Sex-Dependent Effects of Emotional Subliminal Visual Stimuli on a Decision-Making Task

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Abstract

How do covert emotional stimuli affect decision-making? We investigated this question by exposing participants to subliminal visual stimuli during a computerized version of the Iowa Gambling Task (IGT) to assess whether different categories of images (negative, neutral, or positive emotional evaluations) would influence decision-making behavior. Results did show sex-group interactions for IGT scores. In decision learning model simulations, it was found that different models were more appropriate to explain the task performance for different sex-group pairs. Overall, women showed more of an ability to integrate the additive negative signals from the stimuli to make more advantageous decisions than the men; consequently, this made the men more resilient to the negative effects of the positive stimuli on task-performance. When taken with existing research, the results indicate that subliminal emotional stimuli can have subtle, potentially sex-dependent, effects on behavior during the decision-making process.

Keywords: Decision-Making, IGT, Emotion, Simulation

Introduction

How do covert emotional stimuli affect decision-making and choice behavior? There have been several studies that have explored the processes involved in, and the outcomes of, decision-making behavior (e.g., see Lerner et al., 2015; Weber & Johnson, 2008), but relatively few studies that explore decision-making have also explicitly introduced emotional stimuli (Phelps & Sokol-Hessner, 2012) and even fewer have sought to understand the interaction between unconsciously presented emotional stimuli and decision-making. One decision-making study by Winkielman et al. (2005) found that subliminally presented images (emotional faces) influenced judgment and choice during a series of decisions directly following the masked image exposure (with *happy* faces increasing the amount of a beverage poured and consumed, and the purchase price a participant would be willing to pay). These images affected the decision despite not being consciously perceived or semantically related to the series of decisions made after the exposure. Subliminal image presentation can also cause changes in peripheral physiology that may not be perceived, particularly measures related to activation of the LC-Noradrenergic system and amygdala, for example heart-rate and eye-blink response (e.g., Ruiz-Padial et al., 2011). These effects on peripheral physiology are important, as the areas of the brain that are shown to respond to these subliminal stimuli are likely causing these cascades of changes (Öhman & Mineka, 2001; Tamietto & de Gelder, 2010).

The Iowa Gambling task (IGT) has been used to better explain links between changes in peripheral physiology and choice behavior, as well as to better understand some of the brain areas key to decision-making and related physiological behavior during the decision-making process (Bechara et al., 1999).

IGT subjects repeatedly chooses cards from 4 decks of cards. The payoff per card varies, and the subject is asked to maximize their payoff. The decks differ in the payoff they give for each card; some decks give better average payoffs than others, although all have variability. The task is used to study how subjects learn to use the payoffs in their decision-making. For some cognitive deficits the choices are not learned very quickly.

An important finding from Bechara et al. (1999) is that normal participants exhibited different skin conductance response (SCR) behavior than clinical patients with amygdala lesions and those with lesions in the ventromedial prefrontal cortex (VMPFC). These distinct clinical groups exhibited different SCRs both prior to selecting a card from a deck and in response to receiving a net gain or loss after selecting a card; this difference is especially apparent in the disadvantageous decks (those decks that had a negative average payoff). The group with amygdala lesions exhibited both a reduced SCR prior to selecting a card from a deck and a reduced SCR after receiving a reward or loss, while the VMPFC group showed a more attenuated SCR prior to the selection of a card from a deck, indicating that amygdala nuclei may play an important role in giving affective value to representations in decision-making. SCR response patterns by those with amygdala lesions indicated a difficulty with coupling an affective value with the different decks and the cards from those decks.

We sought to better understand behavioral effects of this unconscious emotion perception and decision-making interaction by exposing study participants to subliminal emotional stimuli while they completed the IGT. Behavioral responses to the affective value of objects are mediated by cognitive processes that are modulated by neural processing in the amygdala (Moscarello & LeDoux, 2013; Panksepp et al., 2011; Phelps, 2006). Given that the amygdala is also important for the processing of unconsciously presented emotional stimuli (Tamietto & de Gelder, 2010), the unconscious perception of emotional stimuli may have behavioral effects on decision-making even if the stimuli are not integral to the decisions being made (e.g., Winkielman et al., 2005).

