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Later stages of acute stress impair reinforcement-learning and feedback sensitivity in decision making

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ABSTRACT

Whereas the effects of the early stages of acute stress seem to improve learning and increase loss aversion in decision making, in later stages, the opposite has been found, an impairment in decision making probably due to higher reward-attraction, as the STARS approach suggests. This study aims to investigate the effects of the later stages of acute stress on decision making and its underlying processes using a computational model. We hypothesized that stress would affect underlying cognitive strategies during decision making. Ninety-five participants were randomly distributed into two groups, experimental (N = 46) and control (N = 49). A virtual version of The Trier Social Stress Test (TSST) was used as a laboratory stressor. After 20 min, decision making was assessed by using the Iowa Gambling Task (IGT). The Value-Plus-Preservation (VPP) RL computational model was used to extract decision-making components. As expected, the stressed participants showed deficits in IGT performance on reinforcement-learning and feedback sensitivity. However, there was no gains attraction. These results are discussed by considering that decision making in later stages of acute stress could be based on impairments in prefrontal cortex functioning.

1. Introduction

Hundreds of decisions are made every day, from small decisions (e.g., choosing what to wear) to important ones in domains such as career, health, family, or finances. Making functional decisions throughout our daily lives, which depend on motivational, cognitive, and emotional processes, is important to maintain a healthy quality of life (Pighin, Bonini, Hadjichristidis, Schena, & Savadori, 2020). However, decisions are highly heterogeneous, and what may be an adaptive decision in one context could be detrimental in another (Gigerenzer & Gaissmaier, 2011). Therefore, it is important to consider the specific features of the decisional context.

One of the most widely used tools to measure decision making is the Iowa Gambling Task (IGT; Bechara, Damasio, Damasio, & Anderson, 1994; Bechara & Damasio, 2005), which allows us to study the learning capacity and choice processes underlying decisions made under ambiguity, i.e., when the possible outcomes and their probabilities are unknown (Volz & Gigerenzer, 2012). Briefly, the IGT uses four decks of cards: two disadvantageous decks yield relatively high gains in the short term but huge losses in the long term; by contrast, two other advantageous decks yield lower gains but even lower losses, leading to higher gains in the long term. Each participant must make 100 repeated choices by freely selecting cards from each deck. After each selection, the participants receive gain or loss feedback. Given the ambiguous context, participants' performance mainly depends on their reinforcement-learning capabilities or memory of the prior selections and sensitivity to feedback, which help them to distinguish advantageous from disadvantageous decks. Thus, poor IGT performance is commonly thought to reflect lower learning, characterized by insensitivity to punishments, excessive reward-seeking and risk-taking, insensitivity to future outcomes but an enhanced focus on immediate outcomes (Zeif & Yechiam, 2020), or even poor cognitive strategies during IGT performance characterized by inconsistency during the selections, when the participant does not perseverate with determined decks but rather tends to make selections based on randomness (Singh, 2021).

This poor performance has been related to the effects of acute stress (Cabeza et al., 2021; Schwabe, Tegenthoff, Höffken, & Wolf, 2010; Simonovic, Stupple, Gale, & Sheffield, 2017; Singh, 2021; Starcke & Brand, 2012, 2016), but it also depends on the heterogeneity of the

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stress response, given that it is important to carefully observe which phase is involved when assessing decision making (Starcke, Agorku, & Brand, 2017).

Hence, acute stress is a psychophysiological response that involves two specific systems that can differentially affect decision making: the faster sympathetic nervous system (SNS) activation and the slower hypothalamic-pituitary-adrenal (HPA) axis activity (Hermans, Henckens, Joëls, & Fernández, 2014).

On the one hand, the activation of the SNS occurs immediately after the appearance of the stressor and increases the secretion of catecholamines (Metz et al., 2020). The prefrontal cortex (PFC) is a key region for valuation and reinforcement-learning processes (Gu et al., 2015; Rolls *et al.* 2020), and its activity is modulated by an inverted U-shaped curve of catecholamines. Hence, the first mild-to-moderate catecholamine increase due to stress could enhance the PFC arousal, thus improving decision making, as Pabst, Brand, and Wolf (2013) showed when using a strong laboratory stressor, the Trier Social Stress Test (TSST). However, as soon as catecholamines reach a high level, PFC is taken ''off-line'' in favour of salience-network enhancement (Hermans et al., 2014; Thayer & Lane, 2009). This leads to higher activation in emotional regions such as the amygdala, showing more alertness to exogenous stimuli and making it possible to respond quickly, especially to negative salient stimuli (Hermans et al., 2014; Metz et al., 2020). In this line, the salience-of-losses hypothesis (Margittai *et al.* 2018) states that the sensitivity to negative feedback or punishments (in this case, losses) will be greater, which would favour cautious decisions over reward-seeking. In a context where risk is rewarded, this could be maladaptive; however, as Molins, Serrano, and Alacreu-Crespo (2021) recently found, in a context such as the IGT where reward-seeking is disadvantageous (Bechara et al., 1994), conservative attitudes promoted by this early stage of the stress response were related to higher learning and loss aversion, thus favouring the choice of advantageous decks and, thereafter, decision making. Contrary to the findings of Molins et al., (2021), which focused on the early stages of acute stress on the IGT, the aim of this work was to study what would occur in later stages.

