CONTEXT DEPENDENCE IN PERCEPTUAL AND PREFERENTIAL CHOICE

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SEAN PATRICK CONWAY

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SEAN PATRICK CONWAY

Approved as to style and content by:

Andrew L. Cohen, Chair

Youngbin Kwak, Member

Elizabeth Miller, Member

Jeffrey Starns, Member

Ilia Karatsoreos, Department Chair
Psychological and Brain Sciences

ABSTRACT

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SEAN PATRICK CONWAY

B.A., UNIVERSITY OF WISCONSIN-LA CROSSE

M.S., UNIVERSITY OF WISCONSIN-OSHKOSH

, UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Andrew L. Cohen

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CHAPTER 1

INTRODUCTION

1.1 Overview

Decades of decision-making research has shown that context can, in certain circumstances, systematically affect people's choices. That is, the relative likelihood of choosing one option over another can vary systematically with the menu of options, the *choice set*. This is known as a *context effect*. One notable context effect, the attraction effect, occurs when the choice share of a *target* option is boosted upon the inclusion of a similar but inferior *decoy* option. Another finding, the repulsion effect, occurs when a decoy boosts the choice share of a *dissimilar* option, known as the *competitor*, rather than the target.

The attraction and repulsion effects, originally studied in preferential choice, have recently been shown to occur in simple perceptual choices (Evans et al., 2021; Liao et al., 2021; Spektor et al., 2018, 2022; Trueblood et al., 2013). 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). The goal of this dissertation is to understand how and why these effects occur by employing well-studied statistical models from the psychology and economics literature. Additionally, this dissertation sets out to differentiate the perceptual from decision-making processes that may lead to context effects (specifically, the attraction and repulsion effects).

Below, I introduce the relevant background empirical and theoretical literature in context-dependent choice.

1.1.1 Introducing the Attraction Effect

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. Researchers universally assume that participants use the input they receive (i.e., the value of each option) to arrive at a choice. The study of choice spans multiple fields, including psychology, 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 (McFadden, 2001). In psychology and marketing, however, researchers have identified a set of phenomena that violate such assumptions, by showing that choices vary based on the *choice set*, or the menu of available options. This class of phenomena is known as *context effects* (Adler et al., 2024).

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 by adding more options to a choice set.

This dissertation will explore context effects in both perceptual and preferential decision-making. In particular, I will explore the attraction effect and its reversal, the repulsion effect. I summarize these effects and the relevant literature below.

To begin, I first demonstrate a notable context effect, the *attraction effect*. As a demonstration, see 1.1 (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 give these dimensions generic names to emphasize that they may be anything from the screen size and average lifespan of a television in a consumer choice experiment to the height and width of a rectangle in a perceptual choice experiment.

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. In Figure 1.1 (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:

$$\frac{P(A|[A,B,D_A])}{P(B|[A,B,D_A]} = \frac{P(A|[A,B,D_B])}{P(B|[A,B,D_B]} \tag{1.1}$$

However, in the attraction effect:

$$\frac{P(A|[A,B,D_A])}{P(B|[A,B,D_A]} > \frac{P(A|[A,B,D_B])}{P(B|[A,B,D_B]} \tag{1.2}$$

Thus, IIA is violated.

In the context effects literature, it is common to refer to the similar, dominated option as a *decoy*, the similar dominating option as a *target*, and the dissimilar dominating option as a *competitor*. I adopt this terminology through this dissertation. For

[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.

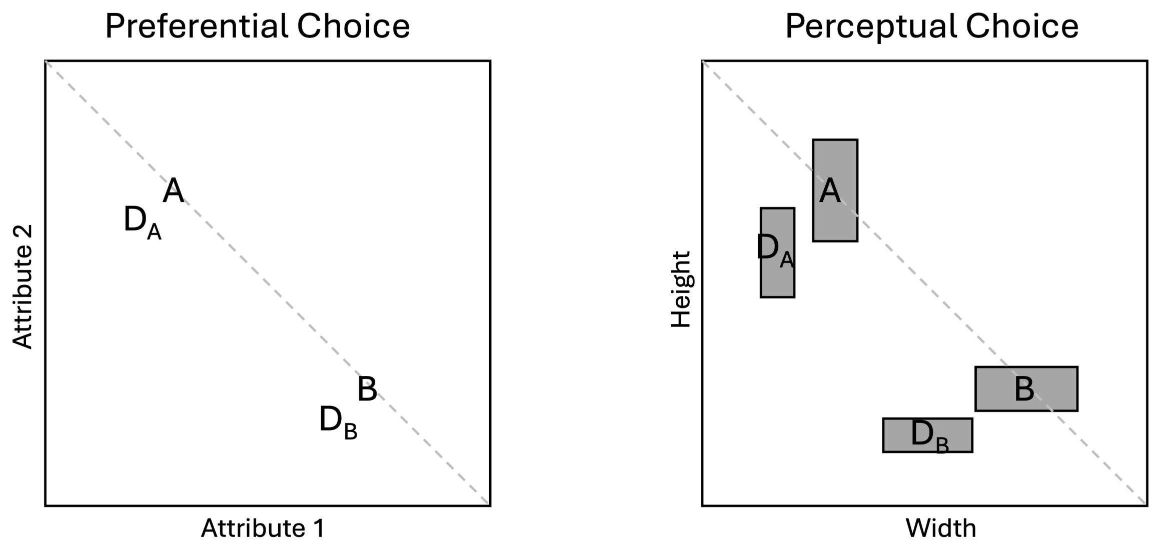

Figure 1.1. A graphical depiction of choice options in the attraction/repulsion effect. Left panel: preferential choice. Right panel: perceptual choice.

example, in the choice set $[A, B, D_A]$, A is the target, B is the competitor, and D_A is the decoy. The decoy is dominated by the target, so no rational agent should intentionally select it over the target (conditional on the assumption that they correctly perceive the dominance relationship).

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. Such a result violates 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:

$$P(A|[A, B]) \geq P(A|[A, B, D_A]) \tag{1.3}$$

[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.

Thus, Huber et al. (1982)'s finding that $P(A|[A,B]) \leq P(A|A,B,D_A)$ violates this assumption. Huber and Puto (1983) replicated these results and also showed that if the decoy has a relatively high value, it can actually take choice shares away from the target. This result suggests that the relative positioning of the decoy to the target can greatly affect patterns of choice, a finding explored by numerous other researchers which has strong theoretical consequences (see below).

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). These effects are well studied and important both practically and theoretically, though the focus of this dissertation is on the attraction and repulsione effects.

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 to be 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, though this assumption can be relaxed by assuming set or alternative specific intercepts (Rooderkerk et al., 2011) or allowing correlations between options and/or attributes (Haaijer et al., 1998). Haaijer et al. (1998) showed that the probit model shows an improved fit to context effect data by allowing such correlations.

In cognitive psychology, researchers have developed process models that attempt to explain the mental processes that lead to context effects in decision-making (Bergner et al., 2019; Bhatia, 2013; 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 a 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 dissertation does not explore the predictive success of these models, nor does it incorporate model fitting to compare these models. Indeed, other researchers have done such analyses (Berkowitsch et al., 2014; Cataldo & Cohen, 2021; Cohen et al., 2017; Evans et al., 2019; Hotaling et al., 2010; Molloy et al., 2019; Turner et al., 2018). Instead, I use behavioral experiments and statistical modeling to understand how context dependence arises in various domains.

The attraction effect is not limited to merely consumer choice. Researchers have found 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), charitable donation (Pittarello et al., 2020), inference (Trueblood, 2012), job candidate selection (Highhouse, 1996), political choice (Pan et al., 1995), 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; Turner et al., 2018; Yearsley et al., 2022).

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 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 (Flynn et al., 2007b). 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 when the decoy is equally similar to both focal options.

CHAPTER 2

PARSING THE ROLE 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 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.

In recent years, researchers have extended context effect research to perceptual choice. 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. See see Figure 1.1 (right panel). Options A and B have equal area but trade off in height and width. [1] Notably, the title of their paper was "Not Just for Consumers: Context Effects Are Fundamental to Decision Making", and in their General Discussion, Trueblood et al. (2013) argued "our experiments suggest that these context effects are a general feature of human choice behavior because they are a fundamental part of decision-making processes. As such, our results challenge explanations of these effects exclusively in terms that are unique to high-level decision making and thus call for a common theoretical explanation that applies across paradigms." (p. 907). According to Trueblood et al. (2013), context effects are not idiosyncratic to high-level choices but are a fundamental feature of choice. Trueblood et al. (2013)

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

also used these perceptual results to argue against the context-dependent advantage (CDA) model developed by Tversky and Simonson (1993) as well as the Leaky Competing Accumulators model of Usher and 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 & Pettibone, 2017, see also). Trueblood (2012) demonstrated context effects in an inference task and argued similarly against loss aversion as a mechanism for context effects.

Frederick et al. (2014) failed to replicate Trueblood et al. (2013)'s finding of the attractione 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 study, comparing the ability of numerous mechanisms assumed by decision models 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 rectangle choice experiment. In the repulsion effect, the competitor's choice share is higher than the target's choice share (Banerjee et al., 2024; Bhui & Xiang, 2021; Evans et al., 2021; Frederick et al., 2014; Liao et al., 2021; Simonson, 2014a; Spektor et al., 2022). In Spektor et al. (2018)'s experiments, the target and competitor options varied in area, such that one option was always larger, but on average they were the same size. The researchers also varied the *target-decoy attribute*

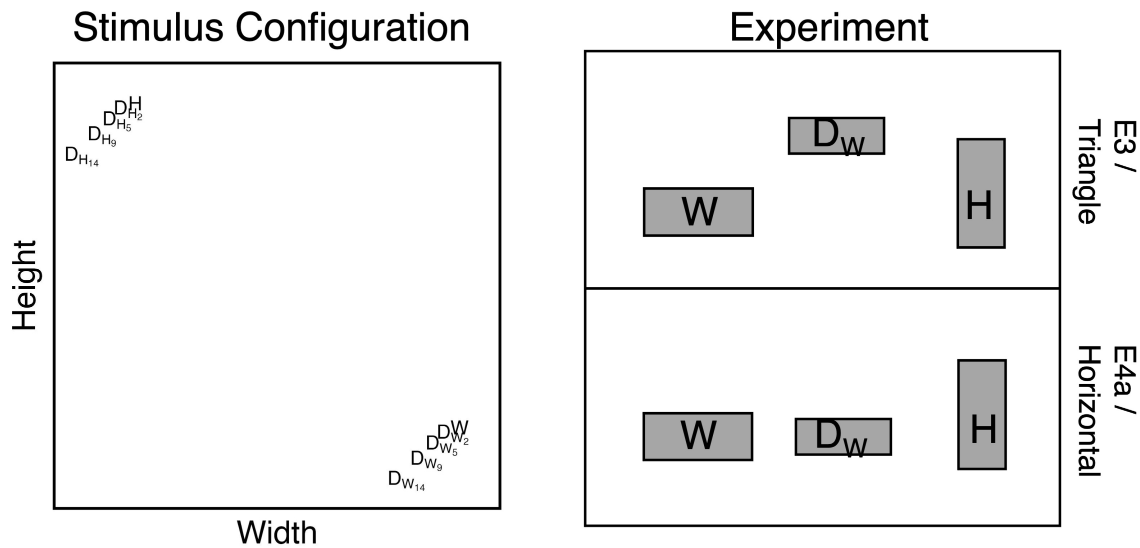

Figure 2.1. Stimulus configuration and example trials from Spektor et al. (2018), Experiments 3 and 4a.

distance (TDD), the percentage difference between the target and decoy areas. For example, if TDD is 2%, the decoy is 2% smaller than the target.

Spektor et al. (2018) ran a total of five experiments. All experiments showed similar results, so I focus on their experiments 3 and 4a, which are the most representative of the article's conclusions. In Experiment 3, the authors varied TDD at four levels: 2%, 5%, 9%, and 14%. The rectangles were arranged in a trianglular display on the screen (see Figure 2.1, Experiment 3), in contrast to Trueblood et al. (2013)'s horizontal display. Spektor et al. (2018) found an empirical repulsion effect such that the competitor was selected more than the target at all levels of TDD (see Figure 2.1).

Spektor et al. (2018) also ran a follow-up experiment using the horizontal diplay of Trueblood et al. (2013) (see Figure 2.1, 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.

