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Choosing the right frame: how context preferences facilitate subsequent decisions

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Context shapes how we perceive choices and, therefore, how we decide between them. For instance, a large body of literature on the "framing effect" demonstrates that people become more risk-seeking when choices are framed in terms of losses. Despite this research, it remains unknown how people make choices between contexts and how these choices affect subsequent decision making. To address these questions, we designed the Frame Selection Task (FST). On each trial in the FST, participants first choose how risky and safe options are framed, either in terms of gains or losses, and then select between them. We found that participants exhibited frame preferences, with a predominant preference for the gain frame, and that they were willing to incur costs to select options within their preferred frame. Moreover, participants selected frames that aligned with their risk preferences: people with stronger risk aversion displayed a stronger gain-frame preference. These results demonstrate how people choose between contexts and that they can combine these preferences with cognitive biases to facilitate decision making.

Imagine it's Friday afternoon, and you need to buy groceries for the upcoming week. Your schedule permits two opportunities to stop by the grocery store. You could go to the store straight from work, around dinner time, and risk purchasing unnecessary snacks inspired by hunger pangs. Alternatively, you could wait until Saturday morning after breakfast, but endure the frustration of navigating through crowded shopping aisles and waiting in long lines. This choice is, in essence, one between different choice contexts[1–4]: both settings offer the same choices, but they differ in how these options are perceived. Despite the ubiquity of decisions between contexts in everyday life, contemporary theories of decision making do not describe how they are made. Here, we report two experiments that start to address this question.

Over the last century, an abundance of research has shown that contexts have a strong impact on decision making[5–8]. Contextual factors, even when irrelevant to the choice options at hand, can change how they are evaluated, leading to irrational behavior. For example, the decoy effect demonstrates that when choosing between two options, the introduction of a third, less desirable option can reverse preferences[9,10]. Similarly, the dud-alternative effect shows that when including irrelevant options (duds), people's preference for their top choice increases[11]. Moreover, extraneous contextual factors such as music[12–14], the order in which options are presented[15–17], and mood[18] influence choice.

The most powerful demonstrations of context effects are found in the literature on risky choice. For example, people's assessment of risk changes based on how choices are visually presented[19] or what other outcomes are experienced in the same context[20,21]. However, the most famous demonstration of context effects on risky choice is the 'framing effect'[22]. People become more risk-averse when choices are framed in terms of gains and more risk-seeking when they are framed in terms of losses, even when choices are equivalent between framing conditions[23–26]. According to prospect theory[22], this phenomenon arises because people experience the negative emotions associated with losing as stronger than the positive emotions associated with winning, an effect known as loss aversion[27].

Because the framing effect is so robust and widely documented, it provides the ideal starting point to document how people choose between contexts (in our case, frames). Even though choices between decision-making contexts are ubiquitous in everyday life, there is surprisingly little research on this topic. In most studies, researchers explicitly manipulate the context to understand their effect on decision making[4,28]. However, there is a modest literature that investigates how people decide in which frame to perceive choices *after* they have been exposed to them. For example, Beggan[29] found that people are more likely to view a hypothetical scenario involving paying a loan back as a gain rather than a loss. That is, after they became familiar with this choice,

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people thought it was more naturally described as involving gains. In a related set of studies[30,31], people were also first presented with a risky choice (involving loss of life, money, or time) and were then asked which of three different frames "most naturally" described the problem. Across several experiments, none of these frames were clearly rated as most natural and participants' risk preferences were independent of the frame they thought was most natural. Even though the findings from these two sets of studies pertain to preferences for contexts, they do not describe the order in which people typically make choices between them. It was also not the case that context choices changed how the choice options were presented. In the grocery store example above, for example, you first choose what time of day to go shopping, and this choice then affects how the options appear. In these studies, however, participants were never asked to choose a context or to make a risky choice in the chosen context. Thus, two important questions remain unanswered.

First, how do people make choices between contexts? It should be noted that it is unclear whether people have context preferences. If they do, it becomes important to understand how these preferences interact with downstream choice preferences. One possibility is that context preferences and primary choice preferences are independent. In the introductory example above, you may simply prefer an empty store for affective reasons, and therefore succumb to more impulse buys when shopping on Friday evening. Alternatively, people may make context choices that are compatible with their preferences. For example, when on a diet, choosing to go shopping on Saturday, on a full stomach, would facilitate this goal. This concept directly aligns with self-nudging[32,33], which is the idea that people can make small strategic changes to their environments that guide them toward their preferred outcomes. That is, people can design their contexts in ways that make it easier for them to make more optimal choices. A similar principle may be at play when people choose between contexts.

These hypothetical interactions between context preference and choice preference depend on the answer to a second question: when people can choose the context, will this choice affect subsequent decisions? In other words, when given a choice between contexts, do people continue to be biased by the chosen context? Interestingly, people show reduced framing effects when analytic processing is encouraged[34], so it is possible that emphasizing a choice between contexts eliminates the subsequent bias. Moreover, in the studies by Fischhoff[30] and van Schie & van der Pligt[31] described above, people's choices did not depend on which frame they thought was more natural. Thus, people may become more resistant to heuristics and biases when they can anticipate the context.

Considering how context preferences may be used to navigate downstream decisions bears a resemblance to the notion of precommitment. When people precommit, they decide to proactively assert themselves into future contexts to help improve their decision making[35–37]. However, they do so by not only modifying the way in which options are presented but also by changing the availability of future choices (e.g., flushing cigarettes down the toilet). Consistent with this idea, reinforcement-learning models of precommitment explain it as a choice between all options (current and future) but using different discount rates[36]. Similar to precommitment, people may select environments that enhance emotional well-being while avoiding those that elicit negative feelings (e.g., choosing alternative routes to avoid traffic-related frustration). This strategy, known as situation selection, facilitates emotion regulation by creating positive emotional states that promote rational decision making[38–40]. However, this strategy also changes the downstream choices available. Another relevant body of research demonstrates that people prefer choosing in contexts with more options[28,41], even though an increased number of choice options makes them less satisfied and more uncertain about their choice[42,43]. Here again, context choice does not just change how options are presented but also directly affects which options are available. Humans are sensitive to this. For example, when choosing between two sandwich shops, people preferred the shop with the smaller assortment when both shops were highly rated but opted for the shop with the larger assortment when they both had low ratings[44]. In short, as far as we are aware, there has been no investigation of how people choose between decision-making contexts when the context only changes how choice options are presented. Thus, the field is ripe for a systematic study of how people choose between decision contexts.

Here, we address this question by incorporating context choice into a well-established version of a framing effect paradigm[24]. In two experiments, participants made choices between risky and safe options. However, before this *downstream* decision was presented, they first chose the context in which this decision would occur, determining whether these choices would be framed in terms of either gains or losses. To foreshadow our results, we find that the framing effect persists even when people choose the context. Additionally, people generally prefer to make decisions framed in terms of gains, but this preference can be offset using incentives. Finally, we show that people's preference for the gain frame is predicted by their preference for risky choice – if they are more risk averse, they show a stronger preference for the gain frame. Our work demonstrates that context choices are an important but understudied form of decision making, and that people can use them to facilitate downstream choice.

Open practices statement

We filed a preregistration for Experiment 1 on July 27, 2022, which can be accessed at osf.io/qr5ev. Experiment 2 was not preregistered. Code and deidentified data for both experiments, along with a codebook employed in jsPsych[45] and the data-analysis scripts are posted at osf.io/p7k9c.

Experiment 1

In order to investigate individuals' preference for making choices in either a gain or loss frame, we designed a new paradigm, the *Frame Selection Task* (FST). The task was modeled after the Demand Selection Task[46], which is a paradigm that measures people's preference for avoiding the exertion of mental effort without explicitly signaling which choice options are associated with increased demand. Instead, the task relies on prior experience driving selections. In this way, the task minimizes the influence of demand characteristics on choice. Here, we used a similar set up to measure frame preferences.