The stress phase that has received the most attention is the late phase. The HPA mechanism is slower. In it, glucocorticoids are released (reaching their peak concentrations approximately 20–40 min after stress onset (Pabst et al., 2013)) and expand the salience-network activity (Hermans et al., 2014). However, glucocorticoids (especially cortisol) play a key role in reward-system modulation by promoting higher levels of striatal dopamine (Scott, Heitzeg, Koeppe, Stohler, & Zubieta, 2006; Wood et al., 2007). This is why the Stress Triggers Additional Reward Salience (STARS) model (Mather & Lighthall, 2012) states that cortisol will promote rewards attraction over sensitivity to punishments, concluding that, under conditions of stress, people usually take more risks and seek immediate reinforcement during decision making (Margittai et al., 2018; Metz et al., 2020). Moreover, impairments in the PFC are especially evident during this phase, resulting in insufficient adjustment from automatic response, altered feedback-processing, and higher inconsistency in their preferences (Fellows & Farah, 2007; Gu et al., 2015; Pabst et al., 2013; Singh, 2021), negatively affecting reinforcement-learning, cognitive flexibility, and rational decision making (Hermans et al., 2014; Van Leeuwen *et al.* 2021).

As can be seen, both increased reward-seeking and PFC impairments could lead to detrimental decision making during the IGT; indeed, this is what has been mainly been observed when performing the IGT in this stress phase (Simonovic, Stupple, Gale, & Sheffield, 2018; Singh, 2021; Starcke et al., 2017; Wemm & Wulfert, 2017). The stressed individuals performed with disrupted learning, showing more automatic processing than deliberate processing, which impaired their capacity to distinguish between advantageous and disadvantageous decisions (Simonovic et al., 2017, 2018). Nonetheless, little is known about the specific cognitive processes that lead to this impaired learning on the IGT under stress, specifically during later phases. In fact, most studies have assessed decision making as a single dimension, only considering the number of good decks chosen relative to bad decks (overall IGT index) or how this index evolves during the task (dividing it into blocks of 20 choices). This impedes disentangling whether the IGT detriments are better explained by the difficulties in reinforcement-learning, mainly attributed to PFC disruption, by greater reward-seeking because of higher activation of the reward-system, or even both at the same time. However, these underlying processes related to cognitive and motivational decision making strategies during the IGT can be further studied by using new developments in computational modelling (Ahn et al., 2014; Serrano et al., 2022; Worthy, Pang, & Byrne, 2013) that make it possible to extract more valuable information about decision-making performance and more precisely describe decision-making deficits.

Here we focus on the Value-Plus-Perseveration (VPP) model (Worthy et al., 2013), which outperformed previous IGT models such as The Expectancy Valence (EV) model and the Prospect Valence Learning (PVL) model, and provides information about relevant cognitive subprocesses that stress could be altering on the IGT. Specifically, the VPP model extracts eight parameters: reinforcement-learning weight (w), memory or learning (A), sensitivity to losses or loss aversion (λ), feedback sensitivity (α), consistency (c), and the perseverance strengths of the decks (k), which depends on both the gains impact (ε_{pos}) and the losses impact (ε_{neg}). Although a computational model (PVL) was recently used to analyse the IGT's cognitive processes under stress, it was done during the early stress response and found higher learning (A) and sensitivity to losses (λ) (Molins et al., 2021). To our knowledge, this is the first study to use computational modelling to analyse how the later stress response influences decision making under ambiguity on the IGT.

