What is the Link Between Emotional Intelligence and Emotion Regulation? Behavioural and Resting-State Functional Connectivity Evidences

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Abstract

A converging body of behavioural findings supports the hypothesis that the dispositional use of Emotion Regulation (ER) strategies depends on trait Emotional Intelligence (trait EI) levels. Unfortunately, neuroscientific investigations of such relationship are missing. To fill this gap, we analysed behavioural and resting state data from 79 healthy participants to corroborate whether the same neural circuit predicting trait EI, also predicts specific ER strategies. An unsupervised machine learning approach (Independent Component Analysis) was used to decompose resting-state functional networks and to assess whether they predict trait EI and specific ER strategies. Behavioural results showed that total trait EI index significantly predicts and negatively correlates with the frequency of use of typical dysfunctional ER strategies (suppression and self-blame). Crucially, we observed that an increased BOLD temporal variability within sensorimotor and language networks predicts both high trait EI and the frequency of use of cognitive reappraisal. By contrast, a decreased variability in language network predicts the use of suppression. These findings support the tight connection between high trait EI and individual tendency to use functional ER strategies, and provide the first evidence that modulations of BOLD temporal variability in specific brain networks may be pivotal in explaining this relationship.

Introduction

Emotion Regulation (ER) is employed to modify current emotional states and adaptively respond to the environment ¹⁻⁴. Not surprisingly, difficulties in ER are involved in compromised well-being and mental health ^{5,6}. Namely, the selection of specific strategies and the excessive or rigid usage of them has been associated with negative outcomes ⁷⁻⁹ contributing to a general distinction between dysfunctional and functional strategies. Among the former, some studies reported that suppression (i.e., the inhibition of the expressive reactions to the emotional events), fails to engender subjective relief after experiencing negative emotions, it comes with several costs in terms of physiological, cognitive and social functioning ^{5,10,11}, and it has been associated with decreased well-being ¹² and several psychopathologies (e.g., depression and anxiety disorders ^{13,14}. Differently, reappraisal (i.e., the ability of cognitively changing the impact of the emotional event) has been generally considered an adaptive strategy, associated with healthiness and personal satisfaction ⁵ and that successfully modulates the affective state ¹⁵ emotion-related peripheral physiological indexes ¹⁶ as well as neural activity ¹⁷.

The simplistic distinction between functional and dysfunctional strategies, however, risks to conceal the role of individual differences in selecting and recurrently using regulation strategies ¹⁸. What leads someone to use one given strategy or to use it more often than others? Even though individuals' dispositions may be crucial to comprehend the variability behind the selection and usage of emotion regulation strategies ¹⁹, investigations in this sense are still scant ^{18,20}. Only recently, an interesting line of research suggests a link between ER style and the construct of Emotional Intelligence ^{18,21}. EI refers to how people experience, understand, and manage emotions both in terms of individuals' abilities (ability EI) and, crucially for the present study, in terms of personal traits (trait EI), that is, on the basis of

individuals' perception of emotional events²². Some studies reported that the ability EI fails in predicting specific emotion regulation processes²³, and when it does, it has to be coupled with perceived competence (trait EI) to comprehend the beneficial consequences of the adaptive response²⁴. Moreover, similar levels of ability EI may result in adaptive as well as deviant responses^{25,26}. The measure of traits EI, then, seems more promising to explain how specific ER processes are selected. More directly, behavioural studies reported that individuals with high levels of trait EI tend to use contextually appropriate regulation strategies, whereas individuals with low levels of EI adopted non-adaptive adjustment styles^{18,27}. However, the causal relationship between trait EI and ER, the nature and the extent of their touchpoint remain unclear, especially in neural terms. The present study, then, aims to corroborate the influences trait EI has on ER style, and to test the hypothesis that their link relies on a shared neural substrate. Indeed, a few neuroimaging studies dealing with trait EI²⁸⁻³⁰ seem to suggest at least a partial neural overlap with findings from neuroimaging studies of ER³¹⁻³⁴. ER processes rely on the activity in brain areas related to both emotion processing (limbic system) and high executive functions (prefrontal regions)³¹⁻³⁶. Moreover, structural studies found a correlation between specific ER style and grey matter alterations in networks including fronto-parietal³⁷ and subcortical³⁸ regions. Similarly, Killgore and Yurgelun-Todd²⁸ found that during presentation of emotional faces, subjects with higher levels of trait EI showed lower activity in limbic and paralimbic regions. More on this, Kreifelts and colleagues²⁹ reported a correlation between traits EI and activity in cortical regions underpinning emotion processing, although they did not find correlation with activity in more subcortical, emotion-related regions (e.g., amygdala, see also³⁹ for similar null results). From a structural neuroimaging perspective, it has been shown that grey matter alterations in fronto-limbic brain areas correlates with traits EI³⁰.

