The Effect of Preference Learning on Context Effects in Multi-alternative, Multi-attribute Choice

Yanjun Liu, Jennifer S. Trueblood

Department of Psychological and Brain Sciences, Indiana University

Author Note

Correspondence may be addressed to Yanjun Liu or Jennifer S. Trueblood, Department Psychological and Brain Sciences, Indiana University, 1101 E 10th St, Bloomington, IN 47405; Email: yanjliu@iu.edu; jstruebl@iu.edu

Abstract

Within the domain of preferential choice, it has long been thought that context effects, such as the attraction and compromise effects, arise due to the constructive nature of preferences and thus should not emerge when preferences are stable. We examined this hypothesis with a series of experiments where participants had the opportunity to experience selected alternatives and develop more enduring preferences. In our tasks, the options are presented in a description-based format so that participants need only learn their preferences for various options rather than the objective values of those options. Our results suggest that context effects can still emerge when stable preferences form through experience. This suggests that multi-alternative, multi-attribute decisions are likely influenced by relative evaluations, even when participants have the opportunity to experience options and learn their preferences. We hypothesize what was learned from experience in our tasks is the weights for various attributes. Through model simulations, we show that the observed choice patterns are well captured by a model with unequal attribute weights. A secondary finding is that the direction of observed context effects is opposite to standard effects and appears to be quite robust. Model simulations show that reserved effects can arise through various processes including representational noise and sensitivity to advantages and disadvantages when comparing options.

Keywords: context effects, inherent preferences, constructed preferences, experience, multi-alternative multi-attribute decision-making

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The decisions we make throughout our lives rely on underlying preferences for various options. For example, imagine that you are choosing among restaurants in your neighborhood for dinner tonight. Suppose that you have lived in your neighborhood for a long time and are very familiar with all of the restaurants. In this case, your substantial dinning experience with these restaurants may provide you with sufficient opportunity to form stable preferences for these options. Under this circumstance, your restaurant choice today may mainly rely on your predetermined (inherent) preferences for these restaurants, allowing you to evaluate the options independently (i.e., absolute evaluation) when making a decision. Inherent preferences are usually regarded as stable dispositions that are constant in varied decision contexts or frames (Simonson, 2008). Studies of both animal (e.g., Ackroff et al., 2012; Sale, 1971) and human choice behavior (e.g., Biehal, 1983; Sullivan and Birch, 1990) suggest that inherent preferences tend to emerge from prior experience and are utilized when decisions involve elements of learned experience and familiarity (e.g., Bettman and Park, 1980).

In contrast, constructed preferences tend to emerge when decision makers' existing preferences are ambiguous. Again, imagine that you are choosing among restaurants for dinner tonight, but this time in an area that you have never explored before. Under this circumstance, you are unlikely to have enduring preferences for restaurants in the new area, and thus you may gravitate towards constructing your preferences by comparing the restaurants to some reference point (i.e., relative evaluation). Under this circumstance, your restaurant decision may strongly rely on constructed preferences rather than inherent preferences. Constructed preferences are usually very malleable and sensitive to decision context (Simonson, 2008; also see Warren et al., 2011 for discussions about various operational definitions of preference construction used in the existing literature). Although previous work has suggested that revealed preferences should reflect both inherent and constructed preferences (i.e., Bettman et al., 1998; Simonson, 2008; Tversky and Simonson, 1993), only a few studies have examined the interplay of these two types of preferences. Some preliminary efforts have conceptualized the functional relationship between inherent and constructed preferences (e.g., a linear combination as addressed in Tversky and Simonson, 1993, or a dynamic transformation as addressed in Kivetz et al., 2008). Additionally, a handful of empirical studies (e.g., hedonistic durability as addressed in Tang, 2016; Tennant and Hsee, 2017) have hypothesized about the different roles of these two types of preferences using observed choice behavior in certain decision domains. In this study, we aim to further explore the interplay of inherent and constructed preferences within multi-alternative, multi-attribute choice.

Given their context-dependent nature, constructed preferences are usually assumed to underlie observed context effects in multi-alternative, multi-attribute choice, such as attraction (Huber et al., 1982), similarity (Tversky, 1972), and compromise (Simonson, 1989) effects. Context effects refer to changes in choices among existing options with the inclusion of additional options in the choice set. The empirical observations of these effects in choice behavior are examples of violations of the principles of classical economic theories of decision-making, including simple scalability, regularity, and independence of irrelevant alternatives (see Huber et al., 1982, for a brief review). In the current paper, we focus on two of these effects, the attraction (Huber et al., 1982) and compromise effects (Simonson, 1989). These two effects are frequently observed to co-occur (e.g., Berkowitsch et al., 2014; Cataldo and Cohen, 2021; Dumbalska et al., 2020; Liew et al., 2016; Trueblood et al., 2015) and likely involve similar cognitive mechanisms (e.g., Roe et al., 2001; Spektor et al., 2021; Spektor et al., 2019).

To illustrate these effects, consider a choice set including two restaurants X and Y (we will refer to these two options as the 'focal' options). Let us assume that X has relatively better service but is more expensive, and Y has relatively worse service but is less expensive. Conventionally, the attraction effect occurs if choices for X increase when the choice set includes an additional decoy R_x that is similar, but slightly inferior to X (in this situation, we will refer to X as the 'target' option). Relative to restaurant X in our example, R_x is more expensive with lower quality of service. A standard compromise effect occurs if choices for X increase when the choice set includes a decoy C_x which turns X into a compromise between C_x and Y. That is, relative to restaurant X, C_x is very expensive but with excellent service. We note that recent studies have also documented reversals in attraction and compromise effects such that the inclusion of attraction and compromise decoys reduced the choice shares of the target option (e.g., Cataldo and Cohen, 2019; Spektor et al., 2019). Current research on context effects is aimed at understanding when and why reversals (or null effects) occur (Spektor et al., 2021).

Theoretically, cognitive models of context effects also generally assume that preferences for various options are constructed over time (e.g., Bhatia, 2013; Cataldo and Cohen, 2021; Noguchi and Stewart, 2018; Roe et al., 2001; Trueblood et al., 2014; Turner et al., 2018; Usher and McClelland, 2004). Most of these models depict the formation of preferences for options as a dynamic accumulation process. The accumulated preferences race against each other, and a choice is made once one of the accumulated preference states reaches a decision criterion. In Multialternative Decision Field Theory (MDFT; Roe et al., 2001), the accumulation of preferences is driven by the comparison of an option to the mean of the others. In other words, the construction of preferences for options in MDFT is exactly a relative-evaluation process. Similarly, regardless of the differences in model structure, the Leaky, Competing Accumulator model (LCA; Usher and McClelland, 2004), the Multi-attribute Linear Ballistic Accumulator model (MLBA; Trueblood et al., 2014), and Multi-alternative Decision by Sampling (MDbS; Noguchi and Stewart, 2018) also depict the construction of preferences as a dynamic accumulation process driven by pairwise relative comparisons between options.

As alluded to above, existing studies and theories of context effects put strong emphasis on the construction of preferences and usually neglect the impact of preferences that could be learned from prior experience. Empirically, most past studies of context effects involved sets of options that are novel to decision makers (e.g., Trueblood et al., 2013; Tsetsos et al., 2012). These novel options leave little room, if any, for inherent preferences to play a role, and subsequently make constructed preferences the most effective for decision makers. Moreover, decision scenarios used in most context-effect studies tend to have low external validity, which also stack the deck against inherent preferences. For example, in a classic multi-alternative, multi-attribute decision scenario about choices of three hypothetical apartments (Evangelidis et al., 2018), participants were asked to make their decisions based only on two attributes, while in reality such decisions usually involve complex consideration over multiple attributes. As pointed out by Simonson (2008), decision makers find it difficult to evaluate the absolute values of options when confronting unusual decision scenarios that they have little experience with in reality, and thus gravitate to relative evaluations under such circumstances.

Recently, with mounting observations of the behavioral differences between description-based and experience-based decisions (i.e, the description-experience gap; Camilleri and Newell, 2013; Hertwig and Erev, 2009), studies have started to examine the impact of experience on context effects (e.g., Ert and Lejarraga, 2018; Hadar et al., 2018; Spektor et al., 2019; Tsetsos et al., 2012). For instance, Spektor and his colleagues (2019) studied context effects with choices among three gambles whose underlying distributions of rewards were learned by the participants through repeated sampling of outcomes rather than being stated upfront. In these studies, participants are simultaneously learning the objective (i.e., experimenter defined) values of ambiguous options along with their subjective values for those options. As a concrete example, this would be similar to a person shopping for a new mattress and having to learn about the firmness of mattresses by lying on them. In addition to learning about the firmness of various mattresses, the individual would also be learning their preference for different levels of firmness. Because most experience-based paradigms require the joint learning of objective and subjective values, these paradigms likely make it more difficult to assess the role of inherent preferences.

In this paper, our goal is to understand whether context effects still emerge when participates have the opportunity to experience selected options and thus develop stable preferences for the options. Unlike traditional experience-based decision tasks, our paradigm presents the options in a description-based format. Thus, participants need only learn their preferences for various options rather than the objective values of those options. As participants become experienced and familiar with options, inherent preferences should start to form and the influences of construction should play less of a role in the decision process.

In Experiments 1 and 2, participants recruited from Amazon Mechanical Turk (MTurk) made decisions about various simple jobs to complete (similar to the decisions our participants make about which HITS to accept in real life). The jobs consisted of simple counting tasks that varied in difficulty and length. On each trial, participants were asked to choose their preferred job from binary and ternary choice sets of jobs. These particular stimuli were selected because of their high external validity (i.e., similar to decisions MTurk workers often make) and offered participants with the opportunity to learn their preferences from both descriptive information about the jobs and by experiencing selected jobs. The experiments were also fully incentivized such that performance on the jobs determined the payments they received.

In some blocks of Experiments 1 and 2, participants had the opportunity to experience their selected jobs. Specifically, in the "choice-counting block", after participants made a choice based on the descriptive information, they were required to complete the selected jobs. In the "choice-only block", participants were asked to make a choice without completing the job. We assess how the experience impacts preference formation and context effects by comparing the choice behavior from these two blocks completed in different orders (i.e., choice-counting → choice-only vs. choice-only → choice-counting).

When participants confront options that they have little or no experience with (i.e., in the choice-only block of the choice-only → choice-counting condition), we expect that the influences of construction to play a dominate role and thus lead to context effects, since inherent preferences have yet to form. If inherent preferences reduce relative evaluations (e.g., Huber et al., 2014; Simonson, 2008), then we expect that experience with selected options (i.e., in the choice-counting block) may lead to the attenuation of context effects. In contrast, if relative evaluations persist even when inherent preferences exist, then context effects could still emerge. In this situation, the intriguing question is whether the observed context effects are similar to those seen when inherent preferences have less opportunity to form.

An unexpected finding in Experiments 1 and 2 is that the direction of the context effects is reversed. While our primary objective is examining the role of experience in context effects, we also explore the secondary finding of reversed effects. To this end, we conducted a third experiment using a more conventional multi-alternative, multi-attribute decision paradigm involving consumer and risky choices to test the robustness of the reversed effects. For five different scenarios, participants were asked to make decisions about consumer goods or gambles based on descriptions of the options. Participants in this experiment did not have the opportunity to experience the selected options. The attribute values of the focal options remained the same across these decision scenarios and were identical to those used in Experiments 1 and 2. By comparing the results from Experiments 1 and 2 with those from Experiment 3, we further investigate the emergence and direction of context effects.

All of the experiments were conducted under IRB #201837 approved by the institutional review board of Vanderbilt University. The pre-registrations for Experiments 2 and 3 and all of the data are available on the Open Science Framework at https://osf.io/mcfk9/?view_only=6bcb63d748e0461684a912302538092d.

Experiment 1

Experiment 1 examined the impact of experience on preferences and context effects. Participants made choices among simple counting jobs and they had the opportunity to complete selected jobs.

Method

Participants

In Experiment 1, in order to have 50 participants in each of four experimental conditions (see Procedure section for details), we recruited 200 participants from MTurk using the CloudResearch platform and 199 participants (111 women, 88 men, age: M = 42, SD = 13.3) completed the study online. The sample size was determined prior to starting the experiment, and the data was analyzed only after all data had been collected.

All participants who completed the experiment were paid a $1.50 base rate and a performance-based bonus ranging from \$0 to \$0.50 to incentivize accuracy. The amount of the bonus was \$0.50 for accuracy above 90%, \$0.25 for accuracy between 80% to 89.9%, and \$0.10 for accuracy between 70% to 79.9%. Participants with accuracy lower than 70% received a bonus of \$0.

Participants who had low accuracy on the counting jobs (i.e., the accumulated accuracy rate on the counting jobs was less than 88%, which is the 20th percentile of all accuracy rates) were excluded from the data analyses. In total, 20% of participants (N = 40) were excluded. After the exclusions based on accuracy, we had 39 participants in condition 1, 41 in condition 2, 39 in condition 3, and 40 in condition 4.

Materials

Participants were asked to make binary and ternary decisions about counting jobs that they preferred to complete. A counting job consisted of a certain number of counting tasks. A counting task had two types of shape items (i.e., a mix of circles and squares) displayed on the screen for participants to count. On each counting task, participants were instructed to count one of the two types of shape items. The counting tasks within a counting job had the same total number of items, and the particular shape (i.e., squares or circles) for counting was randomly selected for each counting job.

The counting jobs varied in two key attributes: difficulty and length. Difficulty was regulated by the number of items presented on each counting task (i.e., Attribute 1) and length was regulated by the total number of counting tasks to complete (i.e., Attribute 2). These key attributes of the decision task were similar to attributes of price and quality in studies of context effects in consumer choice.

There were eight types of counting jobs in total, including two focal options (X, Y), two compromise decoys (C_x and C_y), two attraction decoys (R_x and R_y), one symmetric decoy (S), and one filler (F). The number of objects on the screen per task and the number of tasks were manipulated as depicted in Figure 1. The attribute values of the two focal options X and Y were selected to ensure that both jobs had the same total number of items (i.e., number of objects per task × number of tasks). The attribute values of the two attraction decoys R_x and R_y were selected to ensure that they were inferior to the target options' weakest attribute (i.e., range attraction decoys, Huber et al., 1982; Trueblood et al., 2013). The attribute values of the compromise decoys C_x and C_y were selected to ensure that the target options were located in between the decoy and the competitor on the experimenter defined indifference curve. The stimuli were generated using R Studio and the experiment was programmed in JavaScript.

