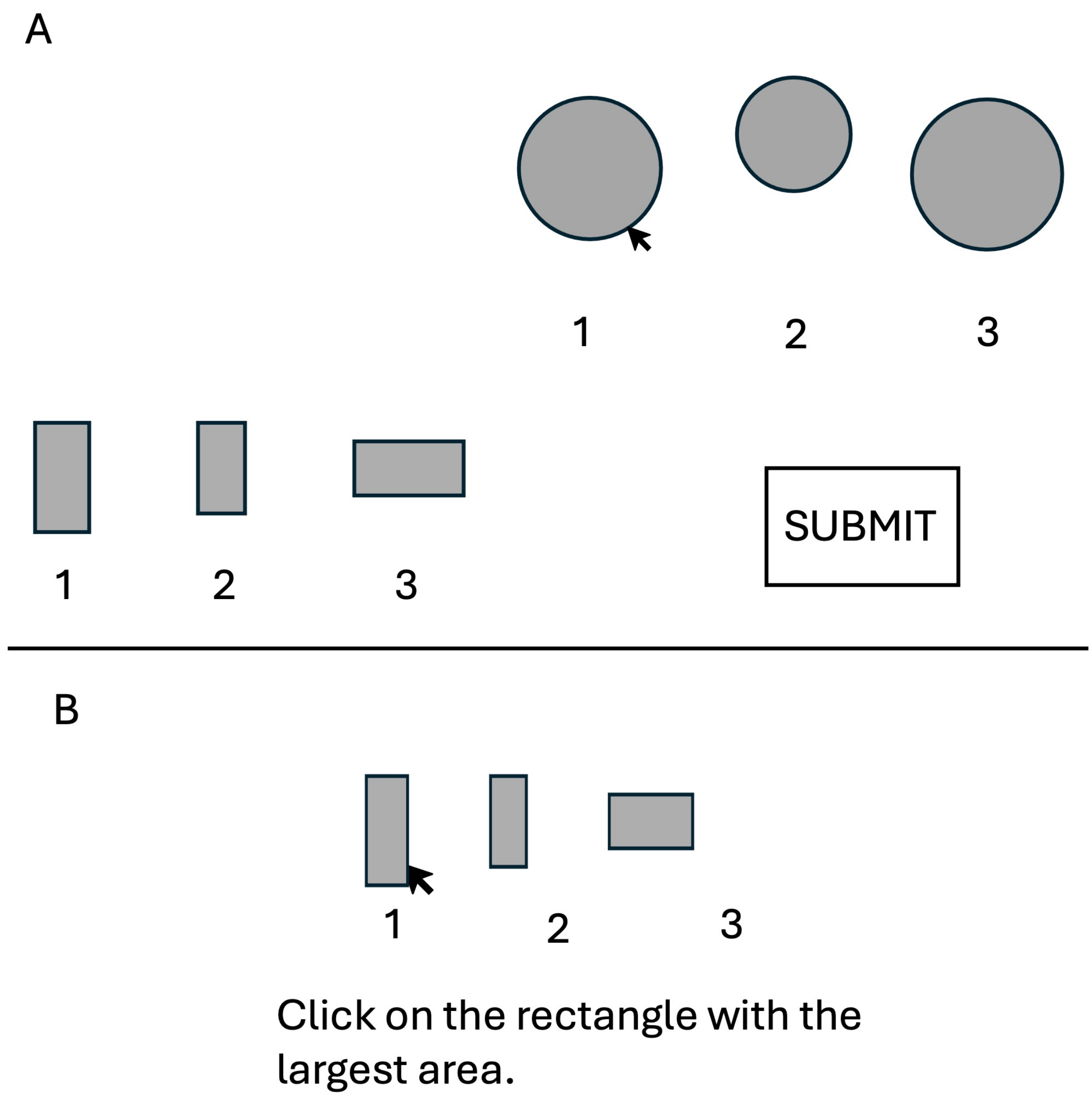

Figure 2.7. Example trials from Experiment 2. A: Circle adjustment phase. B: Choice phase. This an example from the horizontal display condition.

condition. Of the remaining participants, R^2 values were high ($M = .67, SD = .12$), indicating that participants could generally perform the task.

From the 420 partipants whose data I analyzed, I removed outlier trials from the critical trial data. I did so to ensure that any outliers do not influence estimates of ρ_{TD}, ρ_{TC}, or ρ_{CD}. I z-transformed all log circle areas within each participant and diagonal. I remove all critical trials where at least one z-score had an absolute value above 3.5, dropping a total of 102 trials. I dropped 0, 1, 2, and 4 critical trials from 339, 62, 18, and 1 participants, respectively.

After all circle phase data processing, I was left with 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. Note that it is crucial to collect a large amount of data here, as performing Bayesian inference on correlation matrices is prone to underestimation if data are limited (Martin, 2021; Merkle et al., 2023).

For the choice phase, I only retained participants whose data I retained in the circle phase. All choice trials with RTs < 100ms or $> 10,000$ms were removed from analysis.

2.3.2.2 Circle Phase Results

Before modeling the data, I first assessed performance on the critical trials. While in an absolute sense, excellent performance is quite difficult to achieve, good relative performance is necessary for the modeling analysis. I computed the mean difference between actual log area and estimated log area for each subject, stimulus pair (i.e., target-competitor, target-decoy, competitor-decoy), and actual difference. I plot these via a set of boxplots in Figure 2.8. Although participants vary considerably in their judgments, I found that on average, participants' adjusted circle areas increase with the absolute size of rectangles.

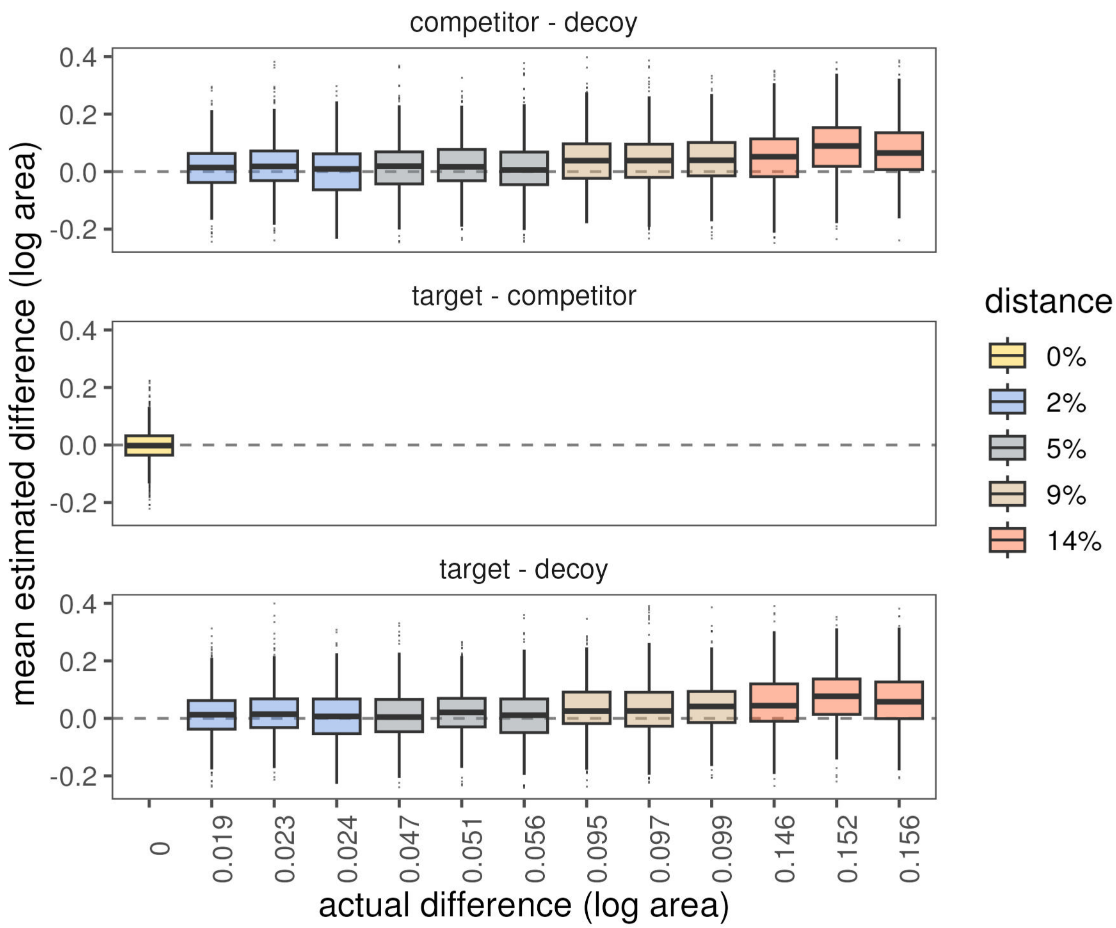

Figure 2.8. Experiment 2 boxplots of subject-level mean error in log-transformed area estimations, split by stimulus pair, TDD, and absolute discrepancy in rectangle area. Note that because the target and competitor rectangles always had equal areas, the true difference is always 0.

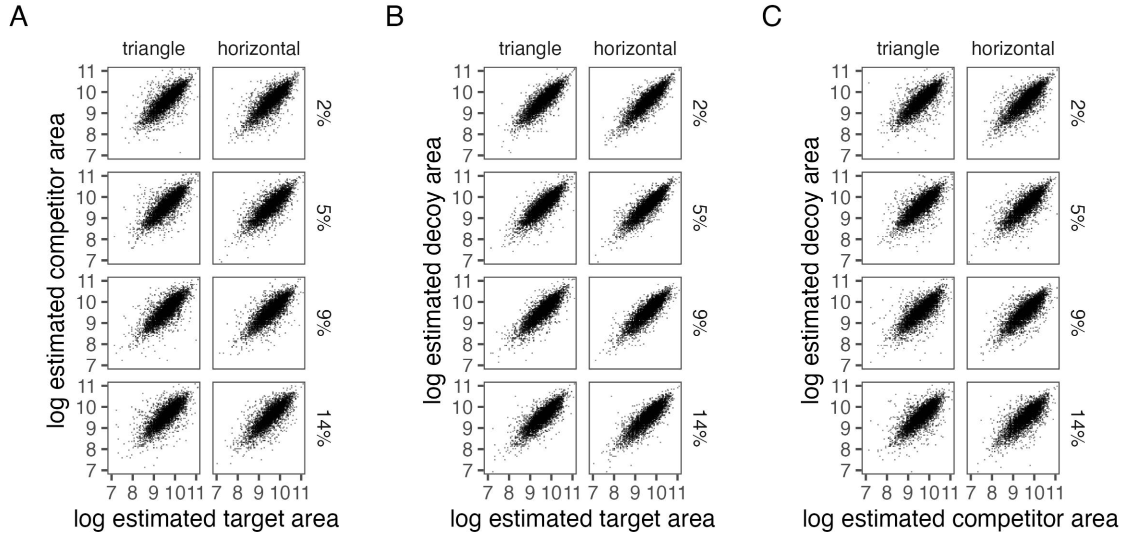

Figure 2.9. Scatterplots of target-competitor (A), target-decoy (B), and competitor-decoy (C) log estimated areas, split by display condition and TDD.

I next present scatterplots of all pairwise circle areas from each trial, see Figure 2.9. I present these to be transparent about the raw data and to illustrate the necessity of a statistical model to understand these correlations.

Computing raw correlations, without accounting for subject-level differences, will grossly inflate the size of these correlations. Moreover, any differences between, say, ρ_{TD} and ρ_{CD} are bound to be small. Additionally, performing inferences about the differences between correlations requires Bayesian inference.

I used Bayesian hierarchical modeling to estimate the parameters of the perceptual model outlined earlier in this chapter. Parameters $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ represent the mean and variance-covariance matrix of a multivariate normal distribution on the perceived areas across trials.

I assume that, for participant i, on each critical trial j, the vector of perceived target, competitor, and decoy areas $\mathbf{X_{ij}}$ is sampled from a multivariate normal distribution with mean vector $\boldsymbol{\mu_{ij}}$ and variance-covariance matrix $\boldsymbol{\Sigma}$.

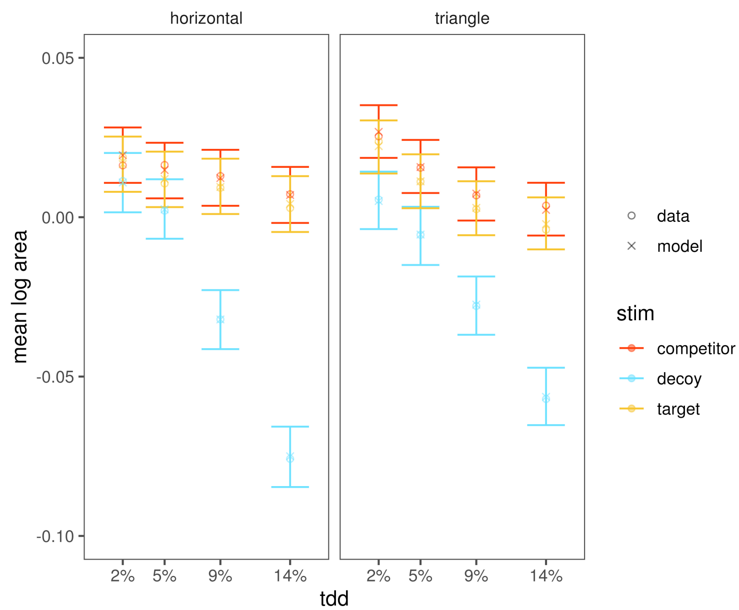

Figure 2.10. Experiment 2 $\boldsymbol{\mu}$ estimates. Model values are means, and the error bars are 95% HDIs.

As discussed in the Introduction, I compute $\boldsymbol{\Sigma}$ by $S\boldsymbol{\Omega}S$, where the diagonal elements of S are population standard deviations and the off diagonal elements are 0. $\boldsymbol{\Omega}$ is 3x3 correlation matrix. Note that there are no participant-level effects in the estimates of $\boldsymbol{\Omega}$.

I focus on the estimates of $\boldsymbol{\mu}$ and $\boldsymbol{\Omega}$ in the main text and discuss the details of the estimation procedure, along with S estimates, in the Appendix.

