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Neural markers of loss aversion in resting-state brain activity

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A B S T R A C T

Neural responses in striatal, limbic and somatosensory brain regions track individual differences in loss aversion, i.e. the higher sensitivity to potential losses compared with equivalent gains in decision-making under risk. The engagement of structures involved in the processing of aversive stimuli and experiences raises a further question, i.e. whether the tendency to avoid losses rather than acquire gains represents a transient fearful overreaction elicited by choice-related information, or rather a stable component of one's own preference function, reflecting a specific pattern of neural activity. We tested the latter hypothesis by assessing in 57 healthy human subjects whether the relationship between behavioral and neural loss aversion holds at rest, i.e. when the BOLD signal is collected during 5 minutes of cross-fixation in the absence of an explicit task. Within the resting-state networks highlighted by a spatial group Independent Component Analysis (gICA), we found a significant correlation between strength of activity and behavioral loss aversion in the left ventral striatum and right posterior insula/supramarginal gyrus, i.e. the very same regions displaying a pattern of neural loss aversion during explicit choices. Cross-study analyses confirmed that this correlation holds when voxels identified by gICA are used as regions of interest in task-related activity and vice versa. These results suggest that the individual degree of (neural) loss aversion represents a stable dimension of decision-making, which reflects in specific metrics of intrinsic brain activity at rest possibly modulating cortical excitability at choice.

1. Introduction

When making decisions under risk people typically display different degrees of *loss aversion* (Kahneman and Tversky, 1979), i.e. higher sensitivity to potential losses than equivalent gains. The consequences of this phenomenon have been described in managerial (Jarrow and Zhao, 2006), financial (Haigh and List, 2005) and political (Berejikian and Early, 2013) settings. Individual differences in loss aversion have been related to gender (Schmidt and Traub, 2002), age (Gachter et al., 2007), and genetic factors affecting thalamic norepinephrine transmission (Takahashi et al., 2013), as well as neural activity and structure (Canessa et al., 2013).

Neuroimaging studies have highlighted the role played by two oppositely valenced neural systems in decision-making. An appetitive system involves the ventral striatum in the network of reward-based behavioral learning (Doya, 2008). This structure displays an asymmetric bidirectional response of activation for gains and deactivation for losses, with the steeper degree of deactivation vs. activation reflecting individual differences in behavioral loss aversion (henceforth “neural loss aversion”; Canessa et al., 2013; Tom et al., 2007). An aversive neural mechanism involves the amygdala, as well as the right posterior insula extending into the supramarginal gyrus (Canessa et al., 2013). These regions, mediating anticipatory responses to aversive events (LeDoux, 2012; Sehlmeyer et al., 2009), are more strongly activated for prospective losses than deactivated for gains. In the right parietal operculum and supramarginal gyrus the degree of asymmetry of this response is additionally related to behavioral loss aversion, thus mirroring the pattern of neural loss aversion observed in the striatum. The bidirectional (gain-loss) signals coded by these regions likely converge to downstream processing structures, e.g. posterior medial frontal cortex (Canessa et al., 2009, 2011, 2013; Tom et al., 2007), where they may underpin cost-benefit analyses (Croxson et al., 2009).

Importantly, however, human and animal studies have shown a more complex pattern in striatal and limbic responses to anticipated

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and experienced outcomes. The striatum has been shown to code expectations about punishments in addition to rewards, i.e. an "aversive" prediction error (Seymour et al., 2007; Delgado et al., 2008) contributing to the anticipation of financial losses (Delgado et al., 2011). Moreover, lesional (Kazama et al., 2012) and electrophysiological (Sangha et al., 2013) evidence of reward-related coding in amygdala neurons supports its role in mediating avoidance learning also by predicting relief (Rogan et al., 2005; Seymour et al., 2005). While the observation of mixed appetitive and aversive neuronal responses is consistent with the aforecited bidirectional gain-loss responses in striatal and insular cortex, further evidence is needed to unveil the role of the these regions, as well as their connecting circuitry, in outcome anticipation and loss aversion.

The relationship between loss aversion and the dynamics of regions involved in affective processing highlights a crucial issue for neural and behavioral sciences (Camerer, 2005). Loss aversion may represent either a *stable* expression of preferences or rather the consequence of a *transient* fearful reaction to choice-related information. Answering this question would inform a more general discussion on the meaning of (ir)rationality in human decision-making. Avoiding losses, indeed, may reflect a genuine expression of preference, rather than a transitory judgment error, if the loss-related aversive feeling is long-lasting (Camerer, 2005).

We addressed these issues by investigating a neural signature of loss aversion in resting-state activity, i.e. the intrinsic pattern of brain functioning in the absence of an explicit task. In this condition, slow synchronous fluctuations of the BOLD signal in different resting-state-networks (RSNs) underlie default connectivity within and between functionally integrated regions (Fox and Raichle, 2007), i.e. those recruited by specific task-related processing (De Luca et al., 2006). We thus predicted that, among different RSNs highlighted by a group Independent Component Analysis, a significant correlation between behavioral loss aversion and the intensity of brain activity would involve the regions displaying neural loss aversion at choice, thus supporting the view of aversion to losses as a stable outcome of processes anticipating prospective affects and bodily states.