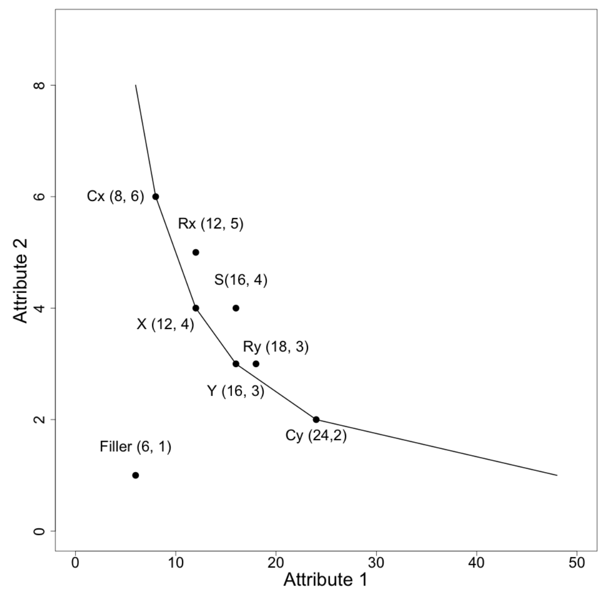

Figure 1
The complete set of counting jobs used in Experiments 1 and 2 in the attribute space of two attributes: (1) number of objects per task and (2) number of counting tasks.

Procedures

At the beginning of the experiment, participants were randomly assigned to one of four between-subject conditions. There were three types of blocks that all participants completed: choice-only (Choice), choice-counting (CC), and counting-only (Counting). The four between-subject conditions were determined by the order of these three blocks: (1) Counting → CC → Choice, (2) Counting → Choice → CC, (3) CC → Choice → Counting, and (4) Choice → CC → Counting. For example, those who were assigned to the Counting → CC → Choice condition always completed the counting-only block followed by the choice-counting block followed by the choice-only block.

In the choice-only block, participants were shown two or three counting jobs on each trial and they were asked to select the counting job they preferred to complete; however, they did not actually complete the selected job. On each trial, one of the seven choice sets was presented: a binary choice set containing the two focal alternatives (X and Y), five ternary choice sets containing the two focal alternatives in addition to one decoy alternative, and a binary filler set containing two identical filler jobs (Figure 1). On each trial, the alternatives were presented in separate boxes (Figure 2 top panel). The display order of the alternatives (i.e., left to right placement of the alternatives on the screen) were counterbalanced within the block. The binary and ternary sets were repeated 6 times and the filler set was repeated four times. Half of the repetitions required participants to count squares and the other half required them to count circles. In total, participants completed 40 trials in the choice-only block. The order of the trials was randomized.

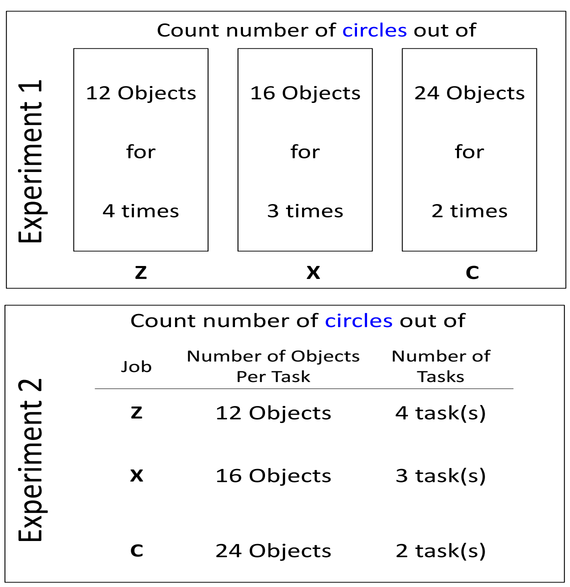

Figure 2
Top: the by-alternative display of a compromise choice set used in Experiment 1; Bottom: the by-attribute display of a compromise choice set used in Experiment 2.

In the choice-counting block, participants were shown two or three counting jobs on each trial and they were asked to select the counting job they preferred to complete. After they made their choice, they performed the selected counting job. Similar to the choice-only block, there were 40 trials in the choice-counting block. On each trial, the choice set and the particular shape (i.e., square vs. circles) to be counted were randomly selected, and the display order of alternatives were counterbalanced. Due to the extra time involved in completing the selected jobs, participants were allowed to take a short break half-way through the choice-counting block.

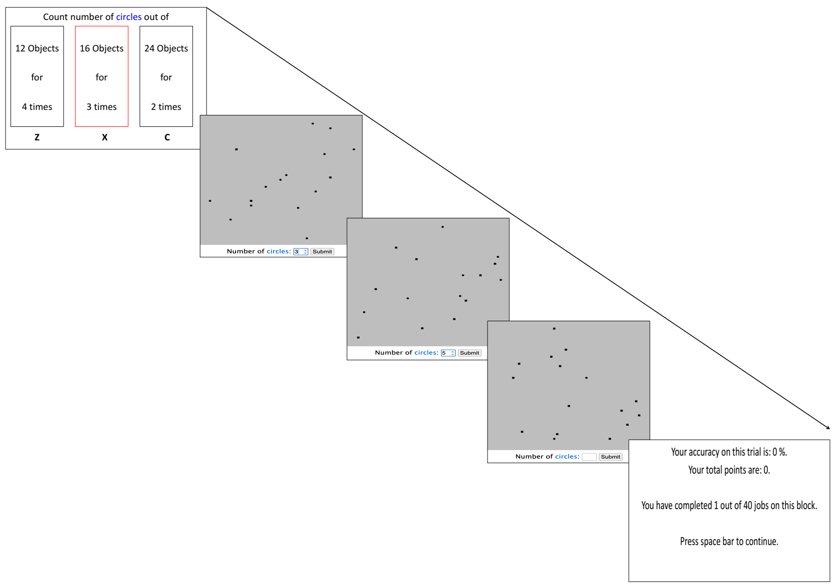

Figure 3

An example of the events on one choice-counting trial from Experiment 1. The first screen included three different counting jobs and the middle option is selected. The middle three screens are examples of the counting tasks for the selected job. The last screen is an example of the feedback participants received.

On each trial in the counting-only block, participants were asked to complete one counting job from the options used in the Choice and CC blocks. Participants completed all eight counting jobs (see Figure 1) in a randomized order. The key attributes of the counting job (i.e, the number of objects per task and the number of tasks) were shown to participants at the beginning of each trial (see Figure 4). The counting-only block occurred either as the first or the last block in the experiment, and was expected to provide basic knowledge of the various counting jobs to the participants.

At the beginning of the experiment, participants were informed that their task was to

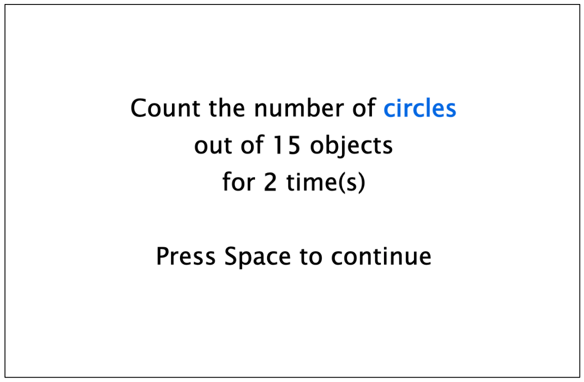

Figure 4
An example of a counting job displayed at the beginning of a trial in the counting-only block.

complete a series of counting jobs. In addition, they were informed that in some blocks, they would be able to choose the counting job they preferred to complete from two to three different possible jobs, while in other blocks they would not have a choice. They were also informed that their performance on the counting jobs would affect the amount of bonus payment they could earn. After they completed two counting jobs for practice, the first experimental block began. The type of block was determined by the block-order condition to which the participant was assigned (see above for details). If it was a choice-only block or a choice-counting block, a choice set of two to three counting jobs would be presented after a blank screen. If it was a counting-only block, a blank screen would be shown for 250 ms followed by a screen containing the counting job description. Once participants were ready to perform the counting job in the counting-only block or after they made a choice in the choice-counting block, they would proceed to their first counting task for the particular job (see Figure 3). After participants submitted their response for the first counting task on the job, the next counting task appeared with a 250 ms lag in between. This process continued until all counting tasks for a particular job had been completed.

Once participants completed all counting tasks on a trial, feedback on accuracy, accumulated points, and the number of completed trials within that block would appear on the screen. Participants could proceed to the next trial by pressing the space bar. In this study, ‘correct’ feedback occurred only when participants correctly answered all counting tasks for a particular counting job. If they responded inaccurately on any counting tasks on the job, it would be considered as ‘incorrect’ (i.e., all-or-none). Participants could earn five points for being correct on a trial or zero for being incorrect. In the choice-only block, participants did not receive accuracy feedback since they did not actually perform the selected counting jobs. In this block, the feedback screen only included the number of completed trials in that block. No points could be earned in the choice-only block. After the feedback screen, participants pressed the space bar to proceed to the next trial. Once participants completed a type of block, they were informed about the type of the next block. After the completion of all block types, participants were informed of their accumulated points and the amount of bonus payment they earned. The bonus payment schedule was described to participants at the start of the experiment.

Results

To examine the effect of experience on choices between the two focal options as well as context effects, we compared the behavioral measures of interests from the conditions where the choice-counting block occurred before the choice-only block (CC $\rightarrow$ Choice) with those from the conditions where the choice-only block occurred before the choice-counting block (Choice $\rightarrow$ CC). We conducted analyses to assess the influence of the counting-only block on participants’ choice behavior and the results show that the choice behavior before and after the counting-only block were very similar (see the Supplementary Materials). Thus, we present the results for the data pooled from choice blocks before and after the counting-only block. That is, we combined conditions 1 and 3 and conditions 2 and 4 for the analyses presented below. In the Supplementary Materials, we also provide analyses examining accuracy and response times for the different counting jobs used in this experiment.

We first examined how preference for the focal options (X and Y) changed with experience of selected options by assessing the choice proportion for X from the binary choice set $\{X,Y\}$ and the ternary symmetric decoy choice set $\{X,Y,S\}$ in different conditions. Then, we assessed the change in the choice proportions for options in the ternary choice sets with context decoys to further support our findings about preference formation as well as to detect the emergence of context effects with experience. We then measured the strength of context effects for different focal options by examining the respective change in the choice proportion for each focal option ($\Delta P_{Target},\ Target = X, Y$; Wedell, 1991). ΔP_{Target} compares the choice proportion for a particular focal alternative in the ternary choice set (i.e, absolute share) when that particular focal alternative is the target and when it is not. It is defined for each focal option separately:

$$\begin{aligned} \Delta P_X &= P(X|\{X,Y,D_x\}) - P(X|\{X,Y,D_y\}), \\ \Delta P_Y &= P(Y|\{X,Y,D_y\}) - P(Y|\{X,Y,D_x\}). \end{aligned} \tag{1}$$

$\Delta P_{Target} > 0$ provides evidence for standard context effects, as the inclusion of the decoy increases the choice proportion for the target option. Conversely, $\Delta P_{Target} < 0$ provides evidence for reversed context effects. $\Delta P_{Target} = 0$ indicates null context effects, as the choice proportion for the focal option remains the same when the choice set includes its corresponding decoy. We also examined the relative choice share for the target (RST; Berkowitsch et al., 2014; Trueblood, 2015) which measures the context effects pooled over the focal options. These results are included in the Supplementary Materials. Finally, we examined the dynamic nature of context effects by assessing the choice proportions from the context choice sets as a function of response times. All the analyses were conducted in Jamovi ("The jamovi project," 2021).

Preference for Focal Options

Preference for the focal options was measured by the choice proportion for X, estimated from the binary choice set including X and Y, and from the symmetric decoy choice set including X, Y, and S. As depicted in the top row of Figure 5, given either the binary choice set $\{X,Y\}$ or the ternary choice set $\{X,Y,S\}$, the focal option Y (which had fewer counting tasks but more items per task) was preferred over X (which had more counting tasks but fewer items per task) in general.

As shown in Figure 5, in the condition where participants started with the choice-counting

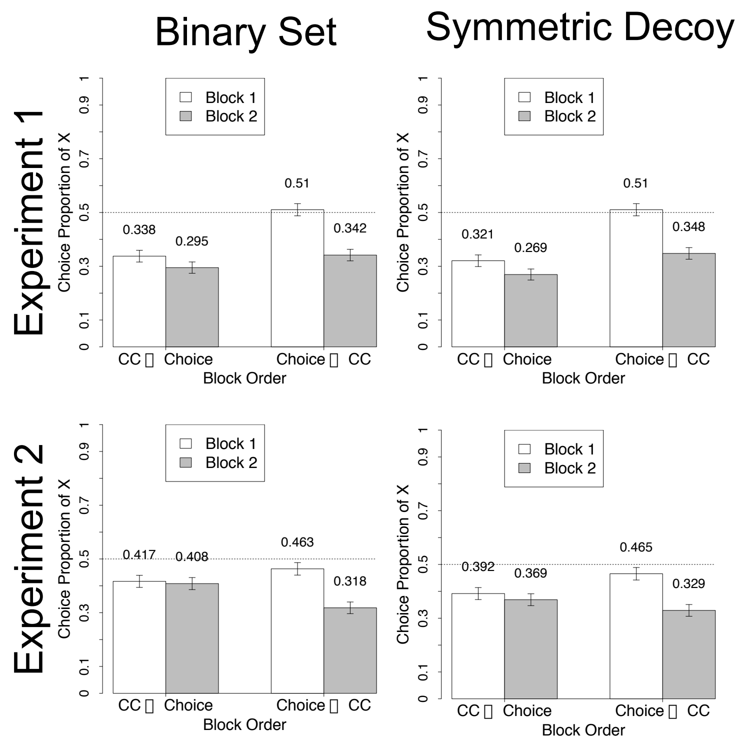

Figure 5

Top: Mean response proportions for X estimated from the binary and symmetric decoy choice sets in Experiment 1. Bottom: Mean response proportions for X estimated from the binary and symmetric decoy choice sets in Experiment 2. The response proportion for the symmetric decoy S was less than 0.06 *in all of the blocks of Experiments 1 and 2, thus these choice proportions are not shown in the figure. The error bars show the standard error of the mean. The white bars indicate block 1 and the gray bars indicate block 2.*

block and then shifted to the choice-only block (CC $\rightarrow$ Choice), the choice proportion for X was similar across the two blocks. While in the condition where participants started with the choice-only block and then shifted to the choice-counting block (Choice $\rightarrow$ CC), the choice proportion for X dropped from an indifferent point (i.e., about 0.5) to clearly below 0.5, reflecting a decrease in the preference for X across the two blocks.

