Self Perception and Risky Decision-Making

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Introduction

Understanding human decision-making is complex. Even in highly simplified cases where people are presented with definite gain and loss values and are able to identify an objectively correct choice, people don't always choose the "right" option (Kahneman & Tversky, 1979). People's decision-making patterns are affected by personal preferences and inclinations that have been modeled through parameters such as loss aversion (Kahneman & Tversky, 1979), approach and avoidance (Loomes & Sugden, 1982), and perseverance (Daw et al., 2011).

Another category of factors that affect decision-making are those that are inherently external. Previous studies have shown how decision-making can be impacted by incidental visual distractions (Hakim et al., 2020), changes in visual salience (Li & Camerer, 2022), and even surprising sounds (Feng & Rutledge, 2024). While studies looking at the effect of general external stimuli on decision-making have been done before, there is little work examining the relationship between specific salient stimuli and the way that people approach risky decisions.

One such stimulus is the presentation of faces. Faces are notable, not only because they are incredibly present in everyone's daily lives, but also because it was important enough that the human brain developed specialized structures specifically for facial recognition (Gomez et al., 2017). It has already been shown that seeing faces - "watching eyes" - certainly changes behavior, specifically discouraging negative social practices and encouraging positive ones (Nettle et al., 2012). However, these results are only consistent when limited to the scope of behavior that has a positive or negative social aspect. The effect of faces on decision-making is much more contested for morally neutral decisions or those impacting only the decision-maker. An example of this is a risky decision-making task where participants can choose between a safe or risky option in order to maximize their points. In cases like these, we have contrasting evidence either showing that perceiving faces makes people take more risks (Li & Peng, 2022) or take fewer risks (Dear et al., 2019).

An often overlooked angle when investigating the relationship between faces and decision-making is the type of face itself. It is possible that two different faces can lead to two different effects on the same participant. The face most likely to elicit a unique reaction is probably one's own. Studies have found that participants shown aged up images of themselves engage in more risk averse, long-termist behavior (Hershfield et al., 2011). However, there are few studies examining the connection between viewing your present face and decision-making, and none that try to show this phenomenon distinctly from the watching eye effect.

The goal of this study is to fill in that gap. By observing risky decision-making behavior in participants when viewing their own faces and then comparing that to their behavior when viewing other people's faces, we will be able to see if viewing your own face uniquely changes the decisions that you make relative to seeing others. The null hypothesis would be that seeing either type of face would have no impact on risky behavior, whereas the alternative hypothesis would be that behavior is different between the two conditions. In accordance with Hershfield et al., 2011, the directional alternative hypothesis would be that participants seeing their own faces would gamble less due to higher loss aversion caused by heightened tendencies to self persevere.