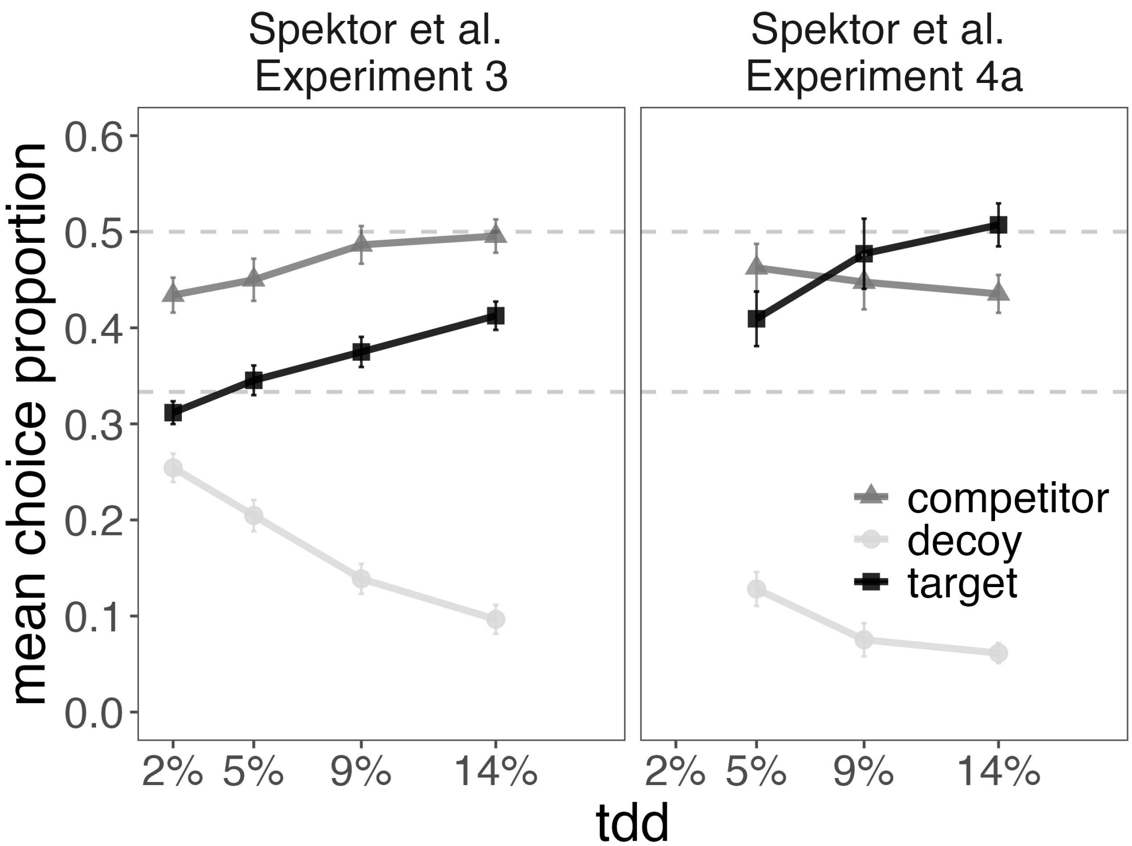

Figure 2.2. Data from Spektor et al. (2018), collapsed across choice set. Error bars are 95% CIs of the mean, computed using the within-subjects error correction from Morey et al. (2008). Dashed lines are drawn at .5 and .33.

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[2]. Relatively low and extremely 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 display configuration. In these experiments, the stimuli were various squares, each containing bars filled 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 target and competitor choices increased with TDD, with target and decoy showing a particularly strong trade-off.

Both Choplin and Hummel (2005) and Yearsley et al. (2022) demonstrated the attraction effects in similarity judgments. In both sets of experiments, participants saw various perceptual stimuli (i.e., ovals, swirled lines, vertical lines) and chose the option most similar to a reference option. Both sets of researchers showed that dissimilar decoy options impacted participants' choices as in the attraction effect.

Researchers are clearly using perceptual experiments to demonstrate context effects and test theory. 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] $RST = \frac{P(T|[T,C,D])}{P(T|[T,C,D)+P(C|[T,C,D])}$. $RST > .5$ indicates the attraction effect, while $RST < .5$ indicates the repulsion effec.t

2.1.1 Understanding Perceptual Choice Experiments

A crucial assumption made by researchers in the above experiments, is that participants are always (or almost always) to correctly perceive the target and competitor as larger than the decoy. This assumption is likely incorrect, as I will show empirically in Experimentn1. Furthermore, researchers 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, are more likely to choose the decoy over the target than 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 likely incorrect, but I believe it is a good place to start in understanding the existing data. I also demonstrate how and under what circumstances it is incorrect later in this dissertation. To begin, I return the results of Spektor et al. (2018).

As reported above, Spektor et al. (2018) demonstrate that a relatively small change in stimulus display (arranging stimuli in a triangle rather than a horizontal line) reverses the attraction effect. Why is this? To begin to answer this question, I highlight the differences between Spektor et al. (2018)'s data and previous context effect data. 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), and these selections are assumed to be the result of inattention or accidental responses. Researchers 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 selected less often in experiment 4a (triangle display) than in experiment 3 (horizontal display). Decoy selections also decrease as the difference between decoy area and target/competitor areas 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 that of competitor-decoy choices). That is, the mean *Relative 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.

There is a large body of psychological research, beginning with the work of Thurstone (1927), of treating the perception of a stimulus as a random variable. In his famous "Law of Comparative Judgment" paper, Thurstone (1927) first showed that researchers can use binary choice proportions to estimate the psychological distance between stimuli, by treating perceptual intensity as a Gaussian random variable. This work led to similar research using Signal Detection Theory (SDT) (Hautus et al., 2021), which also treats psychological quantities (e.g., memory, perception), as random variables. Similarly, Ashby and colleagues' General Recognition Theory (GRT) models the perception of a stimulus as a multivariate normal random variable, where each dimension of the model is the perceived dimension of a stimulus (Ashby & Perrin, 1988; Ashby & Gott, 1988; Ashby & Townsend, 1986). 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) (J. A. Hausman & Wise, 1978; McFadden, 2001; Train, 2009).Often, though not necessarily, these models share the common property that value (whether it is the utility of a consumer product, the perception of magnitude, or the memory signal in a recognition task) is stochastic while choice is deterministic (Benjamin et al., 2009, c.f.)

2.1.2 A Model of Context-Dependent Perceptual Choice

I now introduce the 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, rather than decision tasks. This also 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. In the current modeling framework, I do not treat height and width as independent attributes but rather consider perceived area to be unidimensional. The model is set up to make predictions for a perceptual choice experiment, where participants are presented with 3 perceptual stimuli on each trial. I assume that on each trial i with choice set K, The perception $\mathbf{X_i}$ of all 3 stimuli is sampled from a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$:

$$\mathbf{X}_i \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \tag{2.1}$$

where $\boldsymbol{\mu}$ is a column vector consisting of:

$$\begin{pmatrix} \mu_T \\ \mu_C \\ \mu_D \end{pmatrix} \tag{2.2}$$

where the subscripts T, C, and D indicate target, decoy, and competitor, respectively, and $\boldsymbol{\Sigma}$ is a positive semi-definite 3 x 3 covariance matrix computed as:

$$\boldsymbol{\Sigma} = S\boldsymbol{\Omega}S \tag{2.3}$$

where S is a diagonal matrix consisting of:

$$\begin{pmatrix} \sigma_T & 0 & 0 \\ 0 & \sigma_C & 0 \\ 0 & 0 & \sigma_D \end{pmatrix} \tag{2.4}$$

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

$$\begin{pmatrix} 1 & \rho_{TC} & \rho_{TD} \\ \rho_{TC} & 1 & \rho_{CD} \\ \rho_{TD} & \rho_{CD} & 1 \end{pmatrix} \tag{2.5}$$

with ρ_{TD}, for example, indicating the population-level correlation between target and decoy stimuli.

As mentioned above, the model assumes that value is stochastic while choice is deterministic[3]. 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 is:

$$P(j|i,K) = P(\mathbf{X}_{ij} > \mathbf{X}_{ik}), \forall k \in K, j \neq k \tag{2.6}$$

If all off-diagonal elements of $\mathbf{\Omega}$ are 0, 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 generate model predictions.

This model is 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 inherently in their perceived areas. This, however, is an ad hoc assumption that may describe the data well but will generate limited theoretical insight. Moreover, I wil later present empirical data in this dissertation that, generally speaking, $\mu_T = \mu_C$.

I now consider the role of perceptual correlations between all pairs of stimuli, i.e., ρ_{TC}, ρ_{TD}, and ρ_{CD}. I vary both ρ_{TD} and ρ_{TC} from -1 to 1; in other words, all

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

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 2.3. Here, I assume that $\mu_T = \mu_C > \mu_D$ and that $\sigma_T = \sigma_C = \sigma_D$[4].

Figure 2.3 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 $\rho_{TD} = \rho_{TC} = \rho_{CD} = 0$ model. This model collapses to an Independent Normal Model.

2.1.3 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

[4] In Experiment 2 I present evidence supporting these assumptions

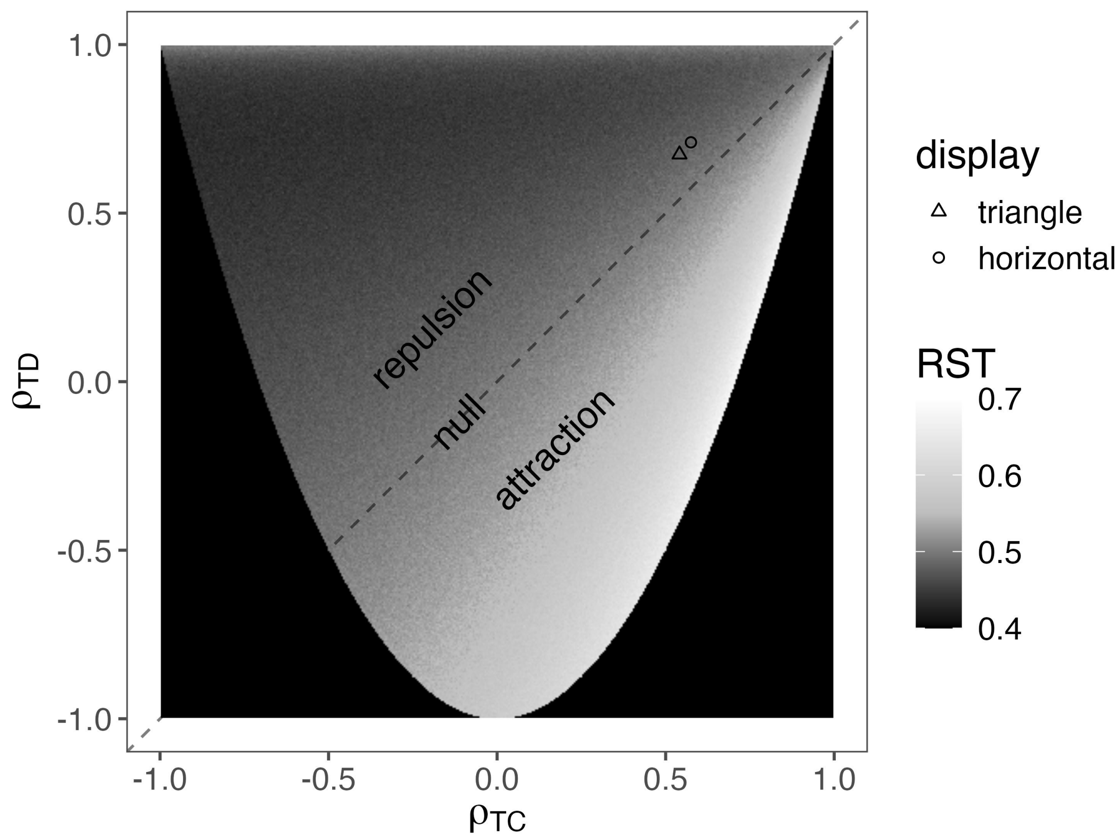

Figure 2.3. Model simulations for the attraction and repulsion effects based on the variation of ρ_{TD} and ρ_{TC}. "Regions" of the plot are labeled based on their qualitative predictions for attraction, null, and repulsion effects. The black region is the area where, due to extreme correlations, a 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.

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 of the model. According to this account, if $\rho_{TD} > \rho_{CD}$, the perceived areas of target and decoy "move" together and the decoy is more likely to exceed the target than the competitor in ternary choice, particularly if perceptual discriminability is low. The repulsion effect may be driven by perception 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 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.

In Experiment 2, I combined a psychophysics task with a choice task to estimate the parameters of the perceptual model. In the first phase of the experiment, participants estimate 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 use the data from the first phase of Experiment 2 to obtain stable estimates of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ in the perceptual model. Finally, I show that the model, conditioned on the observed parameter estimates, naturally predicts a repulsion effect but not an attraction effect.

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-subjects 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[5]. Otherwise, with a few exceptions discussed below, I follow the stimulus construction and experimental design of Spektor et al. (2018), Experiment 3.

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[6] 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 pro-

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

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

portionally 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 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[7].