We expected that decision-making would differ depending on whether the subliminal image presented had negative, neutral, or positive evaluations. We present a study to test this hypothesis. Normally, in non-pathological populations, IGT performance is largely dependent upon learning deck contingencies over-time. This can be represented somewhat as a reinforcement learning process (e.g., with the expectance-valence model or the prospective-valence model; Ahn et al., 2008). To further explore the potential differences between groups (and, later, participant sex), we developed decision learning models (e.g., Ahn et al., 2008) that were run in simulations[1]; this gave us the opportunity to understand potential computational processes affected by the treatment.

Method

97 undergraduate students were recruited as participants for this study (52 males; 45 females). The average ages of males and females were similar at 20.7 and 19.8 (respectively). Electrodermal Activity (EDA) data were collected for the final 66 (37 males and 29 females) participants (data not reported here). All participants were given college course extra credit.

A filter process that removed participants who completed less than 20% of their trials due to time restrictions (max 3.5s per trial) resulted in the removal of 4 participants' data from further analysis; data from 93 total participants were analyzed. The *negative*, *neutral*, and *positive* (image) groups each had 31 participants. We ceased participant enrollment in the study after we crossed a 31 per-group threshold for task-related behavioral analysis and all volunteers had the opportunity to participate.

Participants used a version of the IGT that included a fixed reward and punishment schedule for each deck that was the same as the schedule used for the original IGT by Bechara et al. (2000). A modified computerized version of the IGT was used that runs in Matlab and uses the Psychtoolbox Matlab extensions (Brainard, 1997), which were used due to their high timing accuracy, community support, and cross-platform availability. The specific software used has had IGT-specific timing tests done to confirm timing accuracy (Dancy & Ritter, 2017).

The visual stimuli presented during the IGT were obtained from the International Affective Picture System (IAPS; Lang et al., 1997). Table 1 lists the images used in the image sets used by the groups. Male and female pictures were matched so that, for each group, they had similar valence/arousal/dominance ratings and had a similar content subject; for example, some snake pictures had different ratings between sexes within the IAPS manual, so those images with lower valence/higher arousal ratings among the same category were chosen. Given that picture ratings in all categories differed between sexes, this method allowed more consistency in mean measured quantitative ratings among participant sexes.

Table 1. The IAPS images used in the experiment.

Picture-Set	Picture Numbers
$\text{Negative}_{\text{Male}}$	1050, 1202, 1220, 1304, 1525
$\text{Negative}_{\text{Female}}$	1050, 1120, 1201, 1202, 1525
$\text{Neutral}_{\text{Male}}$	1670, 7006, 7010, 7080, 7175
$\text{Neutral}_{\text{Female}}$	1670, 7004, 7010, 7012, 7175
$\text{Positive}_{\text{Male}}$	4180, 4210, 4232, 4664, 8501
$\text{Positive}_{\text{Female}}$	4505, 4525, 4660, 8001, 8501

Procedure

Before participating in the study, all participants read and signed a consent form approved by the Office of Research Protections (ORP) at Penn State. After consenting to the form, all participants filled out a Positive and Negative Affect Schedule (PANAS) questionnaire. All participants who had their EDA recorded were then fitted with a Q sensor EDA device (Ming-Zher et al., 2010).

Each participant was assigned to one of three groups that determined which set of images they were shown: (a) a *negative* image group that consisted of images

[1] Software available at gitlab.bucknell.edu/AI-CogSci-Group/IGT-Open/

with a low rated valence, and a high arousal; (b) a *neutral* image group that consisted of images with a medium rated valence and a low arousal (c) a *positive* image group that consisted of images with a high rated valence and a high arousal.

In this version of the IGT, participants had a maximum of 3.5 seconds to select a card from one of the four decks and if they failed to make a selection in the allotted time on any trial, a random deck was selected for them. After a card was selected from a deck, a red or black card was shown for 4 seconds. A (group-dependent) image was shown in place of the background image of the box where the reward and losses were shown for 17 ms when the participant selected from deck A or B. If the participant made a selection from deck C or D, a plain gray background image was shown for 17 ms. Directly after this 17 ms, the reward and loss that the participant received in response to their deck selection was presented in the same box for 3.5 seconds. All images used from the image set, as well as the background image used throughout the task, were converted to gray scale. Each intertrial break lasted 3.5 seconds, except every 20th trial, after each of which the participant was asked two questions to assess their awareness of the task itself.