I show mean estimates of $\boldsymbol{\mu}$ (averaged across participants) in Figure 2.10 and show estimates of $\boldsymbol{\Omega}$ in Figure 2.11. As predictd, in both conditions, ρ_{TD} is larger than both ρ_{CD} and ρ_{TC}, while ρ_{CD} and ρ_{TC} do not differ from each other. Interestingly, all ρ parameters from the horizontal condition are larger than the corresponding parameters from the triangle condition. These inferences should, however, be taken cautiously given that I fit the model separately to each condition.

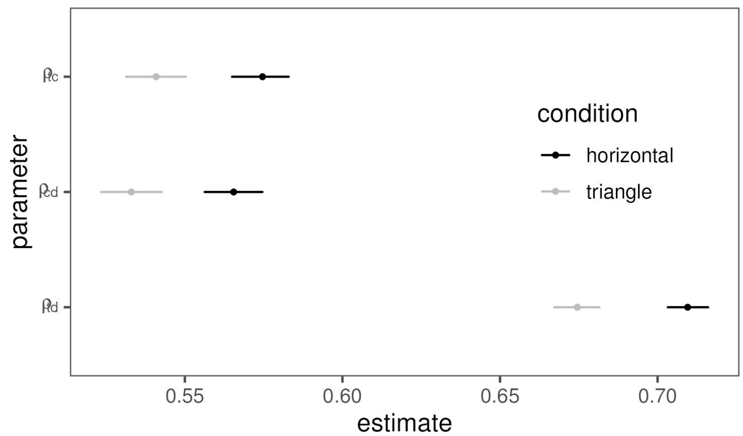

Figure 2.11. Experiment 2 posterior estimates of $\mathbf{\Omega}$ off-diagonal parameters across display conditions. Lines show 95% HDIs. Dots indicate means.

2.3.2.3 Choice Results

I present mean choice proportions across display conditions and TDD in Figure 2.12.

I replicated the qualitative results of Spektor et al. (2018). At low levels of TDD, I find a repulsion effect in both display conditions, where participants reliably choose the competitor more than the target. At higher levels of TDD, I either find a small repulsion effect, where $P(C) > P(T)$ (triangle condition) or an attraction effect, where $P(T) > P(C)$ (horizontal condition). See the Appendix for inferential statistics that support these conclusions.

I also present the mean choice proportions for the current experiment plotted against mean target-decoy discriminability from Experiment 2 in Figure 2.13. 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

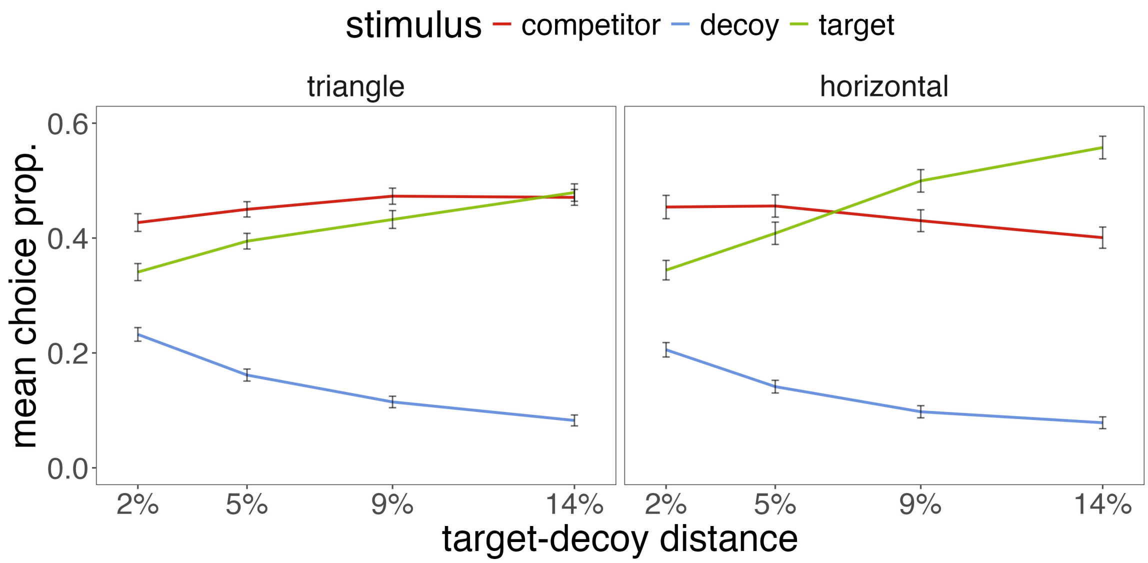

Figure 2.12. Experiment 2 mean choice proportions for target, competitor, and decoy options, by TDD and display condition. Error bars are 95% CIs on the means.

horizontal condition, which facilitates better discriminability in the 2afc discrimination task, also requires less discrepancy between target and decoy size in order for the attraction effect to emerge in the ternary choice task.

2.3.3 Model Simulations

After estimating the parameters of the Thurstonian perceptual choice model and analyzing the choice data, I sought to test whether the model can predict the choice data. It was an open question whether the parameters estimated from actual data would produce qualitatively accurate predictions.

I used the mean estimates of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ to generate predictions at each level of TDD in both display conditions. I present the predicted mean choice proportions in Figure 2.14.

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,

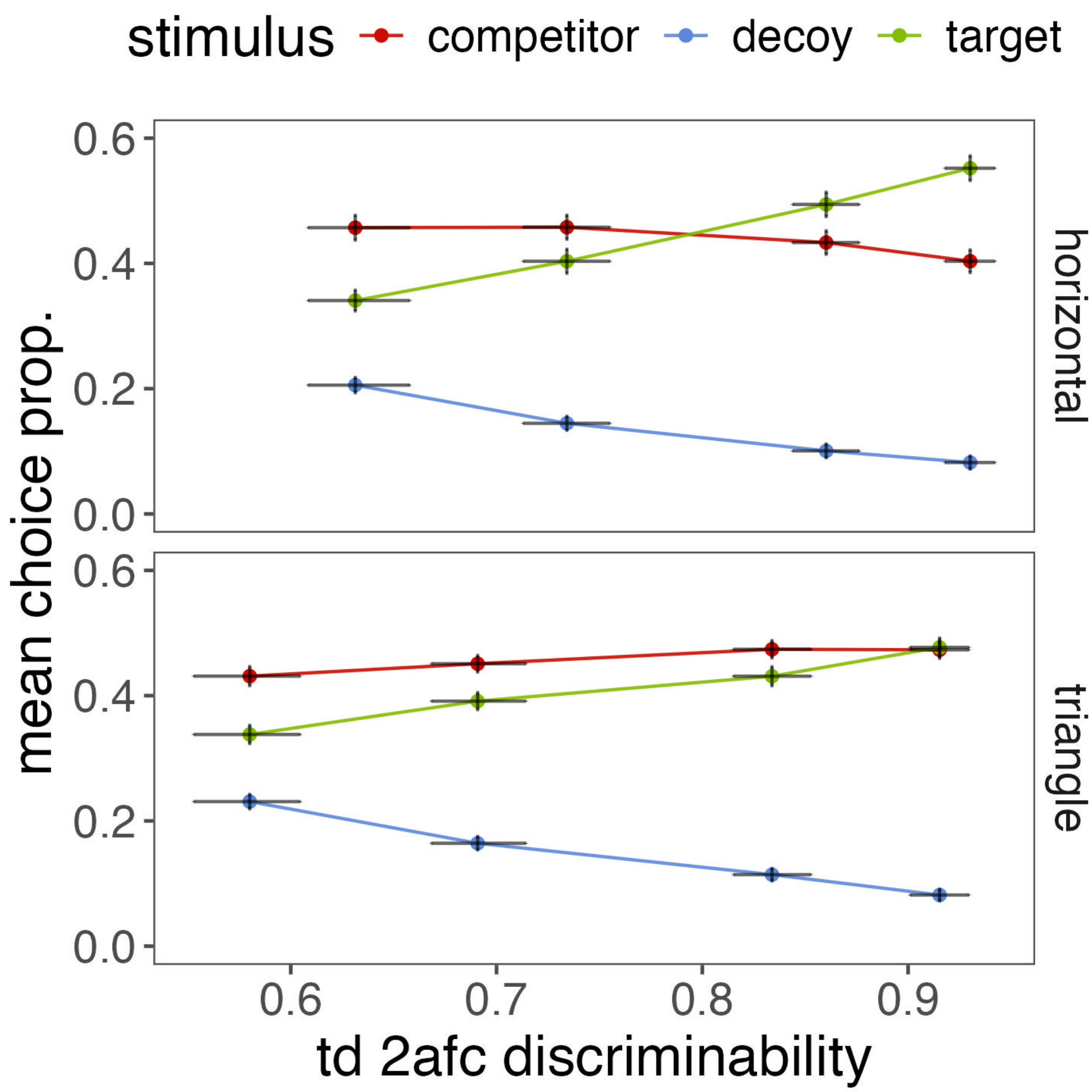

Figure 2.13. Mean target, competitor, and decoy choice proportions (y axis) for each TDD level in Experiment 2, plotted against mean target-decoy discriminability for each TDD level from Experiment 1. The x axis error bars are 95% HDIs on the mean, computed via the Bayesian hierarchical logistic regression from Experiment 1, and the y axis error bars are 95% CIs on the mean.

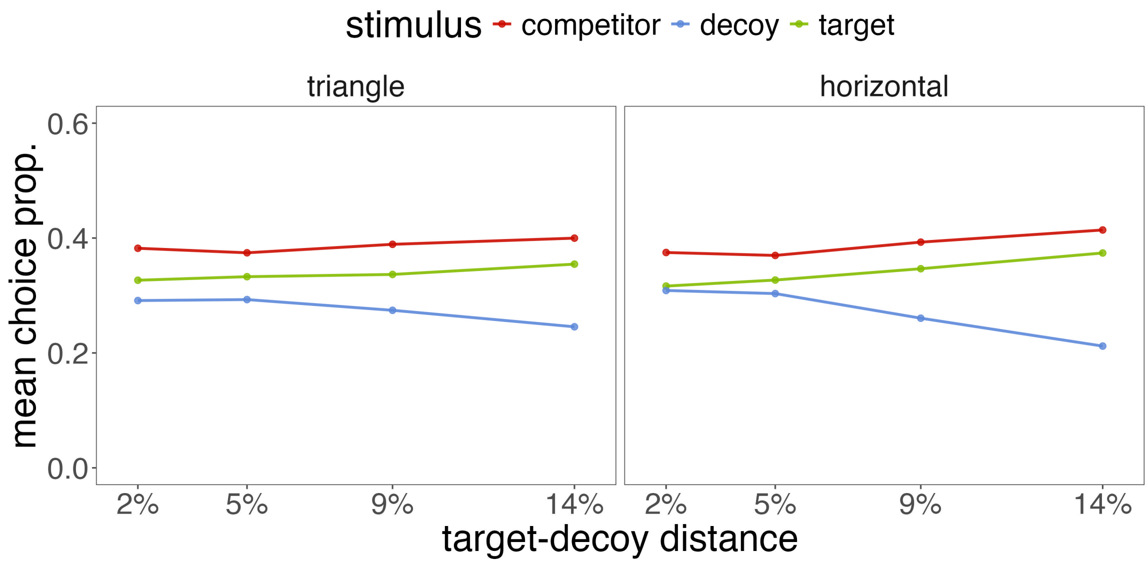

Figure 2.14. Model predictions for the choice data, conditioned on the mean estimated parameters from Experiment 2.

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.

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 $\rho_{CD} > \rho_{TD}$, neither or which were found. The model can produce the repulsion effect from perceptual variability alone, but the attraction effect likely occurs due to higher level decision factors.

2.4 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) 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 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 2.15.

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 ρ_{TD} also allows the decoy to be "pulled up" with the target. These correlations also cause, interestingly enough, $P(TDC) > P(CDT)$. 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.

The correlation between target and decoy perceptions is worth exploring further. Thus far, I have provided 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.

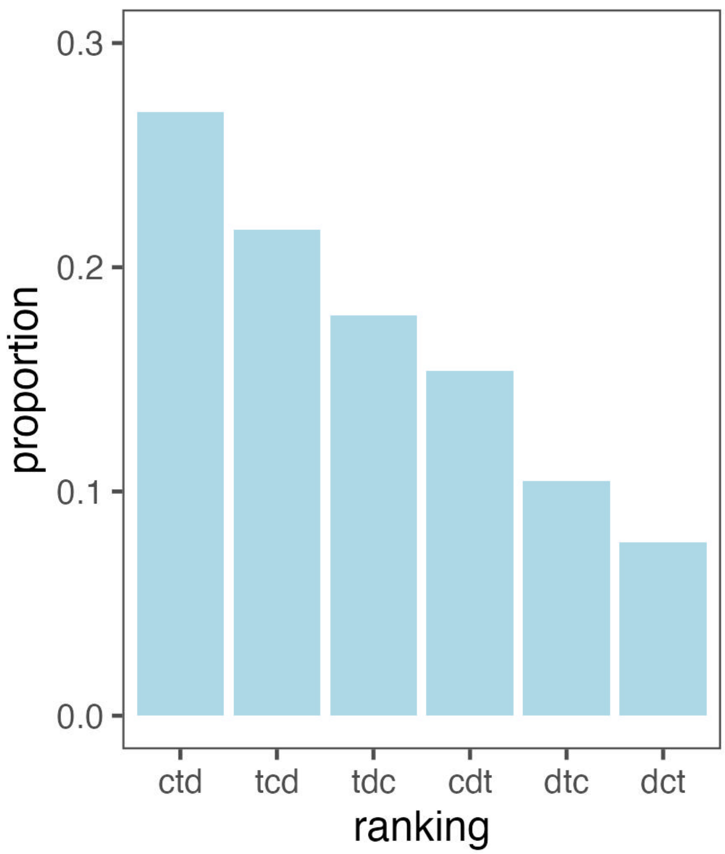

Figure 2.15. Model-simulated ranking proportions, in the order of largest to smallest.

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 neglible. Hasan et al. (2025), however, 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. 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.

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 suggests 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.

Kamakura and Srivastava (1984) incorporated correlations into a multivariate choice model. According to their model, options in a choice set have utilities which are distributed multivariate normal, with non-zero correlations. The correlations are a decreasing function of distance in attribute space. The researchers fit the model to choice data and show that it can account for the similarity effect in choice (i.e., where two similar options "split" choice shares). Future research should consider whether a model whose correlations are based on directly estimated correlations can predict the similarity effect.

