Predicting NCAA Men's Basketball Rankings: How Context Effects Shape Beliefs

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Abstract

We test whether the support one holds about an event is influenced by other hypotheses. We addressed this by examining context effects in subjective probabilities (SPs) when forecasting NCAA men's basketball team rankings. A challenge in investigating context effects with naturalistic stimuli is the need to model the different representations of the options. To do so, we adapted the Spatial Arrangement method to capture individual representations and developed an algorithm to select stimuli. We asked participants steeped in basketball knowledge to create spatial maps for 50 teams. They were then presented with customized triplets of teams and asked to estimate their SP that one team would outrank the others. The study uncovered context effects in SPs, and moderators of the effects. Our findings suggest that similar cognitive processes may govern the construction of belief and preference and highlight the importance of modeling mental representations to understand forecasting scenarios.

Keywords: context effects; representations; subjective probabilities; naturalistic environment; basketball

Introduction

As a passionate basketball fan, imagine the thrill of watching the NCAA final championship with friends, where the UConn Huskies clashed with the San Diego State Aztecs. The atmosphere was electric, filled with intense anticipation. It is very likely that leading up to the game, you discussed the odds of each team winning, debating whether a strong defense or a formidable offense would tip the scales. This assessment was not just about the game. Estimating probabilities is ubiquitous in everyday life. Yet, how people assign subjective probabilities (SPs) is inconsistent: it is influenced by how events are described. For instance, studies have shown that SPs of a person dying from natural causes are lower than the sum of SPs of specific natural causes like heart disease, cancer, or other natural causes, a phenomenon known as subadditivity (Tversky & Koehler, 1994; Rottenstreich & Tversky, 1997).

Support theory

Support theory explains subadditivity and the violation of description invariance by positing that each event description or hypothesis has a level of evidence or support s for its occurrence (Rottenstreich & Tversky, 1997; Tversky & Koehler, 1994). The SP is determined by the ratio of the support for that event to the sum of supports for all considered events. That is the probability of hypothesis A obtaining over B is,

$$P_{A,B}(A) = \frac{s(A)}{s(A)+s(B)} \tag{1}$$

Context effects

As Equation 1 implies, support theory implies that the support for one hypothesis is unaffected by other hypotheses. However, evidence of context effects observed with SP judgments challenges this assumption of invariance (Cai & Pleskac, 2023; Pleskac, 2012; Windschitl & Chambers, 2004). One illustrative example of a context effect is the dud-alternative effect, where a dud hypothesis boosts the SP of a target hypothesis that dominates the dud hypothesis. For instance, people estimated a higher probability of Nairobi, Kenya, being on the equator when presented with a list that included irrelevant options (duds) like Cincinnati, Ohio, and Moscow, Russia (cities that are clearly not on the equator), compared to a list without them (Windschitl & Chambers, 2004). This mirrors the attraction effect in the choice domain (Huber et al., 1982; Trueblood, 2012). For this paper, in general, we refer to the hypothesis that describes the to-be-judged event as the target hypothesis (e.g., Nairobi, Kenya), the hypothesis that is supposed to induce an effect as the decoy hypothesis (e.g., Cincinnati, Ohio), and all the other hypotheses as the competitor hypothesis(es).

Cai & Pleskac (2023) replicated the dud-alternative effect and found evidence for a similarity effect in SPs. A similarity effect occurs when a decoy similar to a target hypothesis is added to the evaluation set, reducing the SP assigned to the target compared to a competitor hypothesis. This result is analogous to the similarity effect in the choice domain (Tversky, 1972; Trueblood, 2012). These results raise the question of whether other context effects in preferential choice also occur in SP. For instance, a compromise effect occurs when a decoy hypothesis is added that is more extreme than a target hypothesis but does not dominate or is dominated by the target or competitor hypothesis. According to the compromise effect from preferential choice (Simonson & Tversky, 1992), adding a compromising hypothesis should increase the probability assigned to the target hypothesis relative to the competitor hypothesis. Here, we investigate whether we can observe attraction, similarity, and compromise effects in the domain of SP judgment. We focus on forecasting the ranking of NCAA men's basketball teams. Such a domain allows us

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to ask if we can observe these effects when participants are forecasting events that take place outside the laboratory.