In the FST, participants choose between safe and risky reward options, similar to prior framing effect paradigms[24]. However, before this choice, participants first select the frame in which these options are presented (Fig. 1). Based on pilot data, we hypothesized that participants would exhibit a stronger inclination towards selecting the gain frame over the loss frame.

Methods

Participants

A total of 141 participants (63 women and 1 non-binary; mean age = 29.1 years, SD = 3.5) were recruited from Amazon Mechanical Turk. Participants were paid a flat rate of six dollars for completing the study with a bonus payment based on performance. The number of participants recruited exceeded the required number of participants (111) to detect an effect size ($|\rho| = 0.3271$ with $\alpha = 0.05$) according to a power analysis conducted in G*Power software[47] based on pilot data. All participants provided informed consent, and the Washington University in St. Louis IRB approved this study.

Procedure

The study was a pre-registration of a pilot study ($n = 46$) composed of two phases and a questionnaire and took 45 min to complete.

Initial Phase. The *initial phase* of the experiment was a replication of a behavioral task that measures framing effects without context choice (as described in De Martino et al.[24]; Fig. 1a). We instructed participants that on each trial they would gamble in a 'casino,' where they would choose between a safe and risky option. These choices were either framed in terms of gains ("gain frame") or in terms of losses ("loss frame"). Specifically, after a fixation cross was displayed (750ms), participants were shown a starting amount of money (e.g., "You receive

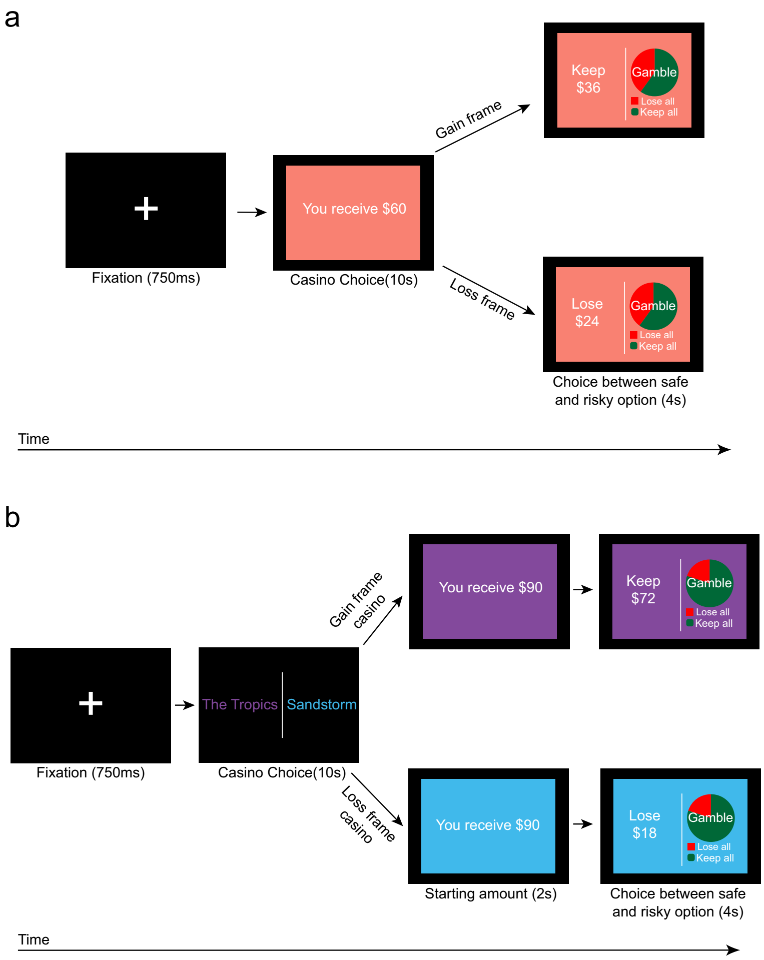

Fig. 1. Frame Selection Task in Experiment 1. In the (a) initial phase participants first saw a starting amount of money, and then saw a safe and a risky option presented in a gain or loss frame. All choices were made in the same casino context. In the (b) Frame Selection Phase, participants first chose between two casinos. One of these always led to a safe and risky option framed in terms of gains, and the other to the same options but framed in terms of losses. As in the Initial Phase, participants first saw the starting amount and then chose between the safe and risky options.

$60") for two seconds. Next, participants chose between a safe and a risky option involving this starting amount. In gain-frame trials, the safe option allowed the participant to retain a subset of the starting amount of money (e.g., "Keep $20"). In loss-frame trials, the safe option indicated the portion of money lost from the starting amount (e.g., "Lose $40"). The risky option was identical in both frames and was represented as a pie chart indicating the probability of keeping the starting amount received.

Participants completed 52 trials (20 gain frames, 20 loss frames, and 12 catch trials). Starting amounts were drawn from a uniform distribution ranging from $50-$100. Possible risky probabilities were 20%, 40%, 60%, and 80% and were balanced across framing conditions. The dollar amount in the safe option was computed so that both the risky and safe options had the same expected value. The order of trial types was randomized for each participant.

The safe option always appeared on the left side of the screen and the risky option on the right side of the screen. Participants were instructed to press the 'F' key to select the safe option and the 'J' key to select the risky option. Participants were given four seconds to choose between the two options.

To make sure that participants were engaged throughout the task, we included twelve 'catch' trials. In catch trials, the expected values of the two options were substantially different. In both frames, the safe option was always 50% of the starting amount. In half of the trials, the risky probability was 95% (favoring the risky option), and in the other half, the probability of the risky option was 5% (favoring the safe option). The catch trials were evenly distributed across frames. We used below-chance performance on these trials as an exclusion criterion: participants needed to choose the option with the higher expected value on 73% of trials to be included in the analysis.

Frame Selection Phase. Next, participants completed the frame selection phase. This phase consisted of 200 trials presented in four blocks of fifty trials (Fig. 1b). On each trial, participants first chose between two fictional casinos. Each casino had an equal probability of appearing on the left or right side of the screen. Participants pressed the 'F' key to select the casino on the left side of the screen and the 'J' key to select the casino on the right side of the screen with a response deadline of 10s. If they did not select a casino in time, a casino was chosen randomly.

Participants then were given four seconds to choose between a risky and a safe option in the chosen casino, the same as in the initial phase. The probabilities of the risky option were randomly selected from the same values used in the initial phase and were evenly distributed across each block.

Critically, one casino always led to choices framed in terms of gains while the other casino always led to choices framed in terms of losses. Everything else was equal. On each trial, the expected value for the safe and risky option did not differ between casinos, so the casinos also had identical expected values.

Unlike prior research in this domain[29–31], we did not ask participants to make explicit choices about their frame preferences. Instead, participants first had to detect the difference in frames between the two casinos, and then use this information to inform their context choice. This feature of the FST follows the Demand Selection Task[46], which uses a similar design to detect preferences for the avoidance of mental effort. By not explicitly referencing the frame differences between casinos, the FST minimizes the influence of demand characteristics[48]. It allows us to measure context choices without requiring people to use explicit assessments of their preferences, which tend to be flawed[49]. In short, the FST provides an implicit, and less biased, way to study context preferences.

In order to reduce the influence of non-frame-related preferences on choice, the two casinos changed from block to block[46]. On each block, the gain- and the loss-frame casinos were given new names and different colors. The casinos' names, colors, and frames were randomized across participants. The colors were strategically picked so no colors were too similar. Participants were given a 30-second break between each block and received no feedback on any trial until the end of the experiment.