Besides structural and task-related functional evidence, and more importantly for the present study, some authors relied on resting-state functional connectivity (RS-FC) to understand the neural signature of ER and EI. RS-FC is a valuable source to understand the neural mechanisms behind several psychological states⁴⁰⁻⁴², as well as emotional processes^{17,31}. In addition, altered functional connectivity appears to be associated with many psychopathologies^{43,44}. Evidence from resting-state studies showed that higher trait EI scores was associated with higher activity in the inferior frontal gyrus (IFG) and in the inferior parietal lobule (IPL), and with less activity in regions of the insula, cingulum, ventromedial prefrontal cortex (vmPFC), amygdala, hippocampus, parahippocampal gyrus⁴⁶, and fusiform gyrus⁴⁵. Moreover, Takeuchi and colleagues⁴⁷, showed that trait EI score positively correlated with resting-state activity between medial prefrontal cortex (mPFC) and the precuneus, the intracalcarine cortex, and between anterior insula (aIC) and the right portion of the dorsolateral prefrontal cortex (dlPFC). In ER context, Pérez and colleagues⁴⁸ reported a negative correlation between the connectivity of the right basolateral amygdala, the left insula, and the supplementary motor cortex (SMA) with the frequency of use of cognitive reappraisal, and a positive correlation between emotion suppression strategy and the activity of the right basolateral amygdala, the dorsal anterior cingulate (dACC), the supplementary motor cortex (SMA), and in the left medial portion of the amygdala. In contrast, Uchida and colleagues⁴⁹ reported a negative correlation between functional connectivity in the amygdala and medial prefrontal cortex

(mPFC) with the success of applying the cognitive reappraisal strategy. It is important to note also that Dörfel and colleagues⁵⁰, failed to replicate and extend both the previously mentioned studies.

Beside inconsistencies, the extant literature makes it reasonable to hypothesize a neural overlap between EI and ER networks. Notably, the inconsistencies in ER and EI studies, may derive from some methodological issues. Indeed, the majority of studies used massive univariate approaches, and a priori selected regions^{28,28,34,45,48,50}. Widely distributed processes, such as ER or EI, may be better captured using multivariate approaches and a network perspective⁵¹. For this reason, in the present study, we adopted a whole brain data-driven approach (Independent Component Analysis, ICA) that allows us to identify the variations of BOLD signal activity over time within major brain networks rather than considering signals from a priori decided regions of interest. ICA, being a blind source separation method, is an unsupervised machine learning approach able to identify non-overlapping independent neural circuits⁵². Such independent circuits represent meaningful naturally separated circuits that bypass anatomically and histologically based regions, and have the advantage of reducing brain complexity into low dimensional spaces⁵¹. The BOLD temporal variability (SD BOLD) for every resting-state network was used to predict tEI and ER strategies. BOLD variability is defined as a fluctuation in neural activity over time, and an increment in this measure reflects greater functional network complexity and is associated with more effective information integration^{53–55}. According to Moreira and colleagues⁵⁶, this feature is particularly relevant for psychological phenomena that develop over time, such as ER^{57,58}, or affective states⁵⁹ and represents an index of the degree of cognitive flexibility⁶⁰.

