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Functional Connectivity with Regions Related to Emotional Regulation is Altered in Emotional Laborers

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Abstract

Emotional labor, characterized by a dysfunctional type of emotional regulation called surface acting, has detrimental psychological consequences on employees, including depression and social anxiety. Because such disorders exhibit psychological characteristics manifested through brain activation, previous studies have succeeded in distinguishing individuals with depression and social anxiety from healthy controls using their functional connectivity characteristics. However, it has not been established whether the functional connectivity characteristics associated with emotional labor are distinguishable. Thus, we obtained resting-state fMRI data from participants in the emotion labor (EL) group and control (CTRL) group, and we subjected their whole-brain functional connectivity matrices to a linear support vector machine classifier. Our analysis revealed that the EL and CTRL groups could be successfully distinguished on the basis of individuals' connectivity patterns, and confidence in the classification was correlated with the scores on the depression and social anxiety scales. These results are expected to provide insight on the neurobiological characteristics of emotional labor and enable the sorting of employees undergoing adverse emotional labor utilizing neurobiological observations.

Key words: fMRI, Resting-state Functional Connectivity, Emotional Labor, Depression, Social Anxiety

1. INTRODUCTION

Social context demands appropriate regulation of emotions, especially in regard to display of emotions. This is particularly true for emotional laborers, who manage emotions for a wage (Hochschild, 1983). Integrating conceptualizations formed by previous work (Ashforth & Humphrey, 1993; Hochschild, 1983; Morris & Feldman, 1996), Grandey (2000) defines emotional labor as an emotion regulation process. As emotional expressions are in discord with the emotions actually felt by emotional laborers (emotional dissonance), emotion regulation strategies are used to narrow the gap. Emotional labor may offer benefits from the organization's perspective in that it implies adherence to its explicit and implicit 'display rules,' which are standards that specify the appropriate expression of emotions that employees should show to the public (Diefendorff et al., 2005;

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Grandey, 2000). For example, if a flight attendant wears a smile instead of expressing anger or irritation toward passengers, the airline may benefit from the external image of kindness. However, previous research suggests that the same may not apply to employees. Emotional labor is known to be closely related to a maladaptive emotion regulation strategy called 'surface acting,' in which employees suppress their true emotions to display mandated emotional expressions (Grandey, 2000). Regarding the process model of emotion regulation proposed by Gross (1998b), surface acting corresponds to the response-focused form of emotional regulation strategy (Huyghebaert et al., 2018) implying suppression, which is known to fail in relieving individuals from experiencing negative emotions, as it occurs after emotional responses (Lee et al., 2016; Lu et al., 2019; Tiphaine et al., 2018). As the implied suppression renders employees to feel inauthentic due to the fact that it does not affect the subjective experience of negative emotions (Grandey, 2000; Gross, 1998a; Gross & Levenson, 1997), surface acting is known to be deleterious. A model suggested by Park et al. (2019) explaining the effect of surface acting on psychological distress demonstrates the mediating role of the aforementioned emotional dissonance (Fig. 1). As such, surface acting is considered maladaptive in that it causes psychological distress via emotional dissonance.

The stated psychological distress is suggested to include adversities like depression and anxiety. One research on call center workers indicates that the level of surface acting in emotional labor is positively associated with depressive symptoms (Kim & Choo, 2017).

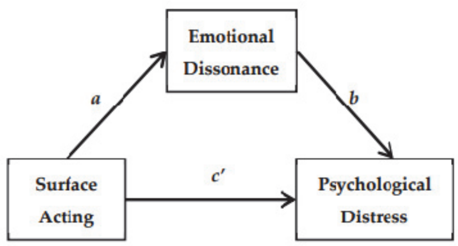

Fig. 1. Model suggested by Park et al. (2019) depicting the effect of surface acting on psychological distress and the mediation by emotional dissonance