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 "valuable" focal options and 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 choie 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 hypotheis 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 $\boldsymbol{\Omega}$. 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 $\boldsymbol{\Omega}$ estimates. It would be of great theoretical interest if individual differences in $\boldsymbol{\Omega}$ 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 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, and new samples may fail to show it. 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 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 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 traditional 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 (Marley & Louviere, 2005).

Researchers have developed theoretical models to account for best-worst choice data. Most best-worst choice models relate best-worst choices to an underlying utility function. Marley and Louviere (2005) developed a class of models known as the *maxdiff* (maximum difference) models of best-worst choice[1]. According to the maxdiff model, given choice set K, the probability of selecting option x as best and option y as worst, where $x \neq y$, is defined computed as:

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

where u_i is the utility of option i, and $BW(x, y)$ indicates the probability of selecting x as best and y as worst. 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.

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 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) examined 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

[1]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 this choice model.

parameter. Modeling datasets containing both preferential and perceptual best-worst choice 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 types of 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. Formally, if $d_b(i)$ is the drift rate for selecting option i as best, then $d_w(i) = 1/d_b(i)$, where $d_w(i)$ is option i's drift rate for worst choices.

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 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

Here, I use the perceptual model 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 perceived area $\mathbf{X_i}$ of all 3 stimuli is sampled from a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ (see Equation 2.4).

$\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ are parameterized the same as in Chapters 1 and 2.

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:

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

while the probability of selecting stimulus j as worst is:

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

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., Ω) 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[2] 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.

[2] I used only those estimated from the triangle condition (See Experiment 2).

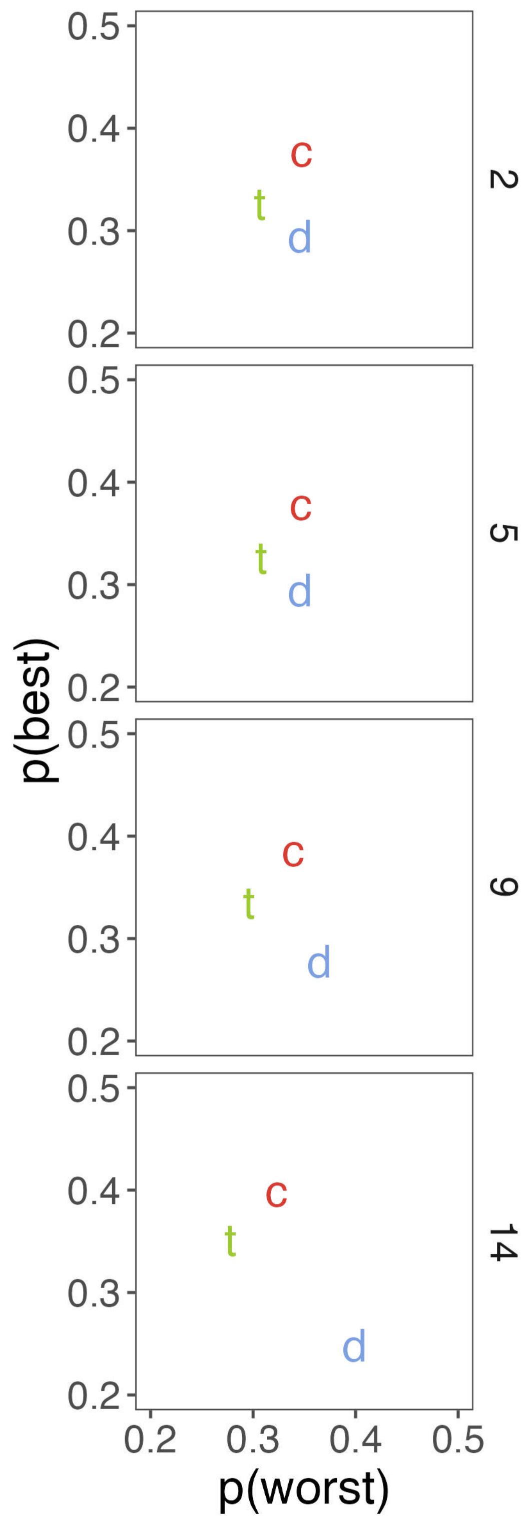

Figure 3.1. Simulated best-worst predictions per the Thurstonian perceptual model. Each row is a different TDD value from Experiment 2.

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 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 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 ρ_{TD} value "pulls up" the target more than the competitor. The similarity, and comparability, of target and decoy entail that the repulsion effect at the best-choice level (Experiment 2) does not necessarily show up at the worst-choice level.

The maxdiff model 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. See Figure **??**.

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.

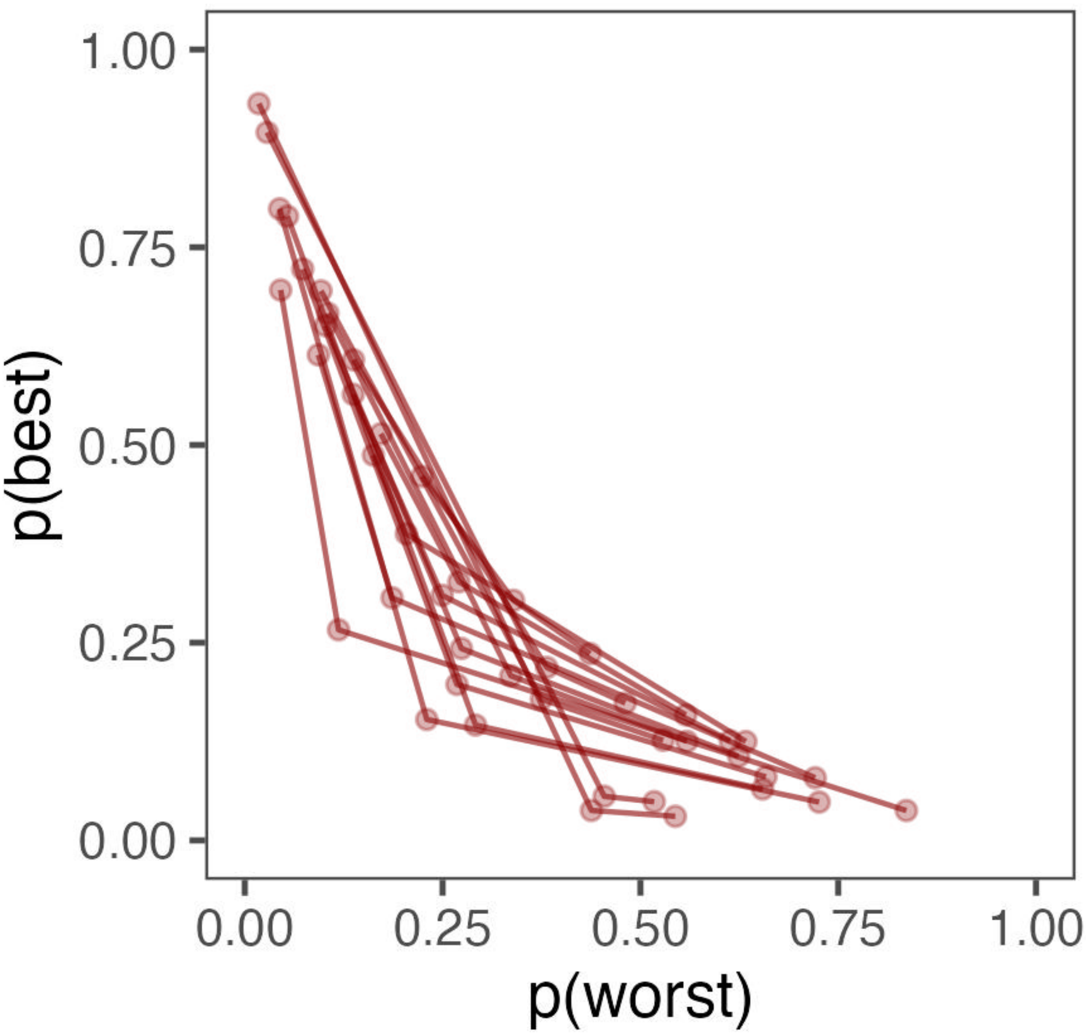

Figure 3.2. Best-worst choice simulations using the maxdiff model. Each curve is a separate simulation. The model predicts a negative, monotonic relationship between best-choice and worst-choice.

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 $W(T) < W(C)$. To test this prediction, I used stimuli identical to those of Experiment 2 and presented stimuli in the triangle display of Experiments 1 and 2. I show that 1) this prediction holds empirically and 2) the maxdiff model cannot account for these results, even when all parameters are free to vary.

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) $<$ 100ms or $>$ 10000ms 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 initially 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 on their chosen rectangle. 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.

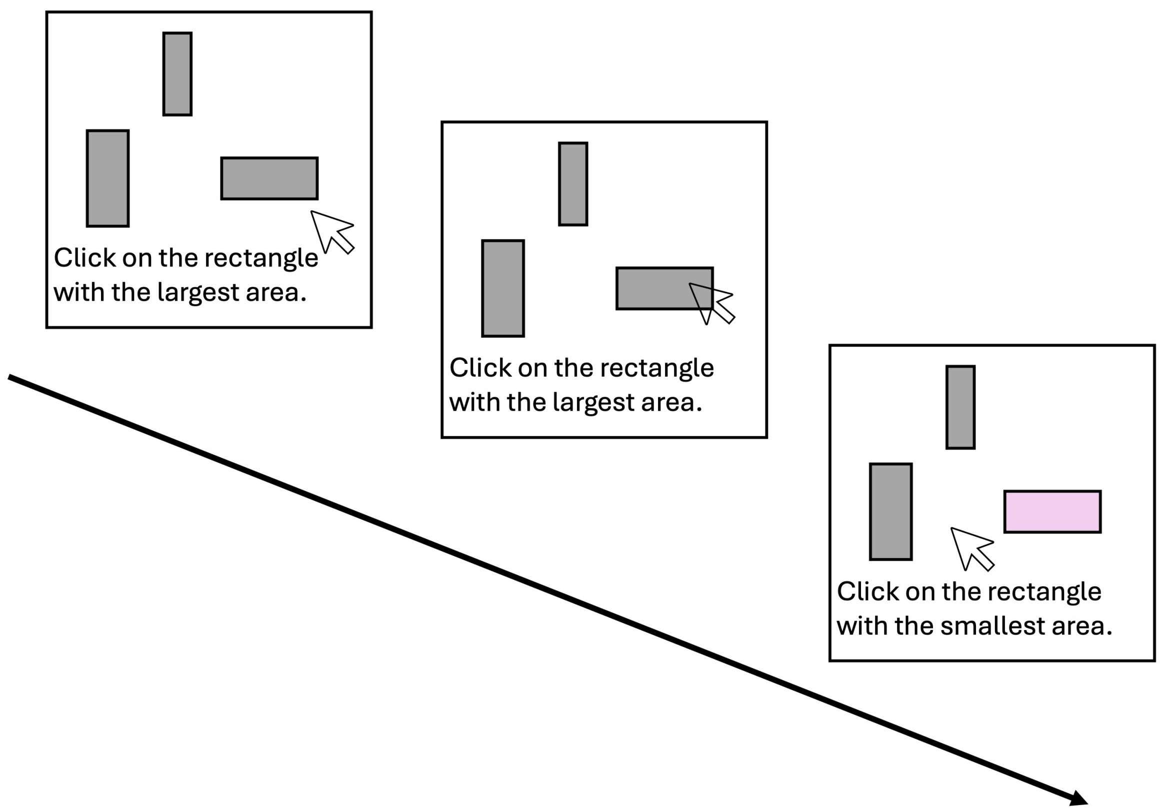

Figure 3.3. A sample experimental trial from Experiment 3. Note that this is a trial in the best-worst condition.

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%($SD = 13.09$). The mean percentage correct for both best and worst choices was 96.98%($SD = 17.12$).

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

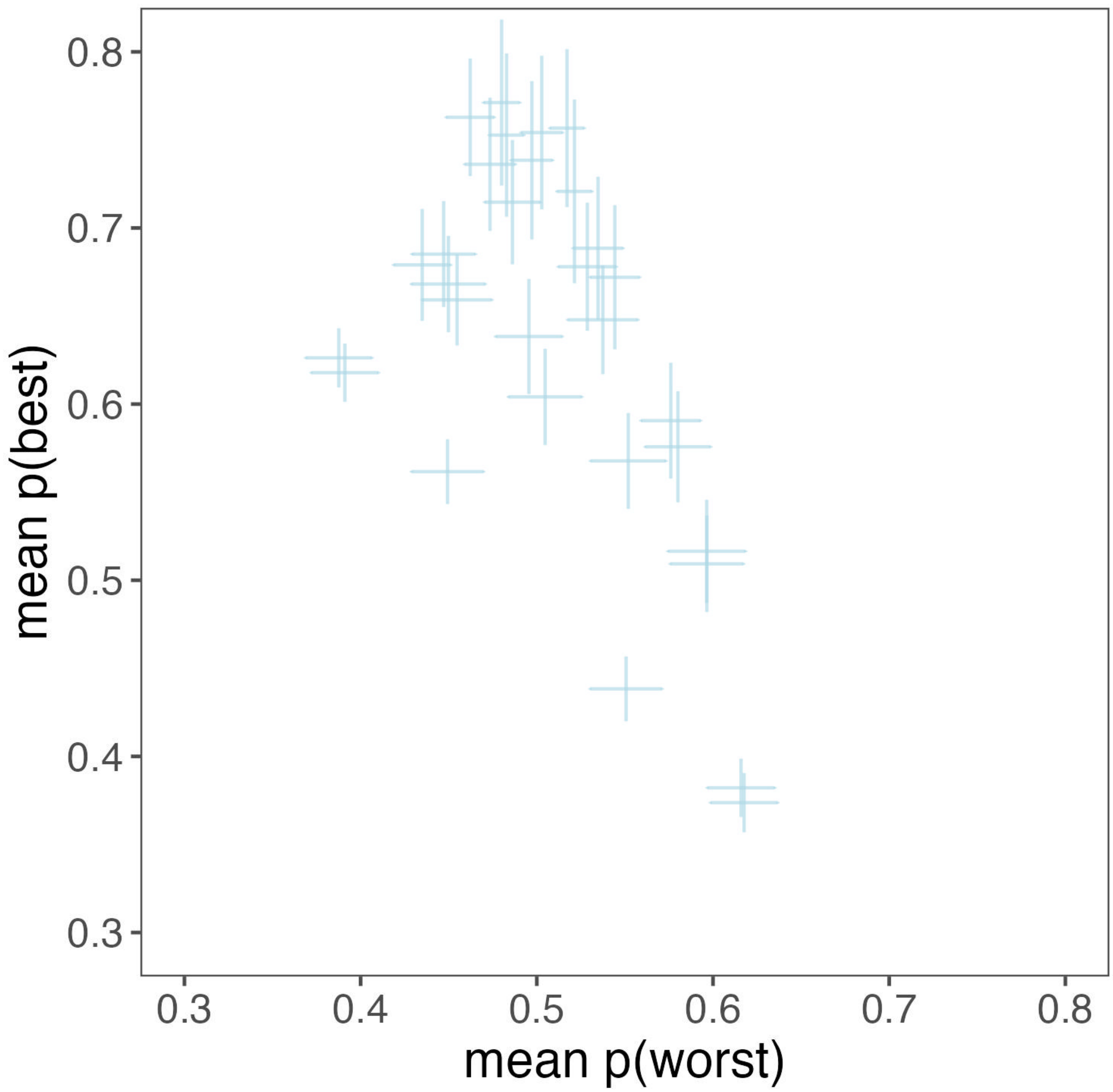

Figure 3.4. Experiment 3 marginal mean best and worst-choice proportions for all unique rectangles, collapsed across choice set. X and Y axis error bars are 95% CIs.

