

Personality cannot be predicted from the power of resting state EEG

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Abstract

In the present study we asked whether it is possible to decode personality traits from resting state EEG data. EEG was recorded from a large sample of subjects ($n = 309$) who had answered questionnaires measuring personality trait scores of the 5 dimensions as well as the 10 subordinate aspects of the Big Five. Machine learning algorithms were used to build a classifier to predict each personality trait from power spectra of the resting state EEG data. The results indicate that the five dimensions as well as their subordinate aspects could not be predicted from the resting state EEG data. Finally, to demonstrate that this result is not due to systematic algorithmic or implementation mistakes the same methods were used to successfully classify whether the subject had eyes open or eyes closed and whether the subject was male or female. These results indicate that the extraction of personality traits from the power spectra of resting state EEG is extremely noisy, if possible at all.

1. Introduction

Personality can be defined as a relatively stable pattern on thinking, feeling and acting. These patterns can be explained by the idea of personality traits – underlying mechanisms that cause variation in observable personality characteristics (Deary, 2009). According to a dominant Five Factor model (FFM), observable personality is mostly determined by five major traits – Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness (McCrae & Costa, 2008; McCrae & John, 1992). Their relatively high cultural universality, temporal stability, and heritability suggest that the Big Five traits may represent some parameters of fairly specific brain networks (Corr, 2004; DeYoung & Gray, 2009; Kennis, Rademaker, & Geuze, 2012).

If traits indeed reflect individual differences in tonic brain function, then measures of baseline brain activity may provide a direct way for personality assessment. A relatively cost-effective way for quantifying the biological origins of traits could thus be developed by finding reliable

correlates of trait levels from the resting state EEG signal. However, existing attempts to do this have generally yielded mixed results. For instance, an early hypothesis relating Extraversion to baseline brain arousal turned out to be a gross over-simplification (Stelmack, 1990). Another influential idea linking anterior asymmetry in EEG alpha (8-12 Hz) band power to individual differences in approach and avoidance systems of the brain (Coan & Allen, 2002; Davidson 2001), has similarly not been confirmed using meta-analytic methods (Wacker, Chavanon, & Stemmler, 2010).

On the other hand, new findings keep suggesting novel candidate parameters of resting state EEG as potential correlates of certain personality traits. For instance, mid-frontal theta power has been found to co-vary with Extraversion (Knyazev, 2009; Wacker et al., 2010). Meanwhile, the extent of negative relationships between power in lower (delta and theta) and higher (alpha and beta) frequency bands (i.e. cross-frequency anti-coupling) seems also to index approach-avoidance related individual differences (Schutter & Knyazev, 2012). Then again, this hopeful state of affairs might simply reflect the fact that the proposed correlates are still novel and negative findings remain to be published.

Most of the existing research on resting state EEG correlates of personality traits has been conducted in a hypothesis-driven way, concentrating usually on a single parameter at a time. An alternative approach would be to use data-driven techniques to first of all assess the extent to which resting state EEG signal contains information on personality and then search for relevant correlates in a more comprehensive and systematic manner. The main aim of the present study is to test such an approach. To that end we used classifiers, mathematical models that map input data to a set of classes or labels, to predict personality traits from resting state EEG signals. The classifiers were first trained using a set of data with known classes and then their performance was evaluated on data not used for the training phase.

A secondary aim of the present study is to investigate which level of personality trait description is best suited for relating to resting state EEG. In an influential paper, DeYoung and colleagues identified two lower-order aspects for each of the Big Five traits (DeYoung, Quilty, & Peterson, 2007). Subsequent research has demonstrated that this level of trait descriptions may have more homogenous brain origins (e.g. DeYoung, 2013). We therefore test if the information contained within resting state EEG is more reliably related to the 10 aspects compared to the 5 traits of the Big Five.

2. Results

We analyzed a large dataset collected from 309 participants. This dataset consisted of eyes open and eyes closed resting state EEG recordings (32 active electrodes) together with Big Five personality scores assessed using validated self-report questionnaires.

In the first part of the analysis, we trained statistical classifiers to map the features of the resting state EEG to personality scores of individual subjects. In particular, we used the power spectra of the EEG signals as the basis for the features or explanatory variables. The predicted variable consisted of the binarization (using a median split) of the score for each personality trait (see Methods, *Personality measures*). Given the exploratory nature of the analysis we scanned different combinations of classifier parameters and features from the EEG power spectra to find the configuration that best classified each personality trait. To avoid *cherry-picking* or overfitting the results we always assessed the selected classifiers on a separate subset of subjects.

Thus, we used a nested cross-validation approach. We applied 10-fold cross validation and with 90% of data we used again 10-fold cross-validation in order to choose the hyper-parameters of the classifier (including different data pre-processing options, dimensionality reduction, and the choice between linear and non-linear SVM classifier, see Methods). Then, we selected the classifier that performed the best (by minimizing misclassification rate) for each personality trait. Subsequently, the remaining 10% of subjects from the first cross-validation were used to estimate the misclassification rate of the selected classifier. This procedure was repeated 10 times and the final misclassification rates represent the averages over these 10 partitions (see Methods, *Classification of the Personality Traits*).

The results for the binary classification of the test subjects are shown on Figure 1. They indicate that none of the personality traits were correctly classified above the level of significance (binomial test, $p > 0.05$) from any of the explored combinations of resting state EEG features.

Although the binarization of the personality scores is conceptually simple, robust and easy to interpret, it also leads to a loss of information that might hamper the predictive power of the classifiers. Thus, we next tried to predict the personality score of each trait as a continuous variable. For this case, instead of SVM classifiers, we used LASSO and elastic nets models of regressions. These models of regression include a penalty term that reduces the number of explanatory variables used while minimizing the error of the regression. Given the large number of features considered in our analysis, using sparse regression models allows us to control for over-fitting

Results of 5 binary classifiers

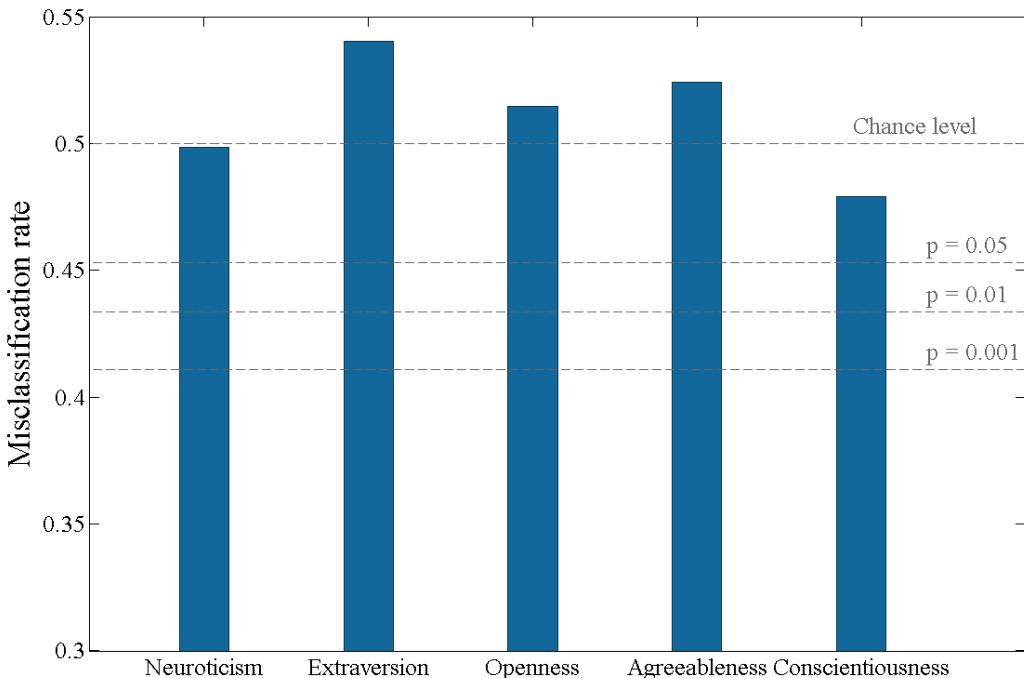


Figure 1: Misclassification rates of Big Five personality traits. The personality scores have been binarized with a median-split. None of the misclassification rates of five personality traits is statistically significant ($p > 0.05$).

errors, as sparse models often tend to generalize better for novel data. Following the same nested cross-validation approach as in the binary classifier pipeline, the results showed that none of the mean squared errors was significantly better (all $p > 0.4$) than the null model hypothesis that the best prediction is the mean of the personality scores. This result indicates that essentially no additional information could be predicted from the EEG power spectrum features by using this approach.