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 target-competitor comparison. Trial order and rectangle order within each trial were randomized.

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 2.1). 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).

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

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

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 triangle 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 2.4. Participants' performance indeed improves with TDD. Furthermore, their performance is better when stimuli are displayed in the horizontal configuration than in the triangle configuration, and it is also better in target-decoy trials compared to competitor-decoy trials. Finally, there is an interaction, such that as TDD increases, the target-decoy performance is even better than the competitor-decoy performance. See the Appendix for inferential statistics which support these conclusions.

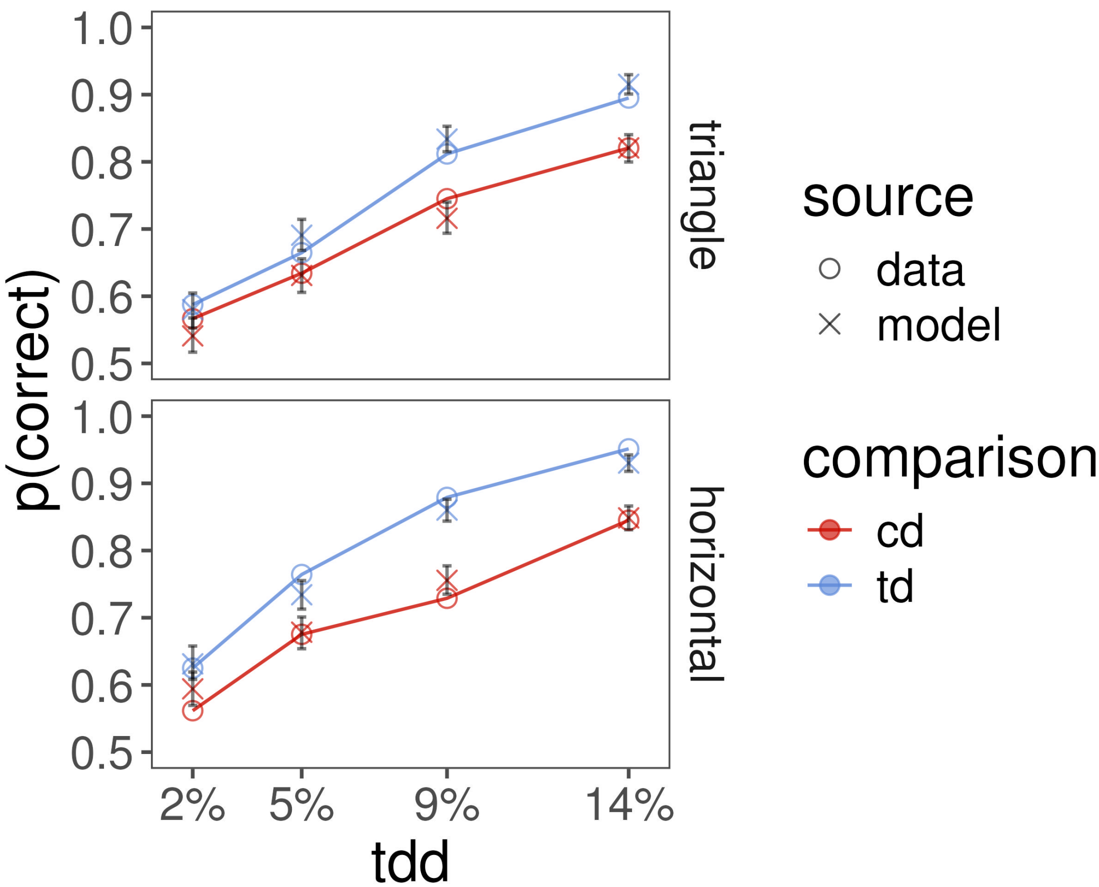

Figure 2.4. Experiment 1, mean choice proportions by stimulus display, TDD, and comparison. td=target-decoy trials, dc=competitor-decoy trials. Model predictions come from the Bayesian hierarchical logistic regression presented in the Appendix. Error bars are 95% HDIs on the mean.

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

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

2.3 Experiment 2

I continue this line of research in Experiment 2, where I used a psychophysics task to estimate the mean perceived area and correlations between perceived area to the target, competitor, and decoy rectangles. The goal of this experiment is to estimate the parameters of the model presented above and to understand the role of perception and decision in producing the repulsion and attraction effects. Experiment 2 used the *method of cross-modal matching* (Stevens & Marks, 1965), where 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 replicate Spektor et al. (2018)'s choice data in a second phase of the experiment. Finally, I used a between-subjects 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 (see procedure below).

On filler trials, I randomly sampled three rectangles by sampling three heights and widths from the distribution $U(56, 195)$px, encompassing 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 inattentive participants.

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 between-subjects and TDD, diagonal, target-decoy orientation within-subjects. After removing participants who did not complete the experiment (see above), there were 223 participants in the horizontal display condition and 230 participants in the triangle display condition.

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 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 2.5). A small amount of jitter ($U(-15, 15)$px) was added to the 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 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[8]. 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.

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 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 here. Participants were told to select the rectangle with the largest area by clicking on it.

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.

The experiment was presented on computer monitors with a resolution of 1920 x 1080 pixels and programmed with GNU Octave (Team, 2019) and PsychoPhysics Toolbox (Brainard, 1997).

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[8]I arrive at this number 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.

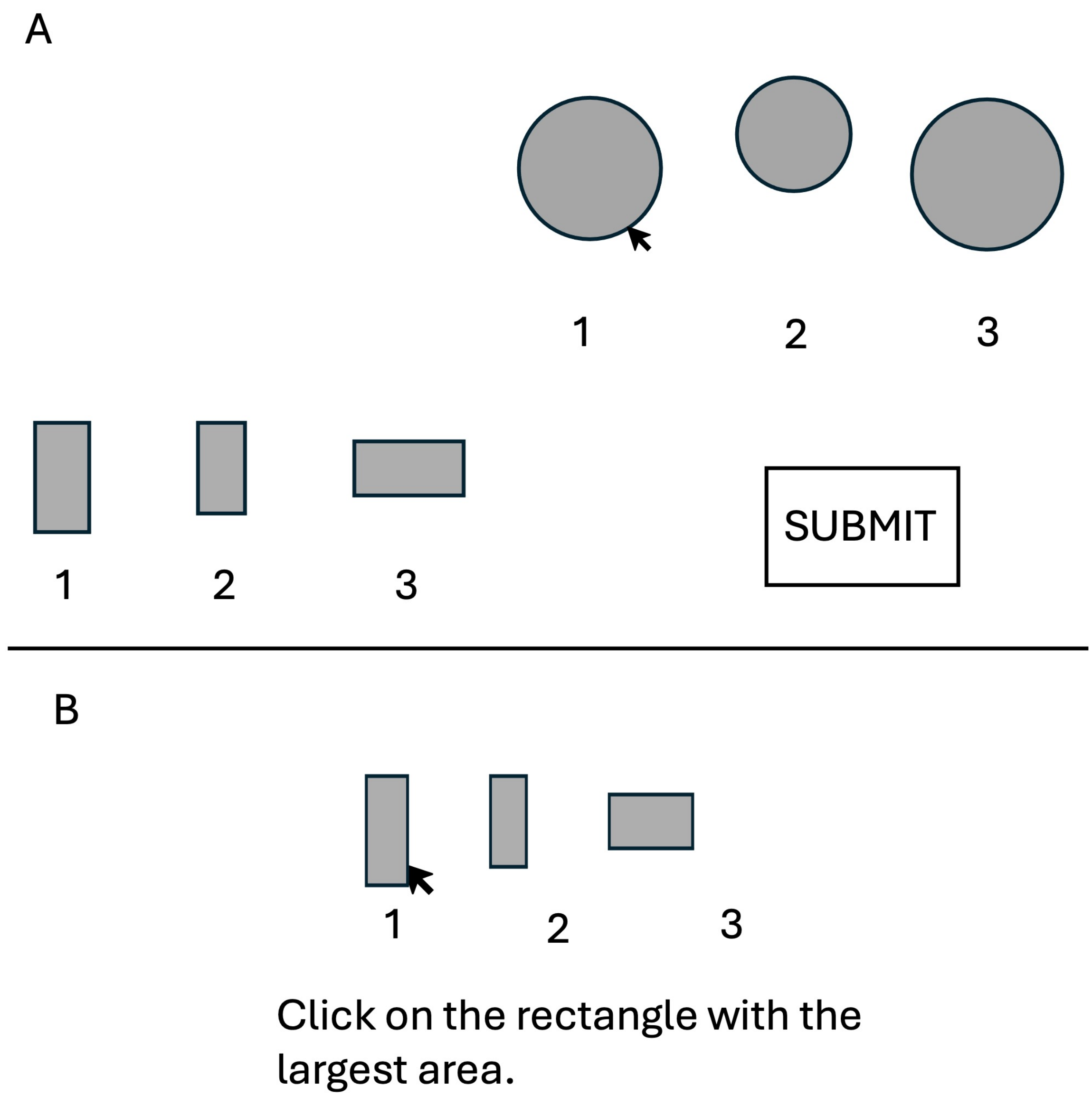


Figure 2.5. Example trials from Experiment 2. A: Circle adjustment phase. B: Choice phase. This an example from the horizontal display condition.

2.3.2 Results

2.3.2.1 Data Processing

Given the difficulty of the circle adjustment task, the data required processing to ensure that outlier trials and participants did not influence our estimates of **Omega**.

First, I removed all participants who did not give correct responses on 75% (6/8) of the catch trials. To respond correctly, participants needed to estimate the largest rectangle to be the as larger than the other two rectangles in the trial. 10 participants were removed from all analyses after they failed to achieve at least 75% correct on catch trials (see below for details). This left a total of 443 participants.

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 subjects, leaving us with a total of $N = 420$ participants, 213in the triangle display condition and 207 in the horizontal display condition. Of the remaining participants, R^2 values were high ($M = .67, SD = .12$), indicating they 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 our 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 trial. I dropped 0, 1, 2, and 4 critical trials from 339, 62, 18, and 1 participants, respectively.

After all circle phase data processing, I were 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 participant's estimated target, competitor, and decoy areas. Note that it is crucial to collect a large amount of data here, as performing Bayesian inference on correlation matrices is not straightforward and is prone to underestimation if data is 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 RT < 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 any 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 2.6. Although participants vary considerably in their judgments, I find that on average, participants' adjusted circle areas increase with the absolute size of rectangles.

I next present scatterplots of all pairwise circle areas from each trial, see Figure 2.7. 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 and trial-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.

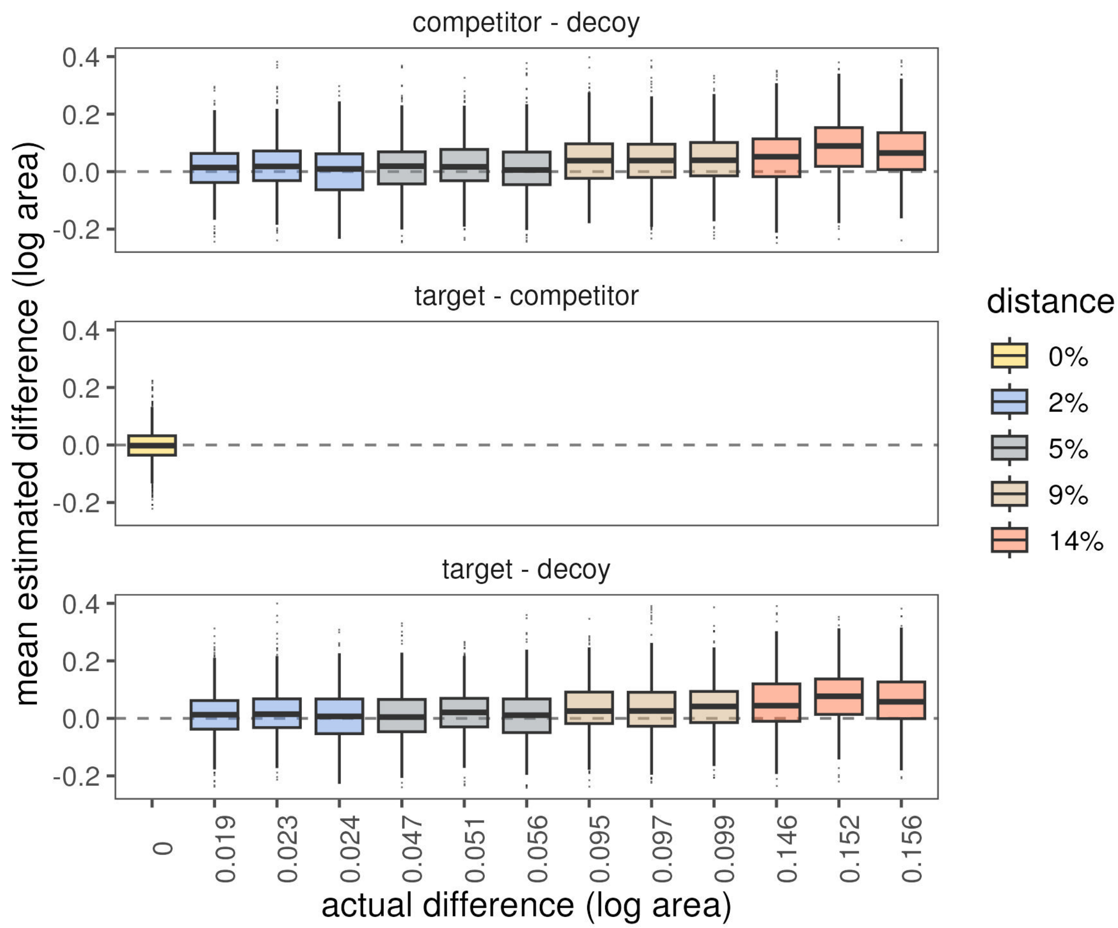


Figure 2.6. Boxplot of subject-level mean error in log-transformed area estimations, split by stimulus pair, TDD, and absolute discrepancy in rectangle area. Note that because the target and competitor rectangles always had equal areas, the true difference is always 0.

