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A Flexible Comparison Process as a Critical Mechanism for Context Effects

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A FLEXIBLE COMPARISON PROCESS AS A CRITICAL MECHANISM FOR CONTEXT EFFECTS

A Dissertation Presented

by

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DEDICATION

To my husband and greatest friend, Zack.

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ABSTRACT

A FLEXIBLE COMPARISON PROCESS AS A CRITICAL MECHANISM FOR CONTEXT EFFECTS

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Context effects such as the attraction, compromise, and similarity effects demonstrate that a comparison process, i.e., a method of comparing dimension values, plays an important role in choice behavior. Recent research suggests that this same comparison process, made more flexible by allowing for a variety of comparisons, may provide an elegant account of observed correlations between context effects by differentially highlighting dimension-level and alternative-level stimulus characteristics. Thus, the present experiments test the comparison process as a critical mechanism underlying context-dependent choice behavior. Experiment 1 provides evidence that increasing a dimension-level property, spread, promotes the attraction and compromise effects and reduces the similarity effect, whereas increasing an alternative-level property, dispersion, introduces an alternative-level bias that influences choice in concert with the decoy. Experiment 2 utilizes eyetracking to test the influence of stimulus presentation format on information acquisition patterns and context-dependent choice behavior. Contrary to predictions, a By-Alternative presentation format appears to increase within-dimension transitions in eye fixations relative to a By-Dimension presentation format.

Lastly, four computational models with theoretical accounts of the development of context effects over time were fit to joint choice and response time data. Though the MLBA provided the best fits to the subject-level mean choice proportions, it could not capture the crossover in preference between the target and competitor across RT quantiles; rather, MDFT and the AAM performed best in this regard. The present work therefore not only provides new insights into the relationship between choice and response times in preferential choice but sets important new constraints for theoretical models that seek to account for such behavior.

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CHAPTER 1

INTRODUCTION

1.1 Overview

Multi-alternative, multi-attribute choice involves selecting one of a set of alternatives, each of which varies on at least two dimensions, such as choosing an apartment, car, or laptop. An important collection of results demonstrates that adding an alternative to a choice set can change preferences among the original alternatives (Huber, Payne, & Puto, 1982; Simonson, 1989; Tversky, 1972). These results suggest that a comparison process, i.e., a method of comparing dimension values, plays an important role in choice behavior. Models of preferential choice tend to assume that comparisons are made strictly between alternatives within single dimensions (Bhatia, 2013; Noguchi & Stewart, 2018; Roe, Busemeyer, & Townsend, 2001; Trueblood, Brown, & Heathcote, 2014; Usher & McClelland, 2004), but offer differing theories of the psychological mechanisms driving observed variability in the strength and co-occurrence of context effects (Berkowitsch, Scheibehenne, & Rieskamp, 2014; Liew, Howe, & Little, 2016; Trueblood, Brown, & Heathcote, 2015).

Recent research suggests a simpler account in which the comparison process itself, made more flexible by allowing for comparisons between alternatives *or* between dimensions, may be a critical mechanism. Specifically, whereas the attraction and compromise effects are facilitated by a format encouraging within-dimension comparisons and impeded by a format encouraging within-alternative comparisons (Cataldo & Cohen, 2018b; Chang & Liu, 2008), the opposite is found for the similarity effect (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b). Together, these studies suggest that a flexible comparison process may be a key mechanism underlying observed correlations between context effects (Berkowitsch et al., 2014; Trueblood et al., 2015) and individual differences (Liew et al., 2016) by differentially highlighting dimension-level (e.g., extremeness and dominance; Simonson, 1989) and alternative-level (e.g., dispersion of dimension values; Chernev, 2004, 2005) stimulus characteristics.

The present experiments test the comparison process as a critical mechanism underlying context-dependent choice behavior. The sections below proceed as follows. I first present three context effects, the attraction, compromise, and similarity effects, as significant behavioral phenomena that demonstrate the importance of the comparison process in preferential choice. I then review previous research demonstrating variability in the occurrence of these effects, namely, a distinction between the similarity effect and the attraction and compromise effects, and evidence that the comparison process may account for this variability. I then present three experiments designed to better characterize the relationship between information acquisition patterns and each of the three context effects. Experiment 1 aims to clarify the dimension- and alternative-level stimulus properties underlying each effect. Results from Experiment 1 provide evidence that increasing a dimension-level property, spread, promotes the attraction and compromise effects and reduces the similarity effect, whereas increasing an alternative-level property, dispersion, introduces an alternative-level bias that influences choice in concert with the decoy. Experiment 2 utilizes eyetracking to test the influence of stimulus presentation format on information acquisition patterns and context-dependent choice behavior. Though Experiment 2 generally replicates the choice and response time results from Experiment 1, the eyetracking data suggest that contrary to predictions, a By-Alternative presentation format increases within-dimension comparisons relative to a By-Dimension presentation format. Potential methodological concerns in interpreting the results of Experiment 2 are discussed.

The results of Experiments 1 and 2 as well as previous research (Cataldo & Cohen, 2018b) demonstrate an intriguing and robust relationship between choice and response time across the attraction, compromise, and similarity contexts that appears independent of presentation format, in which the probability of choosing the target alternative increases over time for the attraction and compromise effects but decreases over time for the similarity effect. Thus, I conclude by fitting the joint choice and response time data with MDFT (Roe et al., 2001), the MLCA (Usher & McClelland, 2004), the AAM (Bhatia, 2013), and the MLBA (Trueblood et al., 2014) to determine possible theoretical accounts for this pattern of results. Consistent with previous research (Evans, Holmes, & Trueblood, 2019), the MLBA provided the best fits to the subject-level mean choice proportions. Importantly, however, it could not capture the crossover in preference between the target and competitor across RT quantiles; rather, MDFT and the AAM performed best in this regard.

1.2 Context Effects

A decision-making context effect is classically defined as a change in preference that occurs when particular alternatives are added to a choice set. Such effects serve as central examples of how the decision process can deviate from the principles of rational choice, and, as a result, have often been used as benchmark behavioral effects for theories of choice. Because individual context effects are associated with specific qualitative and quantitative behavioral predictions, they also represent ideal tools for examining the component processes of decision making.

The three most commonly studied context effects are the similarity, attraction, and compromise effects. To demonstrate, consider the scenario of choosing between several apartments that vary in ratings of their size and location, as depicted in Figure 1. The axes depict the dimension values and each labeled point provides the dimension values of an alternative. First, consider a choice between apartments X and Y. Apartment X rates well on location but poorly on size, and apartment Y rates poorly on location but well on size. Because of the dimension trade-offs, assuming equal dimension weights, these two apartments would be valued equally. Indeed, all alternatives on the diagonal indifference line will have equal value. For the purposes of demonstration, however, assume uneven dimension weighting such that a particular individual values size slightly more than location. Under this assumption, the probability of choosing apartment Y will be slightly greater than the probability of choosing apartment X, i.e., $P(Y \mid X, Y) > P(X \mid X, Y)$.

Suppose that a third apartment becomes available and there is a choice between the three apartments. Continuing to reference the possible alternatives depicted in Figure 1, the attraction effect (Huber et al., 1982) is the finding that the addition of apartment A_X, which is similar to, but dominated by, apartment X, increases the preference for apartment X over apartment Y. The compromise effect (Simonson, 1989) is the finding that the addition of apartment C_X increases preference for apartment X, which now has intermediate values on both dimensions. The similarity effect (Tversky, 1972) is the finding that the addition of apartment S_X, which is similar to, but not dominated by, apartment Y, increases preference for apartment X over apartment Y.

Early research on the similarity, attraction, and compromise effects highlighted the observation that in each case, the introduction of a decoy apartment (A, C, or S; collectively referred to as D) may actually result in a reversal in the order of preference between the original two apartments, e.g., $P(Y \mid X, Y) > P(X \mid X, Y)$ but $P(Y \mid X, Y, D_X) < P(X \mid X, Y, D_X)$. These phenomena violate principles of rational choice known as independence from irrelevant alternatives (Tversky, 1972), which states that the order of preference between two alternatives should be constant regardless of the choice set, and regularity (Huber et al., 1982), which states that the probability of choosing a given alternative must be greater in a subset of choice alternatives than in a superordinate set, e.g., $P(X \mid X, Y) > P(X \mid X, Y, D_X)$. As a result, context effects have come to serve as core examples of how the human decision process deviates from rationality.

More recent work has measured the context effects as a comparison between two three-choice scenarios (Wedell, 1991), one including a decoy designed to increase preference for X (A_X, C_X, or S_X; depicted in black in Figure 1) and one including a decoy designed to increase preference for Y (A_Y, C_Y, or S_Y; depicted in grey in Figure 1). Under this framework, an effect is obtained if $P(Y \mid X, Y, D_X) < P(X \mid X, Y, D_X)$, but $P(Y \mid X, Y, D_Y) > P(X \mid X, Y, D_Y)$. The three-choice definition of a given context effect has two main advantages. First, because the choice probabilities for both X and Y are expected to shift, it allows for two measures of the effect. A shift of both X and Y in the right direction provides strong evidence for the effect. A shift in only one of X or Y, however, may be attributable to a dimension bias effect. For example, a bias for location could produce

$P(X \mid X, Y) > P(X \mid X, Y, S_Y)$ in isolation, i.e., without a parallel shift in Y, because preference only shifts between X and S_Y. Second, because $P(X \mid X, Y, D_X) > P(X \mid X, Y) > P(X \mid X, Y, D_Y)$ and $P(Y \mid X, Y, D_Y) > P(Y \mid X, Y) > P(Y \mid X, Y, D_X)$, the expected effect size should be larger when comparing two three-choice sets. Thus, the three-choice comparison constitutes a clear benefit to the literature by distinguishing context effects from dimensional bias and increasing task efficiency.

Note that a reversal in choice preference is a qualitative effect. In order to quantify a given context effect, previous research (e.g., Trueblood, Brown, & Heathcote, 2014) has measured the extent of the effect by $P(X \mid X, Y, D_X) - P(X \mid X, Y, D_Y)$ and $P(Y \mid X, Y, D_Y) - P(Y \mid X, Y, D_X)$. This formulation now compares choice proportions of the same alternative across choice sets, and therefore no longer requires the assumption that X and Y are associated with particular probabilities in a two-choice scenario, e.g., that Y is initially preferred, $P(Y \mid X, Y) > P(X \mid X, Y)$. The effect holds if these differences are positive. Thus, this reformulation further benefits the literature by allowing for more precise quantitative hypothesis testing. Given the benefits of studying a quantitative shift, I also adopt this approach.

1.3 The Comparison Process

Context effects serve as critical benchmarks for theories of preferential choice. Consequently, several models of preferential choice provide theoretical accounts of the attraction, compromise, and similarity effects, including Multialternative Decision Field Theory (MDFT; Roe et al., 2001), the Leaky Competing Accumulator (LCA; Usher & McClelland, 2004), the Associative Accumulation Model (AAM; Bhatia, 2013), the

Multiattribute Linear Ballistic Accumulator (MLBA; Trueblood et al., 2014), Multialternative Decision by Sampling (MDbS; Noguchi & Stewart, 2018), the Range-Normalization model (RN; Soltani, De Martino, & Camerer, 2012), the Pairwise Normalization model (PN; Landry & Webb, 2017), the Bayesian Model of Context Sensitive Value (BCV; Rigoli, Mathys, Friston, & Dolan, 2017), and the 2N-ary Choice Tree model (Wollschläger & Diederich, 2012). Although these models posit different psychological mechanisms to account for context effects, they all share several central assumptions regarding the decision process. Notably, the majority of the models assume that preference states evolve as a function of within-dimension comparisons. For example, given a choice between apartments X and Y in Figure 1, the choice process is driven by comparisons of the dimension values of X and Y on size and the dimension values of X and Y on location.

Noguchi & Stewart (2014) used an eye-tracking approach to directly test the extent to which within-dimension and within-alternative comparisons lead to context effects. Supporting the within-dimension comparison assumption of the models, they found an overall higher number of transitions in attention between alternatives within a single dimension than between dimensions within a single alternative. However, such attentional transitions appeared to differentially influence the three context effects. In a reanalysis conducted by Cataldo & Cohen (2018b), while the compromise effect increased with the number of within-dimension transitions, the similarity effect decreased, and there was no significant influence on the attraction effect. Thus, information acquisition patterns do not appear to facilitate context-dependent choice in a uniform fashion.

Previous research has shown that the format in which a choice set is presented can alter information acquisition patterns. Specifically, whereas a format that groups information by alternatives can increase within-alternative comparisons between dimensions, a format that groups information by dimensions can increase within-dimension comparisons between alternatives (Bettman & Kakkar, 1977; Biehal & Chakravarti, 1982). Differences in presentation format can, in turn, modulate the effect of context on choice.

Chang & Liu (2008), for example, looked at the effect of presentation format on the compromise effect. In one condition, values were grouped by dimension, i.e., displaying all values for the first dimension together and all values for the second dimension together. In a second condition, values were grouped by alternative, i.e., displaying both dimension values together for each alternative. The By-Dimension grouping produced a standard compromise effect. That is, when given a choice between X, Y, and C_X in Figure 1, alternatives with intermediate values, apartment X in this choice set, were preferred. When grouped by alternatives, however, preference was increased for alternatives in the choice set with low dispersion between dimension values, i.e., dimension values that are similar to each other, regardless of the relative standing of the values to other alternatives. If the competitor has the lowest dispersion in a choice set, as was the case in Chang & Liu (2008), this can reverse the standard compromise effect.

The authors proposed that presentation format influenced the compromise effect by differentially highlighting dimension- and alternative-level stimulus information. Specifically, grouping information by dimensions increases attention to dimension-level characteristics such as the relative values between alternatives within each dimension, thereby facilitating the within-dimension comparison process commonly thought to underlie context-dependent choice. Grouping information by alternatives, in contrast, decreases attention to relative values, and, instead, highlights alternative-level characteristics that may be theoretically counter to the development of classic forms of context-dependent choice, such as dispersion.

Cataldo & Cohen (2018a) extended the logic of Chang & Liu (2008) to predict the effect of presentation format on the similarity effect. Observe that the alternatives X and Y in Figure 1 have the same dispersion of dimension values and, given a choice between only these two alternatives, neither has intermediate values. Given a choice between X, Y, and S_X, however, although Y still has the same dispersion as X, it now has intermediate values, i.e., values that lie between S_X and X. Thus, extrapolating from the results of Chang & Liu (2008), when the presentation format encourages within-dimension comparisons, the addition of S_X should increase choice share in Y. That is, the addition of S_X, in conjunction with a By-Dimension grouping, should actually reverse the similarity effect, akin to a compromise effect. When the presentation format encourages within-alternative comparisons, attention to relative values should decrease, resulting in a standard similarity effect in which choice shares decrease for the target alternative by virtue of its *overall* similarity to the decoy. This prediction was supported by the data. The similarity effect was successfully elicited using a “By-Alternative” presentation format, that is, a format in which choice information was grouped by alternatives but reversed using a “By-Dimension” format, demonstrating that the mechanisms underlying the similarity effect are dependent on the format in which information is presented.

Cataldo & Cohen (2018b) further extended this work by jointly testing the influence of presentation format on the compromise, similarity, and attraction effects with an entirely within-subjects design. The results both replicated the findings of Chang & Liu (2008) and Cataldo & Cohen (2018a) and supported the predicted effect of presentation format on the attraction effect. Specifically, a By-Dimension presentation format elicited a reverse similarity effect and standard compromise and attraction effects, whereas a By-Alternative presentation format elicited a standard similarity effect, reverse compromise effect, and strongly reduced attraction effect (Figure 2). Consistent with previous research (Berkowitsch et al., 2014; Chang & Liu, 2008; Trueblood et al., 2015), this pattern of results holds within subjects. Specifically, participants largely demonstrate the standard similarity effect, reverse compromise effect, and null or reverse attraction effect in the By-Alternative format condition, and the reverse similarity effect and standard compromise and attraction effects in the By-Dimension format condition (Figure 3).

The results of this work highlight two important open questions. First, it is necessary to clarify the role of apparent alternative- and dimension-level stimulus characteristics in each context effect. This is a primary goal of Experiment 1. Second, it is necessary to collect eyetracking measures to directly measure the influence of presentation format on the relative number of within-alternative and within-dimensions comparisons. This is the primary goal of Experiment 2.

CHAPTER 2

EXPERIMENT 1

2.1 Introduction

Multi-alternative, multi-attribute choice involves selecting one of a set of alternatives, each of which varies on at least two dimensions, such as choosing an apartment, car, or laptop. An important collection of results demonstrates that adding a new alternative to a choice set can change preferences among the original alternatives. These "context effects", including the attraction (Huber et al., 1982), compromise (Simonson, 1989), and similarity (Tversky, 1972) effects, strongly suggest that a comparison process, i.e., a method of calculating relative values, plays an important role in choice behavior. Process models of preferential choice tend to assume that such comparisons are made strictly between alternatives within single dimensions (Bhatia, 2013; Roe et al., 2001; Trueblood et al., 2014; Usher & McClelland, 2004), but offer differing theories of the psychological mechanisms driving observed variability in the strength and co-occurrence of different types of context effects (Berkowitsch et al., 2014; Liew et al., 2016; Trueblood et al., 2015).

Recent research suggests a simpler account: that the comparison process itself, made more flexible by allowing for comparisons between alternatives *or* between dimensions[1], may be a critical mechanism. Specifically, whereas the attraction and

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[1] Comparisons between alternatives within a single dimension may be qualitatively different than comparisons between dimensions within a single alternative, most notably because all dimensions being considered within a single alternative must be accepted or rejected jointly. This suggests some integration process that may or may not be separable from the within-alternative "comparison", or relative value. Such a process is beyond the scope of the present paper.

compromise effects are facilitated by a format encouraging within-dimension comparisons and impeded by a format encouraging within-alternative comparisons (Cataldo & Cohen, 2018b; Chang & Liu, 2008), the opposite is found for the similarity effect (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b). Together, these studies suggest that a flexible comparison process may play a key role in producing observed correlations between context effects (Berkowitsch et al., 2014; Trueblood et al., 2015) and individual differences (Liew et al., 2016) by differentially highlighting dimension-level (e.g., dominance, similarity, and extremeness; Simonson, 1989) and alternative-level (e.g., dispersion of dimension values; Chernev, 2004, 2005) stimulus characteristics. Thus, the primary goal of Experiment 1 is to determine the alternative- and dimension-level stimulus properties that promote the attraction, compromise, and similarity effects, as moderated by presentation format.

The present work targets one dimension-level and one alternative-level stimulus property. First, consider the "baseline" choice scenarios depicted in the top left panel of Figure 4. The alternatives X and Y constitute the base pair. The attraction effect (Huber et al., 1982) is the finding that the addition of alternative A_X, which is similar to X but worse on both dimensions, increases the preference for X over Y. The compromise effect (Simonson, 1989) is the finding that the addition of alternative C_X increases preference for X, which now has intermediate values on both dimensions. The similarity effect (Tversky, 1972) is the finding that the addition of alternative S_X, which is similar to Y on both dimensions but is still of equal overall value, increases the preference of apartment X over apartment Y.

The targeted dimension-level stimulus property, “spread”, is defined as the set of absolute differences between alternatives within each dimension. Spread will be manipulated by increasing these differences in the baseline condition by a factor of two (Figure 4, top right panel). Importantly, across conditions, this manipulation preserves the *proportional* differences between dimension values that have historically defined the attraction, compromise, and similarity contexts, i.e., which alternatives are most similar to each other. Greater spread is expected to result in a stronger attraction effect because it decreases the absolute similarity between alternatives, making the dominance relationship more apparent. For this same reason, greater spread is expected to result in a weaker similarity effect; that is, with decreasing similarity between alternatives, the alternative-level similarity between adjacent alternatives is diminished. As these alternatives become more easily distinguished, the choice set becomes more analogous to one with a compromise context, reversing the effect of the decoy. Finally, greater spread is expected to result in a stronger compromise effect, as the extreme alternatives become more polarized. Because spread is a dimension-level stimulus property, its effects are expected to be greater for participants in a By-Dimension presentation format.

Previous research found that a By-Dimension presentation format elicited slower response times than a By-Alternative presentation format (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b). These prior results suggest that highlighting dimension-level stimulus properties increases the difficulty of the choice task, either by making similar alternatives more distinguishable or by emphasizing the extremeness of some alternatives. Thus, to the extent that increased spread similarly increases the difficulty of the choice task, increased spread is also expected to lead to an increase in response times, and to a greater degree in the By-Dimension format than in the By-Alternative format.

The targeted alternative-level stimulus property, “dispersion” (Chang & Liu, 2008), also known as “attribute balance” (Chernev, 2004, 2005) or “extremeness aversion” (Trueblood et al., 2014), is defined as the absolute difference in values within a single alternative. Dispersion is manipulated by shifting the alternatives in a choice set along the indifference line such that one alternative in the base pair has low dispersion (X in Figure 4, bottom left panel and Y in Figure 4, bottom right panel) and the other has high dispersion (Y in Figure 4, bottom left panel and X in Figure 4, bottom right panel). Previous research shows that decision-makers tend to prefer alternatives with low dispersion between dimension values (Chang & Liu, 2008; Chernev, 2004, 2005; Hotaling & Rieskamp, 2018; Simonson & Tversky, 1992). Therefore, X and Y are each expected to be more preferred when they are the low-dispersion alternative.

A sufficient bias towards low-dispersion alternatives may overpower the traditional effects of the decoy. To illustrate, consider the scenario in which alternative X is the low-dispersion alternative (Figure 4, lower-left panel). Recall that the attraction and compromise decoys, A_X and C_X, are more similar to the target than the competitor in a choice set. Thus, if X has low dispersion and is the competitor in an attraction or compromise context, it would be strongly preferred as the only low-dispersion alternative. If X has low dispersion and is the target in an attraction or compromise context, however, dispersion would also be reduced for A_X or C_X. These decoys would therefore also increase in attractiveness, competing with X. Overall, due to shifts in preference between X and the decoy between target conditions, X would be more preferred as the competitor than as the target, resulting in more negative attraction and compromise effects. No corresponding shift in preference would be expected for the high-dispersion alternative, Y, which is consistently unattractive across target conditions.

Recall, however, that the similarity decoy is distinct from the attraction and compromise decoys in that it is more similar to the competitor than the target. This decoy is therefore *less* attractive when it targets a low-dispersion alternative and *more* attractive when it targets a high-dispersion alternative, reversing the influence of dispersion described above. That is, contrary to the attraction and compromise effects, decreased dispersion is expected to result in a more positive similarity effect. Because dispersion is an alternative-level stimulus property, dispersion is expected have a greater effect on choice and response times among participants in a By-Alternative presentation format.

Across all three contexts, the introduction of an attractive, low-dispersion alternative arguably decreases the difficulty of the choice task. Thus, relative to the baseline choice set, choice sets in which either X or Y have low dispersion are expected to elicit faster response times. Because dispersion is more salient in the By-Alternative format, this difference is expected to be greater in the By-Alternative format than in the By-Dimension format.

It is important to clarify here the distinction between discussing the impact of an experimental manipulation on context effects as qualitative or quantitative. Previous work applying categorical manipulations, such as the presentation format manipulations used by Chang & Liu (2008) and Cataldo & Cohen (2018a; 2018b) focused on qualitative shifts, i.e., the presence, absence, or reversal of each context effect in each format condition. The present manipulations of spread and dispersion, however, are quantitative in nature. That is, though I select only two or three “levels” of each manipulation, the magnitude of dispersion and spread in a given choice set is a continuous measure. Further, within each manipulation, the selected levels are not known a priori to be in such qualitatively distinct areas of the attribute space as to elicit qualitatively different effects. I therefore discuss the impact of spread and dispersion on context effects quantitatively.

With this in mind, Experiment 1 has several quantitative hypotheses. First, consistent with previous research (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b; Chang & Liu, 2008), participants are expected to exhibit a more positive similarity effect and more negative attraction and compromise effects in a By-Alternative presentation format condition compared to a By-Dimension presentation format condition. Second, as outlined above, increased spread is expected to result in more positive attraction and compromise effects and a more negative similarity effect relative to baseline, and to a greater degree in a By-Dimension format than in a By-Alternative format. Third, low-dispersion alternatives are expected to result in more negative attraction and compromise effects and a more positive similarity effect relative to baseline, and to a greater degree in a By-Alternative format than in a By-Dimension format.

2.2 Method

2.2.1 Participants

A total of 127 participants (61 in the By-Alternative format condition, 66 in the By-Dimension format condition) were recruited from the UMass undergraduate research participant pool. Participants earned course credit for participation.

2.2.2 Materials

All choice sets consisted of multiple alternatives within one of three product categories, apartments, laptops, or cars, that varied on two dimensions. Alternatives in the apartment choice sets were rated on their size and location, alternatives in the laptop choice sets were rated on their weight and battery life, and alternatives in the car choice sets were rated on their fuel efficiency and safety.

I begin by describing the values of the baseline choice sets, depicted in the top left panel of Figure 4, before describing how these sets were varied across different levels of dispersion and spread. The first set consists of the base pair X and Y. Alternative X rates well on dimension 1 (4) but poorly on dimension 2 (3), and alternative Y rates poorly on dimension 1 (3) but well on dimension 2 (4). Importantly, X and Y have the same expected value (3.5) and dispersion between dimensions (1). The remaining six choice sets were ternary sets consisting of the base pair X and Y as well as each of the following six decoys, which vary in context and target alternative: A_X, A_Y, C_X, C_Y, S_X, or S_Y. The placement of each decoy follows that of previous work (Cataldo & Cohen, 2018). The attraction decoy is rated similarly (.25 of the distance between X and Y) to the target alternative on both dimensions, but worse. The similarity decoy is rated similarly (.25 of the distance between X and Y) to the target alternative on both dimensions, but better on the dimension in which the target alternative rates well and worse on the dimension in which the target alternative rates poorly. Lastly, the compromise decoy is rated such that the ratings of the alternative being targeted fall precisely between the ratings of the decoy and non-target alternative for each dimension.

Recall that the goal of the present experiments is to determine the stimulus properties underlying the attraction, compromise, and similarity effects. Thus, the baseline choice sets were varied across two levels of spread, the absolute differences between alternatives within each dimension, and three levels of dispersion, the absolute difference between dimension values within each alternative. Spread was manipulated such that the base pair of a choice set had a two-unit difference between their ratings within each dimension (see Figure 4, top right panel). Dispersion was manipulated such that each alternative in the base pair of a choice set had either a zero- or two-unit difference between its ratings across the two dimensions, constituting the following pairs: low dispersion X and high dispersion Y (Figure 4, bottom left panel), and high dispersion X and low dispersion Y (Figure 4, bottom right panel). Decoys were added in the same manner as described for the baseline choice sets, preserving proportional differences in each case.

Varying the seven baseline choice sets across one additional level of spread and two additional levels of dispersion resulted in 28 choice sets. To ensure high power within subjects, each of these 28 choice sets was presented with all possible alternative orderings (two for the binary set, six for the ternary sets) across the three product categories, resulting in 456 trials. Each participant also completed an additional 36 "catch" trials that included a dominating alternative in order to identify participants who were not sufficiently engaged in the task. In total, participants completed 492 trials.

Following Tversky (1972, Task B) and Cataldo & Cohen (2018a; 2018b), the dimension values were depicted as filled, horizontal bars (see Figure 5). The values were goodness-of-fit ratings, from "worst for me" (unfilled) to "best for me" (completely filled). This scale standardizes the two dimensions and minimizes concerns about non-monotonic preferences and determining ideal points (e.g., some participants may prefer a small apartment while others may prefer a large apartment). The horizontal length of the bar was determined by multiplying the constant, vertical height of the bar (40 px) by the dimension rating.

Each participant viewed the choice sets in one of two presentation formats: By-Dimension or By-Alternative. Consider the sample stimuli presented in Figure 5. The top and bottom rows demonstrate the By-Dimension and By-Alternative conditions, respectively. In both cases, the ratings are presented as horizontal bars in a matrix, encouraging comparisons within columns rather than within rows. In the By-Dimension condition, the columns of the matrix denote alternatives and the rows denote dimensions, encouraging within-alternative comparisons. In the By-Alternative condition, the columns denote dimensions and the rows denote alternatives, encouraging within-dimension comparisons. The bar lengths were constant across presentation format conditions. The size, safety, and weight dimensions were always presented on the top in the By-Alternative condition and on the left in the By-Dimension condition for the Apartment, Car, and Laptop categories, respectively. Sample stimuli from each level of dispersion and spread are provided in Appendix A.