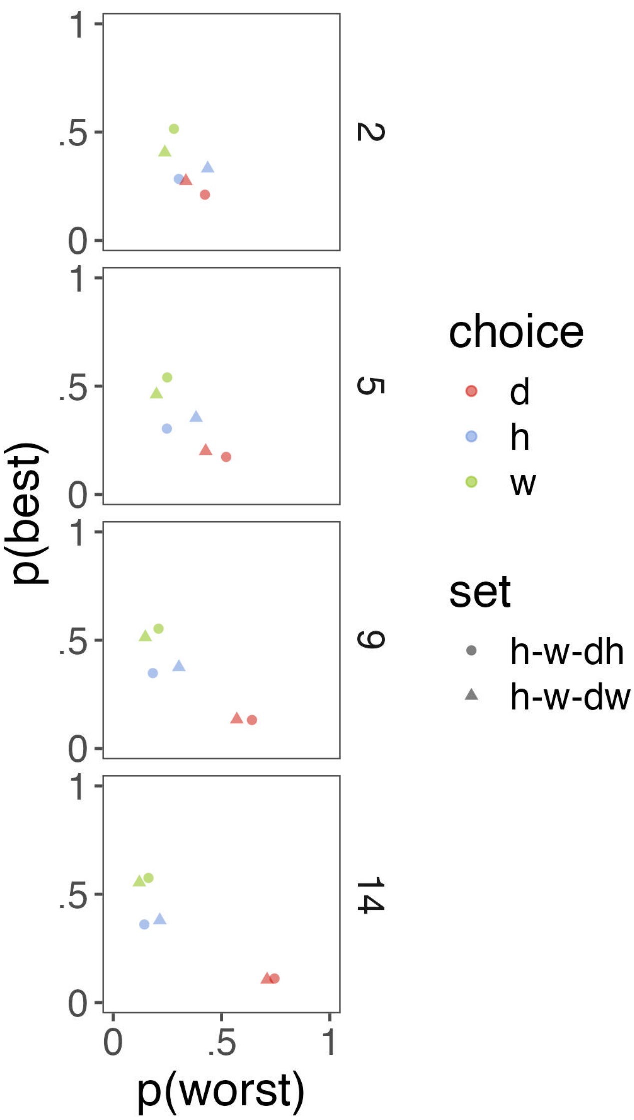

Figure 3.5. Experiment 3 mean best and worst-choice proportions for the h, w, and d rectangles, conditioned on TDD (rows) and choice set (shapes).

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 first turn to the maxdiff model (Marley & Louviere, 2005), which was outlined in the introduction to this chapter. This equation 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

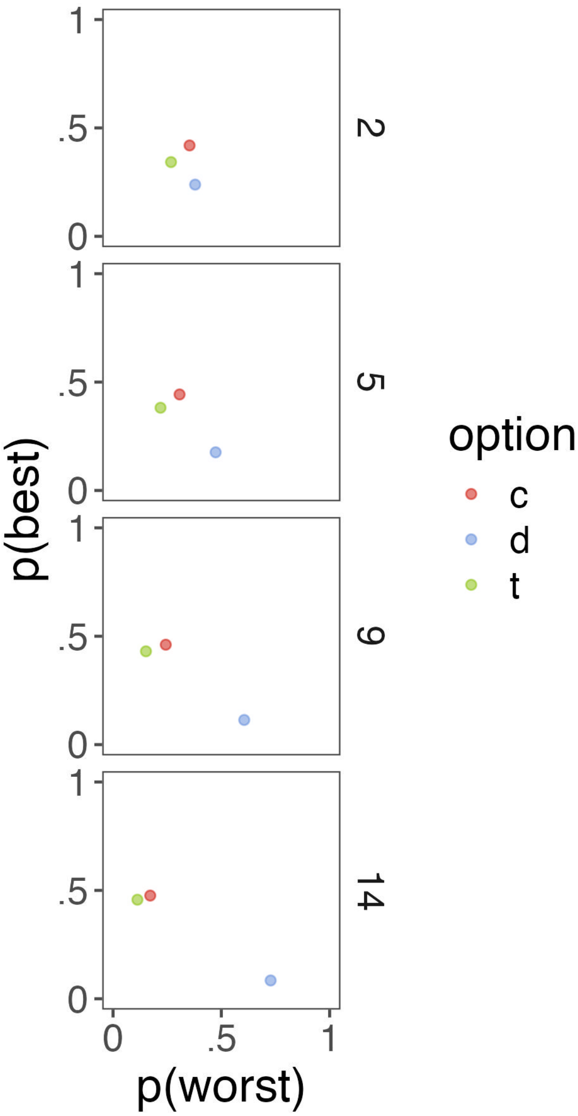

Figure 3.6. Experiment 3 mean best and worst-choice proportions for the target, competitor and decoy rectangles, conditioned on TDD (rows).

the current experiment and show that it is unable to predict the observed dissocations 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 a monotonic relationship between best choices and worst choices. It predicts a repulsion effect in both best choices and worst choices, i.e., $B(C) > B(T) > B(D)$ and $W(D) > W(T) > W(C)$. Given that, in the data, $B(C) - B(T) > W(C) - W(T)$, the best-fitting parameter set is the one that predicts a repulsion effect.

The target-competitor misprediction stems from the fact that the model choices come from the utility of each option, calculated through a linear combination of experimental factors and 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 $W(T) < W(C)$.

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, in support of the Thurstonian perceptual choice model introduced in Chapter 2, correlated valuations can induce dissociations in best-worst choices. 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

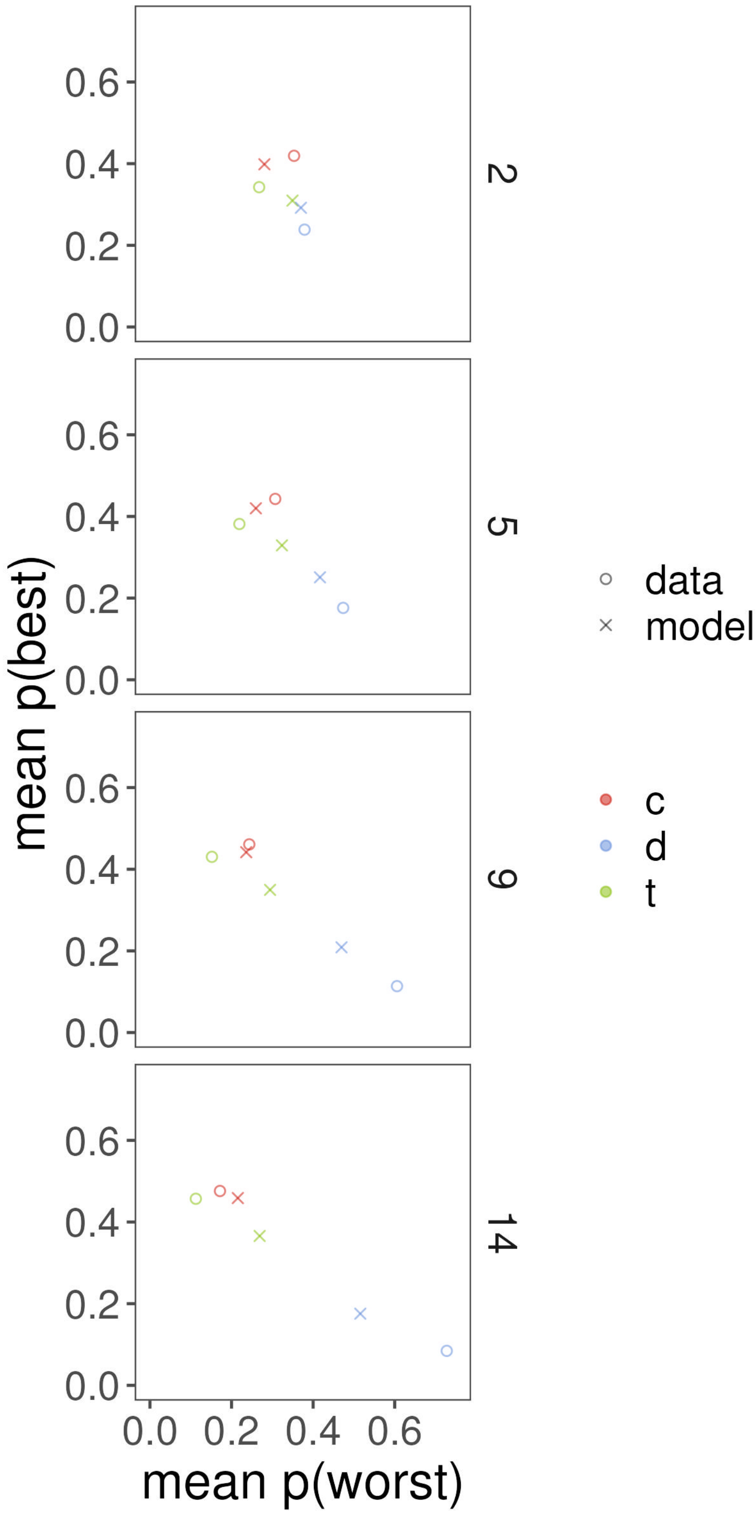

Figure 3.7. Experiment 3 maxdiff model predictions for the mean target, competitor, and decoy best-worst choice proportions.

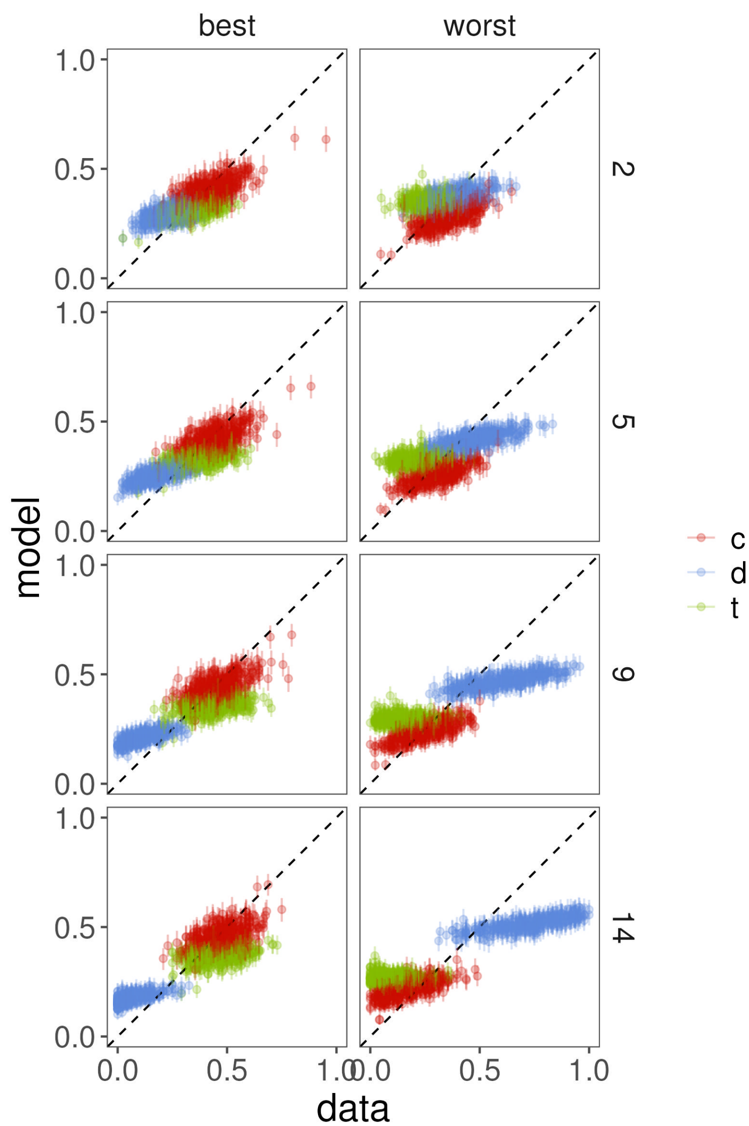

Figure 3.8. Experiment 3 maxdiff model predictions for the mean target, competitor, and decoy best-worst participant-level choice proportions, conditioned on TDD (rows) and choice type, i.e. best v. worst (columns). Vertical error bars are 95% HDIs.

target to be selected as worst ($W(C) > W(T)$). This prediction was made using the perceptual choice model of Chapter 2, conditioned on 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 analysis technique for best-worst choice (de Palma et al., 2017; Hawkins et al., 2014b; Marley & Louviere, 2005; Mühlbacher et al., 2016), cannot accomodate 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) demonstrated set-dependent best-worst choice models, which allows for different context dependence based on choice sets, 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 (de Palma et al., 2017). 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.

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 participant-level data. 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. 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 our case, height/width, TDD, diagonal) are systematically manipulated to examine their impact on preferences. 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 easily accessible WiFi in a 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 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 consumer 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 those 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 aomunt (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 ratings. 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 ρ 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 by collecting 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 $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$

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 ρ_{TD}. I am now interested in whether 1) preferential choice options also exhibit 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 occuring at low and high TDD levels but the repulsion effect occuring at more intermediate TDD levels.

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. 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.