Another research targeting bank clerks presents empirical evidence that emotional labor characterized by emotional dissonance may indeed be related to depression (Cho & Park, 2016). Yom et al. (2017) suggest that emotional laborers may feel that negative emotions are no longer bearable as they continuously display mandatory politeness when feeling these emotions, and that such unbearable emotions lead to depression. Surface acting in emotional labor is also suggested to be positively associated with social anxiety, which in turn is negatively associated with work performance (Reyhanoglu & Balikçioğlu, 2019). A study of nursing students in clinical practice demonstrated that social anxiety is positively correlated with emotional labor (Yeom, 2019). Though the influential direction between emotional labor and social anxiety is yet obscure, it is proposed that emotional laborers refrain from expressing emotions to avoid interpersonal conflict (particularly with superiors, as they require obedience to display rules) that may lead to disadvantages in evaluation (Kang et al., 2018; Yeom, 2019). In this perspective, suppressing negative feelings is a performance in which emotional laborers must accomplish, and the anxiety arising from such performance would be identical to social anxiety.

While depression and social anxiety are primarily perceived as psychological characteristics, many studies show that they are accompanied by abnormalities in brain connectivity (Ding et al., 2011; Pannekoek et al., 2013; Sheline et al., 2010). With the advancement in the neuroimaging field, manifestations of abnormal functional connectivity have been successfully utilized to discriminate individuals with depression and social anxiety from healthy controls via machine learning. For example, a study by Zeng et al. (2012) revealed that depressed patients and healthy controls can be correctly classified with a 94.3% accuracy, and that discriminating functional connections are observed in the default mode network, affective network, visual cortical areas and cerebellum. Similarly, Liu et al. (2015) classified patients with social anxiety disorder from healthy controls with a correct classification rate of 82.5%, using connections in or across the default mode, visual, sensory-motor, affective networks and the cerebellum. However, functional connectivity characteristics associated with emotional labor, including the aforementioned psychological factors of depression and social anxiety, are yet to be investigated. One method of examining such characteristics is the functional connectivity-based MVPA (fcMVPA), which is a relatively novel method that uses functional connectivity as features of MVPA (a multivariate technique that analyzes complex patterns generated by a combination of various features) to detect any information in the whole-brain functional connectivity pattern (Dosenbach et al., 2010). Previous neuroimaging studies using the fcMVPA approach have been successful in applying the method to resting-state or task-based fMRI data to classify clinical populations, such as patients with social anxiety disorder (Pantazatos et al., 2014; Zhu et al., 2017), or depression (Drysdale et al., 2017), and to predict individual traits, such as personality (Dubois et al., 2018a), sustained attention (Rosenberg et al., 2016), or fluid intelligence (Dubois et al., 2018b; Greene et al., 2018).

The present study utilized the fcMVPA method and machine learning algorithm to investigate the neurobiological characteristics associated with emotional labor experience. Through the machine learning classification algorithm, we tested whether emotional laborer (EL) and control (CTRL) groups could be distinguished by patterns of intrinsic connectivity, and examined which regions or networks were most critical in classifying these two groups. Furthermore, correlations between psychological consequences, specifically depression and social anxiety, and classification were examined.

2. METHODS

2.1. Participants

Forty-eight individuals were enrolled in the experiment and underwent the Structured Clinical Interview for DSM-IV administered by a trained interviewer. All of the individuals were included as none of them met the criteria for any psychiatric disease and displayed abnormal cognitive function. Among the individuals, 18 participants (1 male, mean age = 38.2) enrolled as emotional laborers, and 30 participants (14 males, mean age = 25) were assigned to the control group. The 18 participants enrolled as emotional laborers were frontline call center employees recruited from Dasan Call Center. We selected the employees from Dasan Call Center considering that a call center employee is regarded a representative emotional labor occupation. All participants had a normal or corrected-to-normal vision and did not have ferromagnetic implants, tattoos, or head injury. All participants were reimbursed with monetary compensation ($100). This prospective study was approved by the Institutional Review Board of the university, and informed consent was obtained from all subjects.