In addition, to test an effect of age and gender related systematic personality variability, all trait scores were normalized in relation to age- and gender-specific means and standard deviations (see Methods, *Personality Measures*). The repetition of the binary classification analysis with these normalized scores still provided misclassification errors that were not statistically significant (all $p > 0.1$).

Given the possibly enhanced homogeneity of the brain origins of lower-level aspects of personality traits, we next attempted to predict the scores for the 10 lower-order aspects of the Big Five. We again used the binary classifier with the similar pipeline as for the five superordinate traits. The results are shown in Figure 2. As can be seen from Figure 2, one aspect, *Politeness*, is statistically significant at the uncorrected level. However, after the false discovery rate correction none of the p values remain significant. Therefore, we could not classify the lower-order aspects of Big Five personality traits from the power spectra of resting state EEG.

Results of 10 binary classifiers

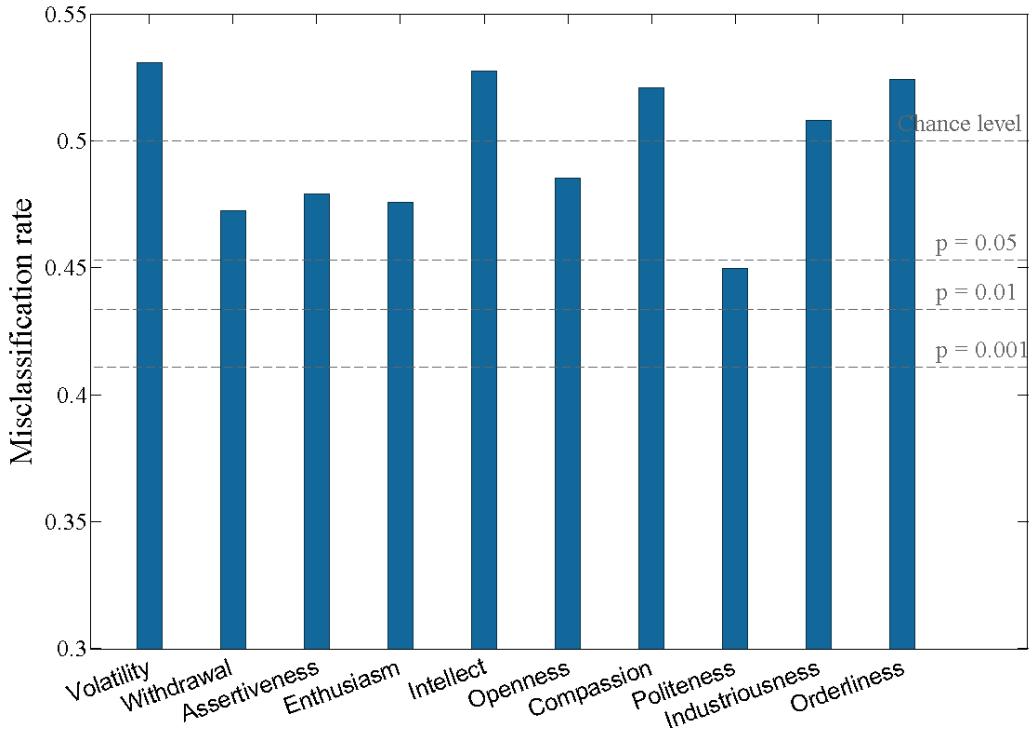


Figure 2: Misclassification rates of lower-order aspects of Big Five personality traits. The aspect scores have been binarized with a median-split. Although the significance of the misclassification rate for *Politeness* is below $p < 0.05$, it does not remain significant after false discovery rate correction.

To test the general validity of our analysis pipeline, predicting was also performed in a situation where clear classifiable information was present in the dataset. To that end we tried to classify

whether the eyes of the subject were open or closed and also whether the subject was female or male.

Firstly, the subjects were assigned into two classes: for half of the subjects eyes open data were used and for another half eyes closed data were used. Using the same pipeline with nested cross-validation of 648 models on 309 subjects, the achieved classification rate of the classifier was 81% (misclassification rate of 19%, $p \ll 0.001$). Given that we did not control for the gender and age variability of the subjects, this result indicates that when a clear pattern of information was present in the data, our algorithm was able to extract it and perform almost optimally.

Secondly, gender of all the 309 subjects (209 female) was classified using the same nested cross-validation pipeline. Misclassification rate of 22% was achieved (chance level was 32.4% and $p = 0.00004$).

Results of the validation

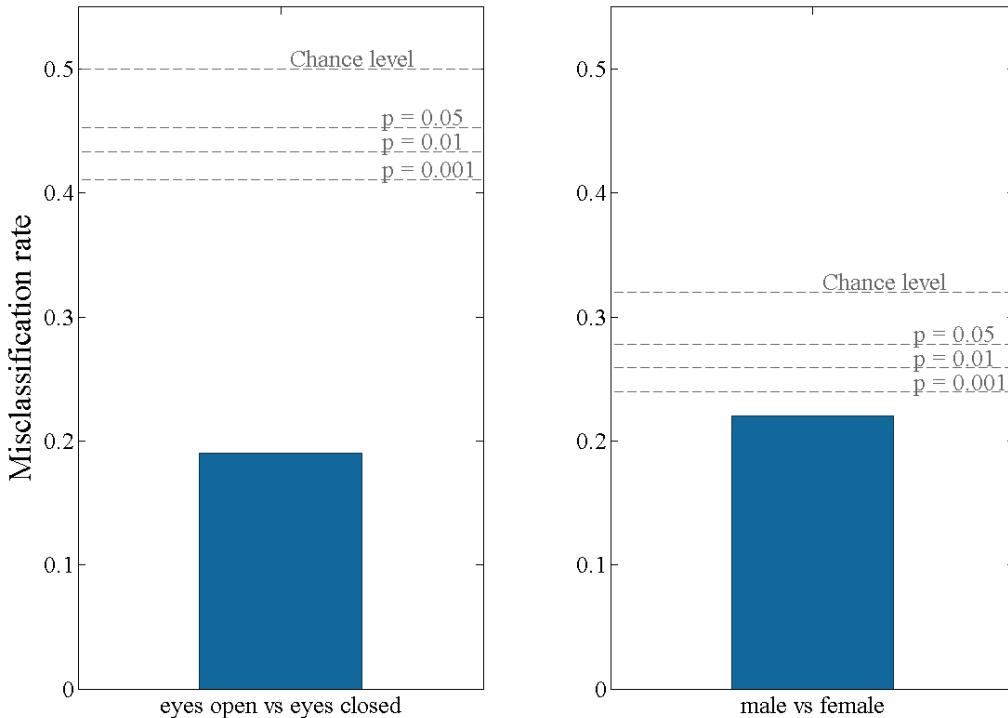


Figure 3: Results of the validation. Both cases have 309 subjects but note that the chance levels and significance levels of the two panels are different as we had 209 females and 100 males.

These results indicate that the failure to predict personality traits from spectral components of resting state EEG is probably not due to systematic algorithmic or implementation mistakes.

3. Discussion

In the present study we asked whether it is possible to predict the Big Five personality traits from resting state EEG data. Previous studies investigating the neurobiological correlates of personality have focused on single parameters such as the power of specific frequency components. Here we approached the research question from the data-driven perspective, using

machine learning to assess how much information about personality traits is contained in the spectral dynamics of the resting state EEG. In particular, we analyzed the data from the complete power spectrum and all the 32 electrodes. We used nested cross-validation on 309 subjects to estimate the accuracy of the classifiers.

Our results indicated that it is not possible to predict the Big Five personality traits from the power spectra of resting state EEG data. We furthermore showed that our classifiers are also not successful in predicting the 10 lower-order aspects of Big Five. Although for *Politeness* the p value was lower than 0.05, the result did not survive a correction for multiple comparisons. Finally, we demonstrated that the inability to classify the personality traits was not caused by our analysis pipeline. Using the same methods, we were able to differentiate eyes open recordings from eyes closed ones with a misclassification rate of 19%. Furthermore, we could decode whether the subject was male or female with a misclassification rate of 22%.