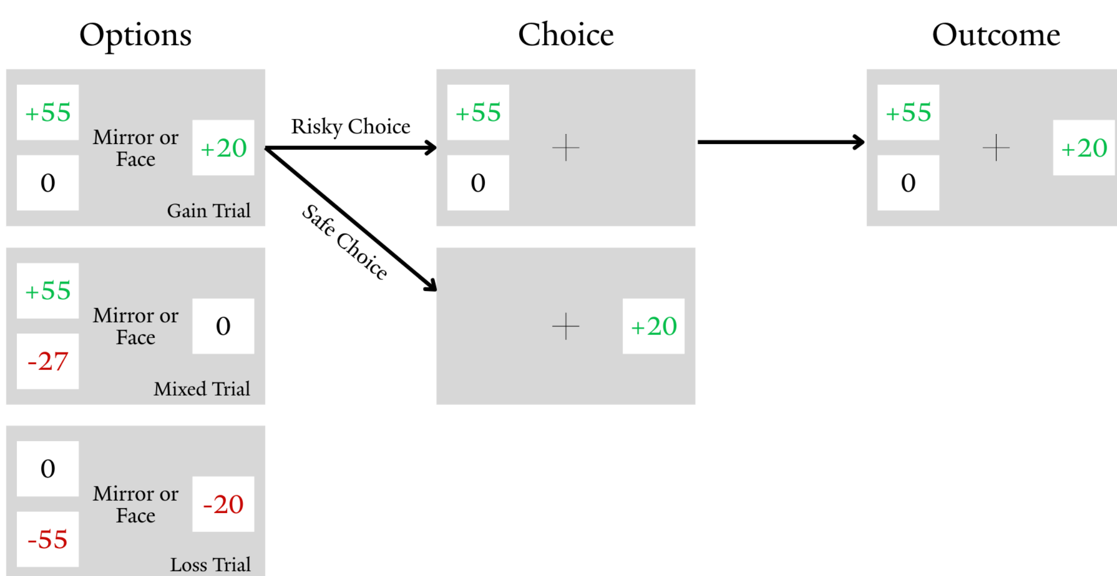
To test whether seeing your own face compared to another face systematically influenced risky decision-making, we are going to alter a well established risky decision-making paradigm (Rutledge et al., 2014; Tom et al., 2007; Sokol-Hessner et al., 2009; Brooks & Sokol-Hessner, 2020) in order to include either a video feed of the participant or a video of a random stranger. Participants will be shown their own face in half their trials, and the face of another person in the other half. Both conditions were chosen to be videos to help symmetrize the potential effects of unwanted confounding variables such as confusion and general distraction. The video feeds, in either case, will provide no information about the task itself, merely being present at the point of decision-making. There is no auditory component to the stimuli.

Methods

The experiment was created using the Gorilla Experiment Builder (https://gorilla.sc/) and participants were recruited online through Prolific (https://www.prolific.co/). The experiments took place between April 20, 2025 and April 23, 2025. Participants were selected to be from either the UK or the US and were screened to ensure that they could read and write English and that they had a working front camera on their laptop. Informed consent was received from all participants. In total, we had 22 participants that completed the study fully.

In each trial of the experiment, participants chose between a safe and risky decision using computer keys, with risky options having an equal probability of winning or losing (the loss always has a lower value than the winning condition and the safe condition, the win always has a higher value than the loss condition and the safe condition). While presented with the options for each trial, the participant is also shown either a video feed of themselves (achieved by turning on their device's front camera), or a video of another stranger's face. There were two videos selected for the stranger's face, one of a man and the other of a woman, both without a clear emotion on their face. Every 5 trials during the face condition, the video that participants were shown would switch, meaning that participants were exposed to both faces an equal number of times. After being given instructions on how to choose the option they want, and being informed that there will be a face in the center of the screen, participants conducted 180 trials.

Figure 1: Experimental Design



90 of these trials were "mirror" trials, where participants were shown faces of themselves, and the other 90 of these trials were "face" trials. The trials were organized such that participants would be shown 45 of a specific type of trial, and then 45 of the other, alternating until they had seen two batches of face trials and 2 batches of mirror trials. Which condition the participant saw first was randomized, with an equal chance of either.