2.2. Clinical assessment

Clinical characteristics of participants, such as depression and social anxiety, were measured through standardized questionnaires. The total score of each participant’s depression was obtained through the Center of Epidemiologic Studies Depression Scale (CESD), which consists of 20 items regarding how frequently depressive symptoms (loss of appetite, depressed mood, difficulty in focusing, loneliness, etc.) occurred during the past week. Participants’ social anxiety was measured using the Liebowitz Social Anxiety Scale (LSAS), which consists of two subscales of anxiety and avoidance in social situations. 24 identical items were rated in terms of both anxiety and avoidance. The total score was calculated through the sum score of both subscales.

The two questionnaires were selected because they have been used in an extensive amount of studies, indicating that they are reliable in assessing depression and social anxiety. The Korean version of CESD and LSAS was used in this study. The Korean version of CESD is acknowledged to show good internal consistency for both non-clinical (.91) and clinical (.89) groups (Cho & Kim, 1993). The Korean version of LSAS is also known to show good internal consistency regarding both subscales in clinical (.92 for anxiety and avoidance) and non-clinical groups (.93 for anxiety and .90 for avoidance; Yu et al., 2007).

2.3. Image acquisition

Neuroimaging data were obtained with a 3T Philips Ingenia MRI scanner (Philips Healthcare, Best, The Netherlands) using a 32-channel head coil. Whole-brain functional images were acquired with a T2*-weighted gradient-echo echoplanar imaging (EPI) sequence (TR = 2000 ms, TE = 30 ms, flip angle = 90°, field of view = 240 × 240 mm, 33 interleaved axial slices without gap, voxel size = 3.75 × 3.75 × 4 mm). The first five dummy volumes were discarded prior to the actual data collection to ensure magnetization equilibrium. Ten minutes of resting-state fMRI (300 volumes) were collected when participants were instructed to keep their eyes closed and not to sleep. A soft foam pad was used to minimize participants' head movement. The high-resolution T1-weighted MRI data were also acquired after functional scans using a 3D T1-TFE sequence (TR = 9.6 ms, TE = 4.6 ms, flip angle = 8°, field of view = 220 × 220 mm; sagittal slices without gap, voxel size = 0.43 × 0.43 × 1 mm).

2.4. Data preprocessing and head motion correction

Functional imaging preprocessing and resting-state functional connectivity analysis were conducted using the Data Processing and Analysis for Brain Imaging (DPABI) toolbox (Yan et al., 2016), which is based on SPM12 (Wellcome Department of Cognitive Neurology, London, U.K.). All functional scans were corrected for slice acquisition timing, realigned to adjust for head motion, co-registered to each participant's high-resolution anatomical images, normalized to standard MNI-152 space, and spatially smoothed using a 6 mm full-width half-maximum (FWHM). These preprocessed data were then submitted to ICA-AROMA, an ICA-based automated tool for removing motion artifact, to minimize head motion confounds that could affect the results of functional connectivity analysis (Pruim et al., 2015a; Pruim et al., 2015b). Additionally, nuisance covariates including mean signals from white matter and cerebrospinal fluid (CSF) masks were then regressed out. The data were also detrended by removing linear trends of time courses and then temporally filtered using a band-pass filter of 0.01-0.08 Hz to reduce the effect of low-frequency drift and high-frequency respiratory and cardiac noise.

2.5. Functional connectivity multivariate pattern analysis (fcMVPA)

To investigate the neurobiological characteristics related to emotional labor experience, we performed a multivariate pattern analysis using functional connectivity features. fcMVPA is a novel data-driven technique that could detect subtle information present in the whole-brain functional connectivity pattern (Dosenbach et al., 2010; Finn et al., 2015), and thus well-suited for exploring how emotional laborers differ from others in terms of neural architecture. By using fcMVPA, we aimed to test whether patterns of intrinsic functional connectivity can differentiate between emotional laborers and healthy controls and, if possible, which networks are the most crucial features that distinguish the two groups.

2.6. Node and edge definition

To define the nodes for functional connectivity that covering the whole-brain, we first parcellated the whole-brain into 246 nodes including both cortical and subcortical regions using the Brainnetome Atlas (Fan et al., 2016). Since this atlas was defined based on structural and functional connectivity, it is suitable for connectivity-based group classification. The mean time-series were then calculated for each region by averaging the BOLD signal time-series of all voxels within each region, resulting in 246 representative time-series for each participant. For each participant, a 246 × 246 connectivity matrix was computed using Pearson correlation coefficients (r) between all pairs of the 246 nodes and then subjected to Fisher's r-to-z transformation. Since these matrices were symmetric with respect to the diagonal, the lower-half triangular parts of these functional connectivity matrices (246 × (246 - 1) / 2 = 30,135) were then used as input features for pattern classification.