Building on the above considerations, the present study is aimed to support and extend previous behavioural findings on the role of trait EI in determining ER strategies, and to disclose which overlapping neural network may subserve this relationship. We hypothesize that the total level of trait EI as well as the score of its subscales (measured by the TeiQueSF questionnaire,⁶¹ significantly predict the use of different emotional regulation strategies (measured by the ERQ,¹² and CERQ questionnaires,⁶²) in the way that the higher the trait EI and/or subscales scores, the higher the usage of ER strategies considered as functional (reappraisal, acceptance, etc), or, on the other side, the lesser the usage of some ER strategies considered as dysfunctional (self-blame, catastrophizing, etc). Then, we delineate the networks underlying EI using an ICA approach on the resting-state functional connectivity, and we assess whether these networks may predict the dispositional use of different ER strategies. We expect to find that the activity in regions responsible for the processing and control of socio-emotional information (e.g., insula, frontal and parietal regions) predicts both the individual differences in EI (as measured by TeiQueSF), as well as the ER usage (measured by ERQ and CERQ). In conformity of the method and neural measure used, these areas will be discussed in terms of common resting state networks.

Results

Behavioural Results

The total EI trait index significantly predict and is negatively associated (negative β values) with the frequency of use of the following strategies: Suppression (ERQ) ($F(1,78)=9.705$, $R^2=0.11$, $p=0.003$; $\beta=-0.335$, $pFDR=0.022$); Self-blame (CERQ) ($F(1,78)=7.867$, $R^2=0.093$, $p=0.006$; $\beta=-0.304$, $pFDR=0.022$); and Catastrophizing (CERQ) ($F(1,78)=8.742$, $R^2=0.10$, $p=0.004$; $\beta=-0.319$, $pFDR=0.022$). For what concerns the four TEIQue-SF factors, Emotionality ($\beta=-0.339$, $pFDR=0.004$), and Well-being ($\beta=-0.239$, $pFDR=0.01$) predict Suppression (ERQ) ($F(4,75)=4.908$, $R^2=0.21$, $p=0.001$); Self-control ($\beta=-0.377$, $pFDR=0.004$), Emotionality ($\beta=0.343$, $pFDR=0.004$), and Well-being ($\beta=-0.339$, $pFDR=0.03$) predict Rumination (CERQ) ($F(4,75)=5.332$, $R^2=0.27$, $p<0.005$); Self-control ($\beta=-0.269$, $pFDR=0.03$), and Well-being ($\beta=-0.332$, $pFDR=0.01$) predict Catastrophizing (CERQ) ($F(4,75)=4.258$, $R^2=0.21$, $p<0.001$); Self-control ($\beta=-0.33$, $pFDR=0.02$) predicts Blaming others (CERQ) ($F(4,75)=2.24$, $R^2=0.12$, $p=0.042$). To conclude, as can be noted from the negative β values of the predictors, the lower is the EI, the higher is the individual tendency to use non-adaptive ER regulation strategies such as Rumination, Blaming others, Catastrophizing, Suppression.

Functional Connectivity Results

Multiple Regression analyses (stepwise) showed that the BOLD variability of IC20 ($\beta=0.295$, $pFDR=0.008$) significantly predicts total EI index ($F(1,77)=7.335$, $r=0.36$, $R^2=0.08$, $p=0.008$); the BOLD variability of IC2 ($\beta=-0.252$, $pFDR=0.025$) significantly predict Self-control ($F(1,77)=5.225$, $r=0.25$, $R^2=0.106$, $p=0.025$); IC18 ($\beta=0.360$, $pFDR=0.003$), IC16 ($\beta=0.239$, $pFDR=0.03$), and IC1 ($\beta=0.208$, $pFDR=0.045$) predict Sociability ($F(3,75)=10.074$, $r=0.458$, $R^2=0.210$, $p=0.001$); finally, IC20 ($\beta=0.380$, $pFDR=0.003$), IC1 ($\beta=-0.309$, $pFDR=0.01$), and IC9 ($\beta=0.235$, $pFDR=0.03$) predict Well-being ($F(3,75)=5.734$, $r=0.432$, $R^2=0.187$, $p=0.001$). To summarize, with the exception of IC1 and IC2 (whose β are negative predictors of respectively wellbeing and self-control factors) the more is the BOLD variability in the others ICs, the higher is the trait EI level. The brain networks identified by the IC's includes clusters of cortical and subcortical regions at a cluster significance level $p<0.05$ ($pFDR$ corrected) and voxel significance $p<0.001$ ($pFDR$ corrected). Based on CONN's correlational spatial match to template approach, the identified ICs are attributable to known resting state networks: IC20 and IC16 = sensorimotor network; IC1 = cerebellar network; IC2 and IC9 = language network; IC18 = visual network.

