Re-evaluating the Numerical-Perceptual Distinction in the Attraction Effect

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Abstract

A widely studied cognitive bias in decision-making is the 'attraction effect' or 'asymmetric dominance effect', where introducing a clearly inferior decoy option to a binary choice set increases the likelihood of choosing the dominating option (target) over the other (competitor). While there is a consensus in the literature that the attraction effect is robust with numerical stimuli, there have been inconsistent results with perceptual stimuli (Frederick et al., 2014). This numerical-perceptual distinction was further supported in some recent studies involving perceptual stimuli claiming to have produced a negative attraction effect (Spektor et al., 2018, 2022). We argue that this distinction is superficial and that people's choice behavior is better explained by inter-attribute relationships. In this study, we conducted two experiments where we showed positive attraction effects with combined perceptual-numerical stimuli (having both perceptual and numerical attributes) and both positive and null effects with numerical stimuli by manipulating the asymmetry in pair-wise comparison difficulty. In Experiment 1, we provided evidence for a strong attraction effect for perceptual-numerical stimuli by ensuring the trade-off between the attributes is difficult. Next, in Experiment 2, we manipulated asymmetry in difficulty between two pairs, including the decoy, while controlling for a confound—target-competitor (TC) comparison difficulty, a factor that has yet to be addressed by studies that have produced a positive attraction effect with perceptual stimuli. To achieve this manipulation, we leveraged findings from mathematical cognition and education research on fraction comparison, effectively activating or suppressing the standard attraction effect through our experimental design. Taken together, the results from both studies challenge the superficial distinction between stimulus types and support a universal cognitive mechanism underlying the ubiquitous attraction effect.

Keywords: attraction effect; context effect; asymmetric dominance; trade-off-difficulty; mathematical cognition; fraction comparison

Introduction

Consider choosing between two magazine subscriptions: digital-only access for $59, or digital plus print access for $125. Many people may be undecided between the lower price of the digital-only option and the added value of having both formats. Now, imagine a third option: print-only access for $125. Although this new alternative offers less for the same price as the digital plus print option, its presence makes the combined subscription appear more attractive.

This phenomenon, known as the *attraction effect* or *asymmetric dominance effect*, violates the regularity principle of rational choice theory, which states that adding an option should not increase the choice probability of an existing one (Luce, 1977). Studies such as Huber et al. (1982) have shown that this effect can be observed both in overall choice patterns and in individual decision-making.

Figure 1 illustrates this effect in an attribute space where higher values on both axes indicate better features. The decoy (D) is inferior to the target (T) on both attributes but not to the competitor (C), which increases the likelihood that decision-makers choose T over C.

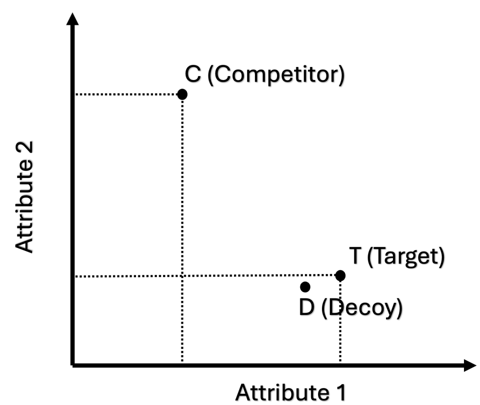

Figure 1: Asymmetric Dominance Effect

While this effect has been observed across various domains and species over the past four decades, recent findings on perceptual stimuli have questioned its domain generality. Choices presented as symbolic digits have shown large attraction effects (Huber et al., 1982; Simonson, 1989). In contrast, Frederick et al. (2014) suggested that perceptual representations often elicit different effects than numeric representations, suggesting that the attraction effect may not be prevalent in choices that involve distinguishing between perceptual attributes. While initial studies in the perceptual domain did demonstrate a positive attraction effect (Choplin & Hummel, 2005; Trueblood et al., 2013), subsequent findings of opposite effects in perceptual tasks (Spektor et al., 2018, 2022) further posed a significant challenge to the claim of the attraction effect's domain generality. Brendl et al. (2023) argued that the quantitative-qualitative difference of the stimuli explained the numerical-perceptual difference. Spektor et al. (2021) highlighted this difference and ascribed it to the presence of attribute concreteness in numerical stimuli, absent in perceptual ones.