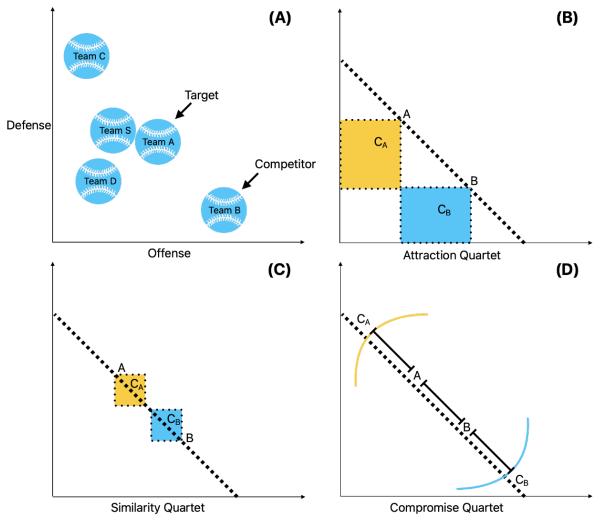

Figure 1: (A) Three context effects when judging which basketball team will win. Team D (or C) will increase Team A's relative probability, resulting in an attraction effect (or a compromise effect). Team S' presence decreases Team A's relative probability, resulting in a similarity effect. (B) The Attraction quartet placements. (C) The Similarity quartet placements. C_A is similar to A (yellow shaded) but not superior or inferior; the same as C_B to B (blue shaded). (D) The Compromise quartets. The distance between A and B is the same as the distance between A and C_A; the same as C_B to B. The possible locations of C_A are indicated in yellow and C_B in blue.

Context effects in naturalistic settings

Asking if we can observe context effects under more realistic conditions raises an important issue for context effects in general. Most studies on context effects use highly constrained, hypothetical stimuli where two precise attributes are shown for each alternative in some table format. But, options people are asked to consider are rarely provided on such a silver platter. In the domain of preference, studies using naturalistic stimuli where just labels or pictures of movie titles or snacks are shown to participants have struggled to demonstrate significant context effects (Frederick et al., 2014; Trendl et al., 2021; Yang & Lynn, 2014). One plausible explanation for the difficulty in observing context effects with these more naturalistic stimuli is the complexity and multi-dimensionality of knowledge in such settings. When individuals make choices, it's challenging to determine which specific dimensions they prioritize. For instance, in the case of predicting basketball team rankings, some people may focus on the offense and the defense, while others might consider how many stars are on the team and if the coach is strong, how big the school is, or even, the strength of the school's football program. This variability in dimensions raises an important challenge in identifying what hypotheses might be a dud, a resembler, or a compromiser for a given target hypothesis. More generally, the issues raise an important requirement for understanding context effects: the need to model the subjective representation of options (Spektor et al., 2021).

Mapping mental representations

Previous studies that aimed to model the latent representation of options have adopted data-driven approaches. These approaches involve extracting latent features from stimuli, such as movies or recipes, using machine learning techniques (Bhatia & Stewart, 2018), or employing similarity ratings between options (Trendl et al., 2021). However, there are limitations to these methods, including only having representations at the group level and not identifying the relevant subjective feature values for each object and participant. Moreover, if the latent features are extracted from text or similar data, then these representations carry with them a strong assumption that participants' subjective representations directly reflect the environmental structures (Shepard, 2001). Here, we take a different approach, adapting the Spatial Arrangement Method (SpAM; Goldstone, 1994)) to measure the mental representations of hypotheses. During SpAM, participants are presented with a dimensional space (we used a two-dimensional space) and are invited to spatially arrange stimuli on a screen, reflecting their subjective perceptions of where the stimuli belong in the space. Such an approach efficiently generates two-dimensional spaces at the individual level (Hout et al., 2013). In our study, we asked participants to map 50 NCAA men's basketball teams in a two-dimensional space with the dimensions determined by the participants. Then, we used these dimensional representations to create individualized stimuli that should induce context effects when forecasting the ranking of the teams.