Among the IC's that were significantly predictive of trait EI, the BOLD variability of IC20 ($\beta=0.494$, $pFDR=0.005$) predicts Cognitive Reappraisal (ERQ) ($F(6,72)=3.224$, $R^2=0.21$, $p=0.007$). Also, the BOLD variability of IC20 ($\beta=0.351$, $pFDR=0.03$), IC16 ($\beta=-0.282$, $pFDR=0.01$) and IC9 ($\beta=0.299$, $pFDR=0.01$), predict Positive Reappraisal (CERQ) ($F(7,71)=3.145$, $R^2=0.23$, $p=0.006$). Finally, the BOLD variability of IC9 ($\beta=-0.360$, $pFDR=0.01$) predicts Suppression (ERQ) ($F(6,72)=2.302$, $R^2=0.16$, $p=0.043$).

As can be noted from the positive β values, the higher is the BOLD variability the higher is the frequency of use of Cognitive Reappraisal and Positive Reappraisal (with the exception of IC16). Whereas, the lower is the BOLD variability the higher is the frequency of use of the Suppression. The brain networks

identified by the IC20, IC16 and IC9 include clusters of cortical and subcortical regions (see Table 1 for details) at a cluster significance level $p < 0.05$ (p FDR corrected) and voxel significance $p < 0.001$ (p FDR corrected) (See Fig. 1).

Table 1

Regions identified in the independent component IC20, IC16, IC9. Clustering indicates the spatial distribution of ROIs at the cortical and subcortical levels. Cluster threshold at $p < 0.05$ (p FDR corrected) and voxel threshold $p < 0.001$ (p FDR corrected, two sided). For each cluster we selected the brain regions with the highest covering proportion (%) of Harvard-Oxford Atlas ROI. Peak are reported in MNI coordinates. L = Left; R = Right; BA = Brodmann Area.

IC	Peak	ROI (Harvard, Oxford Atlas)	p-valueFDR
IC20	-18 + 30 +60	Supplementary Motor Cortex	$p < 0.005$
	-58 -18 +32	R Supramarginal Gyrus	$p < 0.005$
	-60 -20 +30	L Supramarginal Gyrus	$p < 0.005$
	+34 -22 +20	R Hippocampus	$p < 0.005$
	+48 + 04 +26	R Inferior Frontal Gyrus	$p < 0.005$
	-42 -02 -08	Insular Cortex	$p < 0.005$
	+34 -22 +20	L Cerebellum (BA 4-5)	$p < 0.005$
IC9	+18 +08 +14	Thalamus L	$p < 0.005$
	+66 -30 +12	R Superior Temporal Gyrus	$p < 0.005$
	-64 -34 +14	L Superior Temporal Gyrus	$p < 0.005$
	+10 -70 -40	Vermis (BA 8)	$p < 0.005$
	+14 -90 +00	L Intracalcarine Cortex	$p < 0.005$
	-20 -36 -42	L Cerebellum (BA 10)	$p < 0.005$
IC16	-56 -04 +24	Supplementary Motor Cortex	$p < 0.005$
	-64 -36 +44	Supramarginal Gyrus	$p < 0.005$
	+18 +18 -12	L Middle Temporal Gyrus	$p < 0.005$
	+20 -66 -38	Cerebellum (BA 8)	$p < 0.005$
	-22 -68 -40	Cerebellum (BA 7)	$p < 0.005$

Discussion

ER processes are daily employed by individuals to modify the emotional states they are experiencing. However, the individuals' variability to use one or other strategy is still poorly understood. How can such

variability be explained? In the present study we investigated which aspects of trait EI may predict specific ER strategies usage. We were also interested in finding the neural bases associated with EI, by analysing the functional connectivity of naturally grouping circuits decomposed by an unsupervised machine learning approach (ICA). One intriguing question, was whether EI and ER share at least some neural bases. This would be an additional proof of their intimate relationship.