2.7. Connectivity-based multivariate pattern analysis

We conducted fcMVPA to test whether resting-state functional connectivity patterns could be accurately classified based on their group membership (i.e., emotional laborers vs. healthy controls). For these group classification tasks, we employed a SVM with a linear kernel and a constant regularization parameter of $c = 1$ using MATLAB Spider toolbox (http://people.kyb.tuebingen.mpg.de/spider). Classification performance was estimated using a leave-one-out cross-validation (LOOCV) method such that iteratively test data from one participant with an SVM classifier trained with data from the remaining $n - 1$ participants. For each iteration, the accuracy would be 1 if the classifier correctly predicted the class label of the test data, whereas the accuracy would be 0 if the prediction was incorrect. The accuracies calculated from all 48 rounds of iterations were then averaged to obtain a single representative accuracy measure.

It is important to note that the larger number of features does not necessarily improve classification performance in machine learning techniques, because it can suffer from the curse of dimensionality. Also, from a neuroscientific perspective, it is also important to increase the interpretability of fcMVPA results, which would decrease as the number of connectivity features increases. Therefore, in order to simultaneously explore the potentially informative features for discriminating two groups and find out the optimal number of features, we applied a filter-based feature selection method using t-test and then iteratively estimated the classifier performance according to the number of features included. For feature selection, 48 iterations of two-sample t-tests were performed to compare the difference between the means of the two populations (i.e., emotional laborers vs. healthy controls) with the data from 47 out of 48 participants by excluding one sample per each iteration. The t-scores obtained from 48 iterations for each feature were then averaged to generate one representative t-score value for each feature. The 30,135 features were then ranked in descending order according to their absolute t-score value, and the z-score transformation was applied to the r-value of each feature to improve normality. We then compute the classification accuracies as a function of the number of features included, Specifically, in the n-th iteration, SVM using the top n features classified whether the class label of a given vector (i.e., functional connectivity pattern) was 'EL' or 'CTRL'. As a result, this procedure yielded a total of 30,135 LOOCV classification accuracy measures.

2.8. Age control

To minimize the potential effect of age on classification results, we applied the age control method used in a previous study that took a similar connectivity-based multivariate approach (Hsu et al., 2018). Before performing the actual pattern classification analysis, we first computed the Pearson correlation between every edge and age and then excluded any edge that was significantly correlated with age ($p < .05$). Although this control method seems to be so conservative that it eliminates edges associated with age but critical for group classification, it is a necessary procedure given the age difference of our samples.

2.9. Permutation testing

To estimate the statistical significance of our classification accuracies, we calculated the null distributions by performing 1,000 iterations of non-parametric permutation testing. For each iteration of permutation testing, we randomly shuffled the original group labels and then conducted the exact same classification analysis, including feature selection, age control, and LOOCV. The *p*-values were calculated as the proportion of permutations that showed higher than or equal to the original classification accuracies.

2.10. Edge feature characteristics

We summarized the edge features of our final classifier using measures drawn from the graph theory. The degree centrality and betweenness centrality for each node was calculated, and nodes with high degree or betweenness centrality were identified. Degree centrality is defined as the number of edges connected to that node, while betweenness centrality is defined as the number of shortest paths between all pairs of all other nodes that pass through the node (Freeman, 1977; Girvan & Newman, 2002). Betweenness centrality can be easily understood as how much a certain node interferes the shortest paths between two nodes, or as how often a certain node is included regarding all shortest paths. Thus, a node with high betweenness centrality is considered to be important in transferring information across the network because it is more likely to be involved in the flow of information.