Our study aimed to uncover context effects using naturalistic stimuli in the domain of subjective probability judgments. We specifically examined whether context effects were present when predicting the final season rankings of NCAA basketball teams. We first employed SpAM to obtain each participant's mental representations of the basketball teams. Then, we developed a search algorithm that generated personalized hypothesis sets (i.e., target, competitor, and decoy hypotheses), to test for attraction, similarity, and compromise effects at the individual level. In testing for these effects, our study asked participants to estimate the SP that a particular team would be ranked higher than two other teams. For each set of three hypotheses, we obtained the SP (across trials) that each team would be ranked higher. This approach allowed us to test for context effects with these naturalistic stimuli and explore the factors that impact the presence of the context effects.

Method

Participants

We recruited 125 participants through the Prolific online study platform, selectively choosing individuals currently residing in the U.S., aged between 18 and 50, and speaking English. Additionally, these participants self-reported watching basketball. Two participants submitted without completing the study. Five participants did not follow instructions properly (i.e., entered incorrect features), and five participants created representations that were impossible to generate stimuli from. Therefore, there were 113 participants in total for data analysis. All participants were paid $12 for this 60-minute study, and additional reward was given based on their prediction performance.

Materials & Design

The main task of this study for participants was to forecast the N.E.T. rankings for Division I Men's NCAA basketball teams, specifically predicting their standings on the day of the final championship, slated for April 4th, 2023. The forecasts were solicited during the week of March 9th.

Spatial Arrangement Task The experiment consists of two parts: a spatial arrangement task and the SP task. During the spatial arrangement task, participants were asked to situate 50 NCAA basketball teams in a two-dimensional space. First, they identified the two most important features they believed were predictive of a team's ranking. Subsequently, a coordinate system with x and y axes, labeled according to their chosen features, was presented as illustrated in Figure 2. Fifty basketball team logos were listed on the right, with their placements randomized for each participant. Participants then positioned these logos on the coordinate grid by dragging and dropping the logo onto the space. The placement of logos within the coordinates was intended to represent varying levels of the chosen abilities. As demonstrated in Figure 2, logos placed from left to right along the x-axis reflected increasing offensive capabilities. Similarly, logos arranged from the bottom to the top along the y-axis reflected increased defensive capabilities. Participants were instructed that teams aligned along the same 45-degree dashed line represent the same rankings but differ in offense and defense. Therefore, teams positioned in the upper right corner of the grid are considered top-tier, excelling in both dimensions. We incentivized participants based on the correlation between their subjective rankings, derived from their placements of team logos, and the objective rankings, which reflect the actual team standings at the time of the experiment. The max reward was $5 in this part.

Quartet Selection Owing to the unique team representations entered by each participant, we developed a search algorithm that generated, for a given participant, all possible sets of teams that were consistent with a given context effect, and then probabilistically selected among those sets. To test for context effects, we used a design where hypotheses A and B could be both a target and competitor. To do this, we identified a decoy C for each hypothesis for a given pair of hypotheses so that C_A was the decoy when A was the target, and C_B was the decoy when B was the target. This four-option set

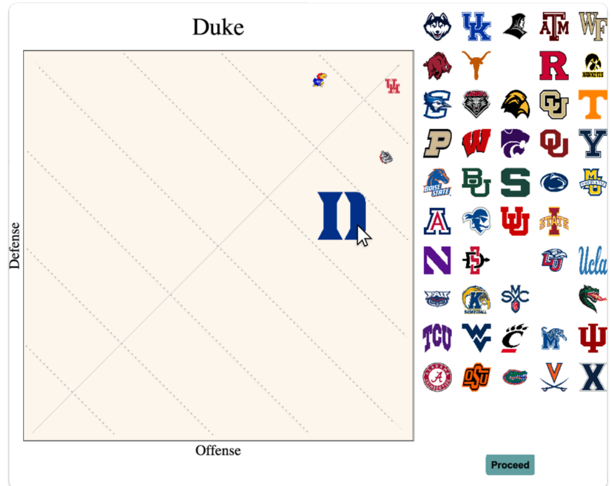

Figure 2: 2D coordinate with participant-labeled dimensions. There is one diagonal arrow pointing from the origin to the upper right corner and several 45-degree dashed lines orthogonal to the arrow. 50 basketball teams are listed on the right. Participants drag and drop the logos to the coordinate.

