Early stages of the acute physical stress response increase loss aversion and learning on decision making: a Bayesian approach

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Abstract: When the cortisol peak is reached after a stressor people learn slower and make worse decisions in the Iowa Gambling Task (IGT). However, the effects of the early stress response have not received as much attention. Since physical exercise is an important neuroendocrine stressor, this study aimed to fill this gap using an acute physical stressor. We hypothesized that this stress stage would promote an alertness that may increase feedback-sensitivity and, therefore, reward-learning during IGT, leading to a greater overall decision-making. 90 participants were divided into two groups: 47 were exposed to an acute intense physical stressor (cycloergometer) and 43 to a distractor 5 minutes before IGT. The Prospect Valence-Learning (PVL) computational model was applied to the IGT to investigate decision-making components (feedback-sensitivity, loss aversion, learning and choice consistency). There were no differences in the overall IGT performance, but physically stressed participants showed greater loss aversion and higher learning than controls. In addition, this loss aversion was linearly related to the learning and the choice consistency. These results would support the potentially beneficial role that early stages of stress could play in decision-making and suggest the need of studying the components that underlie this cognitive skill, rather than addressing it as a single dimension.

Keywords: stress, vigorous physical activity, decision-making, computational model, loss aversion, reward-learning

Introduction

Decision-making refers to the cognitive ability "to choose between competing courses of action based on their relative value of consequences." (Balleine, 2007, p. 8159). Since many decisions are made under stress or elicit stress responses themselves, and brain regions associated with decision-making are sensitive to stress-induced changes (Starcke & Brand, 2012), stress effects on subsequent decision-making have been widely studied. The general conclusion is that stress affects decision-making, however, whether the effect is beneficial or detrimental depends on the task and the context (Starcke & Brand, 2012).

Decision contexts can be described on a continuum from complete certainty to complete ignorance, and can trigger specific decision-making mechanisms (Starcke & Brand, 2012; Volz & Gigerenzer, 2012). Under ambiguity decisions, when uncertainty is high and there exist several outcomes with unknown probabilities (Bechara & Damasio, 2005; Starcke & Brand, 2012; Volz & Gigerenzer, 2012), people could not be able to follow strategies such as utility maximization (von Neumann & Morgenstern, 1944) and would rely on the reward or punishment experiences after each decision. These experiences produce emotions that are linked to the different decision alternatives and act as somatic markers that guide following decisions (Bechara & Damasio, 2005; Poppa & Bechara, 2018). Sensitivity to reward and punishment play a key role in this reinforcement-learning process (Starcke & Brand, 2012). A prominent task to measure decision-making under ambiguity is the Iowa Gambling Task (IGT; Bechara et al., 1994; Bechara & Damasio, 2005; Chiu et al., 2018). In IGT, participants must choose one hundred cards from four decks to get the most benefit. However, they do not know what they will find in those decks, nor that two of them are advantageous and two disadvantageous. They must learn to choose, based on their experiences of reward and punishment, those cards which yield smaller gains but lower losses in the long run, the advantageous decks. Developing this conservative strategy is considered a better decision-making (Bechara & Damasio, 2005; Chiu et al., 2018).

Regarding the stress effect on IGT performance, Reiman & Bechara (2010) highlighted that stress can interrupt the connection between somatic markers and decision-making in healthy population. Stress interferes with the reinforcement-learning process by reducing feedback sensitivity (Lighthall et al., 2013) and impeding attentional disengagement from poorer decks (Simonovic et al., 2018). This can lead to a slower learning during IGT (Preston et al., 2007) and disadvantageous card selections (Alacreu-Crespo et al., 2019; Preston et al., 2007; Simonovic et al., 2016, 2018; Starcke et al., 2017; van den Bos et al., 2009; Wemm & Wulfert, 2017). Nevertheless, studies on stress and IGT administered the decision-making task at times of approximately cortisol peak, where strongest stress effects are expected (Pabst et al., 2013; Starcke & Brand, 2012); that is, they address the slower response to stress, related to the hypothalamus-pituitary-adrenal axis (HPA-axis). Yet, the rapid stress effects on decision making as evoked by the fast activation of the sympathetic nervous system (SNS) and catecholamine's secretion have not received as much attention.