The interaction between the block order and the block number is supported by a logistic mixed effects regression model:
$logit(P(X)) = ln\frac{P(X)}{1-P(X)} = 1 + \text{Block Order} * \text{Block Number} + (1 \mid \text{participants})$. Here, the block order (i.e., CC $\rightarrow$ Choice vs. Choice $\rightarrow$ CC) denotes the order of the choice blocks being completed. The block number (i.e., block 1 vs. block 2) denotes the position of a block. For

instance, in the order CC $\rightarrow$ Choice, block 1 is the choice-counting block and block 2 is the choice-only block. In contrast, in the order Choice $\rightarrow$ CC, block 1 is the choice-only block and block 2 is the choice-counting block. The model predicts the log-odds of choosing X as a linear predictor function of block order and block number after accounting for random effects across participants (i.e., the term (1 | participants) in the formula). 1 denotes the intercept.

The modeling results (conditional R^2 = 0.727 and 0.733, respectively for binary and symmetric decoy choice sets) showed a significant interaction between the block order and the block number on the odds of choosing X (see Table 1). The estimated coefficients showed a stronger decrease in the odds of choosing X from block 1 to block 2 in the Choice $\rightarrow$ CC condition as opposed to the CC $\rightarrow$ Choice condition.

Table 1
Fixed effects estimated from the logistic mixed effects regression model: $logit(P(X)) = 1 + Block\ Order * Block\ Number + (1|participants)$*, where* $P(X)$ *was estimated either from the binary choice sets or the symmetric decoy choice sets in Experiment 1.*

Choice Set	Term	$Exp(\hat{\beta})$	SE	z	p
$\{X,Y\}$	Intercept	0.331	0.247	-4.47	<0.001
	Block Order (1)	2.308	0.492	1.7	0.089
	Block Number (1)	0.414	0.135	-6.55	<0.001
	Block Order (1) * Block Number (1)	0.411	0.268	-3.31	<0.001
$\{X,Y,S\}$	Intercept	0.328	0.248	-4.500	<0.001
	Block Order (1)	3.268	0.495	2.390	0.017
	Block Number (1)	0.390	0.138	-6.820	<0.001
	Block Order (1) * Block Number (1)	0.475	0.275	-2.710	0.007

Block Order: 0 = CC $\rightarrow$ Choice, 1 = Choice $\rightarrow$ CC; Block Number: 0 = block 1, 1 = block 2.

The distinct patterns of change in choice proportions for focal options across different block-order conditions suggest that the experience of selected options impacted preferences. Without experiencing the counting jobs (i.e., in the choice-only block of the Choice $\rightarrow$ CC condition), participants tended to be indifferent about the focal options. But when participants had the opportunity to experience the selected counting jobs (i.e., in the choice-counting block), they showed increased preference for counting jobs with fewer tasks but more items per task (Y) over the ones with more tasks but fewer items per task (X). Moreover, preferences formed during the choice-counting block appeared to carry over to the choice-only block. That is, even when participants were no longer experiencing the selected alternative, their preference for Y still remained.

Context Effects

Choice behavior from the ternary choice sets including compromise and attraction decoys were assessed to test the compromise and attraction effects. These choice sets included decoys targeting either X or Y (see Figure 1). We present the results performed on the choice proportions below and include the analyses performed on the response times in the Supplementary Materials.

Compromise Effect.

Overall Choice Patterns. We observed a strong preference for shorter but more difficult counting jobs in the compromise choice sets. As depicted in Figure 6, in all of the blocks except for block 1 in the Choice $\rightarrow$ CC condition, the option with the fewest number of counting jobs (i.e., Y among $\{X,Y,C_x\}$ and C_y among $\{X,Y,C_y\}$) was strongly favored over the other options. The second most preferred option was the one with the fewest number of items per task (i.e., C_x in $\{X,Y,C_x\}$ and X in $\{X,Y,C_y\}$). These patterns suggest that both attributes contributed to participants' selection of options, but the number of tasks might outweigh the number of items per task.

When shifting from block 1 to 2 in the Choice $\rightarrow$ CC condition, the choice proportion for Y among $\{X,Y,C_x\}$ and the choice proportion for C_y among $\{X,Y,C_y\}$ both increased, while the choice proportions for the other options in the choice sets decreased (see the bottom row of Figure 6). In the CC $\rightarrow$ Choice condition, we observed increased choice proportions for the counting jobs with fewer tasks and this carried over when participants shifted to the choice-only block. These findings suggest that with experience, individuals learned to prefer the shorter but more difficult options. These results are consistent with the inferences drawn from the binary and the symmetric-decoy ternary choice sets.

We also observed evidence of a reversed compromise effect. In all of the blocks across different block-order conditions, the choice proportion for the focal option was lower when the

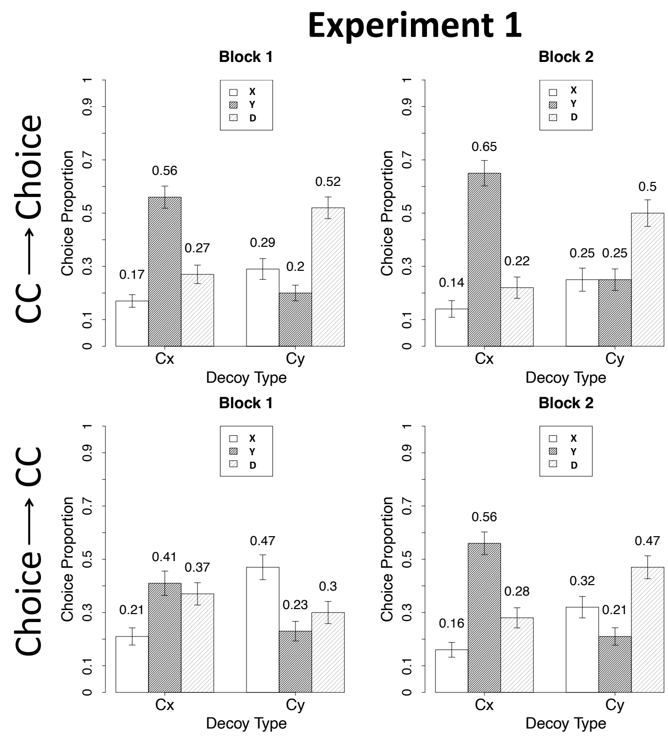

Figure 6

Top: Mean choice proportions for each option in the compromise choice sets in the CC → Choice condition of Experiment 1. Bottom: Mean choice proportions for each option in the compromise choice sets in the Choice → CC condition of Experiment 1. The error bars show the standard error of the mean.

choice sets included its corresponding compromise decoy. Specifically, in the choice set $\{X,Y,C_y\}$, X was selected more often than Y. Likewise, in the the choice set $\{X,Y,C_x\}$, Y was selected more often than X. This suggests that the compromise decoys increased preferences for the competitor options, which is consistent with a reversed compromise effect. The results of a multinomial regression model ($R^2 = 0.061$; Table 2) confirmed the above mentioned patterns. When the decoy type changed from C_x to C_y, the odds of choosing Y over X decreased significantly.

Absolute Share of the Focal Alternatives. Next, we examined the compromise effect for different focal options, X and Y, separately. Consistent with the results presented in the previous section, the observed negative ΔP_X and ΔP_Y values (top row of Figure 7) indicate a decrease in choices for the focal options when the choice sets included the respective compromise decoys,

Table 2

Parameters estimated from the multinomial regression model:
$P(Response) = 1 + Decoy + Block\ Order * Block\ Number$ *for Experiment 1.*

Decoy Type	Response Contrast	Term	$Exp(\hat{\beta})$	SE	z	p
Compromise	Y - X	Intercept	1.50	0.05	8.91	<0.001
		Decoy (1)	0.21	0.09	-17.55	<0.001
		Block Order (1)	0.60	0.09	-5.69	<0.001
		Block Number (1)	1.61	0.09	5.35	<0.001
		Block Order (1) * Block Number (1)	1.22	0.18	1.11	0.27
	D - X	Intercept	1.54	0.04	9.69	<0.001
		Decoy (1)	0.79	0.09	-2.66	0.01
		Block Order (1)	0.69	0.09	-4.30	<0.001
		Block Number (1)	1.29	0.09	2.98	<0.001
		Block Order (1) * Block Number (1)	1.44	0.17	2.14	0.03
Attraction	Y - X	Intercept	1.62	0.04	13.67	<0.001
		Decoy (1)	0.77	0.07	-3.73	<0.001
		Block Order (1)	0.56	0.07	-8.24	<0.001
		Block Number (1)	1.60	0.07	6.65	<0.001
		Block Order (1) * Block Number (1)	1.73	0.14	3.87	<0.001
	D - X	Intercept	0.18	0.07	-23.53	<0.001
		Decoy (1)	1.56	0.14	3.16	<0.001
		Block Order (1)	0.48	0.14	-5.22	<0.001
		Block Number (1)	1.02	0.14	0.16	0.87
		Block Order (1) * Block Number (1)	0.53	0.28	-2.24	0.03

Decoy: 0 = $D_X, 1 = D_Y; BlockOrder : 0 = CC \rightarrow$ Choice, 1 = Choice $\rightarrow$ CC;
Block Number: 0 = block 1, 1 = block 2.

which suggests a reversal in the compromise effect for both focal options. Additionally, the values of ΔP_{Target} were negative in all of the experimental blocks, suggesting that the reversed compromise effect did not attenuate with experience.

Furthermore, ΔP_Y deviated more from zero than ΔP_X in both blocks of the CC $\rightarrow$ Choice condition and in block 2 of the Choice $\rightarrow$ CC condition, suggesting the reversed compromise effect was stronger when Y was the target than when X was the target. This indicates that the compromise decoys had an asymmetric influence on different focal options and the asymmetry of the context effects increased with participants' experience of selected options.

The results of the linear regression model ($\Delta P_{Target} = 1 + Focal\ Option + Block\ Order + Block\ Number$) supported these observed patterns. ΔP_{Target} values were estimated at the individual level prior to the model fitting. The results

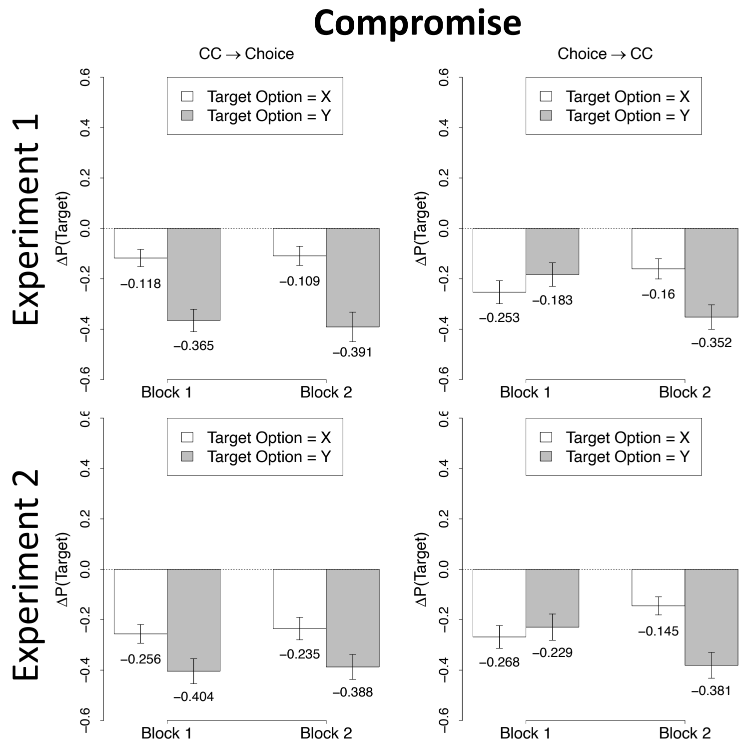

Figure 7

Top: Mean changes in absolute shares of each focal option estimated from choice sets including compromise decoys in Experiment 1. Bottom: Mean changes in absolute shares of each focal option estimated from choice sets including compromise decoys in Experiment 2. Error bars show the standard error of the mean.

($F(4,631) = 6.42,\ p < 0.001,\ R^2 = 0.039$; Table 3) show that the ΔP_{Target} differed significantly for different focal options, X and Y. When Y was the target option, the value of ΔP_{Target} was more negative than when X was the target option, indicating a stronger reversed compromise effect for the favored focal option (Y) than for the unfavorable focal option (X).

Attraction Effect.

Overall Choice Patterns. The choice proportions estimated using the attraction choice sets again suggest strong preference for the shorter but more difficult counting jobs over the longer but easier jobs. As illustrated in Figure 8, the counting job with the fewest number of tasks (Y) was favored the most. The attraction decoys were the least selected options as expected.

With experience, preferences increased for the favored option Y. As depicted in the bottom row of Figure 8, the choice proportion for Y in block 2 was greater than in block 1 in the

Table 3

Results of the linear regression model:
$\Delta P_{Target} = 1 + Focal\ Option + Block\ Order + Block\ Number$ *for choice sets including different decoy types in Experiment 1.*

Decoy Type	Term	Estimate	SE	t	p
Compromise	Intercept	-0.161	0.036	-4.428	<0.001
	Focal Option ($Y - X$)	-0.161	0.032	-4.985	<0.001
	Block Order ($Choice \rightarrow CC - CC \rightarrow Choice$)	0.023	0.046	0.511	0.609
	Block Number ($block2 - block1$)	-0.009	0.046	-0.185	0.853
	Block Order * Block Number	-0.030	0.065	-0.457	0.648
Attraction	Intercept	-0.030	0.018	-1.605	0.109
	Focal Option ($Y - X$)	-0.037	0.016	-2.283	0.023
	Block Order ($Choice \rightarrow CC - CC \rightarrow Choice$)	-0.056	0.023	-2.422	0.016
	Block Number ($block2 - block1$)	-0.015	0.023	-0.643	0.521
	Block Order * Block Number	0.094	0.033	2.889	0.004

Choice $\rightarrow$ CC condition, suggesting preferences increased when participants shifted from the choice-only to the choice-counting block. In the CC $\rightarrow$ Choice condition, the choice proportion for Y was similar to its choice proportion in the choice-counting block of the Choice $\rightarrow$ CC condition. These observations reflect that the preference for the shorter but more difficult counting job increased when participants had the opportunity to experience selected jobs. The results of a multinomial regression model ($R^2 = 0.029$; Table 2) supported the observed patterns.