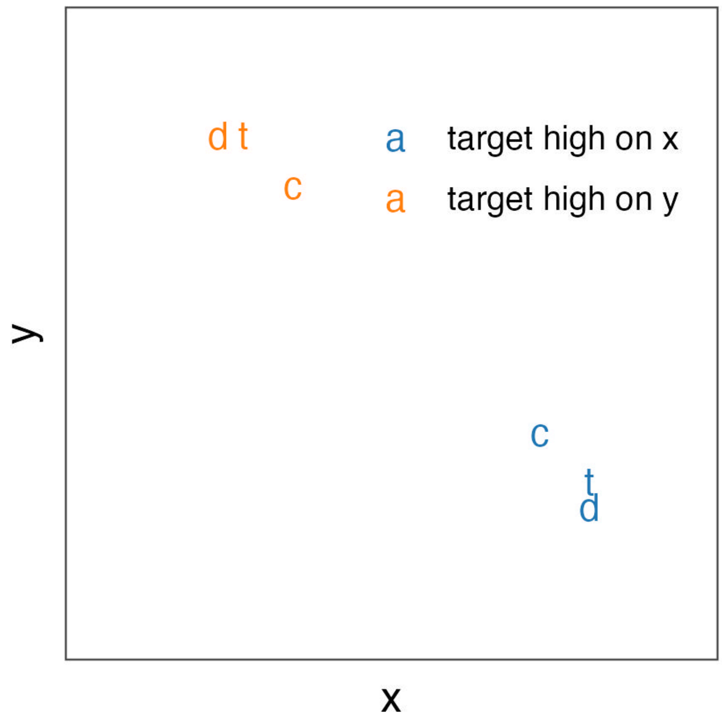

Figure 4.1. Graphical depiction of a subset of the stimuli used in Banerjee et al. (2024), Experiment 5. Target, competitor, and decoy are labeled *t*, *c*, and *d*, respectively. Dimensions are (generically) labeled X and Y.

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

Using these stimuli and across multiple experiments, 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). In other experiments, 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 to 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 target.

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 from 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 posting 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), and product 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.

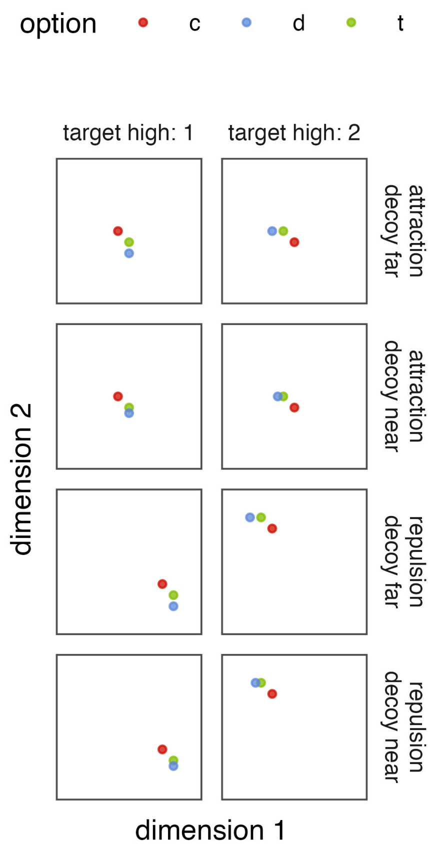

Figure 4.2. Graphical depiction of the critical stimuli from Experiment 4. Rows show the different choice sets designed to elicit the attraction/repulsion effect, with the label also specifying whether the decoy is near or far from the target in attribute space. The columns indicate which dimension the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

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 randomly sampled from the distribution $U(50, 95)$, while the two inferior option's dimension values were sampled from the distribution $U(5, 50)$. All dimension values were rounded to multiples of 5.

In each 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 goals here are, rather, 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 screen to move onto 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).

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.

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

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. These results can be found in the Appendix. Below, I discuss descriptive statistics, but whenever I claim that one parameter value is greater than another, the reader can see the Appendix to

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	$ 0
Product B	5	30	$ 0
Product C	45	25	$ 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	○
Product B	35	10	○
Product C	70	85	○

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

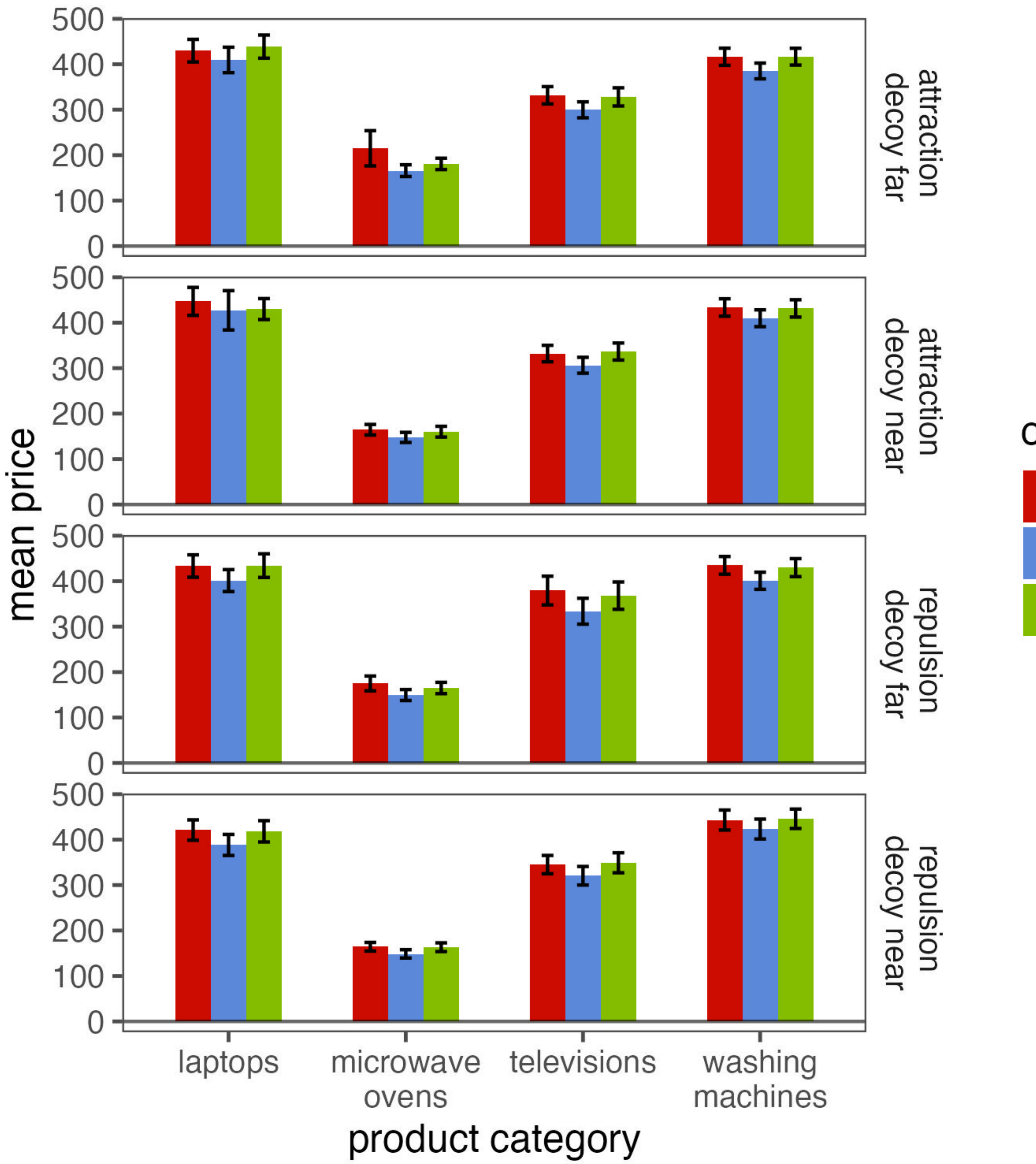

Figure 4.4. Experiment 4 mean prices by product category, option, and trial type. Error bars are ±1 SEM.

support these conclusions. The ordering of these correlations, however, is the same in both the model-based and the descriptive analysis.

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 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.

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 competi-

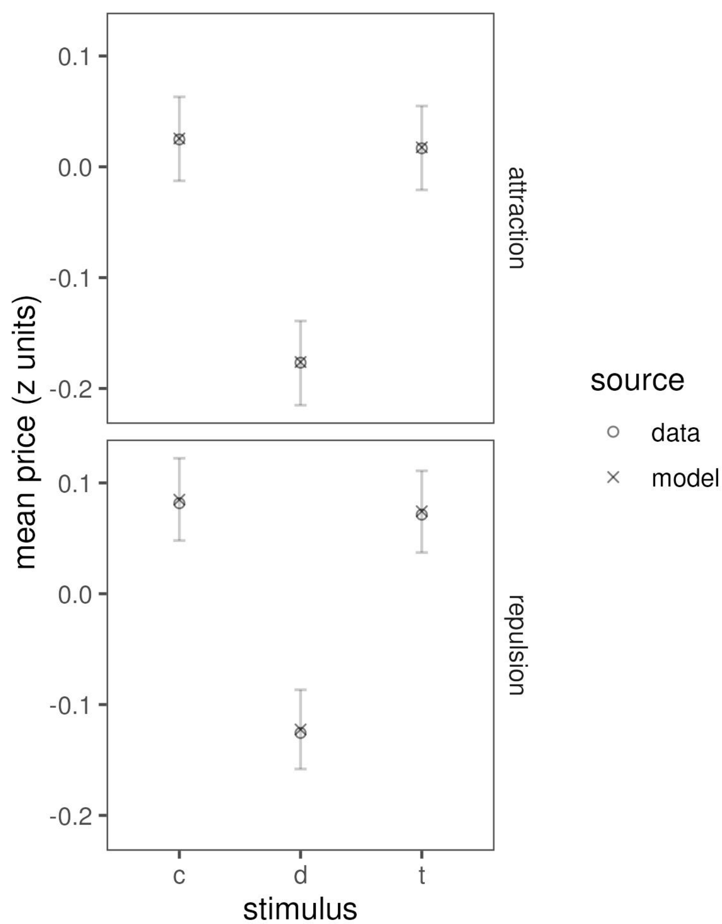

Figure 4.5. Experiment 4 mean prices for target, competitor, and decoy options in both repulsion and attraction trials. Model values are the means from the posterior distribution, and error bars are 95% HDIs.

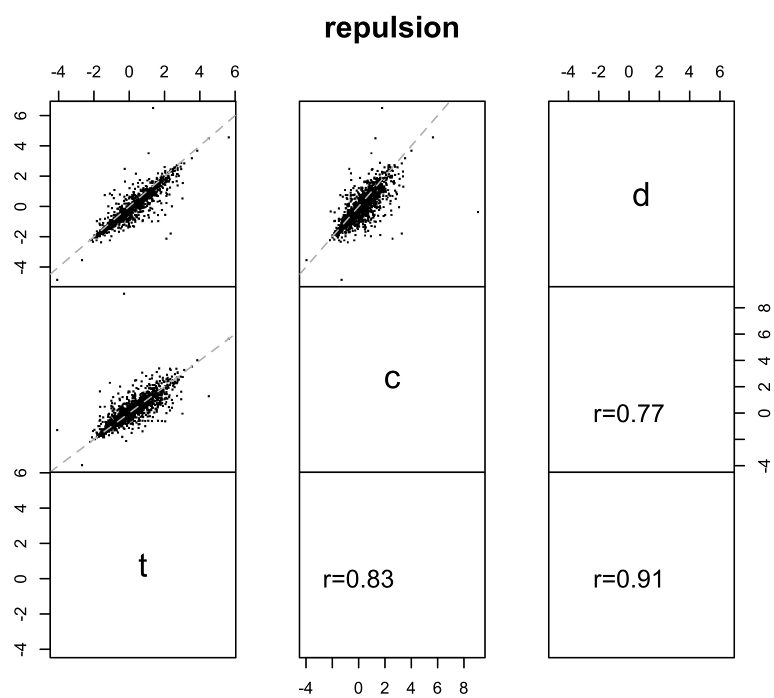

Figure 4.6. Experiment 4 correlation plots for all pairs of stimuli, in trials designed to elicit the repulsion effect. t=target, c=competitor, and d=decoy.

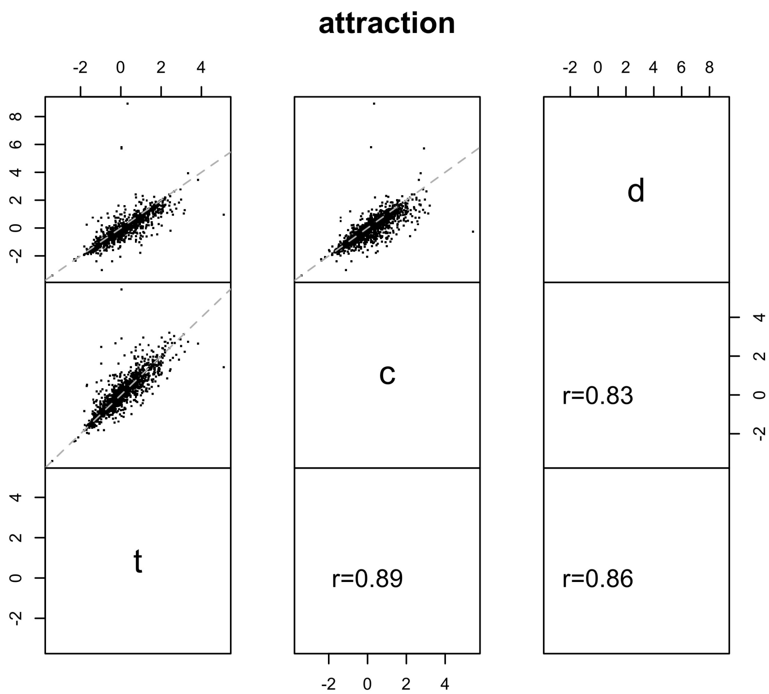

Figure 4.7. Experiment 4 correlation plots for all pairs of stimuli, in trials designed to elicit the attraction effect. t=target, c=competitor, and d=decoy.