Pabst et al. (2013) addressed this issue on risky decision-making, where decision rules are explicit and outcomes probabilities are known. They reported that 5 minutes after the stressor onset, participants improved decision-making by taking less risks than both control and cortisol-peak groups. An explanation can be found in the "salience-of-losses" hypothesis (Metz et al., 2020). This suggests that acute stress produces a higher activation of the salience network; thus, enhancing sensitivity to the negative feedbacks by amplifying loss aversion; that is, the greater sensitivity to losses than to proportional gains (Kahneman et al., 1991). In this line, the central norepinephrine (NE) blockade by propranolol reduced sensitivity to the magnitude of possible losses (Rogers et al., 2004), and a linear relationship was found between NE brain levels and loss aversion (Sokol-Hessner & Rutledge, 2019; Takahashi et al., 2013). Additionally, the salience-of-losses hypothesis would find support in the model of Hermans et al. (2014) who argue that the exposure to acute stress prompt a redistribution of neural resources to a salience network, promoting fear and vigilance, and reducing executive control. Finally, it has been recently confirmed the essential role of Salience Network in the coordination of stress response (van Oort et al., 2017). Therefore, given the IGT nature, the salience-of-losses could favor the reinforcement-learning by enhancing the emotions from punishments and, thus, an advantageous decision-making. However, the rapid stress effects on decision making under ambiguity have never been addressed to date. Our aim is to fill this gap.

On the other side, studies on stress and IGT take the overall performance or the learning-curve during the task as an unidimensional construct of decision-making, but do not take into account that this cognitive ability involves multiple components (Alacreu-Crespo et al., 2020). Decomposing decision-making performance into single components might identify subtle effects of the stress that are not captured by the traditional task scoring. Computational models based on Bayesian logic have been developed to study the underlying processes that guide the reinforcement-learning in the IGT (Ahn et al., 2017). Busemeyer & Stout (2002) proposed the mathematical model Expectancy Valence Learning (EVL), which was subsequently improved with the Prospect Valence Learning (PVL) model by Ahn et al. (2008). PVL redefines the equations for establishing the value of the card and the consistency between choices and expectations, which provides greater explanatory power to the PVL model (Fridberg et al., 2010). Specifically, the PVL model (Ahn et al., 2008) extracts four theorized parameters: feedback sensitivity, loss aversion, learning and consistency. Based on the above and in line with the salience-of-losses hypothesis, it would be logical to expect that acute stress will enhance sensitivity to feedback and loss aversion and, in turn, this will favor learning and following a consistent strategy. This strategy should be shown through the relationship between the different parameters; in other words, the enhancement in sensitivity to feedback and loss aversion should correlate with the learning parameter during the task. In turn, these parameters should be related to the total IGT index.

Finally, regarding the stress induction, studies on stress and IGT used mainly social stressors. However, considering that physical and psychological events that threaten homeostasis are referred to as ‘stressors” (de Kloet et al., 2005), we choose a common systemic stressor: physical exercise. In this sense, systemic stressors act unconsciously influencing decision-making sub-components, such as loss aversion (Pighin et al., 2014). Thus, although healthy, exercise is considered a powerful stressor of the neuroendocrine system since it creates the need to recovery the homeostasis (Hackney, 2006). The SNS and HPA-axis activity increase as the intensity of exercise increases (Hackney, 2006). Moreover, while regular practice is associated with better mental health, a heavy exercise single bout was related to increased perceived stress levels (Hopkins et al., 2012). The decision to use this stressor was justified by the fact that its physiological effects are comparable to those of social stressors (Ponce et al., 2019), but also by the fact that physical stressors emphasize a robust and rapid response of the SNS (Allen et al., 2014; Hidalgo et al., 2019) without the need for interpretation by higher-order brain structures (Pighin et al., 2014). This is particularly relevant if we want to address the early phase of stress. Consistent with this, acute and intense physical activity, regardless of whether it is considered a stressor or not, is being studied in relation to cognitive processes. For example, some studies show that acute aerobic exercise has beneficial effects on memory, favoring the encoding and consolidation of information during learning. Thus, one focus of research is on the temporal effects of acute and intense physical activity on learning and memory processes in young adults (Frith et al., 2017). In addition, it has recently been pointed out that the effect of acute bouts of physical activity on cognitive processes (after such activity) needs to be investigated in more depth, as positive results have been found (i.e. moderate to vigorous intensity activities impacts upon inhibitory control after cessation of the activity bout), but with a low effect size given the wide variety of studies with methodological differences (Pontifex et al., 2019). Furthermore, as it is described in their study, decision-making after this type of physical activity has not been studied, so we believe that this is a gap that should be filled.