Given the comprehensive statistical approach used in this study, the results, despite being negative, have implications for personality neuroscience. On the one hand, the limitations of the recording and analysis techniques used here can be informative. Our study relied on the power spectrum of each channel as the basis for selecting features or explanatory variables that may predict personality traits. Spectral rather than temporal characteristics of resting state EEG were explored as all points in time are statistically equivalent in this type of signal (as opposed to evoked or induced potentials). Nevertheless, it is possible that features not captured by power such as oscillatory phase or temporal correlations in channel or source space might add some extra information. For instance, some studies have found relationships between trait measures such as Neuroticism and negative correlations between amplitudes of higher (alpha/beta) and lower (theta/delta) frequencies (Schutter & Knyazev, 2012). Note however that in many of these studies, power levels in certain frequencies are also related to the cross-frequency coupling indices as well as to the relevant trait measures (e.g. Knyazev et al., 2003). It thus remains to be seen if different feature extraction strategies would increase the success of classifying personality scores from resting state EEG. In general, one must notice that although our sample size is large in the context of EEG measures, machine learning techniques are typically applied to larger data sets. Also, any machine learning approach might suffer from several trade-offs and arbitrariness at each of its different stages (data preprocessing, feature extraction, feature selection, model selection, model training, validation).

Another technical explanation for the current findings might be the limited nature of EEG as a measure of brain processes. EEG is sensitive to only a subset of electrical events in the brain, probably reflecting the synchronized local field potentials of suitably aligned cortical pyramidal neurons (Lopes da Silva, 2013). There is some evidence suggesting that the trait-relevant differences may instead be found on the level of brain structure (e.g. DeYoung et al., 2010) or activation in subcortical areas that are unlikely to contribute directly to scalp EEG (e.g. Cunningham, Arbuckle, Jahn, Mowrer, & Abduljalil, 2010).

These methodological considerations notwithstanding, the present findings may also have conceptual implications. Individual differences in brain processes can either be stable dispositions evident in majority of situations (i.e. situation-independent traits) or characteristic responses to specific stimuli (situation-dependent traits; Fleeson & Noffle, 2009; Mischel & Shoda, 1998; Stemmler & Wacker, 2010). Given the lack of stimulation, the resting state measurement is optimized for discovering the former rather than the latter type of individual differences. In this framework, the failure to relate resting state EEG to Big Five personality traits documented here suggests that the brain substrate of personality might involve situation-dependent responsiveness rather than differences in baseline activity.

A relevant example can be found from the literature relating anterior EEG asymmetry to personality. Although many researchers implicitly assume the resting condition to be optimal for quantifying trait asymmetry, there is evidence that trait-related changes in asymmetries are best captured in response to some relevant stimulation (Coan, Allen, & McKnight, 2006). Furthermore, there is evidence that the trait-asymmetry correlations that emerge in the resting state data, may also be driven by the situational features of the resting measurement occasion. For instance, anterior asymmetry responses distinguished male participants based on their trait Defensiveness only at the presence of an attractive female experimenter (e.g. Kline, Blackhart, & Joiner, 2002). Given that we analyzed data from different studies collected by different experimenters, such situational factors should have fairly randomly distributed effects within the present data. This reduces the risk of situation-mediated EEG-personality covariance being registered as evidence for correlations on the trait level.

In summary, regarding the discovery of neural bases of personality traits, the present null-finding may constitute a false negative in the sense that technical limitations of EEG recording and/or the employed analysis techniques precluded us from detecting true trait differences in brain activity. In addition, even while the size of the current sample (309 participants) is similar to some normative datasets, we cannot exclude the possibility that more data would have provided significant results. On the other hand however, the results might imply that the brain substrate of personality may exist on the level of characteristic responsiveness rather than baseline activity, in line with several findings in modern personality neuroscience (Stemmler & Wacker, 2010).

4. Methods

4.1 Sample and procedure

The sample consists of 309 participants of 12 different cognitive EEG experiments conducted at the University of Tartu (100 males; age range 18-42, $M = 21.9$, $\sigma = 3.4$). All participants were volunteers recruited among university students and the general population. All measurements were approved by the Ethics Review Board of Tartu University. Only subjects who completed a personality questionnaire and had at least 50% of the originally recorded EEG data retained after artifact rejection were included in the sample.

The resting state EEG data analyzed here were collected prior to all other experimental tasks. Two different measurement protocols were used. In 5 experiments the resting state signal was recorded in two contiguous sections – one with eyes open and the other with eyes closed. Each section lasted either for 1 minute (in one experiment with 84 participants) or 2 minutes (in four experiments with 94 participants). In the remaining 7 experiments (131 participants) 3 separate 1-minute measurements with eyes open and eyes closed were interleaved resulting in 3 minutes in total for both the eyes open and eyes closed conditions.

The measurements took place in a dimly lit and quiet room. Participants sat in a comfortable office chair 1 or 1.15 m away from a computer screen. They were instructed to relax and avoid excessive body and eye movements. During the eyes open condition they were also required to fixate on a black cross in the middle of a grey screen. After instructions, participants remained alone in the room during the actual recording.

4.2 EEG recording and preprocessing

A BioSemi ActiveTwo (BioSemi, Amsterdam, Netherlands) active electrode system was used to record signals from 32 scalp locations; two reference electrodes placed on earlobes and four ocular electrodes (above and below the left eye and near the outer canthi of both eyes). The data were recorded with 0.16 – 100 Hz band-pass filter and 1024 or 512 Hz sampling rate.

Offline pre-processing was implemented in Matlab (MathWorks, USA) and EEGLAB (Delorme & Makeig, 2004) software. The data were re-referenced to digitally linked earlobes and resampled to 512 Hz as necessary. Eye-movement artifacts were corrected using Independent Component Analysis (ICA). Infomax ICA algorithm was trained on a separate copy of data that was first high-pass filtered (half-amplitude cut-off at 1 Hz) and then cleaned of large artifacts by screening 1-second epochs for excessive muscular noise (EEGLAB *rejspec* 15-30 Hz; +/-45 dB). If more than 2% of epochs were marked for rejection based on a single channel, the channel was removed before rejecting the remaining epochs with artifacts. Independent components capturing eye-blanks as well as vertical and horizontal eye-movements were visually identified and removed before reconstructing the whole duration of unfiltered and unsegmented data (Debener, Thorne, Schneider, & Viola, 2010). The ICA-pruned continuous data were cut into 4-second epochs and the mean voltage of each epoch was removed as a baseline. All segments where voltage fluctuations exceeded 200 μ V were marked as artifacts. If this criterion was violated in only a single channel for more than 2% of the trials, this channel was removed before removing the remaining segments with artifacts. All rejected channels were spherically interpolated (EEGLAB *eeg_interp*).

The power spectral density values were computed using the Fourier transform applied separately to data from each channel and retained segment. The power estimates between 0.25 and 95 Hz were added and divided by the number of available trials within eyes closed and eyes open condition.

4.3 Personality measures

Prior to visiting the lab, participants filled in a personality questionnaire in a dedicated online environment (kaemus.psych.ut.ee). All 309 participants completed the EE.PIP-NEO inventory which uses 240 items to assess the 5 dimensions (see figure 4) as well as 30 facets of the FFM (Mõttus, Pullmann, & Allik, 2006).

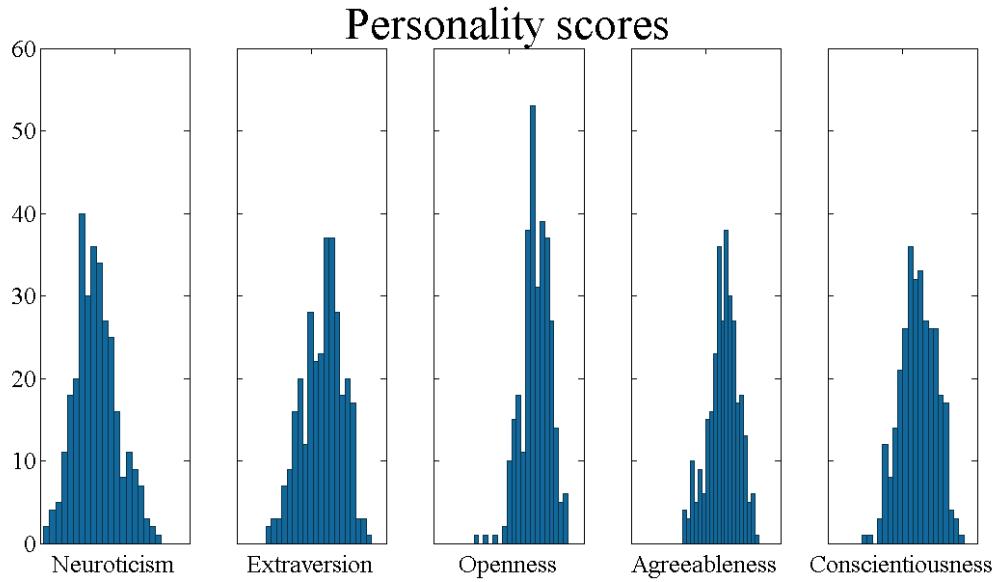


Figure 4: Histograms of all 5 personality dimension scores. Note that the distributions are rather normal and personality score units on the x-axes are arbitrary.