We also observed reversals of the attraction effect. The choice proportion for X was greater in the presence of R_y as compared to R_x; while the choice proportion for Y was greater in the presence of R_x as compared to R_y. This indicates a reversed attraction effect such that the inclusion of the attraction decoys reduced the selection of the respective target options.

Absolute Share of the Focal Alternatives. Figure 9 (top row) illustrates the change in absolute share of the focal options estimated from the attraction choice sets. In all of the blocks, ΔP_{Target} was slightly below zero, suggesting a weak reversed attraction effect on both focal options. There was also a hint of asymmetry in the strength of the effect for different focal options, as ΔP_Y deviated further from zero than ΔP_X. Moreover, this asymmetry seemed to increase with experience, as the difference between ΔP_X and ΔP_Y increased when participants shifted from the choice-only to the choice-counting block. The results from a linear regression

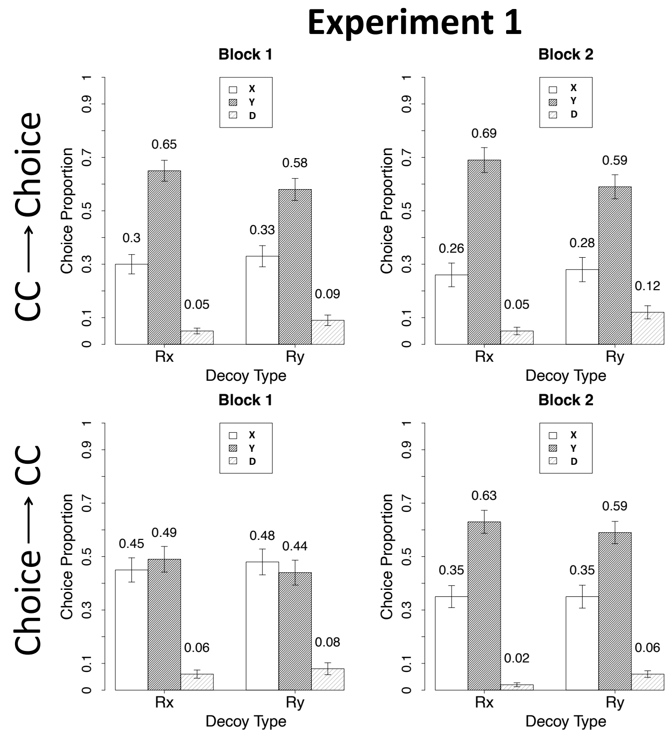

Figure 8

Top: Mean choice proportions for each option in the attraction choice sets from the CC → Choice condition of Experiment 1. Bottom: Mean choice proportions for each option in the attraction choice sets from the Choice → CC condition of Experiment 1. The error bars show the standard error of the mean.

model ($F(4,631) = 4.49, p = 0.001, R^2 = 0.028$; Table 3) confirmed these observations, showing a significant decrease in ΔP_{Target} when the target option was Y as compared to X.

Relationship Between Context Effect and Response Times

The results from ΔP_{Target} analyses indicated that reversals in the compromise and attraction effects occurred in Experiment 1. Although we did not expect these reversals in context effects to occur when we constructed the attribute space, it is not uncommon to observe reversed context effects. In fact, reversals in all three context effects (attraction, compromise and similarity) have been shown to occur when the display of options is manipulated (e.g., Cataldo and Cohen, 2019) and also in different decisional frames (e.g., Cataldo and Cohen, 2020). Furthermore, a meta-analysis conducted by Cataldo and Cohen (2021) showed that the standard

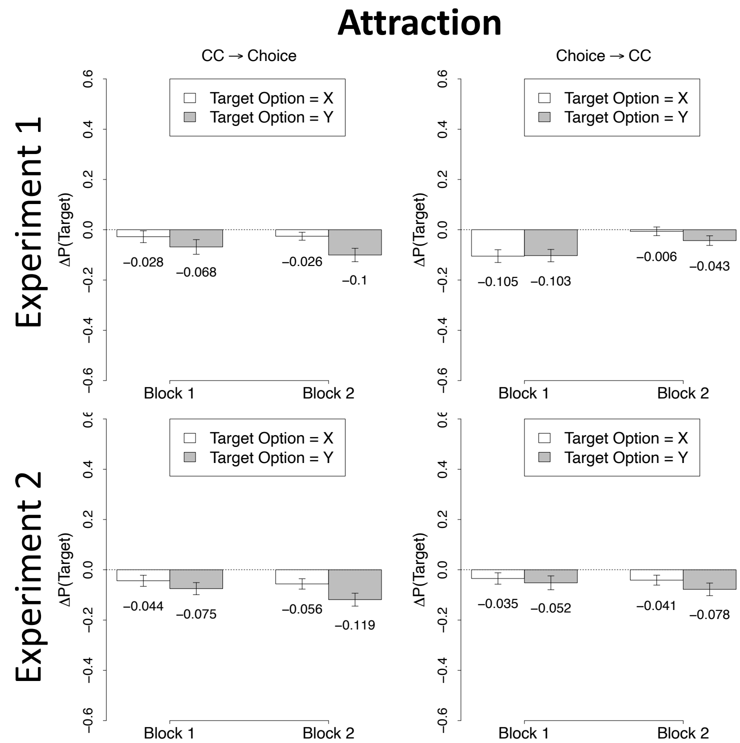

Figure 9

Top: Mean changes in absolute shares of each focal option estimated from the attraction choice sets in Experiment 1. Bottom: Mean changes in absolute shares of each focal option estimated from the attraction choice sets in Experiment 2. Error bars show the standard error of the mean.

attraction and compromise effects are positively associated with internally controlled response times (RTs). Specifically, the reversed attraction and compromise effects tend to occur with shorter RTs and the standard effects tend to emerge with longer RTs.

To this end, we examined the association between the context effects and the internally controlled response times by assessing the trend in response proportions with increasing RTs. Specifically, we calculated four evenly spaced quantiles (20%, 40%, 60%, 80%) using the group-level[1] RT distribution estimated from the choice sets including the same type of context decoys (M = 4.36 and 4.87 sec, SD = 7.80 and 3.16 sec, respectively for the compromise and attraction choice sets; see Figure 10). Then, we divided the RTs into five RT-quantile regions (see

[1] We used the RT quantiles estimated from the group-level to divide responses into groups of different speeds. With such a division, relatively faster participants would contribute more data points to the relatively smaller RT groups and relatively slower participants would contribute more data points to the relatively larger RT groups.

the top row of Figure 10) and estimated the response proportions for choosing the target, competitor, and decoy options within each region.

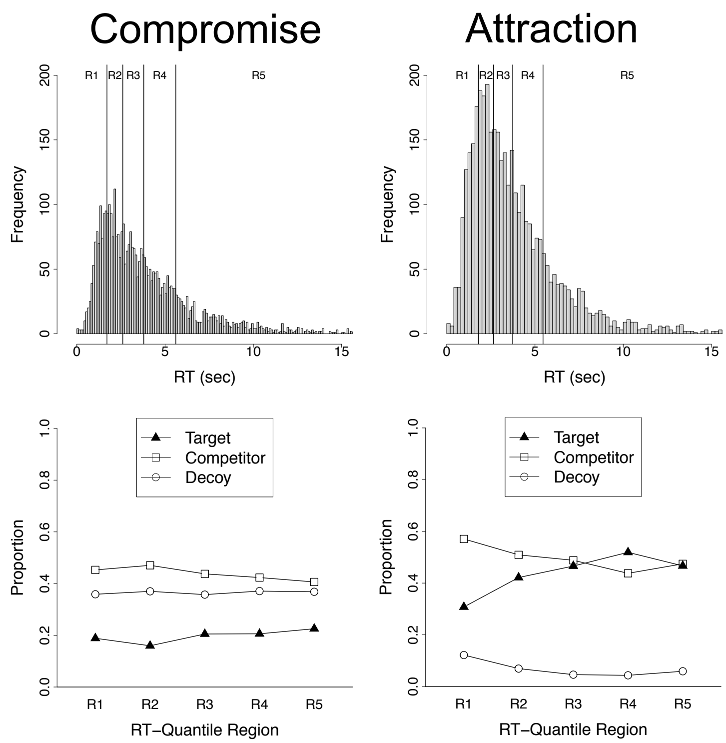

Figure 10
Top: RT distributions estimated for each type of context effect choice set in Experiment 1, which were divided into five evenly spaced RT-quantile regions. Bottom: Choice proportions for targets, competitors, and decoys estimated for each RT-quantile region.

As depicted in Figure 10 (bottom row), the response proportion for targets was below the response proportion for competitors in quantile R1 in both context choice sets, suggesting reversed context effects with faster responses. As RT-quantile region increased, the response proportion for targets tended to increase. In contrast, the response proportion for competitors decreased with increasing RT-quantile. Such a pattern is largely in agreement with previous empirical findings (see overviews in Cataldo and Cohen, 2021) and implies that preferences for the target options increased but preferences for the competitor options decreased with slower responses.

For the attraction choice sets, the choice share of the targets was observed to eventually overcome the choice share of the competitors as RTs increased, indicating a more standard attraction effect over the time course of the deliberation. The results of a logistic mixed effects regression model (conditional R^2 = 0.0267; Table 4) supported this observation. It shows that the response proportion for targets increased significantly with RT-quantile region. This suggests that the weak reversed attraction effect observed in Experiment 1 is in fact an average of the reserved and standard attraction effects over the time course of deliberation. On the other hand, for the compromise choice sets, the results of a logistic mixed effects regression model (conditional R^2 = 0.264; Table 4) did not support an increasing trend in the response proportion for targets with RT-quantile region.

Table 4

Estimated coefficients from the logistic mixed effects regression model:
$logit(P(Target)) = 1 + \textit{RT-Quantile Region} + (1|participants)$ *for Experiment 1.*

Decoy Type	RT-Quantile Region	Exp($\hat{\beta}$)	SE	z	p
Compromise	$< 20\%$	0.178	0.101	-17.059	< 0.001
	$20\% - 40\%$	0.748	0.150	-1.941	0.052
	$40\% - 60\%$	0.968	0.149	-0.219	0.827
	$60\% - 80\%$	1.030	0.150	0.197	0.844
	$80\% - 100\%$	1.116	0.151	0.728	0.467
Attraction	$< 20\%$	0.768	0.033	-8.00	< 0.001
	$20\% - 40\%$	1.640	0.107	4.61	< 0.001
	$40\% - 60\%$	1.963	0.107	6.32	< 0.001
	$60\% - 80\%$	2.429	0.107	8.32	< 0.001
	$80\% - 100\%$	1.969	0.107	6.34	< 0.001

Conclusions

In Experiment 1, we found that preferences for the shorter but more difficult counting job formed with experience, yet context effects (i.e., reversed compromise and attraction effects) were not attenuated. In addition, the reversals of the attraction and compromise effects were stronger for the favored focal option. This result is inline with recent findings by Evangelidis et al. (2018) showing that null / reversed effects are more common for advantaged options. We also observed that as response times increased, the attraction effect became more standard, while the compromise effect remained reversed. This finding is similar to the observation by Cataldo and Cohen (2021) that context effects change with deliberation time.

Experiment 2

Since the results of Experiment 1 may have been influenced by factors such as the display of alternatives (Cataldo and Cohen, 2019) and the all-or-none determination of accuracy on the counting jobs (i.e., jobs were only correct if all tasks were correct), we conducted a pre-registered conceptual replication of Experiment 1 where we varied these factors. In Experiment 2, the alternatives were presented in a by-attribute display (Figure 2) and a continuous score of accuracy was utilized.

Method

Participants

In Experiment 2, 197 paid participants (116 women, 80 men, 1 trans-masculine, age: M = 42, SD = 11.87) were recruited from MTurk using the CloudResearch platform and completed the study online. The sample size, data analyses, and exclusion criteria were pre-registered at https://aspredicted.org/GOJ_GBE.

The compensation consisted of a $1.50 base rate and a performance-based bonus. The amount of the performance-based bonus was determined by participants' accumulated accuracy score (see details in the Procedures section). The amount of the performance-based bonus was $0.50 for an accumulated accuracy score above 90%, $0.25 for an accumulated accuracy score between 80% to 89.9%, $0.10 for an accumulated accuracy score between 70% to 79.9%, and $0 for an accumulated accuracy score below 70%.

Participants with low performance (i.e., the reported counts deviated from the correct counts by over 7.84% which is the 20th percentile of participants' performance) were excluded from the data analyses as described in the pre-registration. In total, about 20% of participants (N = 40) were excluded from the data analyses. After exclusions, 41 participants from condition 1, 45 from condition 2, 38 from condition 3 and 33 from condition 4 were included for data analyses.

Materials

The stimuli values were identical to Experiment 1 (see Figure 1).

Procedures

Similar to Experiment 1, this study again involved three block types: counting-only (Counting), choice-only (Choice), and choice-counting (CC). The order of blocks determined four between-subject conditions: (1) Counting $\rightarrow$ CC $\rightarrow$ Choice, (2) Counting $\rightarrow$ Choice $\rightarrow$ CC, (3) CC $\rightarrow$ Choice $\rightarrow$ Counting, and (4) Choice $\rightarrow$ CC $\rightarrow$ Counting. Participants were randomly assigned to one of the block-order conditions at the beginning of the study.

The trials in the counting-only block were identical to Experiment 1, while those of the Choice and CC blocks differed from Experiment 1 in terms of the alternative display and the scoring of accuracy. In the choice-only block and the choice-counting block, after a blank screen of 250 ms, the counting jobs were displayed in a by-attribute manner. That is, each alternative was presented in a separate row of a table where the number of tasks and the number of objects per task were displayed in separate columns (see bottom of Figure 2). The display order of alternatives (i.e., top to bottom placement in the table) and the type of objects to be counted (i.e., circle or square) were again counterbalanced in Experiment 2, resulting in a total of 40 trials in each of the choice-only and choice-counting blocks. After the completion of a counting job, feedback on accuracy and the number of completed trials within a block appeared. Unlike the all-or-none accuracy scoring in Experiment 1, the accuracy of a completed counting job in Experiment 2 was determined by a continuous accuracy score: $[1 - \frac{|\text{Submitted Counts} - \text{Correct Counts}|}{\text{Correct Counts}}] \times 100\%$. The closer a participant's answer was to the correct answer, the higher the accuracy score was. The further away their answer was from the correct answer, the lower their accuracy score was. Similar to Experiment 1, no feedback on accuracy was presented in the choice-only block. The bonus payment schedule was described to participants at the start of the experiment.