(A,B,C_A,C_B) creates a *quartet*. Panels B through D in Figure 1 illustrate the locations we used to identify decoys for the dud, similarity, and compromise effects for a given target and competitor hypothesis. We applied these definitions across all possible target-competitor hypotheses to generate a population of quartets for each context effect. The algorithm selected five quartets for each context effect to present to participants. The algorithm had four general steps.

Step 1. Initial Triplet Generation: Each test of the context effect is based on identifying three hypotheses: the target, competitor, and decoy. Therefore, at the first step, we identified possible triplets from the 50 teams, generating a total of 117,600 combinations. Next, triplets were identified where two teams (A,B) did not dominate each other (i.e., possible target and competitor), and a third team (i.e., potential decoy) did not dominate either of those teams or was not dominated by both teams.

Step 2. Context-Specific Filtering: In the second step, the algorithm filtered the triplets based on the definitions of the three context effects. In addition, for the similarity effect, it removed triplets where the target-competitor distance was less than three times greater than the target-decoy Euclidean distance. From there, triplets were limited to decoys that met the constraints of either C_A or C_B shown in Figure 1B (Attraction) and C(Similarity). In the compromise effect scenario, the algorithm ensures minimal distance differences between the target, competitor, and decoy (C), making the target a middle option, as shown in Figure 1D.

Step 3. Quartet Creation: To test for a context effect, in general, we compared the SP judgment assigned to A when it was the target (A,B,C_A) to SP assigned to A when it was the competitor (and B was the target) (A,B,C_B). Thus, we searched for triplets when the same two teams were targets and competitors but where they switched roles. These sets of triplets created a quartet (A, B, C_A, C_B).

Step 4. Selection of Quartets: The final stage involved probabilistically selecting quartets. Each quartet was not equally likely. Instead, we quantified the potential effectiveness of the quartets to elicit the possible effect and used it to determine the probability of being selected according to the following expression:

$$P(\text{quartet } i) = \frac{e^{\beta x_i}}{\sum e^{\beta x_i}} \tag{2}$$

The parameter β is a scale parameter, and x_i is a numerical value that represents the effectiveness of the quartet according to definitions of context effects and past work. These factors include, for example, if the two features for the target and competitor pair (A and B) appear to trade off equally. This factor was quantified by the degree to which the angle between the two hypotheses deviated from 45°. For all three effects, the distance between the target and the competitor was a factor, with greater distance being quantified as more effective. In addition, for the similarity quartet selection, closer proximity of the decoy (C) to the target (A, B) was counted as more effective (Trueblood et al., 2014). For the attraction effect, the larger distance between C and A, B, the higher selection probability. The distance between the decoy and the target was relaxed for the compromise effect. Instead, the effectiveness of the quartet was inversely related to the deviation of decoy options (C_A and C_B) from the line connecting target and competitor (AB). Lastly, to avoid forming quartets comprising the same teams repeatedly, the algorithm includes a cost: a penalty is assigned for each unselected team that is the same as any team selected for the quartet. The relative importance of these factors was uncertain, so we treated them with equal weight in our probability calculations. The confidence rating of the teams' locations were also collected. The algorithm worked sequentially selecting among quartets with the most confident teams and then working through other sets.

We generated five quartets (A, B, C_A, C_B) from the team representations for each effect, providing ten triplets of teams for the similarity effect, the attraction effect, and the compromise effect, respectively. In addition, we also created twenty triplets of filler trials. For each team in a triplet, participants judged the SP that the team would rank higher than the other two teams after the NCAA championship. This resulted in a total of 150 trials.

Procedure

First, participants learned how to use the two-dimensional coordinate system in a tutorial where six hypothetical teams (i.e., Team Tiger, Lion, etc.,) competed in a basketball competition. Next, participants proceeded to the spatial arrangement task involving 50 Men's Division I NCAA basketball teams. In this phase, they independently identified the two axes—x and y—that they would use to situate teams, and then they placed all 50 teams in the space. They also reported their confidence in the placement.