The aim of the current study was to assess the effects of later stages of acute stress on decision-making processes. Molins et al., (2021) previously studied the mechanisms of stress during the early stages, demonstrating increased levels of loss aversion and improved decision-making performance in IGT. But this present study aims to further explore these underlying cognitive processes during the later phases of stress to draw deeper conclusions based on prior literature regarding stress dynamics and its onset, since this, as far as we know, is reportedly the first study to examine these processes during the later phases. We hypothesize that, compared to controls, stressed participants will show lower IGT performance, measured by the overall IGT index and the learning-curve. Regarding the VVP model, we expect that its parameters will also indicate dysfunctional decision-making in the stress group. Based on the supposed PCF impairments due to stress (Hermans et al., 2014), and compared to controls, stressed participants will show both lower reinforcement-learning weight (w) and memory (A), as well as less feedback-sensitivity (α) and consistency (c), during deck selections. In addition, and based on the expected higher reward-attraction (Margittai et al., 2018; Mather & Lighthall, 2012), stressed participants will show lower sensitivity to losses relative to gains (λ), and gains (ε_{pos}) will have a higher impact on the perseverance strength of the decks (k), whereas the impact of losses (ε_{neg}) will be lower.

2. Material and methods

2.1. Participants

Based on the average effect size found in a previous study on stress and computational parameters of the IGT (Molins et al., 2021), an a priori power analysis using G*Power indicated a minimum requirement of 85 participants (η_p^2 =.175, power = 95 %, α = 0.05) to perform an ANOVA and compare decision making between groups (experimental vs. control group). We oversampled 10 participants to account for possible exclusions, and so 95 students from the University of Valencia were recruited (age: M = 19.13, SD = 1.875; women: N = 79, (83.2 %)). A self-administered questionnaire was filled out to ensure the following inclusion criteria before starting the protocol: absence of obesity (Body Mass Index (BMI in kg/m^2) > 30)or cardiovascular, endocrine,

neurological, or psychiatric diseases; not consuming drugs habitually or having experienced a highly stressful event in the past month. In addition, all the participants were asked to not consume, in the last 24 h, any psychoactive substances such as drugs, or psychostimulants such as coffee, and not eat, drink, or smoke during the 2 h before the experimental session. The participants were randomly distributed into two groups, experimental (N = 46) and control (N = 49).

2.2. Procedure

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. Testing took place between 15:30 and 19:30. Participants were scheduled to meet in the faculty hall and accompanied in an elevator to avoid using the stairs. The general procedure was explained before the informed consent was signed. Then, they were connected to the BIOPAC MP150 to measure their cardiovascular response during the experiment, which started with 10 min of rest as a habituation phase. The last five minutes were taken as a baseline measure. Next, the experimental group was exposed to the stressor (TSST), whereas the control group was exposed to the distractor task (a documentary that had the same length as the stressor task). After the baseline and stressor or distractor task, the participants were evaluated for negative mood with the Positive and Negative Affect Scale (PANAS), and a Likert-type stress scale (from 1, not at all stressed, to 10, very stressed) was used. Finally, 20 min after the onset of the stressor/distractor, both groups performed the IGT.

2.2.1. Stressor/distractor

Following Montero-López *et al.* (2016), we utilized a software that makes it possible to design of 3D audience, projected onto a 27″ screen at a distance of 1 m from the participant. This is a virtual-reality adaptation of the traditional TSST (Kirschbaum, Pirke, & Hellhammer, 1993), and it consists of three phases, each lasting five minutes. First, participants faced a screen showing a 3D image of a stage curtain, and they were told that they had to give a speech to convince an audience that they were suitable for a position in their dream job. To lend credibility to the experience, a microphone and a camera were added, and participants were told that both the content and formal aspects of their speech would be analysed in real time and that the virtual audience would react accordingly. After the task had been explained to the participants, the "Speech Preparation" phase started, in which the participants had time to prepare and write a draft of the speech. Then, in the "Speech" phase, the draft the participants made was taken away, and they gave the speech about "why they should be hired for a desired job". In this situation, the audience was a virtual jury controlled by the experimenter; at minute 2:30, the "F" key for "Mostly rude/impatient attitude" was pressed to increase the stress levels. Finally, the stressor ended with an "Arithmetic" phase, in which each participant had to face a mental calculation task consisting of performing mental subtractions (e.g., subtracting 7 from 123 as quickly as possible for 5 min and starting again if a mistake is made). Instead, the control group was asked to watch a documentary video of similar length to the stressor.

The TSST-VR facilitated the execution of the study despite COVID-19, avoiding the overcrowding that would occur by including a real audience in the laboratory. Comparable to the original TSST, this protocol has demonstrated good reliability in inducing stress responses, manifested by the increase in heart rate (HR), blood pressure, adrenaline, and cortisol levels, as well as negative mood (Montero-López et al., 2016). However, to ensure that our stress induction was also effective, we assessed HR, negative mood, and subjective stress perception.

2.2.2. Positive and negative affect scale (PANAS)

PANAS (Crawford & Henry, 2004) measures positive and negative mood (α = 0.83). Each dimension is evaluated by 10 Likert-type items, 20 in all (from 1, more than usual, to 4, much less than usual). However, in this study, only the negative affect dimension was analysed. PANAS was evaluated before and after the stressor/distractor.

