The Presence of the Attraction Effect in a Consumer Choice Task Using Scatterplots

Hunter Butz

Submitted to the faculty of the Department of Psychological and Brain Sciences in partial fulfillment of the requirements for the Honors degree in Psychology
Indiana University

April, 2024

Abstract

Human decision-making is influenced by the way choices are presented, with subtle changes in context shaping preferences in systematic ways. One well-documented example is the attraction effect, where introducing an inferior “decoy” option increases the likelihood of choosing a dominant alternative. A key factor in this effect is the saliency of domination - how clearly the decoy is perceived as inferior to the target option. This study examines how visual representations of choice options - specifically, the dispersion of data clusters in a scatterplot - influence decision-making. By manipulating the standard deviation of clusters representing restaurant reviews, I test whether greater dispersion affects choice preferences, particularly in the presence of a decoy. Using scatterplot visualizations, I manipulate the standard deviation of clusters on the scatterplot representing reviews for different restaurants to measure the presence of the attraction effect when participants select between imaginary restaurant options based on the review scores. I find that while this does not lead to an observation of the attraction effect, participants are more likely to select options, even when they are objectively inferior, when the data clusters representing the options have a larger standard deviation. My results show the impact of data presentation on perceptual factors that can influence preference in decision-making tasks.

Introduction

In many situations, the more objectivity in a decision, the better. As juries should be fair, managers should evaluate applicants based on merit, and political incumbents should be elected for their effectiveness. However, decisions, even as important as these, are often not as objective as one would hope. Early models of decision making - such as Luce's Choice Axiom (1959) - propose a fixed and stable model positing that the probability of selecting an option in a multi-alternative decision task is independent of the other available alternatives. Yet, decades of research have revealed systematic deviations from this rule. These deviations, known as *context effects*, occur when aspects of the alternatives influence decision outcomes. Classic examples include the attraction, similarity, and compromise effects -each demonstrating that adding a third option can shift the choice probabilities between two primary options.

Among these phenomena, the attraction effect is perhaps the most prominently studied. To illustrate, imagine a decision between option A and option B, each initially holding a 50% choice share where a decision-maker would be equally likely to choose A or B. When a third option, C, is introduced - one that is similar yet objectively inferior to one of the existing options - the relative attractiveness of that similar option increases. In effect, option C "pulls" choices toward its similar but dominant counterpart, thereby violating the principle of independence from irrelevant alternatives. While other context effects (e.g., the similarity effect, where introducing a similar decoy shifts preference away from a crowded option, and the compromise effect, where an intermediate option is favored) have been documented, the focus of the present study is on the attraction effect.

The extensive literature on context effects spans many settings—from product preferences (Huber et al., 1982) and political choices (O'Curry et al., 1995) to legal decisions (Kelman et al., 1996) and even honeybee food selection (Tan et al., 2014). Yet these studies often report inconsistent or even contradictory results. One explanation for these discrepancies is that various *boundary conditions* - factors that moderate the presence or magnitude of context effects - are at play. Researchers have pointed to variables such as decision time (Pettibone, 2012), spatial arrangement of options (Trueblood et al., 2013; Spektor et al., 2018), decoy viability (Frederick et al., 2014), and even how numerical information is presented (Yang & Lynn, 2014).

A particularly interesting boundary condition is *dominance*, which refers to the clarity of the superiority of one option over another. For the attraction effect to emerge, a decision maker must be able to perceive that one alternative is dominant relative to its competitors. Without such a discernible dominance relationship, the decoy (option C) cannot effectively "pull" choice toward the target. Indeed, Huber et al. (2014) argue that increased uncertainty in dominance relationships leads to a more ambiguous attraction effect. Moreover, research comparing experience-based and description-based choices (Hadar et al., 2018) suggests that in real-world settings - where dominance relationships may be less apparent - the attraction effect is diminished.

Another important factor influencing decision making is the way information is visually represented. The "*precision of representations"* (Spektor et al., 2021, p.13) - which reflects how distinctly differences between options are depicted - plays a key role. Visualizations that clearly highlight differences between attributes help decision makers more quickly discern relationships like dominance. In turn, this increased precision makes context effects (such as the attraction effect) more likely to emerge. Elements such as the spatial arrangement of data points, the dispersion of clusters, and the overall layout all contribute to the clarity (or imprecision) of the information available to the decision maker.