2.2.3 Procedure

Trials were blocked by product category; all other factor levels were randomized within blocks. The order of the blocks was randomized across participants such that only the first block could be used if order effects were observed. Participants were given detailed instructions for the task, including the meaning of the dimensions and a description of the dimension value scale, repeated for the relevant product category before each block. The dimension values were described as follows: "The higher the rating is, the better that [APARTMENT / SMARTPHONE / CAR] rates for you. The lower the rating is, the worse that [APARTMENT / LAPTOP / CAR] rates for you. That is, a high rating under the [SIZE / WEIGHT / FUEL EFFICIENCY] feature doesn't necessarily mean that the [APARTMENT / LAPTOP / CAR] is [LARGER OR SMALLER / LIGHTER OR HEAVIER / MORE OR LESS EFFICIENT], just that it is better suited for you personally." Participants were not explicitly told the presentation format that they were viewing. Instead, they were given the name of a fictional company advertising the products, along with an image demonstrating how that company displays the product ratings (i.e., the presentation format; see Figure 5).

Participants completed three practice trials after the instructions for each block. Each response required pressing a keyboard key associated with the desired alternative. Participants were allowed to take self-paced breaks in their seats between blocks and at the halfway point within each block.

2.3 Results

2.3.1 Choice Behavior

The choice proportions for each alternative in the baseline choice sets alone are presented in Figure 6, broken out by presentation format, target, and product category. Two general observations can be made about preferences for the different alternatives across choice sets. First, the decoy is generally the least preferred alternative in the attraction and compromise contexts but is competitive in the similarity context. Second, participants exhibit some degree of dimension bias in each product category, preferring X (which rates best in location) in the Apartment category, Y (which rates best in safety) in the Car category, and X (which rates best in battery life) in the Laptop category.

Following Wedell (1991), each context effect is measured as a comparison between two three-choice scenarios targeting X or Y. A context effect is obtained if both $\Delta P_X = P(X \mid X, Y, D_X) - P(X \mid X, Y, D_Y)$ and $\Delta P_Y = P(Y \mid X, Y, D_Y) - P(Y \mid X, Y, D_X)$ are positive. Negative values indicate a reverse effect. Because this formulation reduces concerns of dimension bias, the following analyses collapse across product category. Figure 7 shows ΔP for X and Y for each context and presentation format in the baseline choice sets (Figure 4, top left panel). Note that though the same qualitative choice patterns are not found, possibly due to differences in stimulus values, bar height, or increased cross-trial interference from a longer experiment with exposure to a wider range of values, the results replicate the quantitative effects found in Cataldo & Cohen (2018b). That is, participants in the By-Alternative condition (top row) display a more positive similarity effect and more negative attraction and compromise effects than participants in the By-Dimension condition (bottom row).

Now consider the effect of increasing a dimension-level stimulus property, spread. Figure 8 shows ΔP averaged across X and Y for the baseline choice sets (red bars) compared to the choice sets in which the absolute difference between the alternatives within in each dimension has been increased by a factor of two (blue bars; Figure 4, top right panel). As predicted, increased spread decreased the similarity effect and increased the attraction and compromise effects, and to a greater degree in the By-

Dimension condition than in the By-Alternative condition. Note, however, that the attraction context in the By-Dimension condition does not fit this pattern; instead, though numerically in the right direction, there is no meaningful difference between levels of spread. It is possible that the large attraction effect in the baseline choice sets is at ceiling.

Next consider the effect of increasing an alternative-level stimulus property, dispersion. Figure 9 shows ΔP for the baseline choice sets compared to choice sets that have been shifted along the indifference line to manipulate the relative dispersion of the alternatives. Here, ΔP is the average difference across X and Y between target choice sets, matched for dispersion. Red bars represent the average ΔP for moderate-dispersion X and moderate-dispersion Y (baseline choice sets). Yellow bars represent the average ΔP for low-dispersion X (Figure 4, bottom left panel) and low-dispersion Y (Figure 4, bottom right panel). Blue bars represent the average ΔP for high-dispersion X (Figure 4, bottom right panel) and high-dispersion Y (Figure 4, bottom right panel). As predicted, the low-dispersion condition resulted in a numerically increased similarity effect and numerically decreased attraction and compromise effects while the high-dispersion condition resulted in a numerically decreased similarity effect and numerically increased attraction and compromise effects, and to a greater degree in the By-Alternative condition than in the By-Dimension condition. Note again that the attraction context in the By-Dimension condition does not fit this pattern; though it is again numerically in the right direction, there is no meaningful difference between levels of dispersion. As suggested previously, it is possible that the large attraction effect already observed in the baseline choice sets is at ceiling.

A hierarchical Bayesian multinomial regression model was used to test for differences in choice proportions across target, context, product category, dispersion, spread, and presentation format conditions. Details of the model are provided in Appendix B. Inferences are made by calculating the 95% highest density interval (HDI) around the mean of the posterior estimated choice proportions for a given condition. A difference between conditions is indicated by non-overlapping HDIs.

Consider the posterior estimates and HDIs for choice proportions provided in Table 1. As stated above, the decoy is generally the least preferred alternative in any given choice set. Of those, the attraction decoy was least preferred, followed by the compromise and similarity decoys. Further, the different product categories appeared to elicit different dimensional biases. Specifically, participants preferred X (which rates best in location) in the Apartment category, Y (which rates best in safety) in the Car category, and X (which rates best in battery life) in the Laptop category. Note that the apartment choice sets appear to have elicited the least such dimension bias.

Next, I use this model to address the effect of spread and dispersion on context effects across presentation format conditions. The estimated choice proportions and HDIs for ΔP_X and ΔP_Y are provided in Table 2, broken down by format, context, spread, and dispersion. In the baseline choice sets, the numeric increases in the attraction and compromise effects and the numeric decrease in the similarity effect between the By-Alternative and By-Dimension conditions are all statistically supported by non-overlapping HDIs between format conditions. The effects of spread and dispersion on context effects are also supported. That is, in the case of spread, the ΔP_X and ΔP_Y HDIs for the attraction and compromise effects were higher when spread was increased by a factor of two, and the ΔP_X and ΔP_Y HDIs for the similarity effect were lower. This occurs to a greater degree in the By-Dimension condition than in the By-Alternative condition. In the case of dispersion, the ΔP_X and ΔP_Y HDIs were decreased for the attraction and compromise effects and increased for the similarity effect in the low-dispersion condition, and the ΔP_X and ΔP_Y HDIs were increased for the attraction and compromise effects and decreased for the similarity effect in the high-dispersion condition, relative to baseline. This occurs to a greater degree in the By-Alternative condition than in the By-Dimension condition. As noted, however, the attraction effect in the By-Dimension condition was unaffected by manipulations of spread and dispersion.

2.3.2 Response Times

Figure 10 presents mean response times for each target, context, and presentation format condition in the baseline choice sets (Figure 4, top left panel). Contrary to Cataldo & Cohen (2018b), response times in the By-Dimension condition do not appear to be slower than in the By-Alternative condition among these baseline choice sets. Consistent with Cataldo & Cohen (2018b), the similarity context appears to have elicited marginally slower response times than the attraction and compromise contexts across format conditions.

Next consider the effects of spread and dispersion on mean response times. Figure 11 presents mean response times averaged across target for the baseline choice sets (red points) compared to the choice sets with increased spread (blue points; Figure 4, top right panel). As predicted, response times appear to increase with increased spread, but only consistently in the By-Dimension format condition, which was predicted to be more affected by spread. Figure 12 presents mean response times for the baseline choice sets compared to choice sets with a manipulation of dispersion. Red points represent the average response time for the baseline choice sets. Yellow points represent the average response time for choice sets where X has low dispersion (Figure 4, bottom left panel). Blue points represent the average response time for choice sets where Y has low dispersion (Figure 4, bottom right panel). As predicted, response times were slower for the baseline condition compared to the other conditions, suggesting that response times decreased when dispersion was unequal across X and Y. Note that this effect is greater in the By-Alternative condition, which was predicted to be more affected by dispersion, than in the By-Dimension condition.

A hierarchical Bayesian regression model was used to test for differences in response times across target, context, product category, dispersion, spread, and presentation format conditions. Details of the model are provided in Appendix C. Inferences are again based on the 95% HDIs of a response time in a given condition. The estimated choice proportions and 95% HDIs for response times are provided in Table 3. Note that response times were slower for the apartment choice sets than the laptop or car choice sets; this is consistent with the choice behavior described above, in which the apartment choice sets elicited the least dimension bias (and therefore likely represented more difficult choice scenarios). The effect of context was not statistically supported; that is, the 95% HDIs for mean response times for the similarity context overlap slightly with those in the attraction and compromise contexts. Support was found for all other group differences described above. In isolation, the model estimates that the 95% HDIs for mean response times are greater in the By-Dimension condition than in the By-

Alternative condition. When accounting for the effect of spread, however, this difference only emerges among choice sets where spread has been increased by a factor of two. Accordingly, increased spread led to slower response times, but only in the By-Dimension condition. The effects of dispersion are similarly supported by the model in that the 95% HDIs for mean response times are greater in the baseline choice sets, but only in the By-Alternative condition.

2.4 Discussion

Different forms of context-dependent choice, i.e., the attraction (Huber et al., 1982), compromise (Simonson, 1989), and similarity (Tversky, 1972) effects, have historically been explained in terms of dimension-level stimulus properties such as dominance, extremeness, and within-dimension similarity. Recent research suggests, however, that a flexible comparison process may play a key role in producing previously observed correlations between context effects (Berkowitsch et al., 2014; Trueblood et al., 2015) and individual differences (Liew et al., 2016) by differentially highlighting dimension-level *or* alternative-level stimulus properties (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b; Chang & Liu, 2008). Thus, the primary goal of the present experiment was to determine the alternative- and dimension-level stimulus properties that promote the attraction, compromise, and similarity effects.

The results replicate previous work finding that participants in a By-Alternative format condition exhibit a more positive similarity effect and more negative attraction and compromise effects than participants in a By-Dimension format condition. The results extend previous work by demonstrating that these effects may be driven by the differential influence of dimension- and alternative-level stimulus properties on context effects. Increasing a dimension-level stimulus property, spread, facilitated the attraction and compromise effects, impeded the similarity effect, and produced slower response times. These effects occurred to a greater degree in the By-Dimension format condition than in the By-Alternative format condition. This finding suggests that while the attraction and compromise effects are promoted by the classic dimension-level stimulus properties specified by many models of preferential choice, the similarity effect is impeded by them. Specifically, increased spread may serve to highlight the dominance and extremeness properties key to the attraction and compromise contexts, respectively, but diminish the alternative-level similarity between adjacent alternatives that is key to the similarity effect.

Manipulating an alternative-level stimulus property, dispersion, influenced the three effects in a similarly differential fashion. Specifically, low-dispersion alternatives produced more negative attraction and compromise effects and a more positive similarity effect, whereas high-dispersion alternatives produced more positive attraction and compromise effects and a more negative similarity effect. Further, response times were slower in the baseline choice sets than in choice sets with a low-dispersion alternative. These effects occurred to a greater degree in the By-Alternative format condition than in the By-Dimension format condition. However, rather than highlighting properties that are critical or obstructive to each effect, dispersion appears to influence choice *concurrently* with the presence of a decoy. Consider the estimated choice proportions presented in Table 1. Consistent with previous research, decision-makers tended to prefer whichever alternative, X or Y, had the lowest dispersion between dimension values (Chang & Liu, 2008; Chernev, 2004, 2005; Hotaling & Rieskamp, 2018; Simonson & Tversky, 1992). As outlined previously, because the decoy is more similar to the target than the competitor in the case of the attraction and compromise contexts, the attraction and compromise decoys are competitive alternatives when targeting a low-dispersion alternative, taking preference from the target and producing more negative attraction and compromise effects. In the case of the similarity effect, however, the decoy is more similar to the competitor than the target, thus reversing the influence of dispersion to produce a more positive similarity effect.

As stated previously, though only a limited number of discrete choice sets are utilized in the present experiments, manipulations of dispersion and spread are truly quantitative in nature. Their impact on context effects are therefore discussed quantitatively. It is worth noting, however, that the present experiment does not provide evidence that their impact is necessarily continuous. For instance, it is possible that sufficiently increasing spread or dispersion categorically removes the effects of the decoy, as observed in the choice sets where spread has been increased or where the target has high dispersion. Further, it is unclear whether varying the proportional differences between alternatives in the choice set would produce different results. For instance, if the impact of spread is categorical such that the decoy only needs to be sufficiently similar or dissimilar to the adjacent alternative to produce a particular effect, then it is possible that the present results could be produced merely by manipulating the distance of the decoy. Future work utilizing a wider range of choice sets varying in smaller increments is needed to determine the precise influence of these manipulations on choice.

Though the present experiment failed to replicate the main effect of presentation format on response times found in previous work (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b), it seems likely that this is due to the presence of novel interactions of presentation format with dispersion and spread. Specifically, in the By-Dimension condition, response times were slower for choice sets in which spread was increased by a factor of two. This potentially suggests that when the degree of spread between alternatives in a choice set is made apparent, increased spread results in a more difficult choice scenario. In the By-Alternative condition, response times were faster for choice sets that included a low-dispersion alternative. This similarly suggests that when the degree of dispersion within alternatives in a choice set is made apparent, the presence of an attractive, lower-dispersion alternative results in an easier choice scenario.

From a practical standpoint, the present results demonstrate the importance of carefully considering where alternatives are placed in the attribute space. For instance, studies in which it is critical to produce an attraction effect ought to ensure that the decoy has a greater absolute difference from the adjacent alternative than those seeking to produce a similarity effect. Further, research studying any of the three effects ought to carefully control for concurrent effects of dispersion. Such a manipulation is easy to introduce into a choice set unknowingly and can greatly impact interpretation of the results. For instance, a reanalysis of data from the combined inference paradigm originally published in Trueblood, Brown, & Heathcote (2014) and later as experiment E4 in Evans, Holmes, & Trueblood (2019; data provided on OSF: https://osf.io/h7e6v/) demonstrates the influence of dispersion on the compromise effect (Figure 13). Following the labelling of the decoy provided by the authors, and inferring the target by its intermediate placement in each dimension, the two choice sets differ in the magnitude of the context effect; that is, whereas the target is largely preferred in Set 1, the competitor is preferred to the same magnitude in Set 2 (top panel). Inspection of stimuli, however, reveals that the target in Set 1 and the competitor in Set 2 are the same low-dispersion option. Averaging the choice proportions for the target and competitor across sets matches the aggregate values reported by Trueblood et al (2014). Such averaging is common practice in studies of context effects, but as demonstrated here, can obscure possible concurrent mechanisms.

From a theoretical standpoint, the present results lend further support to previous research arguing that models of preferential choice ought to treat the comparison process with more nuance (Cataldo & Cohen, 2018b). That is, the present experiment provides more specific evidence that models of preferential choice would likely benefit from incorporating both dimension-level and alternative-level stimulus properties in their accounts of context effects. Popular models of preferential choice, including Multialternative Decision Field Theory (MDFT; Roe et al., 2001), the Leaky Competing Accumulator (LCA; Usher & McClelland, 2004), the Associative Accumulation Model (AAM; Bhatia, 2013), the Multiattribute Linear Ballistic Accumulator (MLBA; Trueblood et al., 2014), and Multialternative Decision by Sampling (MDbS; Noguchi & Stewart, 2018), all naturally incorporate the influence of spread on context effects by virtue of their emphasis on within-dimension comparisons. However, few models currently account for the influence of dispersion. The AAM includes dispersion as a formal model component, via its associative bias mechanism. The MLBA includes dispersion as a consequence of the extremeness aversion implemented in the subjective mapping function, though this has been noted as an optional component of the model (e.g., Trueblood & Dasari, 2017). MDbS includes dispersion via a modification to the model that allows for comparisons across commensurable dimensions. Note, however, that this is counter to the core assumption of the standard model that comparisons occur strictly within dimensions; furthermore, the same effect of dispersion was observed in an alternative version of this experiment in which objective, non-commensurate dimension values were used in place of ratings. Given the especially large effects of dispersion in the present experiment, future modelling work ought to consider the influence of dispersion more formally, as would naturally be accomplished by allowing for within-alternative comparisons.

Experiment 1 extends previous work by providing specific evidence for the critical role that a flexible comparison process appears to play in preferential choice. Modulating the decision-maker's ability to compare choice information within alternatives or within dimensions facilitates the perception of alternative- and dimension-level stimulus properties, respectively, resulting in differential patterns of context effects. Moreover, the large amount of behavioral data collected for this study, largely within-subjects, presents a strong starting point for determining the stimulus properties that are most critical to successful models of preferential choice. Namely, both dimension-level and alternative-level similarity appear to exhibit a large influence on preference development and should therefore both be accounted for in the decision process.

CHAPTER 3

EXPERIMENT 2

3.1 Introduction

Recent work on the influence of presentation format on context effects suggests that By-Alternative and By-Dimension presentation formats highlight alternative- and dimension-level stimulus properties, respectively, by moderating the number of within-alternative vs. within-dimension comparisons (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b; Chang & Liu, 2008). To more thoroughly assess the extent to which presentation format truly influences information acquisition patterns, however, it is necessary to collect eyetracking measures. Therefore, Experiment 2 extends previous research by utilizing eyetracking to better characterize the influence of stimulus presentation format on context effects.

Experiment 2 will utilize the same stimuli and follow the same procedure as Experiment 1, with the addition of eyetracking. As in Experiment 1 and consistent with previous research (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b; Chang & Liu, 2008), participants are expected to exhibit a more positive similarity effect and weaker or more negative attraction and compromise effects in the By-Alternative presentation format condition compared to the By-Dimension presentation format condition. Second, this pattern is expected to map on to further differences in information acquisition patterns, as measured by eyetracking. Specifically, as suggested by the reanalysis of Noguchi & Stewart (2014) conducted by Cataldo & Cohen (2018b), participants will exhibit more within-alternative transitions in the By-Alternative condition and more within-dimension transitions in the By-Dimension condition.

3.2 Method

3.2.1 Participants

A total of 105 participants (52 in the By-Alternative format condition, 53 in the By-Dimension format condition) were recruited from the UMass undergraduate research participant pool. Participants earned course credit for participation.

3.2.2 Materials

As in Experiment 1, all choice sets consisted of multiple alternatives that varied on two dimensions. To compensate for increased task demands introduced by the eyetracker, Experiment 2 relied on only one product category (apartments). Otherwise, the stimuli were the same as in Experiment 1, resulting in a total of 164 trials.

The dimension values were again depicted as filled, horizontal bars (see Figure 5), with presentation format manipulated between-subjects. Relative to Experiment 1, the height of the bars was reduced to 35 px in order to better spatially separate the choice information. As in Experiment 1, the horizontal length of the bar was determined by multiplying the height of the bar by the dimension rating.

3.2.3 Procedure

Trials were randomized for each participant. At the beginning of the experiment, participants were told the product category within which they will be making selections.

Participants were given the same instructions regarding presentation format and the meaning of the ratings as in Experiment 1. All participants completed three practice trials after reading the instructions and before beginning the test trials.

The experiment was conducted using eyetracking in order to collect additional behavioral measures of comparison style, namely the number of within-dimension and within-alternative transitions, as well as the total number of fixations and average fixation duration. The stimuli were presented on a 17” Vision Master Pro 514 Iiyama CRT monitor connected to a computer interfaced with an SR Research Limited Eye-Link II eye tracking system operating at a sampling rate of 250 Hz.

3.3 Results

3.3.1 Choice Behavior

Figure 14 shows ΔP for X and Y for each context and presentation format in the baseline choice sets (Figure 4, top left panel). The results replicate the quantitative findings of Cataldo & Cohen (2018b) and Experiment 1: Participants in the By-Alternative condition (top row) display a more positive similarity effect and more negative attraction and compromise effects than participants in the By-Dimension condition (bottom row).

Now consider the effect of increasing a dimension-level stimulus property, spread. Figure 15 shows ΔP averaged across X and Y for the baseline choice sets compared to the choice sets in which the absolute difference between the alternatives within in each dimension has been increased by a factor of two (Figure 4, top right panel). As predicted, increased spread numerically decreases the similarity effect and numerically increases the attraction and compromise effects, and to a greater degree in the By-Dimension condition than in the By-Alternative condition. Note, however, that this difference is small for the compromise effect.

Next consider the effect of increasing an alternative-level stimulus property, dispersion. Figure 16 shows ΔP for the baseline choice sets compared to choice sets that have been shifted along the indifference line to manipulate the relative dispersion of the alternatives. As in Experiment 1, ΔP is the average difference across X and Y between target choice sets, matched for dispersion. Red bars represent the average ΔP for moderate-dispersion X and moderate-dispersion Y (baseline choice sets). Yellow bars represent the average ΔP for low-dispersion X (Figure 4, bottom left panel) and low-dispersion Y (Figure 4, bottom right panel). Blue bars represent the average ΔP for high-dispersion X (Figure 4, bottom right panel) and high-dispersion Y (Figure 4, bottom right panel). The low-dispersion condition resulted in a numerically increased similarity effect and numerically decreased attraction and compromise effects while the high-dispersion condition resulted in a numerically decreased similarity effect and numerically increased attraction and compromise effects, and to a greater degree in the By-Alternative condition than in the By-Dimension condition.

A hierarchical Bayesian multinomial regression model was used to test for differences in choice proportions across target, context, product category, dispersion, spread, and presentation format conditions. Details of the model are provided in Appendix D. Inferences are made by calculating the 95% highest density interval (HDI) around the mean of the posterior estimated choice proportions for a given condition. A difference between conditions is indicated by non-overlapping HDIs.

Consider the posterior estimates and HDIs for choice proportions provided in Table 4. As in Experiment 1, there was generally low preference for the decoys; again, the attraction decoy was least preferred, followed by the compromise and similarity decoys.

Next, I use this model to address the effect of spread and dispersion on context effects across presentation format conditions. The estimated choice proportions and HDIs for ΔP_X and ΔP_Y are provided in Table 5, broken down by format, context, spread, and dispersion. In the baseline choice sets, the numeric increases in the attraction and compromise effects and the numeric decrease in the similarity effect between the By-Alternative and By-Dimension conditions are all statistically supported by non-overlapping HDIs between format conditions.

The effects of spread and dispersion on context effects are only partially supported by the model. That is, though Experiment 2 replicates the general pattern found in Experiment 1, the reduced power in Experiment 2 limits the precision of the estimates. In the case of spread, the ΔP_X and ΔP_Y HDIs for the attraction effect were higher when spread was increased by a factor of two, and the ΔP_X and ΔP_Y HDIs for the similarity effect were lower, occurring to a greater degree in the By-Dimension condition than in the By-Alternative condition. The ΔP_X and ΔP_Y HDIs for the compromise effect, however, overlapped across levels of spread in both presentation format conditions. In the case of dispersion, the ΔP_X and ΔP_Y HDIs were decreased or only slightly overlapping with baseline for the attraction and compromise effects and increased for the similarity effect in the low-dispersion condition, occurring to a greater degree in the By-Alternative condition than in the By-Dimension condition. In the high-dispersion condition, the ΔP_X and ΔP_Y HDIs decreased for the similarity effect but overlapped with baseline for the attraction and compromise effects in the high-dispersion condition.

3.3.2 Response Times

Figure 17 presents mean response times for each target, context, and presentation format condition in the baseline choice sets (Figure 4, top left panel). Consistent with Cataldo & Cohen (2018b) and (in part) Experiment 1, response times were greater in the By-Dimension condition than in the By-Alternative condition. Contrary to Cataldo & Cohen (2018b) and Experiment 1, however, the similarity context did not elicit greater response times than the attraction and compromise contexts in either condition.

Next consider the effects of spread and dispersion on mean response times. Figure 18 presents mean response times averaged across target for the baseline choice sets (red points) compared to the choice sets in which the absolute difference between the alternatives within in each dimension has been increased by a factor of two (blue points; Figure 4, top right panel). Response times appear to increase with increased spread; unlike Experiment 1, this effect appears in both presentation format conditions. Figure 19 presents mean response times for the baseline choice sets compared to choice sets that have been shifted along the indifference line to manipulate the relative dispersion of the alternatives. Red points represent the average response time for the baseline choice sets. Yellow bars represent the average response time for choice sets where X has low dispersion X (Figure 4, bottom left panel). Blue bars represent the average response time for choice sets where Y has low dispersion (Figure 4, bottom right panel). Response times were marginally slower for the baseline condition compared to the other conditions, suggesting that response times decreased when dispersion for X and Y was unequal.

A hierarchical Bayesian regression model was used to test for differences in response times across target, context, dispersion, spread, and presentation format conditions. Details of the model are provided in Appendix E. Inferences are again based on the 95% HDIs of a response time in a given condition. The estimated choice proportions and 95% HDIs for response times are provided in Table 6. There is no apparent effect of context or target on response times. The model supports the effects of presentation format and spread as described above, with a greater 95% HDI for mean response times in the By-Dimension condition than in the By-Alternative condition and a greater 95% HDI for response times in choice sets where spread has been increased by a factor of two than in the baseline choice sets. The effect of dispersion is not supported, however: The 95% HDIs for mean response times overlap across levels of dispersion, suggesting that there are no meaningful differences.

3.3.3 Eyetracking Measures

The average total number of fixations per trial tracks closely with the average response time in a given condition. Figure 20 presents the mean number of fixations for the baseline choice sets, broken out by presentation format, context, and target. The mean number of fixations is higher in the By-Dimension condition than in the By-Alternative condition. Figure 21 depicts an increase in the mean number of fixations from the baseline choice sets when spread is increased by a factor of two, and Figure 22 depicts a marginal decrease in the mean number of fixations from the baseline choice sets when dispersion was unequal between X and Y.

The primary goal of Experiment 2 is to determine the influence of presentation format on the relative number of within-alternative vs. within-dimension comparisons, using transitions in eye fixations as a proxy. Any fixation that falls either on a rating bar or within a range equal to half the height of a rating bar (17.5 px) from the perimeter of the bar is counted as a fixation on that bar. Two consecutive fixations between different dimensions within an alternative will be counted as a within-alternative transition, whereas two consecutive fixations between different alternatives within the same dimension will be counted as a within-dimension transition. Two additional categories not of theoretical interest in the present study are also included in the analysis: Two consecutive fixations between different alternatives and in different dimensions will be counted as a "diagonal" transition, and two consecutive fixations on the same rating bar will be counted as "same". All other transitions, e.g., in which at least one fixation is not on a rating bar, are discarded.

The distributions of transitions in eye fixations are completely contrary to the predicted effects. Figure 23 presents the average proportions of each transition, broken out by presentation format and context. The By-Alternative presentation format elicited more within-dimension transitions than within-alternative transitions, whereas the By-Dimension presentation format elicited more within-alternative transitions than within-dimension transitions. Further, neither spread (Figure 24) nor dispersion (Figure 25) appear to have meaningful effects on this general pattern.

A Bayesian hierarchical model for Poisson distributed data was used to test for differences in the number of total fixations across target, context, dispersion, spread, and presentation format conditions. A separate Bayesian hierarchical model for multinomially distributed data was used to test for differences in the proportion of within-alternative, within-dimension, diagonal, and other transitions across target, context, dispersion, spread, and presentation format conditions. Details of the models are provided in Appendix F and Appendix G, respectively. Inferences are again based on the 95% highest density interval (HDI) around the mean of the posterior estimate of interest.

The estimated choice proportions and 95% HDIs for number of fixations are provided in Table 7. There are no apparent effects of target or context on mean number of fixations. The model supports the effects of presentation format, spread, and dispersion as described above, with a greater 95% HDI for mean number of fixations in the By-Dimension condition than in the By-Alternative condition, a greater 95% HDI for mean number of fixations in choice sets where spread has been increased by a factor of two than in the baseline choice sets, and a greater 95% HDI for mean number of fixations in the baseline choice sets than in choice sets where dispersion has been manipulated.

The estimated choice proportions and 95% HDIs for transitions in fixations are provided in Table 8. There are no apparent meaningful effects of target, context, spread, or dispersion on the pattern of transitions. That is, across all conditions, there are mostly within-dimension transitions in the By-Alternative format condition and mostly within-alternative transitions in the By-Dimension format condition.

3.4 Discussion

The choice and response time results of Experiment 2 replicate previous work and the direction of the effects found in Experiment 1. Specifically, participants in a By-Alternative format condition exhibit a more positive similarity effect and more negative attraction and compromise effects than participants in a By-Dimension format condition. Increasing a dimension-level stimulus property, spread, facilitated the attraction and compromise effects and impeded the similarity effect, with increased response times for choice sets in which spread was increased by a factor of two. Manipulating an alternative-level stimulus property, dispersion, influenced choice in concert with the decoy, such that the attraction and compromise effects were more negative for a low-dispersion alternative and more positive for a high-dispersion alternative, with a reversed pattern for the similarity effect. Response times were generally faster when dispersion was unequal between X and Y. Note, however, that not all effects were supported statistically; specifically, the effect of the decoy on high-dispersion alternatives was not consistently different from zero, nor was the effect of dispersion on response times. These distinctions from Experiment 1 are possibly due to the loss of power from the reduced number of trials per participant.