2.2.3. Stress scale

An ad hoc Likert-type 10-point scale was used to assess subjective levels of stress, ranging from 1, "not at all stressed", to 10, "very stressed". Perceived stress was assessed before and after the stressor/distractor phase.

2.2.4. Electrocardiogram (ECG)

The ECG was recorded by using the third Einthoven derivation with 3 electrodes, BIOPAC MP150, a transducer ECG-100 C, and the Acq-Knowledge 4.2.0 software. The sampling frequency was 1000 Hz. The ECG was filtered by a digital Band Pass FIR filter, with a low cut-off frequency of 1 Hz and a high cut-off frequency of 35 Hz (Dellacherie, Roy, Hugueville, Peretz, & Samson, 2011). For each period (baseline, stress/distractor, and IGT), the mean Heart Rate (HR) (bpm) was measured.

2.2.5. Decision-making performance

A computerized version of the Iowa Gambling Task (IGT) was used. On this task, participants should get the maximum benefit from 100 consecutive decisions, with feedback given after each one to adjust the decisions. Participants started with a fictitious capital of 2000€, and they were asked to choose between four decks of cards: two disadvantageous (A and B) and two advantageous (C and D). A and B provide large immediate gains but bigger losses in the long run. In contrast, decks C and D provide lower gains in the short term but greater benefits in the long run. Performance was assessed by calculating the Iowa Gambling (IG) index: subtracting the total selections from decks C and D from the total selections from A and B (IG_{TOTAL}), but also calculating the selections in blocks of 20 trials to study the learning curve. For a more thorough analysis, the VPP model was used to study the underlying processes that guide reinforcement-learning on the IGT.

2.2.6. Value-plus-preservation (VPP) RL model

First, although the literature indicates that the Value-Plus-Perseveration (VPP) model outperforms previous IGT models (Ahn, Busemeyer, Wagenmakers, & Stout, 2008; Busemeyer & Stout, 2002), we wanted to verify whether it was also the best fit for our sample. As a baseline model preceding the VPP, we used: the Prospect Valence Learning (PVL) model (Ahn et al., 2008), which also has good predictive accuracy and parameters close to those of the VPP. We compared the goodness-of-fit of the two models based on the Leave-One-Out Information Criterion (LOOIC; Park, Yang, Vassileva, & Ahn, 2021). Note that the lower the LOOIC, the better its model fit. As expected, the VPP model (LOOIC = 22572.63) outperformed the PVL model (LOOIC = 25227.80), and so the parameters analysed in our sample were those of the VPP.

The VPP model (Worthy et al., 2013) extracts more informative parameters of the behaviour assessed during the IGT than the classic general index. VPP belongs to reinforcement-learning (RL) models of the IGT, which disentangle psychological processes underlying performance on the IGT (Worthy et al., 2013). Specifically, the VPP model is based on Bayesian logic, which extracts eight parameters: Reinforcement-learning weight (w), which ranges from 0 to 1; a high value would indicate that the subject's decisions would rely more on reinforcement-learning based on integrating a reward history from the previous cards and less on biases or heuristics. Memory (A) ranges from 0 to 1; the closer the value is to 1, the less weight is given to the previous experience, which indicates a greater influence of the last card on the expectations of the next choice and quick forgetting of previous selections. In contrast, values close to 0 indicate a predominance of previous experiences. Feedback sensitivity (α) ranges from 0 to 1; the higher this parameter is, the higher the subjective utility, indicating that the performance during the task is controlled by the perceived size of the gains and losses. Values close to 0 indicate that losses and gains are perceived

almost the same, and decision-making would be led by the frequency of gains and losses rather than their size. Consistency (c) ranges from 0 to 5, values close to 0 indicate randomness during the deck selection, and values closer to 5 indicate that the selections are based on the participants' expectations. Sensitivity to losses or loss aversion (λ) ranges from 0 to 5. Values greater than 1 indicate that the participant performed with more sensitivity to losses than to gains, but values lower than one indicate greater sensitivity to gains than to losses. Finally, the perseveration (K) parameter, similar to (A), ranges from 0 to 1 and indicates the perseverance strength of all the decks; the higher this value is, the lower the perseverance would be. This means that a subject with a value closer to 0 would tend to choose the same decks, whereas higher values would indicate more random or exploratory choices, which could be related to disadvantageous decision making based on lower memory or consistency. This parameter is related to (7) positive impact (ε_{pos}) and (8) negative impact (ε_{neg}) parameters and indicates the impact of gains and losses on perseverance behaviour, respectively.