This research stands in contrast with large body of work showing that people find numbers intuitive to process. With more experience with numbers over the course of their lives, symbolic number processing is less associated with more deliberate thought in the prefrontal cortex and more automatic processing in the intraparietal sulcus (Ansari et al., 2005). This is because symbolic number processing is mapped to the approximate number system, which is associated with the processing of numeric magnitudes across modalities (Feigenson et al., 2004). Over development, people show similar logarithmic performance profiles when processing symbolic numbers compared to other perceptual dimensions, such as brightness and loudness. Recent studies have challenged the notion that numerical and perceptual stimuli inherently differ in their susceptibility to the attraction effect. He and Sternthal (2023) proposed that ambiguity resolution drives the effect across stimulus types: when choice ambiguity prompts decision-makers to compare the target and decoy, attraction effects emerge regardless of whether attributes are numerical or perceptual. One goal of the current work is to support this argument and demonstrate that numbers and perceptual stimuli act similarly to influence people's decisions.

Moreover, using a novel set of stimuli, Rath et al. (2024b) showed that their decoy was asymmetrically dominated, i.e., dominated by the target but not by the competitor in pair-wise comparisons. Furthermore, they showed a positive attraction effect in three-option choice sets. They also argued that previous failures to observe the attraction effect with perceptual stimuli (e.g., Spektor et al. (2018, 2022)) were likely due to violations of the *asymmetric dominance* (AD) condition, as the decoys in those studies were easily comparable even to the competitors.

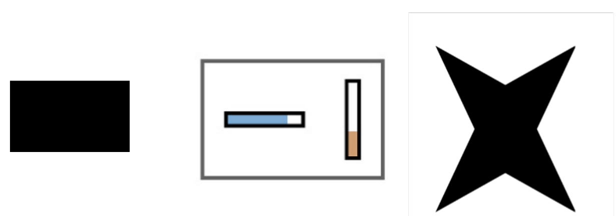

Figure 2: Sample Stimulus adapted from three experiments Spektor et al. (2018), Spektor et al. (2022), and Rath et al. (2024b) in left to right order.

Figure 2 presents sample stimuli from three studies, each illustrating a different relationship between visual attributes and decision tasks: in the first, participants chose the rectangle with the largest area, requiring a simple multiplication of height and width; in the second, they selected the option with the largest combined fill from a horizontal and a vertical bar, which involved a straightforward additive (linear) relationship; in the third, participants judged star-like shapes with varying indentation depth and base width, and were asked to identify the shape needing the least extra material to become a perfect square-a task involving a more complex, nonlinear integration of the two attributes, and thus a less direct mapping from stimulus to decision.

The key question behind divergent findings on the attraction effect is what modulates its presence and strength. While earlier debates focused on stimulus type, recent work by Rath et al. (2024b) shows that the critical factor is whether the decoy meets the AD condition, i.e., being dominated by the target but not the competitor. They demonstrate that the attraction effect reliably appears when AD holds, even with perceptual stimuli. In this paper, we first show with combined perceptual-numerical stimuli (Experiment 1) that AD can be achieved by increasing attribute trade-off difficulty. In Experiment 2, using numerical stimuli in a within-subjects design, we manipulate the presence or absence of AD while controlling a possible confound: target-competitor comparison difficulty, demonstrating that the attraction effect occurs only when AD is satisfied.

Experiment 1

Introduction Real-life decisions often involve difficult-to-trade-off attributes (Bhatia et al., 2025). The choice between two alternatives becomes challenging when trading off their prominent attributes is difficult. A trade-off is defined as a kind of compromise that involves giving up something in return for gaining something else. In economics, a trade-off is often referred to as an "opportunity cost." For example, one might take a day off work to attend a concert, gaining the opportunity to see their favorite band while losing a day's wages as the cost of that opportunity (Vocabulary.com, 2024).

Although Huber et al. (2014) did not explicitly introduce attribute-trade-off-difficulty as a boundary condition, they indirectly hinted at it: *"...for the attraction effect to occur, the decision maker should also be unsure whether a ten-point difference in restaurant ratings is worth a $10 price difference.* This suggests that the difficulty of comparing attributes plays a critical role in the attraction effect.

