Judgment and Decision Making (2025), **20**:e6 1–25
doi:10.1017/jdm.2024.27

REGISTERED REPORT

A registered report on presentation factors that influence the attraction effect

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Received: 18 June 2024; **Accepted:** 26 June 2024

Keywords: context effects; attraction effect; presentation format; by-alternative by-attribute

Abstract

Context effects occur when the preference between two alternatives is affected by the presence of an extra alternative. These effects are some of the most well studied phenomena in multi-alternative, multi-attribute decision making. Recent research in this area has revealed an intriguing pattern of results. On the one hand, these effects are robust and ubiquitous. That is, they have been demonstrated in many domains and different choice settings. On the other hand, they are fragile and they disappear or even reverse under different conditions. This pattern of results has spurred debate and speculation about the cognitive mechanisms that drive these choices. The attraction effect, where the preference for an option increases in the presence of a dominated decoy, has generated the most controversy. In this registered report, we systematically vary factors that are known to be associated with the attraction effect to build a solid foundation of empirical results to aid future theory development. We find a robust attraction effect across the different conditions. The strength of this effect is modulated by the display order (e.g., decoy top, target middle, competitor bottom) and mode (numeric vs. graphical) but not display layout (by-attribute vs. by-alternative).

1. Introduction

Decades of research in psychology, economics, marketing, and neuroscience have been dedicated to understanding context effects in multi-alternative, multi-attribute choice. The overwhelming majority of this work has focused on three specific context effects–the attraction (Huber et al., 1982), similarity (Tversky, 1972), and compromise (Simonson, 1989) effects. These effects occur when choices between two alternatives can vary based on the presence of a third alternative. The three effects are important because they violate the principles of classic economic theories of choice including simple scalability, independence of irrelevant alternatives, and regularity (Roe et al., 2001). Hence, these effects cannot be explained by standard normative models of utility where every option is evaluated independently of each other (but see Farmer et al., 2017; Howes et al., 2016; Kruis et al., 2020 for rational explanations of context effects). Therefore, researchers have looked for psychological explanations for these effects. See Busemeyer et al. (2019); Trueblood (2022); Wollschlaeger and Diederich (2020) for a review of recent findings and computational models.

Research investigating context effects has revealed an intriguing pattern of results (Evans et al., 2021b; Spektor et al., 2021; Trueblood et al., 2015). On the one hand, context effects, and in particular the attraction effect, seem to be robust and ubiquitous. That is, they occur across a broad variety of different domains, including perception (Trueblood, 2015; Trueblood et al., 2013, 2015), risky decision making (Farmer et al., 2017), inference (Choplin and Hummel, 2005; Trueblood, 2012), motor-planning decisions (Farmer et al., 2017), and consumer choice (Dhar et al., 2000; Huber et al., 1982; Mishra et al., 1993; Noguchi and Stewart, 2014; Ratneshwar et al., 1987; Sen, 1998; Wedell and Pettibone, 1996). In addition, research in developmental psychology and behavioral ecology has shown that the attraction effect occurs in children (Zhen and Yu, 2016), monkeys (Parrish et al., 2015), cats (Scarpi, 2011), hummingbirds (Bateson et al., 2003), frogs (Lea and Ryan, 2015), honeybees (Shafir et al., 2002) and even slime molds (Latty and Beekman, 2011). Thus, there is a sense that contextual sensitivity is a universal property of multi-alternative choice behavior. On the other hand, these effects are also fragile, in that they may disappear or even reverse under certain conditions. The pattern of findings where context effects appear, vanish or reverse has sparked a lively debate about the underlying mechanisms responsible for multi-alternative, multi-attribute decision-making (see Cataldo and Cohen, 2019, 2021a; Frederick et al., 2014; Huber et al., 2014; Spektor et al., 2018, 2022; Trendl et al., 2021; Trueblood et al., 2015; Tsetsos et al., 2015; Yang and Lynn, 2014 for examples). Hence, understanding both the presence and absence of these effects is crucial to theory development.

Of the three effects, the attraction effect also known as the asymmetrically dominated alternative effect or the decoy effect (Huber and Puto, 1983; Huber et al., 1982; Simonson, 1989) has received the most attention. In the attraction effect, when choosing between two alternatives—a target and a competitor, the presence of a third decoy alternative that is similar but inferior to the target increases the choices of the target option. The attraction effect has been important both theoretically (Dhar and Glazer, 1996; Huber et al., 1982) as well as in applied settings, such as policy issues (Herne, 1997; Stoffel et al., 2019) and understanding gender bias in hiring decisions (Keck and Tang, 2020).

Recent research investigating the attraction effect has revealed an interesting pattern of findings with it appearing, disappearing or reversing under different conditions based on the way information is displayed (Cataldo and Cohen, 2019, 2021a; Frederick et al., 2014; Spektor et al., 2022; Trueblood et al., 2015; Yang and Lynn, 2014). These findings indicate that the way information is displayed, such as the mode of presentation (e.g., numeric vs. visual, Frederick et al., 2014; Trendl et al., 2021; Yang and Lynn, 2014), presentation order (Evans et al., 2021b), and presentation format (Cataldo and Cohen, 2019; Chang and Liu, 2008), influences the presence of the attraction effect.

Understanding the appearance and disappearance of the attraction effect can aid theory development and ultimately shed light on the processes that govern multi-alternative, multi-attribute choice behavior. For example, Trueblood et al. (2015) and Berkowitsch et al. (2014) showed that the compromise and attraction effects often co-occur while the similarity effect is negatively related to them. This pattern of correlations is now a benchmark for theories of context effects. Going forward, findings in Cataldo and Cohen (2019) and Evans et al. (2021b) showing that the attraction effect depends on presentation layout and presentation order of the options might also become benchmarks for theories of context effects. However, more empirical work is needed to establish these and other moderators of the attraction effect before they are adopted as modeling benchmarks. The present work aims to accomplish this goal.

Current models of multi-alternative, multi-attribute decision-making do not make predictions about the dependence of context effects on presentation formats (Bhatia, 2013; Busemeyer et al., 2019; Noguchi and Stewart, 2018; Roe et al., 2001; Trueblood, 2022; Trueblood et al., 2014; Turner et al., 2018; Usher and McClelland, 2004). These models use attribute values as inputs and describe how these values are transformed and compared to each other over time to produce a choice. They do not explain how the presentation format might affect these mechanisms.

For example, one leading model of context effects is the Multiattribute Linear Ballistic Accumulator (MLBA) (Evans et al., 2019; Trueblood et al., 2014; Turner et al., 2018). According to the MLBA, preference for an option is calculated as a weighted sum of pairwise comparisons between that option and the other options in the choice set. The weights (serving as a proxy for attention) on each pairwise comparison are related to the similarity of the attributes being compared, with more weight placed on options with similar attributes. When a decoy option that is similar but inferior to the target is introduced in the choice set, more weight is placed on that difference. Thus, comparisons of the target and decoy (which are favorable to the target) are weighted more when calculating preference. This leads to the target being chosen more often, resulting in the attraction effect (Trueblood et al., 2014). This model could be extended in various ways to explain the impact of presentation formats on context effects. For example, Evans et al. (2021b) extended the MLBA to explain how the temporal presentation of options influences the attraction effect. With regard to spatial order, the attention paid during a comparison might also be a function of the spatial proximity of different alternatives, where alternative pairs that are spatially close to each other receive more attention. However, in its original form, the MLBA makes no predictions about how attention might depend on the way the information is presented.

To understand the complex dependence of context effects on presentation formats, theorists will have to elaborate on the processes that convert information from the external displays to internal representations (Spektor et al., 2021). One might for example theorize about attentional processes that select information from external displays. These attention processes have been identified to play a central role in decision making (Krajbich, 2019; Krajbich et al., 2010; Noguchi and Stewart, 2018) and multi-alternative, multi-attribute choice (Trueblood, 2022). This may result in modifying a model, as described above in the case of the MLBA, where alternative pairs are selected based on their spatial proximity and other visual factors. Eye tracking studies have suggested that the processes that select information from external displays are important and of theoretical interest since they are interwoven with decision-making processes such as comparison and evidence accumulation (Krajbich, 2019; Krajbich et al., 2010; Noguchi and Stewart, 2014, 2018).

Theory building requires one to have a robust set of empirical findings that lays the groundwork for model development. As we shall see in the following section, existing literature reports conflicting empirical results regarding the impact of presentation format on the attraction effect. Past studies have also used a wide range of tasks and stimuli. For example, some studies have focused on perceptual decision making (Evans et al., 2021b; Spektor et al., 2018, 2022; Trueblood et al., 2013) as compared to preferential choice (Cataldo and Cohen, 2019, 2021b; Frederick et al., 2014). Further, some studies have shown that the attraction effect fails to replicate in certain situations (Frederick et al., 2014; Xiao et al., 2020). This paper builds on recent studies examining the dependence of multiattribute choice on presentation format and provides a comprehensive account of how presentation mode, layout, and order impact the attraction effect, providing rich empirical results for future theory development.

1.1. Presentation format factors

In this section, we review the different presentation factors that are known to affect the attraction effect. We have identified three important factors that are thought to affect the attraction effect—mode of presentation, presentation layout, and presentation order.