Deliberation time is another critical variable. As individuals take more time to analyze their choices, they become better able to perceive relationships among the alternatives. For instance, extended deliberation may reveal the dominance of one option over another, thereby amplifying the attraction effect. However, it is noteworthy that while increased deliberation can enhance the attraction and compromise effects, it appears to have little influence on the similarity effect (Spektor et al., 2021).

Given these variables, a promising way to test these theories is through the use of scatterplots. In the present study, scatterplots serve as a data visualization medium that effectively depicts both the precision of visual representations and the spatial relationships among options. For example, by manipulating the standard deviation of restaurant ratings data, we can create conditions where data clusters are either tightly grouped (high precision) or more dispersed (low precision). Prior work has shown that under the right conditions, scatterplots can elicit the attraction effect (Dimara, 2016). Moreover, research on visual attention indicates that factors such as cluster dispersion can influence how long participants attend to particular options (Etemadpour et al., 2014), further linking perceptual factors to decision-making outcomes.

I hypothesize that the attraction effect will be more pronounced in conditions where the standard deviation of data clusters is lower. In these conditions, the differences between clusters are more precise and discernible, thereby clarifying dominance relationships. I also hypothesize that this effect will peak when all data clusters exhibit a smaller standard deviation, maximizing the precision of representations and the salience of the target-decoy relationship.

Method

Participants

Initially, 333 undergraduate psychology students at Indiana University Bloomington initially volunteered for the current study in exchange for partial credit toward an experiment participation requirement. Three participants were excluded due to not completing the study. Within the study, I included an attention check comprised of 16 questions with an objectively correct choice (one option was clearly, objectively superior to another), and participants who missed three or more of these 16 attention checks were excluded. The attention check threshold caused us to exclude an additional 84 participants yielding 246 participants in our final sample. Of these 246 participants, 76.0% identified as female, 22.0% identified as male, and 2.0% identified other than male or female. Of the 246 participants, they identified their race as follows: 83.3% as white, 10.6% identified as Asian, 1.2% as African American, 0.4% as American Indian or Alaska Native, 0.4% as Native Hawaiian or other Pacific Islander, and 2.8% as any other race. 1.2% of participants preferred not to disclose their race. 7.7% of participants identified as of Hispanic, Latino, or Spanish origin. 91.5% participants identified as of not of Hispanic, Latino, or Spanish origin. 0.8% of participants preferred not to disclose.

Survey

I conducted the experiment through a survey deployed on Qualtrics. The survey consisted of a welcome page where participants received instructions describing the choice task involving making decisions between restaurants using ratings data displayed on a scatterplot before starting the experiment. I created the scatterplots using R. In addition to the choice task, participants also answered demographic questions as well as the Berlin Numeracy Test, a psychometric tool which measures statistical and risk literacy. The Berlin Numeracy Test was intended to measure differences among students with better understanding of statistical concepts, but no major differences were found. An example item from the test is as follows: In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?

Overall, each participant answered 56 trial questions with scatterplot ratings, 3 demographic questions, and 4 Berlin Numeracy questions (Cokely et al., 2012), totaling 63 questions. The median completion time was 9 minutes, 54 seconds. The mean completion time was 20 minutes, 5 seconds, but was skewed by multiple outlier participants who took well above the average completion time to finish.

Procedure

Participants received instructions to choose between imaginary restaurants based on imaginary ratings data displayed in a scatterplot. The ratings data consisted of tastiness and value metrics left by previous customers. Tastiness is defined as how much one enjoys the taste of the food served at the restaurant. Value is defined as the food's affordability - restaurants will have higher value ratings if they have lower prices on a scale of 0 - 100 for each measure. I assigned a number to represent each restaurant and a corresponding point color in the scatterplots with black representing Restaurant 1, grey representing Restaurant 2, and white representing Restaurant 3. Below the ratings scatterplot, participants selected which of the restaurants they would most like to eat at based on the ratings data.

Before beginning the survey, participants received instructions to complete the survey in one sitting. The survey instructions asked participants to disregard all other attributes of the restaurants, such as décor, location, distance, and service to clarify that the only measures to be considered were value and tastiness, and that no inferences be made. This served to reiterate that only the data presented to participants should be used in their decisions. Participants did not receive any feedback during the experiment and had no consequences for their choices, as credit was awarded for general completion of the survey.