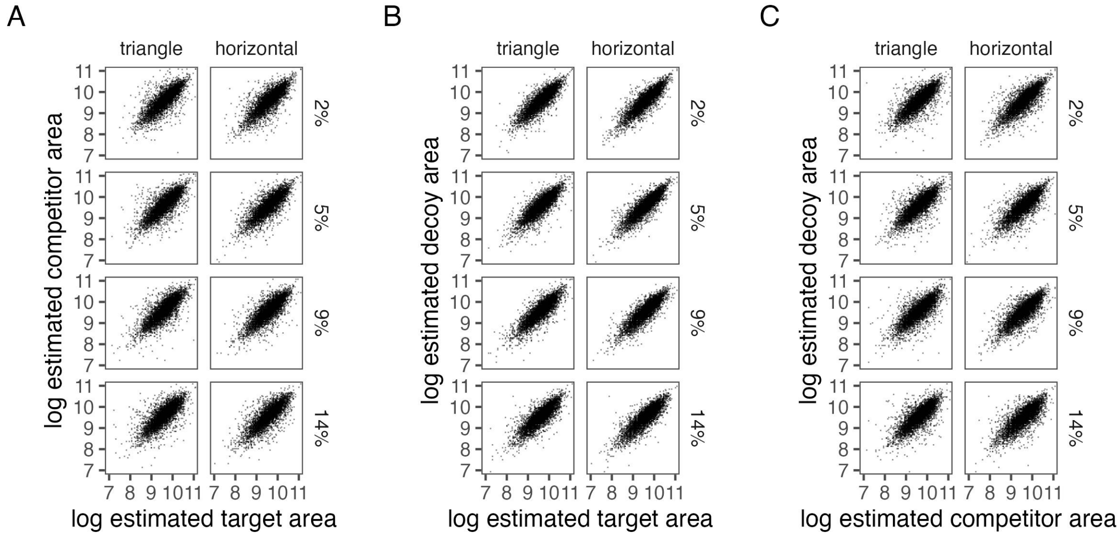


Figure 2.7. Scatterplots of target-competitor (A), target-decoy (B), and competitor-decoy (C) correlations, split by display condition and TDD.

I used Bayesian hierarchical modeling to estimate the parameters of a multivariate normal distribution (as outlined earlier in this chapter). Parameters $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ representing 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 $\boldsymbol{\Sigma}$.

As discussed in the Introduction, I decompose $\boldsymbol{\Sigma}$ into the $S\boldsymbol{\Omega}S$, where the diagonal elements of S are population standard deviations and the off diagonal elements are 0. $\boldsymbol{\Omega}$ is 3 x 3 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 2.8 and show estimates of $\boldsymbol{\Omega}$ in Figure 2.9. As predictd, in both conditions, ρ_{TD} is larger than

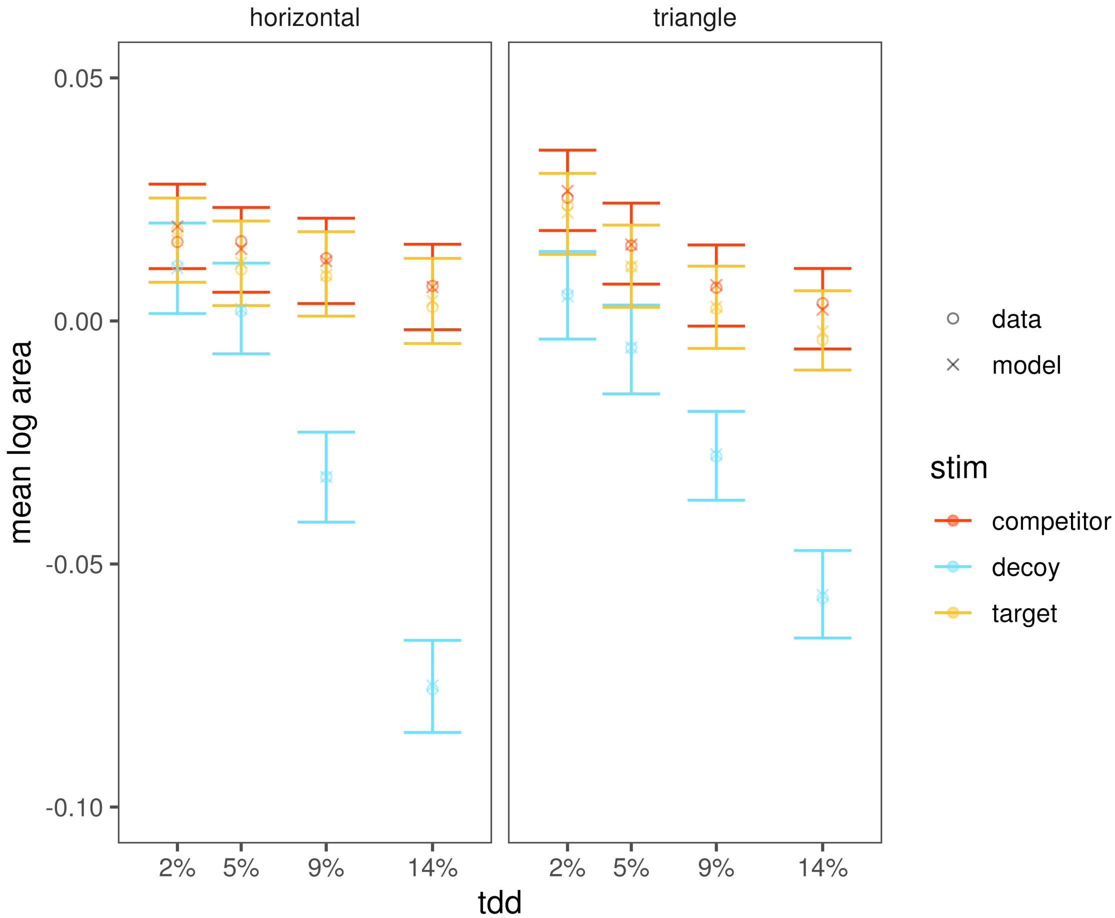


Figure 2.8. $\boldsymbol{\mu}$ estimates from Experiment 2.

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.

2.3.2.3 Choice Results

I present mean choice proportions across display conditions and TDD in Figure 2.10. I replicate 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

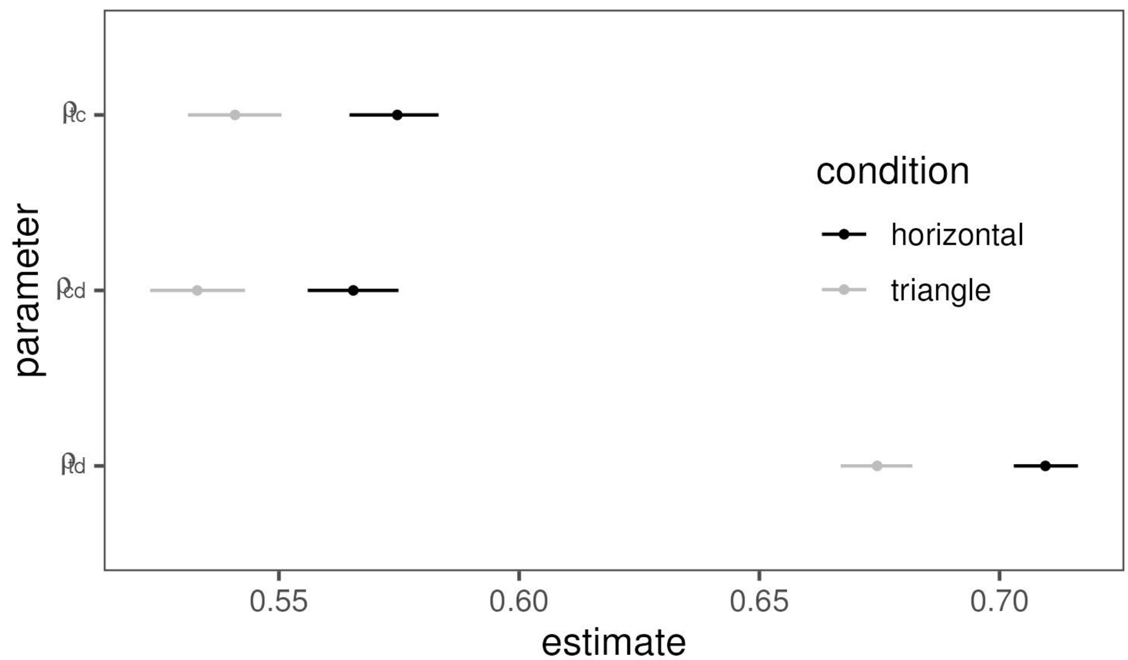


Figure 2.9. Posterior estimates of $\mathbf{\Omega}$ off-diagonal parameters across display conditions. Lines show 95% HDIs. Dots indicate means.

a null effect, where $P(C) \approx P(T)$ (triangle condition) or an attraction effect, where $P(T) > P(C)$ (horizontal condition).

To ensure that this result is not an artifact of averaging across choice sets, I present mean changes in choice proportion for the options w and h across the two choice sets $[w, h, d_w]$ and $[w, h, d_h]$ (see Figure 2.11). These results also show that low levels of TDD create a repulsion effect, while higher levels create a null or attraction effect. See the Appendix for inferential statistics that support these conclusions.

Additionally, I present the mean choice proportions for the current experiment plotted against mean target-decoy discriminability from Experiment 2 in Figure 2.12. These results strongly indicate that the attraction and repulsion effects are related to perceptual discriminability. 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

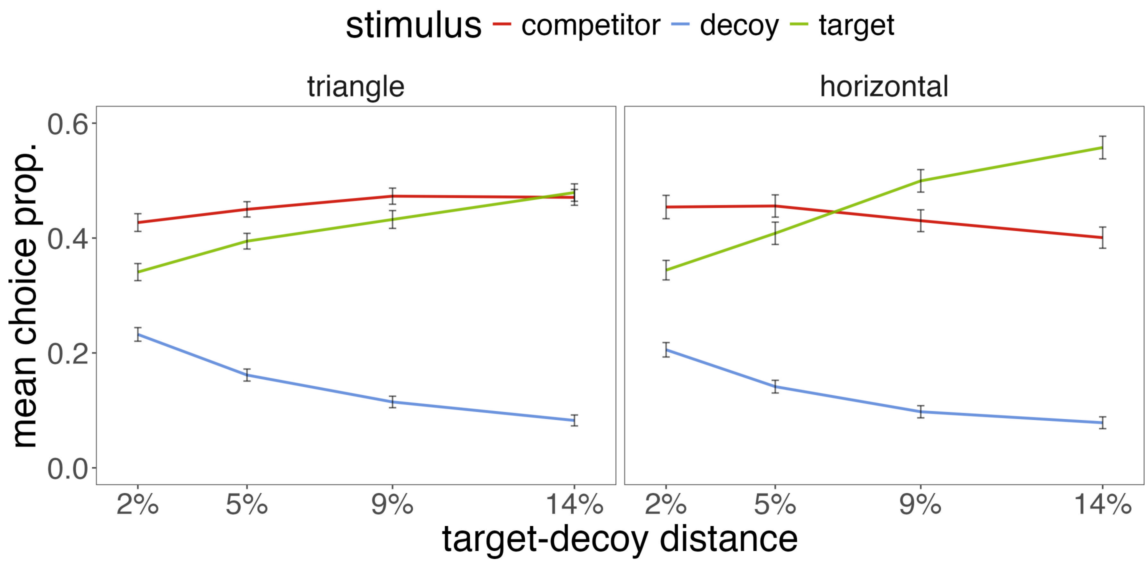


Figure 2.10. Mean choice proportions for target, competitor, and decoy options, by TDD and display condition. Error bars are 95% CIs on the means.