1.1.1. Mode of presentation

Frederick et al. (2014) argued that the attraction effect only occurs for numerically presented stimuli. They showed that most of the previous experiments demonstrating the attraction effect used information presented in a numerical format. They found that the attraction effect failed to generalize to naturalistic stimuli that did not use numbers. For example, in one scenario, they asked participants to choose between apples and oranges shown in pictures, where the decoy option was a moldy apple or a bruised orange. In another image based choice scenario, they asked participants to choose between Tropicana orange juice and milk by targeting the Tropicana orange juice by adding an additional option of a ‘stop and shop orange juice’ as a decoy. They also showed that graphical information, such as pie-charts, did not bring about the attraction effect. These results were further bolstered by Yang and Lynn (2014), who independently found that images, verbal descriptions, and qualitative descriptions failed to produce the attraction effect. For example, in one scenario, participants chose between ‘Coca-Cola’ and ‘Sprite’ with either the decoy ‘Cola’ or ‘Refreshe’, respectively. In another example, participants chose between three named food dishes based on their calorie content and price. The options were ‘Grilled Chicken Caesar Salad’ and a ‘Grilled Steak Caesar Salad’ with either the decoy ‘Crispy Chicken Caesar Salad’ or ‘Flat Iron Steak Frites’, respectively. More recently, Trendl et al. (2021) showed that the attraction effect does not occur for naturalistic stimuli, specifically choices among movies based on their title. Hence, they argued that the attraction effect is very limited and only occurs in highly stylized experiments with numerical stimuli.

This is in contrast to findings that the attraction effect holds with qualitative descriptions (Kivetz et al., 2004; Sen, 1998) and physical objects (Ratneshwar et al., 1987; Simonson and Tversky, 1992). In fact, studies have shown that the attraction effect persists even when participants are asked to perform low-level perceptual tasks such as judging the similarity of shapes (Choplin and Hummel, 2005) or choosing rectangles with the largest area (Trueblood et al., 2013). All of these studies failed to replicate in (Frederick et al., 2014) when picnickers were used as participants (except for Choplin and Hummel (2005) which was not tested). Since then, other studies have recreated the attraction effect using different presentation modes for the options. For instance, Cataldo and Cohen (2019) have recreated the attraction effect using bar graphs. Dimara et al. (2016) have recreated it using scatter plot display formats, and Evans et al. (2021b), Farmer et al. (2017), Trueblood et al. (2015), Turner et al. (2018) recreated it with perceptual stimuli similar to Trueblood et al. (2013). Taken together, Spektor et al. (2021) identified the ‘concreteness’ of representation as an important factor moderating the attraction effect. In our experiment, we use both graphical displays as in Cataldo and Cohen (2019) along with numerical displays to test the importance of presentation mode (see Figure 1 for examples of graphical and numerical stimuli used).

1.1.2. Presentation layout

The presentation layout of information has been shown to influence the presence of context effects (Cataldo and Cohen, 2018, 2019, 2021b; Chang and Liu, 2008; Liu and Trueblood, 2023). In Chang and Liu (2008) and Cataldo and Cohen (2019) the authors showed that changing the display of options from ‘1by-attribute’ to ‘by-alternative’ impacted context effects. The by-attribute format lists alternatives in rows and attributes in columns, which may facilitate easy comparison of the same attribute for different alternatives. The by-alternative format lists alternatives in columns and attributes and rows and is designed to impede comparisons between alternatives, thus different alternatives are compared more holistically rather than by their individual attributes. Cataldo and Cohen (2019) showed that when the alternatives are compared in a by-attribute format, the attraction effect appears. However, when alternatives are compared in a by-alternative format, then the attraction effect disappears. Hence, by-attribute and by-alternative display formats have been identified as strong modulators of the attraction effect (Spektor et al., 2021).

However, other studies examining by-attribute and by-alternative formats have found conflicting results. For example, Cataldo and Cohen (2021b) used both graphical (two experiments) and numerical (three experiments) formats. We reanalyzed their data and found a complex pattern of attraction and repulsion effects (full details and results are presented in the Supplementary Materials). Briefly, similar to Cataldo and Cohen (2019), our reanalysis found that graphical formats showed an attraction effect in the by-attribute format but a weak repulsion effect in one of their two experiments in the by-alternative format. Regarding the numerical format, in one experiment where attributes were presented along rows and alternatives along columns, we found a net null effect. In a second experiment, when alternatives were presented in rows and attributes in columns, we observed a weak attraction effect. Finally, in a third experiment, with a similar format as the second experiment, when boxes were drawn around the attributes, potentially to facilitate more attribute-wise comparison, once again, we observed a net null effect. Liu and Trueblood (2023) conducted experiments where participants had to choose between tasks based on difficulty and length. They used numerical by-attribute and by-alternative formats similar to the ones in this paper. They observed a weak repulsion effect and no attraction effect in all of the

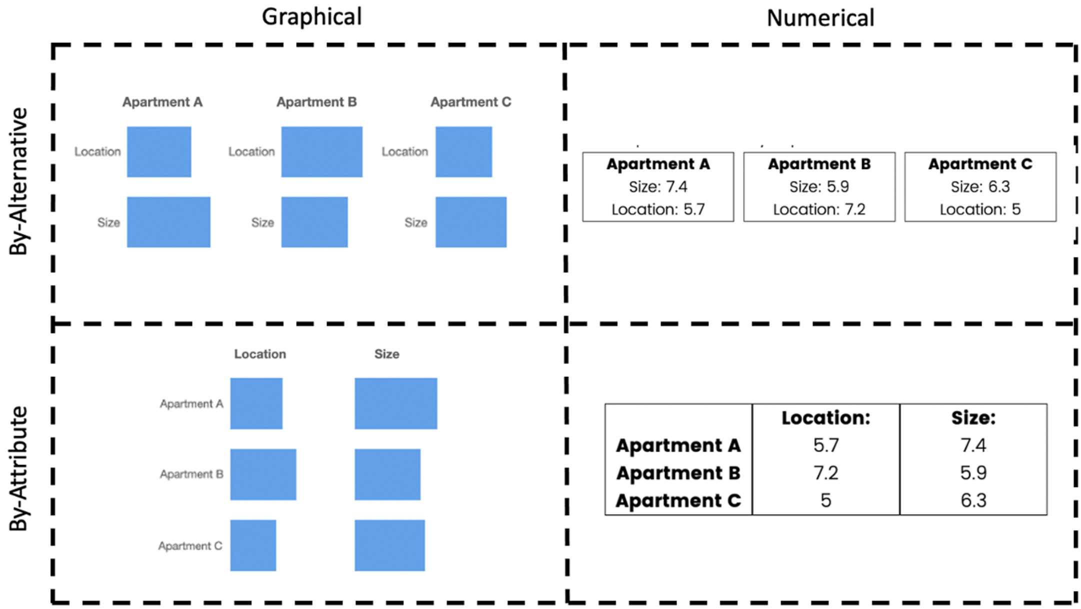

Figure 1. *The same choice set in different presentation formats used in our experiment. The panels on the left show the graphical formats and the panels on the right show the numerical formats. The top row contains examples of the by-alternative layout. The bottom row contains examples of the by-attribute layout. In each condition, Apartments A and B are the target and competitor, respectively. Apartment C is the decoy option that is dominated by A but not by B.*

formats among a large variety of manipulations. These results challenge the ideas that concreteness of representation (Spektor et al., 2021) and numerical formats (Frederick et al., 2014; Yang and Lynn, 2014) are essential to the emergence of the attraction effect.

In our experiment, we follow Cataldo and Cohen (2019) and present information in a by-alternative and by-attribute format to test the importance of the presentation format. We cross this manipulation with presentation mode to examine how presentation format impacts graphical vs. numerical stimuli. See Figure 1 for examples of by-alternative and by-attribute formats used in our experiment.

1.1.3. Presentation order

Evans et al. (2021b) showed that the order in which the three options, target (T), competitor (C) and decoy (D), are presented can modulate the attraction effect. Evans et al. (2021b) reanalyzed data from Trueblood et al. (2015) where the spatial order (i.e., the left to right placement) of the three options was varied. When all orderings were considered together, these stimuli showed a small attraction effect. However, of the 6 orders, 3 orders (CTD, DTC, and TDC, where the order of the letters corresponds to the left, middle, and right placement of options) showed a strong attraction effect, 2 orders (DCT and TCD) showed a strong repulsion effect, and 1 order (CDT) showed a null/weak attraction effect. Their conclusion was that the close proximity of the target and the decoy facilitated a series of comparisons that brought about the attraction effect.

In a reanalysis of Cataldo and Cohen (2021a), we also examined the impact of presentation order on attraction and repulsion effects (full results are presented in the Supplementary Materials). This experiment used graphical formats similar to Cataldo and Cohen (2019) shown in Figure 1. To summarize, the impact of presentation order differed between by-attribute and by-alternative formats for graphically represented options. As mentioned above, the by-alternative format had a weak repulsion effect on average. However, this repulsion effect was only significant in two of the 6 orders—TCD and TDC. In contrast, in the by-attribute format, there was a significant attraction effect on average. However, it was strongly significant in 3 of the 6 orders (CTD, DTC and TDC) and weakly significant in the TCD order. As shown in the Supplementary Materials, these results change slightly when the exclusion criterion is removed.