Participants were randomly assigned to one of two conditions, with either the Tastiness ratings displayed on the horizontal X-axis (TX), or the Value ratings on the X-axis (VX). Participants saw ratings visualizations belonging to their respective groups (VX or TX) with two or three restaurants displayed in every trial. Displayed restaurants each had either a large or small standard deviation in their ratings data. The large standard deviation used was ten units on a scale of 100 and the small standard deviation used was five units on the same scale. In all trials, Restaurants 1 and 2 were competitors. In decoy trials, either Restaurant 1 or Restaurant 2 was the “target” and the other was the “competitor”. A third restaurant, Restaurant 3, appeared as an inferior decoy option to enhance the target restaurant. Each restaurant displayed had 20 ratings plotted in a cluster. The size of the visualizations was consistent across the vertical and horizontal dimensions.

Each participant saw every combination of standard deviation sizes, presence of a decoy, and which restaurant the decoy was targeting (see Table 1). For example, a specific condition may have had a small standard deviation (five units) for the ratings of Restaurant 1, a large standard deviation (10 units) for the ratings of Restaurant 2, and a decoy present for Restaurant 2 where the decoy had a small standard deviation. Participants saw all combinations of these factors in random order, where trial order was shuffled separately for each participant.

In decoy trial combinations (shown in Table 1), Restaurant 1 had a mean X value of 30 and a mean Y value of 70, while Restaurant 2 had a mean X value of 70 and a mean Y value of 30. Restaurant 3, the decoy, had an X value of 30 and a Y value of 50 if acting as a decoy for Restaurant 1, and an X value of 50 and a Y value of 30 if acting as a decoy for Restaurant 2. See Figure 1 for an example visualization. A difference in means of 20 between the decoy and the target option ensured the dominating target option was superior to the decoy option, especially in conditions where one or both restaurants had ratings with a small standard deviation.

In addition to the decoy trials, there were eight different obvious domination visualizations for each condition consisting of a restaurant (Restaurant 1 or 2) clearly dominating one or two other restaurants on the target attribute. Obvious domination trials have a clearly dominant option that a decision maker behaving rationally would always choose, providing instances where there are objectively correct options that can be used to measure the quality of a participant's answers and to exclude participants who fail to meet an objective criterion in these trials. The dominating option had an increased mean score along the target attribute, allowing it to appear as a visibly superior restaurant choice in that dimension compared to other options. In each obvious domination visualization, all restaurants jointly shared either a high or low standard deviation condition (Figure 2). Both participants in the TX and VX groups saw high and low standard deviation obvious domination trials, each with two and three restaurant options including an obvious domination option. Each of the TX and VX groups evaluated four visualizations with two restaurant options and four with three restaurant options, each with a different combination of a large or small standard deviation across all restaurants. Within these sixteen conditions, in the dimension the visually superior option was dominant in, the visually superior option had a mean that was 20 higher than the next highest option. In cases with three restaurants, the mean of Restaurant 3 was 20 units lower along the target attribute than the mean of Restaurant 2, and 40 units lower than the dominating restaurant (Restaurant 1). In obvious domination trials, all restaurant options shared the same mean value score on the non-target dimension.

Table 1

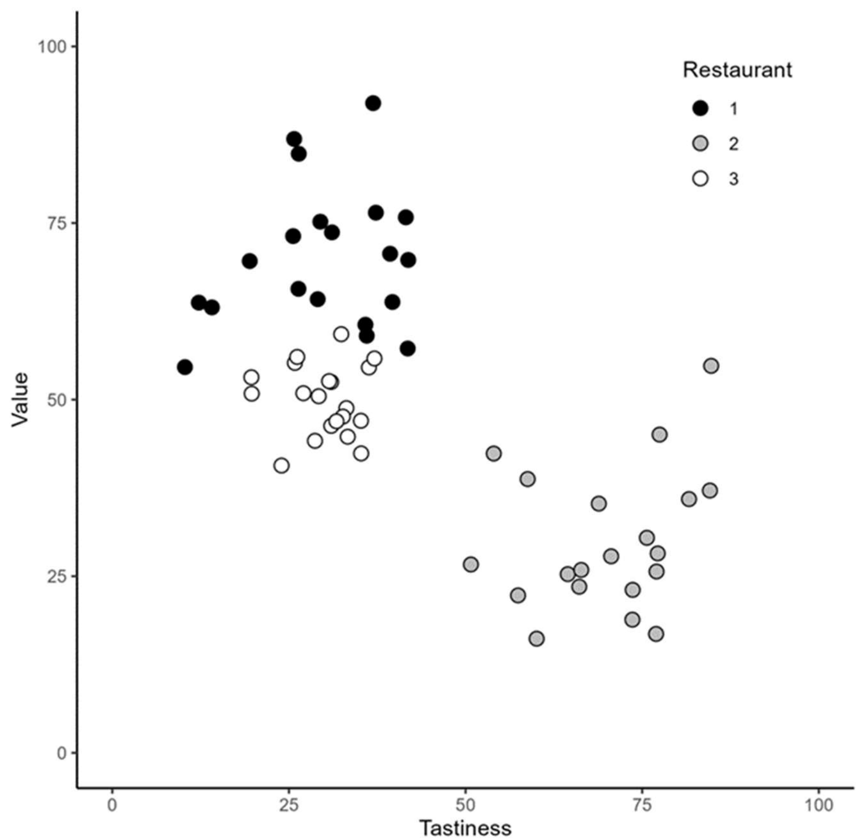
Decoy Trial Condition Combinations when Decoy is Present