TDD levels for the horizontal condition. In other words, the ease of inter-stimulus comparability in the horizontal condition, which facilitates better discriminability in a 2afc task, also requires less discrepancy between target and decoy size in order for the attraction effect to emerge in a ternary choice task.

2.3.3 Model Simulations

After estimating the parameters of the perceptual model and analyzing the choice data, I sought to test whether the model can predict the choice data. Though I showed in the introduction that this is possible, it was an open question whether the parameters estimated from actual data would produce qualitatively interesting 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 2.13.

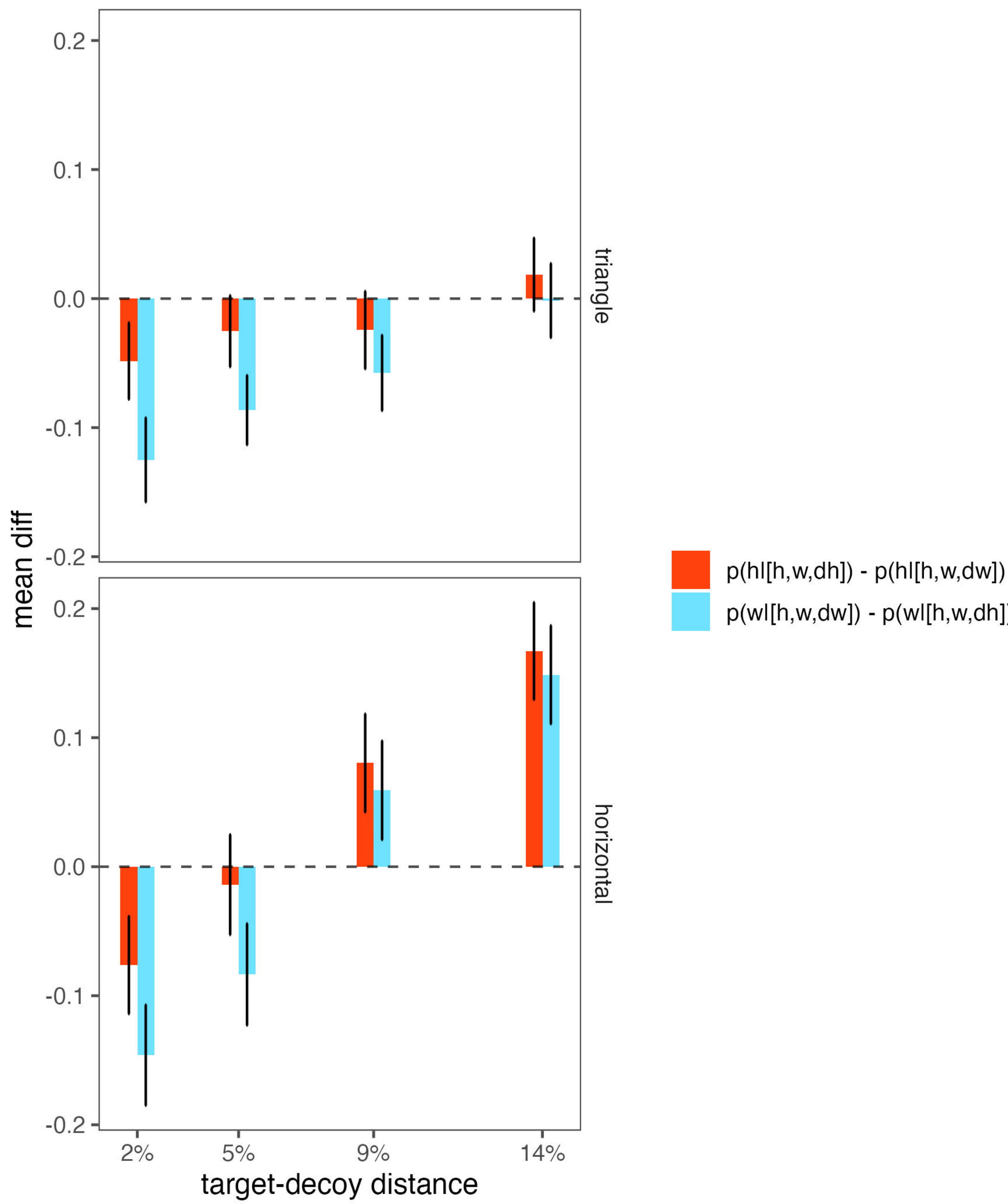


Figure 2.11. Mean changes in choice proportions across choice sets.

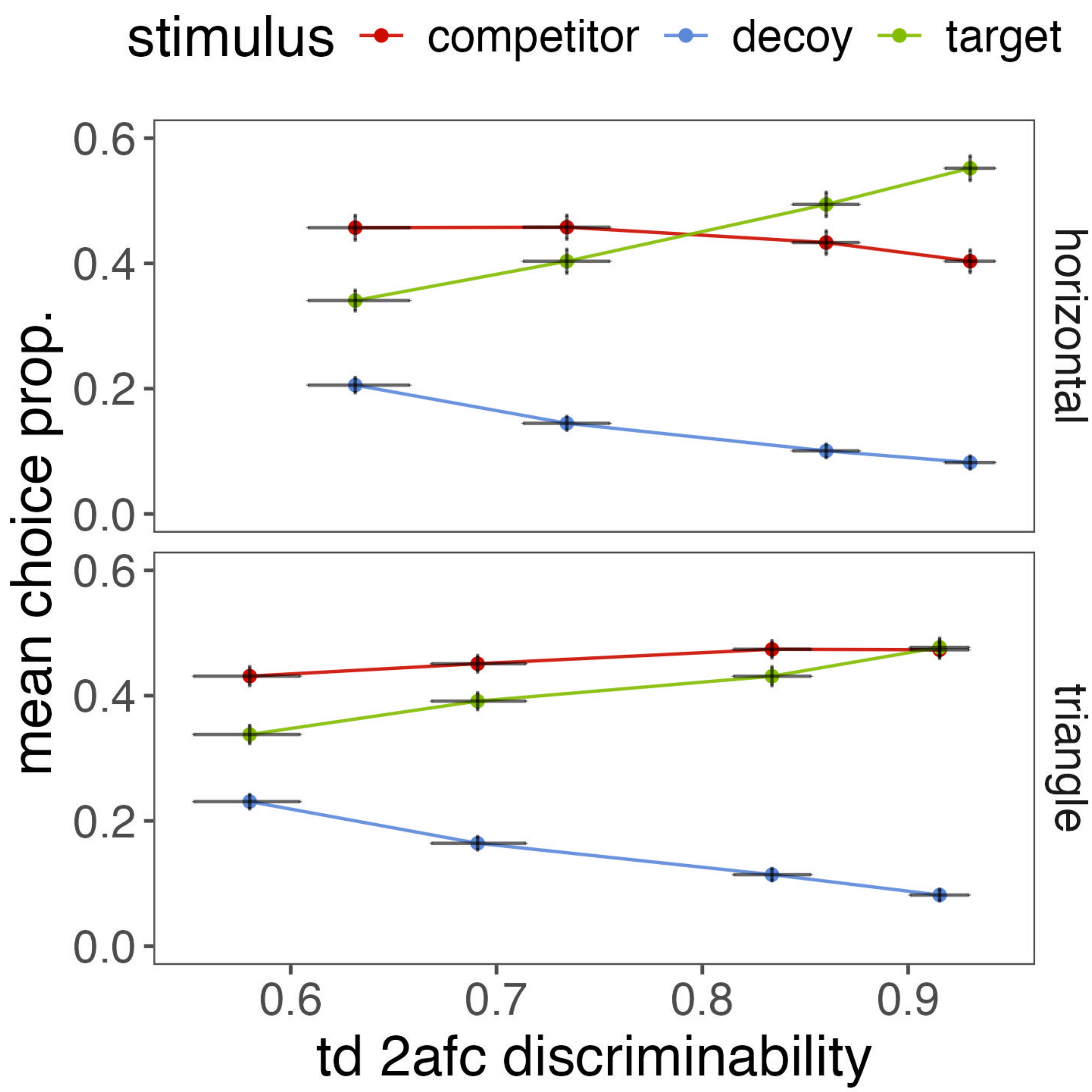


Figure 2.12. Mean target, competitor, and decoy choice proportions (y axis) for each TDD level, plotted against mean target-decoy discriminability for each TDD level from Experiment 1. The x axis error bars are 95% HDIs on the mean, computed via the Bayesian hierarchical logistic regression from Experiment 1 (see Appendix), and the y axis error bars are 95% CIs on the mean.

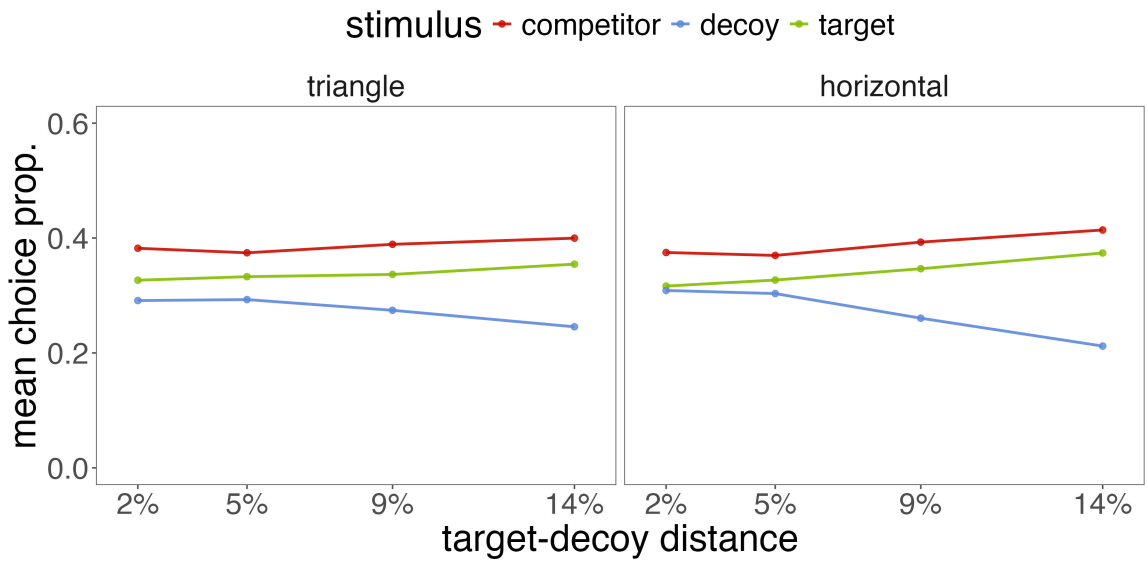


Figure 2.13. Model predictions for the choice data, conditioned on the mean estimated parameters from Experiment 2.

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

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 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, in turn, 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.

Researchers have argued in favor of the ”tainting hypothesis” (Simonson, 2014b; 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 significant. Moreover, the model does not require this tainting to produce the repulsion effect.

2.4.1 A Mechanism for Correlated Valuations

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.

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. 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. They found that listing options by-attribute increased the choice share of the compromise option, relative to a by-alternative display.. Noguchi and Stewart (2014) presented eye-tracking research suggesting that context effects are driven by transitions between pairs of options on a single attribute at a time.

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. The general framework, where inter-stimulus comparison leads to preference, which then leads to choice, is still plausible.

Other researchers have explored correlated valuations in decision-making. 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 are greater for options closer in multiattribute space.

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 here, 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, which may be quite difficult (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. This model proposes a single utility function that determines best and worst choices. Specifically, it proposes 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 (J. Hausman & McFadden, 1984). Furthermore, the maxdiff model predicts a monotonic relationship between best-choice probabilities and worst-choice probabilities (Hawkins, Marley, et al., 2014).

There are several variants of this model (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.

Researchers have explored whether this monotonicity holds empirically. Hawkins, Marley, et al. (2014) examined both preferential and perceptual best-worst choice data using response time modeling. They used the linear ballistic accumulator model (LBA) Brown and Heathcote (2008), which casts the decision process as a race between "accumulators" towards a threshold, where the average accumulation across trials is captured by the drift rate parameter. Modeling datasets containing both preferential and perceptual best-worst choice data, they were able to successfully account

[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 their choice model.

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 captures choices.

In a follow-up article, Hawkins, Marley, et al. (2014) found that, collapsing across choice sets, best-choice probabilities are (negatively) 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.