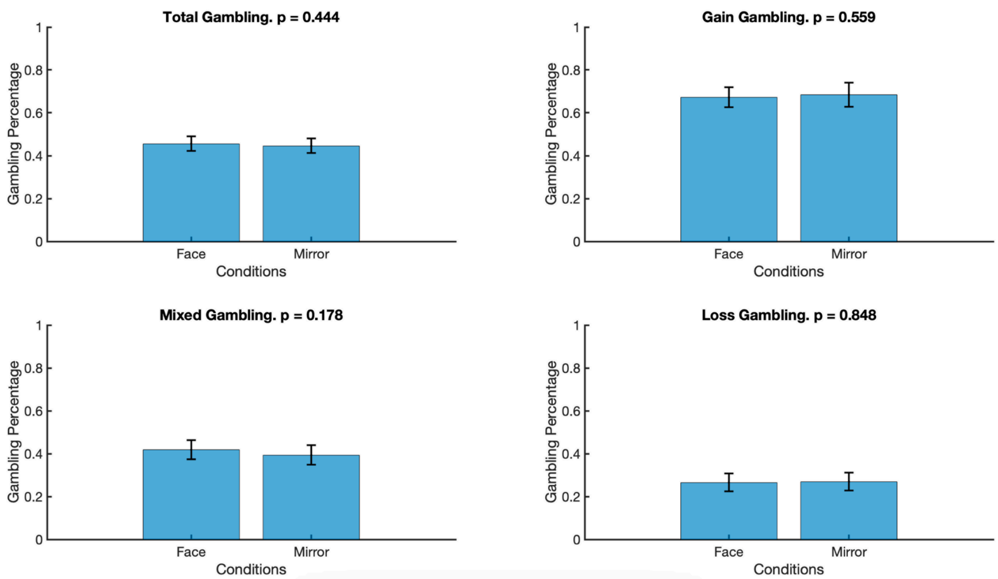
Of the 180 trials, a third of them were gain trials, a third were loss trials, and a third were mixed trials (60 trials for each condition). (1) A gain trial has a positive win and safe value, with a 0 loss value. (2) A mixed trial has a positive win value, negative loss values, and 0 safe value. (3) A loss trial has a negative loss and safe value, and a 0 win value. Within each type of trial, there were multiple ratios created between the safe and risky win outcome (or the risky win and the risky loss outcome for mixed trials) that influenced the attractiveness of the gamble option relative to the safe one. All of the trials were self paced, and average reaction time was 1.78 seconds. Statistical analysis of these trials was conducted using the MATLAB statistics toolbox.

At the end of the main task, participants were given a questionnaire asking about (1) whether their video cameras worked in order to remove participants that weren't exposed to the manipulation and (2) asked to generally describe what they saw during the experiment in order to qualitatively verify if the participants were noticing the manipulation during the task.

Results

The first thing to look at is whether the participants generally gambled more during face trials compared to mirror trials. Participants, on average, gambled 45.61 ± 3.41% (Mean ± SEM) of the time during face trials, and 44.6 ± 3.37% (Mean ± SEM) during mirror trials. This means that the total percentage gambling was not statistically different between these two groups ($p = 0.4438$, two-sided Wilcoxon signed rank test). We can see that this lack of difference between face and mirror trials is consistent regardless of the trial type. Gain face trials have gambling rates of 67.3% ± 4.64% (Mean ± SEM) and gain mirror trials have gambling rates of 68.44% ± 5.67% (Mean ± SEM), which means that they are not significantly different (p = 0.5589, two-sided Wilcoxon signed rank test). Mixed face trials have gambling rates of 41.89% ± 4.51% (Mean ± SEM) and mixed mirror trials have gambling rates of 39.36% ± 4.56% (Mean ± SEM), which means that they are not significantly different (p = 0.1778, two-sided Wilcoxon signed rank test). Lastly, loss face trials have gambling rates of 26.57% ± 4.22% (Mean ± SEM) and loss mirror trials have gambling rates of 26.98% ± 4.18% (Mean ± SEM), which means that they are not significantly different (p = 0.8484, two-sided Wilcoxon signed rank test).