Each parameter of the VPP model was estimated for each participant through Hierarchical Bayesian Analyses (HBA; see Ahn et al., 2008 for more details), performed with the hBayesDM package (Ahn et al., 2014) 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, Guillaume, Sénèque, Olié, and Courtet (2020), we drew 40.000 samples, after a burn-in of 23.333 samples in three different chains (in all, a total of 120.000 samples and 70.000 burn-in). The Gelman-Rubin test (Gelman & Rubin, 1992) was used to study whether 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, which inspect the trace plots that indicate that the MCMC samples are indeed well mixed and converged, were visually inspected.

2.3. Statistical analyses

Kolmogorov-Smirnoff with Lilliefors correction was used to check normality. The α significance level was set at.05. Partial eta square (η_p^2) symbolizes the effect size. All analyses were performed with IBM SPSS Statistics 25, except for the extraction of the VPP parameters, for which R i386 was used. Repeated-measures ANOVAs were used to test the effectiveness of the emotional stress induction, both physiological (HR) and subjective stress (PANAS and stress scale). Additionally, the VPP parameters and IGT index were analysed through general linear models (ANOVAs). Moreover, comparisons of the groups on the VPP parameters were analysed by the highest density interval (HDI); the posterior distribution spread shows the highest probability of 95 %, the most probable values. If HDI excluded 0 from the obtained interval, the comparison was considered significant.

3. Results

3.1. Preliminary analyses

Experimental and control groups were homogeneously distributed (see Table 1) in age, BMI, subjective stress (negative mood and perceived stress), and physiological stress (HR) at baseline. Even though there were more women than men, chi-square tests showed similar proportions in both groups: women, $p = .74$, and men, $p = 1$.

3.2. Stress induction effectiveness

A repeated-measures ANOVA using group (control vs experimental) as a between-factor was used to check the stress induction. For physiological stress, HR analyses showed a significant main effect of the moment (baseline - TSST /video - IGT) $F_{(1,\ 89)} = 4163.12$, $p = .001$, $\eta_p^2 = .979$, power = 1, and a significant group x moment interaction $F_{(1,\ 89)} = 3.95$ $p = .05$, $\eta_p^2 = .42$, power = 0.50. These results indicate that the physiological stress evolution was different for the groups.

Between-group differences showed higher activation (see Table 1) in the experimental group during the TSST/Video phase $F_{(1,\ 91)} = 31.05$ $p = .001$, $\eta_p^2 = .259$, power = 1. However, during IGT performance, there were no significant differences between groups ($p > .05$) (see Fig. 1).

Regarding the subjective stress, negative affect measured by PANAS

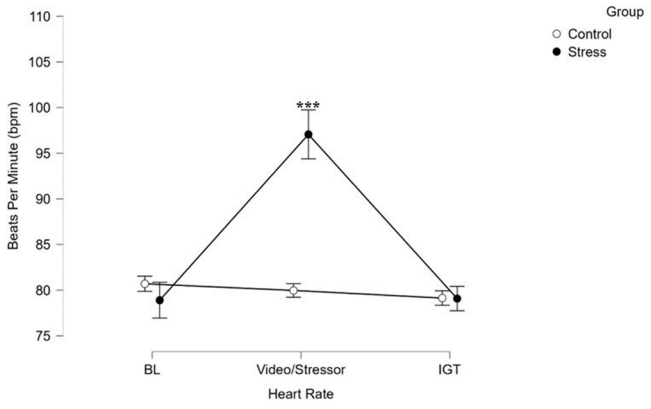

Fig. 1. Heart rate during baseline, stressor/video, and IGT by groups. Stress and Control groups significantly differed in their HR level during the Stressor/Video. Significant contrast at the.001 level; M ± 95 % confidence interval.

Table 1
Homogeneity between groups.

	Experimental (N = 37)	Control (N = 39)	*F*	df between	df intra	*p*-value
Age	$M = 19.33 \pm 2.13$	$M = 18.94 \pm 1.6$	1.012	1	93	0.32
Sex						
Men	14.4 %	18.3 %				
Women	82.6 %	83.7 %				
BMI	$M = 22.06 \pm 10$	$M = 21.59 \pm 2.79$	0	1	93	0.99
Negative affect						
Basal	$M = 19.76 \pm 4.83$	$M = 20.53 \pm 4.47$	0.66	1	93	0.42
Post-stressor	$M = 23.39 \pm 6.03$	$M = 17.14 \pm 4.6$	32.47	1	93	$< 0.001^{***}$
Subjective stress						
Basal	$M = 3.76 \pm 1.91$	$M = 4.14 \pm 1.67$	1.079	1	93	0.30
Post-stressor	$M = 6.43 \pm 1.83$	$M = 3.43 \pm 1.79$	65.32	1	93	$< 0.001^{***}$
Heart Rate						
Basal	$M = 78.89 \pm 10.79$	$M = 80.69 \pm 13.86$	0.480	1	93	0.49
Stressor/distractor	$M = 97.1 \pm 16.05$	$M = 79.96 \pm 13.01$	31.06	1	93	$< 0.001^{***}$
IGT	$M = 78.89 \pm 10.94$	$M = 79.20 \pm 12.5$	0.02	1	93	0.90