Therefore, based on the above, this research aims to investigate if acute and vigorous physical activity has immediate effects in an ambiguity decision-making on IGT, focusing on decision-making components extracted with the PVL model. We hypothesize that 5 minutes after the physical activity, participants will improve decision-making in IGT with respect to the control group. Furthermore, in line with the salience-of-losses hypothesis, the PVL parameters will show that the better performance is related to increased feedback sensitivity and loss aversion, which in turn will lead to improved learning and consistency. Furthermore, we expect the different parameters to be correlated with each other, showing consistency in the strategy of completing the IGT.

Material and methods

Participants

95 students from the University of Valencia were recruited by asking them if they wish to participate in a study in exchange for academic credits. Those interested filled out a self-administered questionnaire to ensure that they met the following inclusion criteria when first contacted: not having cardiovascular, endocrine, neurological or psychiatric

diseases; not consuming more than 5 cigarettes a day; not consuming drugs habitually; not doing more than 10 hours of exercise per week and not having experienced a highly stressful event in the last month. In addition, participants were asked to not perform extenuating exercise or take drugs or alcohol in the last 24h, and not smoke or take stimulant drinks in the 2h before the experimental session. 5 participants were eliminated for not reaching the intensity preset (70 - 80% of maximum heart rate, HR) in the vigorous exercise. A total of 90 participants (age: M = 22.43, SD = 2.5; women: N = 67, (74.4%)) were finally included in the study. These participants were randomly distributed into two groups, experimental (N = 47) and control (N = 43) using random number assignment in Excel. However, we finally prioritized a larger number of participants in the experimental group, considering possible exclusions in case they did not reach the intended vigorous exercise preset.

Procedure

The experimental session was carried out between 15:00 pm and 20:00 pm and lasted approximately one and a half hours. Participants were cited in the University hall and accompanied in an elevator to the laboratory, avoiding the use of stairs. The general procedure was explained, and informed consent was signed. Participants were connected to the electrocardiogram (ECG) and had 10 minutes of rest as habituation. The last 5 minutes of habituation were taken as baseline. Then, experimental group was exposed to stress (physical exercise), while the control group was submitted to a distractor task (watch a construction documentary of similar length to the stressor). Before and after the stressor/distractor, participants were evaluated for positive and negative mood with the Positive and Negative Affect registry, PANAS (Watson et al., 1988). Five minutes after the stressor or control, both groups performed the Iowa Gambling Task (IGT). This study was approved by the Ethics Research Committee of the University of Valencia in accordance with the ethical standards of the 1969 Declaration of Helsinki.

Vigorous Physical Exercise considered as Stressor

As indicated in the introduction, in this study we have used acute high-intensity physical exercise as a stressor. Thus, experimental group was submitted to 15 minutes of exercise in a cycloergometer. Following Frith et al. (2017), the first 5 minutes were used as warm-up. In the following 5, pedaling intensity was progressively increased. Finally, last 5 minutes had to be performed at 70 - 80% of maximum heart rate (HR_{max}), that is, vigorous exercise (Ponce et al., 2019). The specific HR was calculated and adapted for each participant, using the formula of Karvonen et al. (1957), $\left((HR_{max} - HR_{resting}) \times \%intensity\right) + HR_{resting}$, where HR_{max} was estimated with the formula of Tanaka et al. (2001), $HR_{max} = 208 - (0.7 \times age)$; and $HR_{resting}$ was obtained averaging the last 5 minutes of the habituation period (baseline). On average, our sample had to be between 159.23 (*SD* = 2.98) and 171.16 (*SD* = 2.43) bpm (70 and 80% HR_{max}, respectively).

To prove that stress manipulation was effective, we also obtained the HR during IGT and both groups were compared to each other. This contrast was made with absolute HR_{IGT} values, but also with reactivities (HR_{IGT} - $HR_{baseline}$) to control changes relative to the basal level of each participant. In addition, the positive and negative mood before and after the stressor/distractor was also assessed with PANAS.

Electrocardiogram (ECG)

The ECG was recorded using the third Einthoven derivation with 3 re-usable electrodes, BIOPAC MP150, a transducer ECG-100C and the AcqKnowledge 4.2.0 software. The sampling frequency was 1000 Hz. The ECG was filtered by digital Band

Pass FIR filter, with a low cut-off frequency of 1 Hz and a high cut-off frequency of 35 Hz. (Dellacherie et al., 2011). 12 participants showed some ectopic beats which were corrected using the Heart Timing Signal method (Mateo & Laguna, 2003). For each period (Baseline, Stress and IGT), the mean HR (bpm) was extracted.