At a behavioural level, we confirm and extend previous studies suggesting a relationship between low trait EI and maladaptive emotion regulation processes^{18,27}. Indeed, we found that individuals with low levels of trait EI are predisposed to use typical non-adaptive ER style (i.e., suppression, self-blame, and catastrophizing). In particular, low scores in the subscale of "self-control" predispose to blaming others and rumination. Low scores in the "well-being" subscale predispose to the use of suppression, rumination, and catastrophizing. Finally, low scores in "emotionality" predispose to the use of suppression and rumination. In a complementary way, functional connectivity results showed that increased BOLD variability in the sensorimotor network identified by the IC20 predicts high score in the total traits EI index. Modulations of BOLD variability in the same and other networks spanning from the visual, language and cerebellar ones also predicted the four subscales of trait EI. Namely, modulations of BOLD variability in visual, sensorimotor (related to IC16), and cerebellar networks predicted high scores in the subscale of sociability. High score in wellbeing subscale was predicted by increased and decreased bold variability in sensorimotor (related to IC20) and cerebellar networks, respectively. Finally, decreased BOLD variability in language network predicted self-control subscale. Most importantly for the present study, increased BOLD variability in network related to sensorimotor (when identified by the IC20 but not the IC16) and language also predicted the use of reappraisal strategy, as measured by both ERQ and CERQ questionnaires. Interestingly, decreased BOLD variability in the language network also predicted the use of emotion suppression strategy.

Rumination and suppression, the two strategies more often predicted by the subscales of trait EI in the present study, have been usually related to negative outcomes and psychopathologies⁵. Likewise, low level of traits EI are also associated with psychopathological disorders^{63,64}. The link between rumination and "self-control", which is associated with difficulties in managing stressful situations and impulsive behaviours, is supported by recent literature suggesting that impulsivity plays a critical role in rumination, and stressor mediated this association⁶⁵. Low self-esteem (a relevant aspect in the subscale of "well-being" along with the feelings of dissatisfaction) emerged as an important predictor of rumination⁶⁶, and it has been indirectly linked to suppression since involved in shame, which has been already coupled with this regulation strategy^{67,68}. In addition, low emotionality and the related difficulty in emotions recognition and expression⁶¹, may lead individuals to use suppression that occurs late in the process of emotion generation⁶⁹. The trait EI subscale of "sociability" surprisingly did not predict any emotion regulation strategy. This null result can be explained by behavioural evidence showing that low sociability is not associated with high psychological reactivity, negative emotional intensity, dispositional negative affect, and personal distress, as shyness for example does. Low sociability is rather associated with low social support seeking⁷⁰, strategy which may have escaped the taxonomy used in the ERQ and CERQ. In

support of that, trait EI predict social sharing when this latter is included in the set of regulation strategies²³.

At a neural level, we enriched our understanding of the neural overlap between trait EI and ER, by showing that two different networks (sensorimotor and language ones) involved in the former, are also involved in the latter. Among areas of the IC20-related sensorimotor network, the inferior frontal gyrus emerged in previous resting-state study on trait EI⁴⁵ and it was interpreted as a part of a circuit related to social and emotional processing. A positive correlation between the activity of frontal regions and trait EI has also been found by Takeuchi and colleagues⁷¹. On the other hand, the supplementary motor cortex (SMA) and the cerebellum positively correlated with the trait EI⁴⁵, playing a critical role in cognitive control mechanisms. The somatosensory cortex, and its portion of the supramarginal gyrus (SMG) are involved in the recognition of emotions, the understanding of the emotional states of others⁷², and are more generally part of the mirror neuron system^{73,74}. Damasio and colleagues⁷⁵ observed a change in activity in the somatosensory cortex during a task in which subjects reflected on experiences that generated different emotional states. An activation of the somatosensory cortex was also observed in tasks of interoceptive awareness, suggesting that this cortical structure may be involved in the awareness of internal states⁷⁶. Finally, insula is deemed to facilitate social interaction, and decision making by integrating sensory, affective, and bodily information, and it has been traditionally reported as neural correlate of trait EI^{47,77,78}. The functional implications of these areas in socio-emotional processing and cognitive control^{45,79} make intuitive their involvement also in control-related ER processes. Another intriguing finding, indeed, is that the same circuit predicting trait EI, also predicts specific adaptive ER strategy. For example, there is evidence of a correlation between the functional connectivity of the left insula, supplementary motor cortex (SMA)⁴⁸, and inferior frontal gyrus⁸⁰ with the frequency of use of reappraisal. Generally, these areas are implicated in the well-established network underlying cognitive control of emotions by reappraisal^{32,36}. In light of this finding, the negative correlation between the BOLD variability in the IC16-related sensorimotor network and the positive reappraisal may seem incoherent at first sight. However, this result is in line with and corroborate the behavioural ones which shows no association between the trait EI Sociability scale and ER strategies. Indeed, it is worth to bring back that, differently from the IC20, which significantly predicted the total trait EI and the well-being scale, the IC16 predicts the Sociability scale and this may explain why this component yield a negative correlation with ER in neural terms. In addition, how figure 1 shows, the two sensorimotor-related components involved overlapping, but still different brain regions.