Restaurant 1 SD	Restaurant 2 SD	Decoy SD	Decoy Position
Large	Large	Large	Restaurant 1
Large	Small	Large	Restaurant 1
Large	Large	Small	Restaurant 1
Large	Small	Small	Restaurant 1
Large	Large	Large	Restaurant 2

Large	Small	Large	Restaurant 2
Large	Large	Small	Restaurant 2
Large	Small	Small	Restaurant 2
Small	Large	Large	Restaurant 1
Small	Small	Large	Restaurant 1
Small	Large	Small	Restaurant 1
Small	Small	Small	Restaurant 1
Small	Large	Large	Restaurant 2
Small	Small	Large	Restaurant 2
Small	Large	Small	Restaurant 2
Small	Small	Small	Restaurant 2

Figure 1

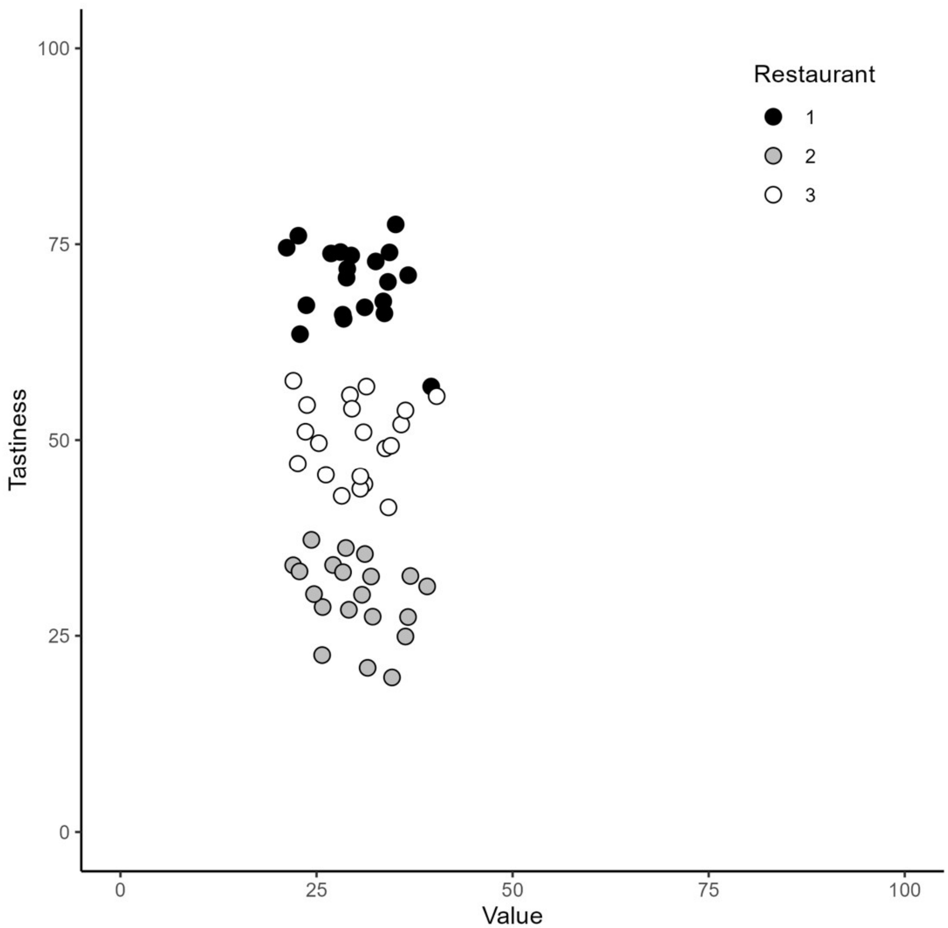
Decoy Trial Visualization



Note. This figure represents the trial ~~“1L.2L.D1S.TX”~~ where Restaurant 1 and Restaurant 2 are in the large standard deviation condition, a decoy is present proximal to Restaurant 1, and the decoy standard deviation is in the small SD condition. The Tastiness attribute is on the X-axis.