Hence, in the by-attribute graphical formats, the attraction effect is the strongest with the same orders as those of the perceptual decision-making from Evans et al. (2021b). However, none of the orders show a repulsion effect. For the by-alternative format, none of the orders showed an attraction effect. However, TCD showed a repulsion effect as in the perceptual decision-making task. Intriguingly, compared to the perceptual decision-making task and the by-attribute graphical display, the reversal with TDC suggests an interaction between presentation layout and presentation order.

In our experiment, we vary the order in which the options are presented to participants to test whether the presentation order continues to influence the attraction effect in all of the conditions mentioned above.

1.2. Experimental Aims

Previous studies have independently examined the impact of various presentation factors on the attraction effect. As mentioned above, these studies have used a vast set of stimuli and tasks and have come to different conclusions. Yang and Lynn (2014) and Frederick et al. (2014) showed that the attraction effect is weaker with graphical stimuli than with numerical stimuli. However, since then, the attraction effect has been recreated using graphical stimuli (Cataldo and Cohen, 2019, 2021a; Spektor et al., 2018; Trueblood et al., 2015). It has also been reversed for numerical stimuli (Liu and Trueblood, 2023) or found to be weaker in our re-analysis of data from Cataldo and Cohen (2021b) with numerical stimuli. There have only been a few studies (Cataldo and Cohen, 2019, 2021a) that examine the dependence of the attraction effect on presentation layout (by-alternative vs. by-attribute). These studies show that presentation layout modulates the attraction effect in graphical displays. The influence of presentation layout on the attraction effect with numerical stimuli has been either null or weakly positive or negative (Cataldo and Cohen, 2021b; Liu and Trueblood, 2023) (but see Chang and Liu (2008) for modulation of the compromise effect with numerical stimuli). The effect of changing presentation order has been shown for perceptual decision-making (Evans et al., 2019), but it remains unknown how order impacts numerical stimuli. In our reanalysis of Cataldo and Cohen (2021a), we showed that the impact of changing presentation order may be different for consumer decision-making in different presentation formats. Hence, empirically, it is not clear which of these effects are robust. Further, as shown with our reanalysis of Cataldo and Cohen (2021a), presentation layout and presentation order might interact with each other. Thus, it is important to systematically vary all of these factors in a single large-scale experiment.

At this point, we reiterate the theoretical positions and predictions made by different studies. Frederick et al. (2014) and Yang and Lynn (2014) predict that the attraction effect will be stronger or only occur when information is represented in numerical formats as compared to graphical formats. Spektor et al. (2021) hypothesized that this might be due to the fact that numerical formats are represented more concretely, making the domination of the decoy by the target clearer. Cataldo and Cohen (2019) predict that the attraction effect will be stronger in by-attribute formats than by-alternative formats since this facilitates more comparisons between options. This is consistent with the idea that certain comparisons are facilitated in certain formats and that these comparisons are integral to the construction of choice (Cataldo and Cohen, 2019; Noguchi and Stewart, 2014, 2018; Spektor et al., 2022). For presentation order, the results from Evans et al. (2021b) indicate that the attraction effect is enhanced when the decoy and the target occupy neighboring positions. This might also be due to an ease of comparison between the target and the decoy.

In order to lay the groundwork for further theory development, we need a comprehensive understanding of how different aspects of presentation format impact multi-alternative, multi-attribute choice. However, it is not clear which of these findings are robust and generalizable. Since existing theories do not naturally (without modification) predict or explain these presentation effects, we think it is important to lay a firm foundation for future theory building. That is the development of new models or extensions to existing models that can account for more complex patterns of behavior. Thus, there is a need to evaluate which of these formats facilitate the attraction effect and which ones potentially reverse it. We address this need in this paper by using a factorial design to carefully manipulate the different presentation factors that are thought to affect the size and direction of the attraction effect.

Further, the combined effects of these factors are not known. For example, Evans et al. (2021b) argued that the presentation order facilitates certain comparisons between options that are spatially closer to each other. Similarly Cataldo and Cohen (2019) argued that by-alternative and by-attribute displays facilitate certain comparisons between the alternatives and attributes. However, when both manipulations are implemented simultaneously, it is not immediately clear what the results will be without an empirical test. Our re-analysis of Cataldo and Cohen (2021a) suggests that there might be interesting ways in which these factors interact with each other.

Our approach differs from the recommendation made by proponents of the crucial experimentation hypothesis (Lakatos, 1974) or the strong induction hypothesis (Platt, 1964) where experiments are designed to test competing models. Instead, we systematically vary factors that are of relevance (Almaatouq et al., 2022; Dubova et al., 2022; Peterson et al., 2021) to multi alternative, multiattribute decision making and the attraction effect more specifically. As mentioned above, the current models of multiattribute choice do not make strong predictions about how presentation formats impact decision-making. This experiment will serve as a high-powered benchmark and provide researchers with a robust set of empirical findings that will aid in future model development (Noguchi and Stewart, 2018; Trueblood et al., 2014; Turner et al., 2018).

2. Method

In our experiment, we examine the presence of the attraction effect among 6 different consumer goods (3 novel goods and 3 goods from Noguchi and Stewart (2014)) by varying the mode of presentation, presentation layout, and presentation order in which the options are displayed. We use 2 different presentation modes (numerical and graphical), 2 different presentation layouts (by-alternative and by-attribute), and 6 different presentation orders. This gives a total of 24 ternary choice conditions. The data and analysis code are available on the Open Science Framework at https://osf.io/wzct3/.

2.1. Participants

We aimed to recruit a total of 2300 participants from Amazon Mechanical Turk using CloudResearch in exchange for a cash payment of $0.50 per person. We included participants who were over 18 years of age and based in the United States with matching IP addresses. To maintain data quality, we only allowed individuals who had a 95% or higher HIT approval rate and were approved by Cloud Research's attention and engagement measures to participate. Using CloudResearch, we also blocked participants based on their list of suspicious geocode locations and with duplicate IP addresses. We pre-registered our manuscript after first stage acceptance on the Open Science Framework (OSF): https://doi.org/10.17605/osf.io/sgj3w. The experiment was approved by the Institutional Review Board at Indiana University. We only consider the data of the individuals who completed the entire experiment.

Since the goals of our experiment are exploratory, we will test the robustness of our results with and without exclusions. We apply two exclusion criteria that are often used in the literature. We included two attention checks in our experiment to exclude participants who were not attentive during the experiment. In previous experiments, for example, Cataldo and Cohen (2019) and Evans et al. (2021b), participants were excluded for failing catch trials. In the same vein, we will exclude participants who chose the decoy option for more than 3 out of 12 trials since they selected an option that was dominated.

Ultimately, a total of 2,293 participants completed the experiment (gender: 903 males, 1357 females, 20 non-binary/third gender, 13 preferred not to say; age in years: $M = 43.3$, SD = 13.4, IQR: 33 – 53; race: 1791 White, 218 Black or African American, 136 Asian, 74 Multiracial, 14 American Indian or Alaska Native, 6 Native Hawaiian or Other Pacific Islander, 54 preferred not to say; income: 163 less than $15,000, 211 $15,000–$25,000, 561 $25,000-$50,000, 525 $50,000–$75,000, 494 $75,000–$120,000, 273 more than $120,000, 66 preferred not to say). As described below, there were four between-subject conditions. In the binary, by-alternative condition we had 147 participants. In the binary, by-attribute condition we had 150 participants. In the ternary, by-alternative condition we had 999 participants. In the ternary, by-attribute condition we had 997 participants. The experiment took an average of 6.8 (IQR: 4.1 – 7.6) minutes to complete.

Sample size calculation: We analyze the attraction effect using the relative choice share of the target (RST) determined by the ternary choice sets (Berkowitsch et al., 2014). The RST is defined as the ratio of the number of times the target has been selected to the number of times the target and the competitor have been selected:

$$RST = \frac{n_{\text{target}}}{n_{\text{target}} + n_{\text{competitor}}}.$$

If the RST is significantly greater than 0.5, then there is evidence of an attraction effect. RST values significantly less than 0.5 provide evidence of a repulsion effect. To estimate the sample size (n), we conducted the following power analysis. We assumed that each trial is a Bernoulli variable with an underlying probability of p of selecting the target. To show evidence of the attraction effect, we need to show that the probability of selecting the target is significantly greater than 0.5 on trials where either the target or competitor was selected (that is, we exclude the trials where the decoy was selected). This is equivalent to testing whether the RST value is significantly greater than 0.5. We tested this using an exact binomial test.

Suppose that we observe that the target has been selected n_{target} out of n ($= n_{\text{target}} + n_{\text{competitor}}$) times. The exact binomial test will be significant if n_{target} is greater than the threshold t that is given by the 97.5^{th} percentile of the binomial distribution generated with a probability of 0.5 with n repetitions. Suppose our desired power is P, we would want this result to be significant with a probability of at least P. We find the smallest n such that the outcome is n_{target} of a binomial random variable generated with a probability p with n trials greater than t with a probability of P. We plot these values for different probabilities of selecting the target p and power P in Figure 2.