3. RESULTS

3.1. Demographic and clinical assessment results

Statistical analyses were conducted using the IBM SPSS Statistics 25 software. Difference in age between the EL group (M = 39.56, SD = 8.26) and CTRL group (M = 25.63, SD = 7.28) was significant ($t(46)$ = 6.10, $p < .001$, Cohen's d = 1.79). It should be noted that one of the participants from the EL group did not answer the CESD and LSAS, thus the number of total participants considered in the questionnaires is 47. Independent samples t-tests were conducted to determine whether there were significant differences in the depression and social anxiety scores. The mean CESD score of the EL group (M = 25.29, SD = 10.37) was significantly higher than that of the CTRL group (M = 13.40, SD = 8.46), $t(45)$ = 4.27, $p < .001$. The mean LSAS score of the EL group (M = 49.00, SD = 18.47) was also significantly higher than that of the CTRL group (M = 25.67, SD = 19.54), $t(45)$ = 4.01, $p < .001$. Demographic and clincal assessmet results are shown in Table 1.

Table 1. Demographic and clinical assessment results

	EL group	CTRL group
Age	M = 39.56 SD = 8.26	M = 25.63 SD = 7.28
CESD	M = 25.29 SD = 10.37	M = 13.40 SD = 8.46
LSAS	M = 49.00 SD = 18.47	M = 25.67 SD = 19.54

3.2. Discriminating between EL and CTRL groups using functional connectivity patterns

To investigate whether the EL and CTRL groups can be distinguished by patterns of resting-state functional connectivity, we performed connectivity-based MVPA. We first parcellated each participant's whole-brain into 246 previously defined nodes and then calculated pairwise correlation coefficients between the mean BOLD signal time-series of these brain regions. Each participant's 246 × 246 connectivity matrix was used as input features for linear SVM classifiers. After eliminating 1,716 edges that were significantly correlated with age ($p < .05$), the remaining 28,419 edges were finally used for pattern classification. To find an optimized classifier model with the highest performance while at the same time having as few features as possible, we first iteratively performed an SVM classification and obtained a LOOCV accuracy as a function of the number of edges included.

For pattern classification, we found that two groups (EL vs. CTRL) could be successfully classified based on their resting-state functional connectivity patterns. The peak classification accuracy reached 91.7% when the top 326 edges were included, suggesting that the two groups showed different intrinsic connectivity pattern. The classification performance then gradually decreased and finally reached a chance-level accuracy of 52.1% when the complete set of edges was included, indicating that additional features not always contributed to classification performance.

To test the statistical significance of the peak classification accuracy obtained from fcMVPA, we conducted permutation testing. By performing 1,000 iterations of permutation, we obtained the null distributions of classification accuracy and the *p*-values were also calculated from these null distributions. The results showed that the permutation accuracies of 1000 iterations remained near 50% except for the initial classification results with few features, which suggests that our classification methods are unbiased. The peak classification accuracy of 91.7% with 326 edges was statistically significant (p = .002; permutation test), indicating that this peak accuracy was indeed derived from two distinct functional connectivity patterns of two groups (Fig. 2).

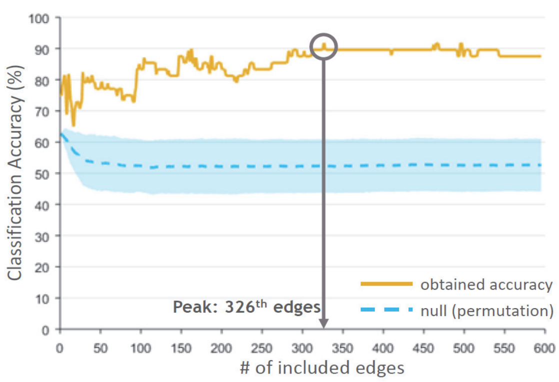

Fig. 2. Classification accuracy performance as a function of number of edges included.