Figure 2: Gambling Percentages for various trial types

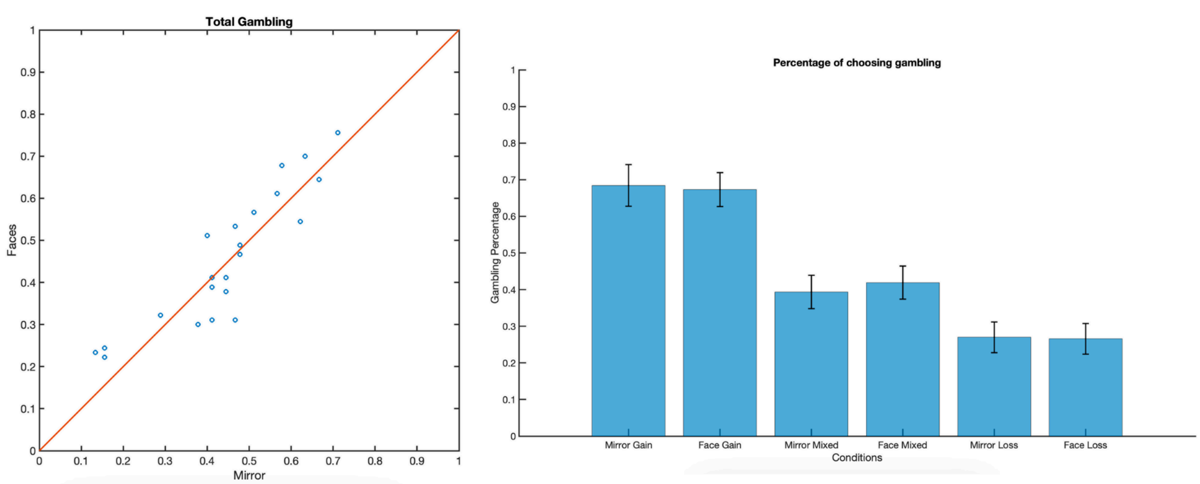


None of the gambling values were outliers, and thus none were removed during the analysis. There are multiple ways to check the quality of our data to ensure that our null model free result is not due to defective data or due to factors such as people not noticing our manipulation. There are three results suggesting our data is reasonable.

Firstly, the gambling patterns between face and mirror trials are consistent at a participant level, suggesting that people had stable patterns throughout the experiment that didn't radically shift due to confounding factors such as boredom with the task. We can also see that all participants are within reasonable ranges of gambling, with none that constantly chose to gamble all the time or went for the safe option every time.

Secondly, the gambling patterns, when divided by trial type, follow logically and in accordance with previous results (Rutledge et al., 2014). Specifically, gain gambling is the most common (67.76% ± 5.04%), mixed gambling is in the middle (40.68% ± 4.42%), and loss gambling is the rarest (26.82% ± 3.87%). These trial types following the gambling percent order that they do, and having values significantly different from each other, indicates that participants were paying attention to the values in the trials and making decisions accordingly and not randomly.

Figure 3: Qualitative Data Checks



Consistent gambling patterns for specific participants. No outliers

Gambling separated by gain, mixed, and loss trials.

The final way to check the soundness of our data is through qualitative participant feedback collected by the questionnaire after the main task. All participants reported that their video camera worked, ensuring that participants were at least exposed to the manipulation. Further, when asked to describe what they saw, every single participant noted the presence of their own face, the man, and the woman, suggesting that they definitely noticed the manipulation. A few quotes indicating that participants noticed the presented stimuli include: "For some reason I thought I was going to lose more often when it was the guy watching me", "I saw a man sometimes, a woman other times, and myself sometimes", and "I wanted to impress the blonde woman with my decisions, and the male was slightly intimidating for some reason." Many of the participants reported having seen the stimulus, but noted that their decision-making was not affected by it.

We can verify the initial model free results by using three separate base models and seeing if there are any notable parameter differences between the face condition and mirror conditions. We can do this by altering the models in order to have a delta parameter, which will be added to the other parameter of interest only during mirror trials. If this delta parameter is significantly different from 0, we can then check the model further to verify if the parameter difference is meaningful between face and mirror trials. There are three models I will be looking at. The first is regular prospect theory (Kahneman & Tversky, 1979) with 4 base parameters (Mu, Lambda, Alpha gain, Alpha loss). The second is the approach avoidance model (Loomes & Sugden, 1982; same as prospect theory + beta gain and beta loss). The final model will be a perseverance model (prospect theory + perseverance parameter, the tendency to repeat the decision made in the previous trial).