To select an estimate of the probability p of selecting the target, we used publicly available data from Noguchi and Stewart (2014) to calculate RST values. We present all of our results in the Supplementary Materials. As described in the following section, these stimuli used identical attribute names and values as some of the stimuli used in our experiment. The RST values were 82.0%, 80.0%, and 64.4% for the stimuli considered in our experiment. However, other studies find much lower values, such as 50.4% and 55.2% in Cataldo and Cohen (2019).

As shown in the figure, the number of trials required changes drastically when the probability of selecting the target is around 0.55. At a reasonably high power of 0.95, we would require about 900 trials to detect an effect with an underlying probability of selecting the target of 0.58 after accounting for the Bonferroni correction at $p = 0.05/24$. Since we have a total of 6 (order) x 2 (layout) x 2 (format) = 24 ternary choice conditions, we need a total of 21,600 ternary choice trials. Since each participant does 12 trials, we obtain about 1,800 participants. Participants choose the decoy option about 5%–10% of the time (Cataldo and Cohen, 2021b; Frederick et al., 2014; Noguchi and Stewart, 2014). These trials will need to be removed from our RST analysis. We account for this in our estimate and obtain our estimate of 2,000 participants. These calculations assume that our analyses are conducted by combining the 6 different consumer goods in our experiment. We also plan to analyze old stimuli (i.e., the three consumer goods from Noguchi and Stewart (2014)) and novel stimuli separately to test for reliability and generalizability. If we consider each of the 6 goods separately, we obtain about 150 trials per

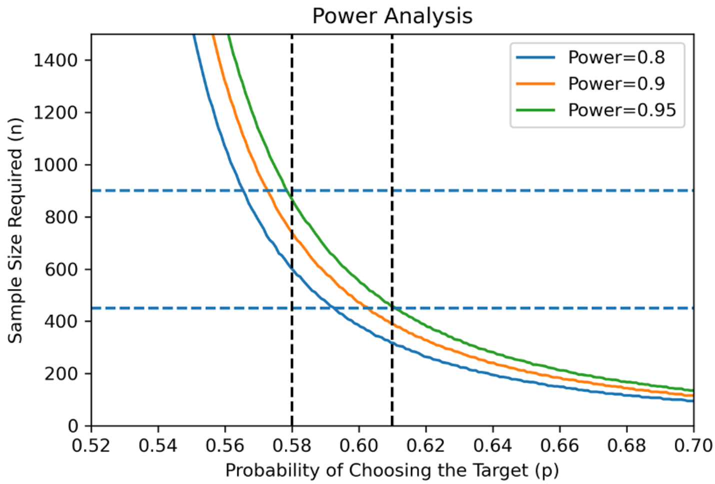

Figure 2. *This figure shows the sample size (n) required for the exact binomial test to be significant for a given power (P). The sample size (n) required is plotted on the y-axis and the unknown underlying probability (p) of selecting the target is plotted on the x-axis. The different lines show the sample size required for different powers P after accounting for the Bonferroni correction at* $p = 0.05/24$. *The vertical lines allow us to see the sample size required for different values of p. The horizontal line at* $n = 900$ *shows that we would be able to detect an effect with* $p = 0.58$ *with a high power* $P = 0.95$. *When old stimuli and novel stimuli are considered separately, we would be able to detect an effect with* $p = 0.61$ *with a power of* $P = 0.95$.

condition. Thus, we will have 450 trials per condition after combining the three old consumer goods and 450 trials per condition after combining the three new consumer goods. This will allow us to detect an effect when the underlying probability of selecting the target is about 0.61 with a power of 0.95 when we separately analyze old and new consumer goods.

We conducted a power analysis using nested model comparison to test the strength of the interaction effects. Here we summarize the key results and provide the details in the Supplementary Materials. We quantify the effect size *e* as the increase in the probability of selecting the target by *e*. We see that with a power of 0.95, for the mode and layout interaction, we can observe an interaction effect of size 0.05 when all the consumer goods are analyzed together and an effect of size 0.07 when old and novel goods are analyzed separately.

For the order and mode interaction, the effect can be driven by different levels of order. The effect can be driven by a single level of order (e.g., DTC: decoy, target, competitor in the numerical mode) or by several different levels of orders interacting with the mode. In the Supplementary Materials, we present the results of the power analysis when there are 1, 2, and 3 possible levels of order interacting with the mode. When we combine all consumer products, with a power of 0.95, we will be able to detect an effect of size 0.09 when there is a single level of order interacting with the mode and 0.07 when two or three levels of order interact with the mode. When old and new goods are analyzed separately, with a power of 0.95, we will be able to detect an effect of size 0.11 when it is driven by one level of order interacting with the mode and an effect of size 0.08 when it is driven by two or three levels. These results are the same for the interaction between order and layout since both mode and layout have the same number of levels.

We only show the results of the three way interaction when a single level of order interacts with the other two variables. When we combine the consumer goods, with a power of 0.95, we will be able to detect an effect of size 0.16. When we analyze old and new goods separately, with a power of 0.95, we will be able to detect an effect of size 0.22.

Table 1. *The attribute values for the 6 stimuli used in the experiment. For each stimulus, there were two different alternatives X and Y.*

Stimulus type	Attribute	X	Y	X_d	Y_d
Highlighters	Brightness (0–1)	0.4	0.8	0.3	0.7
	Capacity (line length in km)	18	10	16	8
Paper towels	Tear Strength (in grams)	800	2,420	395	2,015
	Absorbability (in ml)	52	28	46	22
Walking shoes	Durability (in months)	8	32	2	26
	Comfort (out of 100)	88	64	82	26
Apartments	Size (1–10)	7.4	5.9	6.3	5.2
	Location (1–10)	5.7	7.2	5.0	6.1
Laptop	Battery Life (1–10)	8.2	5.2	7.0	4.1
	Portability (1–10)	4.8	7.9	4.1	6.7
Cars	Safety (1–10)	9.6	8.2	8.7	7.1
	Reliability (1–10)	8.1	9.5	6.7	8.3

Note: Two additional decoy alternatives were X_d and Y_d such that these were strictly dominated by X and Y, respectively. The ternary choice set for each consumer good consisted of X, Y and one of the two decoy options X_d or Y_d. For every participant, for each consumer good, the decoy option was selected randomly. The binary choice set consisted of a choice between X and Y in the two orders.

Apart from the ternary trials mentioned above, to observe choice proportions between the target and the competitor in the absence of the decoy option, we decided to include binary choice trials. These will be presented in 2 different layouts and 2 different formats giving us 4 conditions. Since we will not analyze the binary trials based on order, we do not account for that factor in this calculation (but note that order is randomized). Since we need 900 trials per condition, we will need $3,600$ trials. Since each individual will do 12 trials, we obtain our estimate of 300 additional participants. This takes our total to $2,300$ participants.

2.2. Materials

We used six different consumer goods for our experiment. The consumer goods, attribute names, and attribute values are presented in Table 1. To construct a binary choice set, we present the two alternatives in one of two possible orders *XY* and *YX*. For a ternary choice set where the options are shown in one particular order (e.g., DTC: Decoy, Target, Competitor from left to right), there are 6 choice sets with one decoy (e.g., X_d) and another 6 choice sets with the other decoy (e.g., Y_d), yielding a total of 12 ternary choice sets. For each stimulus, we generated four different question formats in a 2x2 design [mode: graphical vs. numerical] x [layout: by-alternative vs. by-attribute]. Examples of these different formats can be seen in Figure 1.

Since we were primarily interested in studying the importance of presentation format, we uniformly chose attributes that had a positive valence. That is, larger values were considered to be more desirable. As shown in the Supplementary Materials, three of these stimuli - paper towels, highlighters, and walking shoes and their numerical values - were identical to stimuli used in Noguchi and Stewart (2014) and demonstrated strong significant attraction effects (Paper Towels: RST = 82.0%, $p < 0.001$; Highlighter: RST =80.0%, $p < 0.001$; Walking Shoes: RST =64.4%, $p = 0.008$). In the experimental program, one of the attribute values for the walking shoes was erroneously copied from Noguchi and Stewart (2014). Specifically, the comfort for Y_d should have been 58 instead of 26. Despite the error, Y_d is still dominated by Y but not X and serves as an attraction decoy. Hence, we retain the walking shoes in our analyses but do not treat them as an old product. We note that walking shoes show a standard attraction effect when analyzed separately with an RST=61.7%, $p < 0.001$, as shown in the

Supplementary Materials. However, since X_d is from the original Noguchi and Stewart (2014), we do not treat it as a new product either.

The other three consumer goods - apartments, cars, and laptops - have also been used in context effects research (Cataldo and Cohen, 2019; Evans et al., 2019; Simonson and Tversky, 1992). For each product, the two attributes were on a 0-10 scale. In order for X and Y to have similar preference levels (assuming equal weight on the two attributes), the sum of the two attributes of X was similar to the sum of the two attributes of Y. Further, these ratings were mostly in the 4-10 range, so neither option would be too unfavorable on one of the attributes. Here we use novel numerical attribute values for these items to test the generalizability of our results.