The primary goal of Experiment 2 was to utilize eyetracking to better characterize the influence of stimulus presentation format on context effects by analyzing the relative proportion of within-dimension vs. within-alternative transitions in eye fixations. Here, however, the results are less clear. Though the behavioral results suggest the same differential attention to dimension- and alternative-level stimulus properties across presentation format conditions observed in Experiment 1, the relative proportions of within-dimension vs. within-alternative transitions in eye fixations between formats are completely contradictory. That is, while a By-Dimension format elicited a greater effect of spread and a By-Alternative format elicited a greater effect of dispersion, participants in the By-Dimension format condition made mostly within-alternative transitions and participants in the By-Alternative format condition made mostly within-dimension transitions.

Consider the stimuli presented in Figure 5. In each format condition, the ratings are presented as horizontal bars in a matrix, strongly encouraging comparisons within columns rather than within rows. In the By-Dimension condition (top panel), the columns denote dimensions and the rows denote alternatives, encouraging within-dimension comparisons. In the By-Alternative condition (bottom panel), the columns of the matrix denote alternatives and the rows denote dimensions, encouraging within-alternative comparisons. Given the incongruent choice and eyetracking results, it is possible that comparisons are so easy to make within columns that column-wise differences can be perceived without needing to explicitly fixate on each bar – that is, they can be perceived parafoveally.

To explore this behavior more deeply, transitions in eyetracking fixations were summarized by a Payne Index (Payne, 1976), which is a measure of the proportion of within-alternative versus within-dimension transitions in attention during information acquisition, measured here by eye fixations. The Payne Index is calculated by dividing the difference between the number of within-dimension and within-alternative transitions by their sum for each trial, as follows:

$$PI = \frac{t_{dim} - t_{alt}}{t_{dim} + t_{alt}}$$

Thus, ignoring all other types of movements, the Payne Index ranges from -1 (all within-alternative transitions in a given trial) to 1 (all within-dimension transitions in a given trial).

Figure 26 presents the distributions of Payne Indices across trials for each context in each presentation format. The most striking result is the large number of trials with no within-alternative transitions (represented by a Payne Index of 1) in the By-Alternative format. In contrast, though to a lesser extent, the By-Dimension format has a large number of trials with no within-dimension transitions (represented by a Payne Index of -1). At face value, this suggests that it was common for participants in the By-Alternative and By-Dimension format conditions to never attend to differences in values within single alternatives or single dimensions, respectively – or if they did, they relied heavily on working memory. Such behavior is contrary to the behavioral results, in which manipulating the difference between values within single dimensions (spread) had a greater impact in the By-Dimension format, but manipulating the difference between values within single alternatives (dispersion) had a greater impact in the By-Alternative format, suggesting that these comparisons were not only attended to but that this attention was influenced by presentation format in the opposite direction than indicated by the eyetracking data. Thus, the most plausible, though theoretically uninteresting, account of these results is that participants were able to perceive choice information parafoveally, and that differences between rating bars in the same column were particularly easy to compare in this manner. Such behavior would result in a reduced number of transitions in eye fixations between rating bars that may have in fact received greater attention psychologically.

Future work might benefit from utilizing numeric stimuli rather filled bars to reduce parafoveal viewing. Previous work by Noguchi & Stewart (2014), reanalyzed by Cataldo & Cohen (2018b) collected eyetracking measures in a study of context effects with numerically-presented choice information. Their choice results supported the hypotheses of the present experiment: A greater proportion of within-alternative comparisons decreased the compromise effect and increased the similarity effect. No effect was found for the attraction effect, which is historically the most robust. Because column-wise comparisons would no longer necessarily be easier than row-wise comparisons, however, the same manipulation of presentation format would be less effective with numeric stimuli, posing an obstacle for determining the mechanisms at play in this manipulation. It is possible that a similar manipulation to that utilized by Chang & Liu (2008), in which choice information was presented numerically but spatially separated by either alternatives or dimensions, may be effective. Regardless, it would still be possible to determine whether the proportion of within-alternative comparisons influences the effects of spread and dispersion on choice, which may provide further insight into the role of dimension- and alternative-level stimulus properties on choice behavior. This remains an open question.

CHAPTER 4

MODELLING ANALYSIS OF CHOICE AND RESPONSE TIME

4.1 Introduction

Context-dependent choice phenomena demonstrate that preference for an alternative can depend on the other available alternatives. To illustrate, consider choosing between apartments that vary in their rated size and location (Figure 1). Assuming both dimensions are equally important, a choice between Apartments X and Y would be difficult – whereas Apartment X rates well on location, but poorly on size, the reverse is true for Apartment Y. Context effects refer to scenarios in which the addition of a third alternative, referred to as the "decoy", can increase preference for one of the original alternatives, referred to as the "target", relative to the other, referred to as the "competitor". In the case of the attraction effect (Huber et al., 1982), the decoy Apartment A_X is similar to, but dominated by, the target Apartment X. In the case of the compromise effect (Simonson, 1989), the decoy Apartment C_X places the target Apartment X in an intermediate position on each dimension. In the case of the similarity effect (Tversky, 1972), the decoy Apartment S_X is similar to, but not dominated by, the competitor Apartment Y.

A growing collection of studies focusing on the within-subject nature of context effects has found a surprisingly consistent pattern of correlations, such that the attraction and compromise effects are positively correlated with each other but negatively correlated with the similarity effect (Berkowitsch et al., 2014; Liew et al., 2016; Trueblood et al., 2015). Recent research on the possible psychological mechanisms distinguishing the similarity effect from the attraction and compromise effects indicates that the comparison process may play a primary role. Specifically, whereas the similarity effect appears to be facilitated by a “within-alternative” comparison style (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b), in which choice information is primarily compared between dimensions within each alternative, the attraction and compromise effects appear to be facilitated by a “within-dimension” comparison style (Cataldo & Cohen, 2018b; Chang & Liu, 2008), in which choice information is primarily compared between alternatives within each dimension.

Interestingly, these studies have also found a consistent effect of comparison style on response times. Specifically, the within-dimension comparison style facilitating the attraction and compromise effects also produces slower response times relative to the within-alternative comparison style facilitating the similarity effect (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b; but see Experiment 1). Thus, when considering choice and response time jointly, these results suggest that the similarity effect is associated with faster response times, whereas the attraction and compromise effects are associated with slower response times.

Consider the choice proportions conditioned on context and response time quantile presented in Figure 27. The top two panels present data from Cataldo & Cohen (2018b), hereafter referred to as Experiment A, which tested the attraction, compromise, and similarity effects across By-Alternative and By-Dimension presentation formats in an entirely within-subjects design. Response time quantiles were calculated for each participant, collapsing over all other experimental factors. The conditional choice proportions were then calculated for each participant within each quantile, context, and format condition, then averaged. A clear pattern emerges across presentation format conditions: Whereas preference for the target (green circles) increases and preference for the competitor (red triangles) decreases across RT quantiles in the attraction and compromise choice sets, the opposite pattern is found in the similarity choice sets. Qualitatively, faster response times are associated with null or reverse attraction and compromise effects and a classic similarity effect, whereas slower response times are associated with classic attraction and compromise effects and a null or reverse similarity effect.

Importantly, this pattern of results does not appear to be limited to the presentation format manipulation utilized in Experiment A. The remaining panels of Figure 27 present previously unpublished data from four additional experiments. All experiments tested the attraction, compromise, and similarity effects within-subjects, but differed in their presentation of the stimuli. Experiment B (Experiment 1 above) utilized the same presentation format manipulation as in Experiment A with ratings presented as filled horizontal bars, but with presentation format manipulated between-subjects. Experiments C and D presented stimulus values in a numeric matrix, with commensurate ratings of each alternative in each dimension. Experiment E also presented stimulus values in a numeric matrix, but with non-commensurate "objective" scales for each dimension (e.g., the actual square footage of an apartment). Additional methodological details are provided in Appendix H. Critically, when taken together, the pattern of context effects across RT quantiles appears to be quite robust across presentation format, graphical vs. numeric representations, and the commensurability of the two dimensions.

Previous behavioral research explicitly studying the role of response time in the development of context effects has been limited to time pressure manipulations (but see Molloy, Galdo, Bahg, Liu, & Turner, 2019; Simonson, 1989), in which the attraction and compromise effects (Dhar, Nowlis, & Sherman, 2000; Pettibone, 2012; Trueblood et al., 2014) as well as the similarity effect (Trueblood et al., 2014) have all been shown to become more positive the longer participants were told to view the choice alternatives before giving a response. While this is consistent with the present findings for the attraction and compromise effects, it directly contradicts those for the similarity effect. Importantly, however, time pressure manipulations correspond to an *externally* controlled stopping rule, which may produce different choice behavior compared to allowing the decision-maker to rely on their own *internally* controlled stopping rule, as in the present work – and, indeed, the vast majority of research on context-dependent choice.

The focus on external stopping rules may have been motivated in part by limitations in the modelling literature. Several sequential sampling models of preferential choice provide accounts for the development of each context effect over time, including Multialternative Decision Field Theory (MDFT; Roe et al., 2001), the Leaky Competing Accumulator (LCA; Usher & McClelland, 2004), the Associative Accumulation Model (AAM; Bhatia, 2013), and the Multiattribute Linear Ballistic Accumulator (MLBA; Trueblood et al., 2014). All four models generally agree that the attraction and compromise effects increase with time but differ in their predictions of the effect of response time on the similarity effect. Specifically, whereas MDFT and the AAM generally predict that the similarity effect decreases with time, the LCA and the MLBA generally predict it to increase. Testing these accounts by fitting the models to behavioral data with an internal stopping rule, however, can be computationally demanding. Though the MLBA is a computationally simpler model with an analytic solution for both internal and external stopping rules, previous applications of sequential sampling models to response time data have been limited to assuming an external stopping rule in order to make MDFT, the LCA, and the AAM more tractable (Trueblood et al., 2014; Turner, Schley, Muller, & Tsetsos, 2018).

Recently, however, two key advancements have made it possible to fit these models to data while assuming an internal stopping rule. First, Turner & Sederberg (2014) developed the probability density approximation (PDA) method to determine synthetic likelihood functions for models without known analytic solutions. Second, Evans, Holmes, & Trueblood (2019) developed a framework for applying the PDA method to fit MDFT, the LCA, and the AAM along with the MLBA to empirical choice and response time data, with demonstrations across six different studies of context effects. Overall, Evans et al (2019) found that when model fits of choice data were appropriately constrained by response times, the MLBA outperformed MDFT, the LCA, and the AAM. Those results are consistent with the finding that incorporating response times improves the fit of the MLBA to perceptual data (Molloy et al., 2019), and that though it provided weak fits to individual response times, the MLBA outperformed heuristic models in accounting for joint choice and response time data in a preferential choice task (Cohen, Kang, & Leise, 2017).

Although the authors provided demonstrations of each model's ability to predict subject-level choice proportions and response times, their ability to accurately predict the precise relationship between these two measures was less clear; that is, the strength of each context effect as a function of response time – and the ability of each model to account for such relationships – was neither within the scope of their paper nor readily discernable from their presented results. The present work represents that critical next step of more closely examining how well MDFT, the LCA, the AAM, and the MLBA can predict choice behavior as a function of internally-controlled decision time. Specifically, I utilize the code provided on OSF by Evans et al (2019) to determine the extent to which each model can correctly capture (1) the mean choice proportions for each participant, as analyzed by Evans et al (2019); (2) the direction in which preference for each alternative evolves over time for each context; and (3) the crossover in preference for the target and competitor over time for each context.

From a broader theoretical standpoint, the present seeks to determine the extent to which the sequential sampling framework utilized by these models provides a meaningful improvement to their ability to account for choice behavior. Early dynamic choice models extended the basic framework of the Drift Diffusion Model (Ratcliff, 1978), originally developed for perceptual stimuli with fast response times, to account for the effects of response time on preferential choice (e.g., Busemeyer & Townsend, 1993). As discussed, however, utilizing this framework generally comes at significant computational cost. It is therefore critical to assess whether this cost is outweighed by the ability of the models to predict not only stimulus-level response times, but the fine-grained relationship between response times and choice behavior. This is the broader goal of the present work.

Lastly, it is of further note that while Evans et al (2019) provided an impressive range of behavioral data to test their modelling procedure, they also note that the included experiments were limited to domains not traditionally of focus in the study of context effects. That is, though the majority of studies on context effects focus on consumer choice paradigms similar to that of the present work, Evans et al (2019) only examined choice and response time data from studies with either perceptual, inferential, or gambling paradigms. The present work therefore adds important methodological breadth to the experiments analyzed by the previous authors by refocusing this area of study to its traditional domain, consumer choice.

In the following sections, I begin by outlining each model and their accounts of the attraction, compromise, and similarity effects. I then briefly describe the model fitting procedure developed by Evans, Holmes, & Trueblood (2019) and present the best-fitting parameters of each model when applied to data from Cataldo & Cohen (2018b). To preview, consistent with Evans et al (2019), the MLBA provided the best quantitative fits to the data. Importantly, however, the MLBA could not capture the crossover in preference between the target and competitor across RT quantiles; rather, MDFT and the AAM performed best in this regard. I conclude by discussing the implications for future work.

4.1.1 Multialternative Decision Field Theory

MDFT is a sequential sampling model of choice. On every timestep, the participant is assumed to attend to one dimension and the values of the attended dimension are contrasted. These contrasted values are used to update the preference state for each alternative such that the higher or lower a value is relative to the others, the more the preference state increases or decreases, respectively. The alternative with the first preference state to reach a threshold is selected. Two further aspects of the model are important. First, the model specifies a mechanism for forgetting; that is, preference states have some degree of decay back to baseline over time. Second, alternatives can inhibit each other; that is, as the preference state of one alternative increases, it can decrease the preference state of other alternatives. In more recent versions of the model, it is assumed that inhibition increases as two alternatives become more similar (Hotaling, Busemeyer, & Li, 2010).

To demonstrate how MDFT models each context effect, consider again the alternatives depicted in Figure 1. The attraction effect is modeled in MDFT as the result of increased inhibition between similar alternatives. In a choice between the alternatives X, Y, and A_X, negative comparisons between the decoy, A_X, and the target, X, bolster the target but not the more distant competitor, Y. The compromise effect is also modeled as the result of lateral inhibition, this time due to positive correlations between comparisons of the target, X, to the more extreme decoy C_X and competitor Y. Since each of the extreme alternatives is more similar to the target than to each other, comparisons with the target have a greater impact. Further, because comparisons between the target and each of the extreme alternatives are positively correlated, an advantageous comparison for the target inhibits the extreme alternatives (Gigerenzer, 2004; Chapter 7). MDFT models the similarity effect as resulting simply from positively correlated contrasts between each of the similar, non-dominating alternatives, the decoy S_X and competitor Y, and the dissimilar target X. That is, the similar alternatives receive the same advantageous and disadvantageous contrasts, opposite to contrasts involving the target.

MDFT predicts that the attraction and compromise effects will increase over time, including the possibility of a crossover in preference between the target and competitor for both of these contexts (Roe et al., 2001). Lateral inhibition promotes the attraction and compromise effects by bolstering alternatives that dominate nearby alternatives within a given dimension. This bolstering effect increases as the preference states increase over time, resulting in larger attraction and compromise effects with increased deliberation. Though lateral inhibition promotes the attraction and compromise effects, however, it impedes the similarity effect. Lateral inhibition amplifies comparisons between the similar alternatives, equally bolstering their preference states. Over time, the preference states of the similar alternatives exceed that of the dissimilar target, negating or reversing the classic similarity effect. Thus, in contrast to the attraction and compromise effects, MDFT predicts that the similarity effect will decrease with time, however the original paper does not note whether a crossover in preference between the target and competitor is possible (Roe et al., 2001).

Evans et al (2019) made several key changes to MDFT in order to facilitate response time modelling. First, MDFT was converted from its traditional random walk framework to a stochastic differential equation (SDE) framework. Second, a scaling parameter γ was applied to the attended dimension values on each timestep. Third, the duration of time spent attending to each dimension was assumed to be exponentially distributed. Lastly, the standard noise term was replaced with a Wiener process. In total, there are eight free parameters in this implementation of MDFT: the decision threshold a; attention parameters k_1 and k_2 for the first and second dimension, respectively; lateral inhibition ϕ_1; decay ϕ_2; β, which controls the relative impact of dominance over indifference in computing the psychological distance between alternatives; the standard deviation for added noise σ; and a scaling parameter γ. Full details are provided in the original paper (Evans et al., 2019).

4.1.2 The Leaky Competing Accumulator

The LCA is a sequential sampling model of choice in which the participant is assumed to attend to one dimension on every timestep, contrasting the values of the attended dimension. The contrasted values are then used to update the preference state of each alternative such that the higher or lower each value is relative to the others, the more the preference state increases or decreases, respectively. The alternative with the first preference state to reach a threshold is selected. The LCA assumes that loss aversion is a critical mechanism in preferential choice, defined as differential attention to positive and negative differences. Specifically, attention to negative differences, or losses, is defined by a steep and convex function of corresponding positive differences, or gains; thus, negative differences have a greater impact than positive differences of the same magnitude. As in MDFT, alternatives can inhibit each other; unlike MDFT, this inhibition is not distance-dependent.

To demonstrate how the LCA models each context effect, consider again the alternatives depicted in Figure 1. The attraction effect is modeled in the LCA as the result of loss aversion. The relatively distant competitor, Y, is associated with two large negative differences, or "losses", in each of its comparisons with the decoy, A_X, and the target, X; however, the target and the decoy each suffer only one loss of such magnitude. Because the target also dominates the decoy, it is ultimately preferred. The compromise effect is also modeled as the result of loss aversion. The target, X, is associated with two moderate losses in each of its comparisons with the more extreme decoy, C_X, and competitor, Y; however, the extreme alternatives each suffer one moderate and one large loss in their comparisons. The LCA models the similarity effect as resulting simply from positively correlated contrasts between the relatively dissimilar target, X, with each of the more similar alternatives, S_X and Y. That is, the similar alternatives receive the same advantageous and disadvantageous contrasts, which are opposite to the contrasts involving the target. These correlations benefit the target enough to compensate for the impeding effects of loss aversion incurred by its large disadvantageous comparisons with the other alternatives.

The LCA predicts that the attraction, compromise, and similarity effects will all increase with time, including the possibility of a crossover in preference between the target and competitor for all contexts (Marius Usher & McClelland, 2004). The attraction effect is weaker at early timepoints as the decoy shares some of the preference for the target by chance, due to noise in perception of the stimulus values. Over time, the effect of such noise is less impactful. The compromise effect is similarly weaker at early timepoints when fluctuations in the attention switching mechanism have not yet converged on the true probability, resulting in disproportional activation of one dimension over the other, consequently allowing one of the extreme alternatives to dominate in preference. The similarity effect increases over time as the correlated contrasts between the similar alternatives accumulate.

Evans et al (2019) made several key changes to the LCA in order to facilitate response time modelling. As with MDFT, the LCA was converted from its traditional random walk framework to a stochastic differential equation (SDE) framework; the scaling parameter γ was applied to the attended dimension values on each timestep; and the duration of time spent attending to each dimension was assumed to be exponentially distributed. Further, leakage was implemented analogous to the single-dimension LCA (Usher & McClelland, 2001). In total, there are eight free parameters in this implementation of the LCA: the decision threshold a; attention parameters k_1 and k_2 for the first and second dimension, respectively; baseline activation I_0; decay λ; global inhibition β; the standard deviation for added noise σ; and a scaling parameter γ. Full details are provided in the original paper (Evans et al., 2019).

4.1.3 The Associative Accumulation Model

The AAM is a connectionist sequential sampling model of choice that emphasizes the role of dimension values in guiding the information sampling process. Specifically, dimensions that have stronger associative connections with the alternatives in the choice set, i.e., dimensions that have extreme values within one or more alternatives or that are common to several alternatives, will be more highly activated. Such dimensions are therefore more likely to be attended on a given timestep. On each timestep, the values of each alternative in the attended dimension are mapped to "affective values" that are non-negative and increasing for positive dimensions and non-positive and decreasing for negative dimensions. The affective values are then used to update the preference states of each alternative. The alternative with the first preference state to reach a threshold is selected. Like the LCA, alternatives can inhibit each other, but this is not distance-dependent.

To demonstrate how the AAM models each context effect, consider again the alternatives depicted in Figure 1. The AAM models the attraction effect as resulting from the associative connections. The decoy, A_X, and the target, X, are both strongly rated on location, resulting in higher activation for that dimension and, consequently, higher activation for these alternatives over the competitor, Y. Since X dominates A_X, it is ultimately preferred. The compromise effect is similarly modeled as a function of the associative connections. On each dimension, the target, X, benefits from associative connections in each dimension with the more extreme decoy, C_X, and competitor, Y, boosting its overall preference state over the extreme alternatives. The AAM models the similarity effect as resulting from the sequential accumulation of dimension values. That is, the similar alternatives, S_X and Y, receive the same advantageous and disadvantageous contrasts, which are opposite to contrasts involving the more dissimilar target, X. These correlations benefit the target enough to compensate for the impeding effects of its low associative connectivity with the similar alternatives.

The AAM predicts that the attraction and compromise effects will increase with time, including the possibility of a crossover in preference between the target and competitor in the case of the compromise effect but not the attraction effect (Bhatia, 2013). As in the LCA, the attraction effect is weaker at early timepoints when the decoy shares some of the preference for the target by chance, due to noise in perception of the stimulus values. Also following the LCA, the compromise effect is weaker at early timepoints when fluctuations in the attention switching mechanism have not yet converged on the true probability, resulting in disproportional activations of one dimension over the other, consequently allowing one of the extreme alternatives to dominate in preference. In contrast to the LCA, however, the similarity effect is expected to decrease over time. With longer deliberation, more dimensions are activated, leading to greater divergence in the preference states of similar alternatives. The original paper does not predict a crossover in preference between the target and competitor for the similarity effect (Bhatia, 2013).

Evans et al (2019) made several key changes to the AAM in order to facilitate response time modelling. As with MDFT and the LCA, the AAM was converted from its traditional random walk framework to a stochastic differential equation (SDE) framework; the scaling parameter γ was applied to the attended dimension values on each timestep; and the duration of time spent attending to each dimension was assumed to be exponentially distributed (while maintaining the mechanism for dimension activation). Leakage was adjusted in a similar manner to the LCA. In total, there are nine free parameters in this implementation of the AAM: the decision threshold a; attention parameters k_1 and k_2 for the first and second dimension, respectively; k_{scale}, which scales the attention switching duration; subjective mapping parameter α; decay λ; global inhibition β; the standard deviation for added noise σ; and a scaling parameter γ. Full details are provided in the original paper (Evans et al., 2019).

4.1.4 The Multiattribute Linear Ballistic Accumulator

The MLBA is an evidence-accumulation model of choice that separates the choice process into two stages: a front-end stage in which the rates of evidence accumulation are determined based on stimulus characteristics, and a back-end stage that uses these rates to drive a decision process. In the front-end stage, raw stimulus values are first transformed into subjective values such that alternatives with more dispersed dimension values are penalized. Alternatives are then compared by computing the pairwise differences of these subjective values within a dimension. Positive and negative differences are differentially weighted as a function of their magnitude, such that smaller differences are weighted more heavily. These differences are then used to compute the accumulation drift rate for each alternative. In the back-end stage, these rates drive accumulators towards a response threshold. The accumulators are "ballistic", or deterministic; that is, they accumulate without moment-by-moment noise. The alternative associated with the first accumulator to reach a response threshold is selected.

To demonstrate how the MLBA models each context effect, consider again the alternatives depicted in Figure 1. The MLBA models the attraction effect as the result of greater weight placed on smaller differences, conferring a larger advantage on the target, X, which dominates the nearby decoy A_X, relative to the competitor, Y, which is distant to both X and A_X. The compromise effect is modeled as a result of the subjective utility mapping, which penalizes the extreme decoy, C_X, and competitor, Y, whose dimension values are more highly dispersed than those of the target, X. The compromise effect is further supported by the short distance between the target and each of the extreme alternatives. As a result, comparisons involving the target carry more weight than comparisons strictly between the extreme alternatives.

Because the MLBA does not include a sequential sampling process, it is unique among the models discussed here in that it does not model the similarity effect as the result of positive correlations between the similar alternatives. Instead, the MLBA models the similarity effect as resulting from a greater weight for positive differences than negative differences. In Figure 1, the relatively dissimilar target, X, has two large positive differences and two large negative differences resulting from its comparisons with each of the other alternatives. The more similar competitor, Y, and decoy, S_X, each have one large negative difference and one large positive difference from their comparisons with the target, but also one small positive difference and one small negative difference from comparisons with each other. If the large positive differences afforded to the dissimilar alternative outweigh the two large negative differences, then the target will benefit most from the comparison process because of its higher-magnitude differences relative to the similar alternatives. The model's authors suggest that the unequal weights represent a mechanism for "confirmation bias" in which decision-makers are likely to give greater weight to positive differences garnered by alternatives that are presumably already recognized as strong in a particular dimension.

Like the LCA, the MLBA predicts that the attraction, compromise, and similarity effects will all increase over time. However, it is critical to note that the MLBA is computationally limited to predicting only increasing differences between alternatives over time with no crossover in preference. That is, because each preference state evolves at a strictly positive and linear rate, any differences between alternatives present at early timepoints necessarily get larger as deliberation continues. In fact, differences in preference can only become smaller between two time points if the points occur before a crossover point of the two evolving preference states, at which point they would begin to differentiate once again. Such a crossover requires a precise combination of parameter values in the back-end LBA framework. Specifically, to produce the crossover effect, one accumulator must have a high starting value and low drift rate while the other has a low starting value and high drift rate. Since the starting values are sampled from a uniform distribution, this combination is difficult to produce reliably, so much so that the preference reversals observed in the present data are impossible to produce in the aggregate.

Evans et al (2019) made only one change to the MLBA, which was to apply the scaling parameter γ to the dimension values on each timestep. In total, there are nine free parameters in this implementation of the MLBA: maximum starting preference A; the distance from A to the decision threshold b; non-decision time t_0; baseline accumulation rate I_0; decay for positive differences λ_1; decay for negative differences λ_2; dimension weight β; subjective mapping parameter m; and a scaling parameter γ. Full details are provided in the original paper (Evans et al., 2019).

4.2 Method

4.2.1 Behavioral Data

The models were fit to data from Experiment A, previously published by Cataldo & Cohen (2018b). Experiment A has a much larger sample size and a much simpler experimental design than Experiments B-E, with entirely within-subject manipulations and only one product category (apartments). Though the same qualitative pattern of conditional choice proportions across response time quantiles is observed in both presentation format conditions, for simplicity, I only fit the data from the By-Dimension condition. Note that this condition more closely matches the general assumption of most models that choice information is evaluated through pairwise comparisons between alternatives within each dimension. Further, the effect of deliberation time on preference is quantitatively strongest in this condition, making it the best candidate to exert sufficient pressure on the models to produce the correct qualitative pattern.

The original publication noted that due to a coding error, 227 participants were not exposed to all stimuli in a theoretically irrelevant experimental condition (overall expected value of the choice set). Though there are no qualitative differences between these and the remaining participants, to keep a balanced design, Experiment A includes only those 209 participants who received the full stimulus set. The data for each participant consists of 72 test trials from the By-Dimension condition, including two target conditions (D_X and D_Y), two expected values (2 and 3), three contexts (attraction, compromise, and similarity), and six alternative orderings. All test trials consisted of a choice set with three alternatives (target, competitor, and decoy). Further methodological details can be found in Cataldo & Cohen (2018b). Following treatment of Experiment 4 in Evans et al (2019), which is methodologically most similar to the present data, two trials with a response time greater than 40 seconds were excluded from analyses.

4.2.2 Estimation Procedure

The data were fit using the code provided by Evans et al (2019) on OSF (https://osf.io/h7e6v/; downloaded May 3, 2019). Specifically, the trial-level data are fit to SDE versions of MDFT, the LCA, the AAM, and the MLBA to trial-level data using a Bayesian hierarchical framework in which subject-level parameters are sampled from group-level distributions. Further details on priors and the hierarchical structure can be found in the original paper. Parameters are estimated using differential evolution Markov chain Monte Carlo sampling (DE-MCMC; Turner, Sederberg, Brown, & Steyvers, 2013) with 3*k* chains, where *k* is the number of free parameters per participant, with 2500 burn-in steps followed by 1000 saved steps. Note that based on diagnostic plotting, I elected to apply a longer burn-in period than that of Evans et al (2019) in order to ensure that convergence had been achieved. Following treatment of Experiment 4 in Evans et al (2019), which is methodologically most similar to the present data, a 100ms timestep was assumed for response times.

Whereas an analytic solution exists for the MLBA, likelihood functions for MDFT, the LCA, and the AAM have not been derived for an internal stopping rule. Thus, the probability density approximation (PDA) method developed by Turner & Sederberg (2014) is utilized to determine synthetic likelihood functions for these models. In brief, on each step the PDA method samples a set of parameters and simulates a large number of trials (10,000 in the present application) from the model with those parameters. For each possible choice response, the likelihood of the response time data is computed using kernel density estimation. That likelihood is then scaled by the proportion of times the given choice response was made in the simulated data. Full details are provided in Turner & Sederberg (2014).