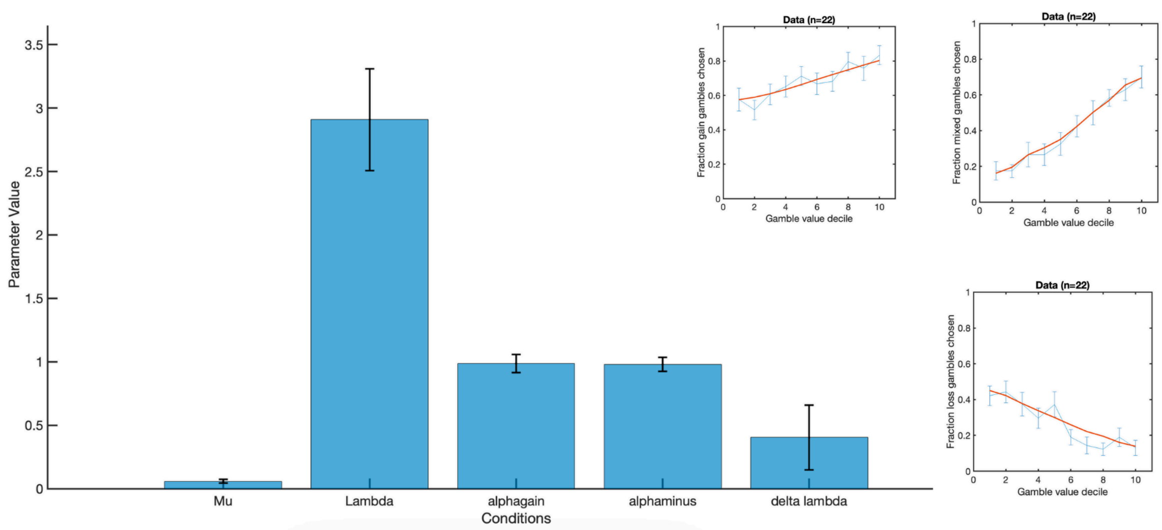
Let's begin by examining prospect theory. The parameter of interest is loss aversion, lambda. Fitting a model with delta lambda gives us a delta parameter with mean 0.4036 ± 0.2558 (Mean

± SEM). This is not significantly different from 0 (p = 0.0625, two-sided Wilcoxon signed rank test). Fitting the model to the data, we can generally see that the values look correct, only missing a few spikes. This means that the prospect theory model results support the model free result that there is no significant effect of face or mirror trials on gambling rates.