2.3. Procedure

During the course of the experiment, every participant answered a total of 12 questions over two blocks. The small number of trials per participant is based on the suggestion made by Lichters et al. (2015) to avoid learning processes in repeated choice and since context effects are thought to be attenuated with a high frequency of repeated choices. In between the two blocks, we included ten filler trials in which participants were asked to name different state capitals in the United States of America. This distractor task was added based on the suggestion by Lichters et al. (2015) and Hutchinson et al. (2000) to avoid carry-over effects and psychological reactivity from previous trials.

At the start of the experiment, each participant was assigned to one of 2x2 between-subjects conditions [choice type: binary, ternary] x [layout: by-alternative vs. by-attribute]. The layout of the options (as shown in Figure 1) remained constant for participants throughout the experiment. The two blocks of the experiment were the graphical block and the numerical block. The order of the two blocks was randomized across participants. For each question, participants, depending on the condition they were assigned, saw two or three options of a consumer good and were asked to select the one that they preferred. The graphical block presented questions in a graphical format using bar graphs and the numerical block presented questions in a numerical format using tables. See Figure 1 for examples of questions in different formats.

Each block consisted of 6 questions with the 6 different consumer goods from Table 1. Each consumer good appeared once in each block. For each consumer good, the decoy (X_d or Y_d) was randomly selected for each question in the first block. Since there were only 2 binary presentation orders (XY and YX), these were randomized for every participant. For the ternary choice condition, the presentation order (of the target, competitor and decoy) was pseudo-randomly varied such that each participant saw all 6 orders. In the second block, the choice sets and order of alternatives were the same as in the first block. The only difference between the first and second blocks was the presentation mode (numerical vs. graphical). The randomization was designed so that each of the 24 ternary conditions - 2 presentation modes, 2 presentation layouts, 6 orders, and 2 decoy types (i.e., X_d or Y_d) - were counterbalanced. The two binary conditions were shown as often as 1 of the 24 ternary conditions, balanced equally in the two presentation orders XY and YX.

There were two attention checks (e.g., the true/false question ‘I have never used a computer’) at different points in the experiment. At the end of the experiment, participants were asked for their demographic information.

3. Planned analyses

In this section, we describe the planned analyses[1]. First, we analyzed each of our 24 ternary choice conditions separately, then we conducted a single factor analysis to test for the attraction effect in

[1]Since our tests were exploratory, a conservative approach to minimize Type-I (false positive conclusion) error would use a Bonferroni correction taking into account all 38 tests [24 single condition analyses; 10 (2 Mode, 2 Layout, 6 Order) single factor analyses; 4 (3 two-way interactions, 1 3-way interaction) interaction tests]. This would result in a p-value cut-off of p=0.05/38 =

different conditions, and finally, we used nested logistic regression model comparisons to test for main and interaction effects. We also planned to conduct the same analyses combining the three stimuli from Noguchi and Stewart (2014) to test for reliability. However, we departed from our planned analysis and excluded the shoes from the old stimuli due to a difference in our stimulus values as compared to the original values as described in Noguchi and Stewart (2014). Additionally, we ran the analyses combining the three novel stimuli to test for generalizability.

3.1. Single condition analysis

We were first interested in a model-free test where we make no underlying assumptions about how the different conditions give rise to the attraction effect. To this end, as described in our power analysis, we conducted an exact binomial test for each of the 24 ternary choice conditions separately to test if the RST value was significantly different from 0.5. We corrected for multiple comparisons using a Bonferroni correction to the p-value, resulting in a significance cutoff of $p = 0.05/24 = 0.002$ for each of the ternary conditions.

3.2. Single factor analysis

We were interested in how the different presentation factors impacted the attraction effect. First, we were interested in testing whether the presentation layout influences the attraction effect (e.g., does the by-attribute layout produce an attraction effect?) To this end, we aggregated all decisions made in the by-attribute layout condition. We then conducted an exact binomial test against a probability of 0.5 to test if the RST value was significantly different. We repeated this for the by-alternative layout. We corrected for multiple comparisons using a Bonferroni correction, setting the significance cutoff at $p = 0.05/2 = 0.025$.

We performed similar analyses for the mode variables and order variables. Since there were two different modes, the Bonferroni correction for multiple comparisons was set at $p = 0.05/2 = 0.025$. Since there were six different orders, the Bonferroni correction was set at $p = 0.05/6 = 0.0083$.

3.3. Interaction effects

To test for interaction effects, we conducted a nested logistic regression model comparison. We set the selection of the target as the dependent variable. We compared the added advantage of including various interaction terms in the model to a null model with only the main effects. We planned to include by-subject random intercepts barring any model convergence issues. We used the likelihood ratio test for our nested model comparison with significance at the $\alpha = 0.05$ level.

We tested for the interaction between mode and format by comparing the null model *Mode* + *Format* to the model with the interaction term *Mode* + *Format* + *Mode***Format*. We tested for the interaction between mode and order by comparing the null model *Mode* + *Order* to the model with the interaction term *Mode* + *Order* + *Mode***Order*. If the interaction tests were significant, we looked at individual contrasts for the mode and order interaction terms. When testing for the interaction between layout and order, our null model was *Layout* + *Order* and our model with the interaction term was *Layout* + *Order* + *Layout***Order*. If the interaction tests were significant, we looked at individual contrasts for the layout and order interaction terms.

To test for three-way interactions, we compared the null model *Mode* + *Layout* + *Order*+ *Mode***Layout*+ *Mode***Order*+ *Layout***Order* to the model with the additional three-way interaction term *Mode* + *Layout* + *Order*+ *Mode***Layout*+ *Mode***Order*+ *Layout***Order*+ *Mode***Layout***Order*.

0.001316. However, this approach would also increase Type-II (false negative conclusion) errors. Hence, we used a Bonferroni correction for each of the analyses separately and report the associated p-value cutoff.

If the interaction test was significant, we looked at individual contrasts for the Mode, Layout, and Order interaction terms.

4. Results

We first present the results of the planned analysis, which was designed to test the robustness of the attraction effect to different conditions. After this, we conducted a comparative study across the different conditions. Analyses using the binary choice data are presented in the Supplementary Materials.

4.1. Single condition Analysis

The results of the single condition analyses are summarized in Table 2. First, we analyzed the data by collapsing across all six product types. Standard attraction effects, indicated by RST values significantly greater than 0.5, were observed in 23 out of 24 ternary choice conditions, after the Bonferroni correction ($p = 0.05/24 = 0.002$). The graphical $\times$ by-alternative $\times$ TCD condition was not significant after the Bonferroni correction but was in the direction of a standard attraction effect ($RST = 0.544, p = 0.008$). Next, we partitioned the data into old products (i.e., Highlighters and Paper Towels from Noguchi and Stewart (2014)) and new products (i.e., Apartments, Laptop, Cars). As described in the methods, we excluded them from the new and old products. After the Bonferroni correction ($p = 0.05/24 = 0.002$), there was a significant standard attraction effect in 20 out of 24 ternary choice conditions for the old products and 11 out of 24 ternary choice conditions for the new products. The results of analyses performed on data sets after exclusions were similar and are reported in the Supplementary Materials.

4.2. Single factor analysis

The results of single factor analyses are summarized in Table 3. Standard attraction effects (i.e., RST values significantly greater than 0.5) were observed across all levels of the three factors of interest (i.e., Mode, Layout, and Order). These results held when the old and new product groups were analyzed separately. The results of analyses performed on data sets after exclusions are similar and are reported in the Supplementary Materials.

4.3. Interaction effects

The results of analyses testing the interaction effects are summarized in Table 4. As described in the planned analysis, we treated the subject as a random effect to account for individual differences. Significant 2-way interactions between Mode and Layout and between Layout and Order were observed when collapsing across all six consumer goods and when analyzing the three new consumer goods separately. None of the interaction terms were significant when analyzing the two old consumer goods. The results of analyses performed on data sets after exclusions are similar and are reported in the Supplementary Materials.

4.4. Main effects

In the single-factor analysis, our goal was to test whether the attraction effect was robust to different experimental manipulations. This did not directly compare the different conditions to each other. To compare the different presentation modes, layouts, and orders to each other, we plotted the change in the RST under the different factors in Figure 3.