Positive and Negative Affect Scale (PANAS)

PANAS (Watson et al., 1988) is a 20 Likert-type items scale (from 1, more than usual, to 4, much less than usual) that evaluates positive mood ($\alpha = .61$) and negative ($\alpha = .64$). Each dimension contains 10 items that must be added. The higher the score, the more positive or negative the mood. PANAS was evaluated before and after the stressor/distractor.

Iowa Gambling Task (IGT)

Decision-making was evaluated through the computerized version of the IGT (Bechara et al., 1994; Chiu et al., 2018). Participants should get the maximum benefit possible over 100 consecutive decisions where they can win and lose money. They can choose from four decks of cards: two disadvantageous (A and B) and two advantageous (C and D). A and B provide large immediate gains, but large losses in the long run. C and D provide lower short-term gains, but lower long-term losses, so their choice leads to higher profit. After each decision, participant receives feedback that can be used to adjust future decisions. Performance was assessed by calculating the Iowa Gambling (IG) index: selections of C and D minus selections of A and B. This index was calculated for the entire task (IG_{TOTAL}), and in blocks of 20 trials to study the learning curve. In addition, the PVL model was used to study the underlying processes that guide the reinforcement-learning in the IGT.

Prospect-Valence Learning (PVL) model

The PVL model with the Delta learning rule (PVL-Delta) (Ahn et al., 2008) was applied to extract 4 parameters. Feedback sensitivity (α), can range from 0 to 1, where values near to 1 implies that the subjective utility is greater; that is,the execution of the task is controlled by the magnitude of the gains and losses; lower values, however, represent that all gains and losses, regardless of their size, are perceived in the same way, so what is relevant is the frequency of gains and losses, rather than their size. Loss aversion (λ), λ can range from 0 to 5, where 1 implies an equal sensitivity to losses and gains, values below 1 indicate greater sensitivity to gains, and values above 1 indicate greater sensitivity to losses (loss aversion). Learning (A), from 0 to 1, represents the weight the subject gives to previous experiences with a deck of cards compared to the weight given to the last result obtained. A higher value of A indicates a greater influence of the last card on the expectations of the deck and quick forgetting of previous selections. On the other hand, a low value indicates the predominance of previous experiences; that is,higher learning. Finally, the consistency (c) parameter, ranging from 0 to 5, indicates whether the participant tends to choose a deck according to his/her expectations or, on the contrary, makes random choices. A value close to 0 would reflect randomness, and a high value would represent greater consistency with expectations.

Each parameter of the PVL-Delta model was estimated for each participant through Hierarchical Bayesian Analyses (HBA; see Anh, 2008 for more details), performed with the hBayesDM package (Ahn et al., 2017) for the R software. The hBayesDM uses Stan 2.1.1 (Stan Development Team, 2017) with the Hamiltonian Monte Carlo (HMC) algorithm as MCMC for sampling the posterior distributions. Following Alacreu-Crespo et al. (2020), we drawn 40.000 samples, after burn-in of 23.333 samples, in three different chains (in sum, a total of 120.000 samples and 70.000 burn-in). The Gelman-Rubin test (Gelman & Rubin, 1992) was used to study if the chains converged

($\hat{R}$) to the target distribution. $\hat{R}$ values of all parameters were 1, which means that convergence was achieved. In addition, to confirm this convergence, the MCMC chains were visually inspected.

Statistical analyses

The results of our study were extracted through Bayesian analyses performed with JASP 0.13.0.0. Bayesian T-Tests for independent samples were used to check homogeneity between control and experimental groups, as well as to study whether there were differences between groups in HR and mood post-stressor, in the PVL-Delta parameters and in the IG_{TOTAL}. A Bayesian repeated measures ANOVA, including group as between-subjects factor, was carried out to study possible differences in the learning curve during the IGT blocks. This analysis compares the null model (without any predictive variables) against three different models: model 1, that contains "Trial Block" factor (the 5 blocks of IGT); model 2, that contains "Trial Block" and "group" (experimental vs control); and model 3, that contains "Trial Block", "group", and their interaction (Trial Block*group). The results report which model obtains the higher evidence. Finally, Bayesian correlations were used to study the possible relationships between the PVL-Delta parameters, as well as between these parameters and the IG_{TOTAL}.