Among the other EI-related networks, our study showed that also the language network is shared with ER style. More specifically, the BOLD variability in this network positively correlates and predicts adaptive (reappraisal) strategy, and negatively correlates with maladaptive (suppression) strategy. Although this result is less common in neuroscientific literature, recent studies highlight that mechanisms related to language and semantic processing may be shared by several emotion regulation strategies⁸¹. Other works provide more direct evidence that language can increase the discreteness of an emotion

experience, facilitating its regulation^{82,83}. Brain regions involved in semantic processing (i.e., temporal pole) are also functionally connected with sensory processing regions (i.e., sensorimotor area) providing representational content for emotions⁸⁴. Further, activation of language areas (e.g., bilateral temporal gyrus) has been associated with adaptive emotion regulation strategies in which verbal labelling of affective state represents a productive way to reach self-awareness, but, critically, these areas were not involved in suppression strategy⁸⁵. This is in line with the negative correlation we found.

The relation between BOLD variability, trait EI and adaptive vs maladaptive emotion regulation strategies can be better understood coming back to what the BOLD variability means. Several studies point out that greater BOLD variability positively influences adaptability, flexibility and efficiency of neural system in response to the multiplicity and uncertainty of environmental stimuli^{53–55, 86}. As a such, it is reasonable that cognitive and affective mechanisms related to the functionally connected regions are better implemented by individuals showing increased temporal variability in the network⁸⁷. Accordingly, our findings suggest that the increased BOLD variability in the sensorimotor and language networks play a critical role in predicting both high level of trait EI and adaptive emotion regulation strategy, in terms of a better social and emotional information integration, self-awareness along with a more efficient cognitive control. That temporal variability in these networks significantly predicts high traits EI and the frequency of use of Cognitive Reappraisal strategy is explained as an adaptive feature of the neural response, allowing the brain to easily access different "states", required to complete cognitive tasks^{88,89}. By the same token, we could also infer that less variability in language network could imply a difficulty of the subjects to process emotional information resulting in the maladaptive emotion suppression strategy. Then, greater temporal variability may represent a neural predisposition marker which facilitate individuals in the stages underlying the dynamic process of emotional regulation, identification, selection, and implementation⁹⁰. This finding provides a context for and corroborate the hypothesis that regulation strategies and their outcome may depend on factor such as the individual differences. Neural flexibility and adaptability increase perception and control of the emotional event determining at the same time the success of an emotion regulation process⁷. Importantly, resting-state functional connectivity may be pretty helpful to investigate task-independent constructs⁹¹ such as those related to personal traits are.

Besides these new findings, the study has some limitations to point out. While the data-driven approach allowed us to consider the activity of the whole brain and the role of naturally grouping circuits, theory driven analyses (i.e., Dynamic Causal Model) that may facilitate inferences with respect to specific brain regions, or to identify causal relationships between them, may be a valuable and complimentary alternative. In addition, the discussed networks as identified by the spatial match included portions of salience and executive networks. Future studies are needed to explore the contributions of such networks to both EI and ER. Finally, building on the existing literature, we focused on trait EI. However, other aspects of EI may be worth to be investigated.

To conclude, the present findings reveal that the role of trait EI in predicting adaptive ER style relies on a shared and more efficient functional connectivity network involved in social and emotional information

processing to understand self and others' affective states, and in top-down mechanisms which contribute to the control of emotions. Consequently, our study not only provide further support to the causal relationship between traits EI and maladaptive ER strategies, but is also represents a first step to understand the neural mechanisms able to explain this relationship. Increased variability of the BOLD signal within a sensorimotor and language networks is a mainstay for the neural structure of high traits EI and at the same time predisposes to the use of adaptive emotional regulation strategy. By contrast, a decreased variability in language network predisposed to the use of a maladaptive emotion regulation strategy.