To test for significance, we conducted a mixed effects logistic regression with the selection of the target as the dependent variable and tested each of the individual factors using a logistic regression

Table 2. *Results of exact binomial tests for each of the 24 ternary choice conditions to test if the RST value was significantly different from 0.5.*

			All products			Old products			New products		
Mode	Layout	Order	RST	*p*-Value	95% CI	RST	*p*-Value	95% CI	RST	*p*-Value	95% CI
Graphical	By-Alternative	CDT	0.593	**< 0.001**	(0.561, 0.625)	0.627	**< 0.001**	(0.572, 0.68)	0.584	**< 0.001**	(0.537, 0.630)
		CTD	0.605	**< 0.001**	(0.573, 0.636)	0.618	**< 0.001**	(0.563, 0.671)	0.618	**< 0.001**	(0.571, 0.663)
		DCT	0.554	**0.001**	(0.522, 0.585)	0.595	**0.001**	(0.538, 0.651)	0.539	0.091	(0.494, 0.583)
		DTC	0.599	**< 0.001**	(0.568, 0.630)	0.655	**< 0.001**	(0.6, 0.707)	0.565	0.006	(0.518, 0.611)
		TCD	0.544	0.008	(0.511, 0.576)	0.567	0.028	(0.507, 0.625)	0.528	0.236	(0.482, 0.573)
		TDC	0.571	**< 0.001**	(0.539, 0.604)	0.571	0.017	(0.513, 0.629)	0.557	0.014	(0.512, 0.602)
	By-Attribute	CDT	0.560	**< 0.001**	(0.528, 0.593)	0.572	0.016	(0.513, 0.629)	0.563	0.007	(0.517, 0.608)
		CTD	0.578	**< 0.001**	(0.546, 0.610)	0.592	**0.001**	(0.536, 0.647)	0.564	0.006	(0.518, 0.609)
		DCT	0.553	**0.001**	(0.520, 0.585)	0.616	**< 0.001**	(0.561, 0.669)	0.511	0.677	(0.464, 0.557)
		DTC	0.666	**< 0.001**	(0.635, 0.696)	0.660	**< 0.001**	(0.606, 0.712)	0.668	**< 0.001**	(0.624, 0.710)
		TCD	0.557	**< 0.001**	(0.525, 0.589)	0.583	0.004	(0.526, 0.639)	0.548	0.039	(0.502, 0.594)
		TDC	0.608	**< 0.001**	(0.576, 0.639)	0.633	**< 0.001**	(0.577, 0.687)	0.576	**0.001**	(0.530, 0.622)
Numeric	By-Alternative	CDT	0.637	**< 0.001**	(0.605, 0.668)	0.694	**< 0.001**	(0.64, 0.744)	0.612	**< 0.001**	(0.566, 0.658)
		CTD	0.643	**< 0.001**	(0.612, 0.674)	0.667	**< 0.001**	(0.612, 0.718)	0.626	**< 0.001**	(0.580, 0.670)
		DCT	0.581	**< 0.001**	(0.549, 0.613)	0.611	**< 0.001**	(0.553, 0.666)	0.549	0.031	(0.504, 0.594)
		DTC	0.677	**< 0.001**	(0.647, 0.707)	0.734	**< 0.001**	(0.681, 0.782)	0.612	**< 0.001**	(0.565, 0.657)
		TCD	0.575	**< 0.001**	(0.543, 0.607)	0.589	0.003	(0.529, 0.647)	0.547	0.040	(0.502, 0.591)
		TDC	0.648	**< 0.001**	(0.616, 0.679)	0.661	**< 0.001**	(0.602, 0.716)	0.619	**< 0.001**	(0.574, 0.662)
	By-Attribute	CDT	0.609	**< 0.001**	(0.576, 0.641)	0.651	**< 0.001**	(0.592, 0.707)	0.591	**< 0.001**	(0.544, 0.637)
		CTD	0.622	**< 0.001**	(0.590, 0.653)	0.670	**< 0.001**	(0.614, 0.722)	0.580	**0.001**	(0.534, 0.625)
		DCT	0.600	**< 0.001**	(0.568, 0.632)	0.649	**< 0.001**	(0.594, 0.701)	0.563	0.007	(0.517, 0.609)
		DTC	0.701	**< 0.001**	(0.671, 0.730)	0.735	**< 0.001**	(0.683, 0.782)	0.651	**< 0.001**	(0.607, 0.693)
		TCD	0.568	**< 0.001**	(0.535, 0.600)	0.619	**< 0.001**	(0.562, 0.674)	0.526	0.282	(0.479, 0.573)
		TDC	0.609	**< 0.001**	(0.577, 0.642)	0.644	**< 0.001**	(0.585, 0.699)	0.558	0.017	(0.510, 0.604)

Note: The analyses were performed on data from (1) all consumer goods (left), (2) old consumer goods from Noguchi and Stewart (2014) (middle), and (3) novel consumer goods (right). *p*-values less than $p = 0.05/24 = 0.002$ are in bold font.

Table 3. *Results of exact binomial tests for the three factors of interest to test if the RST value was significantly different from 0.5.*

		All products			Old product			New product		
Factor	Level	RST	*p*-Value	95% CI	RST	*p*-Value	95% CI	RST	*p*-Value	95% CI
Mode	Graph	0.582	**<0.001**	(0.573, 0.592)	0.609	**< 0.001**	(0.593, 0.624)	0.568	**< 0.001**	(0.555, 0.581)
	Numeric	0.623	**< 0.001**	(0.614, 0.632)	0.661	**< 0.001**	(0.646, 0.677)	0.586	**< 0.001**	(0.573, 0.599)
Display	By-Alternative	0.602	**< 0.001**	(0.593, 0.611)	0.634	**< 0.001**	(0.618, 0.649)	0.579	**< 0.001**	(0.566, 0.592)
	By-Attribute	0.603	**< 0.001**	(0.594, 0.612)	0.636	**< 0.001**	(0.620, 0.651)	0.576	**< 0.001**	(0.563, 0.589)
Order	CDT	0.600	**< 0.001**	(0.583, 0.615)	0.637	**< 0.001**	(0.609, 0.664)	0.588	**< 0.001**	(0.565, 0.610)
	CTD	0.612	**< 0.001**	(0.596, 0.627)	0.637	**< 0.001**	(0.610, 0.663)	0.596	**< 0.001**	(0.573, 0.619)
	DCT	0.572	**< 0.001**	(0.556, 0.588)	0.618	**< 0.001**	(0.591, 0.645)	0.541	**< 0.001**	(0.518, 0.563)
	DTC	0.661	**< 0.001**	(0.646, 0.676)	0.696	**< 0.001**	(0.67, 0.721)	0.625	**< 0.001**	(0.603, 0.647)
	TCD	0.561	**< 0.001**	(0.545, 0.577)	0.590	**< 0.001**	(0.561, 0.618)	0.538	**0.001**	(0.515, 0.560)
	TDC	0.609	**< 0.001**	(0.593, 0.625)	0.627	**< 0.001**	(0.599, 0.655)	0.578	**< 0.001**	(0.555, 0.600)

Note: The analyses were performed on data from (1) all consumer goods (left), (2) old consumer goods from Noguchi and Stewart (2014) (middle), and (3) novel consumer goods (right). *p*-values less than $p = 0.025$ for Mode and Layout, and $p = 0.0083$ for Order are in bold.

Table 4. *Results of nested logistic regression model comparison for each interaction term.*

Data set	Interaction term	χ^2	df	p-Value	Contrast	exp(β)	95% CI
All products	Mode × Layout	5.015	1	**0.025**	Numerical - (Graphical, Numerical) × By-Attribute - (By-Alternative, By-Attribute)	0.970	(0.944, 0.996)
	Mode × Order	4.341	5	0.501			
	Layout × Order	15.045	5	**0.010**	By-Attribute - (By-Alternative, By-Attribute) CTD - (CDT, CTD, DCT, DTC, TCD, TDC)	0.959	(0.904, 1.018)
					By-Attribute - (By-Alternative, By-Attribute) × DCT - (CDT, CTD, DCT, DTC, TCD, TDC)	1.014	(0.956, 1.076)
					By-Attribute - (By-Alternative, By- Attribute) × DTC - (CDT, CTD, DCT, DTC, TCD, TDC)	1.095	(1.030, 1.164)
					By-Attribute - (By-Alternative, By- Attribute) × TCD - (CDT, CTD, DCT, DTC, TCD, TDC)	1.023	(0.964, 1.085)
					By-Attribute - (By-Alternative, By- Attribute) × TDC - (CDT, CTD, DCT, DTC, TCD, TDC)	0.994	(0.936, 1.055)
	Mode × Layout × Order	8.693	5	0.122			
Old Products	Mode × Layout	0.062	1	0.804			
	Mode × Order	5.457	5	0.363			
	Layout × Order	9.078	5	0.106			
	Mode × Layout × Order	3.862	5	0.569			
New Products	Mode × Layout	4.770	1	**0.029**	Numerical - (Graphical, Numerical) × By-Attribute - (By-Alternative, By-Attribute)	0.958	(0.922 0.996)
	Mode × Order	0.933	5	0.968			
	Layout × Order	17.123	5	**0.004**	By-Attribute - (By-Alternative, By-Attribute) × CTD - (CDT, CTD, DCT, DTC, TCD, TDC)	0.924	(0.843, 1.012)
					By-Attribute - (By-Alternative, By-Attribute) × DCT - (CDT, CTD, DCT, DTC, TCD, TDC)	0.980	(0.896, 1.072)
					By-Attribute - (By-Alternative, By-Attribute) × DTC - (CDT, CTD, DCT, DTC, TCD, TDC)	1.199	(1.093, 1.315)
					By-Attribute - (By-Alternative, By-Attribute) × TCD - (CDT, CTD, DCT, DTC, TCD, TDC)	1.015	(0.929, 1.110)
					By-Attribute - (By-Alternative, By-Attribute) × TDC - (CDT, CTD, DCT, DTC, TCD, TDC)	0.944	(0.863, 1.032)
	Mode × Layout × Order	8.776	5	0.118			

Note: Individual contrasts for each significant interaction term are reported. The coding scheme for categorical variables is deviation coding, which compares each level to the grand mean. p-values less than $p = 0.05$ are in bold font.