3.3. Investigation of potential confounds

We next tested whether any other potential confounds might have influenced our main classification results. First, although we used ICA-AROMA tool to remove motion-related artifacts, there may be potential remaining effects of head motion in connectivity analysis (Power et al., 2012). We thus additionally investigated whether EL and CTRL groups show different head motion, defined as the mean framewise displacement (FD). The results showed that the head motion did not significantly differ for EL versus CTRL (t(46) = 0.345, p = .732). More specifically, when we compared each six head motion parameters (i.e., three for mean translation and three for mean rotation) separately, any of these parameters was not significantly different between two groups (Tx, t(46) = .057, p = .955; Ty, t(46) = 1.094, p = .280; Tz, t(46) = .499, p = .620; Rx, t(46) = 1.704, p = .095; Ry, t(46) = .031, p = .975; Rz, t(46) = .015, p = .988). Taken together, these results suggest that our main classification result was not due to potential differences in head motion between two groups.

Next, we note that our sample of participants was not balanced for gender (EL: 1 male, 17 females; CTRL: 14 males, 16 females). We thus tested whether our final classification model with the peak accuracy could predict gender regardless of the original group label (i.e., EL vs. CTRL). The accuracy of gender classification with the same 326 edges was 64.58%, which did not significantly exceed chance (p = .22; permutation test), suggesting that our main classification performance was not due to the imbalanced gender ratio of each group.

3.4. Relating classifier evidence with behavioral measures

To further investigate the nature of our connectivity-based classification results, we computed the distance from hyperplane for each participant and then examined whether this value correlated with behavioral measures. Basically, a binary linear SVM classifier divides the feature space into two spaces corresponding to each class label by finding the optimal decision boundary, which typically referred to as the 'hyperplane'. Thus, while the direction of each participant means the SVM classifier's decision, the distance from the hyperplane can be interpreted as the "confidence" of that decision. In other words, participants farther from the hyperplane in the

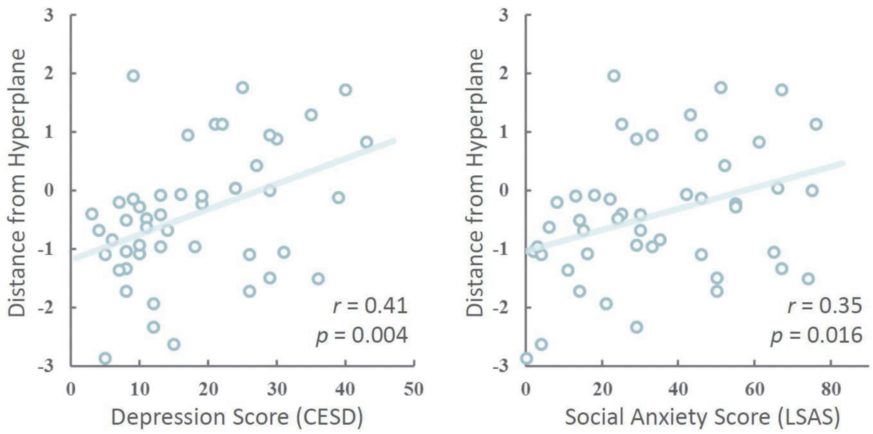

Fig. 3. Correlation between behavioral measures and distance from hyperplane

positive (+) direction can be more confidently classified as 'EL', and participants farther from the hyperplane in the negative (−) direction can be more confidently classified as 'CTRL' (Etzel et al., 2016; Frankland & Green, 2015; Qiao et al., 2017). By calculating these values, we could obtain a continuous one-dimensional measure as a classifier evidence and explore the relationship between this measure and the behavioral characteristics of each participant.

This analysis revealed that the distance from hyperplane showed a significant correlation with the CESD score (r = .40, p < .001), indicating that the higher the depression score, the more confidently the participants were classified as 'EL'. Also, the LSAS score was positively correlated with the distance from hyperplane (r = .35, p < .001), indicating that the higher social anxiety score, the more confidently the participants were classified as 'EL' (Fig. 3).