M, mean; ± , SD; BMI, weight(kg) / height(m)^2; Heart Rate, in bpm. *p*-values were calculated using ANOVAS. * **Significant contrast at the.001 level.

showed a significant main effect of the moment $F_{(1,\ 93)} = 1893.03$ $p = .001$, $\eta_p^2 = .953$, power = 0.1, and a significant group x moment interaction $F_{(1,\ 93)} = 8.7$ $p = .004$, $\eta_p^2 = .086$, power = 0.831. After the TSST/video phase, there were significant differences between the groups. The stressed group showed higher negative affect than the control group (see Table 1).

Finally, perceived stress showed a significant main effect of the moment $F_{(1,\ 93)} = 688.79$ $p = .001$, $\eta_p^2 = .881$, power = 0.1, and a significant group x moment interaction $F_{(1,\ 93)} = 15.03$ $p = .001$, $\eta_p^2 = .139$, power = 0.97. The stressed group showed higher perceived stress than controls after the TSST/video phase (see Table 1).

3.3. IGT index and learning curve

A univariant general linear model ANOVA showed that the classic index IG_{total} was non-significant between groups $F_{(1,\ 95)} = 0.161$, $p = .69$, $\eta_p^2 = .002$, power = 0.068. In addition, repeated-measures ANOVA showed that both groups accomplished the learning curve (see Fig. 2) $F_{(1,\ 93)} = 6.197$, $p = .015$, $\eta_p^2 = .06$, power = 0.693, which means that both groups experienced gradual learning throughout the task. However, there were no significant differences between them on this curve ($p > .05$).

3.4. Decision-making components: VPP model parameters

In relation to VPP parameters, as Table 2 shows, ANOVAs revealed significant differences in memory, loss aversion, feedback sensitivity, consistency, and reinforcement-learning weight, but no differences were found in perseveration or gain or loss impact. Specifically, all these parameters were significantly lower in the stress group, except for the memory parameter, which was higher. Considering that the memory parameter is scored inversely (that is, the higher the parameter, the lower the memory of past choices), all these results are in line with worse performance during the IGT in the stress group, characterized by lower reinforcement-learning, memory, consistency, loss aversion, and sensitivity to feedback. However, HDI showed only significantly lower memory and loss aversion.

4. Discussion

Most studies point out that stress leads to bad decision making (Hinterbuchinger, Kaltenboeck, Baumgartner, Mossaheb, & Friedrich, 2018; Kong, 2020). However, it has been discussed that these effects could depend on the stress phase assessed (Molins et al., 2021). When Molins et al. (2021) measured the influence of stress on the IGT, they reported that the early stages enhanced learning and sensitivity to feedback, whereas other studies found general, deleterious effects on decision making in later stages (e.g., Pabst et al., 2013; Wemm & Wulfert, 2017). However, these studies did not address the specific processes that stress disrupts depending on its timing. Our chosen model, the VPP, offers similar parameters to Molins et al. (2021), but it also provides new parameters, such as reinforcement-learning weight, that give valuable insights into the cognitive processes. Therefore, this work aimed to fill this gap.

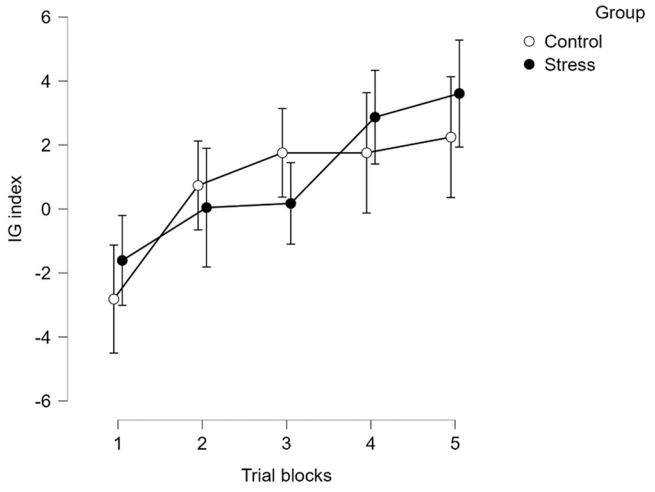

Fig. 2. Between-group comparison of the learning curve throughout the 5 blocks of the IGT. Means and 95 % Confidence intervals.