Walasek and Brown (2023) further emphasized the importance of attribute incommensurability in multi-attribute, multi-alternative choices. They provided a compelling example to illustrate this concept. Imagine comparing two candidates for an assistant professor position at a research-focused university. Assume that the candidates are evaluated based on two distinct attributes: research value, measured by citation counts (e.g., h-indices), and teaching value, measured by student ratings. If only one attribute mattered, the decision would be straightforward: choose the best teacher or the best researcher. However, if the university's guidelines require both teaching and research to be considered, the decision becomes complex. If teaching ratings reflect only teaching value and h-indices reflect only research value, how does one trade-off these two different scores against each other? Walasek and Brown (2023) described such attributes as incommensurate. Similarly, Hayes et al. (2024) demonstrated how manipulating attribute commensurability influences the size of the attraction effect in preferential choice domains. These studies further underscore the significance of attribute comparability in the context effect.

Chang (2013) summarized five distinct ways the term *incommensurability* has been used in the literature, none of which allow for a trade-off between incommensurate attribute values. Attributes can be incommensurate for one or more of the following reasons:

- **Non-compatibility**: Attributes cannot be compared directly.
- **No super-value**: There is no overarching metric to unify the attributes.
- **Trumping/discontinuity/threshold lexical superiority**: One attribute dominates the other(s) beyond a certain threshold.
- **Nonsubstitutability/non-compensability**: Attributes cannot substitute or compensate for one another.
- **No common unit**: Attributes lack a shared unit of measurement.

However, even when attributes are technically commensurate according to these definitions, trade-offs between them can still be challenging due to *representational noise*, which makes it difficult to assess the absolute values of the options' attributes (Simonson, 2008). For instance, Rath et al. (2024b) used a stimulus where two attributes were presented in the same units (distance), but participants found it difficult to determine how much of a change in one attribute could compensate for a change in the other. This demonstrates that trade-off difficulty can arise even when attributes are nominally commensurate.

In this experiment, we use a combined perceptual-numerical stimuli set to explore how trade-off difficulty can manifest even when attributes share a super-value. Specifically, we use the area of alloy pieces represented by filled circles as the perceptual attribute and their price in integer values as the numerical attribute, where the price per unit area serves as the super-value. This design allows us to test the role of attribute-trade-off difficulty in producing the attraction effect in combined perceptual-numerical stimuli set.

The definitions of (in)commensurability provided by Chang (2013) treat incommensurability as a binary variable. However, we argue that trade-off difficulty exists on a continuous scale, reflecting the phenomenological challenge of comparing attributes. Therefore, we prefer the term *attribute-trade-off-difficulty* over *attribute commensurability*, as it better captures the gradational nature of this construct.

Most models of choice propose that in a multi-alternative comparison, alternatives are compared pair-wise (Evans et al., 2021; Kornienko, 2013; Noguchi & Stewart, 2018; Ronayne & Brown, 2017; Russo & Dosher, 1983; Trueblood et al., 2014; Wollschläger & Diederich, 2012). Building on this assumption, we hypothesized that an increased inter-attribute trade-off difficulty in our stimuli would lead to asymmetry in the difficulty of choice in different pairs, ultimately leading to the asymmetric-dominance effect.

Methods Thirty-six participants (Mean age = 21.11 years, SD = 3.42; 27 male, 9 female) with normal or corrected-to-normal vision gave informed consent and took part in the experiment. After the exclusion of 6 participants due to their low scores (< 0.8) in the catch trials, the analysis was conducted on data from 30 subjects. On each trial, the displayed stimulus consisted of three different black-filled circles on a white background. These shapes were arranged in a triangular formation around the center of the screen, with their vertical positions jittered across trials. Figure 3 shows an example trial. Participants were informed that the circular discs were some special alloys whose prices were displayed in white at the center of the disc in arbitrary units. In each trial, the participants were asked to choose the disc with the lowest price per unit area. The two attributes that formed that attribute space were the area of the disc and the price of the disc displayed at its center.