We can think of the parallel best-worst LBA as a process implementation of the maxdiff model (Hawkins, Marley, et al., 2014), which proposes set independence. While researchers have proposed models that allow set dependence (Marley et al., 2008), these models still predict a monotonic relationship between best and worst choices.

It is not always the case, however, that a single latent variable (i.e., utility) underlies choices. Indeed, as I show below, the model from Chapters 1 and 2 predicts, under certain conditions, a dissociation between best and worst choices.

3.1.2 Model-Based Dissociations in Best-Worst Choice

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 perception $\mathbf{X_i}$ of all 3 stimuli is sampled from a multivariate Gaussian distribution with a mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$ (see 2.1).

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

In this chapter, I apply the model to best worst choice. Following conventions in the literature, I use $B(j)$ to denote the probability of selecting option j as best and $W(j)$ to denote the probability of selecting option j 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 selected as best, while the option with the smallest perceived area is 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 demonstrate this using simulations.

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 ($N = 1000000$) number of trials. I collapse over choice set (i.e., whether the target is wide or tall, as in previous simulations) and focus on target, competitor, and decoy choice proportions at each level of TDD. I show these results in figure 3.1, in a state-trace plot (Newell & Dunn, 2008). In a state-trace plot, the analyst plots the values of two dependent variables against each other for a particular experimental condi-

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

tion. State-trace analysis can be controversial (Ashby, 2019; Ashby & Bamber, 2022; Stephens et al., 2020), and statistical inference on state-trace data is not straightforward (Davis-Stober et al., 2016; Sadil et al., 2018). In principle, however, if the analyst can reliably conclude that the data points do not fall on a single curve, they conclude that the data vary on at least 2 latent dimensions. Here, these dimensions are likely means and correlations.

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), it is not, however, least frequently chosen as worst. Specifically, $B(C) > B(T)$, while $W(T) < W(C)$, where $B(i)$ and $W(i)$ are the probabilities that option i is chosen as best and worst, respectively. 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 models predict this because $\rho_{TD} > \rho_{CD} \approx \rho_{TC}$. On the (relatively few) trials where X_D is largest, it is more likely that $X_D > X_T > X_C$ than $X_D > X_C > X_T$. 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.

This dissociation is subtle, and the predicted effect size is small. Indeed, all predicted $W(C) - W(T)$ probabilities 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

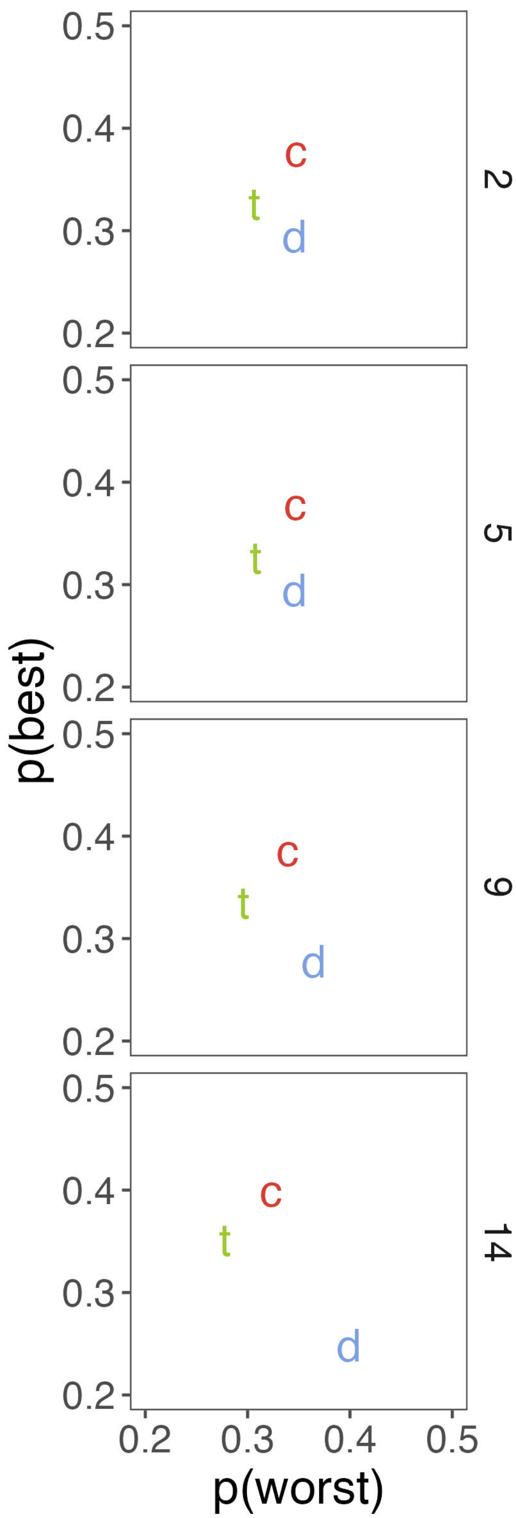


Figure 3.1. Best-worst choice simulations. Each row is a different TDD value from Experiment 2.

indeed occur. I also show that the assumption of monotonicity required by the maxdiff model of best-worst choice can fail empirically.

3.2 Experiment 3

The goal of Experiment 3 was to test the predictions of the 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 (generally) holds empirically and 2 the maxdiff model cannot account for these results, even when all its 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. 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.

After removing poor performing 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; Team, 2019).

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 the 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

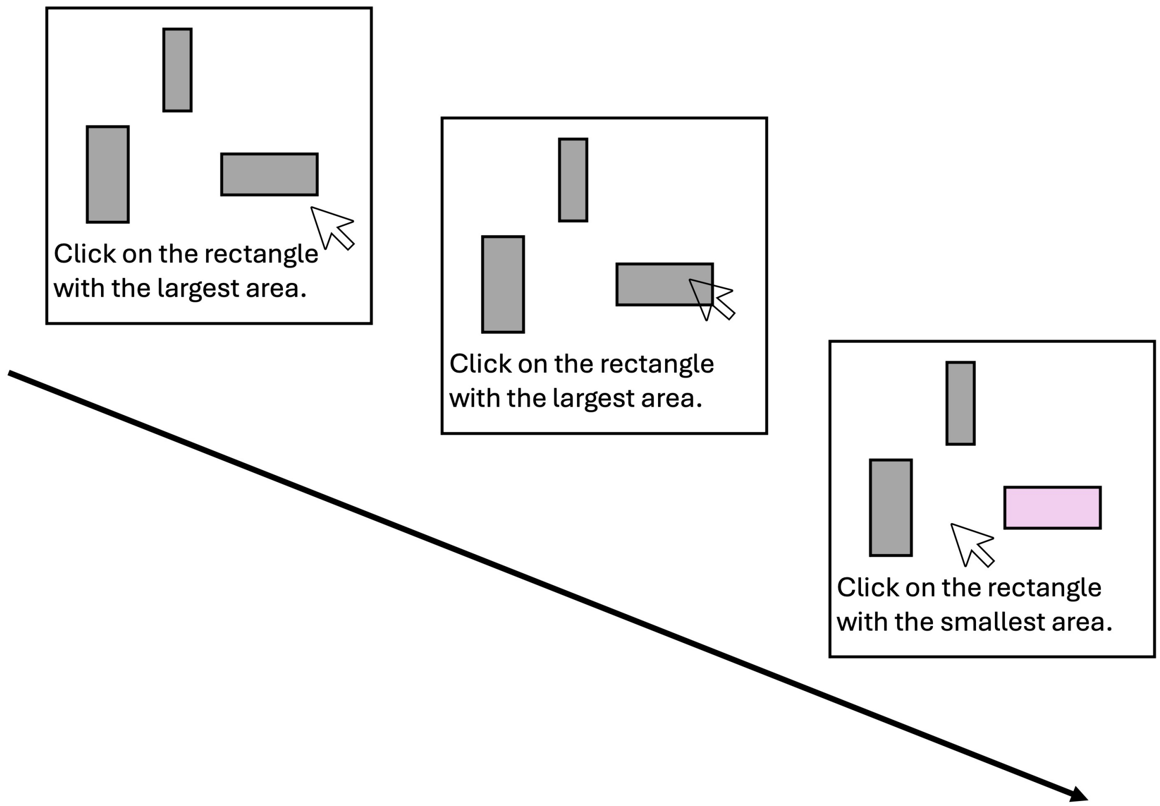


Figure 3.2. An example experimental trial for Experiment 3. Note that this is a trial in the best-worst condition.

an option. Next, participants in the best-worst/worst-best condition selected the smallest/largest rectangle, at which point the trial ended. See 3.2 for an example trial graphic.

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

Participants did not meaningfully differ in their choices by condition, so I collapse over condition for all reported analyses.

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 compute the mean choice proportions for each distinct rectangle, *collapsed across choice* set. Here, I replicate the findings of Hawkins, Marley, et al. (2014), that, when ignoring the effect of context, best choices and worst choices appear to be (negatively) monotonically related. These data are plotted in Figure 3.3.

I now consider choice proportions conditioned on TDD and choice set. Mean choice proportions for these data are plotted in Figure 3.4.

Participants show a consistent bias to choose the w (i.e. the wider rectangle) as largest, a finding also shown in Experiments 1 and 2. Participants also (on average) regularly choose the decoy rectangle as smallest, with the exception of the choice set h, w, d_w and $TDD = 2\%$, where they select 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 is still less likely to be chosen as worst than the competi-

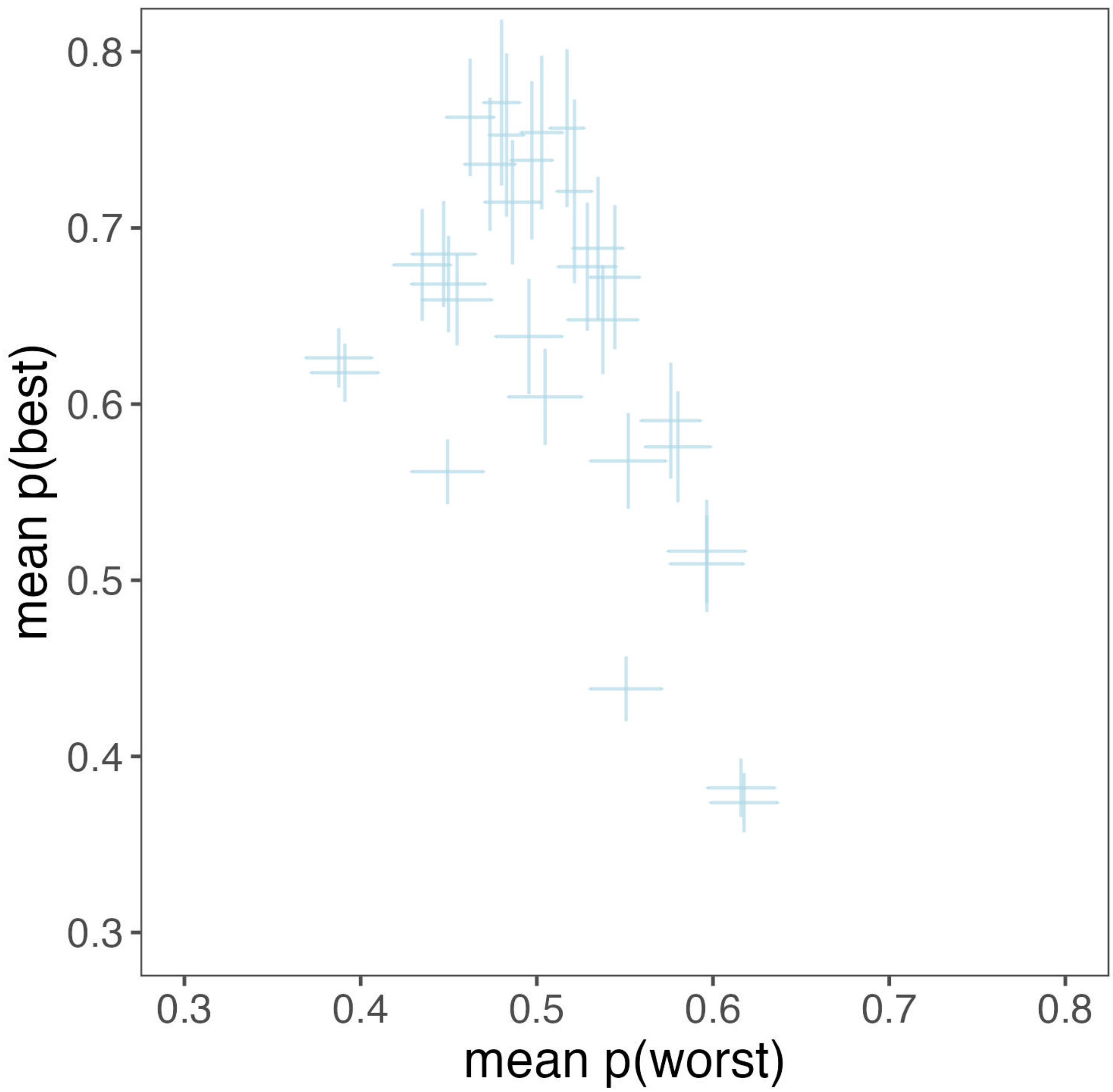


Figure 3.3. Marginal mean best and worst-choice proportions for all unique rectangles, collapsed across choice set. X and Y axis error bars are 95% CIs.

tor, $W(h|h,w,d_h) < W(h|h,w,d_w)$ and $W(w|h,w,d_w) < W(w|h,w,d_h)$, while the competitor option is more likely to be chosen as best, $B(h|h,w,d_w) > B(h|h,w,d_h)$ and $B(w|h,w,d_h) > B(w|h,w,d_w)$. See the Appendix for inferential statistics which support these conclusions.