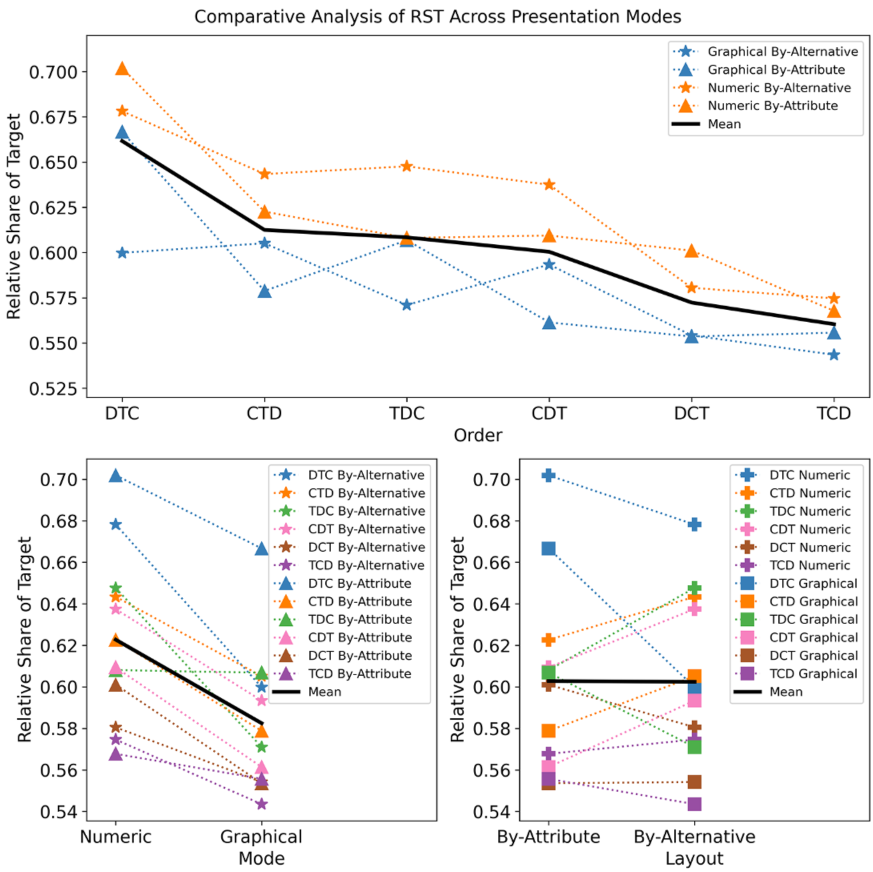

Figure 3. *The comparative dependence of RST on the different factors varied in the experiment. The dependence on order, mode, and layout are shown in the top, bottom left, and bottom right panels, respectively.*

Target Selection ~ Mode + Layout + Order + (1|subject). As in the previous analysis, we use deviation coding so that the comparisons are made to the mean and not to the contrast class. We present our results in Table 5 (left model) (Hlavac, 2022). We also tested models with higher-order interaction terms and presented them in the Supplementary Materials.

From the results in Table 5 and Figure 3, we observed that the different orders modulated the strength of the attraction effect. We also observed the attraction effect is significantly stronger in the DTC condition. It was significantly weaker in the DCT and TCD conditions where the target and the decoy were not adjacent to each other. For the conditions CDT and DTC, the strength of the effect is similar to the mean effect. These results indicate that the strength of the attraction effect is modulated by the order in which the three choice options were presented.

We observed that the strength of the attraction effect was significantly weaker in the graphical format than in the numerical format. There was no difference in the strength of the attraction effect in the by-attribute and by-alternative conditions. These results show that the strength of the attraction effect was modulated by the mode. However, there was no main effect of the layout.

We also tested whether the strength of the attraction effect was different for the old consumer products from Noguchi and Stewart (2014) as compared to the new consumer products. We added an extra variable ‘product type’ and tested another logistic regression: *Target Selection ~ Mode + Layout + Order + Product Type + (1|subject)*. As described in the methods, the products from Noguchi and

Table 5. *Coefficients of regression models of target selection as predicted by different presentation formats and product types.*

	Dependent variable: Target Selection	
	Model:	
	~Order+Mode+Layout +(1|subject)	*~Order+Mode+Layout+Product Type + (1|subject)*
CDT	−0.015	−0.017
	(0.032)	(0.032)
CTD	0.043	0.040
	(0.032)	(0.032)
DCT	**−0.134*****	**−0.134*****
	(0.031)	(0.031)
DTC	**0.270*****	**0.268*****
	(0.032)	(0.032)
TCD	**−0.186*****	**−0.183*****
	(0.031)	(0.031)
Graphical	**−0.090*****	**−0.091*****
	(0.014)	(0.014)
By-Alternative	−0.002	−0.002
	(0.019)	(0.019)
Old products		**0.115*****
		(0.021)
New products		**−0.143*****
		(0.019)
Constant	**0.445*****	**0.476*****
	(0.019)	(0.020)
Oservations	22,524	22,524
Log likelihood	−14,882.870	−14,848.430
Akaike inf. crit.	29,783.740	29,718.870
Bayesian inf. crit.	29,855.940	29,807.110

Note: Standard Errors are presented below the coefficient in rounded brackets.
p-values are Bonferroni corrected to account for the number of coefficients.
p-values less than p = 0.05/7 for the left model and p = 0.05/8 for the right model are in bold.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

Stewart (2014) - highlighter and paper towels—were coded as old. Further, apartments, laptops, and cars were coded as new. Shoes were coded separately. The variables used deviation coding, so the comparison is made to the mean effect. We present our results in Table 5 (right model). We observed that the strength of the attraction effect was modulated by the product type variable, with older stimuli producing a stronger attraction effect. Thus, the specific attributes and attribute values that were used in the experiment were also important in modulating the attraction effect.

5. General discussion

In this paper, we conducted a high-powered pre-registered experiment where we varied the mode (numerical vs. graphical), layout (by-attribute vs. by-alternative), and order as presentation factors thought to modulate the attraction effect (Frederick et al., 2014; Spektor et al., 2021; Yang and Lynn, 2014). Previous literature had suggested that the attraction effect was fragile and required the stimuli to be presented in some specific formats, without which the attraction effect would disappear or reverse. We observed that the attraction effect was robust to each of these factors, often producing strong attraction effects where the target was chosen at an average 1.5 times as often as the competitor (i.e., RST = 0.6). While we observed a robust attraction effect across our various manipulations, the strength of the effect was modulated by the display factors. It was consistently stronger for some factors as compared to others. Specifically, we observed a dependence on order and mode. This indicates that the format in which information is displayed plays a role in decision-making processes.

Regarding order, we found the weakest attraction effect when the target and the decoy were not adjacent to each other. This might be because their adjacency potentially facilitates a comparison between the two, which brings out the dominance of the target relative to the decoy. This is possibly hindered when the competitor is between the target and the decoy. Further, we noticed that the attraction effect is the strongest for the order DTC. This might be because when the decoy is presented first (i.e., left or top), it forms the baseline for future comparisons. The dominance of the target compared to this baseline potentially results in it being perceived as a superior option and finally results in it being chosen. Evans et al. (2021b) also found that the order DTC produced a strong attraction effect in the reanalysis of Trueblood et al. (2015). However, Evans et al. (2021b) also examined the impact of temporal order on the attraction effect and found a different pattern of results. For example, the temporal order TDC (where T is presented first, D second, and C last) produces a strong repulsion instead of an attraction effect. Evans et al. (2021b) model this using a memory component that leads to slower evidence accumulation for a previously presented option. In our task, we do not anticipate any role of memory and hence do not need to account for this effect. Overall, order might interact with other cognitive processes (e.g., memory in Evans et al. (2021b) and attention in the current experiment) and play an important role in the kind of evaluations and comparisons that are made during the decision-making process.

Order produces a remarkably consistent influence on the attraction effect across many different settings. This pattern was similar across the different modes and layouts as depicted in Figure 3. This pattern is similar to the one observed in the analyses reported in the Supplementary Materials using data from Cataldo and Cohen (2021b). Evans et al. (2021b) found a similar pattern in the reanalysis of Trueblood et al. (2015), which used a perceptual decision-making task. These results indicate potential common mechanisms between different kinds of decisions. Hence, we conclude that the influence of order on the attraction effect is a robust finding.

The influence of mode (i.e., numerical vs. graphical) on the attraction effect is in accordance with Frederick et al. (2014), Spektor et al. (2021), and Yang and Lynn (2014), where numerical stimuli are predicted to produce stronger attraction effects. Spektor et al. (2021) suggests that this is driven by the concreteness of the representation, where numerical stimuli bring out the dominance relationship between the target and the competitor. As shown in Figure 3, the influence of mode seems to be robust to the layout and order in which the information is displayed. In an exploratory analysis provided in the Supplementary Materials, we show that the dependence on mode does not hold for all of the consumer goods tested in the experiment. Specifically, it seems to hold for the old consumer goods from Noguchi and Stewart (2014) but not for the novel stimuli. Hence, further exploration is needed to understand how specific attributes and attribute values might interact with the mode.