Figure 4: Prospect Theory Model

Gambling for model predictions against true data, by trial type

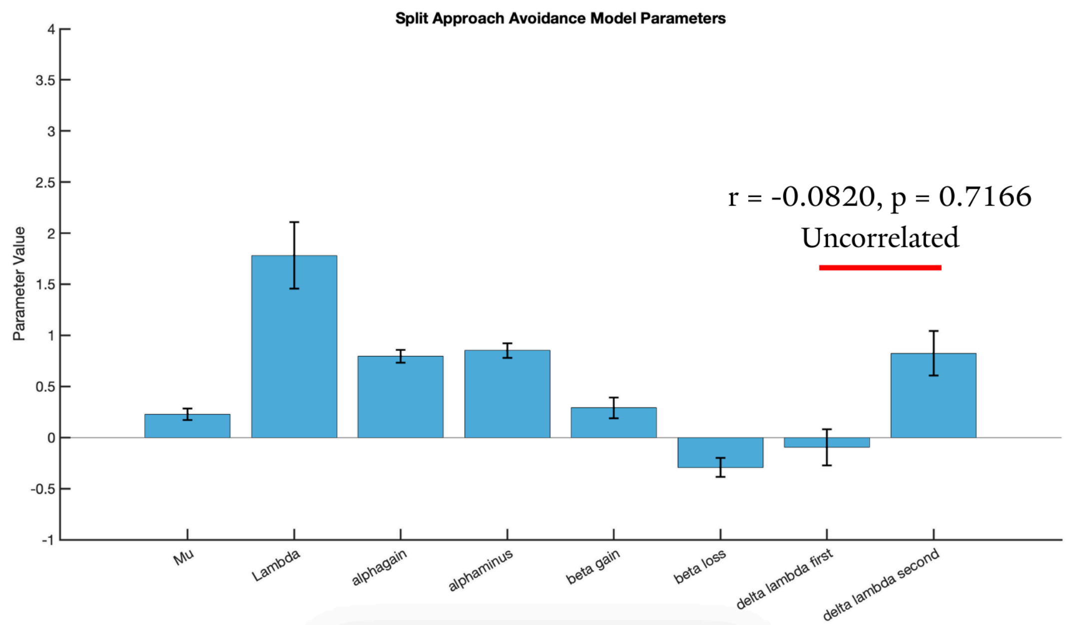
Parameters



The second model to look at is the approach avoidance model. The parameter of interest is loss aversion (lambda) again. Fitting a model with delta lambda gives us a delta parameter with 0.4239 ± 0.1912 (Mean ± SEM). This is significantly different from 0 (p = 0.0495, two-sided Wilcoxon signed rank test). However, doing a BIC model comparison between the approach avoidance model with the delta parameter and without the delta parameter reveals that the model with the delta parameter is worse at explaining the model (sum BIC without delta parameter = 4319.56, sum BIC with delta parameter = 4416.05). Thus, in order to see if the parameter's existence is justified, we can see parameter stability in the first and second half of the trials. Doing this we see that the mean delta lambda parameter in the first half is -0.0973 ± 0.1765

(Mean ± SEM), and is 0.8248 ± 0.2196 (Mean ± SEM) in the second half. The values are significantly different (p = 0.0037, two-sided Wilcoxon signed rank test) and do not have a significant correlation (r = -0.0820, p = 0.7166, pearson correlation coefficient). Thus, the parameter is unstable and not justified, meaning that this model again aligns with the model free null result.

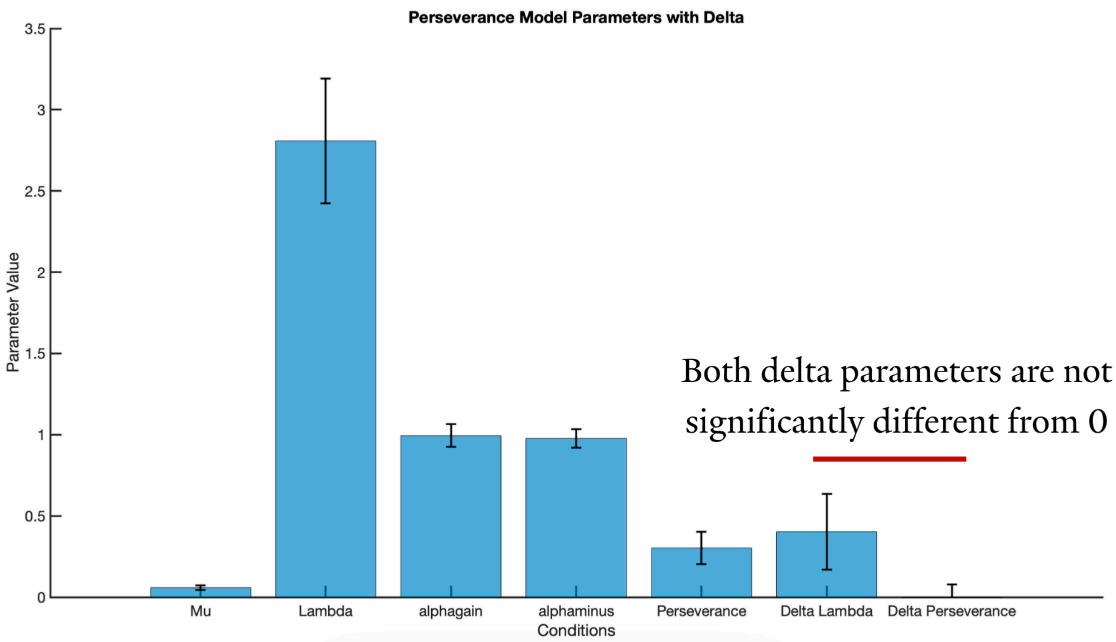
Figure 5: Split Approach Avoidance Model