Predictions were generated from each model by sampling 50 evenly-spaced steps from the posterior distribution, then for each sampled step, simulating the full experiment for 209 synthetic participants from the associated parameter values. The aggregation method was the same as for the experimental data presented in Figure 27. That is, RT quantiles were calculated for each synthetic participant, collapsing over experimental factors. The choice proportions were then conditioned on RT quantile and context for each synthetic participant, then averaged.

4.3 Results

The present work seeks to determine the extent to which each model can correctly capture (1) the mean choice proportions for each participant, as analyzed by Evans et al (2019); (2) the direction in which preference for each alternative evolves over time for each context; and (3) the crossover in preference states for the target and competitor over time for each context. First, consider the mean choice proportions and response times within each context presented in Figure 28. The MLBA is best able to capture the mean choice proportions, whereas the remaining models appear to have difficulty capturing the low preference for the decoy in the compromise and similarity effects. All models appear equally able to capture the mean response times, however here all models have difficulty capturing the fast response times for the compromise and similarity decoys.

Next, consider the subject-level choice proportions within each context plotted against the corresponding predictions from MDFT, the LCA, the AAM, and the MLBA presented in Figure 29. The closer the points are to the diagonal line, the better the model is capturing the data. The results are qualitatively very similar to that of Evans et al (2019). All models do a good job of capturing the mean choice proportions in the attraction context, but only the MLBA performs adequately in the compromise and similarity context. Note, however, that the MLBA does appear to perform slightly worse fitting the present data than in some of the experiments presented in the original paper, possibly due to domain differences. Figure 30 presents the subject-level response time quantiles for each alternative within each context plotted against the corresponding predictions from each model. Again, the closer the points are to the diagonal line, the better the model is capturing the data. All models appear to perform equally well in capturing the response time quantiles for each participant.

All results presented up until now have constituted replications of the results presented in Evans et al (2019). However, as previously stated, these results do not make clear the extent to which the tested models can account for the precise nature of the relationship between choice and response time. With that goal in mind, we now turn to a novel analysis of the predicted choice probabilities for each model conditioned on context and predicted RT quantile, presented in Figure 31. Consistent with the patterns presented in Figure 29, the MLBA appears to best fit the subject-level mean choice proportions. Notably, only the MLBA and the AAM appear able to sufficiently capture how rarely subjects choose the decoy in the compromise context, and only the MLBA is able to capture the low preference for the decoy in the similarity context.

Importantly, however, MDFT and the AAM best capture the qualitative relationship between choice and response time seen in the present data. For the attraction context, only these two models are able to capture the direction in which preference for each alternative changes over time, with increasing preference for the target and decreasing preference for the competitor across RT quantiles. Though the increase is quantitatively best fit by MDFT, only the AAM captures the crossover in preference. For the compromise context, all models are all able to capture the increasing preference for the target and decreasing preference for the competitor across RT quantiles; again, however, only the AAM predicts a slight crossover in preference for the target and competitor. For the similarity context, MDFT and the MLBA are both able to capture the decreasing preference for the target and increasing preference for the competitor. Here, only MDFT is able to capture the crossover in preference for the target and competitor; in the MLBA, the target is consistently preferred across RT quantiles.

The median and 95% highest density interval (HDI) of the log-likelihood and parameter values for each model are presented in Table 9. The log-likelihoods were calculated by summing across subjects for each step in the posterior distribution of each model. The MLBA has the greatest median value (-36,374.72), followed by the LCA (-39,750.59), MDFT (-40,141.91), and the AAM (-41,064.24). Evans et al. (2019) note poor parameter recovery for all of the tested models, consequently cautioning against interpreting the best-fitting parameters. Given that caution, and given that, as in Evans et al. (2019), the focus of the present work is on the ability of the models to recover the data, I repeat that caution here and limit discussion of the recovered parameters. The parameter values are, however, provided. Briefly, note that all models are able to capture the slight bias for the first dimension, location[2]. The MLBA fits suggest greater weight on negative differences than positive differences, producing the reverse similarity effect. The subjective mapping parameter for the MLBA is fairly symmetric around convexity (preferring alternatives with high dispersion) and concavity (preferring alternatives with low dispersion). The MDFT fits suggest low inhibition and moderate decay, whereas the LCA and the AAM fits suggest high inhibition and moderate decay.

[2] Equations 19, 20, 33, 34, 54, and 55 in Evans et al (2019) suggest that greater k_1 and k_2 values correspond to a greater probability of switching *away from* dimensions 1 and 2, respectively. In the provided code, and perhaps more intuitively, the opposite is true; thus, the greater k_1 values in Table 9 reflect greater probability to switch *to* dimension 1, i.e., a greater bias for dimension 1 than dimension 2.

4.4 Discussion

Context effects such as the attraction (Huber et al., 1982), compromise (Simonson, 1989), and similarity (Tversky, 1972) effects constitute a well-studied set of behavioral phenomena that often serve as critical benchmarks in models of decision-making. Recent research on the role of the comparison process in producing context effects suggests that the similarity effect may be associated with faster response times whereas the attraction and compromise effects may be associated with slower response times (Cataldo & Cohen, 2018b). The present work presents a reanalysis of these data, along with data from four previously unpublished studies ranging widely in stimulus representation, supporting that claim (Figure 27). Specifically, while preference for the target alternative increases with response time in the attraction and compromise contexts, it decreases with response time in the similarity context. These results represent a critical contribution to previous studies of response time and context effects, which until now have almost exclusively focused on time pressure manipulations (Dhar et al., 2000; Pettibone, 2012; Trueblood et al., 2014).

Utilizing state-of-the-art code developed by Evans, Holmes, and Trueblood (2019), and based on Turner & Sederberg (2014), four models of preferential choice were applied to a balanced subset of the data from Cataldo & Cohen (2018b). All four models propose clear theoretical accounts for the effect of response time on the attraction, compromise, and similarity effects. In MDFT (Roe et al., 2001), inhibitory connections facilitate competition such that similar alternatives are more highly competitive than dissimilar alternatives. In the LCA (Usher & McClelland, 2004), preference is largely driven by loss aversion, such that disadvantageous comparisons matter more in preference formation than advantageous ones. In the AAM (Bhatia, 2013), associative connections between alternatives increase the activation of dimensions that are strongly represented in the choice set. In the MLBA (Trueblood et al., 2014), alternatives with highly dispersed dimension values are penalized, small differences between alternatives have greater impact than large differences, and confirmation bias provides an additional reward to alternatives with advantageous comparisons. All four models predict that the attraction and compromise effects will increase with increased response time but differ in their predictions for the similarity effect. That is, while MDFT and the AAM predict that the similarity effect will decrease with increase response time, the LCA and the MLBA predict that it will increase.

Consistent with Evans et al (2019), the MLBA provided the best fits to the subject-level mean choice proportions. The importance of context effects in the literature, however, is rooted in their representativeness as deviations from “rational” choice behavior (e.g., Roe et al., 2001). Consequently, determining the scenarios in which these effects (or their reversals) do and do not occur is as important to theory building as successfully capturing their magnitude. The present data constitutes strong evidence that the attraction and compromise effects are associated with slower response times, whereas the similarity effect is associated with faster response times. The MLBA was not able to capture this qualitative pattern; rather, MDFT and the AAM performed best in this regard. Only MDFT was able to correctly capture the direction in which preferences evolved over time for all three contexts, and it was further the only model to capture the crossover in preference for the target and competitor in the similarity context. The AAM, however, was the only model to capture the crossover in preference in the attraction and compromise contexts.

Importantly, despite the success of the models in fitting individual components of the data, none of the models performed particularly well overall. No one model was able to capture the crossover in preferences in all three contexts, and those that came close – MDFT and the AAM – had poor quantitative fits. It is possible that these quantitative shortcomings, specifically their overestimation of preference for the compromise and similarity decoys, might be addressed by adding a subjective mapping function to these models such as the one applied in the MLBA, which penalizes alternatives with highly dispersed dimension values. Previous work has applied a similar subjective mapping function to versions of MDFT with mixed success (Cataldo & Cohen, 2018a; Cohen et al., 2017; Evans et al., 2019), which future work might explore further.

It is also possible that additional models not tested in either the present work or that of Evans et al (2019) may provide viable accounts of the development of context effects over time. Multialternative Decision by Sampling (MDbS; Noguchi & Stewart, 2018) is a recently developed model in which the decision process as is comprised of a series of within-dimension pairwise comparisons between available alternatives and any other alternatives in working memory. MDbS does, however, predict that all three context effects will increase with increased deliberation time, in contrast to the present findings. Additionally, the Models of Attentional Sampling (Cohen et al., 2017) family of models, though not previously tested with context effects, is designed with response times and attentional deployment explicitly in mind. Thus, it constitutes a potentially interesting account of the present data, particularly as it varies across presentation format. Further development of these models is needed to test them in the present framework.

Regardless, none of the tested models in their present forms appear to provide a full account of the relationship between choice and response time. This calls into serious question whether the sequential sampling framework provides enough psychological insight to outweigh its high computational cost. Rather, it is possible that preferential choice represents a decision process that is too qualitatively distinct from the perceptual scenarios in which such models have traditionally found success. Indeed, the present data raise the possibility that a mixture of heuristic and deliberative processes are involved, in which case trying to fit the entire set of response time data with a single parsimonious process may not be useful. Future work in model development might therefore seriously consider taking a step back to determine how best to build a tractable model that still captures the critical relationship between choice and response time.

In a critical step towards that goal, the present work extends that of Evans et al (2019) by presenting data from consumer choice, the domain in which context effects have historically been studied. Notably, it is unclear how well the present results might generalize to non-consumer domains. For instance, consider the choice proportions conditioned on context and response time quantile from experiments E2 and E4 from Evans et al (2019), which consist of data from perceptual and inference-based choice paradigms, respectively (Figure 32). The results are generally consistent with the present findings, but mixed, suggesting that the present results might not emerge in all choice tasks. It is worth noting that the average response times in these experiments (1.28 and 7.32 for E2 and E4, respectively) differed greatly from that of Experiment A (3.59), further suggesting that these differences might reflect distinctions between the decision processes engaged by each task.

An important question for future research, then, is what psychological mechanisms or choice set characteristics associated with response times might lead to standard, null, or reverse context effects. Task difficulty, broadly construed, is a classic choice set characteristic thought to lead to increased response times, and served as an early theoretical account of the attraction and compromise effects (e.g., Simonson, 1989). In the present data, a By-Dimension presentation format produced increased response times as well as more positive attraction and compromise effects, whereas a By-Alternative presentation format produced decreased response times and a more positive similarity effect. Presentation format is thought to differentially facilitate the three context effects by differentially highlighting dimension- and alternative-level stimulus characteristics, and it is possible that increased focus on dimension-level characteristics increases the difficulty of the choice task. Future work is needed to test this account.

Identifying the psychological mechanisms that may plausibly be driving the observed pattern of effects is a much more difficult task, but precisely the one that the present models were developed to tackle. The parameter recovery exercise conducted by Evans et al. (2019) unfortunately resulted in poor performance for all four models, thereby restricting our ability to interpret best-fitting parameter values. As stated, the primary goal of the present work was to test the ability of the models to recover the data, independent of parameter recovery. Regardless, the ability of a model to recover data is less meaningful if it does not aid in revealing the critical psychological processes. Thus, the goal of future modelling work is to not only work towards developing choice models that can sufficiently capture both the quantitative and qualitative patterns in the data, but to further provide a reliable theoretical account of such patterns in preferential choice.

CHAPTER 5

GENERAL DISCUSSION

The attraction, compromise, and similarity effects are critical phenomena in preferential choice in which the availability of an irrelevant alternative can alter preferences among competitive alternatives (Huber et al., 1982; Simonson, 1989; Tversky, 1972). Such context-dependent behaviors are of significant psychological interest because they serve as key examples of how the decision process can deviate from the principles of rational choice. Further, applied research in marketing and consumer behavior has demonstrated that context effects can generalize to non-laboratory settings, suggesting an impact on everyday decisions such as grocery shopping (Doyle, O'Connor, Reynolds, & Bottomley, 1999), online purchases of electronics (Lichters, Bengart, Sarstedt, & Vogt, 2017), and selections from a restaurant menu (Pinger, Ruhmer-Krell, & Schumacher, 2016). Thus, understanding the circumstances in which these effects do and do not occur is of both practical and theoretical importance.

Previous research has found that the attraction and compromise effects tend to be positively correlated with each other but negatively correlated with the similarity effect (Berkowitsch et al., 2014; Liew et al., 2016; Trueblood et al., 2015). Work by Chang & Liu (2008) and Cataldo & Cohen (2018a; 2018b) suggests that a flexible comparison process may be a key mechanism underlying these correlations. Specifically, whereas the compromise effect is facilitated by a presentation format encouraging within-dimension comparisons and impeded by a format encouraging within-alternative comparisons (Cataldo & Cohen, 2018b; Chang & Liu, 2008), the opposite is found for the similarity effect (Cataldo & Cohen, 2018a; Cataldo & Cohen, 2018b).

Together, these studies suggest that the attraction, compromise, and similarity effects are facilitated by distinct stimulus properties. In the case of the attraction and compromise effects, classic dimension-level stimulus properties such as extremeness, dominance, and dimension-level similarity may play a primary role as theorized by popular models (e.g., Bhatia, 2013; Noguchi & Stewart, 2018; Roe et al., 2001; Trueblood et al., 2014; Usher & McClelland, 2004). In the case of the similarity effect, traditionally less-emphasized alternative-level stimulus properties such as dispersion and alternative-level similarity may be key.

The primary goal of the present work was to better characterize the relationship between information acquisition and each of the three context effects. Experiment 1 aimed to clarify the dimension- and alternative-level stimulus properties underlying each effect. Results from Experiment 1 suggest that increasing a dimension-level property, spread, promotes the attraction and compromise effects and reduces the similarity effect, whereas increasing an alternative-level property, dispersion, introduces an alternative-level bias that influences choice in concert with the decoy. Thus, Experiment 1 extends previous work by providing specific evidence for the critical role that a flexible comparison process appears to play in preferential choice. Modulating the decision-maker's ability to compare choice information within alternatives or within dimensions facilitates the perception of alternative- and dimension-level stimulus properties, respectively, resulting in differential patterns of context effects.

Experiment 2 utilized eyetracking to test the influence of stimulus presentation format on information acquisition patterns and context-dependent choice behavior. Though Experiment 2 generally replicates the choice and response time results from

Experiment 1, the eyetracking data suggest that contrary to predictions, a By-Alternative presentation format increases within-dimension transitions in eye fixations relative to a By-Dimension presentation format. Further exploration of the effect of the graphical representation of stimuli on parafoveal information-gathering may be needed to fully reconcile these results.

The results of Experiments 1 and 2 demonstrated an additional intriguing and robust relationship between choice and response time across the attraction, compromise, and similarity contexts that appears independent of presentation format, in which the probability of choosing the target alternative increases over time for the attraction and compromise effects but decreases over time for the similarity effect. To determine possible theoretical accounts for this pattern of results, I fit four sequential sampling models of context effects to methodologically simpler data previously published in Cataldo & Cohen (2018b). Specifically, MDFT (Roe et al., 2001), the MLCA (Usher & McClelland, 2004), the AAM (Bhatia, 2013), and the MLBA (Trueblood et al., 2014) were fit utilizing state-of-the-art methodology developed by Turner & Sederberg (2014) and Evans, Holmes, & Trueblood (2019). Consistent with previous research (Evans et al., 2019), the MLBA provided the best fits to the subject-level mean choice proportions. Importantly, however, it could not capture the robust crossover in preference between the target and competitor across RT quantiles; rather, MDFT and the AAM performed best in this regard.

The present work not only provides new insights into the relationship between choice and response times in preferential choice but sets important new constraints for theoretical models that seek to account for such behavior. That is, despite the success of the models in fitting individual components of the data, none of the tested models were able to account for the full spectrum of results. This calls into serious question whether the sequential sampling framework provides enough psychological insight to outweigh its high computational cost. Rather, it is possible that preferential choice represents a decision process that is qualitatively distinct from the perceptual scenarios in which such models have traditionally found success. As such, future work in model development might seriously consider taking a step back to determine how best to build a tractable model that still captures the critical relationship between choice and response time.

Several important insights drawn from the present research might be used to construct a general framework. First, strong alternative- and dimension-level biases likely play a key role in the development of context effects over time. That is, a decision-maker who strongly prefers a given dimension will likely choose whatever alternative performs best in that dimension, and a decision-maker who is strongly averse to tradeoffs will likely choose whatever alternative has the lowest dispersion. Because relatively little computation is necessary in these cases, such decisions would likely be made quickly, as seen in the present work.

In this framework, the attraction effect likely occurs when the dominance relationship between the target and decoy is detected. This is less likely to occur in early bias-driven response times, producing a reversal of the attraction effect in the form of a classic “split-the-vote” similarity effect, in which the target and decoy are perceived as categorically equal. The compromise effect likely emerges when both dimensions are equally preferred, dispersion is of low importance, and aversion to losses in either dimension increases the attractiveness of the target.

Interestingly, the similarity effect might be viewed in this framework as the opposite of either the attraction or compromise effects. That is, the similarity effect likely *reverses* when a distinction between the competitor and decoy is detected. As with the attraction effect, this is less likely to occur in early bias-driven response times, producing the classic “split-the-vote” similarity effect. In later response times, the similarity decoy may be perceived as inferior to the competitor for having higher dispersion, producing a classic attraction effect, or avoided for incurring a “loss” on one of the dimensions, producing a classic compromise effect. Thus, the similarity effect may be negatively correlated with the attraction and compromise effects simply because the similarity decoy is adjacent to the competitor rather than the target. Such an account is less psychologically interesting than assuming that the similarity effect is produced by a distinct mechanism, but may represent an important theoretical simplification for models of preferential choice.

Table 1: Mean posterior estimates and 95% HDIs for choice proportions by format, target, context, product category, and stimulus set in Experiment 1.

By-Alternative		P(X)			P(Y)			P(D)		
Factor	Level	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High
Target	X	0.423	0.418	0.429	0.411	0.406	0.416	0.165	0.161	0.169
	Y	0.425	0.419	0.429	0.422	0.416	0.426	0.154	0.149	0.158
Context	Attraction	0.451	0.445	0.457	0.447	0.441	0.453	0.102	0.097	0.107
	Compromise	0.434	0.428	0.440	0.429	0.424	0.436	0.136	0.132	0.141
	Similarity	0.387	0.380	0.393	0.373	0.366	0.379	0.240	0.234	0.247
Product	Apartments	0.484	0.478	0.491	0.366	0.359	0.372	0.150	0.145	0.156
	Cars	0.291	0.285	0.297	0.553	0.547	0.559	0.156	0.150	0.161
	Laptops	0.497	0.491	0.503	0.330	0.324	0.336	0.173	0.167	0.178
Set	Baseline	0.429	0.422	0.437	0.399	0.392	0.407	0.171	0.164	0.177
	x2 Spread	0.453	0.446	0.459	0.469	0.461	0.476	0.078	0.074	0.083
	Lo-Disp. X	0.542	0.535	0.549	0.261	0.254	0.268	0.197	0.189	0.203
	Lo-Disp. Y	0.272	0.264	0.278	0.537	0.530	0.544	0.192	0.185	0.198

By-Dimension		P(X)			P(Y)			P(D)		
Factor	Level	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High
Target	X	0.430	0.426	0.435	0.387	0.382	0.392	0.182	0.178	0.186
	Y	0.387	0.382	0.393	0.440	0.435	0.445	0.172	0.169	0.177
Context	Attraction	0.465	0.459	0.471	0.469	0.464	0.476	0.065	0.061	0.069
	Compromise	0.406	0.399	0.412	0.407	0.401	0.414	0.187	0.182	0.192
	Similarity	0.356	0.350	0.362	0.364	0.357	0.370	0.279	0.274	0.285
Product	Apartments	0.469	0.462	0.475	0.381	0.375	0.388	0.151	0.146	0.156
	Cars	0.290	0.285	0.296	0.537	0.531	0.543	0.173	0.169	0.178
	Laptops	0.468	0.462	0.473	0.324	0.318	0.329	0.208	0.204	0.213
Set	Baseline	0.401	0.394	0.409	0.408	0.401	0.415	0.190	0.185	0.196
	x2 Spread	0.440	0.434	0.448	0.436	0.428	0.443	0.124	0.119	0.128
	Lo-Disp. X	0.509	0.503	0.517	0.291	0.285	0.299	0.199	0.193	0.204
	Lo-Disp. Y	0.284	0.278	0.291	0.519	0.512	0.527	0.196	0.191	0.202

Table 2: Mean posterior estimates and 95% HDIs for ΔPX and ΔPY, broken down by format, context, and choice set in Experiment 1.

			ΔP_X			ΔP_Y		
Presentation Format	Context	Choice Set	M	HDI Low	HDI High	M	HDI Low	HDI High
By-Alt.	A	Baseline	-0.065	-0.090	-0.037	-0.048	-0.076	-0.023
		x2 Spread	-0.009	-0.032	0.016	0.014	-0.009	0.037
		Lo-Disp. X	-0.097	-0.125	-0.071	-0.009	-0.033	0.014
		Lo-Disp. Y	-0.006	-0.029	0.021	-0.074	-0.099	-0.045
	C	Baseline	-0.098	-0.123	-0.072	-0.094	-0.121	-0.069
		x2 Spread	-0.067	-0.092	-0.042	-0.017	-0.042	0.009
		Lo-Disp. X	-0.200	-0.225	-0.175	0.018	-0.005	0.041
		Lo-Disp. Y	-0.024	-0.049	-0.002	-0.199	-0.223	-0.172
	S	Baseline	0.131	0.105	0.158	0.139	0.112	0.165
		x2 Spread	0.094	0.069	0.119	0.085	0.059	0.108
		Lo-Disp. X	0.303	0.277	0.333	0.015	-0.010	0.037
		Lo-Disp. Y	0.023	0.001	0.049	0.296	0.270	0.322
By-Dim.	A	Baseline	0.105	0.081	0.128	0.108	0.085	0.134
		x2 Spread	0.116	0.095	0.142	0.132	0.109	0.158
		Lo-Disp. X	0.126	0.104	0.152	0.163	0.142	0.188
		Lo-Disp. Y	0.084	0.060	0.107	0.061	0.037	0.085
	C	Baseline	-0.083	-0.109	-0.059	-0.061	-0.087	-0.037
		x2 Spread	-0.018	-0.041	0.008	0.036	0.009	0.059
		Lo-Disp. X	-0.131	-0.157	-0.109	0.016	-0.007	0.039
		Lo-Disp. Y	-0.036	-0.056	-0.010	-0.105	-0.131	-0.081
	S	Baseline	0.109	0.083	0.134	0.088	0.060	0.113
		x2 Spread	-0.002	-0.027	0.023	-0.027	-0.054	-0.004
		Lo-Disp. X	0.181	0.153	0.205	0.009	-0.014	0.035
		Lo-Disp. Y	0.062	0.041	0.086	0.214	0.188	0.240

Notes: $\Delta P_X = P(X \mid X, Y, D_X)-P(X \mid X, Y, D_Y)$, $\Delta P_Y = P(Y \mid X, Y, D_Y)-P(Y \mid X, Y, D_X)$. A, C, and S refer to the Attraction, Compromise, and Similarity contexts, respectively.

Table 3: Mean posterior estimates and 95% HDIs for response times by format, target, context, product category, and choice set in Experiment 1.

Presentation Format	Factor	Level	M	HDI Low	HDI High
By-Alternative	Target	X	2.239	2.217	2.259
		Y	2.251	2.223	2.276
	Context	Attraction	2.234	2.211	2.257
		Compromise	2.225	2.203	2.249
		Similarity	2.276	2.252	2.299
	Product	Apartments	2.408	2.375	2.440
		Cars	2.298	2.269	2.329
		Laptops	2.030	2.004	2.056
	Choice Set	Baseline	2.305	2.276	2.336
		x2 Spread	2.330	2.300	2.360
		Lo-Disp. X	2.189	2.161	2.217
		Lo-Disp. Y	2.157	2.125	2.186
By-Dimension	Target	X	2.377	2.356	2.397
		Y	2.382	2.360	2.403
	Context	Attraction	2.361	2.337	2.384
		Compromise	2.377	2.355	2.399
		Similarity	2.400	2.378	2.423
	Product	Apartments	2.691	2.657	2.727
		Cars	2.224	2.198	2.248
		Laptops	2.223	2.193	2.253
	Choice Set	Baseline	2.341	2.313	2.368
		x2 Spread	2.559	2.524	2.597
		Lo-Disp. X	2.339	2.312	2.367
		Lo-Disp. Y	2.278	2.250	2.306

Table 4: Mean posterior estimates and 95% HDIs for choice proportions by format, target, context, and choice set in Experiment 2.

By-Alternative		P(X)			P(Y)			P(D)		
Factor	Level	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High
Target	X	0.415	0.405	0.424	0.428	0.418	0.438	0.157	0.149	0.166
	Y	0.387	0.378	0.397	0.452	0.442	0.462	0.160	0.152	0.169
Context	Attraction	0.432	0.421	0.445	0.470	0.458	0.483	0.097	0.088	0.107
	Compromise	0.414	0.402	0.426	0.455	0.443	0.467	0.130	0.122	0.139
	Similarity	0.357	0.344	0.369	0.395	0.382	0.407	0.249	0.237	0.261
Set	Baseline	0.389	0.375	0.403	0.442	0.427	0.457	0.169	0.156	0.182
	x2 Spread	0.405	0.392	0.418	0.499	0.487	0.514	0.095	0.086	0.104
	Lo-Disp. X	0.567	0.552	0.582	0.254	0.239	0.267	0.179	0.167	0.192
	Lo-Disp. Y	0.243	0.230	0.256	0.565	0.549	0.579	0.192	0.180	0.205
By-Dimension		**P(X)**			**P(Y)**			**P(D)**		
Factor	Level	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High
Target	X	0.466	0.456	0.477	0.380	0.370	0.392	0.154	0.145	0.161
	Y	0.414	0.403	0.425	0.439	0.429	0.451	0.147	0.138	0.155
Context	Attraction	0.469	0.456	0.483	0.443	0.430	0.457	0.087	0.078	0.096
	Compromise	0.451	0.437	0.464	0.430	0.416	0.444	0.119	0.109	0.127
	Similarity	0.399	0.386	0.412	0.357	0.344	0.369	0.245	0.232	0.257
Set	Baseline	0.438	0.421	0.454	0.406	0.390	0.422	0.156	0.144	0.168
	x2 Spread	0.472	0.457	0.487	0.439	0.424	0.454	0.089	0.079	0.099
	Lo-Disp. X	0.585	0.569	0.602	0.237	0.223	0.252	0.178	0.165	0.190
	Lo-Disp. Y	0.265	0.251	0.279	0.558	0.542	0.574	0.178	0.166	0.190

Table 5: Mean posterior estimates and 95% HDIs for ΔPX and ΔPY, broken down by format, context, and choice set in Experiment 2.

			ΔP_X			ΔP_Y		
Presentation Format	Context	Set	M	HDI Low	HDI High	M	HDI Low	HDI High
By-Alt.	A	Baseline	-0.002	-0.051	0.046	-0.028	-0.077	0.023
		x2 Spread	0.098	0.052	0.142	0.069	0.024	0.117
		Lo-Disp. X	-0.086	-0.138	-0.036	0.013	-0.033	0.059
		Lo-Disp. Y	-0.032	-0.079	0.015	-0.137	-0.194	-0.084
	C	Baseline	-0.029	-0.080	0.021	-0.045	-0.098	0.008
		x2 Spread	-0.012	-0.059	0.034	0.016	-0.031	0.064
		Lo-Disp. X	-0.141	-0.190	-0.092	0.022	-0.027	0.067
		Lo-Disp. Y	-0.023	-0.066	0.022	-0.188	-0.238	-0.139
	S	Baseline	0.134	0.083	0.183	0.198	0.146	0.251
		x2 Spread	0.058	0.012	0.105	0.087	0.037	0.136
		Lo-Disp. X	0.278	0.226	0.334	0.001	-0.043	0.049
		Lo-Disp. Y	0.081	0.039	0.126	0.281	0.228	0.335
By-Dim.	A	Baseline	0.057	0.003	0.111	0.036	-0.019	0.087
		x2 Spread	0.196	0.146	0.245	0.175	0.124	0.224
		Lo-Disp. X	-0.005	-0.063	0.051	0.085	0.034	0.137
		Lo-Disp. Y	0.057	0.008	0.107	-0.068	-0.123	-0.014
	C	Baseline	0.013	-0.046	0.069	0.091	0.033	0.148
		x2 Spread	0.057	0.003	0.115	0.110	0.055	0.163
		Lo-Disp. X	-0.088	-0.144	-0.034	0.072	0.024	0.122
		Lo-Disp. Y	0.093	0.045	0.144	0.029	-0.027	0.084
	S	Baseline	0.097	0.041	0.151	0.059	0.002	0.114
		x2 Spread	-0.065	-0.114	-0.013	-0.058	-0.109	-0.007
		Lo-Disp. X	0.228	0.173	0.287	-0.043	-0.089	0.005
		Lo-Disp. Y	-0.009	-0.056	0.037	0.228	0.169	0.283

Notes: $\Delta P_X = P(X \mid X, Y, D_X) - P(X \mid X, Y, D_Y)$, $\Delta P_Y = P(Y \mid X, Y, D_Y) - P(Y \mid X, Y, D_X)$. A, C, and S refer to the Attraction, Compromise, and Similarity effects, respectively.