The overall IGT scores did not reflect differences between groups, which is common in typical population samples. Classic IGT scores tend to be more sensitive when comparing pathological conditions. Nevertheless, computational model analysis was able to reveal that there were, using ANOVAs, differences between stressed and non-stressed participants in their underlying decisional components. The former showed general worse decision-making performance; specifically, they exhibited lower learning weight (w), memory (A), sensitivity to feedback (α), consistency (c), and loss aversion (λ), but no differences were observed in perseverance (k) and its related parameters, the impact of gains (ε_{pos}) and losses (ε_{neg}). These results will be discussed in depth below.

First, with regard to stress manipulation, the experimental group reached the highest HR level during the stressor. Moreover, the experimental group also manifested higher perceived stress and negative mood than controls after undergoing the TSST. All these results suggest that the stress induction worked. However, during the IGT performance, there were no significant differences between the groups in their physiological measures. Because participants started with the decision-making phase 20 min after the onset of the stressor, it is possible that recovery of the sympathetic response was almost reached. Thus, we assume that they performed mostly under the influence of the HPA axis and, therefore, under the enhancement of cortisol, whose peak levels are usually found from 20 m to 40 min after the stressor's onset (Gunnar et al., 2021; Pabst et al., 2013; Zimmer, Buttlar, Halbeisen, Walther, & Domes, 2019).

Focusing on decision making, both the total IGT score and the learning curve were similar in both groups. Therefore, our results do not support other studies that found deleterious effects on decision making in later stages (e.g., Pabst et al., 2013; Wemm & Wulfert, 2017). However, as noted above, this classic assessment of IGT may not be reflecting its full complexity because it views decision making as a single dimension and, thus, does not consider the underlying cognitive processes. Therefore, a VPP computational model was used, finding that, although the general IGT scores were not different, decision making was actually affected by stress.

Based on the STARS approach (Mather & Lighthall, 2012), cortisol would promote rewards attraction over sensitivity to punishments, suggesting that in the later stress phases, people would take more risks and seek immediate reinforcement during decision making (Margittai et al., 2018; Metz et al., 2020). Our results may partially support these arguments. As expected, and in contrast to the loss aversion increment that Molins et al. (2021) found during early stages of stress, we found lower loss aversion (λ) during the later phase. However, if this reduction meant that rewards were more attractive, then a greater weight of gains in decision making should also have been found, but this was not the case. In contrast, the perseveration parameter (K) showed no significant differences in its sub-parameters, gain impact (ε_{pos}) and loss impact (ε_{neg}), which indicates that gains and losses had a similar weight in the decision to persevere in choosing a particular deck. Moreover, it should be noted that loss aversion was computed by considering how sensitive someone is to losses relative to gains (Sokol-Hessner et al., 2009). Thus, a reduction in loss aversion, pointed out by HDI analysis, could mean a higher sensitivity to gains, but also a lower sensitivity to losses. Therefore, in the absence of complementary measures to specifically investigate whether gains became more attractive, it is not possible to confirm

Table 2
ANOVAs between groups on VPP model parameters.

	Experimental (N = 37)	Control (N = 39)	*F*	gl entre	gl intra	*p*-value	η_p^2	95 %HDI for Mean Differences
W (RL-weight)	$M = 0.30 \pm 0.37$	$M = 0.67 \pm 0.02$	3823.29	1	95	< 0.001***	.98	[−0.076, 0.779]
A (Memory)	$M = 0.77 \pm 0.0.27$	$M = 0.17 \pm 0.01$	34222.2	1	95	< 0.001***	.99	[−0.997, −0.158]*
α (Feedback sensitivity)	$M = 0.42 \pm 0.05$	$M = 0.56 \pm 0.05$	185.7	1	95	< 0.001***	.67	[−0.153, 0.431]
C (Consistency)	$M = 1.12 \pm 0.20$	$M = 1.92 \pm 0.19$	378.6	1	95	< 0.001***	.80	[−0.516, 2.163]
λ (Loss aversion)	$M = 0.28 \pm 0.10$	$M = 1.06 \pm 0.31$	269.28	1	95	< 0.001***	.74	[0.128, 1.351]*
K (Perseveration)	$M = 0.37 \pm 0.19$	$M = 0.44 \pm 0.13$	3.86	1	95	0.06	0.04	[−0.037, 0.216]
ε_{neg} (negative impact)	$M = -1.06 \pm 1.27$	$M = -1.05 \pm 1.05$	0.001	1	95	0.98	0.00	[−0.787, 0.322]
ε_{pos} (positive impact)	$M = -0.01 \pm 1.01$	$M = -0.20 \pm 0.97$	0.95	1	95	0.33	0.01	[−0.787, 0.322]

M, mean; ± , SD. *p*-values were calculated using ANOVAS. ***Significant contrast at the.001 level. HDI, Highest Density Interval. *Significant interval

whether stress promoted immediate reward-seeking. In fact, a lower sensitivity to losses may also fit within our second hypothesis: PFC disruption under stress.