Figure 2

Obvious Domination Trial



Note. Obvious domination trial example - condition ~~“1SD.2S.3S.VX”~~ where Restaurant 1 dominates Restaurants 2 and 3 on the Tastiness dimension, all low SD, Value attribute on the X dimension.

Participants saw each of the decoy and obvious domination trials twice within their respective orientation group (VX or TX). There were 56 conditions in total, but any one participant, assigned either to the TX or VX group experienced 28 conditions. Each group consisted of every combination of small and large standard deviation ratings and decoy locations for four visualizations with two restaurants and no decoy and sixteen visualizations with two restaurants and a third decoy restaurant. Each group also had eight of the obvious dominance visualizations. In total, each participant completed 56 trials.

Data Analysis

To measure the attraction effect, I calculated Relative Share of the Target (RST), the rate at which a participant chose the target option compared to the competitor, across conditions. RST is defined as:

$$RST = \frac{CS(Target)}{CS(Target) + C\ \ (Competitor)}$$

Where CS(Target) is the choice share of the target, or how often the participant selected the target cluster as a proportion of all selection choices. I then compared between trials to determine the effect of a decoy option on participant choice preferences. The use of relative choice share of the target is normative in decision making studies identifying an attraction effect as demonstrated by Trueblood et al. (2013) and Berkowitsch et al. (2014). In the present experiment, I used an equal-weights approach to calculating participant-level RST. Thus, I used a mixed-effects ANOVA to measure significant differences in RST within and between conditions.

Results

Across all trials with a decoy, the average RST was .50 (SD of .074). The mean RST when the target restaurant had a high SD was .52 (SD of .13) and was .48 (SD of .11) when the target had a low SD. The mean RST when the competitor restaurant had a high SD was .48 (SD of .12) and was .52 (SD of .11) when the competitor had a low SD. The mean RST when the decoy restaurant had a high SD was .49 (SD of .10) and was .51 (SD of .09) when the decoy had a low SD. The effect of cluster SD was not present in binary choice sets with no decoy. The decoy was selected in 10.24% of trials when it was in the large SD condition and in 5.41% of trials when it was in the small SD condition.

Including the possible influence of different effects between the VX and TX conditions, I performed a mixed 2 (X axis variable) x 2 (Decoy SD) x 2 (Target SD) x 2 (Competitor SD) effects ANOVA on RST values. The effect of orientation of the visualization on RST (TX vs. VX) was not significant $F(1, 244)$, $p = .135$, $\eta_p^2 = .009$. The effect of target SD, $F(1, 244) = 15.744$, $p < .001$, $\eta_p^2 = .061$, decoy SD, $F(1, 244) = 11.069$, $p = .001$, $\eta_p^2 = .061$, and competitor SD, $F(1, 244) = 18.212$, $p < .001$, $\eta_p^2 = .069$ each have statistically significant influences on the RST. (Figure 3) A four-way interaction between target SD, decoy SD, competitor SD, and orientation was noted. No other interactions were present.