Then, our search algorithm generated individualized stimuli from participants' unique team representations. In the SP estimation phase, participants judged the SP for those generated teams on a semi-circle scale at the bottom of the screen that stretched from "0%" to "100%". They clicked a mouse along the semi-circle to select a probability. No feedback was given. Each trial was followed by a fixation cross. Participants were incentivized to provide accurate SP judgments using the Brier scoring rule, with the outcomes disclosed on April 4th, 2023.

Results

Spatial arrangement

Participants employed 46 unique features, with 'Winning Percentage', 'Offense', and 'Defense' being the top three most utilized features. To assess the degree to which participants distributed teams across the space, we calculated the correlations between the feature values across teams for each participant. A total of 14 (12%) participants had correlations less than .1, and 24 (21%) participants between .1 and .3 Thus, these participants showed very good distribution across the space, treating the features as largely independent. A total of 15 (13%) participants had a correlation between .3 and .5, and the remaining 60 (53%) participants had correlations between .5 and 0.92. These participants participants treated the features as correlated.

Context effects

We used a Bayesian hierarchical linear regression to analyze the data using a log-odds transformation of the SPs as the criterion. Each regression had the target team (A or B) and decoy location (C_A and C_B) as predictors. We entered "participant" and "quartet" as random effects to account for variations arising from individual differences and the diversity of triplets. We also recorded the triplets' features, such as the distance of target-competitor and target-decoy, among others. We explored how those features of the subjective representation shape the context effects. We report the mean of the posterior distribution of the parameter (b) and two-sided 95 % credible intervals (CI) around each value. The subjective probabilities are logit-transformed after multiplying with 0.9998 to handle ones and adding 0.0001 to handle zeros.

Similarity effect Recall that the decoy should reduce the SP assigned to the target relative to the competitor in the similarity effect. We found in our data that the similarity effect was present but that it depended on the distance between the target and decoy as indicated by a three-way interaction between the target team (A or B), decoy version (C_A or C_B), and the target-decoy distance (b = -0.205, CI [-0.334,-0.071]). Figure 3 plots the SPs for the targets separated by the type of decoy (C_A or C_B) for four different quantiles of target-decoy distance. For the largest target-decoy distance (Q4), when Team A is paired with decoy C_A, it is assigned a lower SP

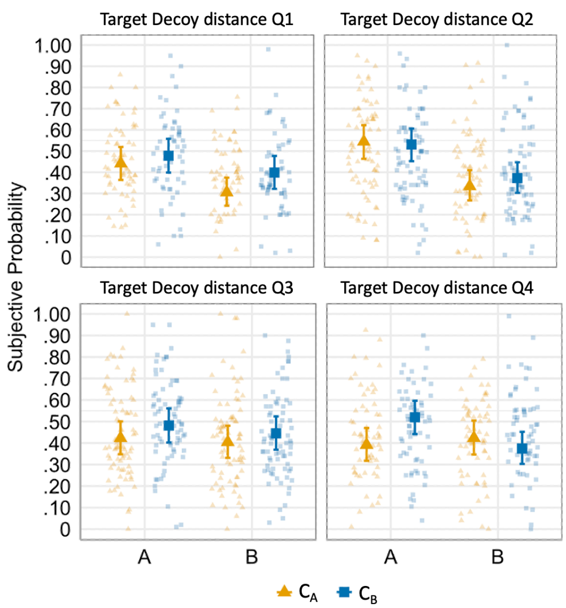

Figure 3: The similarity effect. The smaller dots represent the average subjective probability assigned to A and B per participant. The larger symbols are the posterior predictive means. Error bars the 95 % predicted credible intervals.