In all analyses the Bayes factor (BF_{10}) was extracted. This is the ratio between the likelihood of certainty of the alternative hypothesis (H_1) and the likelihood of certainty of the null hypothesis (H_0): $P(H_1) / P(H_0)$. The Bayes factor allows us to talk about the degree of certainty of the alternative hypothesis, but also of the null hypothesis (Jarosz & Wiley, 2014). The language used to discuss and interpret the Bayes factor was selected following Jeffreys' terminology, as shown in the guide to computing and reporting Bayes Factors (Jarosz & Wiley, 2014). In Table 1 it can be seen this terminology. As an example, if a Bayes factor of 15 were obtained, this would indicate that the alternative hypothesis is 15 times more likely to be true than the null hypothesis, which according to Jeffreys' terminology is considered strong evidence.

Table 1 - Evidence level for both alternative and null hypotheses according to Jeffreys' terminology (seen in Jarosz & Wiley, 2014)

Bayes Factor	Support for H_1	Bayes Factor	Support for H_0
1-3	Anecdotal	1-.33	Anecdotal
3-10	Substantial	.33-.10	Substantial
10-20	Strong	.10-.05	Strong
20-30	Strong	.05-.03	Strong
30-100	Very Strong	.03-.01	Very Strong
100-150	Decisive	.01-.0067	Decisive
>150	Decisive	<.0067	Decisive

Although our hypotheses were directional, given that there is not enough evidence to rely exclusively on this directionality, in our analysis we used the "difference between groups" as an alternative hypothesis, in favor of exploring different results than those hypothesized. For the T-Tests the priors were described by a Cauchy distribution centered around zero and with a width parameter of 0.707. This corresponds to a probability of 80% that the effect size lies between -2 and 2. For the correlations, the priors were described by a beta-distribution centered around zero and with a width parameter of 1. This corresponds to a probability of 80% that the correlation coefficients lie between -.750 and .750. It should be noted that all analyses were replicated by controlling for sex, with similar results. For this reason, the results presented below do not incorporate this variable.

Results

Preliminary Analyses

Through Bayesian T-Tests we checked that the distribution of participants in the experimental and control groups was homogeneous in terms of sociodemographic variables and baseline measures. We also checked if manipulation was effective. As can be seen in Table 2, there was substantial evidence supporting the absence of differences in BMI, pre-stress mood and basal HR, as well as anecdotal evidence for the absence of differences in age. In addition, although there were more women than men, the distribution of both sexes into the two groups maintained substantially the same proportion (see Table 2).

Table 2 – Homogeneity between groups, PANAS and Heart Rate (HR)

	Experimental (N = 47)	Control (N = 43)	BF_{10}
Age	$M = 22.87 \pm 3.11$	$M = 21.95 \pm 1.47$	0.85
Sex			
Men	25.5%	25.6%	$0.25^{\dagger}$
Women	74.5%	74.4%	$0.16^{\dagger}$
BMI	$M = 22.45 \pm 3.22$	$M = 22.70 \pm 2.89$	0.23
PANAS (Baseline)			
Positive affect	$M = 26.46 \pm 4.67$	$M = 27.09 \pm 3.9$	0.27
Negative affect	$M = 20.76 \pm 4.6$	$M = 21.81 \pm 4.47$	0.32
PANAS (pre IGT)			
Positive affect	$M = 26.93 \pm 4.9$	$M = 27.1 \pm 3.89$	0.31
Negative affect	$M = 21.06 \pm 4.51$	$M = 21.64 \pm 4.54$	0.30
HR (Baseline)	$M = 78.68 \pm 10.29$	$M = 79.81 \pm 11.16$	0.26
HR (Stress)	$M = 162.94 \pm 6.62$	$M = 77.79 \pm 13.65$	1.002×10^{48}
HR (IGT)	$M = 95.33 \pm 9.30$	$M = 78.16 \pm 12.49$	4238.1
HR (Reactivity)	$M = 16.19 \pm 12.14$	$M = 0.70 \pm 21.51$	166.01

M, mean; ±, *SD*; BMI, weight(kg) / height(m)^2; Positive mood, sum 10 items of positive mood; Negative mood, sum 10 items of negative mood; HR, Heart Rate (in bpm); HR (Reactivity) HRIGT - HRbaseline; BF_{10}, Bayes Factor from Bayesian T-Test; †These BF were calculated by means of a Bayesian Binomial Test.