2. Materials and methods

2.1. Participants, task and experimental procedure

Fifty-seven right-handed (Oldfield, 1971) healthy volunteers (25 females and 32 males; mean age=23.8 years; standard deviation [sd] =1.8 years) participated in the study. None of the subjects had previously participated in our *f*MRI study on the neural bases of loss aversion (Canessa et al., 2013). Moreover, none of them reported a history of neuropsychiatric conditions or substance abuse, nor was currently taking any medication interfering with cognitive functioning. They gave their written informed consent to the experimental procedure, which was approved by the local Ethics Committee.

Participants performed, outside the MR scanner, a gambling task involving the anticipation of real monetary gains and losses (see Canessa et al. (2013) for a detailed description of the task and experimental paradigm). They were asked to accept or reject a series of 104 mixed gambles offering equal chances (fixed at 50%) to gain or lose different amounts of money, sampled from a symmetrical gain-loss matrix with possible gains and losses being uncorrelated. To avoid possible contaminations of resting-state *f*MRI data by mental activity related to financial outcomes, they were asked to participate in the behavioral task only after the MRI session. Participants' performance resulted either in the increase or decrease of an initial cash endowment that was delivered at least 1 week before task performance to minimize the perception of "windfall" gains. In addition, they completed the short version of the Temperament and Character Inventory (TCI; Cloninger et al. (1994); Italian translation of the revised-TCI by Martinotti et al. (2008)), which measures four dimensions of personality including reward dependence and harm avoidance (data available from 52 out of 57 subjects who agreed to provide personality measures).

2.2. Behavioral analysis

The details of the analysis procedure have been previously reported (Canessa et al., 2013). Briefly, we modeled the probability of accepting the mixed gamble using a logistic psychometric function with separate linear utility functions for gains and losses (Tom et al., 2007):

$$\Pr(Y=1)=\Psi(U_G(G)P_G+U_L(L)P_L)=\Psi\left(\frac{1}{\nu}(\lambda LP_L+(1-\lambda)GP_G)\right)$$

where Pr(Y=1) is the probability of accepting the gamble, $\Psi(\theta)=1/(1+e^{-\theta})$ is the logistic function, $U_G(G)P_G+U_L(L)P_L$ is the expected utility for a mixed gamble, and $U_G(G)=\lambda_G G$ and $U_L(L)=\lambda_L L$ are the linear utility functions ($\lambda_G>0$, $\lambda_L>0$, $G>0$ and $L<0$). As assumed by Prospect Theory, gains and losses can be weighted differently and the utility functions depend on changes in wealth (gains and losses) rather than on the final state of wealth (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). As in Tom et al. (2007) and Canessa et al. (2013) we did not include probability weighting functions and used linear utility functions to allow the comparison between studies. This Expected Utility (EU) model can be re-parameterized in terms of weighted average between gains and losses with a loss aversion $\lambda=\lambda_L/(\lambda_L+\lambda_G)$ and response uncertainty $\nu=1/(\lambda_L+\lambda_G)$ parameters. The loss aversion parameter λ is closely related to the definition of loss aversion used by Tom et al. (2007) ($\lambda_L/\lambda_G=\lambda/(1-\lambda)$). By definition, this parameter indicates a loss averse subject when its value is larger than 0.5. The response uncertainty parameter corresponds to the inverse of the slope of the psychometric function, and reflects how well the model separates the two possible responses.

To test the significance of the loss aversion parameter we also fitted the simpler Expected Value (EV) model to the responses of the subject:

$$\Pr(Y=1)=\Psi(\beta\ EV)$$

where $EV=P_L L+P_G G$ is the expected value of the gamble. Since the EV model is a special case of the previous EU model with loss aversion parameter corresponding to a loss neutral subject (λ=0.5) and $\nu=2/\beta$, the Likelihood Ratio Test (LRT) between the two models follows a χ^2 distribution with 1 degree of freedom. To estimate participants' risk aversion, the EV model was extended to include the risk as follows:

$$\Pr(Y=1|P_G,G,P_L,L)=\Psi(\beta_0+\beta_1 EV+\beta_2 R)$$

where the risk $R=(G^2P_G(1\text{-}P_G)+L^2P_L(1\text{-}P_L))^{1/2}$ corresponds to the SD of the possible outcomes of the gamble. In this model, the 'indifference' straight line $EV=\gamma_O+\gamma_R R$ with $\gamma_O=-\beta_O/\beta_1$ and $\gamma_R=-\beta_2/\beta_1$ expresses a trade-off between the expected value *EV* and the risk *R* of the gambles toward which the participant has no preference. A positive slope γ_R indicates a risk-averse person who accepts more risky gambles only with a commensurate increase of their expected value.

2.3. Resting-state fMRI data collection

We collected functional T2*-weighted MR images with a 3 T Philips Achieva scanner (Philips Medical Systems, Best, NL), using an 8-channels Sense head coil (sense reduction factor=2). Functional images were acquired using a T2*-weighted gradient-echo, echo-planar-imaging (EPI) pulse sequence (36 continuous ascending transverse slices covering the whole brain, tilted 30° downward with respect to the bicommissural line to reduce susceptibility artifacts in orbitofrontal regions; TR=2000 ms, TE=30 ms, flip-angle=85°, FOV=192 mm×192 mm, slice thickness=3.7 mm, interslice gap=0.55 mm, in-plane resolution=2 mm×2 mm). The rs-*f*MRI session included 150 volumes (corresponding to 5 min), preceded by 6 "dummy" functional volumes covering the amount of time needed to