We observed a null effect of the layout (i.e., by-alternative vs. by-attribute) in our experiment. In an additional analysis presented in the Supplementary Materials, we only used data from the graphical mode, which is very similar in format to the stimuli used in Cataldo and Cohen (2019), and still observed a null effect. This is a failure to replicate the results of Cataldo and Cohen (2019). It is worth noting that there are differences in our experiment and Cataldo and Cohen (2019), such as the number of trials and differences in participants, which could potentially explain the discrepancy in results. The number of trials could modulate the attraction effect since decision-makers might develop decision strategies to reduce mental effort during the course of a long experiment with a large number of trials (Ahn et al., 2015; Lichters et al., 2015). Such strategies might be more sensitive to differences in the ease of comparing options and thus reveal differences between presentation layout as found in Cataldo and Cohen (2019). Strategies to reduce mental effort are less likely to be adopted in short experiments with a small number of trials (such as the present one). Our findings call into question the unified impact of layout on the attraction effect.

We observed that the attraction effect is at an average stronger for the consumer goods from Noguchi and Stewart (2014) compared to novel consumer goods tested in our experiment. This might be because the consumer goods were chosen from Noguchi and Stewart (2014) based on their ability to produce strong attraction effects, resulting in a selection bias. This might also be due to many potentially confounding differences between the two sets of consumer goods. For one, the consumer goods—paper towels, highlighters, and walking shoes in Noguchi and Stewart (2014) were everyday low-value consumer goods. On the other hand, the novel consumer goods—apartments, laptops, and cars were high-value goods that are purchased rarely. Second, the attributes for the novel stimuli used a 1–10 scale and had similar units. The attributes for the older stimuli used different scales and had different units. Specifically, Hayes et al. (2024) showed that when attributes are on a similar scale, individuals can make inter-attribute comparisons, which can impact the presence of the attraction effect. Thus, we find that the specific attributes and attribute values can modulate the strength of the attraction effect.

As discussed in the introduction, interactions between attentional processes and decision making have been invoked to explain context effects (Cataldo and Cohen, 2019; Spektor et al., 2021; Trueblood, 2022). Trueblood et al. (2022) proposed a promising approach to model multi-alternative, multi-attribute choice using an attentional process that informs a preference accumulation process. In this model, a Markov attentional process probabilistically selects the options and attributes that are compared at any given moment in time. Preference is accumulated for the attended options until a threshold is reached, triggering a decision. Trueblood et al. (2022) showed that the dependence of the attraction effect on spatial order can be explained by the Markov attention process by allowing the probabilities with which options are selected and compared to depend on their spatial proximity. For example, the model allows for larger transition probabilities when options are spatially adjacent. Thus, when the target and decoy are adjacent (such as in the order DTC), the model predicts that these two options will be compared more, thus leading to a stronger attraction effect. Further, Hayes et al. (2024) expanded this framework and allowed for between-attribute comparisons when attributes are on a common 0–10 scale, like the new stimuli in our experiment. They found that between-attribute comparisons reduced the strength of the attraction effect. Formats such as graphical displays might also allow for between-attribute comparisons since an individual can easily compare the size of bars for different attributes. The facilitation of between-attribute comparisons in graphical displays could explain the observed reduction in the attraction effect. Thus, the theory of attentional dynamics described in Hayes et al. (2024) and Trueblood et al. (2022) is potentially a unifying framework to explain our findings.

From a practical and applied perspective, decision-making biases can be used to design choice architectures to improve the quality of decisions (Lichters et al., 2017; Thaler et al., 2013). The attraction effect has been suggested as a method to help individuals make better decisions such as selecting more healthy food choices (van den Enden and Geyskens, 2021) or buying eco-friendly goods (Guath et al., 2022). Our findings have a direct implication for the format in which information about the choices can be displayed to produce the strongest effect. Our findings suggest that the information should be presented numerically, and the target and the decoy should be presented adjacent to each other to maximize the choice share of the target. Choice architects can utilize the presentation format as an additional dimension to aid in improving decisions.

5.1. Constraints on generality

In our study, we varied a large number of presentation factors and observed how they modulated the attraction effect. Despite our efforts to comprehensively test a large number of formats, there were additional presentation formats that we did not test in our experiment. For instance, we did not arrange the options in a triangle as in Noguchi and Stewart (2014). Apart from presentation formats, additional experimental factors can modulate the strength of the attraction effect like time pressure (Cataldo and Cohen, 2021b; Evans et al., 2019; Spektor et al., 2021) or the number of trials (Lichters et al., 2015). Future experimenters might vary some of these factors to understand which ones might reverse the attraction effect.

In our experiment, we only used a single set of attribute values for the target and competitor options for each product (see Table 1). Future experiments might vary the attribute values in order to more comprehensively test how attribute values influence the attraction effect. Experimenters that vary these values will face an additional challenge since it is more difficult to calculate the RST when the target and competitor options can take on a larger range of values. Innovative experimental designs and forms of inference will need to be considered (see for example, Dumbalska et al. (2020)).

All our options were presented with explicit attribute values. In some studies, the attributes are not presented explicitly to the participants (Dumbalska et al., 2020; Frederick et al., 2014; Trendl et al., 2021). These kinds of stimuli (e.g., pictures of different fruits) might require the decision maker to generate attributes and convert these attributes to internal representations which might not be accounted for by the way we varied the 'mode' (numerical vs. graphical).

We only studied value-based consumer decision-making. However, there are additional decision-making paradigms such as perceptual decisions (Trueblood et al., 2015), inter-temporal choice (Gluth et al., 2017), risky gambles (Frederick et al., 2014), and even memory tasks (Maylor and Roberts, 2007) that have been used to study the attraction effect. While we observed choice patterns that were consistent with findings from other paradigms, it is still an important theoretical question of whether people use the same mechanisms for attribute comparisons and integration across domains (Frederick et al., 2014; Shimojo et al., 2003; Trueblood et al., 2013). Future experiments might vary the task (e.g., consumer choice vs. perceptual choice) along with the presentation format to test how the presentation format impacts choice across different tasks.

5.2. Future directions

Overall, our findings challenge researchers to provide explanations to account for the dependence of the attraction effect on presentation formats. As discussed in the introduction, the existing multi-alternative multi-attribute models in their current form do not give an account as to how presentation might impact choice. Cataldo and Cohen (2019) and Trueblood et al. (2022) suggest that attention and comparisons are critical for multiattribute choice. Spektor et al. (2021) argue that the stimulus representation also plays a key role. While all of these ideas are related, they could be theoretically and computationally instantiated in different ways. Our data can help inform such theoretical developments.

One explanation for the dependence of the attraction effect on presentation formats relates to the interaction of attention and decision-making processes (Trueblood et al., 2022). Future research could further investigate the interactions among presentation formats, attention, and decision-making. For example, previous studies using process tracing have revealed that transitions between alternatives often predict the final decision (Marini et al., 2023; Noguchi and Stewart, 2014). Additionally, research indicates that different multiattribute tasks exhibit distinct between and within-attribute transitions

(Yang and Krajbich, 2023), as suggested in Hayes et al. (2024). Interestingly, a bottom-up manipulation of attention did not alter the comparison process (Hasan and Trueblood, 2024), suggesting that attention allocation may be influenced by decision strategies (Callaway et al., 2021) and top-down features like value (Towal et al., 2013). By coupling process tracing methods with presentation-format-based manipulations, researchers might discover significant differences in attention allocation and choices across different presentation formats.

Registered reports were introduced to increase transparency in the scientific process, validate experimental designs, and reduce publication bias against research outcomes (Chambers, 2013; Chambers and Tzavella, 2022; Henderson and Chambers, 2022). While registered reports are primarily used for confirmatory research (Henderson and Chambers, 2022) (e.g., Evans et al., 2021a; Saribay et al., 2020; Zgxonnikov et al., 2019), these processes can also improve the quality and trust of exploratory research (Dirnagl, 2020; McIntosh, 2017). Some journals have introduced a separate publication category called 'exploratory reports' to encourage researchers to conduct exploratory research, independently from the conventions of hypothesis-testing methods (McIntosh, 2017). We hope that findings, such as ours, from exploratory registered reports will be able to serve as a strong basis for fostering theoretical development.

6. Conclusion

We undertook a registered report to conduct a high-powered exploratory study to understand the dependence of the attraction effect on presentation formats. We varied the mode (numerical vs. graphical), the layout (by-alternative vs. by-attribute) and the order (e.g., DTC - Decoy-Target-Competitor) in which options were displayed. We recruited over 2,000 people and recorded over 24,000 choices on value-based consumer decisions. We observed a robust attraction effect across each of these factors. The strength of the effect was modulated by the order and the mode but not by the layout. These empirical findings are not directly predicted by any of the modeling paradigms and can be used as a foundation for theory development.

Acknowledgments. We thank William Hayes for his assistance with the power analysis and his helpful comments. We also thank Hoyoung Doh for his useful comments.

Funding statement. This work was supported by the Estes summer fellowship from Indiana University to EH and NSF grant 1846764 / 2305559 to J.S.T.

Data Availability Statement. The data and analysis code are available on the Open Science Framework at https://osf.io/wzct3/.

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Cite this article: Hasan, E., Liu, Y., Owens, N., and Trueblood, J. S. (2025). A registered report on presentation factors that influence the attraction effect. *Judgment and Decision Making*, e6. https://doi.org/10.1017/jdm.2024.27