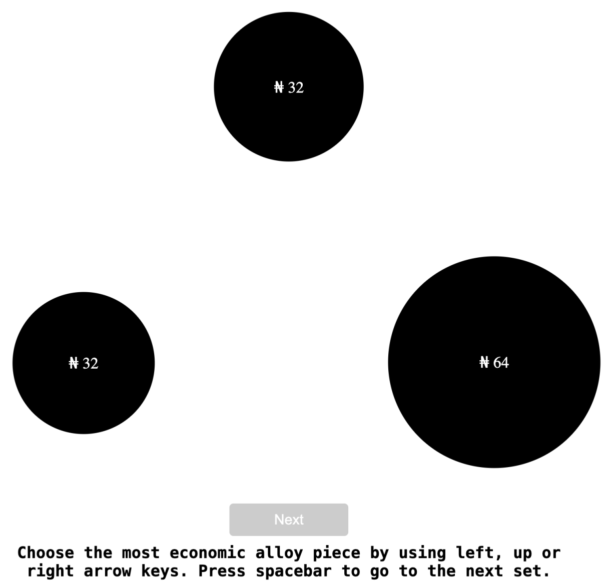

Figure 3: Example Trial in Experiment 1

Following Trueblood et al. (2013), one set of circles was created using a bivariate normal distribution with a mean area of 28000 pixels and a mean price of 28. The variance for the area and the price were 28000 pixels and 28, respectively, and there was no correlation between the variances, allowing for variability in the task. A second set of circles were matched in price per unit area but were twice the area of the first set. One of these sets was considered the target, while the other was the competitor. The third set (i.e., decoy circles) was created such that, in the attribute space, it was placed close to the smaller circle for half the trials and close to the larger one for the remaining half, effectively creating two sets of contexts. We included all three types of decoys: range, frequency, and range-frequency decoys (Huber et al., 1982). Participants completed 36 trials in each of the contexts. Additionally, 12 catch trials were included as exclusion criteria, in which one circle in each trial clearly had the lowest price per unit area. The presentation order of all 84 trials was randomized. Participants were instructed to respond as fast and as accurately as possible using the left, up, and right keys.

Results and Discussion We quantified context effects using the equal-weights version of *Relative Choice Share of the Target* (RST) (Katsimpokis et al., 2022). RST measures how often the target is chosen over the competitor, with 0.5 indicating the absence of a context effect. RST is computed as:

$$RST_{\mathrm{EW}} = \frac{1}{2}\left(\frac{T_X}{T_X + C_X} + \frac{T_Y}{T_Y + C_Y}\right)$$

Here, T_X and C_X are the number of target and competitor selections, respectively, when the decoy favors option X, and T_Y and C_Y are the corresponding counts when the decoy favors option Y. An RST value above 0.5 suggests a positive attraction effect, and values below 0.5 indicate a reversed effect.

A one-tailed t-test was performed to compare the RST values against the null value of 0.5. The mean RST ($M = 0.591$, $SD = 0.109$) was significantly higher than the null value of 0.5; $t(29) = 4.593$, $p < 0.001$. The effect size was large (Cohen's $d = 0.839$). A Bayesian one-sample t-test further supported this result, yielding a Bayes factor of $\mathrm{BF}_{10} = 273.75$ (using a Cauchy prior with $r = 0.4$), indicating strong evidence in favor of the alternative hypothesis ($H_1 : \mathrm{RST} > 0.5$). Figure 4 depicts the violin plot for the overall RST values.

The results provide further evidence that perceptual stimuli are just as effective as numerical stimuli in producing the standard attraction effect. More importantly, they show that increasing the inter-attribute trade-off difficulty produces the AD of the decoy and, hence, the asymmetric-dominance effect. This experiment could be treated as a conceptual replication of (Rath et al., 2024b) while violating yet another definition of incommensurability (no super-value).

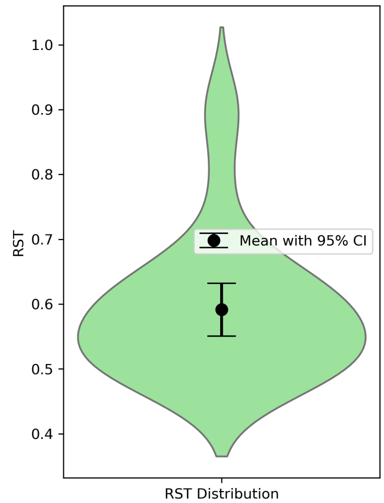

Figure 4: RST Distribution in Experiment 1

Experiment 2

Introduction We assume that, compared to stimuli used in previous studies that failed to produce a positive attraction effect in the triangular arrangement, our stimuli introduced greater competitor-decoy (CD) comparison difficulty due to increased attribute trade-off difficulty, leading to AD of the decoys. We argue that both Rath et al. (2024b) and experiment 1 in the current study followed a similar approach to increase CD comparison difficulty and reported positive attraction effects.