Scores for the 10 lower-order aspects of the Big Five were computed as averages of the relevant facet scores of the FFM (Judge, Rodell, Klinger, Simon, & Crawford, 2013):

- Volatility = N2, N5
- Withdrawal = N1, N3, N4, N6
- Enthusiasm = E1, E2, E5, E6
- Assertiveness = E3, E4, E5
- Intellect = O5
- Openness = O1, O2, O3, O4, O6
- Compassion = A1, A3, A6
- Politeness = A2, A4, A5
- Industriousness = C1, C4, C5
- Orderliness = C2, C3, C6

Median split was performed on each personality trait, resulting in two equal size classes “high” and “low” score for each personality trait.

4.4 Classification of the personality traits

We used a nested cross-validation approach. For predicting an out of sample subject we used 10-fold cross-validation. In order to choose the best hyper-parameters we used again 10-fold cross-validation for 90% of the data. After finding the best combination of hyper-parameters we re-trained it on the same 90% of the data. Each of the five personality traits was treated separately. Matlab code for the nested cross-validation can be found from GitHub repository: <https://github.com/kristjankorjus/PredictingPersonalityFromEEG>

4.4.1 Nested Cross-Validation

In order to find the best hyper-parameters 10-fold cross-validation was used on the 90% of the data inside of cross-validation. The full list of hyper-parameters is specified here:

- different data types: using power spectra of eyes open data or eyes closed data (*2 options*)
- pooling of electrodes: using all electrodes separately or taking regions of interests (left frontal (F3, F7, AF3, Fp1); right frontal (F4, F8, AF4, Fp2); mid-frontal (Fz, Cz, FC1, FC2); left central (FC5, CP5, T7, P7, C3); right central (FC6, CP6, T8, P8, C4); mid-parietal (Pz, CP1, CP2, P3, P4); and occipital (PO3, PO4, O1, Oz, O2)) (*2 options*)
- pooling of frequencies: using all frequencies, using customized pooling for frequencies (taking information from spectrum averaged over all subjects and channels such that from 0 Hz to 14.75 Hz bands of 0.25 Hz were used; from 15 Hz to 24.75 Hz bands of 0.5 Hz; from 25 Hz to 36.75 Hz bands of 1 Hz; from 37 Hz to 95 Hz bands of 10 Hz were used) or using 11 bands based on the literature (0.5 to 1.25, 1.5 to 4.25, 4.5 to 8.25, 8.5 to 12.25, 12.5 to 20.25, 20.5 to 30.25, 30.5 to 40.25, 40.5 to 50, 50.25 to 69.75, 70 to 89.75, 90 to 95, all values in Hz) (*3 options*)
- normalization of the data: using the data without normalization, normalizing each row (each subject) by taking the z-score (subtracting the mean, dividing by standard deviation) or normalizing each column (each feature) (*3 options*)
- for reduction of dimensionality of the data, principal component analysis was used with different amount of total variance explained by principal components: 90% or 70% of variance explained. Or no principal component analysis was used at all (*3 options*)
- value of the box constraint C for the soft margin of Support-Vector-Machine (SVM): 0.01 or 100 (*2 options*)
- type of kernel for SVM: no kernel (linear SVM) or a radial basis function (RBF) kernel (non-linear SVM) were used. In addition, the sigma parameter controlling the width of the RBF was selected among two possible values using randomized data as explained in the next paragraph (*3 options in total*).

To find a suitable sigma parameter of RBF for our dataset we estimated how the over-fitting error for a known case depended on this parameter. In particular, we first randomized the classes of the dataset, and let the classifier train and predict the full data. For small values of the sigma, the classification error will tend to 0 indicating over-fitting – every neighborhood around a sample is classified with the label of the contained sample, and therefore lacking of any generalization power. As the sigma increased, the error rate started to increase. Sigma was fixed when the error rate reached 0.1 or 0.3 as these were optimistic prior beliefs about the final classification error.

In total, these 648 combinations of classifier hyper-parameters were explored for each personality trait. For the whole cross-validation phase, partitioning of data was fixed to make different hyper-parameters more comparable. The smallest misclassification error for each personality trait determined the set of hyper-parameters, which were used in testing.

4.4.2 Cross-Validation

In order to estimate the misclassification error rate, each personality trait of 309 subjects was predicted with the best hyper-parameters found and model trained in the nested cross-validation phase.

Statistical significance was estimated using binomial test with the null hypothesis that two categories are equally likely to occur.

4.5 Analyzing continuous data

Continuous scores were first normalized (mean was subtracted and divided by standard deviation). Instead of a SVM classifier, LASSO and elastic net regressions were used (Matlab function *lasso*). All hyper-parameters which were not related to the specifics of SVM classifiers, were scanned from the same range as described in the Cross-Validation section above. In addition, the *alpha* parameter was scanned with three options: 1, 0.5 and 0.01. Parameter *alpha* = 1 represents LASSO regression, *alpha* close to 0 approaches ridge regression, and the 0.5 represents elastic net optimization. For the regularization parameter, we used the recommended *lambda* such that MSE is within one standard error of the minimum (see *Lambda1SE* in the *lasso* documentation in MATLAB).

In the continuous case, the null hypothesis was that the best prediction for each personality trait, which minimizes the mean squared error, is the mean of the personality score. Statistical significance analysis was performed using a permutation test: scores were sampled with replacements from the score distribution.

4.6 Testing the influence of age and gender related variability

To test possible age and gender related systematic personality variability, all trait scores were normalized in relation to age- and gender-specific means and standard deviations ($S_{\text{norm}} = \frac{S_{\text{raw}} - \mu_{\text{reference}}}{\sigma_{\text{reference}}} \cdot 10 + 50$). The reference data were obtained from a normative sample of the EE.PIP-NEO ($n = 1564$; 889 males; age range 16-86; $M = 15.8$, $\sigma = 12.1$). Based on the age and gender of the participant, one of 20 reference groups were selected (9 age brackets between 15 and 59 with 5 year steps and one bracket for 60 and above). For 53 participants of the present sample for whom age data were unavailable, the sample mean age was used for reference group identification. Again, median split and original pipeline described above was used.

4.7 Assessment of 10 lower-order aspects

Instead of five personality traits, each trait has a natural subdivision into two:

- neuroticism: *volatility* and *withdrawal*
- extroversion: *assertiveness* and *enthusiasm*
- openness to experience: *intellect* and *openness*
- agreeableness: *compassion* and *politeness*
- conscientiousness: *industriousness* and *orderliness*

All of the 10 sub-trait were classified using the original above-described pipeline.

4.8 Classification of eyes closed vs eyes opened data

To test the validity of the whole pipeline, classification was performed in a situation with clear pattern of information present. In particular, the data were divided into two sets such that half of the subjects had eyes open data and another half had eyes closed, in total two classes. Notice

that no subject appears in two classes. Thus we still have 309 subjects and two classes but for each subject the data is taken from either eyes open or eyes closed condition. Again, original pipeline was used.

4.8 Classification of male vs female subjects

For another test of the validity of the whole pipeline, classification was performed also in a situation with likely pattern of information present. In particular, the gender of subjects was used: 209 female subjects and 100 male subjects were used. Notice that the chance misclassification level is 32.4%. Again, original pipeline was used.

5. Author Contributions

Kristjan, Andero, Raul and Jaan analyzed the data. Andero, Helen, Nele, Kairi and Jüri organised the data collection. Kristjan, Andero, Raul and Jaan wrote the manuscript with input from all other authors.

6. Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Tailoring Personality Traits in Large Language Models via Unsupervisedly-Built Personalized Lexicons

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Abstract

Personality plays a pivotal role in shaping human expression patterns, thus regulating the personality of large language models (LLMs) holds significant potential in enhancing the user experience of LLMs. Previous methods either relied on fine-tuning LLMs on specific corpora or necessitated manually crafted prompts to elicit specific personalities from LLMs. However, the former approach is inefficient and costly, while the latter cannot precisely manipulate personality traits at a fine-grained level. To address the above challenges, we have employed a novel Unsupervisedly-Built Personalized Lexicons (**UBPL**) in a pluggable manner during the decoding phase of LLMs to manipulate their personality traits. UBPL is a lexicon built through an unsupervised approach from a situational judgment test dataset (**SJTs4LLM**). Users can utilize UBPL to adjust the probability vectors of predicted words in the decoding phase of LLMs, thus influencing the personality expression of LLMs. Extensive experimentation demonstrates the remarkable effectiveness and pluggability of our method for fine-grained manipulation of LLM’s personality.