To incentivize choice behavior, we informed participants that five trials (one trial from the initial phase and four trials from the frame selection phase) would be randomly selected and scored at the end of the experiment. If participants did not make a choice on a trial that was selected, they received $0 from that trial. Participants received a bonus of $1 for every $100 they won on these five trials. Participants earned an average performance bonus of $1.85.

At the end of the Frame Selection Phase, participants completed the General Risk Propensity Scale (GRiPS)[50], an eight-question questionnaire, to assess their general risk propensity. We added a question as an attention check and used this question as an exclusion criterion. The order of the questions was randomized for each participant.

Analysis

Twenty-six participants were excluded from the analysis (18.4% exclusion rate). Each of them failed to meet at least one of the following criteria: (a) failing to complete all phases of the task, (b) repeating the experiment more than once, (c) performing no better than chance on catch trials in the initial phase, or (d) failing other exclusion criteria outlined in the pre-registration. These additional exclusion criteria included self-reported colorblindness, failure to pass attention check on GRIPS survey, and failure to engage with the task by pressing only the 'F' key or only the 'J' key, by pressing no keys, or selecting only one frame during the first block in the frame selection phase. A detailed breakdown of participant exclusions is provided in the Supplementary Materials. For the main analyses, we excluded catch trials and trials in which the participant did not respond.

To measure framing effects, we conducted one-tailed, paired t-tests to determine whether the proportion of selecting the risky option was statistically greater in the loss frame than in the gain frame for both phases. Additionally, to determine frame preference, we calculated the proportion of selecting the gain frame across all trials for each participant. We then ran a one-tailed, one-sample t-test to assess whether this proportion of choosing the gain frame was statistically greater than 0.5. Moreover, to examine the relationship between risk and frame preferences, we measured risk preference by solely analyzing risky choices made in the initial phase

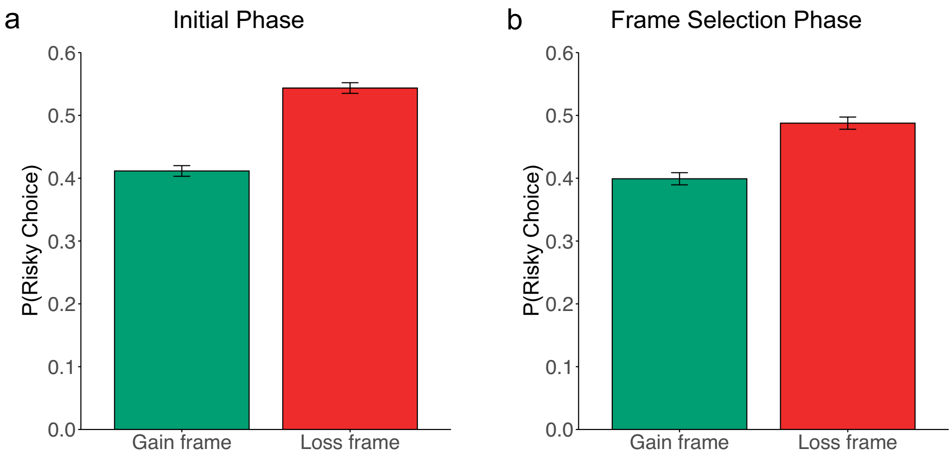

Fig. 2. Proportion of risky choices in the (**a**) Initial Phase and (**b**) Frame Selection Phase in Experiment 1. Error bars represent within-subject standard errors from the mean.

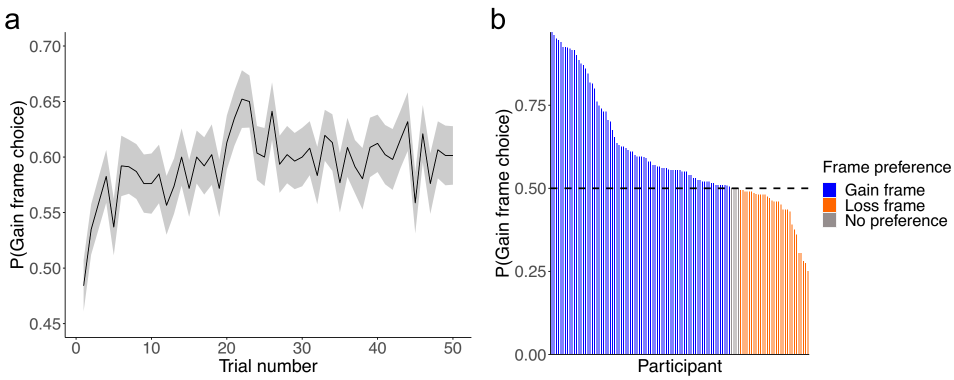

Fig. 3. Frame preferences in Experiment 1. (**a**) Proportion of gain frame choices across the Frame Selection Phase. Shaded area represents standard error from the mean. (**b**) Distribution of gain-frame preferences.

of the study. We only assessed risk preferences from choice in the initial phase, since this measure can be biased by the frame preference in the frame selection phase. We then used this proportion of risky choice selection to predict the proportion of gain-frame selection in the frame selection phase employing a mixed-effects model. For both experiments in this paper, we used R[51] for all analyses and set a significance level of $\alpha = 0.05$ for all statistical tests.

Results

Framing effects

We found that participants preferred making risky choices when options were presented in a loss frame rather than a gain frame in the initial phase ($M = 13\%$, $t(114) = 7.77$ $p < 0.001$, Cohen's $d = 0.59$, 95% CI [0.10, ∞]), replicating the classic framing effect[23–26] (Fig. 2a). We also found a framing effect in the frame selection phase ($M = 9\%$, $t(114) = 4.56$, $p < 0.001$, $d = 0.33$, 95% CI [0.056, ∞]) of the experiment (Fig. 2b), demonstrating that framing effects arise even when participants choose the frame.

We conducted a post-hoc ANOVA to examine how the magnitude of the framing effect varies across the phases of the experiment, specifically assessing the impact of frame and phase on risky choice selection. The analysis revealed a significant main effect of frame ($F(1, 114) = 47.90$, $p < 0.001$), confirming the presence of a framing effect. Additionally, there was a main effect of phase ($F(1, 114) = 5.48$, $p = 0.02$), indicating that the likelihood of selecting the risky choice decreased once participants could choose their frame (i.e., during the Frame Selection phase). The interaction between frame and phase was also significant ($F(1, 114) = 6.02$, $p = 0.02$), suggesting that the framing effect diminished during the Frame Selection phase, primarily due to a reduction in risky choice selection in the loss frame.

Frame preference
Figure 3a shows the average progression of preference for the gain frame over the course of each block. On average, participants preferred making decisions in a gain frame ($M = 59\%$, $t(114) = 5.98$, $p < 0.001$, Cohen's $d = 0.56$, 95% CI [0.57, ∞]). Note that Fig. 3b illustrates that even though the average frame preference in this task is for the gain frame, the modal response is closer to 50%. This pattern of results is often observed in the Demand Selection Task[46,52,53], on which we based the design of the FST.

In short, this modal response is driven by a group of participants that select between casinos based on criteria that are unrelated to their frame. For example, their choices may be driven by the casinos' appearance (e.g., color or name) or by perceived but spurious relationships between the qualities of the safe and risky choices observed in the same casino (e.g., repeating casinos that previously provided a high expected value). Because the appearance of the casinos was randomized across blocks[46] and the properties of the risky choices were independent of the frame, such preferences appear as but are not necessarily reflective of indifference. This modal response could also be driven by a lack of detection[54] or a general tendency to balance frame selection. The General Discussion will explore this nuance further. Nevertheless, the average preference for the gain frame is noteworthy, and the observed heterogeneity in frame preferences proved valuable for the individual difference analyses presented below.