Table 6: Mean posterior estimates and 95% HDIs for response times by format, target, context, and choice set in Experiment 2.

Presentation Format	Factor	Level	M	HDI Low	HDI High
By-Alternative	Target	X	2.708	2.674	2.741
		Y	2.711	2.678	2.744
	Context	Attraction	2.710	2.677	2.745
		Compromise	2.706	2.673	2.740
		Similarity	2.712	2.679	2.746
	Set	Baseline	2.703	2.654	2.753
		x2 Spread	2.895	2.835	2.959
		Lo-Disp. X	2.628	2.579	2.678
		Lo-Disp. Y	2.611	2.559	2.662
By-Dimension	Target	X	3.006	2.972	3.039
		Y	3.007	2.973	3.039
	Context	Attraction	3.004	2.969	3.037
		Compromise	3.007	2.974	3.042
		Similarity	3.008	2.974	3.043
	Set	Baseline	2.997	2.946	3.049
		x2 Spread	3.181	3.125	3.243
		Lo-Disp. X	2.948	2.898	2.997
		Lo-Disp. Y	2.900	2.849	2.951

Table 7: Mean posterior estimates and 95% HDIs for number of eyetracking fixations by format, target, context, and choice set in Experiment 2.

Presentation Format	Factor	Level	M	HDI Low	HDI High
By-Alternative	Target	X	11.467	11.362	11.576
		Y	11.617	11.507	11.723
	Context	Attraction	11.533	11.402	11.656
		Compromise	11.474	11.347	11.598
		Similarity	11.618	11.491	11.752
	Set	Baseline	11.652	11.491	11.791
		x2 Spread	12.415	12.232	12.622
		Lo-Disp. X	11.053	10.896	11.204
		Lo-Disp. Y	11.058	10.888	11.213
By-Dimension	Target	X	12.889	12.779	13.003
		Y	12.926	12.808	13.037
	Context	Attraction	12.631	12.499	12.778
		Compromise	13.012	12.874	13.152
		Similarity	13.079	12.936	13.209
	Set	Baseline	12.930	12.775	13.090
		x2 Spread	13.898	13.691	14.107
		Lo-Disp. X	12.525	12.363	12.672
		Lo-Disp. Y	12.275	12.098	12.446

Table 8: Mean posterior estimates and 95% HDIs for eye transitions by format, target, context, and set in Experiment 2.

By-Alternative		P(Within-Alt)			P(Within-Dim)			P(Diagonal)			P(Same)		
Factor	Level	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High
Target	X	0.189	0.180	0.199	0.541	0.529	0.554	0.101	0.938	0.109	0.169	0.159	0.177
	Y	0.186	0.178	0.195	0.544	0.532	0.556	0.094	0.087	0.100	0.176	0.168	0.183
Context	A	0.182	0.169	0.191	0.558	0.542	0.580	0.090	0.081	0.098	0.171	0.162	0.179
	C	0.193	0.183	0.202	0.528	0.513	0.541	0.105	0.096	0.116	0.174	0.165	0.183
	S	0.189	0.180	0.196	0.542	0.530	0.557	0.098	0.089	0.106	0.172	0.162	0.179
Set	Baseline	0.189	0.181	0.198	0.537	0.525	0.549	0.098	0.090	0.105	0.176	0.168	0.184
	x2 Spread	0.199	0.189	0.212	0.526	0.512	0.539	0.104	0.095	0.114	0.170	0.159	0.179
	Lo-Disp. X	0.181	0.171	0.193	0.559	0.543	0.584	0.089	0.079	0.099	0.169	0.159	0.179
	Lo-Disp. Y	0.180	0.165	0.193	0.548	0.532	0.565	0.099	0.091	0.108	0.173	0.164	0.182

By-Alternative		P(Within-Alt)			P(Within-Dim)			P(Diagonal)			P(Same)		
Factor	Level	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High	M	HDI Low	HDI High
Target	X	0.419	0.408	0.430	0.339	0.329	0.348	0.096	0.089	0.103	0.146	0.139	0.153
	Y	0.408	0.397	0.419	0.347	0.338	0.357	0.097	0.089	0.104	0.148	0.141	0.154
Context	A	0.409	0.398	0.420	0.343	0.332	0.354	0.098	0.091	0.105	0.149	0.142	0.156
	C	0.418	0.407	0.432	0.341	0.329	0.351	0.098	0.091	0.105	0.144	0.136	0.152
	S	0.413	0.403	0.424	0.345	0.335	0.355	0.095	0.086	0.102	0.147	0.139	0.153
Set	Baseline	0.414	0.403	0.424	0.343	0.334	0.353	0.097	0.090	0.103	0.146	0.139	0.153
	x2 Spread	0.409	0.399	0.420	0.342	0.332	0.353	0.102	0.095	0.109	0.146	0.138	0.153
	Lo-Disp. X	0.410	0.397	0.421	0.344	0.334	0.355	0.096	0.087	0.102	0.149	0.143	0.157
	Lo-Disp. Y	0.421	0.404	0.438	0.342	0.330	0.354	0.092	0.083	0.100	0.145	0.137	0.152

Notes: A, C, and S refer to the Attraction, Compromise, and Similarity effects, respectively.

Table 9: Median and 95% HDI of the log-likelihood and group-level parameter values for MDFT, the LCA, the AAM, and the MLBA when fit to data from Experiment A.

MDFT

	LL	a	k_1	k_2	ϕ_1	ϕ_2	β	σ	γ
Median	-40,141.91	50.073	4.105	2.179	0.003	0.805	2.795	22.993	47.708
HDI Low	-40,292.99	46.560	0.195	0.081	0.000	0.074	0.137	21.590	43.250
HDI High	-40,007.31	55.519	15.813	9.667	0.012	1.670	7.489	24.972	53.272

LCA

	LL	a	k_1	k_2	I_0	λ	β	σ	γ
Median	-39,750.59	68.415	6.159	3.416	4.812	0.514	0.932	12.849	13.604
HDI Low	-39,879.89	53.733	0.275	0.137	4.189	0.455	0.829	9.671	10.017
HDI High	-39,636.30	91.205	22.193	14.078	5.395	0.572	0.997	15.439	16.207

AAM

	LL	a	k_1	k_2	k_{scale}	α	λ	β	σ	γ
Median	-41,064.24	9.087	7.426	4.652	0.111	0.409	0.041	0.986	0.235	7.809
HDI Low	-41,405.50	7.169	0.258	0.198	0.004	0.359	0.002	0.940	0.009	1.848
HDI High	-40,797.69	11.493	27.188	18.951	0.572	0.454	0.205	0.999	1.026	11.387

MLBA

	LL	b	A	t_0	I_0	λ_1	λ_2	β	m	γ
Median	-36,374.72	0.859	5.283	0.055	1.131	0.381	0.321	0.097	1.054	1.390
HDI Low	-36,433.39	0.058	1.556	0.004	1.035	0.352	0.297	0.004	0.306	1.327
HDI High	-36,319.98	1.958	7.968	0.123	1.219	0.409	0.346	0.424	1.982	1.459

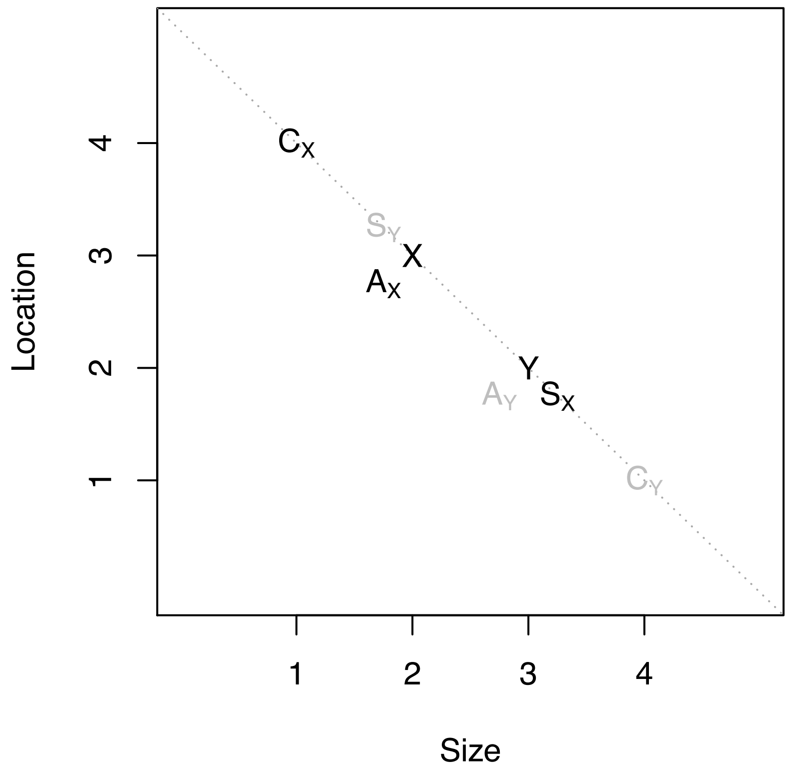


Figure 1: General demonstration of choice alternatives used to elicit the attraction, compromise, and similarity effects. Each label represents the dimension values of an apartment. Apartments 'X' and 'Y' constitute the base pair. Adding the decoy 'A' elicits the attraction effect, 'C' elicits the compromise effect, and 'S' elicits the similarity effect. Subscripts denote the apartment from the base pair targeted by the decoy.

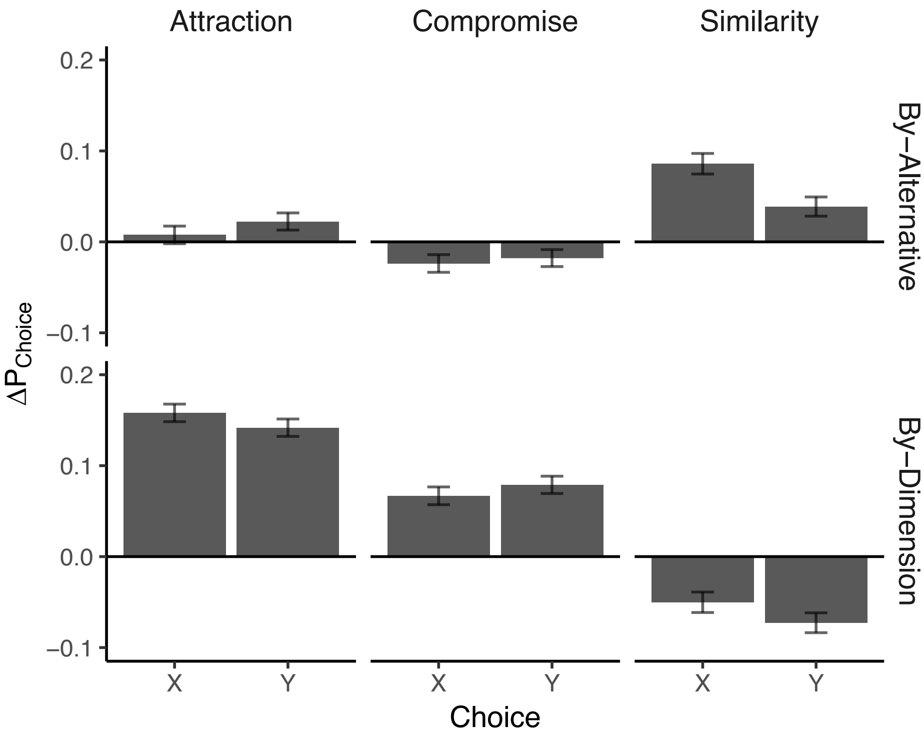


Figure 2: Differences in choice proportions for alternatives X and Y in Cataldo & Cohen (2018b), broken out by context and presentation format condition. A positive value represents a standard effect. Error bars are between-subject standard errors.

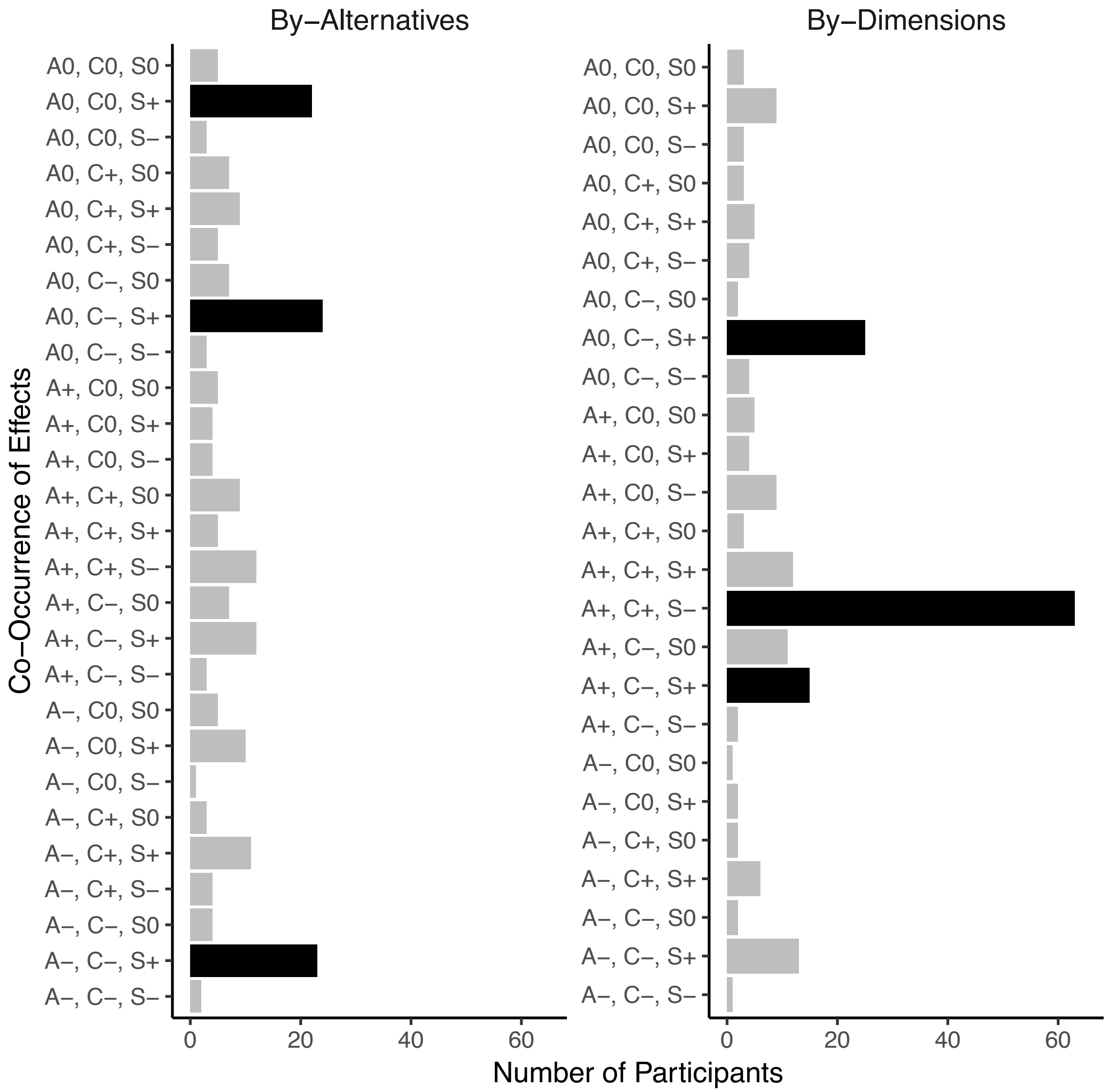


Figure 3: The number of participants in Cataldo & Cohen (2018b) that exhibited each possible combination of the three context effects across three categories of magnitude, null/absent (<0.04 & >-0.04, denoted '0'), negative/reverse (≤-0.04, denoted '-'), or positive/standard (≥0.04, denoted '+'). Effects are averaged across choice set. Black bars denote the three most common combinations in each presentation format.

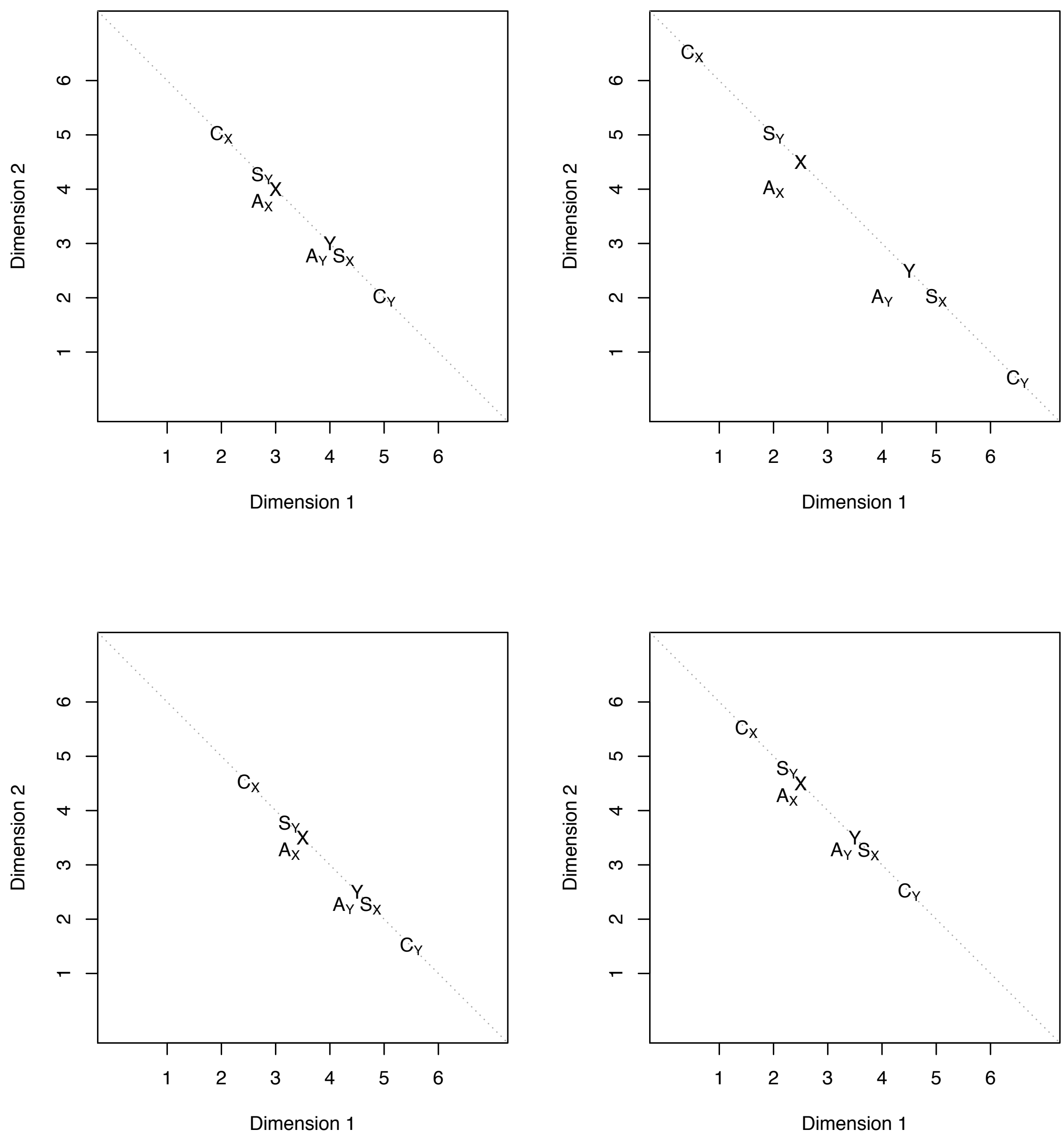


Figure 4: Stimulus values across three levels of dispersion in Experiment 1. Each label represents the dimension values of an alternative. Alternatives 'X' and 'Y' constitute the base pair. The decoys 'A', 'C', and 'S' elicit the attraction, compromise, and similarity effects, respectively. Subscripts denote the alternative from the base pair targeted by the decoy. The top left panel depicts the baseline choice sets. The top right panel depicts the baseline choice sets with high spread. The bottom panels depict the baseline choice sets shifted along the dotted indifference line such that either X (left) or Y (right) have low dispersion.

Figure 5: Sample stimulus of a ternary choice set. The top panel depicts a By-Dimension presentation format. The bottom panel depicts a By-Alternative presentation format.

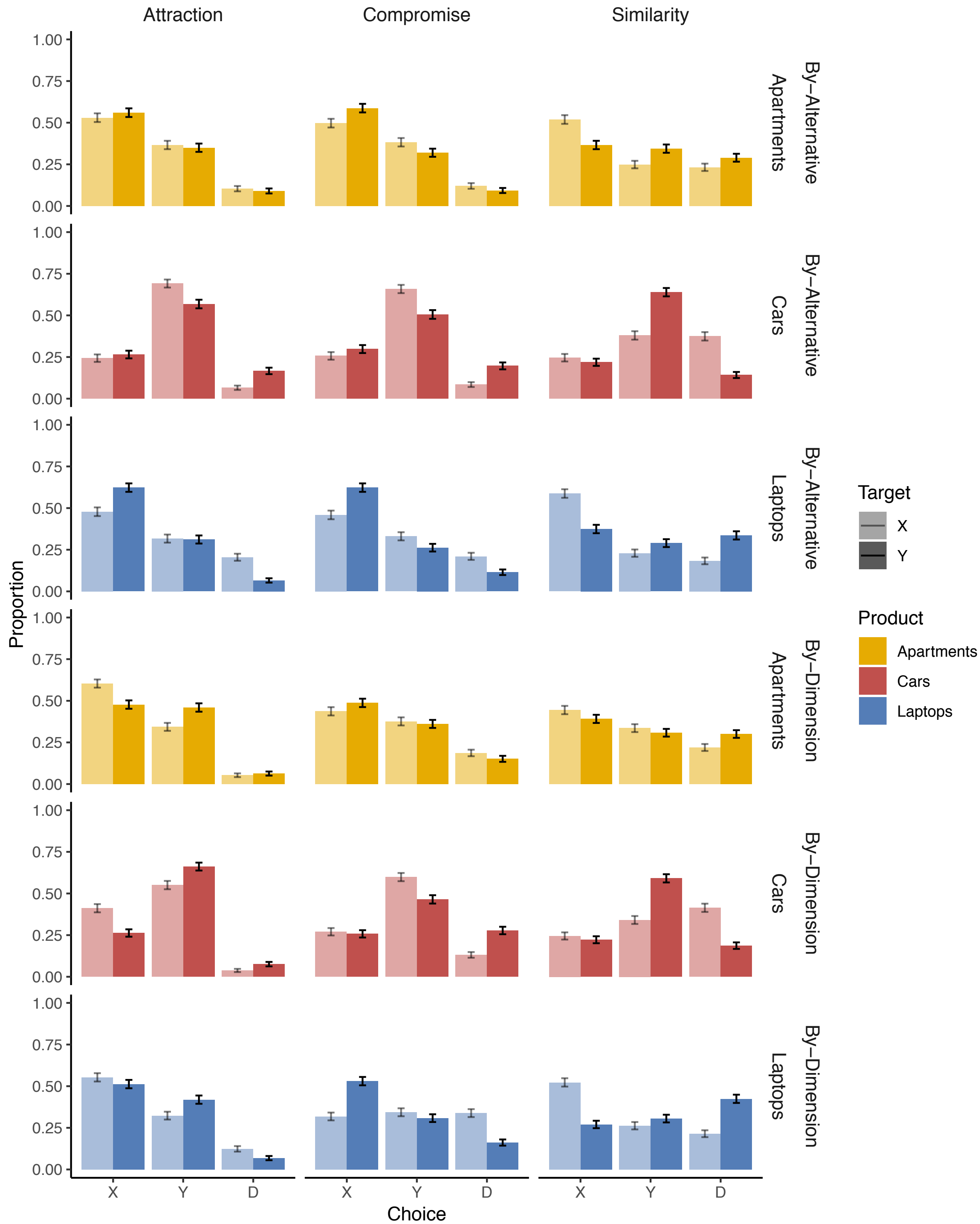


Figure 6: Choice proportions for each alternative in the baseline choice sets in Experiment 1, broken out by presentation format, context, product category, and target. Error bars are between-subject standard errors.

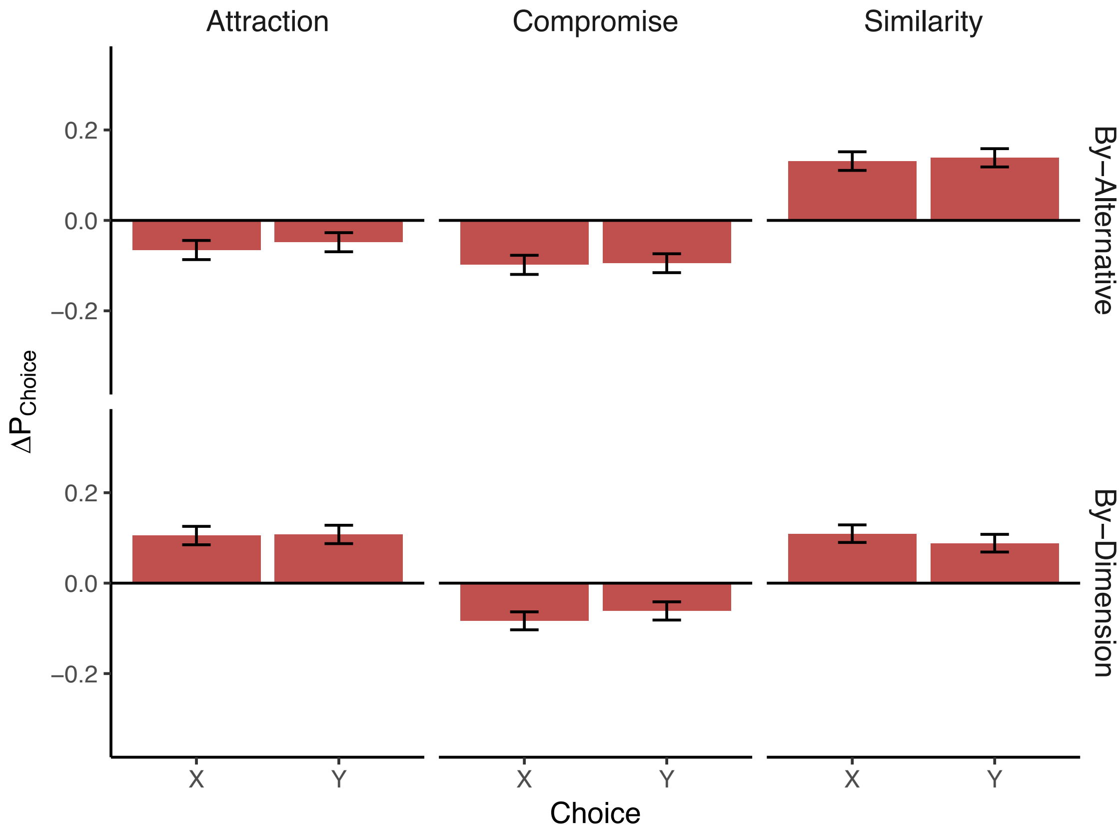


Figure 7: Differences in choice proportions for alternatives X and Y in the baseline choice sets (Figure 4, top left panel) for Experiment 1, broken out by context and presentation format condition. A positive value represents a standard effect. Error bars are between-subject standard errors.

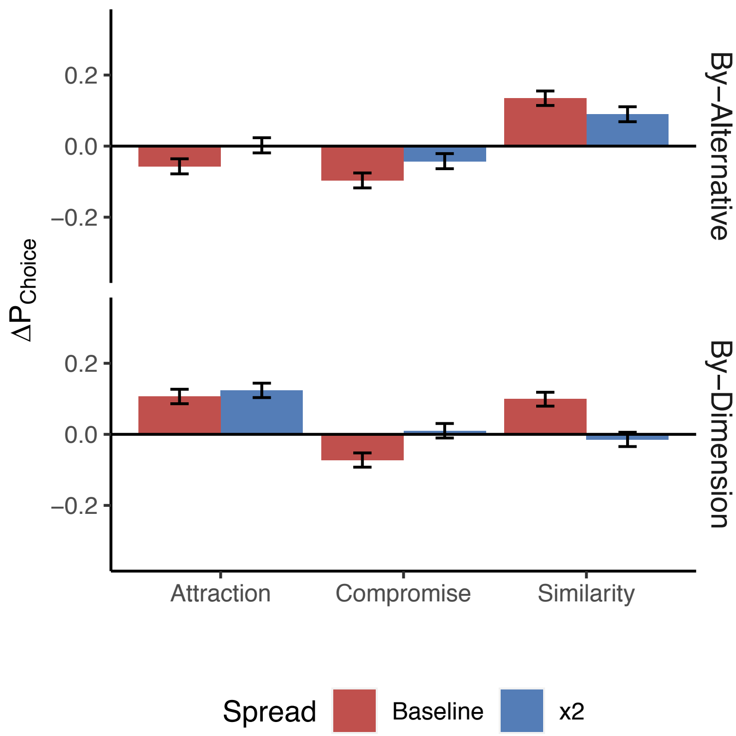


Figure 8: Differences in choice proportions for alternatives X and Y in Experiment 1 across levels of spread, averaged across target, for each context and presentation format condition. Red bars represent the baseline choice sets (Figure 4, top left panel). Blue bars represent choice sets in which the absolute differences between alternatives within each dimension have been increased by a factor of two (Figure 4, top right panel). A positive value represents a standard effect. Error bars are between-subject standard errors.