Methods

Participants

The data analysed in this study were selected from the open-source dataset "Max Planck Institute Leipzig Mind-Brain-Body Dataset LEMON"⁹². Subjects were recruited by researchers at the University of Leipzig, in Germany, between 2013 and 2015. For this study, we extracted a subset of participants with no substance use or abuse, or familiarity with alcohol dependence, and past or present psychopathologies diagnosis at screening. The subset was therefore composed of 79 subjects (23 females; age range: 20-35 years; mean education: 12.39 years). We extracted raw data from structural MRI scans (T1 Weighted - MP2RAGE) and functional MRI scans (rs-fMRI). With regards to behavioural data, the scores of the following questionnaires were selected: teiQUE-SF (Trait EI Questionnaire - Short Form), ERQ (ER Questionnaire) and CERQ (Cognitive ER Questionnaire).

MRI Data Acquisition

Structural and functional MRI data in the LEMON dataset were acquired with a 3 Tesla MRI scanner (Verio, Siemens Healthcare GmbH). During the acquisition, subjects were asked to remain awake with open eyes while looking at a low-contrast fixation cross. For our analyses we considered a BOLD rs-fMRI scan, using T2-weighted multiband EPI* sequence (TR=1400 ms, TE=30 ms, flip angle=69°, echo spacing=0.67 ms number of volumes=657, voxel size=2.3 mm, total acquisition time was 15 min 30 s) and T1-weighted structural volumes acquired using MP2RAGE sequence (TR=5000 ms, TE=2.92 ms, TI1=700 ms, TI2=2500 ms, FOV=256 mm, voxel size=1 mm isotropic) The structural volumes were acquired with 176 slices interspersed during 8min 22s of scanning⁹².

Questionnaires

Behavioural data used in the present study consist of 3 self-administered questionnaires. The Trait EI Questionnaire Short-Form (TEIQue - SF) was used to measure EI as a personality trait⁶¹. The questionnaire, administered in the German version⁹³ and measures four factors: well-being, self-control, emotionality, sociability, and a total index of trait EI that consists of the average of the above factors. The Emotion Regulation Questionnaire (ERQ), adopted to measure the interindividual differences in the

frequency of use of ER strategies ¹². The ERQ questionnaire was administered in the German version ⁹⁴, and consists of 10 items that allow a measure of the tendency to use two strategies of ER: cognitive reappraisal (6 items) and suppression of emotions (4 items). The Cognitive Emotion Regulation Questionnaire (CERQ), administered in the German version ⁶², was used to measure the cognitive strategies that characterize the individual's style of ER. The questionnaire consists of 36 items divided into 9 scales that measure five strategies defined as adaptive: acceptance, positive refocusing, refocus on planning, focus on positivity, putting into perspective, and four non-adaptive strategies: self-blame, blaming others, rumination, catastrophizing ⁹⁵.

Behavioural Analyses

To test the first hypothesis of the present study, namely that trait EI predicts ER style, we implemented two different analyses using SPSS Statistics for Windows, version 25.0 (SPSS Inc., Chicago, Ill., USA). In the first we implemented a Multivariate Linear Regression (MLR) with ERQ and CERQ questionnaires as dependent variables, while the total trait EI was included as a predictor. Moreover, to assess the effect of every subscale of trait EI, we next implemented a Multivariate Multiple Linear Regression (MMLR) with each subscale of the ERQ and CERQ questionnaires as dependent variables, and the four factors of the TeiQue-SF as predictors. Type I error was controlled by applying false discovery rate (FDR) correction to p-values.