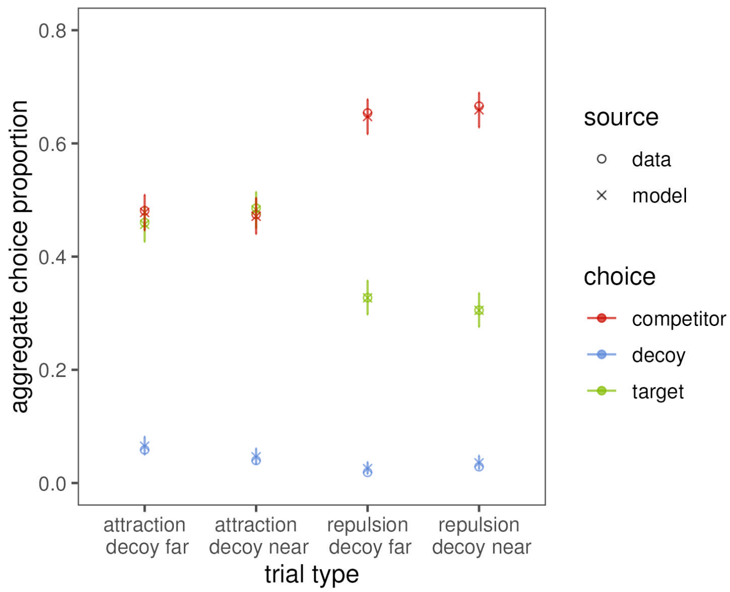

Figure 4.8. Experiment 4 aggregate choice proportions for each trial type, TDD, and option. Data points are aggregate choice proportions, while model points are posterior means computed from the Bayesian Dirichlet-multinomial model presented in the Appendix. Error bars are 95% HDIs.

tor 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 $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ 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[1]. The model always chooses the option perceived as most valuable, regardless 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:

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

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 effect. 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

[1]This also assumes ties are not possible, which is true if and only if perceived area is absolutely continuous.

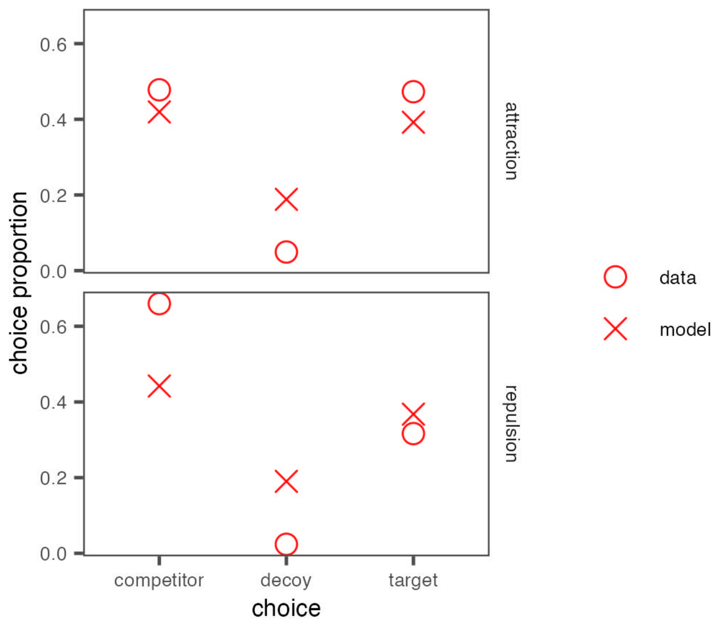

Figure 4.9. Experiment 4 data vs. Thurstonian model predictions.

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 correlations in choice environments of varying comparability.

CHAPTER 5

COMPARABILITY IN PERCEPTUAL CHOICE

5.1 Introduction

Thus far in the dissertation, I have used stimuli from the attraction and repulsion effect to explore 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 understand 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 [1]. 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-

[1]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).

Many theoretical accounts of decision-making rely on the comparison process to account for context effects. 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. This comparison is 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, repulsion, 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 nullified) 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 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 to 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 an 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 adressed in future work.

5.2 Experiment 5

Experiment 5 adresses the effect of comparability in perceptual choice. To do so, I incorporated *symmetrically dominated decoys*. A symmetrically dominated decoy is not only dominated by both focal options, but 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. The target option is 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 becauses 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%.

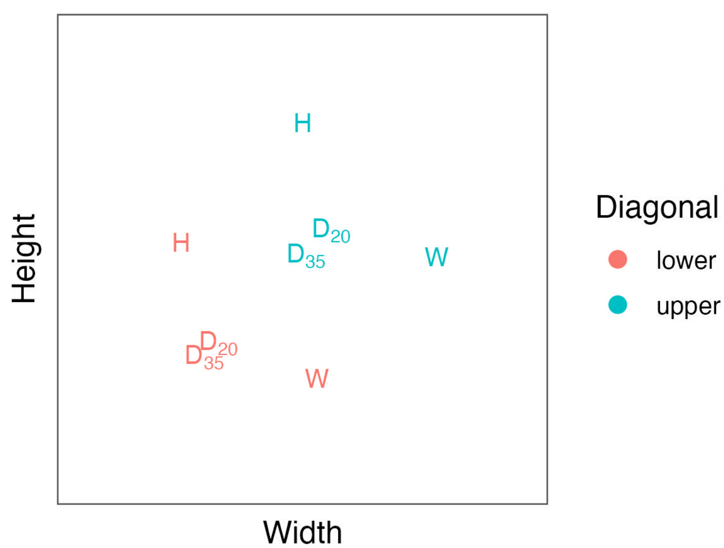

Figure 5.1. Graphical depiction of critical stimuli from Experiment 5. The stimuli fall on two diagonals, labeled as upper and lower. The H rectangles are taller than wide, while the W rectangles are wider than tall. The decoy (D) rectangles are equally wide and tall (i.e., squares), and the subscripts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

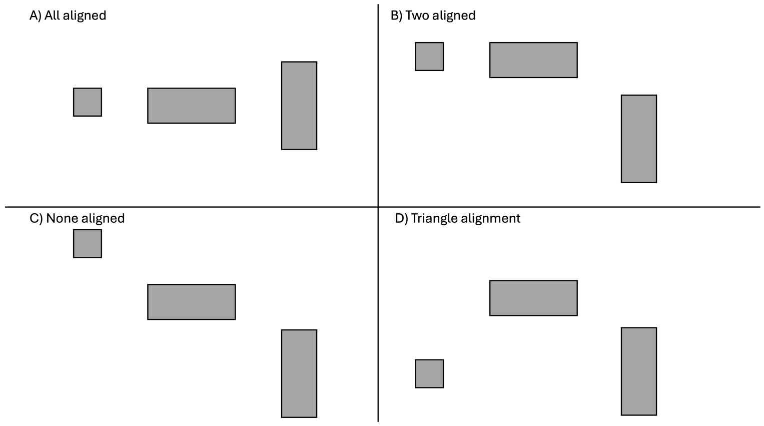

Figure 5.2. Critical trials from Experiment 5.

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) x 2 (TDD: 20%, 35%) x 4 display: (all-aligned, two-aligned, none-aligned, triangle) x 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), and two smaller options were randomly sampled from the lower diagonal. Here, one option was always much larger than the other two, allowing me to remove participants who did not perform poorly. 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 in 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

Participants performed well on the non-critical 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

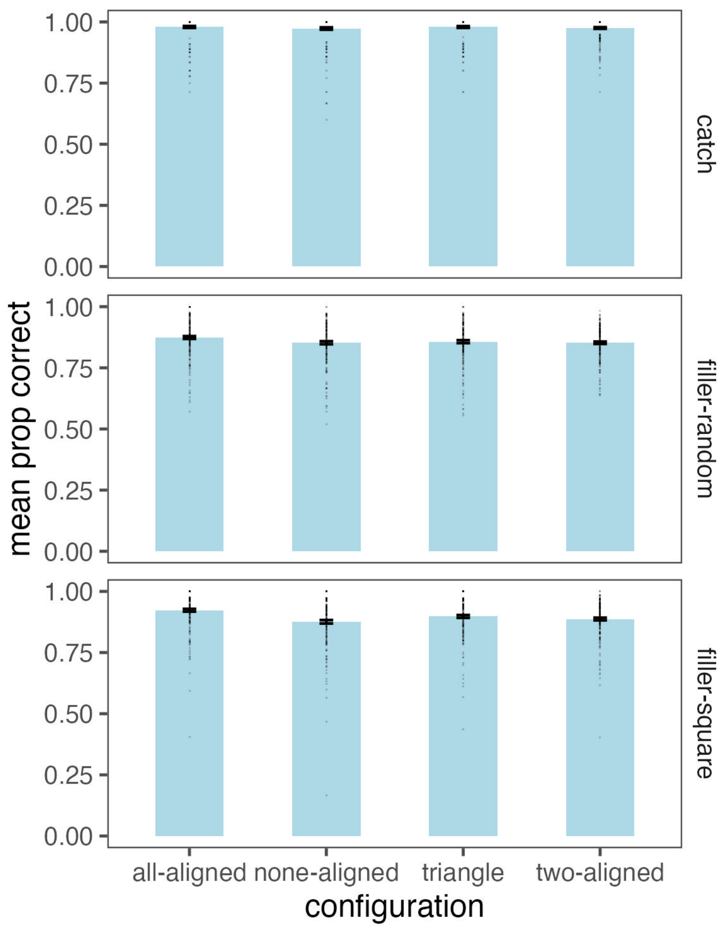

Figure 5.3. Results from non-critical trials in Experiment 5. Rows show trial types. Bars show mean proportion correct in a given condition, with the error bars showing ±1SE. Dots show individual participant proportion correct.

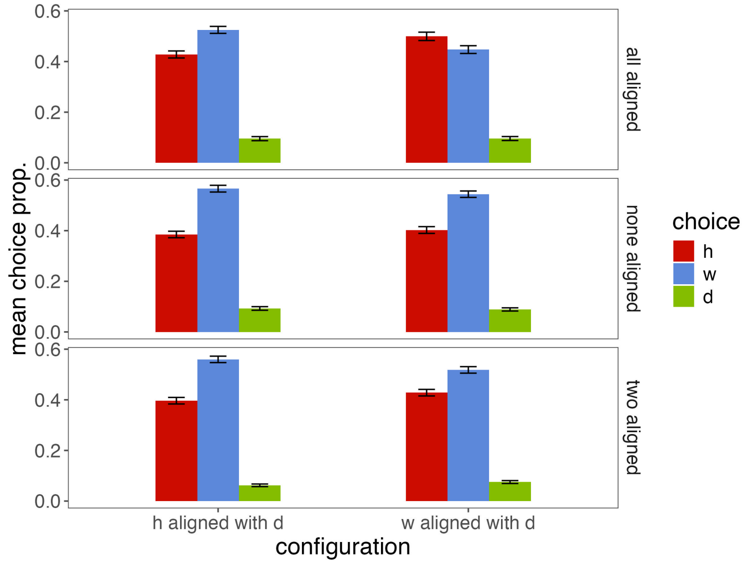

Figure 5.4. Results from critical trials in Experiment 5. Mean choice proportions for the H, W, and D rectangles conditioned on alignment and configuration.

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.

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 appears to occur in the none-aligned and all-aligned conditions, which suggests a position bias. I address this concern in the inferential statistics.

I next 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.

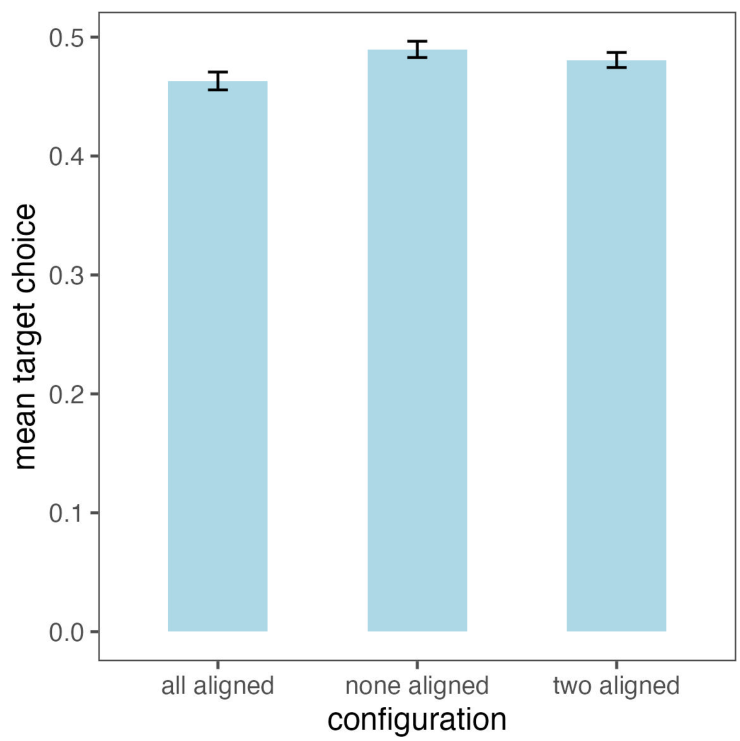

Figure 5.5. Experiment 5 mean target choice proportions by configuration.

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.

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 position biases.

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 conditon, 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, can be affected by context. These context effects occur when the relative choice for a particiular option varies with situational properties. In particular, the set of other options available affect 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 not by choice set but by the presentation format of options in simple perceptual choice.

In Chapter 2, I used a Thurstonian perceptual choice model (Thurstone, 1927) to measure the correlation between valuations in the attraction and repulsion effect. In Experiment 2, I collected valuations (area estimations for simple rectanges) 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 ρ_{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 non-monotonic relationship is not predicted by the maxdiff model, a highly influential of best-worst choice (Marley & Louviere, 2005). 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 reliability measured using Pearson correlations. Though other researchers have proposed correlations as a measure of similarity between options in a choice set (Kamakura & Srivastava, 1984; Natenzon, 2019), this study 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. 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[1]. 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.

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

[1]See the diagonal line from Figure 2.4 for evidence of this result.

not systematically affect target or competitor choice, and that the repulsion effect 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 rnuning 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.

APPENDIX A

BAYESIAN LOGISTIC REGRESSION MODEL OF 2AFC DISCRIMINABILITY FROM EXPERIMENT 1

I analyzed the 2AFC data from Experiment 1 using Bayesian Hierarchical Logistic Regression.

Recall that in this experiment, participants were presented with three stimuli (target, competitor, and decoy rectangles). They were then asked to select the largest rectangle out of a pair of two of these options. In other words, there are three trial types: target/competitor (TC), target/decoy (TD), and competitor/decoy (CD). As discussed in the main text, I remove the TC trials from all substantive analyses, as well as the $TDD = 0\%$ trials.