Risk preference and frame choice
Since individuals have different risk preferences[55] and are susceptible to framing effects when making decisions[26,56], we hypothesized that people who tend to be risk-averse would exhibit a stronger preference for the gain frame while those who tend to be risk-seeking would prefer the loss frame. To test this hypothesis, we examined the correlation between risky choice selection in the initial phase and frame preference. We found that participants who exhibited risk-seeking tendencies did not demonstrate a significantly stronger preference for the loss frame ($r = 0.08$, $p = 0.38$, 95% CI [-0.10, 0.26]). This preregistered analysis did not replicate prior findings from our pilot study.

However, the pre-registered analysis assumed that the frame would not impact risky choice selection. Nevertheless, our results indicate that participants are more inclined to choose the risky option in a loss frame rather than a gain frame. As a result, the framing context may have an impact on individuals' risk preferences, thereby invalidating the assumption made in the pre-registration. To estimate the impact of frame and frame preferences more precisely on risk preferences, we employed an exploratory mixed-effects model (refer to the Supplementary Materials for the full output of the mixed-effects model).

The mixed-effects model revealed that the interaction between frame context and frame preference significantly affected risky choice selection (M = -0.16, t(113) = -3.22, $p = 0.0017$, 95% CI [-0.25, -0.062]). Individuals with a stronger preference for the gain frame showed lower risk preference in the gain frame (Fig. 4), but this relationship did not exist for risk preference in the loss frame.

We also investigated whether giving participants control over frame choice reinforced their risk preferences. Specifically, we analyzed whether participants with a gain-frame preference selected the risky option less frequently during the frame selection phase compared to the initial phase. To test this, we calculated the difference in the proportion of risky choices between these phases and ran an exploratory hierarchical regression model with frame preference as a predictor. The model revealed that participants with a strong preference for the gain frame were significantly less likely to choose the risky option in the frame selection phase than in the initial phase (M = -0.41, t(113) = -4.54, $p < 0.001$, 95% CI [-0.59, -0.23]). This suggests that participants' risk preferences become accentuated when they can choose between frames.

Finally, we examined the correlation between people's self-reported risk-taking behavior and frame preference and found that participants who self-assessed as being more risk-seeking based on the GRIPS did not show a significant preference for the loss frame ($r = 0.05$, $p = 0.62$, 95% CI [-0.14, 0.23]).

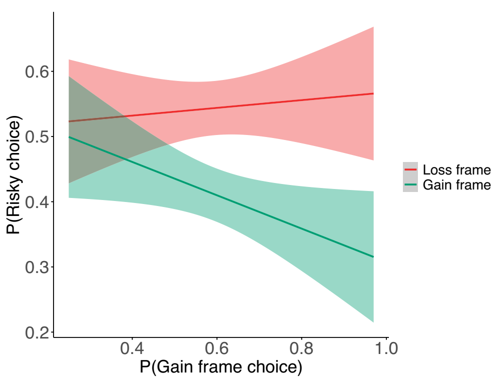

Fig. 4. Results of mixed-effects model in Experiment 1. The graph shows the relationship between the proportion of risky choice selection in the Initial Phase (split by frame) and frame preference in the Frame Selection phase. These results show that people with stronger risk preferences (measured in the gain frame) have stronger loss-frame preferences. Shaded area represents standard error from the mean.

Discussion

The current study provides evidence that participants exhibit a preference for choices presented in a gain frame over a loss frame, even in a context in which there was no difference between frames in terms of expected payoffs and where differences between casinos were not explicitly signaled but needed to be inferred. In other words, participants exhibit preferences for not only risky compared to safe gambles but also for how these choices are presented. This finding illustrates that people care not only *what* they choose but also *how* they choose. This insight introduces several new lines of inquiry. For example, it is unclear whether people are willing to trade off their frame preference against reward or whether this preference only surfaces when the options result in the same expected reward. Therefore, we designed Experiment 2 to determine whether people's preference for the gain frame reduces when the loss frame carries a higher expected value.

Experiment 2

We used a within-subject variant of the FST (inspired by a Demand Selection Task developed by Devine & Otto[57]) to examine the interaction between frame preference and expected reward. The experiment consisted of six casinos, with participants repeatedly selecting between pairs of them. Each casino was associated with a specific expected reward and frame. We predicted that higher rewards would offset participants' preferences for the gain frame. Additionally, we hypothesized that people would be willing to give up money to make choices in gain-frame casinos. Consequently, we sought to determine how much higher the expected reward in the loss-frame casinos needed to be so participants no longer exhibit frame preferences (i.e., the 'indifference point'). Finally, this experiment allowed us to once again test for any relationship between baseline risk preference and frame choice.

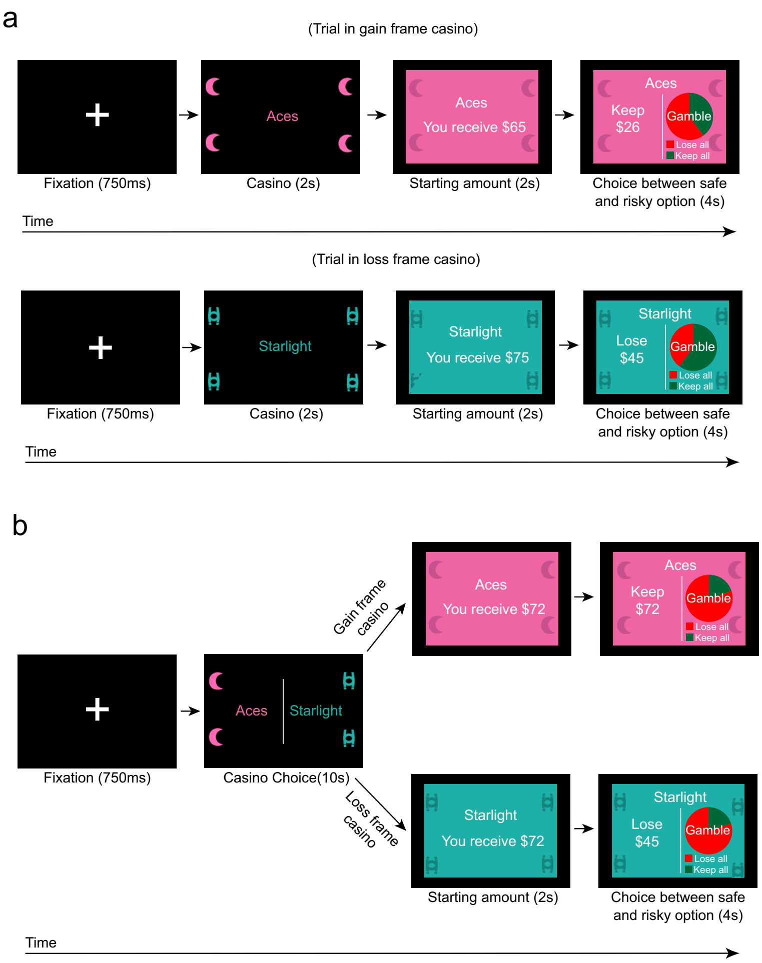

Fig. 5. Frame Selection Task in Experiment 2. In the (**a**) Learning Phase, participants learned about the properties of several casinos. On each trial, they first saw a starting amount, and then they chose between a safe and risky option presented in a gain or loss frame (4s). In the (**b**) Frame Selection Phase, participants chose between pairs of casinos, comprising the same casinos encountered in the Learning Phase, and then chose between a safe and risky option.

In the first phase of the task, now called *the learning phase*, participants completed the same task as in Experiment 1 except they made choices in independent casinos. In the following *frame selection phase*, participants chose between combinations of casinos learned in the learning phase.

Methods

Participants

A total of 119 undergraduate students (70 women and 2 non-binary; mean age = 20.0 years, SD = 1.5) from Washington University in St. Louis participated for course credit. Additionally, participants could earn a $15 Amazon gift card based on performance in the experiment. We recruited participants until the participant pool closed at the end of the year. All participants provided informed consent, and the Washington University in St. Louis IRB approved this study.