Results

Similar to Experiment 1, we examined the impact of experience with selected jobs on preferences of focal options and context effects in conditions where the choice-counting block occurred before the choice-only block (CC $\rightarrow$ Choice) and where the choice-only block occurred before the choice-counting block (Choice $\rightarrow$ CC). Data from conditions 1 and 3 and conditions 2 and 4 were combined for these analyses, since the choice behavior before and after the counting-only block was very similar (results of the analysis comparing the choice behavior before and after the counting-only block are included in the Supplementary Materials).

Preference for Focal Options

Similar to what we found in Experiment 1, the focal option with fewer counting tasks and more items per task (Y) was favored over the focal option with more counting tasks and fewer items per task (X). In addition, the change in choice proportions for X differed between the block-order conditions (see bottom row of Figure 5). In the CC $\rightarrow$ Choice condition, choice proportions for X remained below 0.5 and at a similar level in blocks 1 and 2; whereas in the Choice $\rightarrow$ CC condition, choice proportions for X decreased from about 0.5 in block 1 to below 0.5 in block 2. This pattern was supported by a logistic mixed effects regression model (conditional $R^2 = 0.765$ and 0.760, respectively for the binary and the symmetric decoy choice sets). As shown in Table 5, there was a significant interaction between the block order (i.e., the order of blocks being completed by participants) and the block number (the position of the block being completed in each block-order condition) on the odds of choosing X, but there was no significant main effect of block number. This implies that the odds of choosing X remained at a similar level in blocks 1 and 2 in the CC $\rightarrow$ Choice condition, but decreased significantly in the Choice $\rightarrow$ CC condition. These results indicate that preferences for the focal option with fewer tasks but more objects per task (Y) formed with experience, and carried over to choices in the choice-only block.

Table 5

Fixed effects estimated from the logistic mixed effects regression model:
$logit(P(X)) = 1 + Block\ Order * Block\ Number + (1|participants)$*, where* $P(X)$ *was estimated either from the binary choice sets or the symmetric decoy choice sets in Experiment 2.*

Choice Set	Term	$Exp(\hat{\beta})$	SE	z	p
$\{X,Y\}$	Intercept	0.450	0.275	-2.903	0.004
	Block Order (1)	0.513	0.138	-4.834	<0.001
	Block Number (1)	0.772	0.550	-0.471	0.638
	Block Order (1) * Block Number (1)	0.317	0.276	-4.168	<0.001
$\{X,Y,S\}$	Intercept	0.353	0.273	-3.811	<0.001
	Block Order (1)	0.494	0.139	-5.094	<0.001
	Block Number (1)	1.255	0.544	0.417	0.677
	Block Order (1) * Block Number (1)	0.415	0.277	-3.182	0.001

Block Order: 0 = CC $\rightarrow$ Choice, 1 = Choice $\rightarrow$ CC; Block Number: 0 = block 1, 1 = block 2.

Context Effects

Compromise Effect.

Overall Choice Patterns. The choice patterns observed for the compromise choice sets in Experiment 2 replicated those observed in Experiment 1. First, we observed strong preference for the counting jobs with fewer tasks. As depicted in Figure 11, Y and C_y were selected most often in the choice sets $\{X,Y,C_x\}$ and $\{X,Y,C_y\}$, respectively. Furthermore, preference for the favored options increased with experience of the selected jobs. When the participants shifted from the choice-only to choice-counting block, the choice proportion for Y in $\{X,Y,C_x\}$ and C_y in $\{X,Y,C_y\}$ increased from below 0.5 to above 0.5. When the choice-counting block occurred before the choice-only block, the choice proportion for the favored options remained at a similar level. Additionally, between the less favored options (that is, X vs. C_x in $\{X,Y,C_x\}$ and X vs. Y in $\{X,Y,C_y\}$), the option with the advantage on the other key attribute (i.e., number of items per task) was preferred. This suggests that decisions were influenced by both attributes, although the number of tasks might outweigh the number of items.

We also observed evidence of a reversed compromise effect, similar to results in Experiment 1. These results are supported by a multinomial regression model ($R^2 = 0.072$; see Table 6).

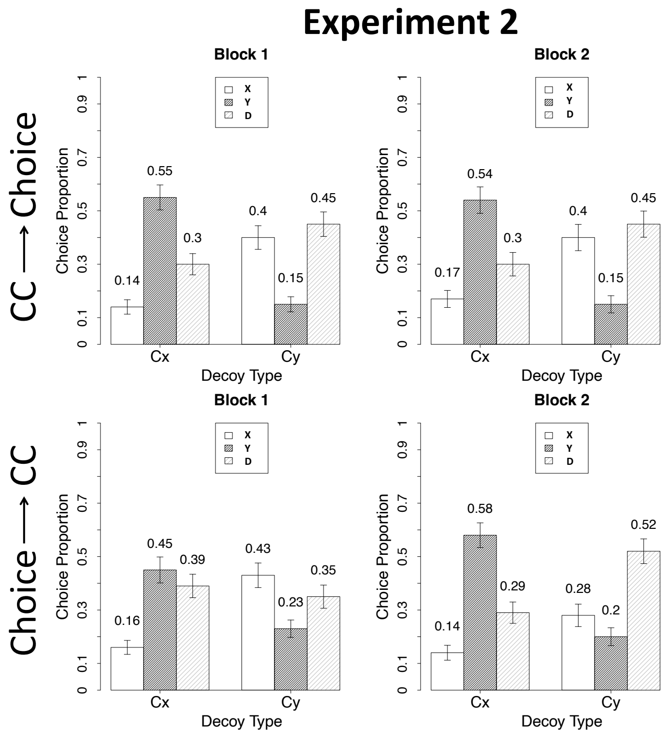

Figure 11

Top: Mean choice proportions for each option in the compromise choice sets in the CC → Choice condition of Experiment 2. Bottom: Mean choice proportions for each option in compromise choice sets in the Choice → CC condition of Experiment 2. The error bars show the standard error of the mean.

Absolute Share of the Focal Alternatives. The negative ΔP_{Target} values (bottom row of Figure 7) show a decrease in absolute share of the focal options when they were the targets, which suggests the reversed compromise effect occurred for both focal options. Furthermore, the impact of the compromise decoys was stronger on the preferred option Y than on X. This pattern is supported by a linear regression model ($F(4,623) = 4.71,\ p < 0.001,\ R^2 = 0.029$; Table 7), which suggests that ΔP_{Target} decreased significantly when Y was the target option. In other words, the reversed compromise effect was stronger when Y was the target than when X was the target.

Attraction Effect.

Overall Choice Patterns. The choice patterns observed for the attraction choice sets in Experiment 2 (Figure 12) replicated those observed in Experiment 1. The option with the fewest tasks (Y) was the favored option. Further, choice proportions for Y increased when participants

Table 6

Parameters estimated from the multinomial regression model:
$P(Response) = 1 + Decoy + Block\ Order * Block\ Number$ *for Experiment 2.*

Decoy Type	Response Contrast	Term	$Exp(\hat{\beta})$	SE	z	p
Compromise	Y - X	Intercept	1.31	0.05	5.67	<0.001
		Decoy (1)	0.13	0.09	-21.26	<0.001
		Block Order (1)	1.19	0.09	1.94	0.05
		Block Number (1)	1.25	0.09	2.43	0.02
		Block Order (1) * Block Number (1)	1.84	0.18	3.38	<0.001
	D - X	Intercept	1.59	0.04	10.43	<0.001
		Decoy (1)	0.55	0.09	-6.72	<0.001
		Block Order (1)	1.16	0.08	1.76	0.08
		Block Number (1)	1.21	0.08	2.23	0.03
		Block Order (1) * Block Number (1)	1.68	0.17	3.09	<0.001
Attraction	Y - X	Intercept	1.34	0.03	8.54	<0.001
		Decoy (1)	0.77	0.07	-3.88	<0.001
		Block Order (1)	1.04	0.07	0.60	0.55
		Block Number (1)	1.44	0.07	5.32	<0.001
		Block Order (1) * Block Number (1)	1.68	0.14	3.76	<0.001
	D - X	Intercept	0.16	0.07	-25.53	<0.001
		Decoy (1)	1.59	0.14	3.27	<0.001
		Block Order (1)	0.75	0.14	-2.02	0.04
		Block Number (1)	1.26	0.14	1.64	0.10
		Block Order (1) * Block Number (1)	0.59	0.28	-1.89	0.06

Decoy: 0 = $D_X, 1 = D_Y$; $BlockOrder: 0 = CC \rightarrow$ Choice, 1 = Choice $\rightarrow$ CC;
Block Number: 0 = block 1, 1 = block 2.

had the opportunity to experience selected options. We also observed a reversed attraction effect across all blocks. This effect held even when participants had the opportunity to experience selected options. These results were confirmed with a multinomial regression model ($R^2 = 0.014$; Table 6).

Absolute Share of the Focal Alternatives. The negative ΔP_{Target} values (see bottom row of Figure 9) show that the absolute share of the focal options decreased when they were the target, indicating that the reversed attraction effect occurred for both focal options. Furthermore, the ΔP_{Target} values suggests that the effect was stronger when focal option Y was the target option. This asymmetric influence of the attraction decoys on different focal options was supported by a linear regression model ($F(4,623) = 2.17,\ p = 0.071,\ R^2 = 0.0137$; Table 7), which suggests that ΔP_{Target} decreased significantly when the target option was Y as compared to X. In short, as

Table 7

Results of the linear regression: $\Delta P_{Target} = 1 + Focal\ Option + Block\ Order + Block\ Number$ *for the choice sets including different decoy types in Experiment 2.*

Decoy Type	Term	Estimate	SE	t	p
Compromise	Intercept	-0.268	0.036	-7.399	<0.001
	Focal Option ($Y - X$)	-0.125	0.033	-3.824	<0.001
	Block Order ($Choice \rightarrow CC - CC \rightarrow Choice$)	0.081	0.046	1.762	0.079
	Block Number ($block2 - block1$)	0.019	0.046	0.410	0.682
	Block Order * Block Number	-0.033	0.065	-0.503	0.615
Attraction	Intercept	-0.0408	0.019	-2.211	0.027
	Focal Option ($Y - X$)	-0.0372	0.017	-2.234	0.026
	Block Order ($Choice \rightarrow CC - CC \rightarrow Choice$)	0.0161	0.024	0.684	0.494
	Block Number ($block2 - block1$)	-0.0281	0.023	-1.207	0.228
	Block Order * Block Number	0.0119	0.033	0.357	0.721

observed in Experiment 1, the reversed attraction effect was stronger for the favored focal option (Y) than for the unfavorable focal option (X) in Experiment 2.

Relationship Between Context Effect and Response Times

We again examined the association between the context effects and response times by assessing the change in response proportions across RT-quantile regions (M = 4.25 and 4.71 sec, SD = 7.97 and 19.1 sec, respectively for the compromise and attraction choice sets). Similar to Experiment 1, the RT-quantiles were calculated at the group-level, separately for the attraction and compromise choice sets (see top row of Figure 13). The response proportions were estimated for the data within each of the five RT-quantile regions.

Similar to Experiment 1, the response proportion for targets was clearly below the response proportion for competitors in the R1 quantile which contained the fastest responses (see bottom row of Figure 13) for both the compromise and attraction choice sets. This suggests a reversal in context effects occurred with fast responses. With an increase in the RT-quantile region, the response proportion for targets increased while the response proportion for competitors decreased. The increase in the response proportion for targets was confirmed by the results of a logistic mixed effects regression model (conditional R^2 = 0.304 and 0.030, respectively for the compromise and attraction choice sets; Table 8), showing that the response

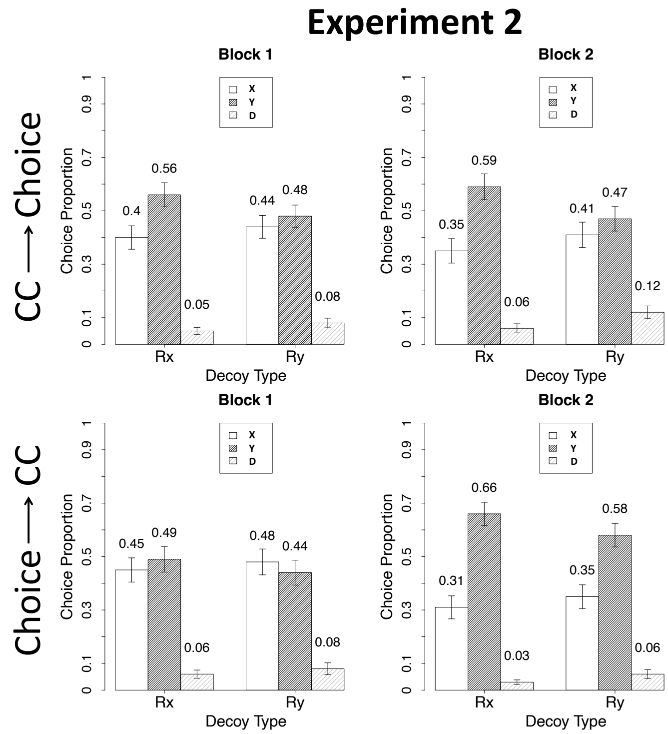

Figure 12

Top: Mean choice proportions of each option in attraction choice sets in the CC → Choice condition of Experiment 2. Bottom: Mean choice proportions of each option in attraction choice sets in Choice → CC condition of Experiment 2. The error bars show the standard error of the mean.

proportion for targets was significantly larger in the RT-quantile regions containing slower responses than in the RT-quantile regions containing faster responses. Such an increasing pattern in the response proportion for targets indicates that standard context effects tended to emerge when participants took a longer time to make a choice.

For the compromise choice sets, despite the increasing trend, the response proportion for targets was never above the response proportion for competitors in all of the RT-quantile regions, which is in agreement with the strong reversed compromise effect inferred from the ΔP_{Target} analyses. Yet for the attraction choice sets, the response proportion for targets was observed to eventually overcome the response proportion for competitors, which suggests a mixture of a reversed attraction effect for faster responses and a standard attraction effect for slower responses.