3.5. Edge feature characteristics

Since the edges of our classification model are distributed throughout the whole-brain, we summarized the edge features of our final classifier using measures drawn from the graph theory. First, we calculated the degree centrality. The node with the highest degree centrality was the superior parietal lobule (SPL). In addition, several other nodes including the inferior parietal lobule (IPL), posterior superior temporal sulcus (pSTS), thalamus, medial frontal gyrus (MFG), superior frontal gyrus (SFG) also showed higher degree centrality. To further explore the characteristics of the edge feature of our classifier, we additionally calculated the SVM weight for each edge. The SVM weight was calculated via the Spider Machine Learning Toolbox (http://people.kyb.tuebingen.mpg.de/spider). Detailed explanation on

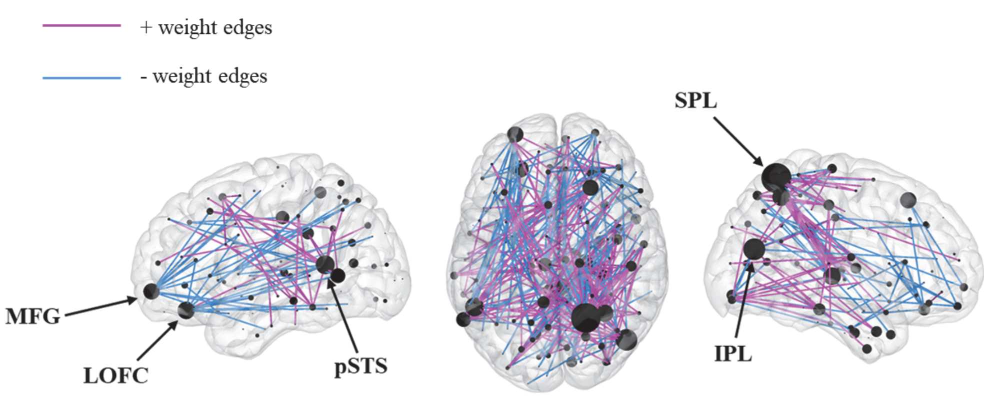

Fig. 4. Edge feature characteristics

the speficic formula used can be found in the article by Qiao and colleagues (2017). When the degree centrality was computed separately according to the sign of SVM weight (i.e., + weight for EL, - weight for CTRL), the SPL and IPL showed higher degree centrality calculated from + weight edges, and the OFC and MFG showed higher degree centrality calculated from – weight edges (Fig. 4).

Next, we also computed the weighted betweenness centrality with the SVM weight for each edge. The results were similar to the results of the previous degree centrality analysis. The node with the highest betweenness centrality was the SPL, and the MFG, SFG, OFC, thalamus, pSTS, IPL nodes also showed higher value of weighted betweenness centrality.

4. DISCUSSION

In the present study, we investigated whether EL and CTRL groups showed distinct patterns of resting-state functional connectivity. The results revealed that the classification of these two groups based on functional connectivity features was successful. Further detailed analysis suggested that these classification results might be related to the emotional laborers' depression or social anxiety symptoms due to the experience of emotional labor, rather than other confounds such as head motion, age, or gender. Given the data-driven nature of our fcMVPA approach and the distributed nature of the edges used in our classification model, we summarized the edge features using graph theory measures to explore the potential hub regions critical to discriminate these two groups. The results showed that several parietal and frontal regions including SPL, IPL, OFC, MFG, and SFG might be the hub regions that make the connectivity patterns of the two groups different.

The hub regions elicited in the present study are in line with previous research on the neural basis of emotion regulation. The IPL and SPL are suggested to be related to the appraisal process in emotion regulation based on experiments using emotional stimuli and fMRI observations (Drabant et al., 2009; McRae, 2010; Ochsner et al., 2002; Roberto, 2013). While one study discovered hyper-connectivity between the periaqueductal gray and the IPL in social anxiety disorder patients (Anteraper et al., 2014), a study on mindfulness-based stress reduction, which is a well-known emotion regulation strategy, showed an increase of response in the IPL and SPL regions in social anxiety patients after 8 weeks of practice reflecting attentional engagement (in contrast to avoidance) to the given emotional probe (Goldin et al., 2013). Moreover, resting-state connectivity between the SPL and regions or networks such as the ventral caudate, default mode network, and both cerebral hemispheres are characteristic in depression (Cieri et al., 2017; Yang et al., 2017).