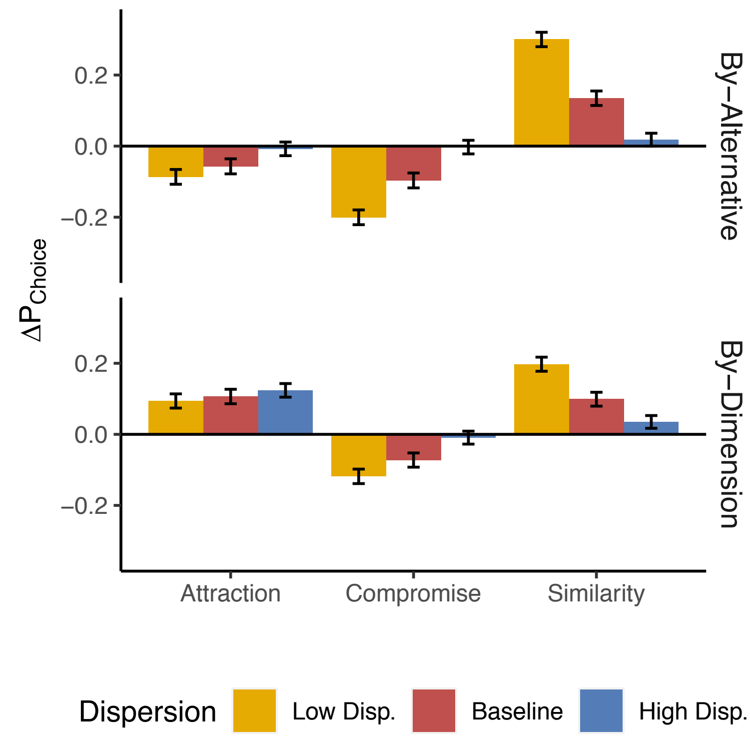


Figure 9: Differences in choice proportions for alternatives X and Y in Experiment 1 across levels of dispersion, averaged across target, for each context and presentation format condition. Red bars represent the average ΔP for moderate-dispersion X and moderate-dispersion Y (Figure 4, top left panel). Yellow bars represent the average ΔP for low-dispersion X (Figure 4, bottom left panel) and low-dispersion Y (Figure 4, bottom right panel). Blue bars represent the average ΔP for high-dispersion X (Figure 4, bottom right panel) and high-dispersion Y (Figure 4, bottom right panel). Error bars are between-subject standard errors.

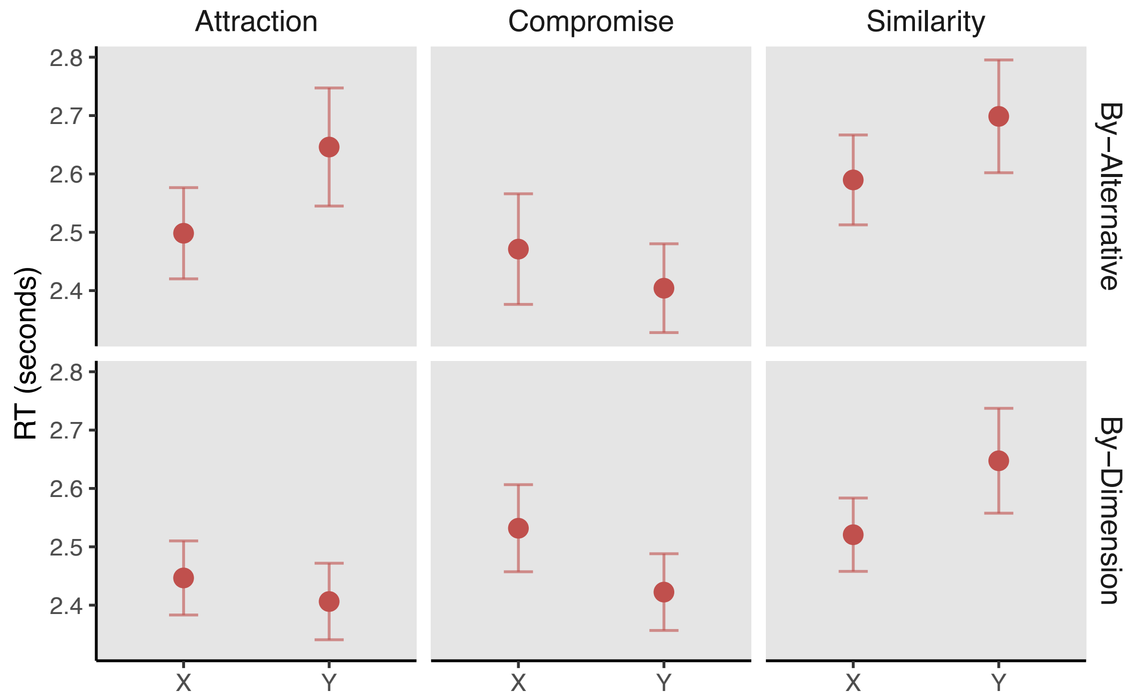


Figure 10: Mean response times in the baseline choice sets in Experiment 1, broken down by target, context, and presentation format. Error bars are between-subject standard errors.

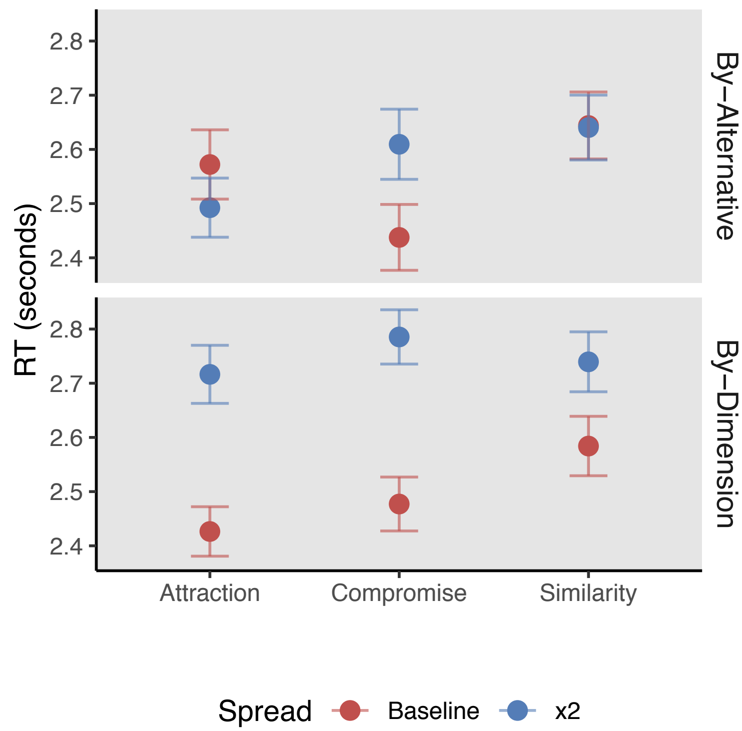


Figure 11: Mean response times in Experiment 1 across levels of spread, broken down by target, context, and presentation format. Red points represent the baseline choice sets (Figure 4, top left panel). Blue points represent choice sets in which the absolute differences between alternatives within each dimension have been increased by a factor of two (Figure 4, top right panel). Error bars are between-subject standard errors.

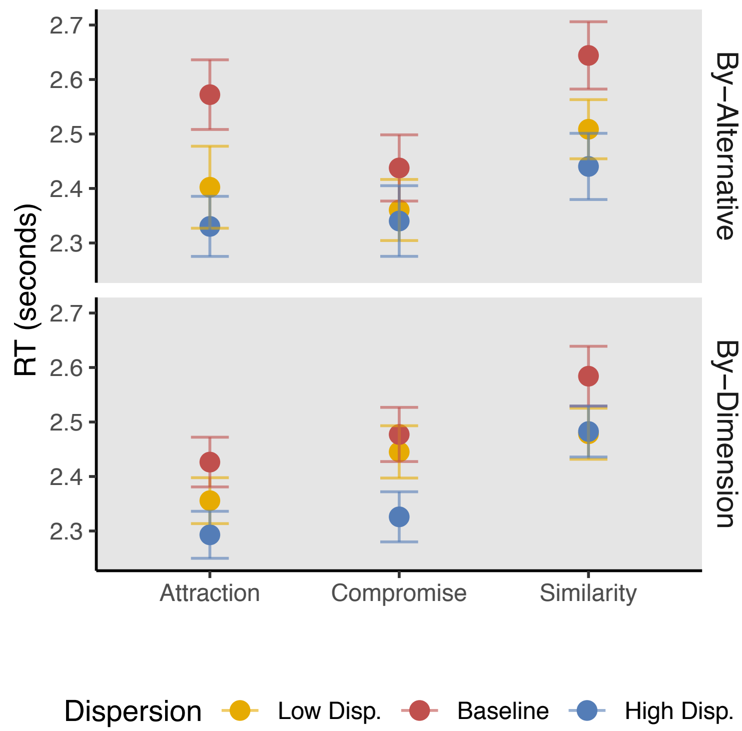


Figure 12: Mean response times in Experiment 1 across levels of dispersion, broken down by target, context, and presentation format. Red points represent the average response time for the baseline choice sets. Yellow points represent the average response time for choice sets where X has low dispersion X (Figure 4, bottom left panel). Blue points represent the average response time for choice sets where Y has low dispersion (Figure 4, bottom right panel). Error bars are between-subject standard errors.

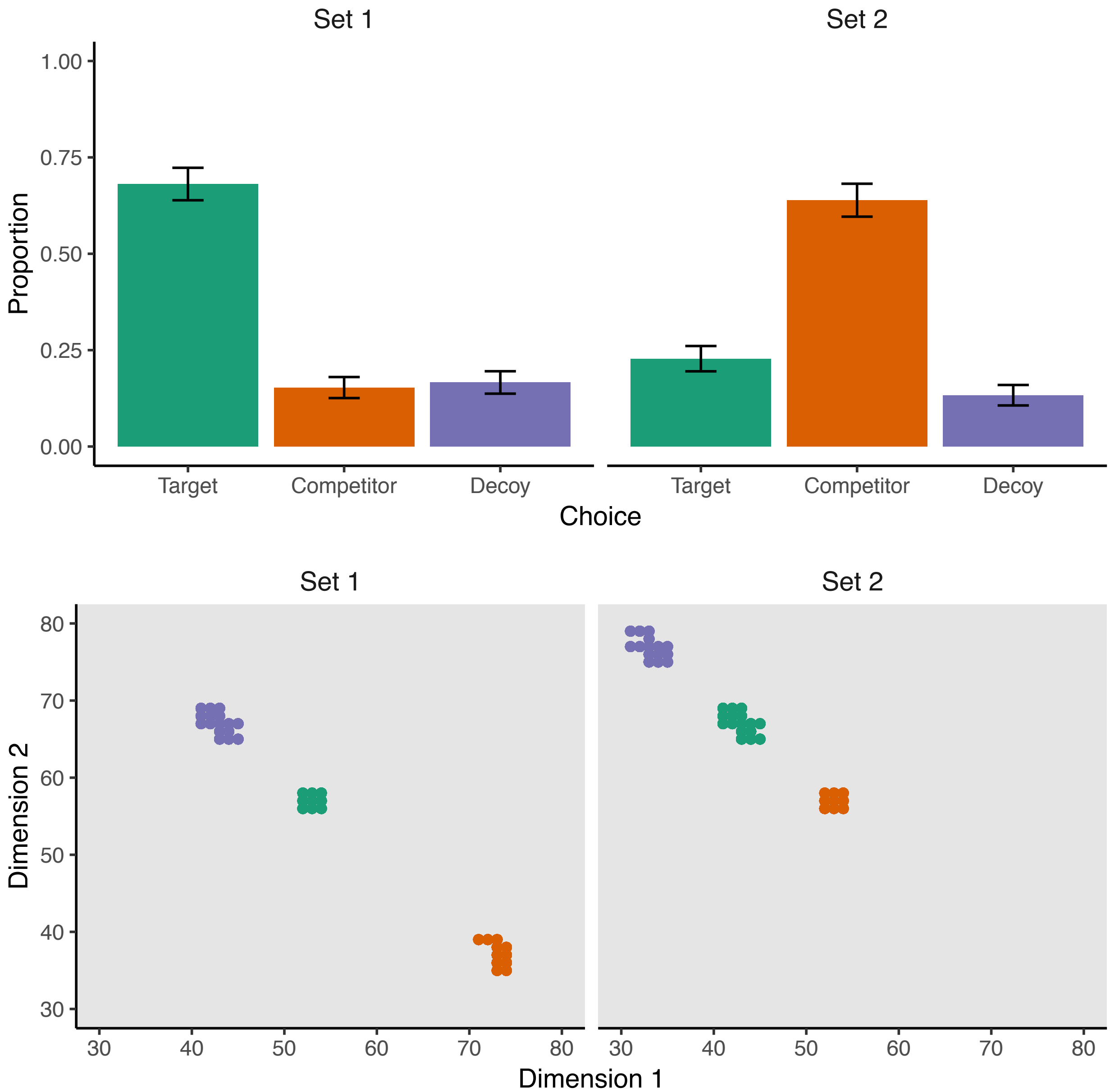


Figure 13: Reanalysis of data from the combined inference paradigm originally published in Trueblood, Brown, & Heathcote (2014) and later as experiment E4 in Evans, Holmes, & Trueblood (2019; data provided on OSF: https://osf.io/h7e6v/). Error bars are between-subject standard errors.

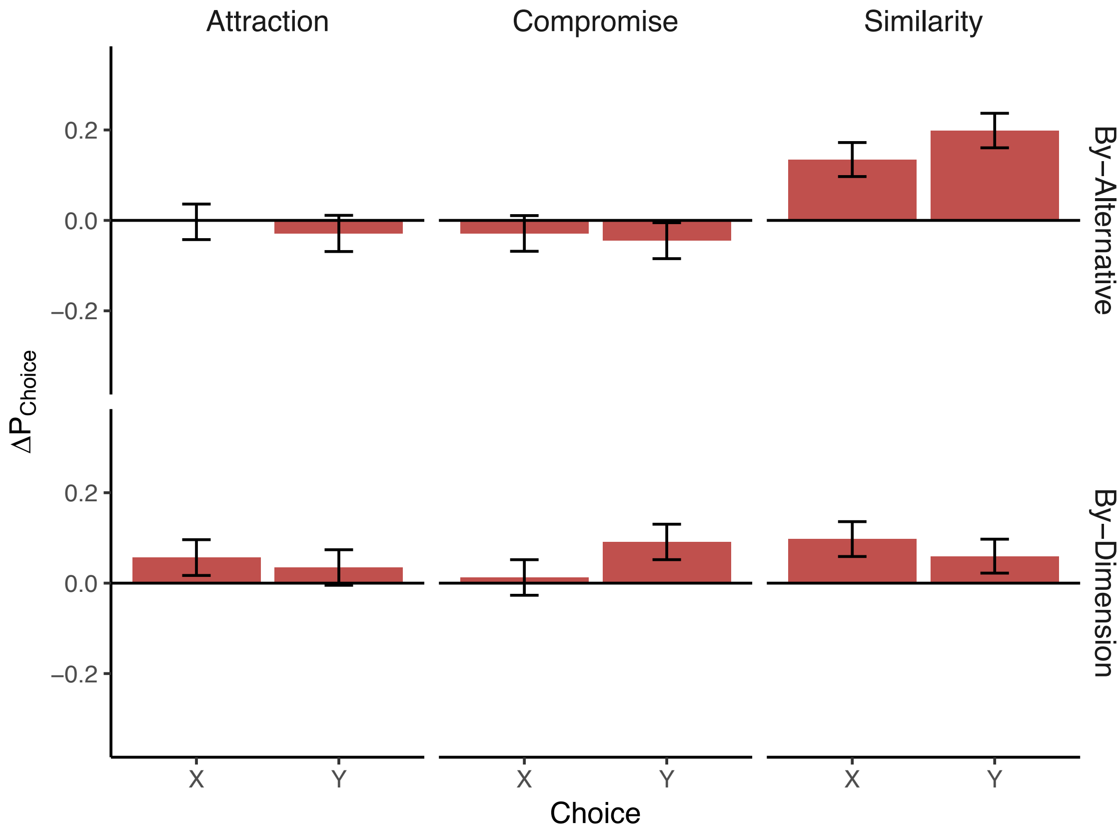


Figure 14: Differences in choice proportions for alternatives X and Y in the baseline choice sets (Figure 4, top left panel) for Experiment 2, broken out by context and presentation format condition. A positive value represents a standard effect. Error bars are between-subject standard errors.

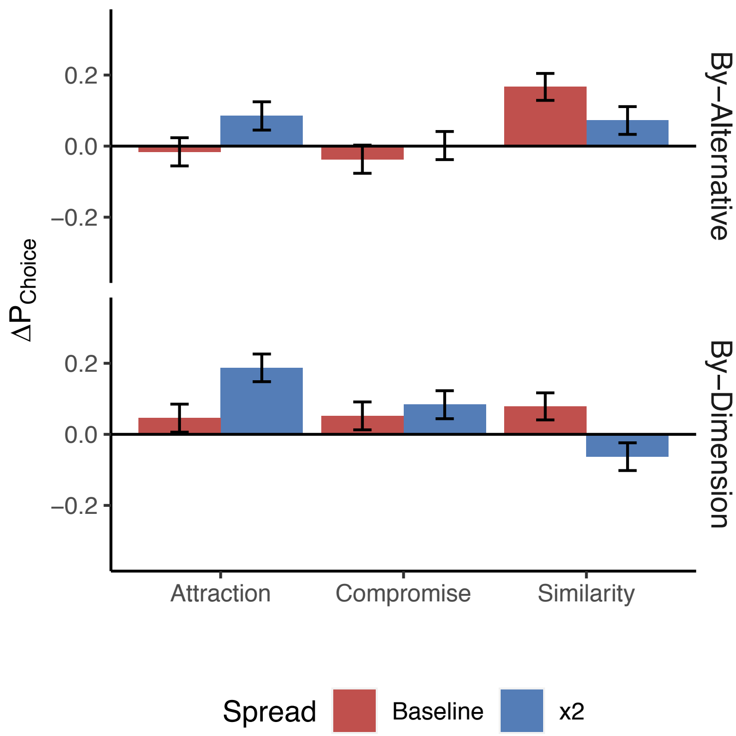


Figure 15: Differences in choice proportions for alternatives X and Y in Experiment 2 across levels of spread, averaged across target, for each context and presentation format condition. Red bars represent the baseline choice sets (Figure 4, top left panel). Blue bars represent choice sets in which the absolute differences between alternatives within each dimension have been increased by a factor of two (Figure 4, top right panel). A positive value represents a standard effect. Error bars are between-subject standard errors.

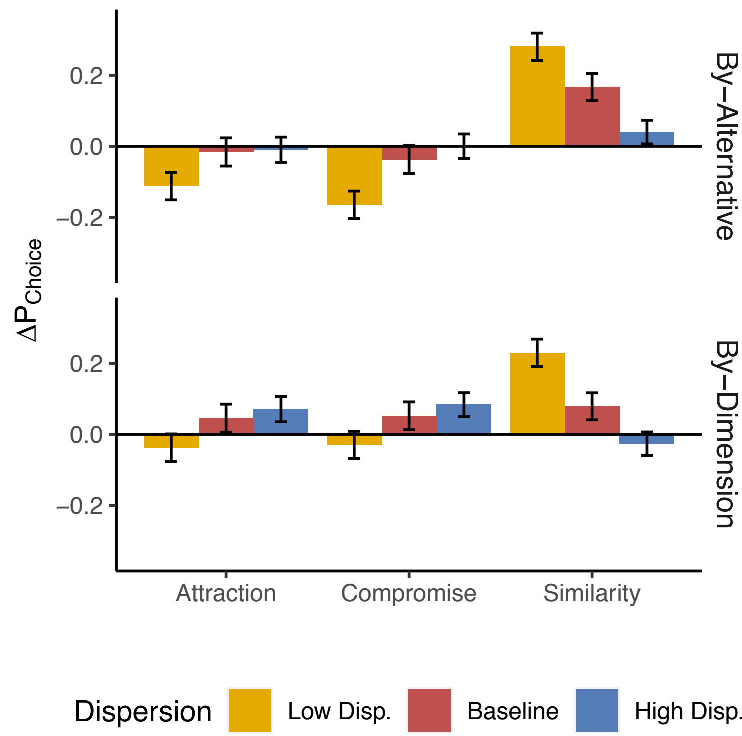


Figure 16: Differences in choice proportions for alternatives X and Y in Experiment 2 across levels of dispersion, averaged across target, for each context and presentation format condition. Red bars represent the average ΔP for moderate-dispersion X and moderate-dispersion Y (Figure 4, top left panel). Yellow bars represent the average ΔP for low-dispersion X (Figure 4, bottom left panel) and low-dispersion Y (Figure 4, bottom right panel). Blue bars represent the average ΔP for high-dispersion X (Figure 4, bottom right panel) and high-dispersion Y (Figure 4, bottom right panel). Error bars are between-subject standard errors.

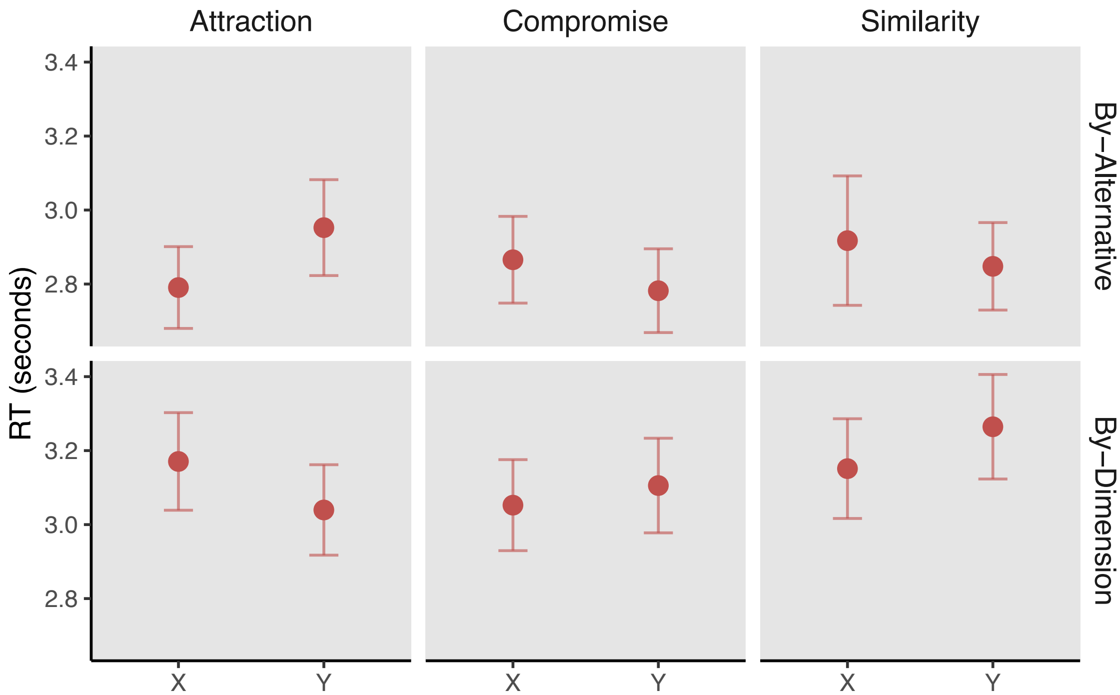


Figure 17: Mean response times in the baseline choice sets in Experiment 2, broken down by target, context, and presentation format. Error bars are between-subject standard errors.

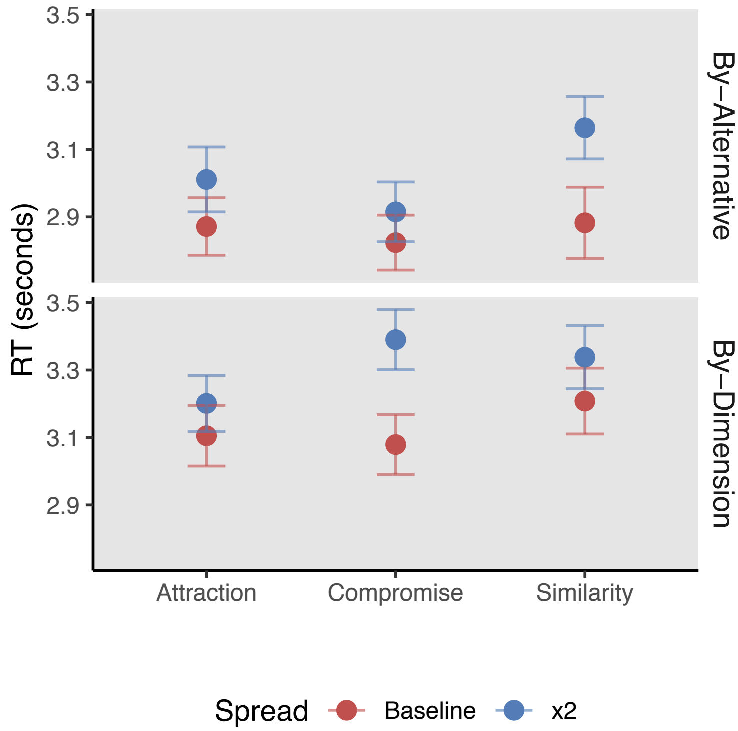


Figure 18: Mean response times in Experiment 2 across levels of spread, broken down by target, context, and presentation format. Red points represent the baseline choice sets (Figure 4, top left panel). Blue points represent choice sets in which the absolute differences between alternatives within each dimension have been increased by a factor of two (Figure 4, top right panel). Error bars are between-subject standard errors.

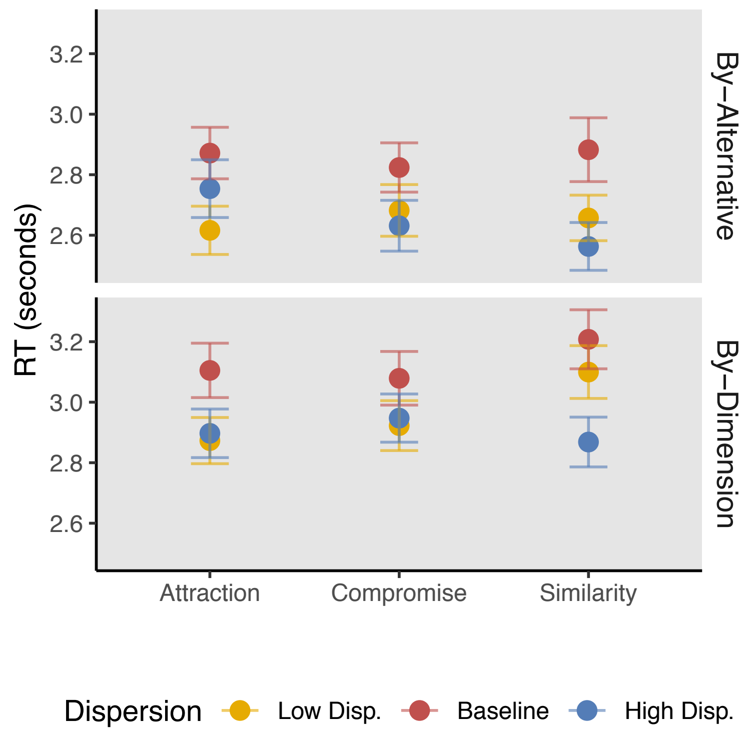


Figure 19: Mean response times in Experiment 2, broken down by target, context, and presentation format. Red points represent the average response time for the baseline choice sets. Yellow points represent the average response time for choice sets where X has low dispersion X (Figure 4, bottom left panel). Blue points represent the average response time for choice sets where Y has low dispersion (Figure 4, bottom right panel). Error bars are between-subject standard errors.