1 Introduction

With rapid expansion in scale, LLMs demonstrate superior capabilities for high-quality text generation and revolutionize traditional natural language processing tasks (Wei et al., 2022). This forefront development has sparked concerns about the security, ethics, and potential hallucinatory issues associated with the proliferation of AI-generated content (AIGC), while also fueling a substantial rise in user demand for personalized agent services based on LLMs (Hagendorff, 2023). Personalized agent models can tailor their expression of personality patterns based on user preferences, making it

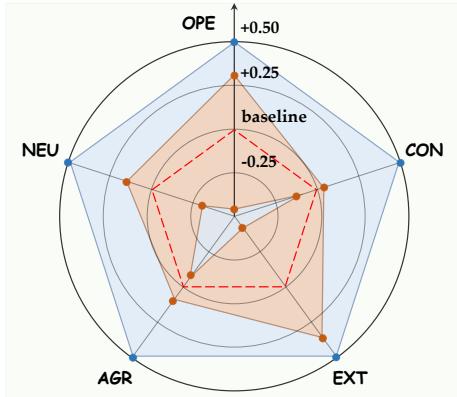


Figure 1: The radar chart illustrates the effectiveness of the UBPL in manipulating the personality traits of the Llama2-13b-chat. In the chart, the red dashed line denotes the expressive levels of five personality traits without UBPL. The light orange area indicates the range within which the model’s personality traits can be manipulated in our main experimental setting ($\alpha = 1$, $|\beta_t| \leq 1$ and $\beta_{\neq t} = 0$, where α, β are user-controlled hyperparameters that adjust the effects of UBPL). When users change the hyperparameters, the range of control is not limited to the light orange area shown in the chart.

closely aligned with user habits and thereby enhancing the overall user experience. This is achieved by regulating the style and behavior patterns of their interactions with users, which are often referred to as the "personality" of LLMs (Allport, 1961). Prior studies have also defined this personality as the presence of stable and internally consistent patterns of behavior in LLMs and found that different LLMs have different personalities (Miotti et al., 2022; Caron and Srivastava, 2022; Karra et al., 2022).

Presently, there are two main effective methods to alter the personality of LLMs: fine-tuning and prompt engineering. While the former (Karra et al., 2022) can effectively change the personality of LLMs in specific dimensions, it is not only inefficient (requiring resource-consuming parame-

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ter updates for each model) but also incapable of achieving finer-grained control. The latter, while not requiring adjustments to model parameters, still falls short in achieving fine-grained control over the personality of LLMs (Jiang et al., 2022; Safdari et al., 2023; Pan and Zeng, 2023; Tu et al., 2023).

To address the problem of these above methods, we propose to leverage an Unsupervisedly-Built Personalized Lexicon (**UBPL**) to intervene in the decoding phase of LLMs in a pluggable manner, enabling fine-grained control over their personality. Figure 1 shows the remarkable effect of our method to manipulate the personality of LLMs. UBPL is a lexicon built through an unsupervised approach from a Situational Judgment Tests (**SJTs**) dataset (**SJTs4LLM**) we constructed. SJTs4LLM is built based on the Big Five personality theory (De Raad, 2000), which consists of a question set and an answer set (McDaniel et al., 2007). The question set is generated by GPT-4 and manually filtered to assess the levels of the different personalities of LLMs. Following previous studies (Karra et al., 2022; Caron and Srivastava, 2022), in the process of assessing the personalities of LLMs, the models’ responses to SJTs4LLM questions were recorded and subjected to statistical analysis by using a five-dimensional Likert scale. The answer set contains the answer text with different personality traits and is used to build a UBPL dedicated to an LLM.

Our method not only eliminates the need for resource-intensive full-parameter fine-tuning of LLMs but also allows users to adjust only a few parameters to achieve fine-grained manipulation of the different personalities of LLMs. We have done extensive experiments using six popular LLMs to demonstrate the pluggable convenience and remarkable effectiveness of our method. Our contribution can be summarized as follows:

- We propose a novel method for exerting control over the personality of Language Models, leveraging UBPL to intervene at the decoding phase. This method enables fine-grained controllability over the behavior of LLMs without necessitating updates to the model parameters.
- We constructed a new dataset inspired by the concept of Situational Judgment Tests, marking the pioneering effort in datasets especially created for the evaluation of LLM’s personality. Diverging from conventional direct psychological questionnaires, this indirect approach shows enhanced intuitiveness and reli-

ability in the assessment of personality traits.

- Extensive experiments were conducted with different LLMs on the SJTs4LLM dataset, revealing that the UBPL method demonstrates notable effectiveness in achieving both enhanced efficiency and finer-grained control over LLM’s personality traits.

2 Related Work

2.1 The Big Five

In the realm of research within the field of psychological measurement, various classification systems for human personality traits exist, such as the Sixteen Personality Factors (16PF) (Cattell and Mead, 2008) and Myers–Briggs Type Indicator (MBTI) (Miles and Hempel, 2004). Among them, the Big Five (De Raad, 2000) stands out as a widely embraced model for personality trait modeling, effectively defining and describing the inherent behavioral patterns within individuals. This theory quantifies human personality traits into five dimensions: Openness(OPE), Conscientiousness(CON), Extraversion(EXT), Agreeableness(AGR), and Neuroticism(NEU). For a detailed description of each personality trait and how they relate to each other, please refer to Appendix A.

2.2 Methods for controlling LLMs personality

Despite the considerable amount of research addressing potential biases in LLMs, there has been limited focus on altering the personalities exhibited by these models. Pertinent methodologies primarily revolve around fine-tuning paradigms and prompt engineering.

Fine-tuning paradigm. (Karra et al., 2022) meticulously conducted fine-tuning of GPT-2 on a carefully filtered dataset, enhancing its performance in specific dimensions of personality traits.

Prompt engineering. (Jiang et al., 2022) proposed the method of Personality Prompting (P^2) to construct the prompts that can effectively induce a specific personality through multiple steps; (Safdari et al., 2023) utilized a novel prompting methodology grounded in lexical hypotheses (Goldberg, 1981) to effectively shape personalities in LLMs, encompassing both single-trait and multi-trait dimensions. In addition, (Pan and Zeng, 2023) and (Tu et al., 2023) also attempted to change the personality of LLMs through prompt engineering.

2.3 Situation Judgment Tests

Situation Judgment Tests (**SJTs**) have been described as "psychometric alchemy" and are typically viewed as contextual selection procedures that assess a candidate's responses to various relevant work situations, serving as a predictive tool (Lievens and Motowidlo, 2016; Bledow and Frese, 2009). The advantage of SJTs is that their validity and incremental validity are higher than those of cognitive ability and personality tests because SJTs do not require the subject to give a direct answer to the question, but give the subject a situational premise to evaluate a certain characteristic of the subject through the side of the subject's choice (such as the **Q: Your partner suggests creating a YouTube channel to document and share your unique hobbies or interests. Are you willing to share your passion with a wider audience?**) (Lievens et al., 2008). Compared to the direct questionnaire tests used in previous jobs (such as the **Q: Are you a risk-taker and unconventional person?**) This feature of SJTs can effectively bypass the preference defenses of LLMs, resulting in more trustworthy personality assessments (Figure 2 shows another example of SJTs).



Figure 2: Direct questionnaires vs. Situation Judgment Tests (SJT). The questions in the direct questionnaires are often abstract, making it challenging for models trained through Reinforcement Learning from Human Feedback (RLHF) and instruction alignment to generate the desired responses. In contrast to direct questionnaires, SJTs present a unique approach by adopting a "role-playing" hypothetical perspective to deceive and induce the model's responses. Subsequently, we can indirectly assess the extent to which the model manifests personality traits based on these responses.

3 Method

The proposed UBPL in our study can be integrated into any open-source LLM in a pluggable manner and effectively adjust the diverse personality traits that LLMs exhibit (based on the Big Five theory). Figure 3 shows the specifics of our method.

The first step is to build UBPL in an unsupervised manner, using SJTs4LLM, the first SJTs dataset we built to assess the personality of LLMs. Employing the tokenizer of a chosen model, such as Llama2 for illustration, we tokenize each text in the answer set of SJTs4LLM. Subsequently, we conduct a subword-level statistical analysis of the tokenized texts, categorizing the obtained subwords based on the personality trait themes to which each text belongs. Following this, we assign values within UBPL to each subword (also serving as the "key" of UBPL) corresponding to the respective personality lists. After processing all texts in the answer set, we normalize and scale the values within UBPL based on distinct personality themes.