In a more comprehensive network perspective, the high centrality demonstrated by certain nodes suggest further implications. As a part of the default mode network, the SPL is proposed to be involved in the notion of 'surveillance' or 'watchfulness' to environmental cues in resting-state (Davey et al., 2016). Based on the high LSAS score and focused connectivity to the SPL, it is plausible to interpret that the EL group may exhibit excess surveillance, especially to social cues, even when tasks are absent. This interpretation is further supported by the fact that the pSTS, which was observed as another key node, is known to be a focal point of the brain network for social perception (Lahnakoski et al., 2012). It is also noteworthy that the IPL, which is also a part of the default mode network, functions as a critical convergence area for various networks concerning attention and social interaction (Kernbach et al., 2018; Segheir, 2013), and serves as a key region for social cognition (Numssen et al., 2021). Notably, regarding its function in attention, it is suggested that the IPL is associated with allocating attention to relevent information, encoding salient stimuli, and maintaining attention (Ciaramelli et al., 2008; Singh-Curry & Husain, 2009). These network characteristics altogether may reflect the prolonged distress the call center workers experience receiving constant complaints from other people and the sensitivity they possess in discerning others' emotions, perhaps to express their own as the display rules require.

The result that the OFC, which is well-known as part of the limbic system (Mega et al., 1997), was also a hub region differentiating the EL group and CTRL group supports possibilities of abnormalities in emotion regulation. Many studies confirm the OFC's association with the emotion regulation process, including emotional control, reappraisal and behavioral expression of emotions (Davidson et al., 2000; Golkar et al., 2012; Hooker & Knight, 2006; Shimamura, 2000). For example, the BOLD signal in the OFC increased when participants were instructed to suppress their emotional reactions in response to a sad film (Lévesque, 2003). Moreover, connectivity between the OFC and amygdala is suggested to predict successful emotion regulation (Banks et al., 2007). Such observed association of the OFC may be related to the pervasive surface acting emotional laborers experience.

To our knowledge, this is the first neuroimaging study to examine the neurobiological characteristics of emotional laborers. Previous studies on emotional labor have often focused on the psychological mechanisms of emotional labor (Grandey & Gabriel, 2015). Taking advantages of both resting-state fMRI that can identify important neural changes including the occupational effects and machine learning technique that can detect subtle information, we showed that fcMVPA would provide a useful method to examine the neural mechanisms associated with work experience such as emotional labor. Although our exploratory data-driven approach provides an important starting point for studies on the neural characteristics of emotional laborers, further research is needed to unravel the neurocognitive basis of emotional labor.

Apart from results based on neurobiological measurements, clinical assessments also presented some noteworthy implications on the mental health of emotional laborers. The mean CESD score of the EL group was higher than the traditional cutoff score of 16 for clinically screening major depression. This result is in line with previous research suggesting that emotional laborers may indeed experience depressive symptoms (Cho & Park, 2016; Kim et al., 2002; Kim & Choo, 2017). Similarly, the mean LSAS score of the EL group was also higher than the suggested cutoff score of 30 (Rytwinski et al., 2009) for classifying social anxiety. Though study on the relation between social anxiety and emotional labor is less robust than that of depression and emotional labor, our data suggests that emotional laborers are more vulnerable to social anxiety than others. Future research may investigate factors such as avoidance of interpersonal conflict that may explain this relation. As a whole, the results on our questionnaires raise alarm to managing the psychological adversities of emotional labor.

Although our study holds important implications, it is not without its limits. We used several methods to control the effects of confounds such as head motion, age, and gender. However, it is possible that these effects still remain because our data set was not matched for these variables, and the two groups lack in homogeneity. In addition, our classification results do not provide a causal relationship between the experience of emotional labor and the structure of functional connectivity. Thus, future studies with a larger, well-controlled sample and longitudinal data would provide more rigorous findings on the influence of emotional labor on the neural structure.

5. CONCLUSION

In summary, classification between emotional laborers and controls based on resting-state functional connectivity was successful. Our findings suggest that functional connectivity-based MVPA is an especially useful technique to explore the occupational effects on the brain. Moreover, by showing that several parietal and frontal regions play a key role in distinguishing these two groups, we provide an important starting point to further study the neural basis of emotional labor.

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