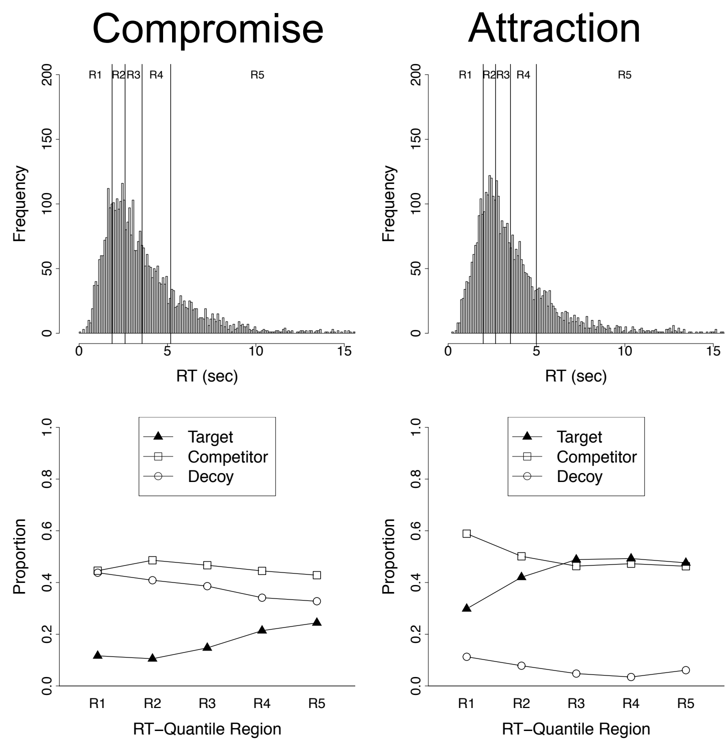

Figure 13

Top: RT distributions divided into five evenly spaced quantiles for compromise and attraction choice sets in Experiment 2. Bottom: Choice proportions for targets, competitors and decoys estimated for each RT-quantile region for different context effects.

Conclusions

Similar to Experiment 1, we observed in Experiment 2 that preferences for the shorter but harder counting job formed through experience, while the reversed compromise and attraction effects were not mitigated. The asymmetry in the strength of context effects for different focal options was also replicated. Both the compromise and attraction effects were stronger for the favored focal option than for the unfavorable option. Additionally, as response times increased, more standard context effects started to emerge. Thus, Experiment 2 replicated all of the main findings from Experiment 1, suggesting that the results of Experiment 1 were not due to the display layout or payment scheme.

Table 8

Estimated coefficients from the logistic mixed effects regression model:
$logit(P(Target)) = 1 + RT\text{-}Quantile\ Region + (1|participants)$ *for Experiment 2.*

Decoy Type	RT-Quantile Region	Exp($\hat{\beta}$)	SE	z	p
Compromise	R1 ($<$ 20%)	0.126	0.112	-18.496	$<$0.001
	R2 (20% – 40%)	0.788	0.179	-1.335	0.182
	R3 (40% – 60%)	1.176	0.171	0.944	0.345
	R4 (60% – 80%)	1.646	0.168	2.965	0.003
	R5 (80% – 100%)	2.012	0.170	4.105	$<$0.001
Attraction	R1 ($<$ 20%)	0.764	0.034	-7.960	$<$0.001
	R2 (20% – 40%)	1.708	0.109	4.910	$<$0.001
	R3 (40% – 60%)	2.254	0.109	7.460	<.001
	R4 (60% – 80%)	2.292	0.109	7.590	$<$0.001
	R5 (80% – 100%)	2.149	0.111	6.920	$<$0.001

Experiment 3

In Experiments 1 and 2, we observed reversals of the standard attraction and compromise effects. Moreover, these reversals were observed even when participants had the opportunity to experience selected options. These findings raise the question of whether the observed reversals are associated with the experience-based nature of the task. To assess this possibility, we conducted a pre-registered experiment using the same attribute values of the focal options in Experiments 1 and 2 but with different hypothetical decision scenarios where participants did not have the opportunity to experience selected options. The experiment followed a conventional multi-alternative, multi-attribute decision paradigm, involving consumer and risky choices. Participants were presented with five different decision scenarios where they made decisions about consumer goods and gambles.

Method

Participants

100 paid participants (60 women, 40 men, age: M = 40.36, SD = 13.50) were recruited from MTurk using the CloudResearch platform and completed the experiment online. The sample

size, data analyses, and exclusions were pre-registered at https://aspredicted.org/GH2_QS3.

All participants were compensated \$0.50 for the completion of the experiment. 14 participants were excluded from data analyses due to low accuracy on attention-check trials (accuracy rate below 70% as predetermined in the preregistration). After the exclusions, a total of 86 participants were included in the data analyses of Experiment 3.

Materials

In this experiment, participants were asked to make choices based upon the values of two attributes for five different decision scenarios (see Table 9). In scenarios S3 and S5, the attribute values of the options (X, Y, C_x, C_y, R_x, R_y and S) were identical to those used in Experiments 1 and 2 (see Figure 1). In particular, larger attribute values were less appealing (e.g., higher price in scenario S3). Conversely, in scenarios S1, S2 and S4, the attribute values of the symmetric and attraction decoys were adjusted (see Figure 14), since larger attribute values were more appealing in these scenarios (e.g., value of reward in scenario S4).

Table 9
Scenarios used in Experiment 3

Scenario	Options	Attribute 1	Attribute 2
S1	Package of light bulbs	Number of months a light bulb lasts	Number of light bulbs per package
S2	Bundle of mini chocolate eggs	Number of mini eggs per bag	Number of bags per bundle
S3	Car	Price (in thousands)	Fatality Rate (%)
S4	Gamble	Reward (\$)	Number of times a reward is won out of ten times it is played
S5	Neighborhood in Houston	Driving time to workplace (minutes)	Number of floods in neighborhood in the last ten years

Procedures

There were five blocks for the five different decision scenarios in this study. At the beginning of each block, participants were asked to imagine a particular scenario. For each scenario, they made a series of choices involving two to three options based upon the two attributes for the scenario (see Table 9). Participants were told to base their decisions only on the attributes provided. Similar to Experiments 1 and 2, each block had six choice sets of interests: a binary choice set including the focal options (X, Y) and five ternary choice sets including a

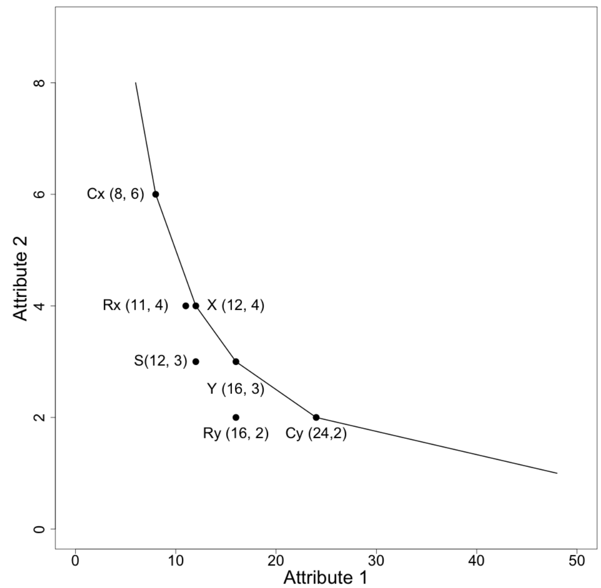

Figure 14
Options used in scenarios S1, S2 and S4 of Experiment 3 shown in the attribute space defined by two attributes.

compromise (C_x, C_y), attraction (R_x, R_y), or symmetric decoy (S). In addition, each block had four attention-check choice sets, which contained a clearly superior option. Thus, each block had a total of ten trials.

At the beginning of a trial, after a 250-ms blank screen, a choice set was randomly selected and presented in a by-attribute manner on the screen. After a choice was made, feedback on the number of trials completed within the block appeared. Participants continued to the next trial by pressing the space bar. After participants completed all of the trials within a block, the instructions for the scenario of the next block appeared. The order of the five blocks was fully randomized.

Results

In this experiment, we are interested in examining whether the reversed context effects observed in Experiments 1 and 2 occur in hypothetical decision scenarios.

Preference for Focal Options

As depicted in the top row of Figure 15, participants on average preferred option Y over X in scenarios S1, S2, S3, and S5, and option X over Y in S4 (Gamble). The choice proportions for the focal option X, estimated from both the binary choice set and the symmetric decoy choice sets, were below 0.5 in S1, S2, S3 and S5 but above 0.5 in S4. The results of a logistic mixed effects regression model (conditional $R^2 = 0.106$ and 0.086, respectively for the binary and symmetric decoy choice sets; Table 10) confirmed this observation, as the odds ratio of choosing X increased dramatically in S4.

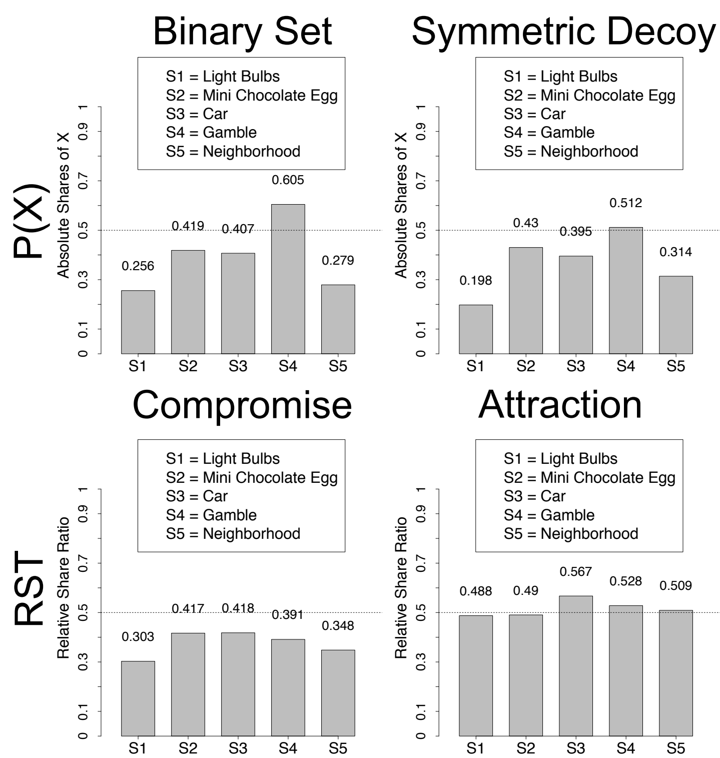

Figure 15

Results for Experiment 3. Top: Choice proportion for focal option X estimated from the binary choice set $\{X,Y\}$ (left) and the symmetric decoy choice set $\{X,Y,S\}$ (right). The choice proportion for the symmetric decoy S was less than 0.1 *in all of the scenarios and thus not shown. Bottom: RST values for each scenario for the compromise and attraction effect choice sets.*

Such a pattern suggests that in the scenarios about purchasing fast-moving consumer products (S1 and S2), participants tended to prefer the bundles with more items (Y) over the bundles with fewer items (X), even though each item lasted a shorter amount of time. In the loss

Table 10

Fixed effects estimated from the logistic mixed effects regression model:
$logit(P(X)) = 1 + Scenarios + (1|participants)$*, where* $P(X)$ *was estimated either from the binary choice sets or the symmetric decoy choice sets in Experiment 3.*

Choice Set	Scenarios	$Exp(\hat{\beta})$	SE	z	p
$\{X,Y\}$	Intercept	0.623	0.110	-4.291	<0.001
	S2 (Mini Chocolate Egg)	2.160	0.334	2.307	0.021
	S3 (Car)	2.056	0.334	2.157	0.031
	S4 (Gamble)	4.669	0.339	4.546	<0.001
	S5 (Neighborhood)	1.146	0.347	0.393	0.695
$\{X,Y,S\}$	Intercept	0.562	0.110	-5.250	<0.001
	S2 (Mini Chocolate Egg)	3.107	0.351	3.230	0.001
	S3 (Car)	2.685	0.352	2.800	0.005
	S4 (Gamble)	4.331	0.352	4.170	<0.001
	S5 (Neighborhood)	1.870	0.359	1.740	0.081

Intercept = S1.

situations (S3 and S5), participants preferred the option with a lower cost but higher likelihood of a loss (Y) over the option with a higher cost but lower likelihood of a loss (X). In contrast, in the gamble situation (S4), participants preferred the option offering a smaller reward with a higher probability (X) over the option offering larger reward with a lower probability (Y). The observed risk-seeking behavior in the loss situations and risk-aversion in the gamble situation is consistent with previous empirical evidence on framing effects in risky decision-making (e.g., Kahneman and Tversky, 1979; Tversky and Kahneman, 1981; Zhang et al., 2017).

Context Effects

Since the primary goal for Experiment 3 is to examine whether reversals in context effects occur in hypothetical decision scenarios, we present the analyses using the relative choice share for the target (RST) to illustrate the general trend of context effects for each scenario, as RST reflects context effects pooled across both focal options. The RST is defined as

$$\begin{aligned} RST_D &= \frac{P(Target)}{P(Target)+P(Competitor)} \\ &= \frac{P(X|\{X,Y,D_x\})+P(Y|\{X,Y,D_y\})}{2-P(D_x|\{X,Y,D_x\})-P(D_y|\{X,Y,D_y\})}, \end{aligned} \tag{2}$$

where D denotes the type of context decoy (i.e, compromise or attraction), and D_i denotes the context decoy targeting a particular focal alternative i (i.e., X or Y). The RST measures the choice proportion for the target option out of the choices for all of the focal options (combining across the two different decoy locations). When the RST > 0.5, this provides evidence for standard context effects.

Similar to Experiments 1 and 2, we also examined ΔP_{Target} values and the results are in the Supplementary Materials. In short, the results of the ΔP_{Target} analyses suggest a reversed compromise effect occurred when the favored focal option was the target, but not when the unfavorable focal option was the target.

Compromise Effect. The observed RSTs for the compromise choice sets (bottom left of Figure 15) were below 0.5 in all the decision scenarios. Such a pattern is supported by a logistic mixed effects regression model (conditional R^2 = 0.038; Table 11), showing the odds of choosing the target was significantly lower than the odds of choosing the competitor and did not differ significantly across different decision scenarios.

Attraction Effect. The RSTs estimated from the attraction choice sets were close to 0.5 (bottom right of Figure 15). The results of a logistic mixed effects regression model (Conditional R^2 = 0.004; Table 11) showed that the odds of choosing the target were not significantly different from the odds of choosing the competitor and did not differ across different decision scenarios. This suggests that the attraction decoys resulted in a null attraction effect in all of the scenarios in Experiment 3.