However, when attribute trade-off difficulty is increased by the choice of attributes, target-competitor (TC) comparisons also become more difficult for the same reasons that CD comparisons become challenging. This introduces a potential confound in both studies.

Thus, we cannot definitively claim that the positive effect observed in our study is solely due to the restoration of AD, nor can we attribute the negative effects in previous studies solely to its absence. When TC comparisons are easy, decision-makers can form a clear prior preference between the target and the competitor, which diminishes the effect of an added undesired decoy (Huber et al., 2014; Rath et al., 2024a).

To date, we have not identified perceptual stimuli where CD comparison difficulty can be manipulated independently of TC comparison difficulty. In Experiment 2, we used fractions, which allowed us not only to test both the presence and absence of the attraction effect with numerical stimuli but also to better control for the mentioned confound.

People's ability to process numbers very quickly is advantageous in many aspects of decision-making and information processing (Feigenson et al., 2004; Moyer & Landauer, 1967). However, it can interfere with understanding one abstraction that mathematics has built using numbers — fractions. People find fractions difficult to understand and reason about (Behr et al., 1984; Lortie-Forgues et al., 2015). One reason for this is because the symbolic numbers present in fractions are not sufficient to determine their magnitude. A small fraction can consist of larger numbers, for example, $\frac{1283}{11823}$ and a larger fraction can include smaller numbers, for example, $\frac{1}{3}$. In this example, both the numerator and the denominator in the larger fraction contain clearly larger numbers, and it is often the choice students make when asked to pick the larger fraction. This is called the *natural number bias*, the automatic processing of symbolic number can interfere with how people judge the magnitude of fractions (Alibali & Sidney, 2015; Ni & Zhou, 2005; Reinhold et al., 2023). To properly compare fractions, one should suppress the urge to solely compare the magnitudes of the number, and integrate these magnitude representations with the rules of fractions. Studies have since also found the existence of a *reverse natural number bias*, where people judge the fractions with smaller numbers as the larger fractions, a likely overcorrection to the natural number bias (Barraza et al., 2017; DeWolf & Vosniadou, 2011; DeWolf & Vosniadou, 2015; Obersteiner et al., 2020). However, evidence also suggests that people are also able to perceive the holistic magnitude of a fraction, as the strength of the natural number bias decreases the greater the distance between two fractions being compared (Barraza et al., 2017; Park et al., 2021).

People's perceptions of the magnitudes of fractions are also determined by the strategies they know, by the strategies they use, and by the properties of the fractions themselves, and how the properties of the fractions interact with their strategies (Fazio et al., 2016; Obersteiner et al., 2022; Reinhold et al., 2023; Siegler et al., 2013). When asked to report how they compare fractions, people report a variety of strategies that range from componential, focusing on values and magnitudes of the numerators and denominators, to holistic, which involve determining the magnitude of the fraction itself (Obersteiner et al., 2022). Sometimes, these strategies are valid, for example, a componential strategy when people compare the multiplicative relationship between numerators of the fractions and compare it to the denominators to make a judgement. However, people also use heuristics that are not valid for all fractions. One example is a frequently reported holistic strategy called benchmarking, where they find a familiar fraction (benchmark) close to the fraction they need to compare, and compare the other fraction (or a benchmark close the other fraction) to this benchmark (DeWolf & Vosniadou, 2011; Liu, 2018; Obersteiner et al., 2020). Errors in finding the nearest benchmark can invalidate this strategy. People also often compare the differences between the numerator and denominator of each fraction and compare them to determine which of the two fractions is greater (Gómez & Dartnell, 2019; Obersteiner et al., 2022). This componential strategy, called gap comparison, fails, for example, when $\frac{31}{71}$ is compared to $\frac{13}{23}$. This rich complexity in how people process fractions allows us to manipulate the difficulties of pairwise comparisons. For example, comparisons with higher ratio distances are easier, comparisons with common components are easier, comparisons with divisible numerators and denominators are easier, etc.

This experiment serves three main purposes. First, to blur the numerical-perceptual distinction, we aimed to test whether the attraction effect could be activated or deactivated through a separate manipulation. Second, we sought to control for the confound introduced in Experiment 1, and the use of fractions provided greater flexibility in this regard. Third, we employed a within-subjects design to control for individual differences.