The final model to check is the perseverance model. We can check two parameters of interest here. Firstly, the lambda parameter as usual, and secondly, the perseveration parameter itself. We can start by noting that this model, with just the addition of the perseverance parameter and not the delta parameter, is a better model than base prospect theory, justifying the parameter's existence (With perseverance, sum of BIC = 4407.08, without perseverance, sum of BIC = 4459.56). Including the delta parameter for lambda, delta has a mean of -0.4014 ± 0.2337, which is not significantly different from 0 (p = 0.1396, two-sided Wilcoxon signed rank test). We can also try a delta parameter for perseverance. Doing this, delta now has a mean of -0.0128 ±

0.0803, which is not significantly different from 0 (p = 0.6148, two-sided Wilcoxon signed rank test). Fitting the two delta parameters together yields similar results (both are not significantly different from 0, indicating no effect. p = 0.1080 and 0.5481 respectively, two-sided Wilcoxon signed rank test). Thus, the perseverance model also aligns with the other models and the initial model free result, indicating that there is no significant difference between a face or mirror trial on gambling behavior, with no significant change to loss aversion either.

Figure 6: Perseverance Model with both Delta parameters



Discussion

When examining the various factors that influence the way that people make decisions, you might believe that viewing yourself in a mirror, perceiving yourself, would change the way that you engage in risky behavior. Based on previous studies showing that people exposed to aged up versions of themselves engage in more long termist, self preserving behavior (Hershfield et al., 2011), you might think that seeing yourself in the mirror would have similar effects on gambling patterns. However, based on the results of this specific experiment we have conducted, such an effect does not exist. The model-free analysis showed no meaningful changes in gambling patterns, even when split by trial type, and model-based analyses showed that participants did not meaningfully change their lambda or perseverance parameters based on whether they were seeing a face or mirror trial. We also showed that this null result is likely not due to randomness or faulty data due to the many quality checks mentioned in the results section.

However, before claiming that we have a null result conclusively, I would like to point out multiple limitations of this experiment that might influence the results, which future versions of this experiment could consider adjusting. Firstly, the experiment does not attempt to make participants actually believe that the wins or losses they experience matter beyond being numbers on a screen. Self preservation might be a real effect when seeing yourself in the mirror, but it might not manifest within a situation where almost all participants do not feel worried about actually losing anything tangible. Future experiments could entice participants with real money proportional to the number of points that they earn in the experiment to make it feel more realistic. Secondly, the stimuli might simply have been ignored. Participants reported that they saw the stimulus, but some also pointed out that they were “looking at the numbers, not the faces”. Given the design of the experiment, it is completely possible for participants to entirely focus on the numbers and barely look at the faces, severely limiting the effect of the manipulation. Future versions of the experiment can have periods of time when participants are only able to look at the faces and not the numbers, ensuring that the stimulus is fully noticed. Lastly, several participants noted that the strangers’ faces were “bored and unresponsive” which is why they “didn't pay attention to them”. Future versions of the experiment could have more responsive videos that reacted to wins or losses, not only ensuring people looked at the manipulation more often, but also making the experiment feel more realistic, as in real world contexts people often make facial expressions in response to the decisions that we make.

In conclusion, while our current results indicate that there is no difference in your gambling patterns when you are seeing yourself compared to when you are seeing others, both from model-free and model-based lenses, we have received incredibly useful feedback and information that can guide future studies in this field. Decision making is influenced by countless factors, and even a step as small as this towards understanding the complicated mechanisms behind it is important and beneficial. We all see faces every day. We should know how they impact the choices we make.

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