Regarding the stress manipulation effectiveness, it was proved that, during the last 5 minutes, experimental group HR was within the expected according to the vigorous intensity preset (bpm was between M = 157.86, SD = 2.98 y M = 170.23, SD = 2.43). In addition, we can see that there was decisive evidence supporting the HR differences between groups during the last 5 minutes of the stressor/distractor, during IGT, as well as in HR reactivity. However, there also was substantial evidence against the differences post-stressor at a subjective level, e.g. in the emotional state assessed with PANAS.

Behavioral results: IG index and the learning curve

Regarding the learning curve, the Bayesian repeated measures ANOVA revealed that the main factor "Trial blocks" (each of the 5 IGT blocks) obtained the highest Bayes factor, with decisive evidence with respect to the main effect "group" (BF_{10} = 293.08) and substantial evidence with respect to the interaction "moment" x "group" (BF_{10} = 7.32). Thus, both groups increased performance throughout the task in a similar way, without differences in their evolution during the IGT (see Figure 1).

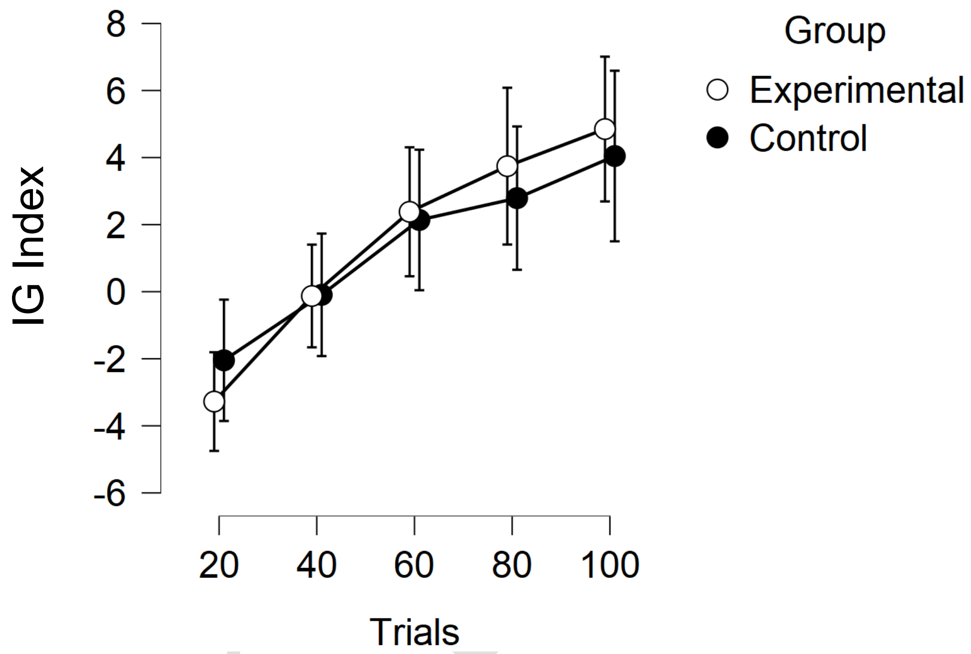

Figure 1 - Between groups comparison of learning curve along the 5 blocks in the Iowa Gambling Task. Means and 95% Confidence intervals.

Decision-making components: PVL-Delta parameters

A Bayesian T-Test for independent samples revealed that there was decisive evidence (BF_{10} = 509.98) in support of the differences between groups in loss aversion (λ). The experimental group showed greater λ (M = 1.38, SD = 0.91) than the control (M = 0.61, SD = 0.6). Moreover, we found decisive evidence (BF_{10} = 710.31) supporting the existence of differences in the learning (A) parameter. Specifically, the experimental group obtained a lower score (M = 0.29, SD = 0.17), with respect to the control group (M = 0.50, SD = 0.27), which means a higher learning in the stressed participants. However, there also was substantial (*BF_{10}* = 0.22) and anecdotal (*BF_{10}* = 0.35) evidence in favor of the absence of differences in feedback sensitivity (α) (experimental group, *M* = 0.22, *SD* = 0.04; control group, *M* = 0.22, *SD* = 0.09) and consistency (*C*) (experimental group, *M* = 0.70, *SD* = 0.49; control group, *M* = 0.79, *SD* = 0.27), respectively.