After the IGT was completed, participants filled out a second PANAS questionnaire and then (as needed) had the EDA device removed. Participants were then asked "Did you discover anything new by the end of the game?" and were partially debriefed on the task itself. Participants then completed the Affective Neuroscience Personality Scales (ANPS) questionnaire and were fully debriefed before ending the study session.

Results

To understand the results, we used both traditional statistical techniques (e.g., one-way and repeated measure ANOVAs), as well as results from decision learning models. While the ANOVAs were useful for understanding general differences between participant groups, the decision-learning models allowed us to explore potential differences in the computational processes that may govern group differences.

Analysis of Initial Hypotheses

We hypothesized that the score would be different between the negative, neutral, and positive image groups, and that performance would be highest in the negative image group and lowest in the positive image group. A one-way ANOVA for cumulative score (total score at the end of the IGT) did not show a statistically significant difference between groups ($F(2,90) = 0.81$, $\eta^2 = .02$). We also hypothesized that score would improve over the course of the task (indicating a learning of the advantageous decks) and that this improvement would also differ between groups. A 3 (image group) x 5 (block) mixed-model ANOVA for score revealed a statistically significant block factor, showing that learning occurred ($F(4,360) = 13.22, p < .0001, \eta_p^2 = .13$), but did not show a statistically significant block:group interaction ($F(8,360) = 0.40, \eta_p^2 = .01$).

Post-hoc Analysis

Additional analysis of the data indicated that participant sex was a behavioral factor. Figure 1 shows mean cumulative scores by group for both males and females. The distribution of mean scores on the task among groups is mirrored between males and females; the mean cumulative score for the positive group among females (-2.4) is closer to the negative group mean cumulative score in male participants (-3.4) than the positive group mean score in male participants (11.6).

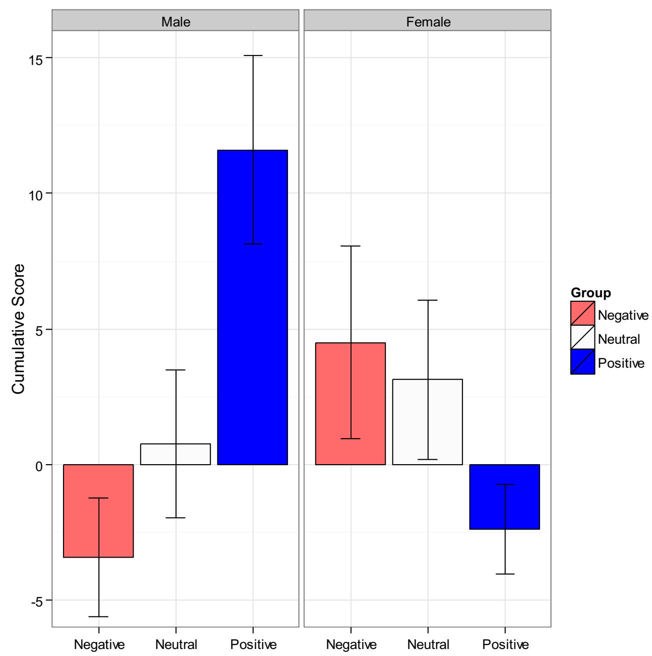

Figure 1 Cumulative score for male (left) and female (right) participants at the end of the task. (The error bars represent the standard error means)

A 2 (sex) x 3 (group) ANOVA for cumulative score showed a marginally statistically significant sex:group interaction ($F(2,87) = 2.77, p = .07, \eta_p^2 = .06$). A 2x3x5 mixed-model ANOVA for score showed a statistically significant block factor ($F(4,348) = 13.55, \eta_p^2 = .13$) and a statistically significant block:sex:group interaction ($F(8,348) = 2.12, p = .034, \eta_p^2 = .05$) indicating a difference in trends between sex:group pairs.

Thus, we see that the effect of stimuli valence had an effect on the cumulative score on this task, but that the positive and negative valence images appear to have different effects on men and women.