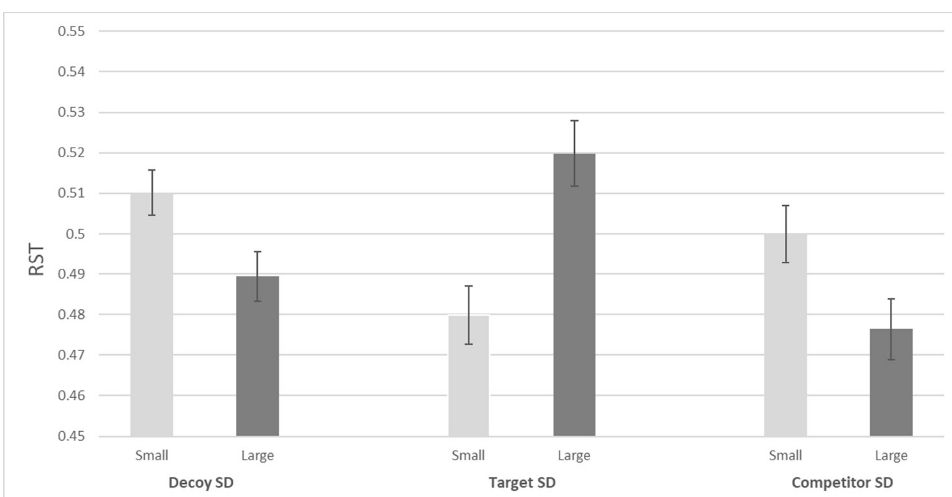
In non-decoy trials, participants greatly favored tastiness over value regardless of cluster size. The cluster scoring higher on tastiness and lower on value was selected in binary choice sets 79.64% of the time (74.3% when tastiness was the x-axis attribute and 85.0% when tastiness was the y-axis attribute). The cluster scoring higher in value was selected the other 20.36% of the time (15.0% of selections when value was the x-axis attribute and 25.7% of selections when value was the y-axis attribute). To determine the presence of an attraction effect in only asymmetrically advantaged alternatives as described by Huber et al. (1982), these choice shares were compared to their ternary counterparts where a decoy alternative was present. The choice shares did not differ significantly from binary choice shares, indicating that there is not an asymmetric attraction effect. Selection rates in ternary sets for tastiness were 75.0% as the x-axis attribute and 83.6% as the y-axis attribute. For value, the selection rates were 15.1% when value was the x-axis attribute and 26.5% when it was the y-axis attribute.

Response Time

The mean response time across all participants, measured as the time between the appearance of each visualization and the participants' first click on a choice option, was 4.269 seconds with a standard deviation of 6.238 seconds.

Figure 3

Effect of Cluster Type on RST



The mean response time using the data for the last click on each trial, measured as the time between visualization appearance and answer submission, was 4.722 seconds with a standard deviation of 6.496 seconds.

Selection Trends

In trials with a decoy, participants selected the target at a rate of 45.49%. In this same set of trials, participants selected the decoy 7.83% of the time. The SD of the decoy had a strong correlation with selection – in the small SD condition, participants selected the decoy on average 5.41% of the time, while in the large SD condition, it was selected 10.24% of the time, $t(245) = 6.73$, $p < .001$. Similarly, participants selected the competitor 44.58% of the time in the small SD condition and 49.62% of the time in the large SD condition, $t(245) = 3.67$, $p < .001$. In attention check trials participants selected the 'correct', objectively superior cluster 96.78% of the time.

Discussion

The results of the present study fail to support the hypothesis that increased domination saliency would positively correlate with the presence of an attraction effect. I found no evidence of an attraction effect in this study, as the mean RST was below 0.499.

One reason for failing to observe an attraction effect is that the attraction effect is correlated with decoy type. Among range, frequency, and range-frequency decoys, frequency decoys are shown to have the smallest attraction effect (Huber et al., 1982; Trueblood et al., 2013). When designing the experiment, I selected a frequency decoy (rather than a range decoy) for practical purposes. A range decoy increases the range on the lower-scoring axis between the target and the decoy. A frequency decoy increases the frequency of choices that have the same score for the lower-scoring axis. In the current experimental setup, frequency decoys would have a weak-attribute mean of 30 and would be dominated on the stronger attribute. A range decoy would have a strong-attribute mean of 70, same as the target, and instead be dominated on the weak attribute. Range decoys fall closer to the attribute limits of a plot, and with large SDs, range decoy ratings would have either had negative values or would have been compressed at the axis limits. To fix this, one would either need to move the cluster that extends beyond the attribute limits or change the range of space the cluster filled by lowering the SD. Lowering the SD posed the risk of making differences between conditions less apparent. Therefore, I opted to use a frequency decoy position where, if a singular line were to be drawn through both the decoy and target clusters, the line would be parallel rather than perpendicular to the axis closest to the target cluster. Overall, the usage of a frequency decoy both prevents decoy clusters crossing axis boundaries and ensures adequate space between the decoy and target needed for a clear dominance relationship while maintaining significant differences between SD conditions (large and small SD).

Dimara et al. (2016) find sufficient evidence of the attraction effect using scatterplots in their experiment. However, the experimental setup slightly differed in the present experiment. While the target, decoy, and competitor were all clusters each composed of 20 data points each, Dimara et al. use a single data point as each of the target and competitor, with much larger clusters acting as the decoy. The experimental setup used in the present study may have more uncertainty when participants make decisions, thus reducing the potential for the attraction effect to take place in the restaurant choice task by reducing attribute concreteness.