Table 11

Fixed effects estimated from the logistic mixed effects regression model:
$logit(RST_D) = 1 + Decision\ Scenarios + (1|participants)$ *for Experiment 3.*

Decoy Type	Scenarios	$Exp(\hat{\beta})$	SE	z	p
Compromise	Intercept	0.584	0.098	-5.490	<0.001
	S2 (Mini Chocolate Egg)	1.678	0.283	1.828	0.068
	S3 (Car)	1.675	0.281	1.832	0.067
	S4 (Gamble)	1.492	0.286	1.397	0.162
	S5 (Neighborhood)	1.235	0.291	0.726	0.468
Attraction	Intercept	1.070	0.070	0.935	0.350
	S2 (Mini Chocolate Egg)	1.010	0.225	0.053	0.958
	S3 (Car)	1.380	0.223	1.433	0.152
	S4 (Gamble)	1.180	0.223	0.725	0.469
	S5 (Neighborhood)	1.090	0.221	0.388	0.698

Intercept = S1 (Light Bulbs).

Relationship Between Context Effect and Response Times

To assess the relationship between context effects and response times, we divided the responses into five evenly spaced RT-quantile regions and examined the change in response proportions for the target and competitor options. Here, we present the results using the RT data combined across the five different scenarios (M = 6.14 and 4.45 sec, SD = 7.96 and 8.76 sec, respectively for the compromise and attraction effect choice sets). The results based upon the RT quantiles estimated separately for each scenario are included in the Supplementary Materials.

As depicted in Figure 16, in the R1 region which contained the shortest responses, the response proportion for targets was below the response proportion for competitors in both the compromise and attraction choice sets, suggesting reversals in context effects occurred with fast responses. As RTs increased, the response proportion for targets increased, while the response proportion for competitors decreased. This suggests that the more standard context effects started to emerge with slower responses in Experiment 3.

The results of a logistic mixed effects regression model supported the increasing trend in the response proportion for targets with the RT-quantile region (conditional R^2 = 0.198 and 0.027, respectively for the compromise and attraction choice sets; Table 12). Specifically, the odds of

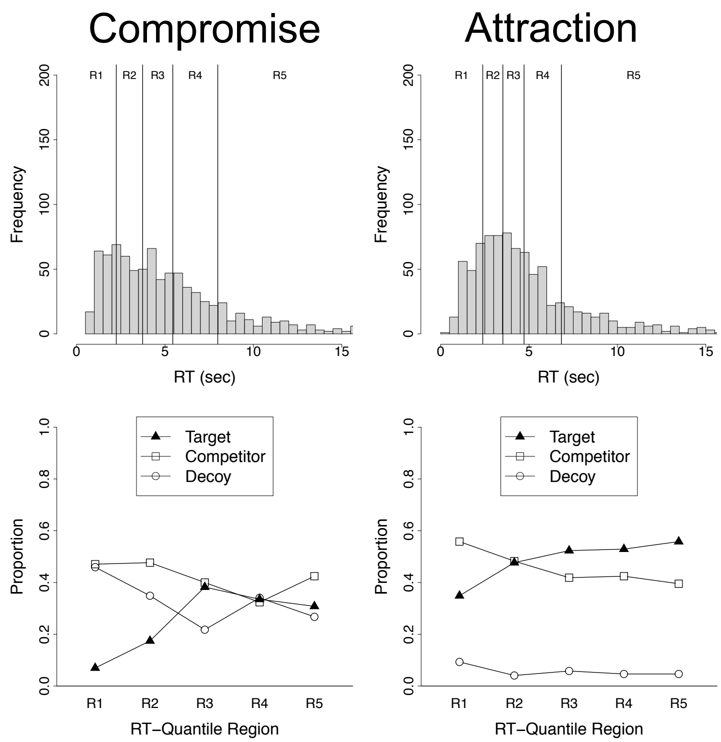

Figure 16
Top: RT distributions in Experiment 3 for the compromise and attraction choice sets divided into five evenly spaced quantiles. Bottom: Choice proportions for target, competitor and decoy options estimated for each RT-quantile region.

choosing the target increased when responses shifted from the relatively faster RT-quantile regions to the relatively slower RT-quantile regions.

Similar to Experiments 1 and 2, in the compromise choice sets, the increase in the response proportion for targets was not enough to overcome the response proportion for competitors, even in the slowest RT-quantile region (R5). This is consistent with the average strong reversed compromise effect inferred from the RST analyses. On the other hand, in the attraction choice sets, the response proportion for targets overcame the response proportion for competitors in the later RT-quantile regions, suggesting a shift from the reversed attraction effect to a standard attraction effect over the time course of deliberation.

Table 12

Estimated coefficients from the logistic mixed effects regression model:
$logit(P(Target)) = 1 + \textit{RT-Quantile Region} + (1|participants)$ *for Experiment 3.*

Decoy Type	RT-Quantile Region	Exp($\hat{\beta}$)	SE	z	p
Compromise	R1 ($<$ 20%)	0.280	0.108	-11.800	<0.001
	R2 (20% – 40%)	2.912	0.370	2.890	0.004
	R3 (40% – 60%)	8.587	0.351	6.120	<0.001
	R4 (60% – 80%)	6.943	0.353	5.490	<0.001
	R5 (80% – 100%)	6.336	0.358	5.150	<0.001
Attraction	R1 ($<$ 20%)	0.947	0.069	-0.794	0.427
	R2 (20% – 40%)	1.701	0.221	2.402	0.016
	R3 (40% – 60%)	2.049	0.221	3.243	0.001
	R4 (60% – 80%)	2.097	0.221	3.348	<0.001
	R5 (80% – 100%)	2.358	0.222	3.868	<0.001

Conclusions

In Experiment 3, the reversed compromise effect still emerged in the hypothetical decision scenarios and was consistently stronger for the favored option. The attraction effect was on average null. However, the direction of both effects shifted from reversed to more standard with increasing response times. We note that these results are similar to those from Experiments 1 and 2.

Model Simulations Investigating the Role of Experience and Reversals in Context Effects

Our primary findings showed that context effects persisted when participants had the opportunity to experience selected jobs similar to when they did not. In particular, experiencing selected options resulted in clear preferences in binary choice, but context effects were still observed in ternary choice. Interestingly, the context effects were consistently stronger for the preferred focal option. These findings raise the questions of what are participants learning from the experience in our task, and what role does experience play in the emergence of context effects. We propose that participants might be learning attribute specific preferences, corresponding to attribute weight parameters in computational models of context effects. These attribute specific preferences are enduring and remain stable across different context choice sets.

A secondary finding in this paper is the reversal of the attraction and compromise effects. These reversals appear to be robust to display format, payoff scheme, and problem domain in our study. Currently, the factors that lead to standard versus reversed context effects are not well understood (Spektor et al., 2021). We examine two hypotheses that may account for the reversals in context effects. One is the asymmetrical sensitivity to advantageous and disadvantageous comparisons during deliberation. The other hypothesis builds off of recent research related to representational noise by Spektor et al. (2021).

We explore these hypotheses through model simulations. We note that our goal is to illustrate possible explanations for the behavioral patterns that we observe in our experiments. We acknowledge that there are likely other explanations for our findings, beyond those described below.

Experience and Context Effects

Most computational models of context effects (e.g., Bhatia, 2013; Cataldo and Cohen, 2021; Noguchi and Stewart, 2018; Roe et al., 2001; Trueblood et al., 2014; Turner et al., 2018; Usher and McClelland, 2004) incorporate attribute (or attention) weights that reflect the subjective importance of different attributes. Theoretically, if participants are learning attribute weights, this would result in a situation where one attribute weight is much larger than the other. In many models of context effects, the effects persist when the weights are manipulated (i.e., Bhatia, 2013; Roe et al., 2001; Trueblood et al., 2014; Usher and McClelland, 2004). This is because the other mechanisms of the model, such as relative evaluations, are unaltered.

To illustrate the impact of attribute weights on context effects, we conducted model simulations using the Multi-attribute Linear Ballistic Accumulator model (MLBA; Evans et al., 2019; Trueblood et al., 2014) where we varied the attribute weight parameter. The MLBA model belongs to the class of evidence accumulation models (in the case of preferential choice, often called preference accumulation models). In the MLBA model, different options are represented by independent accumulators that race towards a decision threshold. The accumulator that reaches the threshold first results in a choice of the corresponding option. The rate of preference accumulation for each option (called the drift rate) depends on the characteristics of the options.

The drift rate for a particular option is a weighted sum of pairwise comparisons between that option and the other options. The weights on the pairwise comparisons are defined in terms of the similarity of options being compared, modeled using an exponential decay function. Different decay functions are used for positive and negative differences, so that negative (i.e., disadvantageous) differences could be weighted more heavily (reflecting loss aversion) or positive (i.e., advantageous) differences could be weighted more heavily (reflecting a confirmation bias, Nickerson, 1998). Finally, the two attribute values can be weighted differently, so that one attribute factors more strongly into the calculation as compared to the other (e.g., price could be weighted more than quality if someone is very price sensitive). The key parameters of the MLBA model that we explore in our simulations are the attribute weight parameter (termed β) governing the attribute specific biases and the decay parameters (termed λ_{pos} and λ_{neg}) governing the sensitivity to positive and negative attribute differences. More details about the model are presented in the Supplementary Materials.

As reflected in the findings from binary choice sets in Experiments 1 and 2, experiencing selected jobs resulted in a clear preference for counting jobs with fewer tasks. This suggests that experience might lead to the formation of preferences for specific attributes (i.e., weights on attributes), which would not necessarily alter how options are compared to one another. To evaluate this hypothesis, we simulated the choice behavior from the MLBA model assuming either no attribute bias or a bias toward Attribute 2 (similar to what we observed in our empirical results). The simulation procedures are detailed in the Supplementary Materials.

The simulated results (Figure 17 and 18) supported our hypothesis that if experience leads to the formation of attribute specific preferences, then context effects can still emerge. In this case, the context effects observed in our simulations emerge in an asymmetrical fashion for different focal options, similar to the behavioral data. As shown in the top row of Figure 17, when the attributes had equal weight (i.e., $\beta = 1$), the choice proportions for the focal options in the binary choice set reflected vague preferences (i.e., the two options were selected about equally often). In ternary choice, similar ΔP_{Target} values were observed for both focal options, suggesting symmetrical strength of the context effects on the focal options (see Figure 17). In contrast, when a bias toward Attribute 2 (i.e., $\beta > 1$) was introduced, the choice patterns in binary choice (see the top row of Figure 18) reflected a strong bias toward the focal option with an advantage on the preferred attribute (i.e., Y). In ternary choice, the context effects still emerged, but the strength of the context effects was asymmetrical. Moreover, if the decay parameter for disadvantageous comparisons was larger than the decay parameter for advantageous comparisons (i.e., $\lambda_{pos} < \lambda_{neg}$), then the simulated choice behavior qualitatively reflected the empirical results. That is, reversed context effects were stronger for the preferred focal option. We discuss this matter in more detail below.

Reversals in Context Effects

Across Experiments 1-3, we find robust evidence for reversed context effects. All three experiments use very similar (if not identical) attribute values. It is possible that the nature of the attribute information we used may be relevant to how the context effects emerged. The two hypotheses we propose are (1) asymmetrical sensitivity to advantageous and disadvantageous comparisons and (2) representational noise. Below we investigate these hypotheses separately and show that either one can result in reversed context effects.

Asymmetrical Sensitivity to Advantageous and Disadvantageous Comparisons

As described above, the MLBA model weights pairwise comparisons between options based on the similarity of the options being compared. The basic idea is that options that are difficult to discriminate (i.e., more similar) receive more weight (which could reflect increased attention) than those that are easy to tell apart. As similarity judgments are often found to violate symmetry (Nosofsky, 1991; Tversky, 1977), the MLBA model incorporates two parameters (λ_{pos} and λ_{neg}) for positive and negative attribute differences. Our simulation results (Figure 17) showed that the mere manipulation of these parameters could produce a full range of

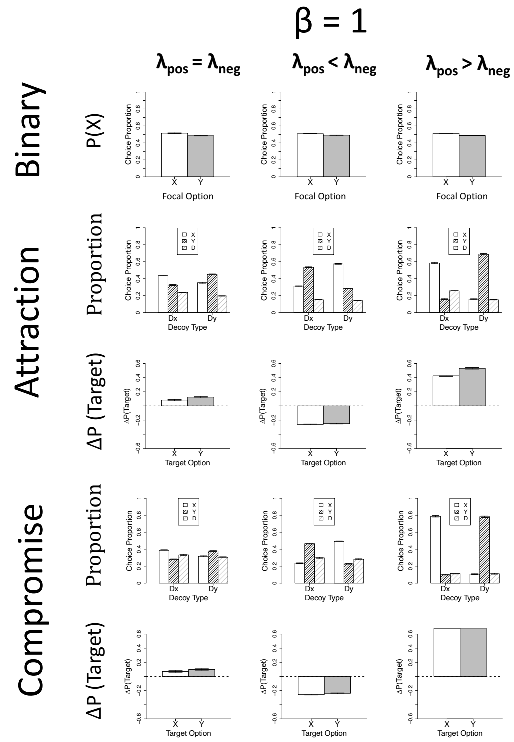

Figure 17

Observed choice behavior of the MLAB model with no attribute bias. β *notates the attribute weight. When* $\beta = 1$*, the model places equal weight on both attributes. The* λ*'s are the similarity decay parameters for disadvantageous and advantageous comparisons.* $\lambda_{pos} < \lambda_{neg}$ *reflects higher sensitivity to advantageous comparisons (i.e., disadvantageous comparisons decay faster and thus have less impact).* $\lambda_{pos} > \lambda_{neg}$ *reflects a higher sensitivity to disadvantageous comparisons.* $\lambda_{pos} = \lambda_{neg}$ *reflects identical sensitivity toward disadvantageous and advantageous comparisons.*

context-effect patterns (including both standard and reversed effects). When advantageous comparisons were weighted equally as disadvantageous comparisons (i.e., $\lambda_{pos} = \lambda_{neg}$), the models produced standard compromise and attraction effects. When there is higher sensitivity for disadvantageous comparisons (i.e., $\lambda_{pos} > \lambda_{neg}$), stronger standard context effects were observed. When there is higher sensitivity for advantageous comparisons (i.e., $\lambda_{pos} < \lambda_{neg}$), reversals of the compromise and attraction effects were observed. Note that the λ's are parameters in an exponential decay function, where a larger parameter value means faster decay and thus has less impact.