Procedure

The study was a modification of the FST and composed of two phases and took one hour to complete (Fig. 5).

Learning Phase. Participants first completed the *learning phase* of the experiment. This phase was a modification of the initial phase in Experiment 1. Specifically, participants gambled in seven different casinos compared to one casino in Experiment 1. They completed 56 trials, with 8 trials in each casino. On each trial, participants chose between a risky and safe option within a casino. The design of the task was the same as Experiment 1, except the casino's name was displayed at the start of each trial for 2 s (Fig. 5a). The choice options were presented in the same way as in Experiment 1 and used the same probabilities, keys to make choices, and time constraints. Three casinos always led to a gain-frame trial while three casinos always led to a loss-frame trial. The final, seventh, casino always led to catch trials. These catch trials were identical to the catch trials used in Experiment 1 and led to an equal number of gain- and loss-frame trials.

Importantly, we manipulated the starting amounts, and thus the expected rewards, for each of the six non-catch trial casinos. For both frames, there was a low, medium, and high value casino. The medium and high value casinos yielded rewards that were 1.2X and 1.4X higher, on average, than the low value casino. The catch trial casino was always assigned as a low value casino. The assignment of name, color, and shape to casinos was randomly chosen for each participant. An example of a casino assignment is shown in Fig. 6.

The starting amount for a trial was randomly drawn from a normal distribution with means based on the value of that casino. These normal distributions had means of $60 (low), $72 (medium), and $84 (high) and a standard deviation of 3.65. The standard error of 3.65 was chosen so there would be a 5% overlap across distributions.

Participants were instructed to pay attention to any differences between these six casinos because they would be interacting with them throughout the task. Therefore, we anticipated participants would learn the expected value and frame of each casino.

Frame Selection Phase. Next, participants completed the *frame selection phase.* This phase was a modification of the frame selection phase in Experiment 1. On each of the 204 trials, participants chose between pairs of casinos they encountered in the learning phase (Fig. 5b). After their choice, they decided between a risky and safe option in the chosen casino. Participants encountered each possible combination of one gain and one loss-

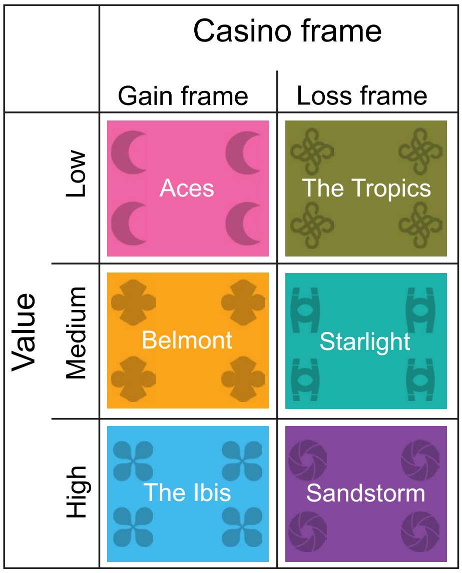

Fig. 6. An example of an assignment of casinos. The assignment of name, color, and shape was randomly chosen to a value (low, medium, or high) and frame (gain or loss), creating a casino assignment in Experiment 2.

frame casino 20 times, resulting in 180 trials. In the remaining 24 trials, participants chose between casinos with the same frame (either two gain-frame casinos or two loss-frame casinos). For these 'same-frame trials,' each of the six pairs appeared four times throughout the task. The order of trials was randomized for each participant.

Casinos and choice options were displayed the same as in Experiment 1, and participants made selections using the same keys and were given the same time constraints as in Experiment 1. Participants were not given feedback after choosing a safe or risky option and received a 30-second break after completing 51 trials.

We used the same-frame trials to measure whether participants learned the expected values of the casinos. Since expected reward is the only difference between these casinos, selecting the casino with the higher expected reward demonstrated that participants learned the casinos' relative values. As a cut-off, we determined that participants who chose the casino with the higher expected value on 60% of same-frame trials would be classified as having learned the casinos' relative values.

To incentivize choice behavior, we informed participants that five trials (one trial in the learning phase and four trials in the frame selection phase) would be randomly selected and scored at the end of the experiment. If participants did not make a choice on a trial that was selected, they would receive $0 from that trial. Participants who scored in the top 5% of highest scores received a $15 Amazon gift card.

Analysis

Twenty-two participants were excluded from the analysis (18.5% exclusion rate). Using the same exclusion criteria as Experiment 1, each of these participants failed to meet at least one of these criteria and were removed from the analysis (refer to the Supplementary Materials for a detailed breakdown). Additionally, 50 participants performed better than 60% on same-frame trials. For the main analysis, we excluded catch trials from the learning phase, same-frame trials in the frame selection phase, and trials where the participant did not respond.

Our main analysis focused on trials where participants chose between casinos with different frames. We employed a logistic mixed-effects model, with participants as a random intercept, to predict selection of the gain frame based on the degree to which the gain frame was better or worse than the loss frame. Specifically, we divided the expected reward of the gain-frame casino by the expected reward of the loss-frame casino for each casino pair, which we will refer to as the gain/loss ratio. We then used the average fits for the mixed effects model to calculate the indifference point, the ratio of gain/loss frame values at which the predicted preference for the gain frame is 50% (see Supplementary Materials for the full output).

We examined framing effects for both experiments using the same statistical tests as Experiment 1. Additionally, to measure whether participants exhibited a frame preference, we only included trials in the frame selection phase where participants chose between casinos with the same assigned value since these choices were not biased by the casinos' expected rewards. We then conducted the same statistical test as in Experiment 1. Moreover, we exclusively used these trials to analyze the relationship between risk and frame preference, using the same method as in Experiment 1.

Results

In this section, we first report framing effects. We then report frame preferences and determine the indifference point, referring to how much higher the expected reward in the loss-frame casino needs to be for participants to be equally likely to choose either frame. We then discuss how individual risk preferences affect frame selection preferences. Finally, we report how participants' abilities to learn the expected rewards influences their underlying frame preferences.

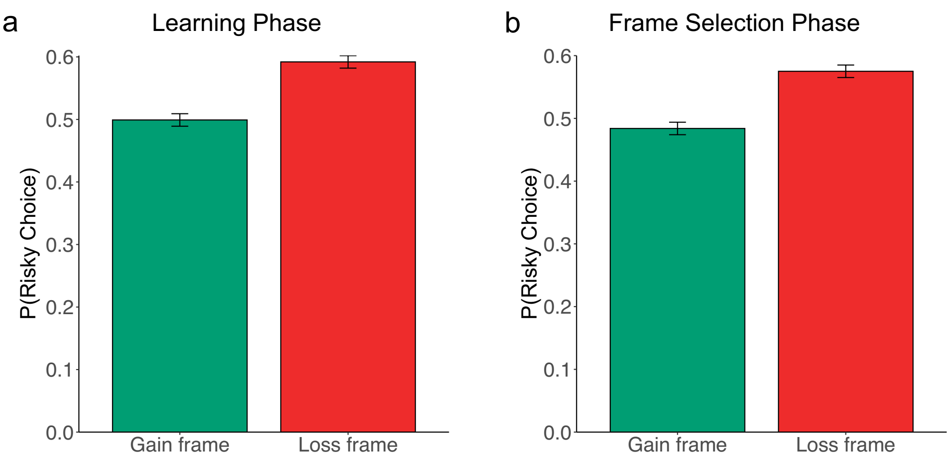

Fig. 7. Proportion of risky choices in the (**a**) Learning Phase and (**b**) Frame Selection Phase of Experiment 2. Error bars represent within-subject standard errors from the mean.