Using Decision-Learning Models

Though using methods such as those used above are useful for finding differences between groups, simulations of decision-learning models can also be useful as they allow one to explore theoretical aspects of the computation leading to learning and decision-making performance. We ran simulations of decision-learning models to explore how different groups may have evaluated positive and negative payoffs (utility), how they learned these utilities after experiencing them (learning rule), and how these learned expectations may have influenced participants' actual choice (choice probability rule). This resulted in simulation parameter sweeps on 8 total models (2 per category); each model was run 100 times during the parameter sweep using the MindModeling@Home cognitive research system.

Functions Used to Construct the Models The two utility functions used were the expectancy utility function (hereinafter referred to as EU) and the prospect utility function (hereinafter referred to as PU). EU contains a parameter meant to specify a model's attention to loss (w in eq. 1). Instead of assuming a subjective utility that is linearly proportional to the payoff amount, PU uses a non-linear function (e.g., Tversky & Kahneman, 1992) to better account for the gain-loss frequency effect (whereby multiple small losses have a larger effect on choice behavior than a single loss equal to the sum of the smaller losses. In (eq. 2) $net(t)$ represents the net amount gained (or lost) on trial t, w is a loss-aversion parameter, and γ governs the shape of the equation.

$$u(t) = (1 - w) * rew(t) - w * loss(t) \tag{1}$$

$$u(t) = \begin{cases} net(t)^{\gamma} & \forall\ net(t) \geq 0 \\ -w * |net(t)|^{\gamma} & \forall\ net(t) \geq 0 \end{cases} \tag{2}$$

For learning, the Rescorla-Wagner, or delta, rule (Rescorla & Wagner, 1972) and the decay reinforcement rule (Erev & Roth, 1998) were used in separate decision models. In the Rescorla-Wagner rule (eq. 3) α represents a learning rate that determines the effect of the the prediction error (the utility minus the current expectancy). The same parameter provides a slightly different representation for the decay reinforcement rule (shown in e. 4). Here, the rule represents a recency parameter, which determines discount of past expectancy when updating with the new utility. Both the delta and decay rules are represented in Table 2 as *Del* and *Dec*, respectively.

$$E_i(t) = E_i(t-1) + \alpha * (u(t) - E_i(t-1)) \tag{3}$$

$$E_i(t) = \alpha * E_i(t-1) + u(t) \tag{4}$$

Finally, every model had one of two choice rules: trial-dependent and trial-independent. These rules define a parameter that affects the probability of selecting a card from each deck θ in equation 5. In this case, θ affects the propensity to explore or exploit the problem space. When the parameter is low, the model is more likely to *explore* and select a *random* deck, and when it is higher it will *exploit* its knowledge and be more likely to select the decks that have a higher utility. The trial-dependent rule (eq. 6) is affected by the number of trials which the model has completed and the *consistency* parameter c, while the trial independent rule (eq. 7) is only affected by the parameter c (and thus static during the task).

$$P\big(D_i(t+1)\big) = e^{\theta(t) * E_i(t)} / \sum_{j=1}^{4} e^{\theta(t) * E_j(t)} \tag{5}$$

$$\theta(t) = (t/10)^c \tag{6}$$

$$\theta(t) = 3^c - 1 \tag{7}$$

Model Results As one may predict from the human results reported above, the models that best matched human behavior differed between sex-group pairs. To find the best matching models we calculated the R^2 for each model-parameter-set combination using the proportions of cards selected from each deck during that particular block (i.e., four proportions adding to 1.0 in each of the five blocks). This measure was chosen because it allowed us to further specify how different processes (i.e., models) may explain not only the overall performance (i.e., score), but the proportions of cards selected from decks in each block that define the overall performance. Table 2 lists the top model (and related parameters) for each sex-group combination.

Table 2. Models and corresponding parameters that best matched each sex:group pair. Dec = Decay; Del = Delta; TI = Trial Independent; TD = Trial Dependent. All R^2 (19) p < .01

Sex:Group	Model	c	w	γ	α	R^2
Male:Neg	PU-Dec-TI	-9.25	5.2	.35	.15	.87
Male:Neu	PU-Dec-TD	-8.25	4.1	.20	.93	.89
Male:Pos	PU-Del-TI	-1.50	.13	.00	.75	.88
Female:Neg	PU-Del-TI	-5.50	2.5	.65	.43	.87
Female:Neu	PU-De1-TI	-6.75	6.8	.15	.30	.92
Female:Pos	PU-Dec-TI	-2.50	0.5	.25	.25	.89

While there were varying parameters for all models a variant of the prospect utility (PU) model showed the greatest match to all of the sex:group pairs. The same model had the highest R^2 for the negative scoring performance group for each sex (females in the positive group and males in the negative group). The male:neutral group was the lone group pair to show the highest R2 with a trial dependent model.