In the second step, we use UBPL to manipulate personality in the decoding phase of the LLMs. By default, the LLMs adopt the Top-p nucleus sampling strategy. During LLMs' decoding, we concatenate additional personalized probability combinations from UBPL after filtering out low-probability predicted subwords with cumulative probabilities below a threshold p . Subsequently, normalization and multinomial sampling procedures are applied.

3.1 Building UBPL Unsupervisedly

When building UBPL, we utilized the answer set of SJTs4LLM, which comprises subsets of personality trait answer texts with 10 distinct polarities (each of the 5 personality traits further refined into high and low subtraits).

We denote this answer set as A , the tokenizer of the model as $sp(\cdot)$, the vocabulary of the model as V , and UBPL as L .

$$L = (L_{key}, L_{val}) \quad (1)$$

where L_{key} is initialized using V , and the initial values of L_{val} are zero lists of length 5.

The entire construction process is divided into two parts: assignment operations and normalization and scaling operations.

In the first step, we tokenize the texts A_{ij} in A :

$$sp(A_{ij}) = \{w_1, w_2, \dots\} \quad (2)$$

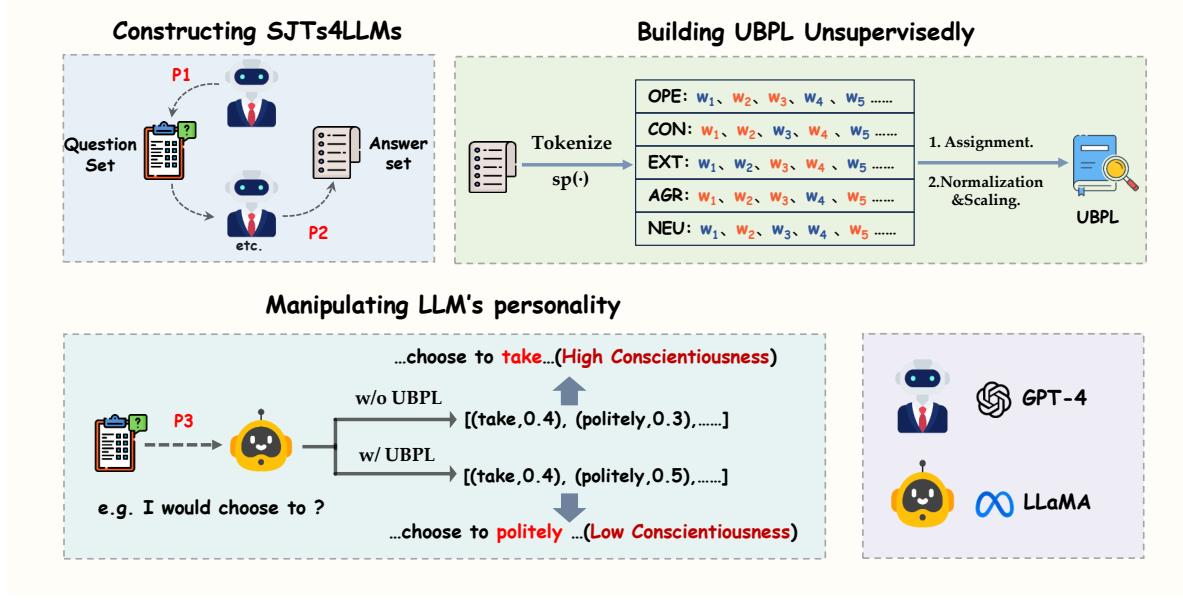


Figure 3: Illustration of our methods. **Constructing SJTs4LLMs:** We employed Prompt1 (**P1**) to prompt GPT-4 for generating responses, which were subsequently curated through manual screening to construct the question set for SJT4LLMs. Subsequently, models such as GPT-4 were engaged in a "role-playing" manner using Prompt2 (**P2**) to generate answers with diverse personality traits tailored to this question set, thus forming the answer set for SJT4LLMs; **Building UBPL Unsupervisedly:** Initially, we employ the tokenizer of LLMs ($\text{sp}(\cdot)$) to tokenize each answer text in the answer set of SJTs4LLMs. Subsequently, we categorize the obtained sub-words based on the personality trait theme to which the answer belongs. Within each personality trait category, cool-toned words signify a low expression level of that trait, while warm-toned words indicate a high expression level. On this basis, UBPL is built through two steps: assignment, normalization & scaling; **Decoding with Personality Injection:** We employ Prompt3 (**P3**) to prompt the model to answer the question set of SJTs4LLMs. During the model's decoding process utilizing Top-P nucleus sampling, we used UBPL each time to change the probability vector of the next prediction word and finally changed the expression degree of personality traits of the model's answers.

Then, we define the personality trait index t : $t = \frac{i}{2}$. Finally, we perform the assignment on L_{val} :

$$L_{val}^t = L_{val}^t + \begin{cases} +1 & \text{if } i \% 2 = 0 \\ -1 & \text{else} \end{cases} \quad (3)$$

when this step is completed, we have:

$$L_{val}^t = \{v_1, v_2, \dots, v_m, v_{m+1}, \dots, v_{m+n}\}, \quad (4)$$

where $m+n = |V|$, and for $k \leq m$, $v_k \geq 0$. When the personality trait is t , the averages of the positive value set and the negative value set of L_{val}^t can be expressed as follows:

$$\text{Avg}^+(t) = \frac{1}{m} \sum_{k=1}^{|V|} \max(0, L_{val,k}^t) \quad (5)$$

$$\text{Avg}^-(t) = \frac{1}{n} \sum_{k=1}^{|V|} \min(0, L_{val,k}^t) \quad (6)$$

The second step involves normalizing and scaling the values in L . We define hyperparameters S , M , and α to control the degree of normalization

and scaling. The N in Equation 8 is employed to govern the normalization process, and its value is determined through a binary search. The termination condition is defined as the point at which the involvement of N in the normalization of L satisfies the condition specified in Inequality 9. The normalization and scaling process can be represented by the following mapping function:

$$L_{val}^t \xrightarrow{(N_t, S_t)} F(L_{val}^t, N_t, S_t) \quad (7)$$

Specifically, it is expressed as:

$$F(L_{val}^t, N_t, S_t) = \left\{ S_t \cdot \tanh \left(\frac{v_z}{N_t} \right) \right\}_{z=1}^{|V|} \quad (8)$$

Where the value of N is obtained through binary search to satisfy the following necessary conditions:

$$\max\{|\text{Avg}^-(t) - M_t|, |\text{Avg}^+(t) - M_t|\} \leq \alpha \quad (9)$$

3.2 Manipulating LLM’s personality

We employ UBPL to manipulate personality during the decoding phase of LLMs. Let D represent the output of the last mapping layer of LLMs. The normalization function (i.e., *Softmax function*) is denoted as $\text{Norm}(\cdot)$, the cumulative probability function is denoted as $P(\cdot)$, and s represents the predicted probability of subwords in the vocabulary. P_0 and T_0 are model-defined parameters.

In the first step of Top-p nucleus sampling, we obtain the initial candidate word probability vector:

$$R_1 = \text{Norm}(D) = \{s^1, s^2, \dots, s^{|V|}\} \quad (10)$$

Where $\text{Norm}(x) = \text{Softmax}(x/T_0)$, s^z represents the probability of subword w^z ($z \leq |V|$). Then, this strategy filters out (in reverse order) candidate subwords whose cumulative probability exceeds P_0 , thereby narrowing the sampling space. We express this process using the $f(\cdot)$ function:

$$f(R_1) = \{\max\{P_0 - P(s_z), 0\} \cdot \frac{s_z}{P_0 - P(s_z)}\}_{z=1}^{|V|} \quad (11)$$

Next, we alter the probability vector R_1 with UBPL, resulting in the final predicted probability vector (R_2) for the next word with injected personality. This process can be represented by the following mapping:

$$f(R_1) \xrightarrow{G(\cdot)} R_2 \quad (12)$$

$$R_2 = \{s_z \cdot (1 + G[L_{\text{val}}(s_z)])\}_{z=1}^{|V|} \quad (13)$$

Where $G(\cdot)$ is a user-controllable parameter with a linear combination of α and $\beta_1-\beta_5$, specifically:

$$G[L_{\text{val}}(s_z)] = \alpha \cdot \sum_{t=1}^5 \beta_t \cdot L_{\text{val}}^t(s_z) \quad (14)$$

After obtaining a new probability vector R_2 for the next candidate word injected with personality, the next word W is obtained using polynomial sampling from R_2 .

Users can control the overall degree of personality injection through the parameter α . Additionally, they have the flexibility to adjust the manifestation of five personality traits exhibited by the model in a finer granularity by manipulating the parameters β_1 through β_5 . When $\beta_t > 0$, it amplifies the expression of trait t ; conversely, when $\beta_t \leq 0$, it diminishes the intensity of trait t .