Neuroimaging Analyses

Pre-processing and functional connectivity analysis were conducted using CONN MATLAB Toolbox (version 18b) ⁹⁶. Firstly, we implemented CONN's default pre-processing pipeline using SMP12 default parameters which includes the following steps: functional realignment and unwarping, translation and centering, functional outlier detection (conservative settings), functional direct segmentation and normalization (1mm resolution), structural translation, and centering, structural segmentation and normalization (2,4 mm resolution), functional and structural smoothing (spatial convolution with Gaussian kernel 8 mm). Next, *the denoising* phase was implemented. The objective of this phase is the identification and elimination of confounding variables and artefacts from the estimated BOLD signal. Briefly, these factors are derived from three different sources (BOLD signal coming from white matter or cerebrospinal fluid masks, parameters and outliers defined in the pre-processing step, and an estimate of the pre-processing the subjects' motion parameters) ⁹⁷. Once identified, the factors are entered into a regression model (Ordinary Least Squares) as covariates. Finally, a 0.0008–0.09 Hz temporal band-pass filter standard for resting-state connectivity analyses was applied to the time series. Next, the functional connectivity analysis has been implemented. For this study, we chose to use a data-driven approach by implementing a group-Independent Component Analysis (group-ICA). The group-ICA implemented by CONN includes the following steps: pre-conditioning variance normalization, concatenation of the BOLD signal along the temporal dimension, dimensionality reduction at the group level, fast-ICA for spatial component estimation, and the back-projection for spatial estimation on the individual subject ⁹⁷. The number of independent components to be identified was set to 20⁹⁸. In order to separate noise

components from the underlying resting-state networks, every identified IC were visually inspected. Subsequently, one out of 20 ICs (IC17), due to its extent, did not allow for the delineation of specific areas and was discarded from the following analyses. Finally, we extracted the temporal variability of each IC's, calculated in CONN as SD of each BOLD time-series⁹⁷. Type I error was controlled using cluster-size-based false discovery rate (FDR) correction ($p < 0.05$, voxel thresholded at $p < 0.001$ (Worsley et al., 1996), within each analysis). Next, to assess the relationship between IC's temporal variability and both trait EI and ER, we implemented 2 different analysis by using SPSS Statistics for Windows, version 25.0 (SPSS Inc., Chicago, Ill., USA). Firstly, to address which of the 20 identified IC's predicted the trait EI, we tested the individual explanatory variables effect (IC's BOLD variability values) on the TEIQue-SF factors and total index by using a Multiple Linear Regression model (Ordinary Least Squares) with a stepwise method (forward) for each dependent variable. Because we do not expect that all the identified components to be related to the investigated construct, we chose a method of fitting regression models in which the choice of predictor variables is made by an automatic procedure. This methodology consists of testing the incremental predictivity of the model: starting from a model with no predictor, each explanatory variable is added to the model and compared to the inclusion or exclusion threshold criterion (in our case predictor's p-value ≤ 0.05 for inclusion) until the model reaches its maximum predictivity. Finally, the BOLD temporal variability of IC's that resulted to be significant predictors of trait EI in the previous analysis were entered a Multivariate Multiple Regression (MMR) as independent variables to predict ER scores (ERQ and CERQ subscales). To avoid multiple comparisons issues, type I error was controlled applying false discovery rate correction (FDR) within each analysis.

Declarations

Data Availability

The complete LEMON Data can be accessed via Gesellschaft für wissenschaftliche Datenverarbeitung mbH Göttingen (GWDG) <https://www.gwdg.de/>. Raw and preprocessed data at this location is accessible through web browser https://ftp.gwdg.de/pub/misc/MPI-Leipzig_Mind-Brain-Body-LEMON/ and a fast FTP connection (ftp://ftp.gwdg.de/pub/misc/MPI-Leipzig_Mind-Brain-Body-LEMON/). In the case the location of the data changes in the future, the location of the dataset can be resolved with PID 21.11101/0000-0007-C379-5 (e.g. <http://hdl.handle.net/21.11101/0000-0007-C379-5>).

Author contributions

F.Z. conceived the work, analysed data, wrote the manuscript. B.M. wrote the manuscript. A.G. prepared figure and reviewed the manuscript.

Competing Interests

The authors declare no competing interests.

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Figures

Figure 1

Representation of the ICs shared by trait EI and ER. A) IC20; B) IC9; C) IC16. Left of the panel: 3D inflated brain model for the three ICs (cluster significance $pFDR < 0.05$ and voxel significance $pFDR < 0.001$). Color bar represents positive t -values in orange and negative t -values in blue. Right of the panel: Relation between the ICs and the subscales of trait EI and ER questionnaires. In red, the positive relation; In blue, the negative relation. C. Reappraisal = Cognitive Reappraisal; P. Reappraisal = Positive Reappraisal