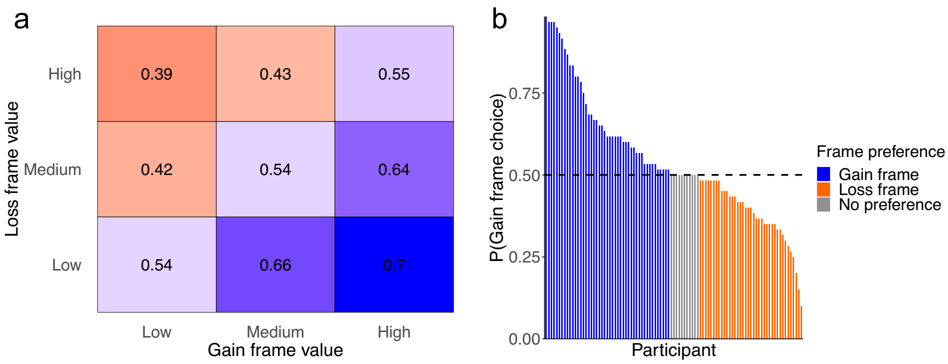

Fig. 8. Frame preferences in Experiment 2. (**a**) The average proportion of gain-frame preferences for each possible combination of gain and loss-frame casinos. (**b**) Distribution of gain-frame preferences.

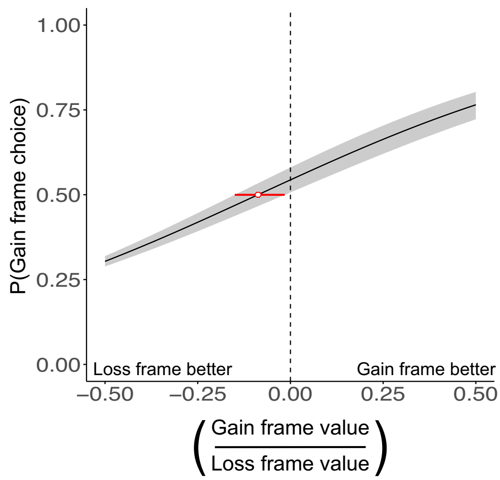

Fig. 9. Results of the logistic regression mixed-effects results predicting choice from ratio of gain and loss-frame casino values in Experiment 2. The error lines show 95% confidence intervals. The vertical dotted line denotes when the casinos have the same expected value (ratio = 1). The indifference point and confidence intervals are shown in red.

Framing effects

We replicated the results from the first experiment since participants preferred making risky choices when options were presented in a loss frame in the learning phase ($M = 9\%$, $t(96) = 4.64$, $p < 0.001$, Cohen's $d = 0.51$, 95% CI [0.060, ∞]) and in the frame selection phase ($M = 9\%$, $t(96) = 4.58$ $p < 0.001$, Cohen's $d = 0.38$, 95% CI [0.058, ∞]) of the experiment (Fig. 7).

The ANOVA confirmed these findings, revealing a significant main effect of frame ($F(1, 96) = 31.01$, $p < 0.001$). However, there was neither a significant main effect of phase ($F(1, 96) = 0.96$, $p = 0.33$) nor interaction effect between phase and frame ($F(1, 96) = 0.01$, $p = 0.94$), which contrasts with the results from Experiment 1. We discuss this discrepancy in the General Discussion.

Frame preference

The mixed logistic regression indicated that participants were inclined to select the casino with the higher expected value ($M = 2.01$, $z = 25.86$, $p < 0.001$, 95% CI [1.86, 2.16]). Additionally, we found that participants had a general bias for selecting the gain-frame casino ($M = 0.18$, $z = 2.34$, $p = 0.019$, 95% CI [0.027, 0.32]), replicating the frame preference results found in the first experiment. The gain-frame preference for each casino value type is shown in Fig. 8a. Indeed, when we directly inspected the trials where participants chose between a gain- and loss-frame casino with the same value, we found that participants selected the gain-frame casino more ($M = 54\%$, $t(96) = 2.12$, $p = 0.018$, Cohen's $d = 0.21$, 95% CI [0.51, ∞]). We should note that, even though there was a significant preference for the gain frame, we again observed a modal gain-frame preference of 50% (see General Discussion).

Most importantly, we found that participants were willing to incur a cost when making choices in a gain frame compared to a loss frame (Fig. 9). Specifically, the logistic mixed-effects model suggested that participants would be indifferent between frames when the value of the gain-frame casino was 0.92 (95% CI [0.86, 0.98]) times smaller than the loss-frame casino. In other words, the model suggests that participants would prefer making choices in the gain frame until they would have to pay an additional 8 cents for every dollar to stay in the gain frame.

Risk preference and frame choice

Next, we turned our attention to the relationship between risk preference and frame choice. Since the mixed-effects model used in the first experiment was exploratory, we conducted the same mixed-effects model to replicate the results obtained in the first experiment (see Supplementary Material for full output of mixed-effects model). As a reminder, in Experiment 1, we found frame preference was only predictive of risky choice preference when options were presented only in a gain frame.

In this experiment, we found that participants with a stronger preference for the gain frame were less likely to select risky choices (M = -0.05, $t(95) = -4.62$, $p < 0.001$, 95% CI [-0.066, -0.027]). However, the mixed-effects model revealed that the interaction between frame context and frame preference was no longer significant (M = -0.02, $t(95) = -0.31$, $p = 0.76$, 95% CI [-0.12, 0.088]). In other words, we found that risk preference was predictive of frame choice not only when choices were presented in the gain frame (as in Experiment 1) but also when they were presented in the loss frame (Fig. 10). In the General Discussion, we will discuss this difference between experiments in detail.

Next, we investigated whether risk behavior intensified during the frame selection phase compared to the learning phase. Employing the same regression model as in Experiment 1, we found that participants with stronger preferences for the gain frame were less likely to choose the risky option during the frame selection phase than in the learning phase (M = -0.32, $t(95) = -3.57$, $p < 0.001$, 95% CI [-0.50, -0.14]). This indicates that participants' risk preferences were more pronounced based on their frame preferences and their control over frame selection.

Expected reward preference vs. frame preference

So far, the analyses have not considered that participants may differ in the degree to which they learned the casinos' values. Therefore, we divided the participants into two groups based on whether participants selected the casino with the highest expected value on same-frame trials on at least 60% of trials. We refer to participants who learned the expected rewards as value-sensitive ($n = 50$) and those who did not as value-insensitive ($n = 47$). Despite not learning the expected values of the casinos, we found that value-insensitive participants were still engaged with the task and exhibited frame preferences ($M = 55\%$, $t(46) = 2.06$, $p = 0.02$, Cohen's $d = 0.30$, 95% CI [0.51, ∞]). In contrast, value-sensitive participants did not display any frame preferences ($M = 53\%$, $t(49) = 1.03$, $p = 0.15$, Cohen's $d = 0.15$, 95% CI [0.48, ∞]).

To further understand their different behaviors, we ran an exploratory mixed-effect logistic regression model for each group (see Supplementary Materials for full outputs), explaining frame choice as a function of expected value. Surprisingly, not only the value-sensitive group ($M = 3.68$ $z = 31.15$, $p < 0.001$, 95% CI [3.45, 3.91]) but also the value-insensitive group ($M = 0.44$, $z = 4.04$, $p < 0.001$, 95% CI [0.22, 0.65]) preferred choosing casinos with the higher expected reward. These findings suggest that both groups were, in fact, sensitive to the rewards. However, participants in the value-sensitive group were more sensitive to the expected rewards when

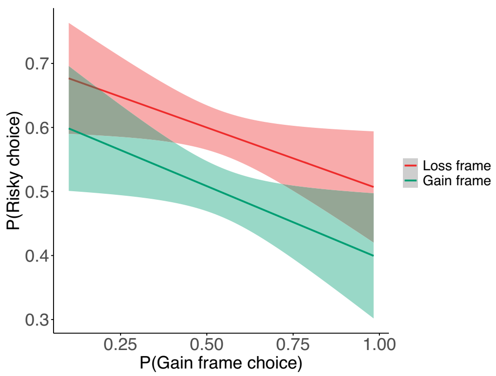

Fig. 10. Results of mixed-effects model in Experiment 2. The graph shows the relationship between the proportion of risky choice selection in the Learning Phase (split by frame) and frame preference in the Frame Selection phase. These results show that people with stronger risk preferences (across both frames) have stronger loss-frame preferences. Shaded area represents standard error from the mean.

making choices, as indicated by the substantially larger slope estimate. This finding is not too surprising since the participants' sensitivity to value is likely to transfer from the same-frame to different-frame trials.