A.1 Model Details

The model predicts the probability of discriminating the target/competitor from the decoy option. According to the model, discrimination D for participant i on trial j is:

$$D_{ij} \sim Bernoulli(\theta_{ij}) \tag{A.1}$$

To compute θ_{ij}, I first compute η_{ij} from linear combination of the relevant variables.

$$
\begin{aligned}
\eta_{ij} = {} & (\beta_0 + S_{0_i}) + (\beta_{\text{or}} + S_{\text{or}_i}) \cdot \text{or}_{ij} + (\beta_{\text{horiz}} + S_{\text{horiz}_i}) \cdot \text{horiz}_{ij} \\
& + (\beta_{\text{TD}} + S_{\text{TD}_i}) \cdot \text{TD}_{ij} + (\beta_{\text{TDD5}} + S_{\text{TDD5}_i}) \cdot \text{TDD5}_{ij} + (\beta_{\text{TDD9}} + S_{\text{TDD9}_i}) \cdot \text{TDD9}_{ij} \\
& + (\beta_{\text{TDD14}} + S_{\text{TDD14}_i}) \cdot \text{TDD14}_{ij} + (\beta_{\text{TDD5xTD}} + S_{\text{TDD5xTD}_i}) \cdot \text{TDD5}_{ij} \cdot \text{TD}_{ij} \\
& + (\beta_{\text{TDD9xTD}} + S_{\text{TDD9xTD}_i}) \cdot \text{TDD9}_{ij} \cdot \text{TD}_{ij} + (\beta_{\text{TDD14xTD}} + S_{\text{TDD14xTD}_i}) \cdot \text{TDD14}_{ij} \cdot \text{TD}_{ij}
\end{aligned} \tag{A.2}
$$

All β terms are fixed effects, and all S terms are random (participant) effects. β_{or} is the fixed effect of orientation, where or_{ij} is a dummy variable which $= 0$ if the target and decoy are taller than wide and $= 1$ if the target and decoy are wider than tall. β_{TD} is the fixed effect of comparison, where TD_{ij}=0 for CD trials and $TD_{ij} = 1$ for TD trials. The TDD variable has 4 levels (2%, 5%, 9%, and 14%), so I include three dummy variables ($TDD5$, $TDD9$, and $TDD14$) and treat 2% as the reference level for TDD. I also include the interaction to capture the additional boost / decrement to TD over TC trials at each level of TDD.

η_{ij} is then transformed to the probability scale using the logit function:

$$
\theta_{ij} = \frac{1}{1 + e^{-\eta_{ij}}} \tag{A.3}
$$

A.2 Prior Distributions on Parameters

- $\beta_0 \sim \mathcal{N}(0, 5)$
- $\beta_{or} \sim \mathcal{N}(0, 5)$
- $\beta_{horiz} \sim \mathcal{N}(0, 5)$
- $\beta_{TD} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD5} \sim \mathcal{N}(0, 5)$

- $\beta_{TDD9} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD14} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD5xTD} \sim \mathcal{N}(0, 2.5)$
- $\beta_{TDD9xTD} \sim \mathcal{N}(0, 2.5)$
- $\beta_{TDD14xTD} \sim \mathcal{N}(0, 2.5)$
- $S_{0_i} \sim \mathcal{N}(0, \sigma_{S_0})$
- $S_{or_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{horiz_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TD_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TDD5_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TDD9_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TDD14_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TDD5xTD_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TDD9xTD_i} \sim \mathcal{N}(0, \sigma_S)$
- $S_{TDD14xTD_i} \sim \mathcal{N}(0, \sigma_S)$
- $\sigma_{S_0} \sim \text{LogNormal}(0, 2.5)$
- $\sigma_S \sim \text{LogNormal}(0, 2.5)$

Note that the model assumes equal variance for all random effect distributions aside from the random intercepts.

A.3 Modeling Results

The model was coded in Stan (Carpenter et al., 2017) and implemented using the RStan package (Stan Development Team, n.d.). The sampler ran 5 chains, each for 2500 iterations. Posterior diagnostics indicated that the sampler converged.

A.3.1 Parameter estimates.

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

Parameter	M	SD	CI low	CI high
β_0	0.44	0.06	0.32	0.57
β_{or}	-0.54	0.06	-0.66	-0.43
β_{horiz}	0.23	0.06	0.12	0.34
β_{TD}	0.17	0.08	0.01	0.33
β_{TDD5}	0.40	0.08	0.23	0.56
β_{TDD9}	0.81	0.09	0.64	0.98
β_{TDD14}	1.45	0.10	1.25	1.64
$\beta_{TDD5xTD}$	0.14	0.12	-0.09	0.36
$\beta_{TDD9xTD}$	0.61	0.13	0.36	0.85
$\beta_{TDD14xTD}$	0.79	0.15	0.50	1.10
σ_{S_0}	0.20	0.04	0.12	0.29
σ_S	0.34	0.03	0.29	0.39

Table A.1. Parameter estimates for Bayesian Hierarchical Logistic Regression from Experiment 1 Data, including means, standard deviations, and 95% Credible Intervals.

Inference is made by examining the posterior distributions of the fixed effect parameters (i.e., all β values).

APPENDIX B

BAYESIAN HIERARCHICAL MODELING OF CIRCLE ESTIMATION DATA FROM EXPERIMENT 2

I analyzed the circle estimation data (Experiment 2) using the multivariate Thurstonian perceptual model first presented in Chapter 2.

B.1 Model Details

The model assumes that, for participant i on trial j, the vector of perceived areas $\boldsymbol{X}_{ij}$ is sampled from a multivariate normal distribution with parameters $\boldsymbol{\mu}_{ij}$ and $\boldsymbol{\Sigma}$. That is,

$$\boldsymbol{X}_{ij} \sim \mathbf{N}(\boldsymbol{\mu}_{ij}, \boldsymbol{\Sigma}) \tag{B.1}$$

Using Bayesian statistical modeling, I simultaneously estimated the parameters $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ for the model outlined in Chapter 2. Note that I allow $\boldsymbol{\mu}$ to vary systematically over trials and participants, but Σ remains constant. I estimate $\boldsymbol{\mu}$ using hierarchical regression while allowing the components of $\boldsymbol{\Sigma}$ (i.e., $\boldsymbol{\sigma_T}$, $\boldsymbol{\sigma_C}$, $\boldsymbol{\sigma_D}$, ρ_{TD}, ρ_{TC}, ρ_{CD}) to vary freely.

I estimated the model separately for the triangle and horizontal condition. I first walk through the computation of $\boldsymbol{\mu}$, followed by the computation $\boldsymbol{\Sigma}$. I also show the prior distributions on each parameter separately for each of these components, and then I explain the modeling procedure and results. Note that the model predicts mean-centered log-transformed estimated area.

B.1.1 $\boldsymbol{\mu}$ Parameterization

I used the model to predict the mean area μ_{ijk} for the ith participant on the jth trial for the kth stimulus. There were $k = 3$ stimuli on each trial. If $k = 1$, the stimulus is the target; If $k = 2$, the stimulus is the competitor; If $k = 3$, the stimulus is the decoy. Thus, $\boldsymbol{\mu}$ can be broken down into μ_{ij1} (target), μ_{ij2} (competitor), and μ_{ij3} (decoy). Note that some parameters are common to all stimuli (e.g., the effects of diagonal or orientation), while others are common only to a particular option (e.g., the effect of competitor vs. decoy vs. target).

μ_{ij1} is computed as:

$$\begin{aligned}\mu_{ij1} = (S_{0_i} + \beta_0) + \beta_{or} * \mathrm{or}_{ij1} + \beta_{\mathrm{diag2}} * \mathrm{diag2}_{ij} + \\ \beta_{\mathrm{diag3}} * \mathrm{diag3}_{ij} + \beta_{\mathrm{TDD5}} * \mathrm{TDD5}_{ij} + \\ \beta_{\mathrm{TDD9}} * \mathrm{TDD9}_{ij} + \beta_{\mathrm{TDD14}} * \mathrm{TDD14}_{ij}\end{aligned} \tag{B.2}$$

S_{0_i} is a random intercept for participant i. β_0 is the fixed intercept. β_{or} is the fixed effect of orientation, where or_{ij1} is a dummy variable which = 0 if the target is taller than wide and = 1 if the target is wider than tall. β_{diag2} is the fixed effect of the middle diagonal, which = 1 if the all stimuli on the trial fall on the middle diagonal and = 0 otherwise. β_{diag3} is the fixed effect of the upper diagonal, which = 1 if all stimuli on the trial fall on the upper diagonal and = 0 otherwise. β_{TDD5} is the fixed effect of TDD 5, and $TDD5_{ij}$ is a dummy variable which = 1 if $TDD = 5\%$ and = 0 otherwise. β_{TDD9} is the fixed effect of TDD 9, and $TDD9_{ij}$ is a dummy variable which = 1 if $TDD = 9\%$ and = 0 otherwise. β_{TDD14} is the fixed effect of TDD 14, and $TDD14_{ij}$ is a dummy variable which = 1 if $TDD = 14\%$ and = 0 otherwise.

μ_{ij2} is computed as:

$$\mu_{ij2} = (S_{0_i} + \beta_0) + \beta_{\text{or}} * \text{or}_{ij2} + \beta_{\text{diag2}} * \text{diag2}_{ij} + \beta_{\text{diag3}} * \text{diag3}_{ij} + \beta_{\text{TDD5}} * \text{TDD5}_{ij} + \beta_{\text{TDD9}} * \text{TDD9}_{ij} + \beta_{\text{TDD14}} * \text{TDD14}_{ij} + \beta_{\text{comp}} \tag{B.3}$$

S_{0_i} is a random intercept for participant i. β_0 is the fixed intercept. β_{or} is the fixed effect of orientation, where or_{ij2} is a dummy variable which = 0 if the competitor is taller than wide and = 1 if the competitor is wider than tall. β_{diag2} is the fixed effect of the middle diagonal, which = 1 if the all stimuli on the trial fall on the middle diagonal and = 0 otherwise. β_{diag3} is the fixed effect of the upper diagonal, which = 1 if all stimuli on the trial fall on the upper diagonal and = 0 otherwise. β_{TDD5} is the fixed effect of TDD 5, and $TDD5_{ij}$ is a dummy variable which = 1 if $TDD = 5\%$ and = 0 otherwise. β_{TDD9} is the fixed effect of TDD 9, and $TDD9_{ij}$ is a dummy variable which = 1 if $TDD = 9\%$ and = 0 otherwise. β_{TDD14} is the fixed effect of TDD 14, and $TDD14_{ij}$ is a dummy variable which = 1 if $TDD = 14\%$ and = 0 otherwise. β_{comp} is a parameter that reflects the possibility of estimation bias for the competitor.

μ_{ij3} is computed as:

$$\mu_{ij3} = (S_{0_i} + \beta_0) + \beta_{\text{or}} * \text{or}_{ij3} + \beta_{\text{diag2}} * \text{diag2}_{ij} + \beta_{\text{diag3}} * \text{diag3}_{ij} + (\beta_{\text{TDD5}} + \beta_{\text{TDD5}D}) * \text{TDD5}D_{ij} + (\beta_{\text{TDD9}} + \beta_{\text{TDD9}D}) * \text{TDD9}D_{ij} + (\beta_{\text{TDD14}} + \beta_{\text{TDD14}D}) * \text{TDD14}D_{ij} \tag{B.4}$$

S_{0_i} is a random intercept for participant i. β_0 is the fixed intercept. β_{or} is the fixed effect of orientation, where or_{ij3} is a dummy variable which = 0 if the decoy is taller than wide and = 1 if the decoy is wider than tall. β_{diag2} is the fixed effect of the middle diagonal, which = 1 if the all stimuli on the trial fall on the middle diagonal and = 0 otherwise. β_{diag3} is the fixed effect of the upper diagonal, which = 1 if all stimuli on the trial fall on the upper diagonal and $= 0$ otherwise. β_{TDD5D} is the fixed effect of TDD=5, and $TDD5D_{ij}$ is a dummy variable which $= 1$ if $TDD = 5\%$ for the decoy and $= 0$ otherwise. β_{TDD9D} is the fixed effect of TDD 9 for the decoy, and $TDD9D_{ij}$ is a dummy variable which $= 1$ if $TDD = 9\%$ and $= 0$ otherwise. β_{TDD14D} is the fixed effect of TDD 14 for the decoy, and $TDD14D_{ij}$ is a dummy variable which $= 1$ if $TDD = 14\%$ and $= 0$ otherwise.

Note that there is a common set of parameters for each level of TDD and additional set of parameters for each level of TDD that only apply to the decoy. In the data, it was clear that participants often adjusted the target and competitor relative to the decoy. In other words, even though the physical size of both target and competitor remains constant across TDD, participants' *estimation* of their size varied with TDD. The inclusion of a separate set of parameters for TDD that only apply to the decoy allows for a "deflection" of the decoy size, relative to target and competitor size.

Note the following reference points for the variables:

- TDD: 2%
- Orientation: taller than wide
- Diagonal: lower
- Stimulus: target

The β_0 parameter captures the fixed of a tall target on the lower diagonal at 2% TDD, and all other parameters reflect deflections from this.

B.1.1.1 Prior Distributions on Parameters

Below are shown the following prior distributions on each parameter relevant to $\boldsymbol{\mu}$:

- $\beta_0 \sim \mathcal{N}(0, 5)$

- $\beta_{or} \sim \mathcal{N}(0, 5)$
- $\beta_{diag2} \sim \mathcal{N}(0, 5)$
- $\beta_{diag3} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD5} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD9} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD14} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD2D} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD5D} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD9D} \sim \mathcal{N}(0, 5)$
- $\beta_{TDD14D} \sim \mathcal{N}(0, 5)$
- $\beta_{comp} \sim \mathcal{N}(0, 5)$
- $S_{0_i} \sim \mathcal{N}(0, \sigma_{S_0})$
- $\sigma_{S_0} \sim \text{Half-Cauchy}(0, 2.5)$

B.2 Σ Parameterization

Σ is a positive semi-definite 3x3 covariance matrix computed as:

$$\mathbf{\Sigma} = S\mathbf{\Omega}S \tag{B.5}$$

where S is a diagonal matrix consisting of:

$$\begin{pmatrix} \sigma_T & 0 & 0 \\ 0 & \sigma_C & 0 \\ 0 & 0 & \sigma_D \end{pmatrix} \tag{B.6}$$

and $\mathbf{\Omega}$ is a correlation matrix:

$$\begin{pmatrix} 1 & \rho_{TC} & \rho_{TD} \\ \rho_{TC} & 1 & \rho_{CD} \\ \rho_{TD} & \rho_{CD} & 1 \end{pmatrix} \tag{B.7}$$

Estimation of S was straightforward. I simply freely estimated the three standard deviation parameters σ_T, σ_C, and σ_D.