These results are more easily understood by plotting mean target, competitor, and decoy choice proportions across TDD levels, collapsed over choice set. See Figure 3.5 for these data.

The best-choice proportions replicate the repulsion effect initially found by Spektor et al. (2018) and replicated in the current Experiment 2, where the competitor is more likely to be chosen as best at low TDD levels, while the target and competitor are 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 Modeling.

To analyze the data, I fitted both the maxdiff model and a hierarchical Dirichlet-multinomial model. The goal of the former modeling analysis is to test the ability of a standard best-worst choice model to account for the observed dissociations in the data. The goal of the latter modeling analysis is to provide a statistical account of the data and ensure the main conclusions (i.e., $B(C) > B(T)$ and $W(C) > W(T)$ are reliable. I show the substantive aspects of the maxdiff modeling here, but I present the hierarchical Dirichlet-multinomial model in the Appendix.

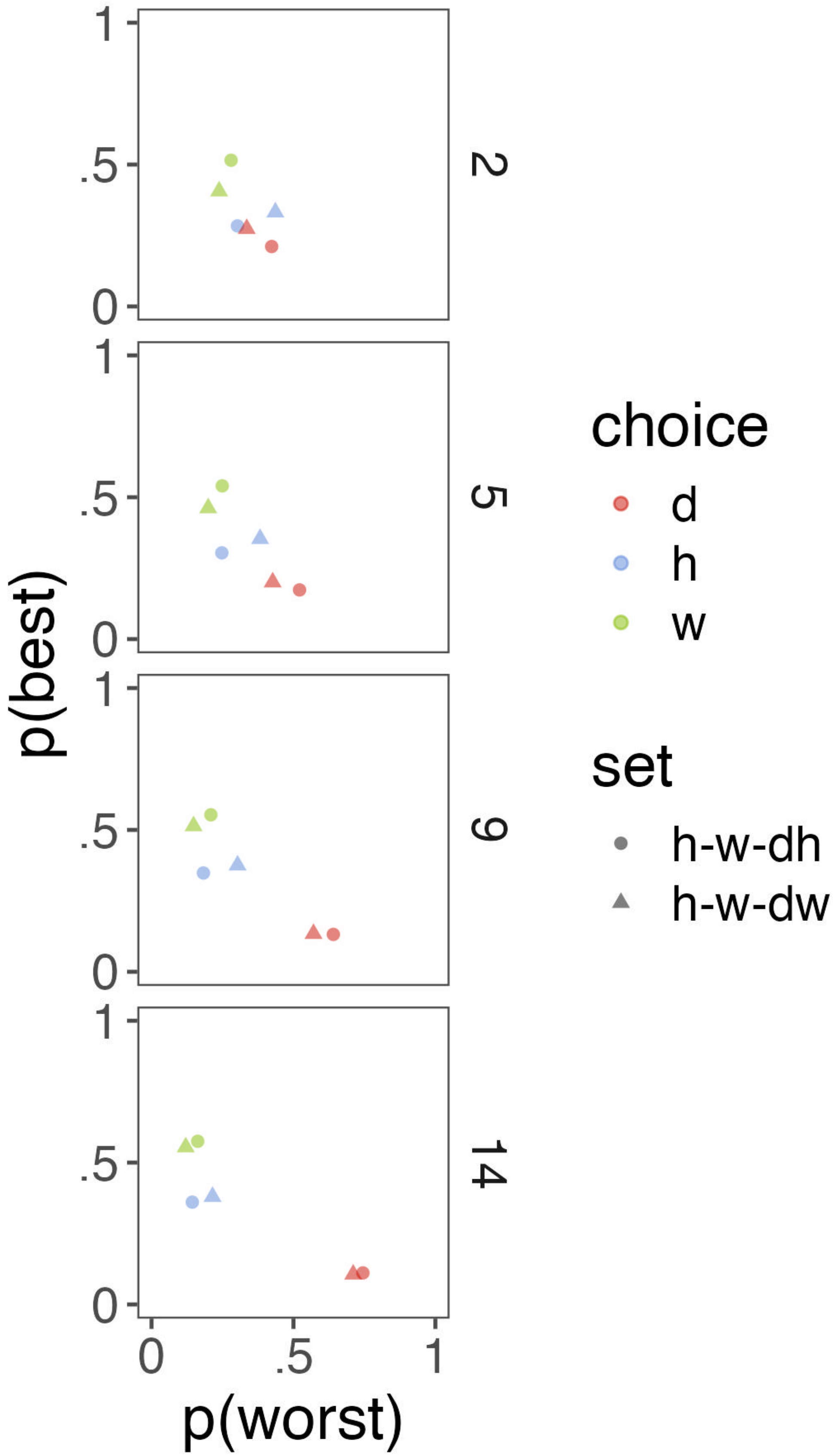


Figure 3.4. Mean best and worst-choice proportions for the h, w, and d rectangles, conditioned on TDD (rows) and choice set (shapes).

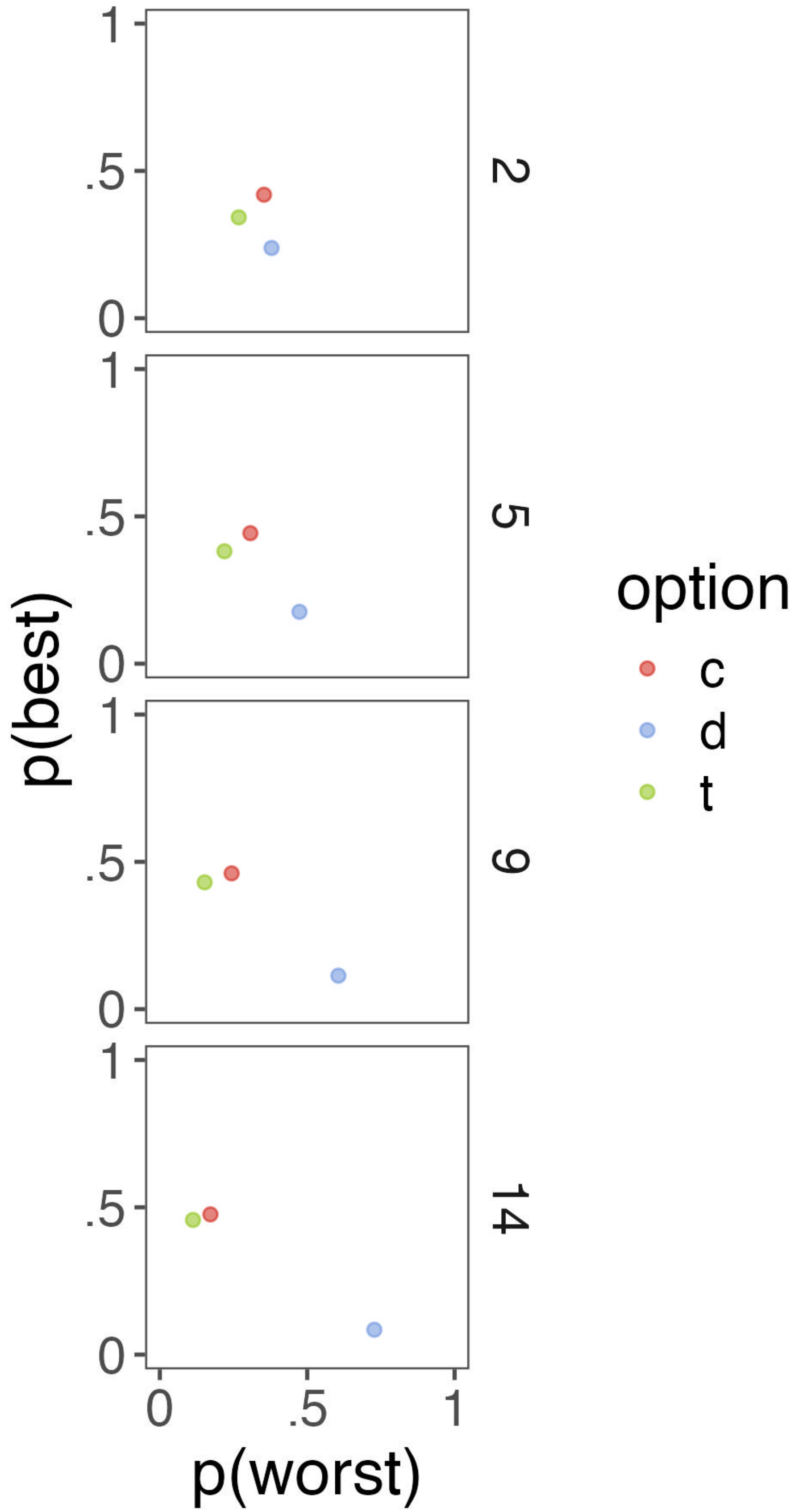


Figure 3.5. Mean best and worst-choice proportions for the target, competitor and decoy rectangles, conditioned on TDD (rows).

3.2.2.5 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 and y, $x \neq y$ increases monotonically with the difference in their estimated utilities (see 3.1). This model is the most commonly used (and arguably the simplest) analysis technique for best-worst choice data. I applied this model to 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 3.6.

The model clearly mispredicts the data. It predicts that target and competitor are chosen at the nearly the same rate for both best and worst choices. It fares better at predicting decoy choices but is still quantitatively off.

The target-competitor misprediction stems from the fact that the model choices ceom 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 predictions in 3.7. The generally does a poor job at accounting for participant worst-choice proportions, though it performs fair in the best choice condition.

The maxdiff model is an extension of the MNL model and thus relies on the assumption of Generalized Extreme Value distributed errors. This assumption may

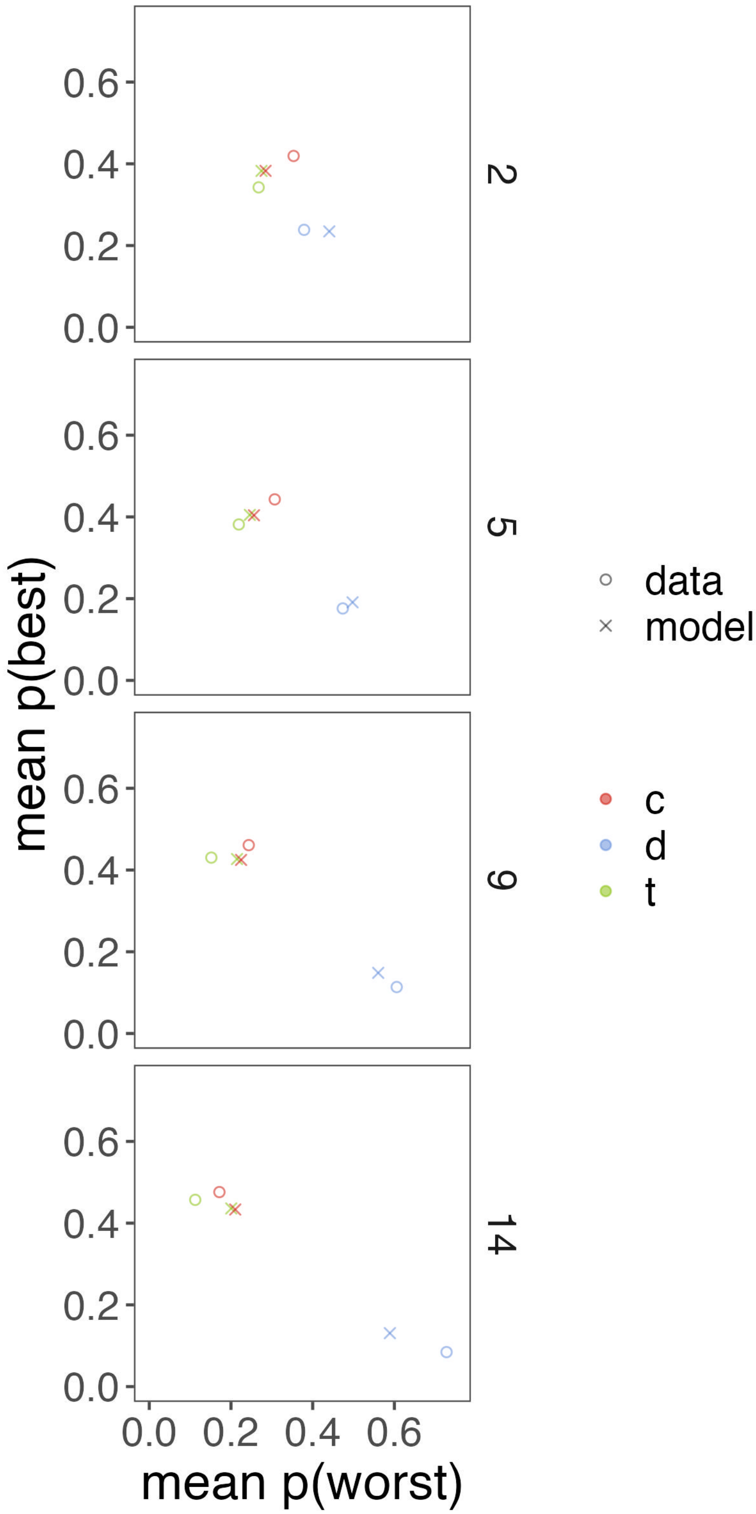


Figure 3.6. Maxdiff model predictions for the mean target, competitor, and decoy best-worst choice proportions.