In the present experiment, findings show that as the decoy's SD increases, the RST decreases. Using the logic from Spektor et al. (2018), the relationship between decoy SD and RST on its own may indicate that as the decoy size increases it reduces the distance between the target and decoy, reducing the saliency of domination and decreasing the potential for an attraction effect. However, the present experiment also indicates RST increases when the SD of the target is larger. Theoretically a larger target SD would reduce the saliency of the dominance relationship by reducing the standardized distance between the target and decoy clusters, but that is not the present conclusion. Additionally, the SD of the competitor influenced RST – in the large SD condition, RST decreased, which cannot be an effect due to the saliency of domination as the competitor is not involved in the domination relationship.

The present findings suggest, more generally, that as a data cluster fills more visual space, a participant is more likely to select that cluster. Etemadpour et al. (2014) find in an eye-tracking experiment that attention to a data cluster scales with the sparsity rather than the size of the cluster on a scatterplot. Theoretically, this effect would carry over between our small and large SD conditions in the present study, indicating a perceptual effect given the findings from Pleskac et al. (2023) and Armel et al. (2008) that preference is positively correlated with attention. Indeed, in addition to the general effects of target, competitor, and decoy SD on RST (which is a measure of participant's selection of the target, specifically), post-hoc tests also find that the decoy and competitor options were also more likely to be selected when it had a large SD.

Divis et al. (2023) find that participants are likely to overestimate the mean value of a cluster when it has a higher SD, particularly due to the tendency for higher SD clusters to have the higher outlier data points that shift participants interpretation of the data. A similar effect occurs in the present study, as I find that clusters are selected more when they have a high SD vs a low SD. However, the objectively inferior decoy option also demonstrates this trend: participants choose the decoy with a higher SD almost twice as often as the low SD decoy option (10.24% vs 5.41% of trials). These results indicate that the data interpretation effect Matzen et al., (2023) and Divis et al. (2023) note may not explain my findings, as the high SD decoy clusters would not contain the highest point on the scatterplot – the target cluster contained many points with values that were higher on the y-axis, which should nullify this effect.

Scatterplots are one of many data visualizations used in our everyday life that can be affected by cognitive biases. When investigating the presence of one of the most well-known and notable of these biases in consumer decision making, the attraction effect, I did not find evidence of its presence under my experimental conditions. However, I did find the RST to be significantly affected by the sparsity of the cluster used to represent an option in our restaurant decision task. Further analysis revealed participants chose each cluster at increased rates when their SD was higher, which alongside previous research investigating choice biases when viewing scatterplots, indicates a perceptual effect that leads participants to make choices that are generally not normative for consumer decisions. Rather than choosing the "less risky" option when deciding between restaurants, as is expected in human decision-making tasks, consumers opted for riskier options, with risk being demonstrated by a greater range in attribute values. This finding underscores the complexity of decision-making processes and highlights the importance of considering visual cues in understanding consumer behavior beyond conventional norms.

References

Armel, K. C., Beaumel, A., & Rangel, A. (2008). Biasing simple choices by manipulating relative visual attention. *Judgment and Decision Making, 3*(5)*,* 396–403. https://doi.org/10.1017/s1930297500000413

Arrow, K. J. (1963). *Social choice and individual values.* Yale University Press.

Berkowitsch, N. A. J., Scheibehenne, B., & Rieskamp, J. (2014). Rigorously testing multialternative decision field theory against random utility models. *Journal of Experimental Psychology: General, 143(3),* 1331–1348. https://doi.org/10.1037/a0035159

Cai, X., & Pleskac, T. J. (2023). When alternative hypotheses shape your beliefs: Context effects in probability judgments. *Cognition, 231*

https://doi.org/10.1016/j.cognition.2022.105306

Cokely, E., Galesic, M., Schulz, E., & Garcia-Retamero, R. (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making, 7,* 35–47.

Dimara, E., Bezerianos, A., & Dragicevic, P. (2017). The attraction effect in information visualization. *IEEE Transactions on Visualization and Computer Graphics, 23(1),* 471–480. https://doi.org/10.1109/tvcg.2016.2598594

Divis, K. M., Matzen, L. E., Haass, M. J., & Cronin, D. A. (2023). Perceptual biases in scatterplot interpretation. In *Visualization Psychology* (pp. 273–291). Springer International Publishing.