To estimate $\mathbf{\Omega}$, I used the LKJ distribution (Lewandowski et al., 2009) to set priors on the Cholesky factorization of the correlation matrix Ω. This was done to ensure that the resulting variance-covariance matrix $\mathbf{\Sigma}$ is positive semi-definite, a requirement of the multivariate Gaussian distribution. The critical inferences, however, are performed on the off-diagonal elements ρ_{TC}, ρ_{TD}, ρ_{CD} in each display condition. I set priors on the σ parameters using the Half-Cauchy distribution (Gelman, 2006).

B.2.0.1 Prior Distributions on Parameters

Below are shown the following prior distributions on each parameter relevant to $\mathbf{\Sigma}$.

- $\sigma_T \sim$ Half-Cauchy$(0, 2.5)$
- $\sigma_C \sim$ Half-Cauchy$(0, 2.5)$
- $\sigma_D \sim$ Half-Cauchy$(0, 2.5)$
- $\mathbf{\Omega} \sim$ LKJCorr$(\eta = 1)$

B.3 Modeling Results

The model was implemented using the Stan programming language (Carpenter et al., 2017) using the cmdstanr interface (Gabry et al., 2024) in R .

I ran the model for 2500 iterations (not including warm-up) with 4 chains for each display condition. Posterior diagnostics indicated that the sampler converged in each condition.

Below I show parameter estimates for each display condition and relevant parameter. I exclude the estimates of the participant effects S_{0_i} for brevity. Estimates are rounded to two or three decimal places, depending on the size of the parameter.

The posterior estimates indicate that $\rho_{TD} > \rho_{TC} \approx \rho_{CD}$ in each display condition, in accordance with the predictions. Furthermore, the absolute values of all ρ values are greater in the horizontal condition than in the triangle condition, suggesting that the horizontal condition better facilitates comparisons.

The β estimates are generally as expected. The β_{diag} estimates show that participants increased their area estimations with the absolute size of the stimuli. Participants also decreased the size of decoy estimations as TDD increased. They also, to some extent, decreased the size of target and competitor estimations as TDD increased (captured by the β_{TDD5}, β_{TDD9}, and β_{TDD14}) parameters, indicating that participants adjusted the target and competitor relative to the decoy.

Interestingly, the β_{or} estimates indicated that participants rated wider stimuli larger than tall stimuli in the horizontal condition, but they rated taller stimuli larger than wide stimuli in the horizontal condition. This effect is quite small, but is nonetheless present in the parameter estimates.

Participants also rated the competitor slightly larger than the target, particularly in the triangle condition, although this effect is quite small. This effect was indeed to small to show differences in any single TDD level (see Figure 2.10.

Display Condition	Parameter	*M*	*SD*	HDI lower	HDI upper
Horizontal	β_0	−0.41	0.02	−0.44	−0.38
	β_{or}	0.003	0.002	−0.001	0.007
	β_{diag2}	0.47	0.01	0.46	0.48
	β_{diag3}	0.80	0.01	0.79	0.81
	β_{TDD5}	−0.005	0.01	−0.017	0.007
	β_{TDD9}	−0.007	0.01	−0.019	0.005
	β_{TDD14}	−0.01	0.01	−0.02	−0.0005
	β_{TDD2D}	−0.006	0.004	−0.013	0.001
	β_{TDD5D}	−0.01	0.004	−0.016	−0.003
	β_{TDD9D}	−0.04	0.004	−0.05	−0.04
	β_{TDD14D}	−0.08	0.004	−0.09	−0.07
	β_{comp}	0.003	0.002	−0.002	0.007
	σ_{S_0}	0.19	0.01	0.17	0.21
	σ_T	0.337	0.002	0.334	0.340
	σ_C	0.341	0.002	0.338	0.345
	σ_D	0.337	0.002	0.333	0.340
	ρ_{TC}	0.575	0.005	0.565	0.584
	ρ_{TD}	0.710	0.004	0.703	0.716
	ρ_{CD}	0.575	0.005	0.565	0.584
Triangle	β_0	−0.40	0.01	−0.42	−0.38
	β_{or}	−0.006	0.002	−0.01	−0.002
	β_{diag2}	0.47	0.005	0.455	0.474
	β_{diag3}	0.81	0.005	0.80	0.82
	β_{TDD5}	−0.01	0.006	−0.03	0.0003
	β_{TDD9}	−0.02	0.006	−0.03	−0.008
	β_{TDD14}	−0.03	0.006	−0.04	−0.01
	β_{TDD2D}	−0.0172	0.004	−0.024	−0.01
	β_{TDD5D}	−0.0167	0.004	−0.0237	−0.01
	β_{TDD9D}	−0.03	0.004	−0.037	−0.02
	β_{TDD14D}	−0.05	0.004	−0.06	−0.05
	β_{comp}	0.005	0.002	0.0001	0.009
	σ_{S_0}	0.15	0.01	0.14	0.17
	σ_T	0.335	0.002	0.332	0.338
	σ_C	0.338	0.002	0.335	0.341
	σ_D	0.335	0.002	0.331	0.338
	ρ_{TC}	0.541	0.005	0.531	0.551
	ρ_{TD}	0.675	0.004	0.667	0.682
	ρ_{CD}	0.533	0.005	0.523	0.543

Table B.1. Parameter estimates for Bayesian Hierarchical Thurstonian Model from Experiment 2 Circle Phase Data, including means, standard deviations, and 95% Credible Intervals.

APPENDIX C

INFERENTIAL STATISTICS FOR EXPERIMENT 2 CHOICE DATA

Following Katsimpokis et al. (2022), I performed inference on *Absolute Share of the Target*, a variant of RST that corrects for a bias in RST. AST is an unweighted average of the target choice proportion from each choice set. Here, AST is computed as:

$$\begin{aligned} AST = 0.5 * (&\frac{P(H|H,W,D_H)}{P(H|H,W,D_H) + P(W|H,W,D_H)} + \\ &\frac{P(W|H,W,D_W)}{P(W|H,W,D_W) + P(H|H,W,D_W)}) \end{aligned} \tag{C.1}$$

I computed AST for each participant in each display condition at each level of TDD. I first present the analyses from the triangle condition followed by those from the horizontal condition.

C.1 Triangle Condition Analysis

I performed a one-way within-groups ANOVA testing the effect of TDD on AST in the triangle condition. The results were significant, $F(3, 636) = 79.97, p < .001$. I then performed a follow-up one-sample t-test on AST at each level of TDD, using the within-participants error correction from Cousineau and O'Brien (2014) and comparing the mean AST value to the null value .5. I compared each p-value to a Bonferroni-corrected α level of $\alpha = \frac{.05}{4} = .0125$.

The AST value was significantly different from .5 at TDD=2%, $t(212) = -18.4, p < .001$, $M = .34$, 95%CI[.33, .36], indicating a repulsion effect.

The AST value was significantly different from .5 at TDD=5%, $t(212) = -13.2, p < .001$, $M = .39$, 95%CI[.38, .41], indicating a repulsion effect.

The AST value was significantly different from .5 at TDD=9%, $t(212) = -7.45, p < .001$, $M = .43$, 95%CI[.42, .45], indicating a repulsion effect.

The AST value was significantly different from .5 at TDD=14%, $t(212) = -2.34, p = .002$, $M = .48$, 95%CI[.46, .49], indicating a slight repulsion effect. Note that the mean $P(T) > P(C)$ in Figure 2.12; however, those values are not equally weighted.

C.2 Horizontal Condition Analysis

I again performed a one-way within-groups ANOVA testing the effect of TDD on AST in the horizontal condition. The results were significant, $F(3, 618) = 176.10, p < .001$. I then performed a follow-up one-sample t-test on AST at each level of TDD, using the within-participants error correction from Cousineau and O'Brien (2014) and comparing the mean AST value to the null value .5. I compared each p-value to a Bonferroni-corrected α level of $\alpha = \frac{.05}{4} = .0125$.

The AST value was significantly different from .5 at TDD=2%, $t(206) = -15.6, p < .001$, $M = .34$, 95%CI[.33, .36], indicating a repulsion effect.

The AST value was significantly different from .5 at TDD=5%, $t(206) = -8.12, p < .001$, $M = .41$, 95%CI[.39, .43], indicating a repulsion effect.

The AST value was not significantly different from .5 at TDD=9%, $t(206) = -0.04, p = .10$, $M = .50$, 95%CI[.48, .52], indicating a null effect.

The AST value was significantly different from .5 at TDD=14%, $t(206) = 5.00, p < .001$, $M = .56$, 95%CI[.54, 58], indicating an attraction effect.

I also plot mean AST values for each TDD level in each display condition in Figure C.1.

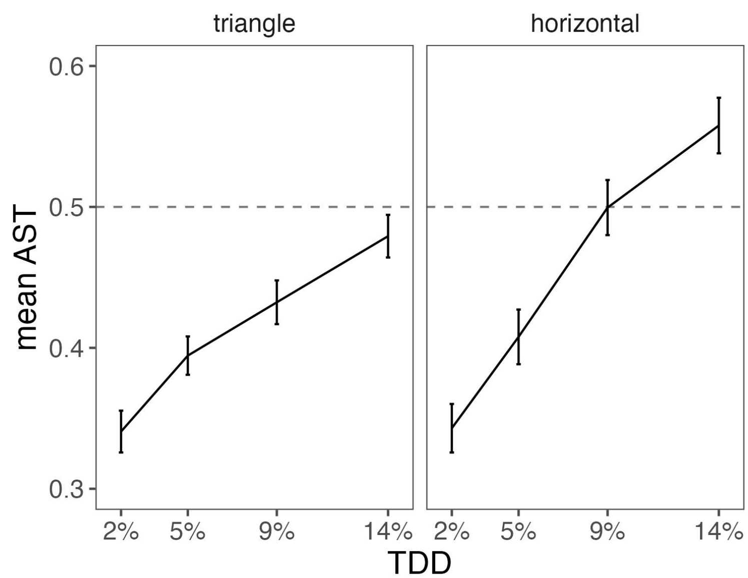

Figure C.1. Mean AST values for each display condition and TDD level from Experiment 2. Error bars are 95% CIs with the within-participants error correction from Cousineau and O'Brien (2014).

APPENDIX D

MAXDIFF MODELING FROM EXPERIMENT 3

According to the maxdiff model of best-worst choice (Marley & Louviere, 2005), the probability $BW_K(x, y)$ of selecting option x as best and y as worst from choice set K is computed as:

$$BW_K(x, y) = \frac{e^{u_x - u_y}}{\sum_{\substack{p,q \in K \\ p \neq q}} e^{u_p - u_q}} \tag{D.1}$$

where u_i is the utility of option i.

Below I present the details of the maxdiff modeling, as applied to the data from Experiment 3.

D.1 Model Details

Following typical approaches in the choice modeling literature, I estimated the utility of each option in the choice set using linear regression.

According the model, the utility U_{ijk} for participant i on trial j and option k is computed as:

APPENDIX E

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.

E.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:

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

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:

$$\begin{pmatrix} \mu_{T_j k} \\ \mu_{C_j k} \\ \mu_{D_j k} \end{pmatrix} \tag{E.2}$$

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

$$\mathbf{\Sigma}_k = S\mathbf{\Omega}_k S \tag{E.3}$$

where S is a diagonal matrix consisting of:

$$\begin{pmatrix} \sigma_T & 0 & 0 \\ 0 & \sigma_C & 0 \\ 0 & 0 & \sigma_D \end{pmatrix} \tag{E.4}$$

with σ_T, σ_C, σ_D being the standard deviations for target, competitor, and decoy, respectively. $\mathbf{\Omega}_k$ is a correlation matrix:

$$\begin{pmatrix} 1 & \rho_{TC_k} & \rho_{TD_k} \\ \rho_{TC_k} & 1 & \rho_{CD_k} \\ \rho_{TD_k} & \rho_{CD_k} & 1 \end{pmatrix} \tag{E.5}$$

with ρ_{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.

E.2 Prior Distributions on all Parameters

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

- $\sigma_T \sim$ Half-Cauchy$(0, 2.5)$

- $\sigma_C \sim$ Half-Cauchy$(0, 2.5)$

- $\sigma_D \sim$ Half-Cauchy$(0, 2.5)$

- $\boldsymbol{\Omega_k} \sim$ LKJCorr$(\eta = 0.5)$

E.3 Parameter Estimates

For brevity, I omit $\boldsymbol{\mu}$ and σ estimates and show only ρ estimates below.

Trial Type	Parameter	*M*	*SD*	HDI lower	HDI upper
Attraction	$\boldsymbol{\rho}_{TC}$	.87	0.005	.86	.88
	$\boldsymbol{\rho}_{TD}$	.87	0.005	.86	.88
	$\boldsymbol{\rho}_{CD}$	.83	0.007	.81	.84
Repulsion	$\boldsymbol{\rho}_{TC}$	.77	0.008	.75	.79
	$\boldsymbol{\rho}_{TD}$	.87	0.005	.86	.88
	$\boldsymbol{\rho}_{CD}$	.69	0.011	.67	.72

Table E.1. ρ Parameter estimates for Bayesian Hierarchical Thurstonian Model from Experiment 4 Pricing Data, including means, standard deviations, and 95% Credible Intervals.

APPENDIX F

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.

F.1 Dirichlet-Multinomial Choice Model

According to the model, the vector $\boldsymbol{C_{ijkl}}$ 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

$$C_{ijkl} \sim \text{Multinomial}(\boldsymbol{\theta_{ijkl}}) \tag{F.1}$$

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

$$\boldsymbol{\theta_{ijkl}} \sim \text{Dirichlet}(\boldsymbol{\alpha_{ijkl}}) \tag{F.2}$$

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

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

$$\boldsymbol{\alpha_{ijkl}} \sim \text{LogNormal}(1, 1) \tag{F.3}$$

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

Trial Type	**TDD**	**Option**	*M*	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 F.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 G

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 G.1.

Parameter	*M*	*SD*	HDI lower	HDI upper
β_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 G.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-alingned 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 $M = -.27$.

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