Correlations between PVL-Delta parameters and IG index

We addressed the possible relation between the general IG index and the parameters of the PVL-Delta model, as well as the internal relations between these parameters. As can be seen in Table 3, the Bayesian correlations provided substantial evidence in support of the absence of correlation between IG_{TOTAL} and PVL-delta parameters. However, decisive evidence of the correlation between loss aversion and both feedback sensitivity and learning were found. In addition, the correlation between loss aversion and consistency received strong evidence. Feedback sensitivity received substantial evidence in support of its negative correlation with learning, and substantial evidence against its correlation with consistency. Finally, substantial evidence against the correlation between learning and consistency was also found.

Table 3 - Bayesian correlations between IG index and PVL-Delta parameters

Variable		1	2	3	4
1. IG_{TOTAL}	Pearson's r	—			
	BF_{10}	—			
2. Learning	Pearson's r	0.054	—		
	BF_{10}	0.149	—		
3. Feedback sensitivity	Pearson's r	-0.126	-0.308	—	
	BF_{10}	0.262	9.714	—	
4. Constancy	Pearson's r	-0.040	-0.127	0.100	—
	BF_{10}	0.141	0.267	0.202	—
5. Loss aversion	Pearson's r	-0.009	-0.513	0.385	0.320
	BF_{10}	0.132	65541.006	132.470	13.936

Discussion

Previous works studied the delayed psychosocial stress influence on IGT (e.g. when the cortisol-peak was approximately reached) and reported a deleterious effect in the decision-making (e.g. Preston et al., 2007; Simonovic et al., 2016, 2018; Starcke et al., 2017; van den Bos et al., 2009; Wemm & Wulfert, 2017). This research aimed to study whether a vigorous physical activity (named as stressor) could produce the opposite effect, and improving decision-making under ambiguity, as Pabst et al. (2013) found in risky contexts. Attending to the IGT classical scoring, our results suggest that physically stressed participants did not perform better than non-stressed participants, but neither did they perform worse. Yet, if we attend to decision-making underlying components, physically stressed participants showed higher sensitivity to punishments (losses) and a greater learning. These results will be discussed in depth below.

First, with regard to stress manipulation, using a vigorous physical activity, all participants in the experimental group reached the pre-set HR level and therefore a vigorous exercise intensity (Ponce et al., 2019). Furthermore, experimental and control group differed in HR during IGT, both in absolute and relative values. The experimental group showed greater physiological activation, in line with the expected physiological effects of stress influence. By the other side, substantial evidence was found against the differences in post-stress mood. This could indicate that although the stressor affected physiologically, it had no influence on the subjective emotional level, as was the case with most studies using psychosocial stressors (e.g. Alacreu-Crespo et al., 2019; Pabst et al., 2013). Nevertheless, systemic stressors can influence cognition even when they are not interpreted by higher-order brain structures, but only processed in limbic forebrain structures, which are implicated in automatic processing (Pighin et al., 2014; Sawchenko et al., 2000).

Regarding decision-making, the total score and the learning curve during the task were similar in both stressed and non-stressed participants. This would support the idea that stress is not necessarily harmful, but also seems to contradict what was observed in Pabst et al. (2013), where stress increased overall performance by facilitating conservative choices. An explanation could be, as mentioned, that vigorous physical activity did not generate emotional discomfort. Moreover, Pabst et al. (2013) used a decision making task with an uncertainty of risk while we used a task with an uncertainty of ambiguity. Therefore, physiological activation may be enough to affect risky decision making (Pighin et al., 2014), but not decision making under ambiguity. However, it should also be noted that the classic form of scoring IGT assumes decision-making as a single dimension, which could not be reflecting its full complexity (Alacreu-Crespo et al., 2020). This is especially relevant if we consider that both the experimental and control groups were composed of young, healthy participants. Since both groups should not face difficulties in learning the appropriate strategy in IGT (Bechara et al., 1994), the margin for improvement in the task may not be large enough to be observed with the overall score.