Finally, we again found that participants in the value-insensitive group preferred the gain frame as indicated by the significant bias term in the model ($M = 0.25$, $z = 2.38$, $p = 0.017$, 95% CI [0.040, 0.46]), while those in the value-sensitive group did not ($M = 0.10$, $z = 0.95$, $p = 0.34$, 95% CI [-0.12, 0.33]).

To more formally compare these two groups, we next ran a mixed-effects model predicting frame choice based on both expected value and value sensitivity group. This model revealed a significant main effect of expected value ($M = 2.05$, $z = 25.73$, $p < 0.001$, 95% CI [1.90, 2.21]), replicating our previous findings that participants preferred casinos with higher expected rewards. While there was no main effect of group ($M = -0.07$, $z = -0.954$, $p = 0.34$, 95% CI [-0.22, 0.08]), we found a significant interaction effect between expected value and group ($M = 1.62$, $z = 20.29$, $p < 0.001$, 95% CI [1.46, 1.78]). Specifically, participants in the value-sensitive group were more likely to select the gain-frame casino when it had a higher expected reward. In contrast, participants in the value-insensitive group consistently preferred the gain-frame casino, regardless of expected value. Note that we found qualitatively similar results when using a continuous version of participants' value sensitivity as a regressor instead of the categorical one reported above (see Supplementary Materials for full report). These results reveal a potential role for a hierarchy in value signals during context choice. We return to this in the General Discussion.

Discussion

We found that participants exhibit a preference for choices presented in a gain frame over a loss frame, replicating the results from the first experiment. Additionally, participants were willing to incur a cost to make choices in their preferred frame context. This finding illustrates that people value having the ability to decide how they choose and are willing to pay for this choice. We again found that risky choice predicts frame choice. Finally, we found that people varied in the degree to which the expected value of the casino dictated their frame choice. The group of participants that were sensitive to expected value during same-frame choices use this information more during choices between loss and gain frames and did not exhibit a frame preference. On the other hand, participants who were not sensitive to the casino's expected values revealed a preference for the gain frame (although this preference was not statistically different from the frame preference of the value-sensitive group).

General discussion

In everyday life, we often can choose the context in which we want to make decisions, but scientific research on this topic is sparse. Therefore, we developed the FST. In this task, people choose how subsequent choices will be framed. Across two experiments, we found that people preferred making choices framed in terms of gains, and that they were even willing to incur a cost to do so. We also extended the classic framing effect[22] by demonstrating that people exhibit framing effects even when they choose the framing context. Finally, we found that participants' risk preferences predicted frame choice, with individuals who tended to be risk-averse preferring the gain frame.

To the best of our knowledge, our experiments are the first to investigate how people choose between contexts. Prior work by Beggan[29] and Wang and Fischbeck[58] demonstrated that people are more likely to interpret certain scenarios (e.g., paying back a loan) in a gain frame, but these people did not choose how this choice was framed. Instead, they had to indicate which frame most naturally fit a choice that was already presented. In contrast, we show that people carry context preferences that they use to determine how subsequent choices are presented. Our results also indicate that these preferences can be offset by incentives and affect subsequent decision making. Taken together, these findings suggest that choices between contexts can be understood in the same value-based decision-making framework as traditional risky choice. Moreover, we provide a new experimental paradigm that can be used to measure context preferences without explicitly signaling this difference between choice options.

It should be noted that a modest body of prior research demonstrates that participants do not show any systematic preferences when asked which frame most naturally described risky choices[30,31]. At first glance, these results seem to stand at odds with each other. However, there are critical differences between these programs of research. First, rather than just thinking about the conceptual match between choice problems and frames, participants in our study first chose the frame and then bore the consequences. In addition, participants were never explicitly asked to base their decisions on the casino's frames. This difference highlights the importance of using incentive-compatible research designs with real consequences when trying to understand human behavior.

It is worth mentioning that, even though we found significant preferences for the gain frame in both experiments (and in the pilot study), we found a modal preference around 50%. At first glance, this seems to contradict our claim that people generally prefer the gain frame. However, the FST allows people to choose between options based on factors orthogonal to the frame. For example, participants may have strongly preferred particular colors, symbols, or names of the casinos and made choices to see those more. Because we varied these factors across trials and blocks in both experiments, these frame-unrelated preferences lead to choices that suggest indifference between frames. However, they do not necessarily reveal indifference. These superficial differences between casinos may have simply been more noticeable than their frames for a certain proportion of our participants. In other words, these participants may have had a frame preference that was overshadowed by the preferences for other factors that we varied in this design. Therefore, we are hesitant to interpret the modal 50% gain-frame preference as only reflecting true indifference between frames.

The reason we varied several characteristics between multiple pairs of casinos was specifically to reduce the influence of frame-unrelated preferences on frame choice. In an FST with just one pair of casinos, for example, a strong preference for a particular color would have looked like a strong preference for either the gain or the loss frame, even though it was neither. By varying visual characteristics across blocks (Experiment 1) and trials (Experiment 2), such frame-unrelated preferences lead to frame preferences that settle around indifference. In fact, we have found a similar modal response around indifference in several versions of the Demand Selection

Task[46,53,59], which inspired the design of the FST. This task has repeatedly revealed average preferences for lines of actions that demand the least amount of effort[46,52,60]. In short, this is a necessary feature of tasks that aim to measure preferences without explicitly drawing attention to the intended manipulation.

The FST in Experiment 1 also allowed people to decide between casinos based on spurious beliefs about the relative difference in their relative reward. Even though our experimental design ensured that both casinos and all choice options carried the same expected value within each trial, participants may still have believed that prior experiences in a casino predicted future ones. For example, participants may have assumed that observing a high expected reward in a particular casino means that it is currently more valuable, potentially using some form of reinforcement learning to guide decision making[61]. Indeed, we found that people were more likely to repeat a casino choice if it yielded a high expected value in the previous trial ($M = 7\%$, $t(114) = 6.85$, $p < 0.001$, Cohen's $d = 0.40$, 95% CI [0.05, 0.09]) or a large probability of winning the risky option ($M = 6\%$, $t(114) = 5.75$, $p < 0.001$, Cohen's $d = 0.37$, 95% CI [0.04, 0.08]). Because these patterns are orthogonal to the casinos' frames, these response strategies also drive gain-frame selection rates toward indifference.

Considering this preponderance of alternative choice strategies, it is noteworthy that we observed an average preference for the gain frame and several intriguing individual difference relationships that predict this preference. However, it remains possible that some participants had no strong preference for either frame, perhaps due to their failing to detect differences in framing or because they truly find them equally valuable. Alternatively, they might have adopted a self-nudging strategy[32,33], balancing their frame selections to minimize bias in their choices.