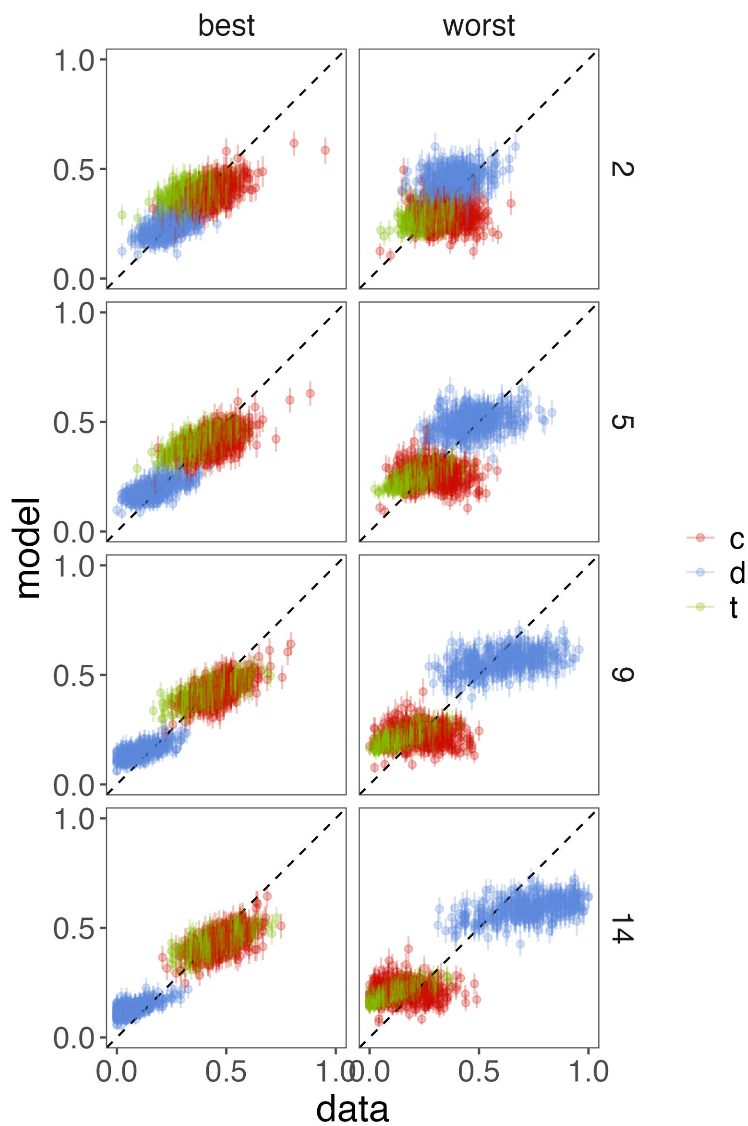


Figure 3.7. Maxdiff model predictions for the mean target, competitor, and decoy best-worst participant-level choice proportions, conditioned on TDD (rows) and choice type, i.e. best v. worst (columns). Vertical error bars are 95% HDIs.

be incorrect, but regardless of the parametric model chosen, any model relying on a single utility representation for best and worst choices will fail to predict this result.

3.3 Discussion

In Experiment 3, I showed that, in support of the perceptual choice model introduced in Chapter 2, correlated valuations can induce dissociations in best-worst choices. Spefically, given a target, competitor, and decoy option (using the terminology from the attraction effect), the competitor is more likely than the target to be selected as best ($B(C) > B(T)$), but the competitor is also more likely than the target to be selected as worst ($W(C) > W(T)$). This prediction was made using the 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 quite atypical in psychology and even relatively uncommon in the cognitive modeling literature.

The maxdiff model, the most common analysis technique for best-worst choice (Hawkins, Marley, et al., 2014; Marley & Louviere, 2005; Mühlbacher et al., 2016), cannot accomodate this effect.

The maxdiff model assumes that, when selecting the best and worst option, the decision-maker picks the option with the highest and lowest utilities, respectively. This is not the only model considered by researchers, however. 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) 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. Their results, while sophisticated and convincing, is limited by relying on statisical evidence; the current experiment demonstrates a qualitative effect that the maxdiff model cannot accomodate.

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).

Note that the perceptual model, used for the current predictions, does use a common utility scale for both best and worst choices. However, these utilities are not independent, as assumed by the maxdiff model. Thus, the claims of Hawkins, Marley, et al. (2014) and Hawkins et al. (2019) are not necessarily falsified; rather, they are amended to account for correlations between option utilites.

Due to the small effect size, I required 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.

Though not an identical paradigm to best-worst choice, researchers have shown that allowing participants to reject all options from a set can affect choice. Tversky and Shafir (1992) showed that people are more likely to reject all options if the options trade off on attributes compared to if one dominates the other. Other researchers have demonstrated that forced choice and free choice (when rejection is possible) can create markedly different choice patterns (Brazell et al., 2006; Chernev et al., 2015; Dhar, 1997a, 1997b; Dhar & Sherman, 1996; Dhar & Simonson, 2003; Noguchi & Hills, 2016; Parker & Schrift, 2011).

I did not fit the perceptual model to Experiment 3. Such a task is not straightforward given estimation issues with the multinomial probit model (Train, 2009), and I already have estimated parameters from Experiment 2. It also seems unreasonable to expect researchers to fit a multivariate Thurstonian model to most best-worst choice studies, given limitations in data and (likely) issues with parameter identifiability.

The central purpose for conducting best-worst choice studies is to identify the preference distributions of participants 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 a series of all 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 consumer choice research can create 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 physician experience in a hospital 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 model of choice from the ground up in a simplified choice environment. T

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. I used stimuli created by previous researchers and below I demonstrate results similar to Chapter 2.

4.1.1 Expanding the Research to Consumer Choice

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

In most (but not all) 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 we are 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, we can obtain reliable estimates of the ρ parameters. As in Experiment 2, where we were concerned with whether participants' estimates of perceived size increased with absolute size (regardless of how it deviated from actual size), we are 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 (n.d.) 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) 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 seek to collecting continuous (pricing) ratings to estimate the multivariate normal parameters $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ for the choice model from Chapter 2 and use it 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-trinary form of the repulsion effect using the stimuli depicted in Figure 4.1. 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.

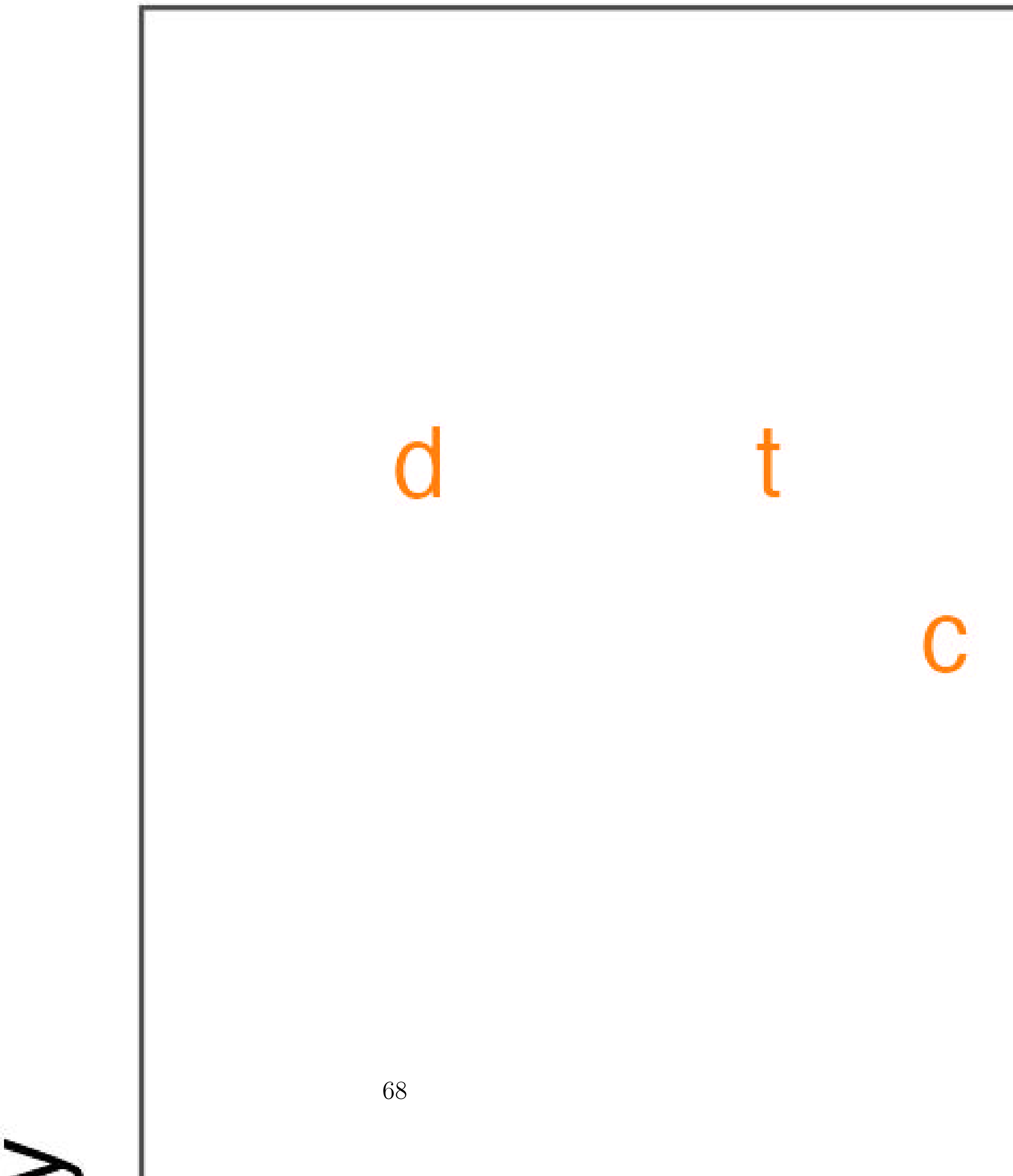
Using these stimuli, and across multiple experiments, Banerjee et al. (2024) showed that the competitor's choice share increased from binary to trinary choice sets, $P(C|[T, C, D]) > P(C|[T, C])$, in violation of the regularity principle (Marley, 1989). They also showed that the repulsion effect decreased with TDD[1].

This version of the repulsion effect is distinct from the repulsion effect found by Spektor et al. (2018) because the researchers compared binary to trinary choice rather than trinary to trinary choice. That is, one might "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 with the decoy. However, the fact that the target was always more extreme to the competitor is limiting.

Banerjee et al. (2024) argued that their results are consistent with the "tainting hypothesis" (Simonson, 2014b) 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 creation procedure, in addition to posting their data online, so their stimuli were a perfect candidate for the current Experiment 4.

[1] The stimuli varying in TDD are not depicted in Figure 4.1 and were not tested in the current Experiment 4


d
t
c

4.2 Experiment 4

With Experiment 4, I sought to collect ratings and choice data in a preferential choice experiment using (a subset of) Banerjee et al. (2024)'s stimuli. I used these data to estimate the parameters of the choice model from Chapter 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 $5 for their participation. 24 participants were removed from all analyses for failing catch trials (see below), leaving a final sample size of 113. The mean age was 38.89 ($SD = 11.48$). 61 participants identified as female, 50 identified as male, 1 participant identified as non-binary, and 1 participant preferred not to say.

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