Nevertheless, if we examine the other parameters provided by the PVL-Delta model, relevant information is revealed. In fact, as Pighin et al. (2014) reported, systemic stressors that act unconsciously influence decision-making sub-components, such as loss aversion (Pighin et al., 2014). Results partially supported our hypotheses, evidencing differences in two of the four PVL parameters: loss aversion and learning. The control group exhibited low loss aversion (λ) level (0.61). In fact, based on the PVL-Delta criteria, this value indicates more sensitivity to gains, rather than loss aversion. Recently, Alacreu-Crespo et al. (2020) showed that healthy controls also had an average λ of 0.40 in IGT. This might suggest that unlike in risky tasks, where it is usually assumed that losses loom larger than gains (Kahneman & Tversky, 1979), people may be more sensitive to gains than losses under ambiguity. Nevertheless, it could also be due to other modulating factors, such as the initial instruction given in IGT: "you must achieve as much money as you can", which could be encouraging the search for gains (Cunningham et al., 2008). More research is needed to answer these questions; however, this result would be in line with the need to contextualize loss aversion rather than consider it as a ubiquitous and generalizable phenomenon (Gal & Rucker, 2018; Mrkva et al., 2020). By the other side, after vigorous physical activity participants showed high loss aversion (λ = 1.38) and, therefore, a higher level than controls. This result supports our hypothesis that stress would increase loss aversion. In turn, this could be in line with the salience of losses hypothesis (Metz et al., 2020). This hypothesis states that stress produces a relocation of the brain resources in favor of the amygdala and in detriment of the prefrontal cortex. The amygdala is one of the main neural bases of loss aversion, constituting, with the insula, an aversive system that responds to negative emotional stimuli (Molins & Serrano, 2019; Sokol-Hessner & Rutledge, 2019). Thus, in line with Sokol-Hessner et al. (2013), if the amygdala is more responsive, negative stimuli could be more easily detected and rejected, which leads to an increased loss aversion. Additionally, this result is according to the reported impact that vigorous intensity aerobic activities have upon inhibitory control in young adults (Pontifex et al., 2019).

Regarding the learning parameter (*A*), as was hypothesized, physically stressed participants had lower levels of *A* than controls; they exhibited a greater learning based on their previous decisions during the task (Ahn et al., 2008, 2017). In addition, a close negative correlation was observed between this parameter (*A*) and loss aversion, which would indicate that loss aversion was somehow implicated in the acquisition of the expectancies about the IGT's decks. It could be seen that the feedback sensitivity *(α)* parameter also correlated negatively with learning (*A)*. However, as was established by the PVL-Delta model (Ahn et al., 2008, 2017), and supported by our results, α indicates the feedback sensitivity and it is directly related to loss aversion. Therefore, we could argue that, ultimately, it was the loss aversion increment who played a fundamental role in the higher learning of the stressed participants. Moreover, loss aversion was also related to a more consistent IGT strategy, e.g., fewer random choices. All these results would support the potentially beneficial role that early stages of stress could play in decision making under ambiguity. These results could explain the lack of results obtained with a similar stressor in short-term memory and learning (Frith et al., 2017); that is, loss aversion could be influencing learning processes, although more research is needed. Thus, and contrary to what a later stage seems to produce, the fast stress response could promote an alertness that increases sensitivity to punishments (losses), which helps them to act as somatic markers in following decisions (Poppa & Bechara, 2018; Starcke & Brand, 2012). These markers could warn of which decks provide punishment and facilitate their avoidance. It has been seen in previous works that this negative reinforcement, as opposed to comparable positive reinforcement, would lead to greater learning (Öhman & Mineka, 2001; Vaish et al., 2008).

Our study is not exempt from limitations. As White & Raven (2014) sustained, in an exercise of such intensity, it is expected that the effects would not only be mechanical, e.g. focused on the heart, but of greater magnitude, involving the fast release of catecholamines and the slower HPA-axis activation. Nevertheless, other measures such as cortisol, alpha-amylase or catecholamines would complement our results to better address the extent to which the stressor affected the organism. On the other hand, although the role of sex was considered by adjusting results by sex, the disproportionate sample (most women) makes it difficult to draw conclusions. Further research is needed to conclude whether our results are generalizable to both sexes, including, in the case of women, the control for menstrual cycle and intake of oral contraceptives. Finally, vigorous physical activity did not produce effects at the emotional level, however, these effects may alter the results. Future research should explore these issues further.

Nevertheless, our work provides a first step in understanding how rapid stress response, obtained using vigorous physical activity, could improve ambiguous decision-making. On the one hand, it highlights the importance of studying the components that underlie this cognitive skill, rather than addressing it as a single dimension. On the other, our results emphasize the need to better contextualize the study of stress and loss aversion, since both phenomena have been usually considered in a negative way but may constitute an advantage depending on the context. They could favor the reinforcement-learning in complex decision-making. Finally, it is also noteworthy that a stressor as common as physical exercise may be affecting our cognition, in line with embodied brain approaches.

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