Etemadpour, R. (2014). Eye-tracking investigation during visual analysis of projected multidimensional data with 2D scatterplots. *Proceedings of the 5th International Conference on Information Visualization Theory and Applications.* https://doi.org/10.5220/0004675802330246

Frederick, S., Lee, L., & Baskin, E. (2014). The limits of attraction. *Journal of Marketing Research, 51(4),* 487–507. https://doi.org/10.1509/jmr.12.0061

Hadar, L., Danziger, S., & Hertwig, R. (2018). The attraction effect in experience-based decisions. *Journal of Behavioral Decision Making, 31(3),* 461–468. https://doi.org/10.1002/bdm.2058

Heath, T. B., & Chatterjee, S. (1995). Asymmetric decoy effects on lower-quality versus higher-quality brands: Meta-analytic and experimental evidence. *Journal of Consumer Research, 22(3),* 268. https://doi.org/10.1086/209449

Hong, M.-H., Witt, J. K., & Szafir, D. A. (2022). The weighted average illusion: Biases in perceived mean position in scatterplots. *IEEE Transactions on Visualization and Computer Graphics, 28(1),* 987–997. https://doi.org/10.1109/tvcg.2021.3114783

Huber, J., Payne, J. W., & Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research, 9(1),* 90. https://doi.org/10.1086/208899

Huber, J., Payne, J. W., & Puto, C. P. (2014). Let's be honest about the attraction effect. *Journal of Marketing Research, 51(4),* 520–525. https://doi.org/10.1509/jmr.14.0208

Kelman, M., Rottenstreich, Y., & Tversky, A. (1963). Context-dependence in legal decision making. In *Social choice and individual values* (pp. 61–94). Yale University Press. https://doi.org/10.1017/cbo9781139175197.003

Luce, R. D. (1959). *Individual choice behavior.* John Wiley & Sons.

Mourali, M., Böckenholt, U., & Laroche, M. (2007). Compromise and attraction effects under prevention and promotion motivations. *Journal of Consumer Research, 34(2),* 234–247. https://doi.org/10.1086/519151

Pettibone, J. C. (2012). Testing the effect of time pressure on asymmetric dominance and compromise decoys in choice. *Judgment and Decision Making, 7(4),* 513–521. https://doi.org/10.1017/s1930297500002849

Simonson, I. (1989). Choice based on reasons: The case of attraction and compromise effects. *Journal of Consumer Research, 16(2),* 158. https://doi.org/10.1086/209205

Simonson, I., & Tversky, A. (1992). Choice in context: Tradeoff contrast and extremeness aversion. *Journal of Marketing Research, 29(3),* 281. https://doi.org/10.2307/3172740

Spektor, M. S., Bhatia, S., & Gluth, S. (2021). The elusiveness of context effects in decision making. *Trends in Cognitive Sciences, 25(10),* 843–854. https://doi.org/10.1016/j.tics.2021.07.011

Spektor, M. S., Kellen, D., & Hotaling, J. M. (2018). When the good looks bad: An experimental exploration of the repulsion effect. *Psychological Science, 29(8),* 1309–1320. https://doi.org/10.1177/0956797618779041

Sue O'Curry, Y. P., & Pitts, R. (1995). The attraction effect and political choice in two elections. *Journal of Consumer Psychology, 4(1),* 85–101. https://doi.org/10.1207/s15327663jcp0401_04

Tan, K., Dong, S., Liu, X., Chen, W., Wang, Y., Oldroyd, B. P., & Latty, T. (2014). Phantom alternatives influence food preferences in the eastern honeybee *Apis cerana. Journal of Animal Ecology, 84(2),* 509–517. https://doi.org/10.1111/1365-2656.12288

Trueblood, J. S., Brown, S. D., Heathcote, A., & Busemeyer, J. R. (2013). Not just for consumers. *Psychological Science, 24(6),* 901–908. https://doi.org/10.1177/0956797612464241

Tversky, A. (1972a). Elimination by aspects: A theory of choice. *Psychological Review, 79(4),* 281–299. https://doi.org/10.1037/h0032955

Tversky, A. (1972b). Choice by elimination. *Journal of Mathematical Psychology, 9(4),* 341–367. https://doi.org/10.1016/0022-2496(72)90011-9

Wu, C., & Cosguner, K. (2020). Profiting from the decoy effect: A case study of an online diamond retailer. *Marketing Science, 39(5),* 974–995. https://doi.org/10.1287/mksc.2020.1231

Yang, S., & Lynn, M. (2014). More evidence challenging the attraction effect. *Journal of Marketing Research, 51(4),* 508–513. https://doi.org/10.1509/jmr.14.0020