In this experiment, all participants completed two conditions in a within-subjects block design. The key manipulation involved the asymmetry in difficulty between the CD and TD comparisons, hereafter referred to as *CD–TD difficulty asymmetry* (abbreviated as ΔDiff). We implemented two levels of ΔDiff: *High* and *Low*, while keeping the TD comparison consistently easy across both conditions. This design effectively controlled for the difficulty of the TC comparison. We hypothesized that in the *High* ΔDiff condition, participants would exhibit a positive attraction effect, whereas in the *Low* ΔDiff condition, the effect would be negligible or absent. Additionally, we predicted a significant difference in RST values between these two conditions.

Methods Fifty-five participants (Mean age = 21.63 years, SD = 3.33; 39 male, 16 female) with normal or corrected-to-normal vision gave informed consent and took part in the experiment. Figure 5 displays an example trial.

To determine which fraction triplets to present to participants, we first needed to operationalize how easy it is to perceive the holistic magnitude of a fraction, i.e., the super-value of a fraction. This was determined as the geometric mean of a series of conditions, where the presence of a condition was represented as 1.05 and the absence as 0.05 instead of 1 and 0 to prevent the geometric mean from evaluating to 0 in the absence of any condition. The conditions were: (1) when the number of common factors between the numerator and denominator is greater than or equal to 4, (2) when the ratio represented by the fraction is ± 0.15 of a whole number, (3) when the numerator is perfectly divisible by the denominator, and (4) when the denominator was divisible by 5.

We also defined the ease of comparing two fractions to each other. Similarly, this was the geometric mean of a series of conditions with a 0.05 offset. The conditions were: (1) the fraction sharing a common component (this factor was weighted 4 times more than the others), (2) the comparison being gap congruent (the item with the larger numerator and denominator difference being the correct answer) and the ratio between the gaps of the two fractions being greater than or equal to 1.5, (3) the ratio between the numerators being less than or equal to 5.05 (this includes the most well-known portion of the multiplication table) and ratio between the numerators being ± 0.15 of a whole number, (4) the same for the denominator, and (5) the ratio between the holistic magnitudes of the fraction being greater than 2 (very distant) or close to 1 ± 0.15 (very close). These scores, informed by research on how people use strategies to compare fractions, helped determine the items present in the two conditions.

We ensured that all stimuli in each condition fell between ease ranges, which greatly reduced the potential of confounds playing a role in the effect we observed. To determine the triplets, we first started with a set of all fractions with numerators and denominators with whole numbers greater than 1 and less than 100, where the numerator was not equal to the denominator. Using this set of fractions, we randomly sampled potential trials and assessed them through our criteria until we generated 30 items. Similar to Experiment 1, we used this set of 30 items to create two sets of triplet contexts, hence 60 trials in each condition. For items in the ΔDiff: *Low* condition, we ensured that the decoys were similarly easy to compare with the target and the competitor, i.e., the ratio between the ease scores for target-decoy and competitor-decoy comparisons were constrained to be less than 2 and we set a minimum ease value for these comparisons (0.4). For the ΔDiff: *High* condition, the ratio between the ease scores was constrained to be greater than 4, that is, the decoy was significantly easier to compare with the target fraction than the competitor fraction. All target and competitor ratios were constrained to be between 2 and 5.5. However, the ratios themselves were constrained to not be ±0.15 of a whole number ratio.