As Hermans et al. (2014) reported, acute stress, and especially its later phase, will have deleterious effects on PFC functioning, which can be responsible for impairments in decision making (Pabst et al., 2013). These impairments result in insufficient adjustment of automatic responses, altered feedback-processing, and higher inconsistency in the preferences (Fellows & Farah, 2007; Gu et al., 2015; Pabst et al., 2013; Singh, 2021), negatively affecting reinforcement-learning, cognitive flexibility, and rational decision making (Hermans et al., 2014; Van Leeuwen et al., 2021). This is supported by our results for the parameters of the VPP model. Contrary to what was found in the early stress phase, when stressed participants exhibited higher sensitivity to punishments and, with it, higher learning during the IGT (Molins et al., 2021), we found that, during the later stress stage, stressed participants manifested a lower reinforcement-learning weight (w), which indicates that they had difficulties learning from the rewards (gains) and punishments (losses) that each chosen card provided (Ahn et al., 2014). In fact, they also showed a lower sensitivity to feedback (α) that might be responsible for these reinforcement-learning deficits. Accordingly, the memory (A) and the consistency (c) parameters revealed that stressed participants experienced quicker forgetting of previous selections and higher inconsistency in their choices. Thus, the lower loss aversion found may be better explained by the deficits in feedback sensitivity than by a possible enhancement of the salience-network activity, leading to higher reward-attraction.

Unfortunately, our study has some limitations. First, although physiological and subjective stress has been demonstrated, no hormonal analysis or neuroimaging was performed, and so robust conclusions cannot be drawn regarding cortisol, catecholamines, or salience-network functioning and their effects on the PFC. Therefore, research will be needed to clarify whether our results can actually be attributed to the effect of this hormone on decision making. However, the VPP parameter results can be explained by the aforementioned hypothesis, in addition to what Molins et al. (2021) found in early stages of stress. Moreover, although the role of sex was considered by adjusting the results by sex, the significant number of women in our sample might have influenced the results obtained because sex differences have been shown in IGT performance and in the stress response (Kluen, Agorastos, Wiedemann, & Schwabe, 2017; Lighthall et al., 2012; van den Bos, Homberg, & de Visser, 2013; Wemm & Wulfert, 2017). Thus, even though sex differences were controlled, the disproportionate sample makes it difficult to draw conclusions. Finally, the HDI group comparison did not show the same ANOVA results for the VPP parameters, specifically for reinforcement learning, feedback sensitivity, and consistency. This was expected because all the values inside the HDI have a higher probability density than any value outside the HDI; therefore, it includes the most credible values but is also more restrictive (Kruschke, 2015). We found significant results for memory and loss aversion, showing that there was a strong difference in IGT performance between groups on these parameters, and so it can be concluded that these two cognitive processes may play a major role in stress mechanisms. However, for further studies, we strongly recommend contrasting HDI in a larger sample size, given that the other parameters, the reinforcement-learning weight parameter (W) and perseveration parameter (K), were close to achieving significance. As evidenced by the ANOVA tests, this may indicate a statistically significant trend in their results. Although the lack of sample size may diminish its precision, this does not necessarily mean that there were no statistically significant differences between the groups.

5. Conclusions

Our results seem to favour the hypothesis that the PFC activity is constrained in the later phases of the stress response. Thus, stressed participants showed a disadvantageous performance, where their decisions were inconsistent and not based on reinforcement-learning or memory. Moreover, even though loss aversion was lower, it seems to fit better within a general alteration in feedback sensitivity due to PFC impairment, rather than within the salience of gains expansion that we hypothesized based on the STARS approach, given that higher reward-attraction was not found in this study. Nevertheless, we suggest that future studies especially address the neurobiological processes during the autonomic response by performing further neuroendocrine analyses. They should also consider the possibility of using neuroimaging techniques to study the functioning of different brain structures such as the PFC, not only right after the stressor, but considering all the dynamics of the systems related to the stress response, such as the salience-network or the executive control network, from the onset of the stressor.

Disclosure statement

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this manuscript.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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