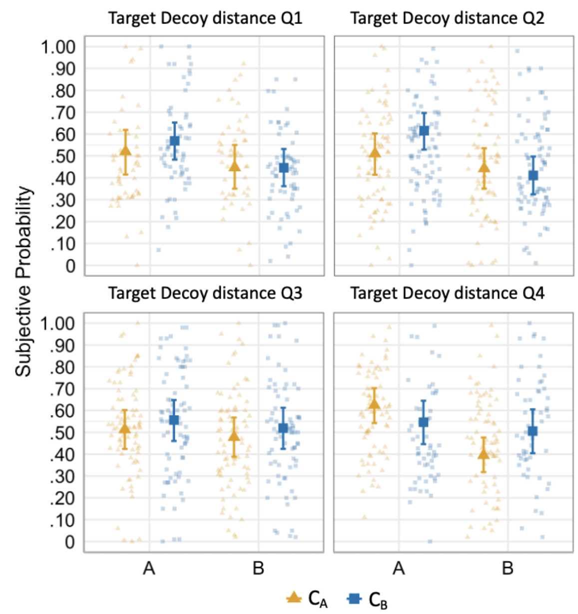

Figure 4: The attraction effect. The smaller dots represent the average subjective probability assigned to A and B per participant. The larger symbols are the posterior predictive means. Errors bars the 95 % predicted credible intervals.

than its pairing with decoy C_B. Conversely, Team B is assigned a lower SP when paired with C_B vs C_A. However, the similarity effect does not manifest with smaller target and decoy differences. This suggests that a larger perceived difference between the target and decoy leads to the similarity effect. Interestingly, this finding diverges from simulation results (Trueblood et al., 2014), which indicate that closer proximity between target and decoy enhances their perceived similarity, leading to a stronger similarity effect. An explanation for this discrepancy could be that a certain degree of difference is necessary to form a sense of similarity between two objects.

Attraction effect We also found that the target-decoy distance impacted the attraction effect. Recall that according to the attraction effect the decoy should increase the SP assigned to the target. We tested the interaction between Teams (*A* or *B*), the decoy version (C_A or C_B), and the target-decoy distance, revealing a credible three-way interaction.(b = 0.214, CI [0.053, 0.372]). Figure 3 illustrates the SPs for the targets separated by the type of decoy (C_A or C_B) for four different quantiles of target-decoy distance. This pattern is primarily driven by two effects: an attraction effect is observed in the fourth quartile (Q4), where the target-decoy distance is relatively large, while a repulsion effect occurs when the distance is small (Q2). A repulsion effect arises when the decoy decreases the target's attractiveness, reversing the expected attraction effect. This pattern is consistent with findings from previous simulation studies (Trueblood et al., 2014), which suggest that a greater distance between the target and the decoy typically indicates a more pronounced dominance of the target. Moreover, this observation resonates with Liao et al. (2021), who further delineated the impact of target-decoy distance, highlighting both repulsion and attraction effects.

Compromise effect Recall the compromise effect occurs when an extreme decoy makes the target hypothesis a compromise between the decoy and the competitor. In doing this, according to the effect, the SP assigned to the target should increase relative to the competitor. Our analysis did not uncover evidence of a compromise effect.

We did find in exploratory analyses that there was a pattern consistent with the compromise effect, but it depended on two factors: (i) the competitor-decoy (C-D) distance; and (ii) the deviation of the decoy from line between AB. Entering these two factors—C-D distance and the decoy's deviation—into a Bayesian hierarchical linear regression with Teams (A or B) and decoy version (C_A or C_B) revealed a credible four-way interaction (b = 0.571, CI [0.045,1.098]). To unpack this interaction, we performed a mean split of the data by the C-D distance and the deviation of the decoy, creating four groups with a comparable number of trials. Splitting the data this way shows that when the C-D distance is large and the tradeoff in terms of attributes of the decoy is similar to A, B, there was a tendency between Team and decoy version consistent with a compromise effect (b = 0.172, CI [-0.02,0.368]) (see bottom right panel). This pattern of results indicates that the further apart the extreme options makes the middle option more of a balanced compromise choice.