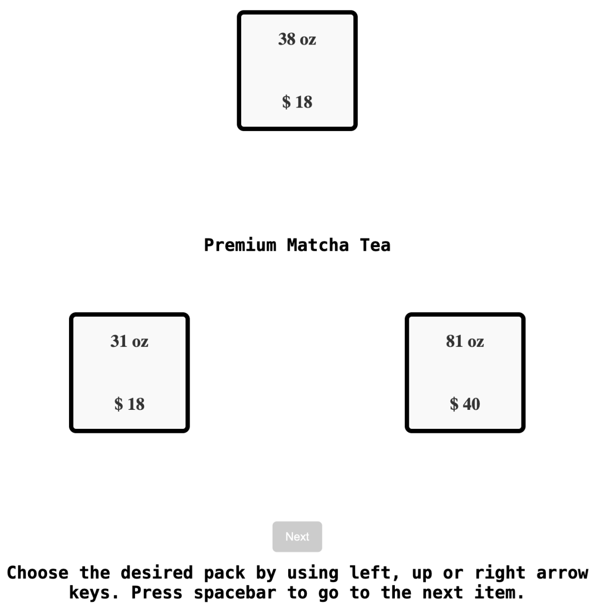

Figure 5: Example Trial for Block H in Experiment 2

Results and Discussion We conducted two two-tailed one-sample t-tests on RST values from both blocks (ΔDiff: *High*, ΔDiff: *Low*) against the null value of 0.5. For ΔDiff: *Low*, RST $(M = 0.507, \mathrm{SD} = 0.081)$ was not significantly different from 0.5 $(t(54) = 0.597, p = 0.553, \text{Cohen's } d = 0.080)$. Figure 6 shows two violin plots for the two block conditions. The Bayesian one-sample t-test supported this result, with a Bayes factor of $\mathrm{BF}_{10} = 0.176$ (using a Cauchy prior with $r = 0.7$), indicating strong evidence for the null hypothesis $(H_0 : \mathrm{RST} = 0.5)$.

For ΔDiff: *High*, RST $(M = 0.545, \mathrm{SD} = 0.095)$ was significantly different from 0.5 $(t(54) = 3.468, p = 0.001, \text{Cohen's } d = 0.468)$. The test yielded a Bayes factor of $\mathrm{BF}_{10} = 26.808$ (using a Cauchy prior with $r = 0.7$), indicating strong evidence for the alternative hypothesis $(H_1 : \mathrm{RST} \neq 0.5)$. We next conducted a paired t-test between the RST values from the two conditions. The RST difference $(M = 0.038, \mathrm{SD} = 0.093)$ was significantly different from 0 $(t(54) = 3.010, p = 0.004, \text{Cohen's } d = 0.410)$.

To test for order effects, we performed a Monte Carlo permutation test. We randomly shuffled the block order assignments while keeping the within-subject block structure intact and repeated this process over 10,000 permutations to generate a null distribution of the test statistic. The p-value, calculated by comparing the observed statistic to the null distribution, was 0.158, indicating no significant order effect on RST values.

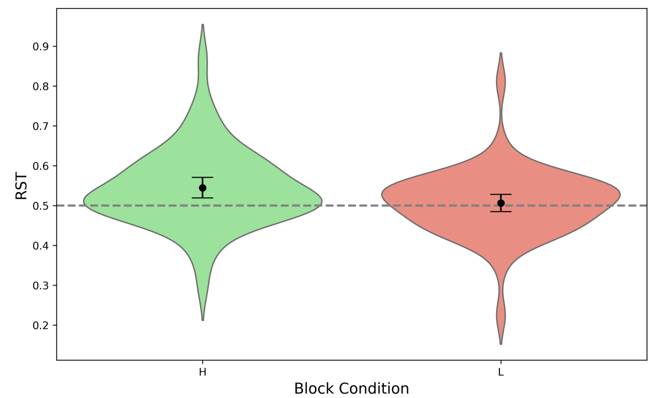

Figure 6: RST Distributions for two blocks in Experiment 2

Conclusion

In this study, we presented two experiments which demonstrated the lack of a numerical-perceptual divide in the attraction effect. In Experiment 1, we successfully produced a strong positive effect using stimuli that incorporated both perceptual and numerical attributes, where inter-attribute trade-offs were difficult. In Experiment 2, a within-subjects design, we extended this to numerical stimuli using fractions. We demonstrated that the standard attraction effect could be controlled by manipulating the asymmetry between target-decoy and competitor-decoy comparisons. Experiment 1 highlighted the role of inter-attribute trade-off difficulty, a concept distinct from traditional definitions of incommensurability, which typically treat commensurability as a binary variable — either allowing or disallowing trade-offs entirely. In contrast, we operationalized inter-attribute trade-off difficulty as a continuous variable, capturing gradations in how difficult it is to compare attributes. Experiment 2 not only blurred the distinction between numerical and perceptual domains but also leveraged findings from education and mathematical cognition research on fractions to manipulate the attraction effect.

Together, these experiments deepen our understanding of context effects by revealing a key cognitive mechanism behind the phenomenon, reinforcing that superficial distinctions between numerical and perceptual contexts are less consequential than previously thought. Ultimately, our results support the idea that higher inter-attribute trade-off difficulty facilitates the attraction effect—both by increasing the difficulty of choice between targets and competitors and by introducing asymmetries in pairwise comparisons between target-decoy and competitor-decoy pairs, corroborating the pairwise comparison argument in choice models.

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