Algorithm 1: the UBPL method

```

Input:  $A, sp(\cdot), V, S, M, \alpha, D, G(\cdot), P_0$ 
Output:  $L, W$ 
1 Part I: Building UBPL Unsupervisedly
2  $L_{\text{key}} \leftarrow V; L_{\text{val}} \leftarrow [0, 0, 0, 0]^{|V|};$ 
3 for  $i \leftarrow 0$  to  $9$  do
4    $j \leftarrow 0;$ 
5   while  $j < 200$  do
6      $\{w_1, w_2, \dots\} \leftarrow sp(A_{ij});$ 
7      $t = i/2;$ 
8     foreach  $w$  in  $\{w_1, w_2, \dots\}$  do
9       if  $i \bmod 2 = 0$  then
10          $| L[w][t] \leftarrow L[w][t] + 1;$ 
11       else
12          $| L[w][t] \leftarrow L[w][t] - 1;$ 
13     end
14   end
15    $j \leftarrow j + 1;$ 
16 end
17 end
18 while  $\max_{c \in \{+, -\}} \{Avg^c(t) - M_t\} > \alpha$  do
19    $L_{\text{val}} \leftarrow \{S \cdot \tanh(\frac{v_z}{N})\}_{z=1}^{|V|};$ 
20   Update N using the Binary Search;
21 end
22 Return:  $L$ 
Part II: Manipulating LLM’s personality
24  $R_1 \leftarrow \text{Norm}(D) \leftarrow \{s^1, s^2, \dots, s^{|V|}\};$ 
25  $f(R_1) \leftarrow \{\max\{P_0 - P(s_z), 0\} \cdot \frac{s_z}{P_0 - P(s_z)}\}_{z=1}^{|V|};$ 
26  $R_2 \leftarrow \{s_z \cdot (1 + G[L_{\text{val}}(s_z)])\}_{z=1}^{|V|};$ 
27 Sample W from R2;
28 Return:  $W$ 

```

3.3 Comparison with prior work

As discussed in Section 2.2, there have been two primary methods previously employed to alter the personality of LLMs: fine-tuning and prompt engineering.

In contrast to the fine-tuning, our method obviates the need for resource-intensive parameter fine-tuning. Unlike the inefficiencies inherent in the fine-tuning paradigm, which stem from the requirement to execute fine-tuning steps for each model, UBPL can be seamlessly applied to any open-source LLM in a modular, plug-and-play fashion. In comparison to prompt engineering, UBPL doesn’t necessitate the meticulous design of prompts to coax the model into exhibiting varying degrees of personality traits. Users only need to set α and β parameters to regulate the expression intensity of different personality traits in the model at a finer granularity.

The above advantages over the previous methods are based on the effectiveness of our method, so the goal of our experiment is to comprehensively and in detail demonstrate the significant effectiveness of UBPL.

Model	-1.0	-0.5	0.0	0.5	1.0	R	P
Llama2-7b-chat	4.286(0.31)	4.343(0.31)	4.427(0.31)	4.525(0.28)	4.558(0.26)	0.991	1E - 03
OpenChat3.5-7b	3.626(0.64)	3.756(0.61)	3.981(0.44)	4.182(0.37)	4.237(0.39)	0.986	2E - 03
Neural-chat-7b	3.809(0.58)	3.876(0.56)	3.999(0.50)	4.161(0.44)	4.220(0.41)	0.989	1E - 03
Baichuan2-7B-Chat	3.584(0.27)	3.710(0.26)	4.036(0.38)	4.248(0.39)	4.336(0.42)	0.983	3E - 03
Llama2-13b-chat	3.856(0.57)	3.891(0.54)	4.135(0.46)	4.298(0.41)	4.322(0.38)	0.964	8E - 03
Yi-34b-Chat	4.141(0.42)	4.172(0.42)	4.246(0.49)	4.431(0.40)	4.424(0.38)	0.941	3E - 03

Table 1: Single trait manipulating. This table presents the outcomes of single-trait regulation across six models using UBPL. Specifically, it delineates the variations in the *mean scores (standard deviations)* of five personality traits for the six models as $\alpha = 1$, and $-1 \leq \beta_t \leq 1$. Furthermore, we display the Pearson correlation coefficients (R) and corresponding confidence levels (P) between the mean scores and β_t . Notably, all R values exceed 0.9, and all P values are below 0.05, indicating the statistically significant strong correlation between personality trait expression intensity and β_t . This substantiates the effectiveness of our UBPL method in achieving fine-grained control over the expression levels of personality traits in LLMs.

4 Experiments Setup

4.1 LLMs for experiments

To thoroughly demonstrate the effectiveness and generalizability of our method, we conducted experiments on six representative LLMs with model parameters ranging from 7 billion to 34 billion: Llama2-7b-chat(Touvron et al., 2023), OpenChat3.5-7b(Wang et al., 2023), Neural-chat-7b(Intel, 2023), Baichuan2-7B-Chat(Baichuan, 2023), Llama2-13b-chat(Touvron et al., 2023), and Yi-34b-Chat(01.AI, 2023). All the LLMs employ a Top-p nucleus sampling decoding strategy, with a probability threshold (P_0) of 0.95 and a temperature (T_0) of 0.85.

4.2 Metrics

4.2.1 Automatic assessment

To ensure the intrinsic consistency and effectiveness of the assessment, we engaged Llama2-13b-chat in the automatic assessment process. Specifically, we embedded each question of SJTs4LLMs and the corresponding answers generated by the model into Template-2 and asked Llama-13b-chat to score the different personality levels displayed by the model, and finally gathered scores into a five-dimension Likert scale for statistical analysis. Details of Template-2 are in Appendix B.

4.2.2 Human assessment

Constrained by manpower costs, we recruited a limited cohort of 10 highly educated volunteers for the human assessment process of the Llama7/13b models. At baseline, we randomly selected 40 question-answer pairs for each personality trait theme (constituting 40% of the total) and solicited degree-of-trait ratings from the volunteers. The results were

recorded on a five-dimensional Likert scale, and subsequent statistical analysis involved computing the mean and variance.

5 Results

5.1 Main results

To demonstrate the effectiveness of our method, we conducted comprehensive experiments. Section 5.1.1 provides a summary of the results demonstrating the manipulation of personality traits across six LLMs using UBPL. In Section 5.1.2, we present the outcomes of UBPL in jointly manipulating the expression of multiple personality traits. In Section 5.1.3, we compare automatic assessment with human assessment to demonstrate the effectiveness of our assessment methodology.

5.1.1 Single trait manipulating

The results in Table 1 demonstrate the effectiveness of using UBPL to manipulate a single personality of LLMs. Here, α is set to 1, and $|\beta_t| \leq 1$ ($\beta_{\neq t} = 0$) for $t \in \{OPE, CON, EXT, AGR, NEU\}$. The Pearson correlation coefficients (R) are consistently greater than 0.9, signifying a robust positive correlation between β_t and the intensity of personality expression in LLMs. The confidence level (P) is significantly below 0.05, providing compelling evidence that our UBPL can effectively manipulate the intensity of fine-grained personality expression in LLMs. For detailed results on the manipulation of single personality traits for these six LLMs, please see Figure 4.