Moreover, when the model incorporates both unequal sensitivity in the comparison

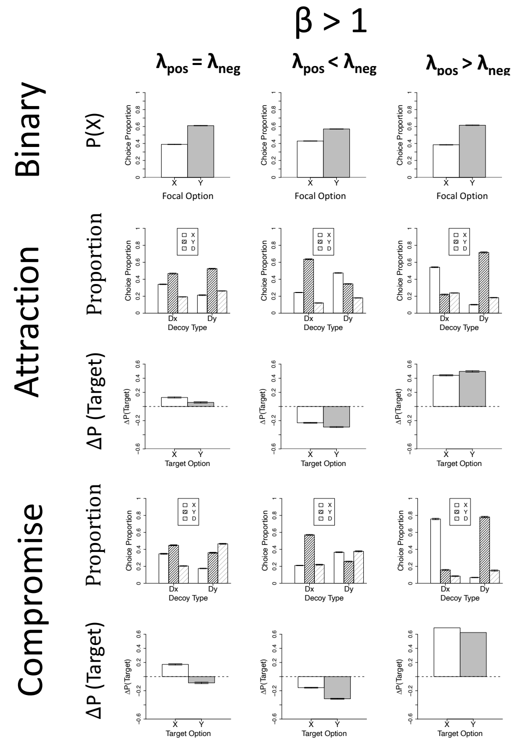

Figure 18

Observed choice behavior from the MLBA model with bias toward Attribute 2. β *notates the attribute weight. When* $\beta > 1$, *the model places more weight on Attribute 2. The* λ*'s are the similarity decay parameters for disadvantageous and advantageous comparisons.* $\lambda_{pos} < \lambda_{neg}$ *reflects higher sensitivity to advantageous comparisons (i.e., disadvantageous comparisons decay faster and thus have less impact).* $\lambda_{pos} > \lambda_{neg}$ *reflects a higher sensitivity to disadvantageous comparisons.* $\lambda_{pos} = \lambda_{neg}$ *reflects identical sensitivity toward disadvantageous and advantageous comparisons.*

process and unequal attribute weights, the simulated results (Figure 18) show stronger standard attraction and compromise effects for the preferred focal option when $\lambda_{pos} > \lambda_{neg}$. In the case when $\lambda_{pos} < \lambda_{neg}$, simulated results show stronger reversed attraction and compromise effects for the preferred focal option. We note that an attribute bias alone can produce reversals of context effects, but the reversals were only present for the preferred option (see Supplementary Materials). Reversals for both focal options were produced only after the MLBA model incorporated unequal sensitivity to positive and negative attribute differences in addition to the attribute bias.

These findings illustrate that the underlying cognitive mechanisms for the reversed and standard context effects may not differ in the preference-construction process (in the MLBA model, this is the race between accumulators driven by relative evaluations of options). Instead, subtle changes in how comparisons are weighted, could play an essential role in how context effects appear.

Representational Noise

The second hypothesis for reversals in context effects builds off of recent research by Spektor et al. (2021). They suggest that reversals of context effects might be due, in part, to the dynamic representation of option information. Spektor et al. (2021) argued that the representation of the options might unfold as a dynamic process of encoding. At the beginning of the encoding process, the representation of the options may involve a lot of noise. However, over the time course of deliberation, the representation of the options might sharpen, converging to the true values of the options. We note that this hypothesis is in contrast with conventional models for context effects where option information is a static input to the models (e.g., Bhatia, 2013; Roe et al., 2001; Trueblood et al., 2014; Usher and McClelland, 2004).

Such a theory might also explain why context effects change over time. For example, Cataldo and Cohen (2021) found consistent changes in context effects with internally controlled response times. Across eight experiments, they showed that with increasing response times the reversal in the compromise and attraction effects became weaker and the standard effects started to emerge. In the current studies, we observe a similar pattern between RTs and context effects. For compromise effect choice sets, the choice share of the target options consistently increased with RT quantiles, while the choice share of the competitor options decreased. Similarly, for the attraction effect choice sets, the choice share of the target and competitor options were also observed to change in opposite directions across RT quantiles.

In our experiments, the options are described as numbers. Thus, there should be no ambiguity in the objective representation of the options. However, it is possible that there is uncertainty in the subjective representation of options. In particular, in Experiments 1 and 2, the attributes describe features of the job (such as number of objects per task), which might be hard for participants to evaluate subjectively. For example, participants might have a difficult time evaluating the subjective difference between 12 and 16 objects per task.

To examine the hypothesis that reversals could be due to a dynamic (subjective) representation process, we conducted simulations to assess the frequency of observing the correct context effect relationships among options as a function of the representation precision (controlled by the attribute variance), using the attribute values utilized in the current studies (see Figure 1). In the simulations, the representation of the two attribute values for each option were sampled from a bivariate normal distribution, where the mean of the distribution was equivalent to an option's true attribute values. Additionally, we assumed that the variance for the two attributes was different, with the variance for Attribute 1 (i.e., number of objects per task) being higher than Attribute 2 (i.e., number of counting tasks). We hypothesized that individuals have a noisier representation of the number of objects on the screen than the number of tasks to perform. For example, participants might find it more difficult to distinguish between 12 and 16 objects on the screen as opposed to 3 or 4 tasks to perform. Detailed simulation procedure can be found in the Supplementary Materials.

Our simulation results (Figure 19) replicated the findings in Spektor et al. (2021, Box 1). That is, as the precision of the representation increased, the correct dominance relationship among options emerged so that the standard compromise and attraction effect relationships occurred more frequently. Moreover, the results showed that the impact of representation precision was stronger for the compromise effect choice sets than for the attraction effect choice sets. In addition, for the compromise effect choice sets, the results suggest that the correct dominance relationship occurred more frequently for X as compared to Y. These results are qualitatively consistent with the empirically observed patterns of choice behavior in the current studies. For example, we find stronger reversals in the compromise effect than in the attraction effect. Additionally, we find a larger reversed compromise effect for Y as compared to X (see Figure 7). We note that these simulations only examine the dominance structure of the alternatives and not choices. Future research could examine how such representations could be

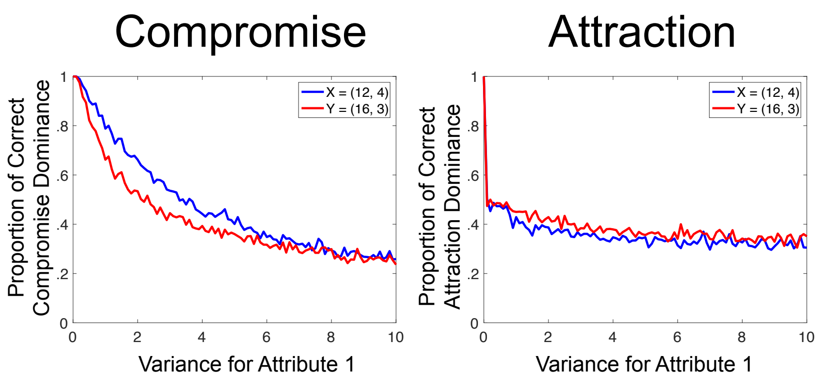

Figure 19

Left: observed frequency of the correct compromise effect relationship among options. Right: observed frequency of the correct attraction effect relationship among options.

incorporated into existing or new models of context effects.

Conclusions

In this section, we used model simulations to understand two key findings from our experiments: (1) context effects persisted in ternary choice even when participants had the opportunity to experience options and developed clear preferences in binary choice and (2) the presence of robust reversals of the compromise and attraction effects. We first hypothesized that experiencing selected options in our tasks helped participants form attribute specific preferences. Using the MLBA model, we showed that an attribute bias can lead to increased choices for the option with an advantage on the preferred attribute in binary choice. However, in ternary choice, the attraction and compromise effects still occurred. While these simulations were conducted with the MLBA model, most computational models of context effects have similar attribute (or attention) weights and will produce similar results. With regards to reversals in context effects, we examined two possible explanations. One hypothesis was related to asymmetrical sensitivity to advantageous and disadvantageous comparisons. This particular hypothesis is specific to the MLBA model, which proposes that options are evaluated through pairwise comparisons weighted by the similarity of the options being compared. Allowing asymmetries in similarity judgments gives the MLBA model the flexibility to accommodate a wide range of behavioral patterns, including both standard and reversed context effects. The second hypothesis we explore is related to representational noise and is not specific to a particular model. Our goal in this paper is not to compare different theories or champion one theory over another. Rather, our goal is to put forth different explanations for the puzzling behavioral patterns we observe. Future work is needed to thoroughly test these different theories.

General Discussion

In the current study, we assessed the impact of experience of selected options on context effects with a series of experiments to understand whether context effects can emerge when stable preferences have a chance to develop. The results from Experiment 1 showed that when people have the opportunity to experience selected options, preferences form for a certain focal option (i.e., the counting job with fewer tasks but more objects per task). Even though preferences developed with experience, context effects (i.e., reversed compromise and attraction effects) still occurred. These findings were replicated in Experiment 2 using a different display layout and payment scheme, suggesting that the observed effects are robust.

The results of Experiments 1 and 2 suggest that the influence of preference construction impacts decisions even when inherent preferences are accessible. In these two experiments, when participants had no experience with the options, their preferences for the focal options were relatively ambiguous (i.e., focal options were selected roughly equally). As expected, context effects emerged in this situation, which suggests the use of relative evaluations during deliberation (Simonson, 1989). Yet, in the situation where participants had substantial experience with the options, context effects still appeared. This suggests that the decision process might be dominated by relative evaluations, even when inherent preferences might exist.

We note that the aforementioned findings might also occur if our manipulations in Experiments 1 and 2 were not sufficient enough to promote the formation of inherent preferences. If this were the case, then we would expect to see ambiguous preferences even when participants had the opportunity to experience selected options. Nevertheless, in both experiments, we do see clear preferences in binary and symmetric decoy choice sets when participants gain experience with the options. Thus, we believe our manipulations were sufficient in generating clear preferences among options, suggesting stable preferences were formed.

We also note that in this study, participants are selectively learning preferences. Specifically, they only experienced the options that they selected and thus only had the opportunity to learn about their preferences for the selected options. An analogous life example would be choosing which flavor to sample in an ice cream shop. When encountering multiple flavors, people usually sample (i.e., experience) a small set of the flavors of interest before they make up their mind on a particular flavor. This is similar to what happens in the choice-counting block where participants select a job to complete. The job that is more favored would be experienced more frequently. For future studies, it would be interesting to assess if merely experiencing options has a similar effect on preference formation. For example, future studies could choose options for participants to experience and compare the results to situations where participants have free choice.

Another limitation of the current study is that we do not know if our conclusions regarding the effect of preference learning on context effects generalizes to standard context effects. Across all of our studies, we only observed reversed context effects and thus it is unknown if we would see similar results for standard effects. We note that model simulations using the MLBA model suggest that our findings for reversed effects should hold for standard effects, but future research is needed to verify this empirically.

An important question is why do context effects persist even when participants have experience with selected options. We hypothesized that the experience in the current studies may relate to the learning of attribute weights. We investigated this hypothesis through model simulations using the MLBA model (Trueblood et al., 2014), and discovered that the choice patterns produced by the model were qualitatively consistent with the empirical findings when the model incorporated an attribute bias. These results suggest that experience may lead to attribute specific preferences, but does not alter the preference-construction process, which is driven by relative evaluations in many computational models of context effects (such as pairwise comparisons in MLBA).

A secondary observation in the current experiments is the consistent reversals in context effects. In both Experiments 1 and 2, the inclusion of the compromise decoys consistently reduced the choice share of the target options, indicating a clear reversed compromise effect. The inclusion of the attraction decoys also reduced the choice share of the target options slightly, suggesting a weak reversed attraction effect. Using identical attributes values from Experiments 1 and 2 in hypothetical decision scenarios, we again observed reversals in the compromise effect in Experiment 3. These findings suggest that the reversals in context effects observed in our current study might be related to the nature of the attribute information.

As addressed in Cataldo and Cohen's work (2019), display layout is one of the factors (see Spektor et al., 2021 for review) that can lead to varying patterns of context effects. However, we find reversals of context effects in both by-alternative and by-attribute display layouts. While this might at first appear contradictory to Cataldo and Cohen (2019), our results are consistent with findings reported in Cataldo and Cohen (2021). Specifically, they find a null effect of display layout for context effects when attribute values are presented numerically (see Experiments C and D in Cataldo and Cohen, 2021) rather than graphically. Thus the impact of display layout on context effects might interact with the presentation mode (graphical versus numerical) of the attribute values. Future work is needed to explore this possibility in more detail.

We proposed two possible mechanisms for reversals of context effects and investigated them through model simulations. Using the MLBA model, we showed that by manipulating the sensitivity to advantageous and disadvantageous comparisons, both standard and reversed context effects could be produced without altering the core deliberation mechanisms of the model. The other hypothesis we explored was from Spektor's representational theory (Spektor et al., 2021). Simulations showed that improvements in representational precision of the options, postulated to improve with increased deliberation, could lead to an increase in the occurrence of the correct representations for dominance structure of options. These changes in representational precision could result in a dynamic pattern of context effects, qualitatively consistent with what we observed in our studies.

The goal of the model simulations was to illustrate possible explanations for the complex set of behavioral patterns we observed in our experiments. We note that these simulations do not provide definitive evidence on the exact mechanisms for the empirical findings. Rather, they illustrate that the pattern of results we observe can arise through subtle changes to weight parameters and / or the inclusion of representational noise. Importantly, fundamental aspects of preference construction process were not altered in the simulations. Specifically, in the MLBA model, the preference state for each alternative was determined through a relative evaluation process involving pairwise comparisons. This process was unchanged across the various simulations. Further empirical and theoretical work are necessary to investigate the exact cognitive factors that elicit reversals in context effects.

In sum, the current study documents the emergence of context effects when stable preferences have the opportunity to form. It also documents the robust presence of reversed attraction and compromise effects. Model simulations help shed light on these findings and offer new hypotheses about how experience impacts the preference construction process and the mechanisms that can give rise to reversed context effects. To further understand the fundamental cognitive principles underlying context effects, we believe it is essential for future theoretical developments to consider the role of both inherent and constructed preferences, as well as the dynamic interplay between standard and reversed effects.

Author Contributions

Yanjun Liu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization; Jennifer Trueblood: Conceptualization, Methodology, Writing - Review & Editing, Supervision, Project administration, Funding acquisition.

Acknowledgments

This work was supported by NSF grant 1846764 to JT. We thank Yun-Jang Liu for excellent research assistance.

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