We also found a credible interaction when the C-D dis-

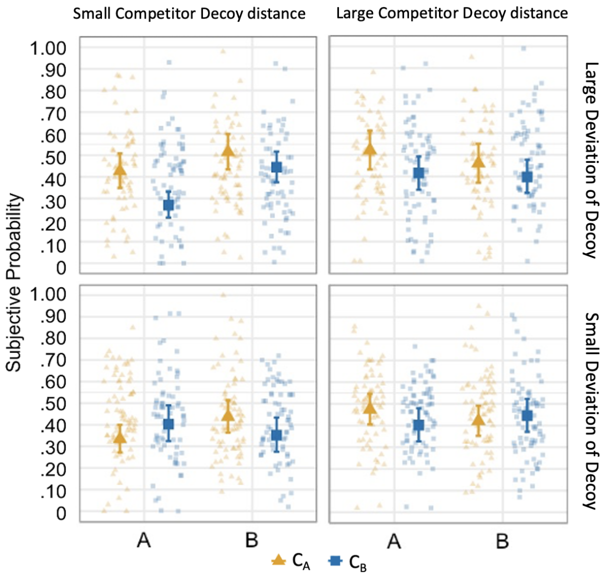

Figure 5: The compromise effect. The smaller dots represent the average subjective probability assigned to A and B per participant. The larger symbols are the posterior predictive means. Errors bars the 95 % predicted credible intervals.

tance is small, and the decoy is also close to the target (b = -0.288, CI [-.0532, -0.05]) (see lower left panel). This pattern contrasts with the compromise effect prediction, which anticipates an increase in SP of the target when positioned as a middle compromiser between the decoy and the competitor. Instead, it aligns with the similarity effect predictions, suggesting a decrease in SP for the target when it is in close proximity to the decoy. This pattern creates a challenge to discern whether the target acts as a compromiser or a resembler.

General Discussion

Our study investigated context effects in SP judgments within a naturalistic setting, focusing on NCAA basketball team rankings. We adapted SpAM to capture individual representations of the teams and generated meaningful triplets through a search algorithm. A key aspect of the study was analyzing how the relationship between teams in the subjective representations—distances between options and their relative locations—affects these context effects.

Factors that influence context effects

The attraction effect was observed when the distance between the target and the decoy was large, indicating that the greater the target's perceived dominance, the larger the attraction effect. Regarding the similarity effect, we found that a noticeable difference between the target and the decoy was crucial for creating a sense of similarity. The results showed that the compromise effect became more pronounced as the extreme options were placed further apart, and the balance of attribute trade-offs among options was maintained.

Altogether, these effects suggest that the psychological space where participants represent their hypotheses and the relationship between them in this space has an important influence on the equal weights on two dimensions, enhancing the perception of a target as a compromise choice. These insights contribute to our understanding of how spatial relationships in a psychological space influence decision-making processes.

Subjective representations may help reveal the elusive nature of context effects

Although context effects are often identified in decision making studies, their nature remains elusive (Spektor et al., 2021; Trueblood, 2022). Extensive research across various tasks and species confirms their existence (Trueblood et al., 2013, 2014; Farmer et al., 2017; Parrish et al., 2015). Yet, intriguingly, these effects can diminish or even invert when minor changes are made to the spatial presentation of choices on a screen (Spektor et al., 2021). Such variability has led some researchers to question the overall significance of context effects (Frederick et al., 2014; Huber et al., 2014).

In laboratory settings, participants process stimuli and then form task representations. This controlled environment allows researchers to manage the information presented to participants and seemingly induce context effects. However, this becomes more complicated in naturalistic settings where choice options are not easily observable. The variability in knowledge representations among individuals makes selecting stimuli challenging.

One key aspect that is often neglected in this work is the role the psychological representation of the options plays on the context effects (Spektor et al., 2021). Our results support this claim. The methods we developed here provide a way to directly examine how the psychological representation of options impacts the context effect. Our study showed that the relationship between the target, competitor, and decoy options is crucial in the effects. Moreover, the SpAM method allows us to examine how task and situation variables impact the representations. For instance, Spektor et al. (2021) suggests factors like stimuli's spatial arrangement, attributes' concreteness, and the time allocated for deliberation. Our methods provide a means to examine these hypotheses directly.

Moreover, our methods lend themselves to helping advance the computational modeling of judgment and decision making. To date, most models are designed and tested on tasks when the objective values of attributes are given (Bhatia, 2013; Roe et al., 2001; Trueblood et al., 2014). But, what happens when the attributes are not given, as is often the case with more naturalistic stimuli (Bhatia & Stewart, 2018; Trendl et al., 2021)? Modeling the subjective representation of options is a first step in answering this question.

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