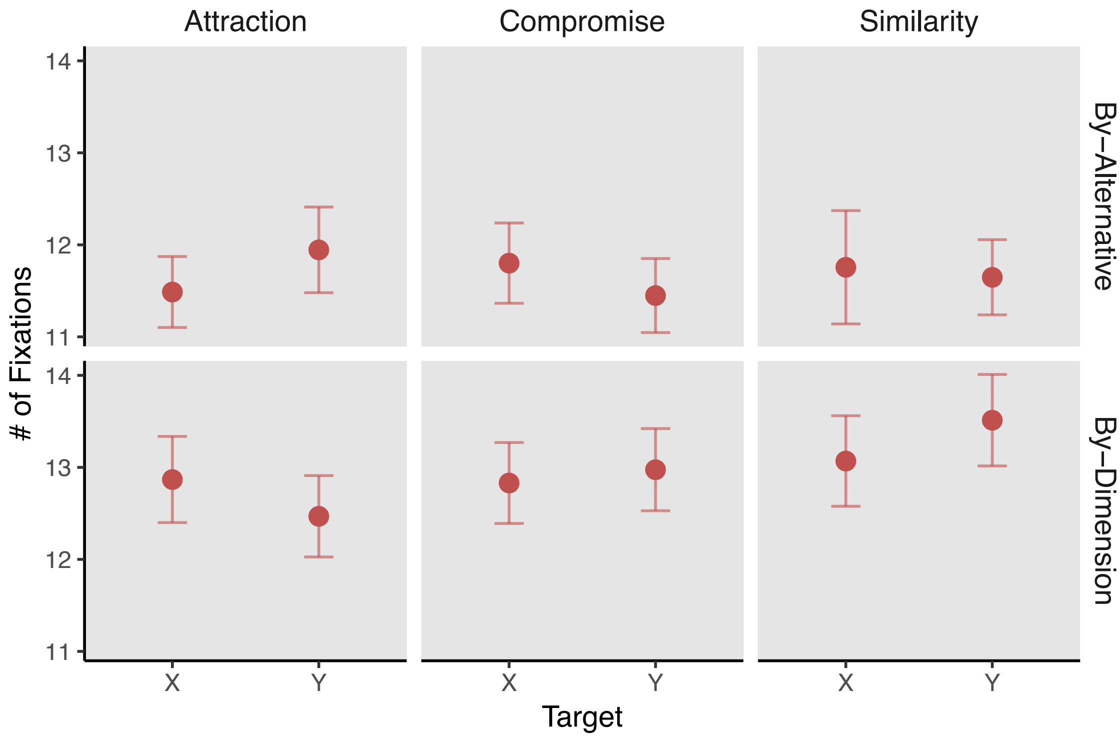


Figure 20: Mean number of eye fixations in the baseline choice sets in Experiment 2, broken down by target, context, and presentation format. Error bars are between-subject standard errors.

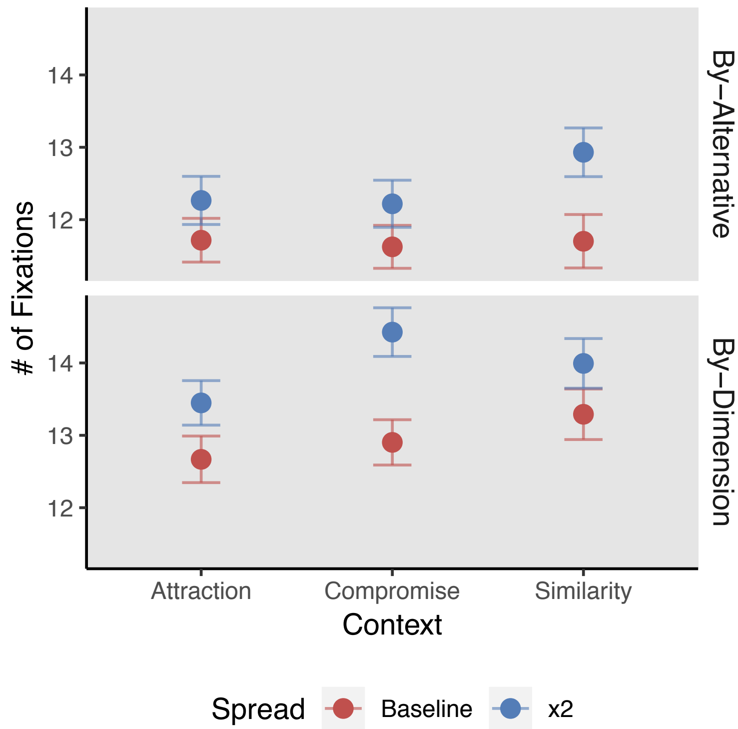


Figure 21: Mean number of eye fixations in Experiment 2 across levels of spread, broken down by target, context, and presentation format. Red points represent the baseline choice sets (Figure 4, top left panel). Blue points represent choice sets in which the absolute differences between alternatives within each dimension have been increased by a factor of two (Figure 4, top right panel). Error bars are between-subject standard errors.

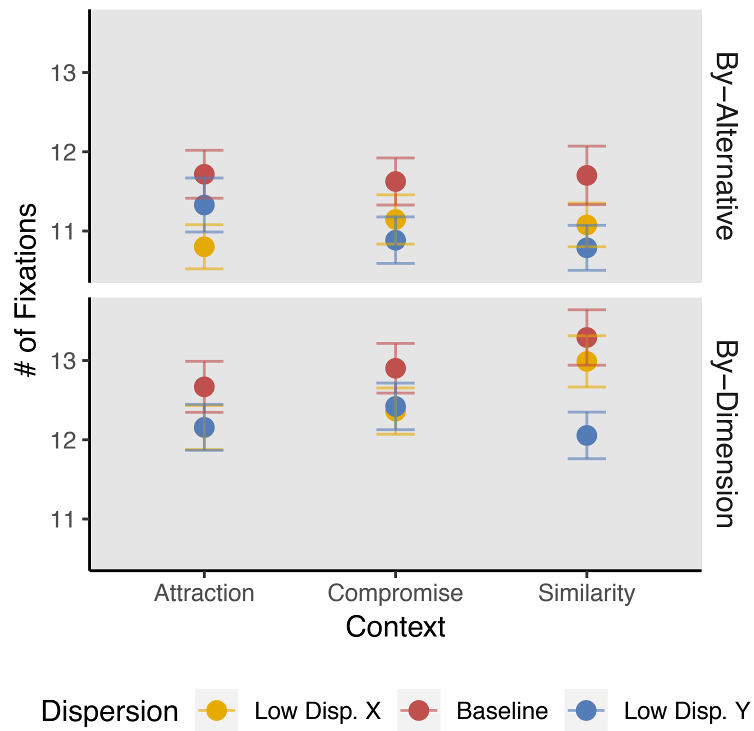


Figure 22: Mean number of eye fixations in Experiment 2 across levels of dispersion, broken down by target, context, and presentation format. Red points represent the average number of fixations for the baseline choice sets. Yellow points represent the average number of fixations for choice sets where X has low dispersion X (Figure 4, bottom left panel). Blue points represent the average number of fixations for choice sets where Y has low dispersion (Figure 4, bottom right panel). Error bars are between-subject standard errors.

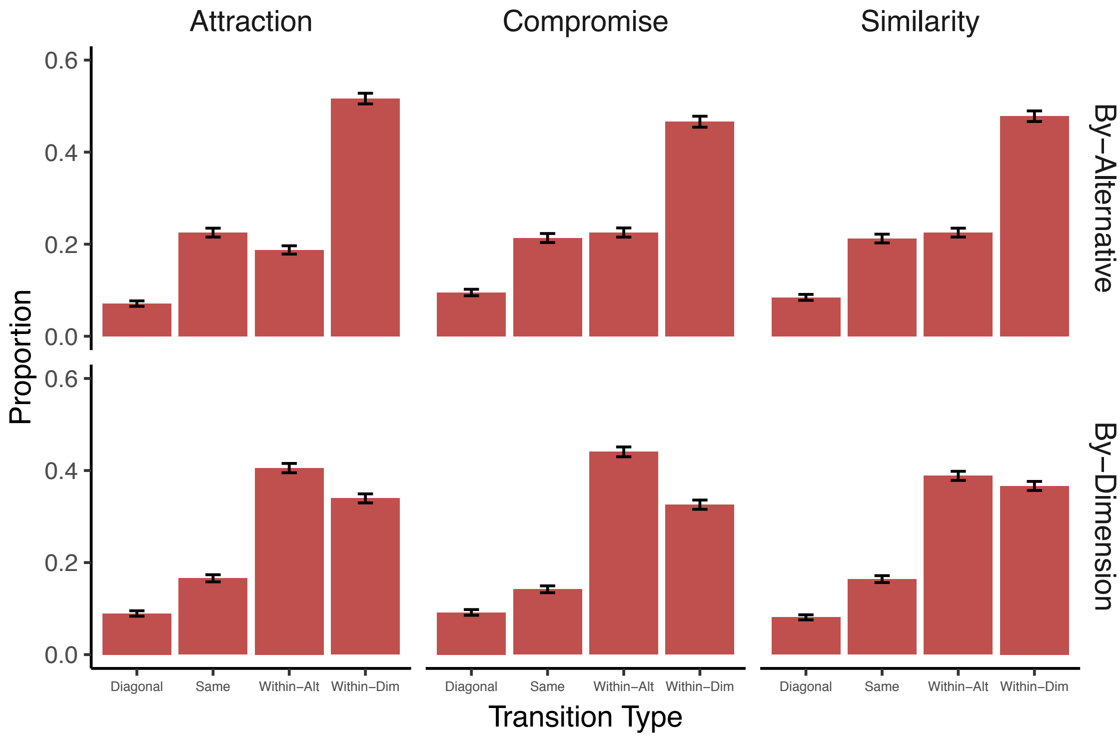


Figure 23: Proportions of each type of transition in eye fixations in the baseline choice sets in Experiment 2, broken down by context and presentation format. Error bars are between-subject standard errors.

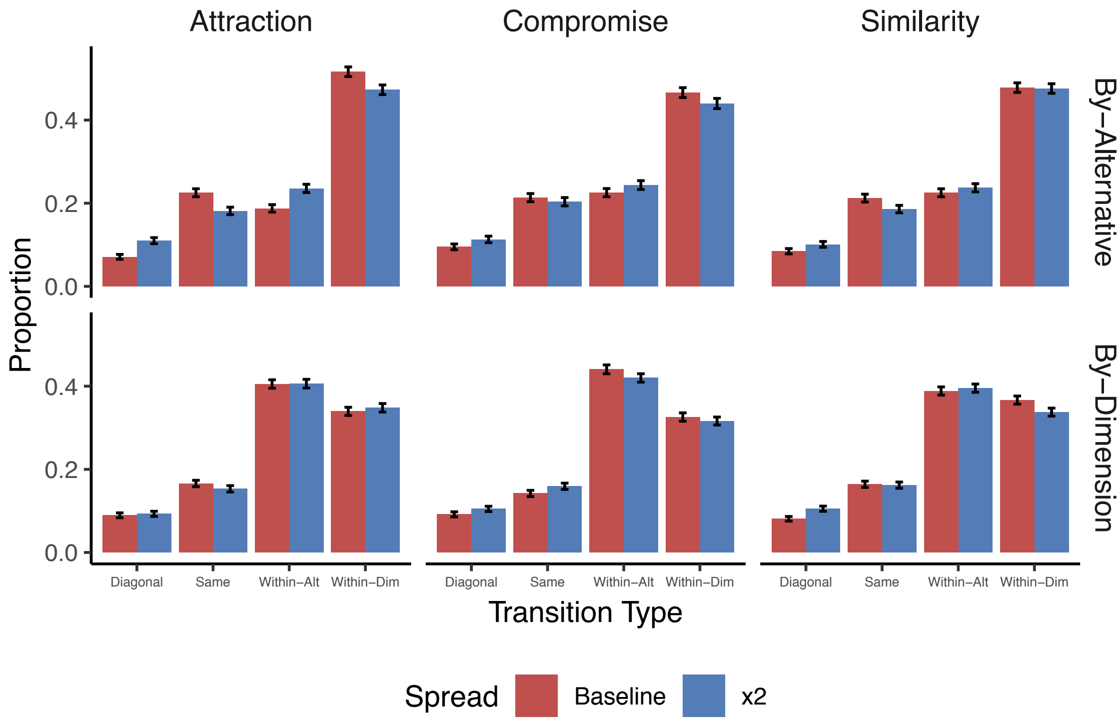


Figure 24: Proportions of transitions in eye fixations in Experiment 2 across levels of spread, broken down by context and presentation format. Red bars represent the baseline choice sets (Figure 4, top left panel). Blue bars represent choice sets in which the absolute differences between alternatives within each dimension have been increased by a factor of two (Figure 4, top right panel). Error bars are between-subject standard errors.

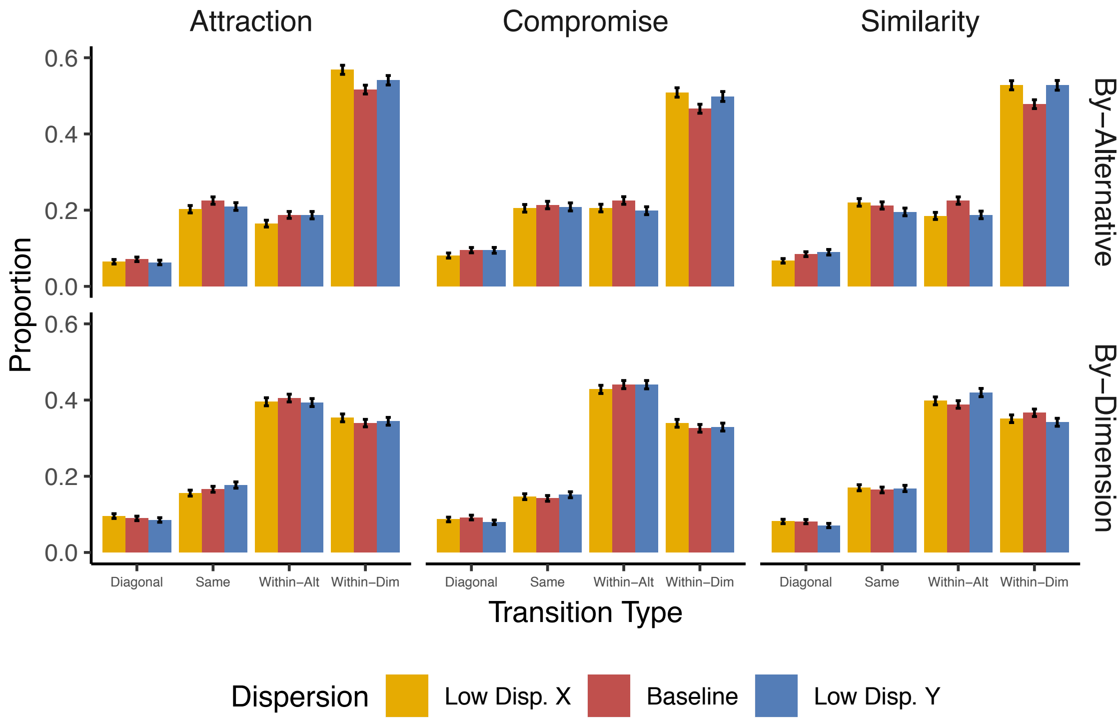


Figure 25: Proportions of transitions in eye fixations in Experiment 2 across levels of dispersion, broken down by context and presentation format. Red bars represent the average proportions for the baseline choice sets. Yellow bars represent the average proportions for choice sets where X has low dispersion X (Figure 4, bottom left panel). Blue bars represent the average proportions for choice sets where Y has low dispersion (Figure 4, bottom right panel). Error bars are between-subject standard errors.

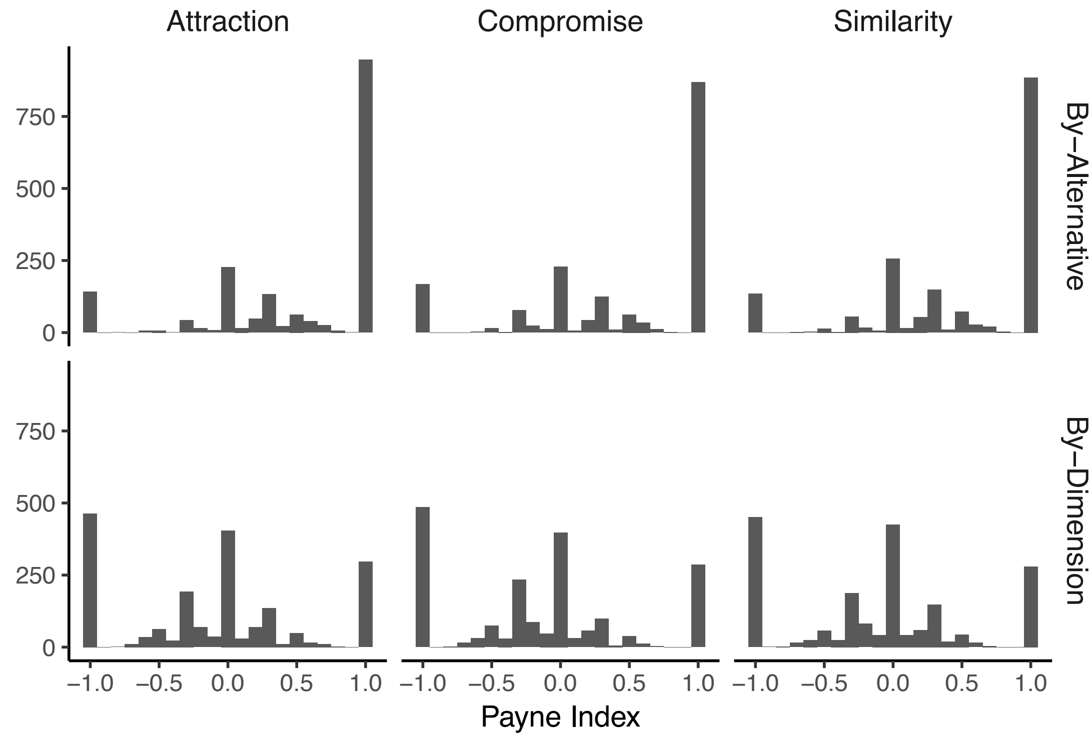


Figure 26: Distributions of Payne Indices (Payne, 1976) for trials within each context and each presentation format. Values of -1 represent trials with no within-dimension transitions in eye fixations. Values of 1 represent trials with no within-alternative transitions in eye fixations.

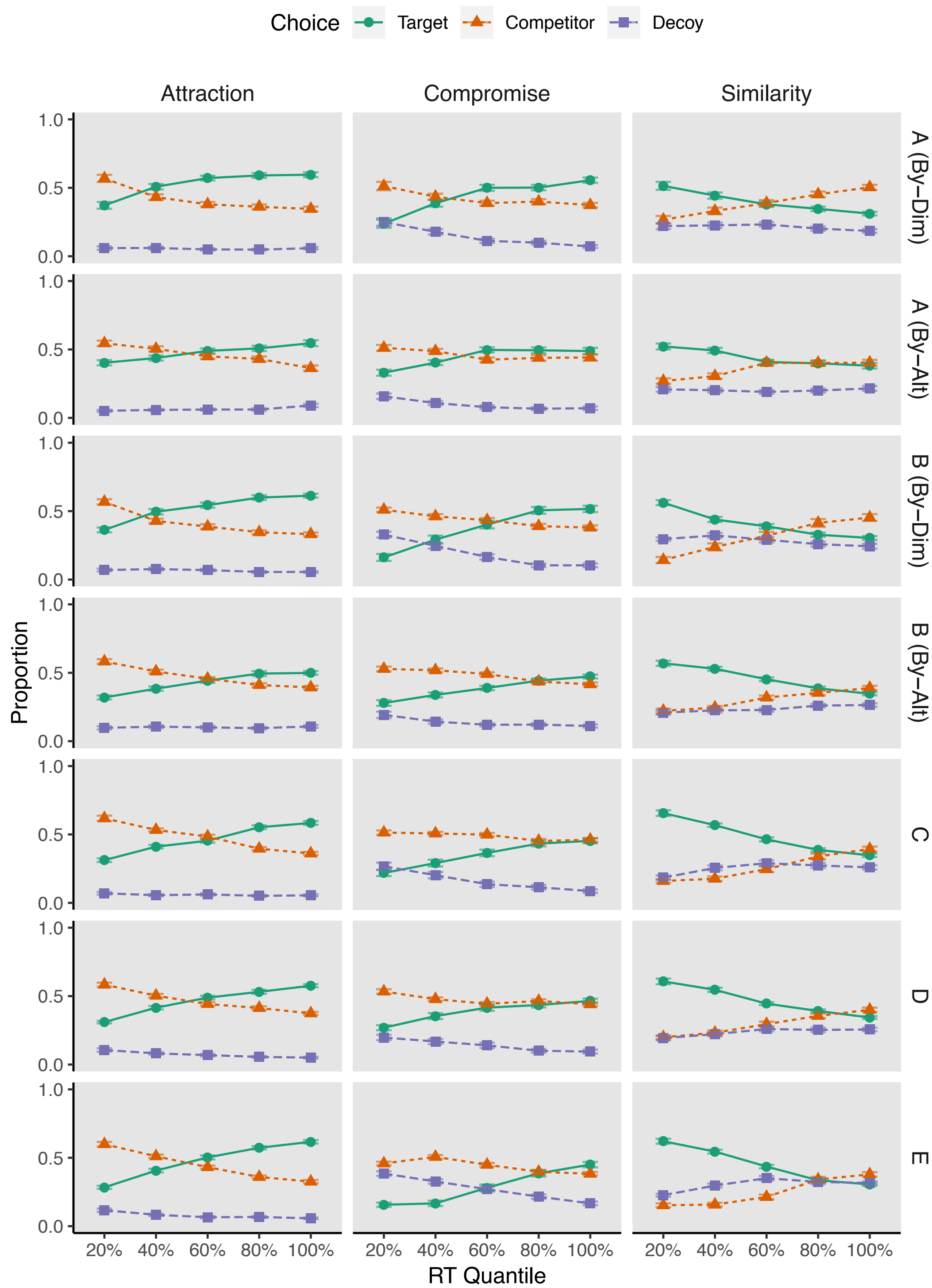


Figure 27: Choice proportions conditioned on context and RT quantile for seven groups of participants from five experiments. Experiment A is data published by Cataldo & Cohen (2018b). Experiments B-E are similar experiments testing all three context effects within subjects, but with variations in stimulus presentation (see Appendix H for details).

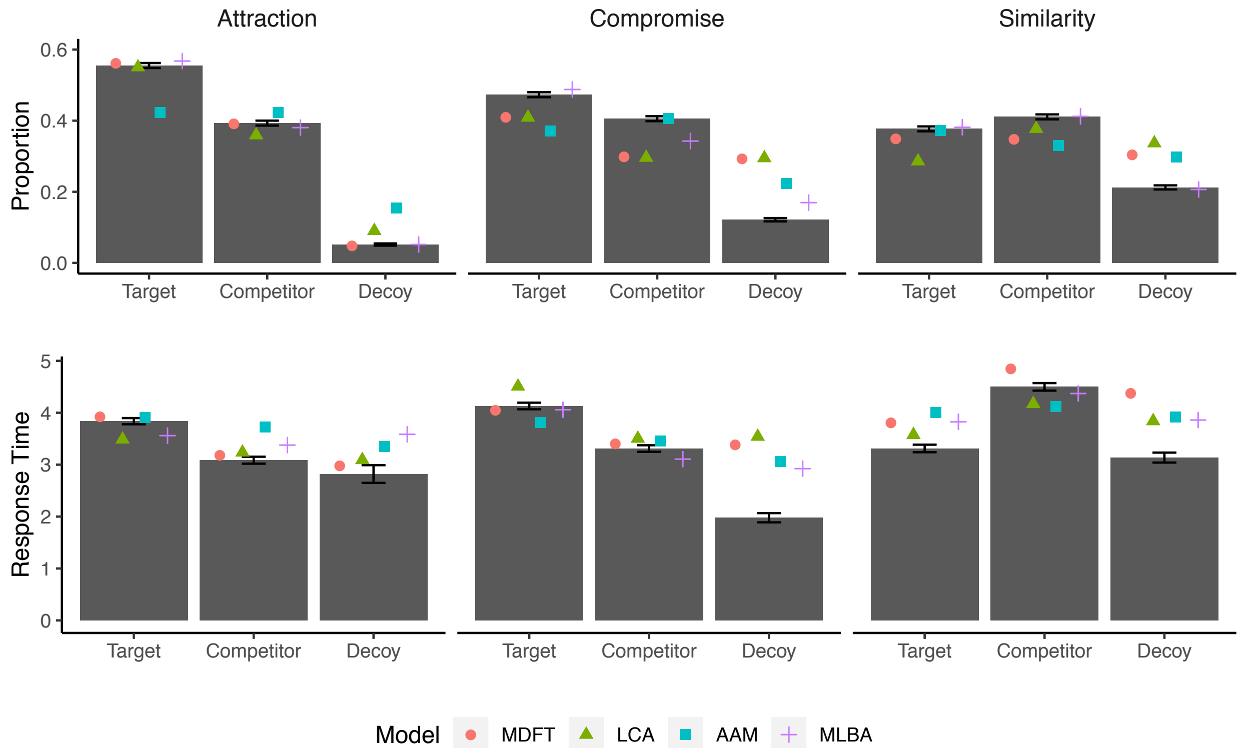


Figure 28: Mean choice proportions (top panel) and response times (bottom panel) within each context. Bars represent data from Experiment A. Points represent predicted values from MDFT, the LCA, the AAM, and the MLBA, after fitting each model to Experiment A.

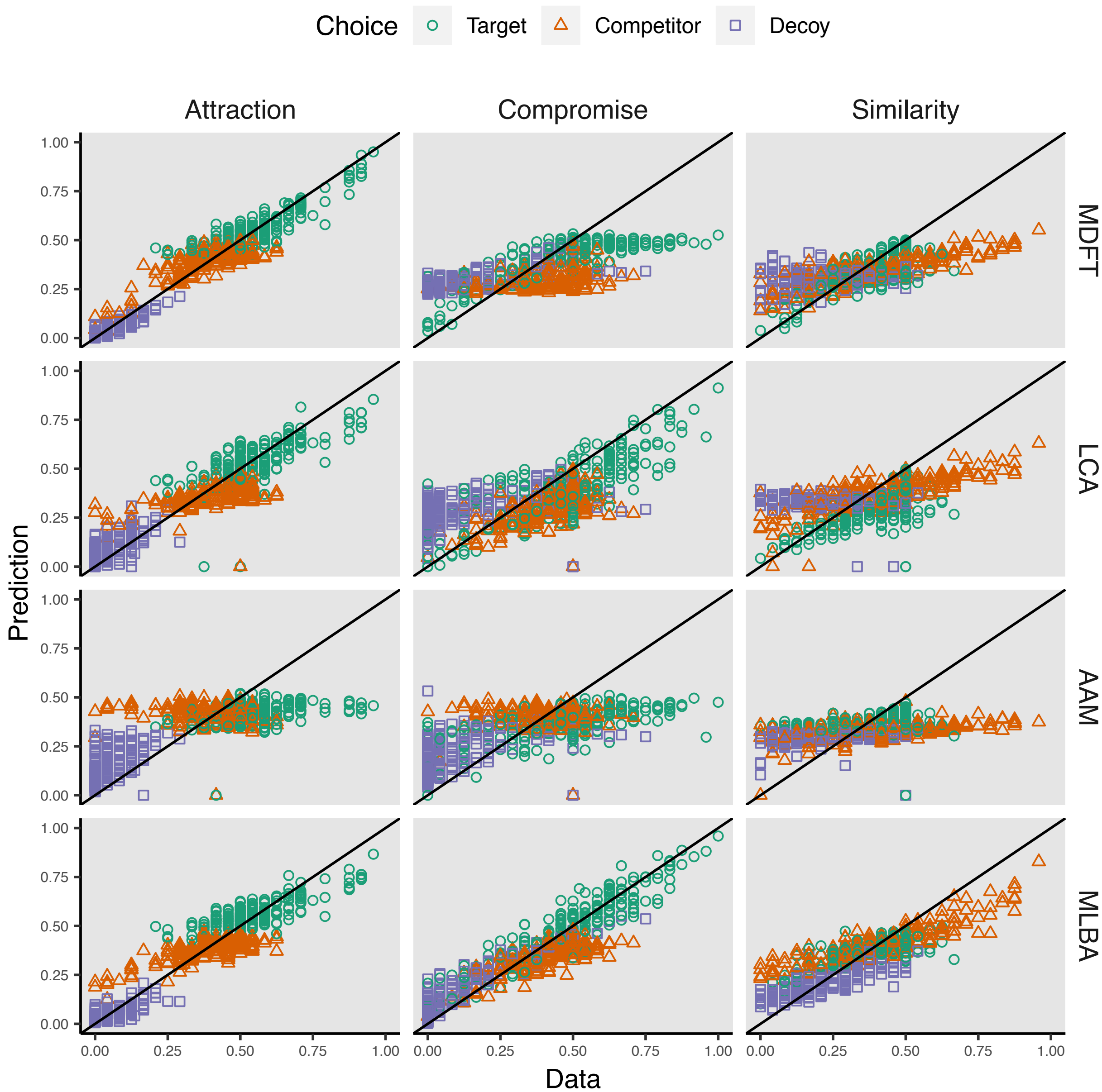


Figure 29: Subject-level choice proportions within each context plotted against predicted values from MDFT, the LCA, the AAM, and the MLBA, after fitting each model to Experiment A.