Discussion and Conclusion

These data indicate that the subliminal emotional stimuli had an effect on decision-making. There appears to be an important interaction between sex and emotional decision-making. Even though the stimuli were presented subliminally and were non-integral to the choices made, participants exposed to affectively charged stimuli responded differently to the outcomes of deck selections and performed better or worse on the task, depending on sex and the valence of the stimuli.

We did not find statistically significant evidence for a between group (negative, neutral, or positive) difference in IGT scores. However, we did find that there were significant differences between groups for IGT scores when factoring in participants' sex. What's more, mean scores among males showed a trend opposite of females across groups. These results seem to indicate that the stimuli had opposite effects on males and females.

This may be due to these stimuli affecting portions of the affect-memory coupling portion of the decision-making process that can go unnoticed without conscious reflection by the decision-maker. This seems likely given the mirrored distributions, but with similar performance between men and women in the neutral group. Indeed, the simulation model results showed that males in the negative group and females in the positive group were similar to the same class of model.

Similar to the results from a previous study by Aïte et al. (2013), the image-deck congruency also affected the participant's decision-making behavior, albeit differently in men and women. Though females exhibited a pattern similar to Aïte et al. (2013) with the cumulative score for the negative image group being the highest and the cumulative score for the positive group being the lowest, males exhibited the opposite behavior and the image effect was intensified. Indeed, a more recent review points to a difference between men and women in decision-making behavior during the IGT (van den Bos et al., 2013). In the study presented here, women perhaps showed more of an ability to integrate the additive negative signals from the stimuli to make more advantageous decisions than the men; this explanation, would also apply to men, making them more resilient to the negative effects of the positive stimuli on task-performance. The difference in this affective signal integration may be partially due to the differences in amygdala activity found in men and women (e.g., Cahill, 2006; Hamann et al., 2004). These differences may have also led to a difference in memory processes predominantly used to make decisions, as the differences in models (particularly learning processes) may suggest. A decay-based learning rule would better lend itself to a more hippocampal/declarative memory, time-dependent (e.g., Anderson et al., 1999) emphasized decision-making process.

While this study yields interesting and worthwhile results, there were limitations in the study that restricted the scope of analysis and discussion. Our study is somewhat limited in that we were unable to compliment the results with neuroimaging data (e.g., fMRI). Neuroimaging data could allow more comment on the neural process mediated reasons that we found a difference in decision-making performance between groups that was dependent on participant sex.

Furthermore, the model analysis could be expanded in the future. Indeed, it may also be interesting to integrate an affective component into the simulations to more directly account for the stimuli. This would allow a finer analysis of the computational processes at work, albeit with a more complex model.

The aim of this study was to better understand how non-integral, subliminal stimuli may affect decision-making behavior and physiological responses during decision-making. Though we found some expected image-deck congruency effects, these were not as prevalent as originally hypothesized and participant sex also played a role in how decision behavior was unconsciously moderated by the stimuli. More study is necessary to better understand how these unconsciously perceived stimuli are affecting the process of decision-making.

Nonetheless, this work provides evidence that non-integral subliminal stimuli may affect decision-making behavior at several points in the process depending on stimuli characteristics relative to the decision-maker, and reward and punishment contingencies present in the series of decisions. The work also provides evidence that methods of affective intervention during decision-making (e.g., presentation of an emotionally charged image to an individual as a part of a decision to purchase an item) should take into consideration the potential effects of the stimulus on males and females. The stimulus will likely have dissimilar effects and may have completely contrasting effects on individual choices based upon the sex of the decision-maker; this could lead to unintended behavioral consequences.

Acknowledgements

This work was partially funded through support from the Bunton-Waller Fellowship (CLD), the Alfred P. Sloan Foundation Graduate Scholarship (CLD), and the Pennsylvania Space Grant Consortium Graduate Research Fellowship (CLD). The authors thank Jack

Harris at AFRL (711 HPW) for his advice with regards to using the MindModeling@Home platform.

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