We found that framing effects persist when people can choose framing conditions. However, the results regarding the degree of persistence were mixed. In Experiment 1, the effect diminished as participants were less inclined to select the risky choice after opting for the loss frame. In Experiment 2, the magnitude of the framing effect did not change between the learning phase and the frame selection phase. Therefore, we cannot determine whether and why the framing effect diminishes when given a context choice. It is also possible that the effect diminished in the frame selection phase of Experiment 1 simply because it occurred later in the experiment. If participants become less sensitive to framing over time, then one would expect a smaller effect in the second phase of the experiment regardless of whether it involves context choices. Future research could explore this issue by testing whether the framing effect is reduced in the frame selection phase if it occurs in the first part of the experiment. Nonetheless, it is important to emphasize that our findings indicate that framing effects occur even when participants can choose their frame.

Together with frame preferences, this persistence of framing effects induces strong selection bias. That is, individuals who prefer the gain frame chose more safe gambles because the framing effect biases them towards that option. Analogously, participants with a loss-frame preference selected more risky choices. It is tempting to view this as a compounding effect of irrational behavior. However, people may also use context choice to plan toward situations in which desired decisions are more likely to be made. As noted in the introduction, this idea bears similarity to the notion of precommitment[35–37]. Here, however, people select contexts that they know steer them towards specific situations, instead of limiting future choices. Alternatively, such a behavioral policy may arise due to associative learning. People may just repeat certain context choices because they previously led to desirable choice outcomes without ever considering their consequences. Such "model-free" decision-making strategies are common in human and animal behavior[62–64].

Indeed, our data shows some evidence that frame choices are at least partially informed by risk preference. In all experiments (a pilot study and the two experiments described here), we found that participants with stronger risk preferences were more likely to prefer the loss frame. Importantly, we measured risk preferences before participants made any frame selections, ruling out that this relationship was simply driven by an interaction between (unrelated) frame preferences and the framing effect. As a result, this finding suggests that people prefer contexts that provide a higher likelihood of selecting actions that match their propensity towards risk: risk-averse individuals tend to opt for the gain-frame context since it makes them more likely to choose the safe option. Thus, they tend to place themselves in a context that aligns with their risk-averse tendencies. As outlined in the Introduction, this behavior reflects the concept of self-nudging[32,33], with people choosing contexts that guide them toward choices that align with their risk preferences. Again, these findings do not tell us whether this relationship is inferred through effortful deliberation or learned associatively. Future studies may disentangle these different hypotheses. One potentially fruitful way to do so is to use the notion that planning carries a cognitive cost[65,66], which predicts that the relationship between risk preference and frame choice would break down under cognitive load[67].

Even though most participants preferred the gain frame, there was substantial variance in this measure across subjects. We have already discussed potential reasons why some of the variance may be driven by factors unrelated to frame preferences. However, it is plausible that some variance is driven by individual preference related to frame preference. For example, regulatory fit theory[68–70] suggests that when people are promotion-focused (i.e., motivated by achievement and advancement), they are more influenced by options framed in terms of gains. In contrast, when they are prevention-focused (i.e., prioritize security and avoiding negative outcomes), they are more inclined to prefer options framed in terms of losses. Therefore, people may prefer the gain frame if they are generally more promotion-focused and prefer the loss frame if they are more prevention-focused. Note that this prediction doesn't just bear out on an individual differences level but also predicts within-person shifts in frame preference as a function of internal shifts in focus.

People may also prefer frames that they find less cognitively demanding to process or easier to mentally convert to the alternative frame. The task design may have influenced the average frame preference: because participants can only win money, the gain frame could be perceived as presenting the outcomes more clearly. Future work can investigate these individual and situational preferences when examining frame preferences. For example, one could structure the task to involve material losses in each trial to test whether this leads to participants preferring the loss frame. If participants favor the loss frame in this context, this indicates that frame preferences are situation-dependent. Conversely, if they maintain a preference for the gain frame, this suggests that context and frame preference are independent.

An important question for future research is whether this variance in frame preferences correlates with other individual difference measures. For example, frame preferences may be driven by affective predispositions (after all, prospect theory suggests that losses register as particularly aversive). Another intriguing possibility is that frame preferences track certain aspects of psychopathology. Participants with a gambling addiction may show gain-frame preferences since they perceive them as 'wins.' Alternatively, they may prefer loss frames because they are more thrilling. Finally, the degree of frame preference may be predicted by participants' inclination towards deliberation[71] such that participants who are more reliant on automatic processing show a stronger "irrational" preference for a particular choice context.

In fact, the results of Experiment 2 suggested that participants' choices became less driven by the casinos' frames when they learned their expected rewards. We suggest two hypotheses for this result. First, it is possible that learning all aspects (frame and expected reward) of each casino was too demanding, so participants needed to prioritize learning some of them. Therefore, some participants may have prioritized learning the rewards, while others may have prioritized learning the frames. A second hypothesis is that the value of the framing context and expected rewards are not encoded using a converging central valuation system but rather by separate systems that encode their value independently[72]. If these two systems are organized hierarchically, with representations of primary value taking precedence, then frame preferences would only affect behavior if no higher-order value has been learned. Future investigations can pit these hypotheses against each other, potentially by asking participants to explicitly recall the frame and value of the casino after the choice phase. The former hypothesis predicts that people's memory should align with their behavioral policy (people that select based on frames should have worse memory for rewards), whereas the latter allows for both value representations to exist even if one is more important. Additionally, it would be interesting to determine how people prioritize other factors, such as decision time, over frame contexts.

In this paper, we decided to use the framing effect to study context choice because it is one of the most well-established and robust behavioral effects in modern psychology[73]. However, context effects have an impact on many forms of behavior beyond risk attitude. Therefore, future research could examine how other contextual preferences change choice selection. For example, it would be interesting to understand whether individuals prefer adding inferior choices alongside superior options: people value having more choice options[5,74], but research on the dud-alternative[11] and decoy[9] effects suggests that inclusion of inferior choices leads them to behave irrationally. The general approach of the FST can be easily adapted to capture other context preferences, hopefully contributing to a more comprehensive understanding of how they influence decision making.

Limitations

Our studies have a few limitations that we should discuss. While we found an association between risk attitudes and frame preference, we cannot establish a causal relationship or rule out the possibility of a third variable that may account for the observed association.

Additionally, the discrepancy in the relationship between risk preference and frame choices across experiments raises some questions. In Experiment 1, we observed this relationship as an interaction effect, whereas, in Experiment 2 (along with our pilot study), this appeared as a main effect. Risk preference consistently predicted frame choice when options were presented in a gain frame. However, this pattern was not consistently observed when choices were presented in a loss frame, as it was only evident in Experiment 2 (and the pilot study). The reasons for this inconsistency remain unclear; however, we hypothesize that decisions in the loss frame are less indicative of risk preference because they are also influenced by individuals' aversion to losses[27,75]. In a loss-frame context, looming potential losses may overshadow risk preferences, making choices less reflective of risk preferences. As a result, this would make risky choices in a loss frame a less suitable measure for individual difference analyses.

Conclusion

Our results provide some of the first evidence that people have context preferences and that these bias subsequent choices. These findings have real-world implications, prompting us to think about how context preferences interact with more primary decisions and how we can use this knowledge to achieve higher-order goals more optimally. For example, even though people may be more inclined to gamble in places that display options in terms of winnings, they will be inclined to place less risky bets. From a theoretical perspective, our results and the novel FST provide a new framework for researchers to study how humans make decisions and what happens if humans can control how they encounter those decisions.

Data availability

The preregistration for Experiment 1 was preregistered on July 27, 2022, and can be accessed at osf.io/qr5ev. Experiment 2 was not preregistered. Code and deidentified data for both experiments, along with a task code employed in jsPsych and the data-analysis scripts are posted at osf.io/p7k9c.

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L.S.T.: Conceptualization; Methodology; Software; Formal analysis; Investigation; Methodology; Writing – original draft; Writing – review & editing.W.K.: Conceptualization; Methodology; Writing – original draft; Writing – review & editing.

Declarations

Competing interests

The authors declare no competing interests.

Additional information

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