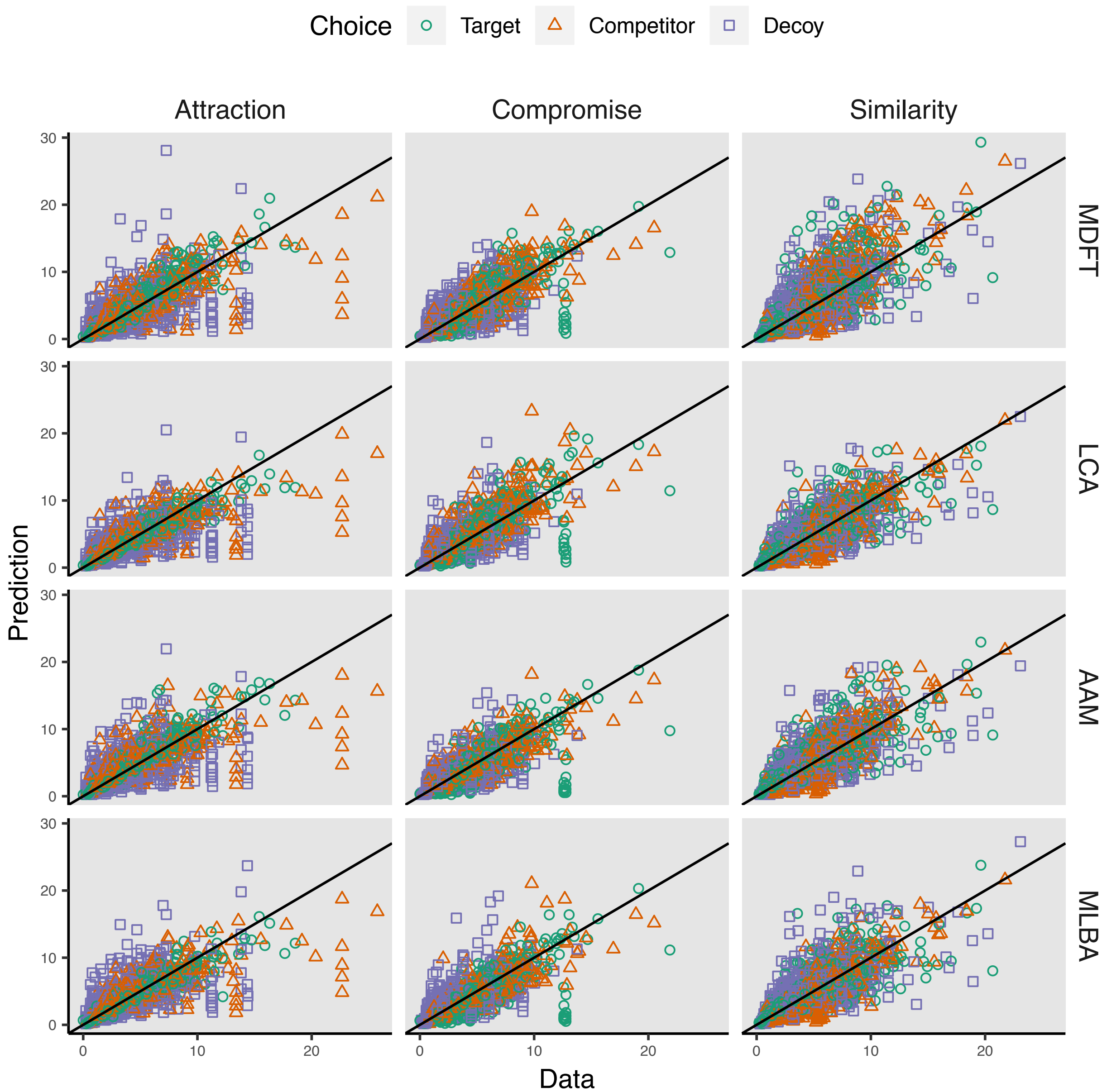


Figure 30: Subject-level response time quantiles (.1, .3, .5, .7, .9) for each alternative within each context plotted against predicted values from MDFT, the LCA, the AAM, and the MLBA, after fitting each model to Experiment A.

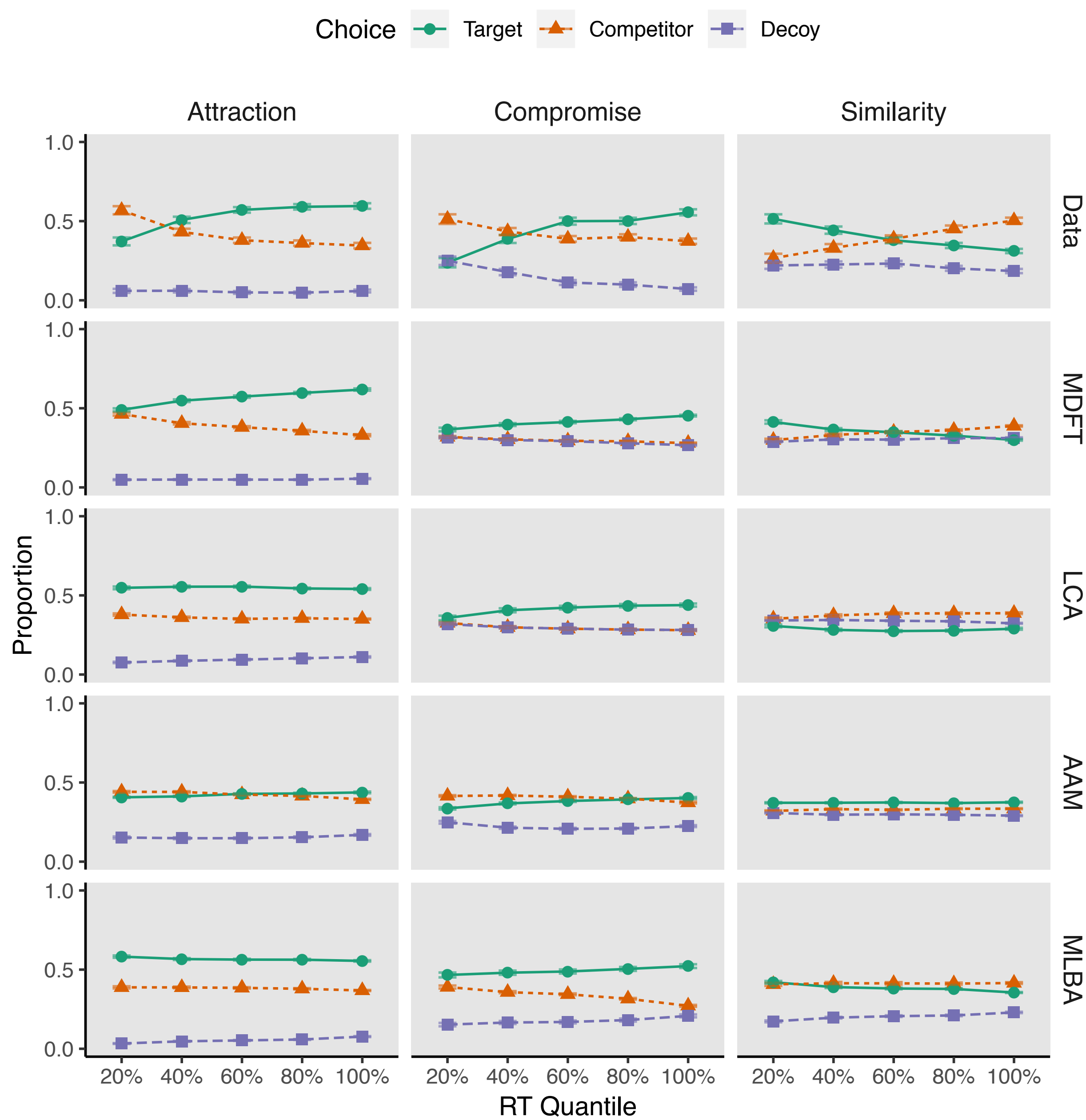


Figure 31: Predicted choice proportions conditioned on context and predicted RT quantile for MDFT, the LCA, the AAM, and the MLBA, after fitting each model to data from Experiment A (top panel).

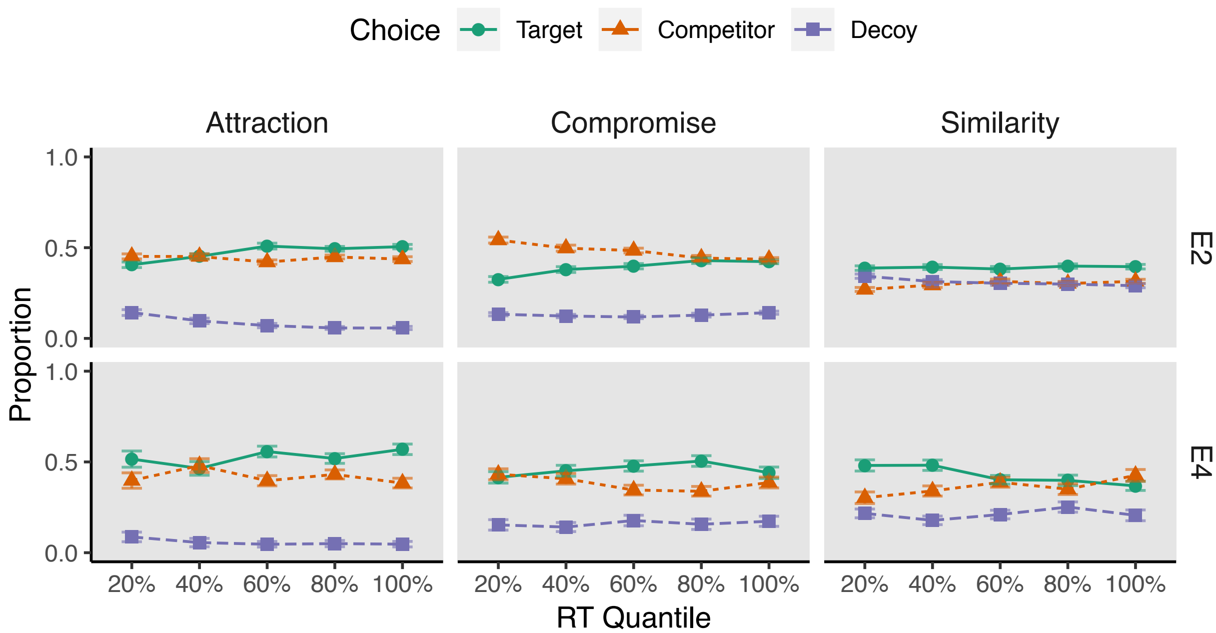


Figure 32: Choice proportions conditioned on context and RT quantile for experiments E2 and E4 from Evans et al (2019).

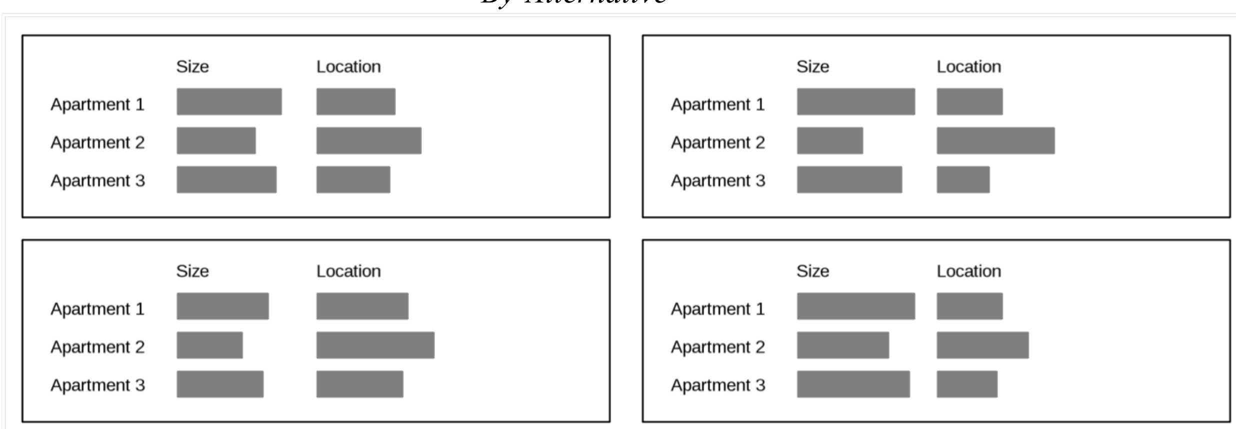
APPENDIX A

SAMPLE STIMULI FROM EXPERIMENT 1

All stimuli depict an attraction choice set in which the decoy, Apartment 3, targets Apartment 1.

By-Dimension

By-Alternative



APPENDIX B

BAYESIAN HIERARCHICAL MODEL OF CONTEXT EFFECTS (EXP. 1)

Based on principles and tools provided in Kruschke (2014), a hierarchical Bayesian multinomial regression model was developed to test for differences in choice proportions across levels of presentation format, target, context, product category, dispersion, and spread. Each participant's choice probabilities are assumed to be multinomially distributed with parameters N^{stim}, the number of times each stimulus is presented, and π, the choice probabilities. For each participant *p* in each format condition *c* and for each target condition *j* (D_X or D_Y) in each context *k* (attraction, compromise, or similarity) in each product *l* (apartments, cars, or laptops) in each level of dispersion *m* (low-dispersion X and high-dispersion Y, the baseline choice sets, or high-dispersion X and low-dispersion Y) and each level of spread *n* (the baseline choice sets or sets in which spread was increased by a factor two), the choice probabilities are determined using a two-stage process. First, for each alternative *a* the model sums the following effects: an intercept, $\mathcal{E}^{0}_{cpa}$; the target of the decoy, $\mathcal{E}^{target}_{cpja}$; the context, $\mathcal{E}^{context}_{cpka}$; the product category, $\mathcal{E}^{product}_{cpla}$; the dispersion, $\mathcal{E}^{dispersion}_{cpma}$; the spread, $\mathcal{E}^{spread}_{cpna}$; the interaction of target, context, and product, $\mathcal{E}^{targ*cont*prod}_{cpjkla}$; the interaction of target, context, and dispersion, $\mathcal{E}^{targ*cont*disp}_{cpjkma}$; the interaction of target, context, and spread, $\mathcal{E}^{targ*cont*spread}_{cpjkna}$; and all subordinate two-way interactions. This result, $\varphi_{cpjklmna}$, is then submitted to a softmax transformation, which determines the probabilities of the multinomial likelihood. Specifically, the probability of selecting each alternative *a* is

$\frac{\exp(\varphi_{cpjklmna})}{\Sigma \exp(\varphi_{cpjklmn.})}$. The prior probability of each effect $\mathcal{E}$ is assumed to be normally distributed with a mean of zero and a standard deviation of $1/_{\sigma}{}^{2}$, in which σ is sampled from an uninformed uniform hyperprior ($L = 0.001, U = 1000$). Note that the baseline choice set serves as a level of both dispersion and spread but is only sampled once by the model.

APPENDIX C

BAYESIAN HIERARCHICAL MODEL OF RESPONSE TIMES (EXP. 1)

Based on principles and tools provided in Kruschke (2014), a hierarchical Bayesian regression model was developed to test for differences in response times across levels of presentation format, target, context, product category, dispersion, and spread. Response times are assumed to be log-normally distributed with parameters μ, the mean log response time, and σ, the standard deviation of the log response times. For each participant *p* in each format condition *c* and for each target condition *j* (D_X or D_Y) in each context *k* (attraction, compromise, or similarity) in each product *l* (apartments, cars, or laptops) in each dispersion *m* (low-dispersion X and high-dispersion Y, the baseline choice sets, or high-dispersion X and low-dispersion Y) and each spread *n* (the baseline choice sets or sets in which spread was increased by a factor two), the mean log response times are modelled as the sum of the following effects: an intercept, $\mathcal{E}_{cp}^{0}$; the target of the decoy, $\mathcal{E}_{cpj}^{target}$; the context, $\mathcal{E}_{cpk}^{context}$; the product, $\mathcal{E}_{cpl}^{product}$; the dispersion, $\mathcal{E}_{cpm}^{dispersion}$; the spread, $\mathcal{E}_{cpn}^{spread}$; the interaction of target, context, and product, $\mathcal{E}_{cpjkl}^{targ*cont*prod}$; the interaction of target, context, and dispersion, $\mathcal{E}_{cpjkm}^{targ*cont*disp}$; the interaction of target, context, and spread, $\mathcal{E}_{cpjkn}^{targ*cont*spread}$; and all subordinate two-way interactions. The prior of each effect $\mathcal{E}$ is assumed to be normally distributed with a mean of zero and a standard deviation of ${}^{1}/{}_{\sigma}{}^{2}$, in which σ is sampled from a uniform hyperprior ($L = 0.001, U = 1000$). The standard deviation of the log response times for each participant *p* in each level of each condition has a gamma prior parameterized in terms of the group-level mean and standard deviation. That is, $\alpha = \frac{(\mu^{\sigma}_{cjklmn})^2}{(\sigma^{\sigma}_{cjklmn})^2}$ and $\beta = \frac{\mu^{\sigma}_{cjklmn}}{(\sigma^{\sigma}_{cjklmn})^2}$. The group-level mean μ^{σ}_{cjklmn} and standard deviation σ^{σ}_{cjklmn} are each sampled from uniform hyperpriors ($L = 0.001, U = 1000$). Note that the baseline choice set serves as a level of both dispersion and spread but is only sampled once by the model.

APPENDIX D

BAYESIAN HIERARCHICAL MODEL OF CONTEXT EFFECTS (EXP. 2)

Based on principles and tools provided in Kruschke (2014), a hierarchical Bayesian multinomial regression model was developed to test for differences in choice proportions across levels of presentation format, target, context, dispersion, and spread. Each participant's choice probabilities are assumed to be multinomially distributed with parameters N^{stim}, the number of times each stimulus is presented, and π, the choice probabilities. For each participant *p* in each format condition *c* and for each target condition *j* (D_X or D_Y) in each context *k* (attraction, compromise, or similarity) in each level of dispersion *m* (low-dispersion X and high-dispersion Y, the baseline choice sets, or high-dispersion X and low-dispersion Y) and each level of spread *n* (the baseline choice sets or sets in which spread was increased by a factor two), the choice probabilities are determined using a two-stage process. First, for each alternative *a* the model sums the following effects: an intercept, $\mathcal{E}^{0}_{cpa}$; the target of the decoy, $\mathcal{E}^{target}_{cpja}$; the context, $\mathcal{E}^{context}_{cpka}$; the dispersion, $\mathcal{E}^{dispersion}_{cpma}$; the spread, $\mathcal{E}^{spread}_{cpna}$; the interaction of target, context, and dispersion, $\mathcal{E}^{targ*cont*disp}_{cpjkma}$; the interaction of target, context, and spread, $\mathcal{E}^{targ*cont*spread}_{cpjkna}$; and all subordinate two-way interactions. This result, $\varphi_{cpjklmna}$, is then submitted to a softmax transformation, which determines the probabilities of the multinomial likelihood. Specifically, the probability of selecting each alternative a is $\frac{\exp\,(\varphi_{cpjkmna})}{\sum \exp\,(\varphi_{cpjkmn.})}$. The prior probability of each effect $\mathcal{E}$ is assumed to be normally distributed with a mean of zero and a standard deviation of ${1/_{\sigma}}^2$, in which σ is sampled from an uninformed uniform hyperprior ($L = 0.001, U = 1000$). Note that the baseline choice set serves as a level of both dispersion and spread but is only sampled once by the model.

APPENDIX E

BAYESIAN HIERARCHICAL MODEL OF RESPONSE TIMES (EXP. 2)

Based on principles and tools provided in Kruschke (2014), a hierarchical Bayesian regression model was developed to test for differences in response times across levels of presentation format, target, context, dispersion, and spread. Response times are assumed to be log-normally distributed with parameters μ, the mean log response time, and σ, the standard deviation of the log response times. For each participant *p* in each format condition *c* and for each target condition *j* (D_X or D_Y) in each context *k* (attraction, compromise, or similarity) in each dispersion *m* (low-dispersion X and high-dispersion Y, the baseline choice sets, or high-dispersion X and low-dispersion Y) and each spread *n* (the baseline choice sets or sets in which spread was increased by a factor two), the mean log response times are modelled as the sum of the following effects: an intercept, $\mathcal{E}_{cp}^{0}$; the target of the decoy, $\mathcal{E}_{cpj}^{target}$; the context, $\mathcal{E}_{cpk}^{context}$; the dispersion, $\mathcal{E}_{cpm}^{dispersion}$; the spread, $\mathcal{E}_{cpn}^{spread}$; the interaction of target, context, and dispersion, $\mathcal{E}_{cpjkm}^{targ*cont*disp}$; the interaction of target, context, and spread, $\mathcal{E}_{cpjkn}^{targ*cont*spread}$; and all subordinate two-way interactions. The prior of each effect $\mathcal{E}$ is assumed to be normally distributed with a mean of zero and a standard deviation of ${}^{1}/{\sigma}^{2}$, in which σ is sampled from a uniform hyperprior ($L = 0.001, U = 1000$). The standard deviation of the log response times for each participant *p* in each level of each condition has a gamma prior parameterized in terms of the group-level mean and standard deviation. That is, $\alpha = \frac{(\mu_{cjkmn}^{\sigma})^2}{(\sigma_{cjkmn}^{\sigma})^2}$ and $\beta = \frac{\mu_{cjkmn}^{\sigma}}{(\sigma_{cjkmn}^{\sigma})^2}$. The group-level mean μ_{cjkmn}^{σ} and standard deviation σ_{cjkmn}^{σ} are each sampled from uniform hyperpriors ($L = 0.001, U = 1000$). Note that the baseline choice set serves as a level of both dispersion and spread but is only sampled once by the model.

APPENDIX F

BAYESIAN HIERARCHICAL MODEL OF EYE FIXATIONS (EXP. 2)

Based on principles and tools provided in Kruschke (2014), a hierarchical Bayesian regression model was developed to test for differences in the average total number of eyetracking fixations across levels of presentation format, target, context, dispersion, and spread. The average total number of fixations are assumed to be Poisson distributed with the rate parameter λ. For each participant *p* in each format condition *c* and for each target condition *j* (D_X or D_Y) in each context *k* (attraction, compromise, or similarity) in each dispersion *m* (low-dispersion X and high-dispersion Y, the baseline choice sets, or high-dispersion X and low-dispersion Y) and each spread *n* (the baseline choice sets or sets in which spread was increased by a factor two), the rate of eyetracking fixations is modelled as the exponentiated sum of the following effects: an intercept, $\mathcal{E}_{cp}^{0}$; the target of the decoy, $\mathcal{E}_{cpj}^{target}$; the context, $\mathcal{E}_{cpk}^{context}$; the dispersion, $\mathcal{E}_{cpm}^{dispersion}$; the spread, $\mathcal{E}_{cpn}^{spread}$; the interaction of target, context, and dispersion, $\mathcal{E}_{cpjkm}^{targ*cont*disp}$; the interaction of target, context, and spread, $\mathcal{E}_{cpjkn}^{targ*cont*spread}$; and all subordinate two-way interactions. The prior of each effect $\mathcal{E}$ is assumed to be normally distributed with a mean of zero and a standard deviation of ${}^{1}/{}_{\sigma}{}^{2}$, in which σ is sampled from a uniform hyperprior ($L = 0.001, U = 1000$). Note that the baseline choice set serves as a level of both dispersion and spread but is only sampled once by the model.

APPENDIX G

BAYESIAN HIERARCHICAL MODEL OF TRANSITIONS IN EYE FIXATIONS (EXP. 2)

Based on principles and tools provided in Kruschke (2014), a hierarchical Bayesian multinomial regression model was developed to test for differences in proportions of transitions in eye fixations across levels of presentation format, target, context, dispersion, and spread. Each participant's transition probabilities are assumed to be multinomially distributed with parameters N^{stim}, the number of transitions, and π, the transition probabilities. For each participant *p* in each format condition *c* and for each target condition *j* (D_X or D_Y) in each context *k* (attraction, compromise, or similarity) in each level of dispersion *m* (low-dispersion X and high-dispersion Y, the baseline choice sets, or high-dispersion X and low-dispersion Y) and each level of spread *n* (the baseline choice sets or sets in which spread was increased by a factor two), the transition probabilities are determined using a two-stage process. First, for each transition type *a* the model sums the following effects: an intercept, $\mathcal{E}^{0}_{cpa}$; the target of the decoy, $\mathcal{E}^{target}_{cpja}$; the context, $\mathcal{E}^{context}_{cpka}$; the dispersion, $\mathcal{E}^{dispersion}_{cpma}$; the spread, $\mathcal{E}^{spread}_{cpna}$; the interaction of target, context, and dispersion, $\mathcal{E}^{targ*cont*disp}_{cpjkma}$; the interaction of target, context, and spread, $\mathcal{E}^{targ*cont*spread}_{cpjkna}$; and all subordinate two-way interactions. This result, $\varphi_{cpjklmna}$, is then submitted to a softmax transformation, which determines the probabilities of the multinomial likelihood. Specifically, the probability of making each type of transition *a* is $\frac{\exp(\varphi_{cpjkmna})}{\sum \exp(\varphi_{cpjkmn.})}$. The prior probability of each effect $\mathcal{E}$ is assumed to be normally distributed with a mean of zero and a standard deviation of ${}^{1}/_{\sigma}{}^{2}$, in which σ is sampled from an uninformed uniform hyperprior ($L = 0.001, U = 1000$). Note that the baseline choice set serves as a level of both dispersion and spread but is only sampled once by the model.

APPENDIX H

METHODS OF MODELLING EXPERIMENTS B-E

Experiments B-E largely followed a similar methodology. In each experiment, participants were recruited from the UMass undergraduate research participant pool and earned two course credits for participation. Each participant viewed 432 test trials designed to elicit either the attraction, compromise, or similarity effect, as well as 24 trials consisting only of the binary pair X and Y and 36 "catch" trials that included a dominating alternative in order to identify participants who were not sufficiently engaged in the task. Only the test trials were used in the modelling analyses. The number of participants recruited for each experiment as well as the number excluded based on their performance in the catch trials is provided in Table H1.

In each experiment, all choice sets consisted of multiple alternatives within one of three product categories: apartments, laptops, or cars, that varied on two dimensions. Alternatives in the apartment choice sets were rated on their size and location, alternatives in the laptop choice sets were rated on their weight and battery life, and alternatives in the car choice sets were rated on their fuel efficiency and safety. In each test trial, alternative X rated well on dimension 1 but poorly on dimension 2, and alternative Y rated poorly on dimension 1 but well on dimension 2. The attraction decoy was rated similarly (.1 or .25 of the distance between X and Y for numeric and graphical formats, respectively) to the target alternative on both dimensions, but worse. The similarity decoy was rated similarly (.1 or .25 of the distance between X and Y for numeric and graphical formats, respectively) to the target alternative on both dimensions, but better on the dimension in which the target alternative rates well and worse on the dimension in which the target alternative rates poorly. Lastly, the compromise decoy is rated such that the ratings of the alternative being targeted fall precisely between the ratings of the decoy and non-target alternative for each dimension.

The experiments differed in stimulus representation, as outlined in Table H1. Experiment B presented subjective rating values (in which a higher rating represents a better value for the individual) in a graphical format, as in previous work by Cataldo & Cohen (2018a; 2018b). Experiments C and D presented subjective rating values numerically. Experiment E utilized numeric representations of objective measurements of each dimension.

Table H1. Additional methodological details for modelling experiments B-E.

Experiment	N	Trials per Context	Stimulus Format	Products	Dimension Scale
A (By-Dim)	209	24	Graphical (filled horizontal bars) with dimensions in columns and alternatives in rows.	Apartments	1-5 Subjective rating
A (By-Alt)	209	24	Graphical (filled horizontal bars) with alternatives in columns and dimensions in rows.	Apartments	1-5 Subjective rating
B (By-Dim)	66	144	Graphical (filled horizontal bars) with dimensions in columns and alternatives in rows.	Apartments Cars Laptops	0-7 Subjective rating
B (By-Alt)	61	144	Graphical (filled horizontal bars) with alternatives in columns and dimensions in rows.	Apartments Cars Laptops	0-7 Subjective rating
C	58	144	Numeric matrix with alternatives in columns and dimensions in rows.	Apartments Cars Laptops	0-7 Subjective rating
D	75	144	Numeric matrix with dimensions in columns and alternatives in rows. Boxes were drawn around rows.	Apartments Cars Laptops	0-7 Subjective rating
E	82	144	Numeric matrix with dimensions in columns and alternatives in rows.	Apartments Cars Laptops	150-1065 square feet 4-45 minute commute 1-5 official safety rating 14-57 miles per gallon .86-9 lbs 3-14.2 hours battery life

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