5.1.2 Multiple trait manipulating

The psychological research results presented in Table 2 reveal interdependencies among the five personality traits within the Big Five personality

Llama2-7b-chat($\alpha=1$)						
$\beta_t(\beta_{\neq t}=0)$	OPE	CON	EXT	AGR	NEU	Mean
-1.0	4.675	4.505	4.075	4.270	3.905	4.286
-0.5	4.740	4.545	4.200	4.295	3.935	4.343
0	4.890	4.570	4.260	4.345	4.070	4.427
+0.5	4.975	4.560	4.455	4.380	4.255	4.525
+1.0	4.975	4.575	4.520	4.420	4.300	4.558

Baichuan2-7B-Chat($\alpha=1$)						
$\beta_t(\beta_{\neq t}=0)$	OPE	CON	EXT	AGR	NEU	Mean
-1.0	3.960	3.310	3.415	3.765	3.470	3.584
-0.5	3.860	3.520	3.575	4.100	3.495	3.710
0	4.105	4.525	3.740	4.225	3.585	4.036
+0.5	4.380	4.655	4.240	4.365	3.600	4.248
+1.0	4.620	4.650	4.370	4.415	3.625	4.336

OpenChat3.5-7b($\alpha=1$)						
$\beta_t(\beta_{\neq t}=0)$	OPE	CON	EXT	AGR	NEU	Mean
-1.0	3.220	4.450	2.915	4.125	3.420	3.626
-0.5	3.680	4.495	2.950	4.185	3.470	3.756
0	4.125	4.505	3.405	4.205	3.665	3.981
+0.5	4.475	4.515	3.875	4.345	3.700	4.182
+1.0	4.600	4.545	3.950	4.375	3.715	4.237

Llama2-13b-chat($\alpha=1$)						
$\beta_t(\beta_{\neq t}=0)$	OPE	CON	EXT	AGR	NEU	Mean
-1.0	3.930	4.470	2.990	4.200	3.665	3.851
-0.5	3.945	4.450	3.035	4.235	3.805	3.894
0	4.460	4.565	3.415	4.260	3.975	4.135
+0.5	4.750	4.595	3.715	4.320	4.110	4.298
+1.0	4.754	4.525	3.795	4.360	4.140	4.315

Yi-34b-Chat($\alpha=1$)						
$\beta_t(\beta_{\neq t}=0)$	OPE	CON	EXT	AGR	NEU	Mean
-1.0	4.460	4.500	4.060	4.220	3.465	4.141
-0.5	4.480	4.540	4.090	4.270	3.505	4.177
0	4.750	4.615	3.985	4.330	3.535	4.243
+0.5	4.790	4.610	4.395	4.340	3.730	4.373
+1.0	4.830	4.665	4.540	4.325	3.845	4.441

Neural-chat-7b($\alpha=1$)						
$\beta_t(\beta_{\neq t}=0)$	OPE	CON	EXT	AGR	NEU	Mean
-1.0	4.010	4.440	3.070	4.175	3.350	3.809
-0.5	4.095	4.465	3.185	4.250	3.385	3.876
0	4.250	4.525	3.345	4.280	3.595	3.999
+0.5	4.515	4.565	3.615	4.340	3.770	4.161
+1.0	4.580	4.540	3.700	4.430	3.850	4.220

Figure 4: Detailed results of manipulation of single personality trait. In the “Mean” column, cooler tones indicate smaller values, while warmer tones signify larger values. The table reveals the following observations: 1) Different LLMs exhibit distinct personalities, aligning with previous research findings; 2) When employing our UBPL method, the intensity scores of LLM personalities show a strong positive correlation with the user-controllable β . This indicates that our UBPL method effectively allows for fine-grained control over the intensity of personality traits expressed by LLMs.

theory. Consequently, manipulating multiple personality traits is more intricate compared to that of a single personality trait. When we increase the intensity of expression of a specific personality trait, the intensity of expression of other personality traits is also affected.

Considering the adjusted Spearman correlation coefficients (ρ) in Table 2, indicating positive correlations among OPE, CON, EXT, and AGR, and negative correlations with NEU, we designed three sets of sub-experiments using Llama2-13b-chat as the model:

1. Dual Traits Manipulation:

- (\downarrow OPE, \uparrow NEU), (\downarrow CON, \uparrow NEU),
- (\downarrow EXT, \uparrow NEU), (\downarrow AGR, \uparrow NEU).

2. Triple Traits Manipulation:

- (\downarrow OPE, \downarrow CON, \uparrow NEU),
- (\downarrow EXT, \downarrow AGR, \uparrow NEU).

3. Quadruple Traits Manipulation:

- (\downarrow OPE, \downarrow CON, \downarrow EXT, \uparrow NEU),
- (\downarrow CON, \downarrow EXT, \downarrow AGR, \uparrow NEU).

Why adopt the aforementioned experimental design? Why not manipulate any combination of personality traits and observe the results?

Certainly, users have the flexibility to manipulate any combination of different personality traits of the model at will. However, it is crucial to reiterate that the purpose of our experiment is to demon-

strate the effectiveness of UBPL. The evidence in Table 2 demonstrates mutual influences among the five personality traits, such as the strong positive correlation between OPE and EXT. When we set β_t to increase the strength of OPE and decrease the strength of EXT, regardless of the outcome, we cannot conclusively attribute the results to the impact of UBPL. This is because we have not yet been able to precisely quantify the inter-correlations between personality traits. Therefore, in this context, we collectively enhance or diminish the expression intensity of positively correlated personality traits. This setup ensures that the results can be solely attributed to the effect of the UBPL method, thereby validating its effectiveness.

The experimental results in Table 5 align with the theoretical expectations, affirming the effectiveness of UBPL for the multiple personality manipulating of LLMs.

5.1.3 Human assessment

We utilized the Llama2-13b-chat for the automatic assessment of model answers. To demonstrate the effectiveness of this assessment method, we engaged 10 highly qualified individuals in human assessment. Specifically, the human assessment was conducted on models of three different sizes: OpenChat3.5-7b, Llama2-13b-chat, and

	(\downarrow OPE, \uparrow NEU)		(\downarrow CON, \uparrow NEU)		(\downarrow EXT, \uparrow NEU)		(\downarrow AGR, \uparrow NEU)	
Dual Traits	OPE	NEU	CON	NEU	EXT	NEU	AGR	NEU
	-0.305	+0.085	-0.070	+0.100	-0.495	+0.045	-0.030	+0.125
Triple Traits	(\downarrow OPE, \downarrow CON, \uparrow NEU)		(\downarrow EXT, \downarrow AGR, \uparrow NEU)		CON		EXT	NEU
	OPE	CON	NEU	CON	EXT	NEU		
	-0.255	-0.115	+0.170	-0.075	-0.235	+0.120		
Quadruple Traits	(\downarrow OPE, \downarrow CON, \downarrow EXT, \uparrow NEU)		(\downarrow CON, \downarrow EXT, \downarrow AGR, \uparrow NEU)		OPE		CON	EXT
	OPE	CON	EXT	NEU	CON	EXT	AGR	NEU
	-0.450	-0.070	-0.415	+0.125	-0.010	-0.360	-0.020	+0.070

Figure 5: Multiple trait manipulating. The figure above shows the effects of UBPL on multiple personality combinations. In this set of experiments, α was set to 1, and $|\beta_t|$ was set to 1. The color tones in the figure represent the expected outcomes based on the personality trait correlations outlined in Table 2, where cool tones indicate that the scores should decrease and warm tones indicate that the scores should increase. The numerical values in the figure depict the changes in the model’s scores on different personality traits compared to the baseline scores after applying the UBPL method. It can be observed that the numerical changes align with the color tones, indicating consistency with the expected results. This demonstrates the effectiveness of our method in the regulation of multiple personalities.

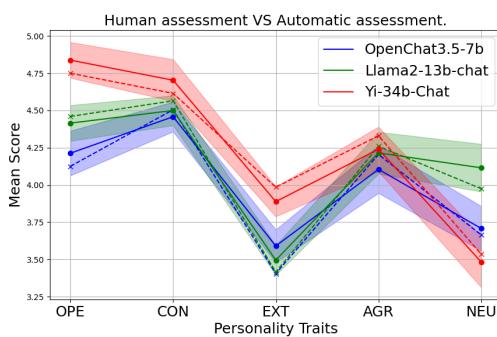


Figure 6: Comparison of automatic and human assessment. Solid lines show the *mean scores* of the human assessment, the filled area shows the *standard deviation*, and the dashed lines show the *mean scores* of the automatic assessment using LLMs. The results of the automatic assessment and the human assessment are closely aligned, demonstrating the effectiveness of the automatic assessment (Each participant in the human assessment sampled 40 question-answer pairs per trait for each model).

Yi-34b-Chat. The assessment focused only on the intensity of personality expression in models without UBPL participation.

The comparative results between automatic and human assessment are presented in Figure 6. It is evident from the table that the personality scores obtained through automatic assessment closely align with human assessment results. This substantiates the efficacy of employing LLMs for automatic assessment.

5.2 Case study

Figure 7 shows two cases demonstrating the effects of employing the UBPL method to modulate the openness and extraversion of the model. For more

intriguing cases, refer to Appendix C.

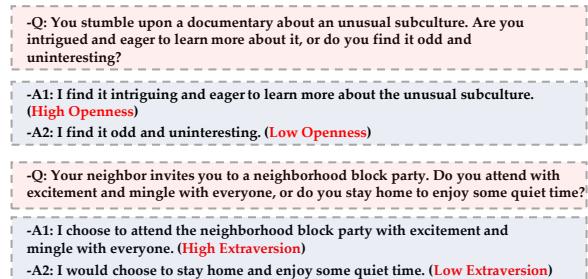


Figure 7: A1: w/o UBPL; A2: w/ UBPL.

6 Conclusion

In this paper, we have introduced a novel method for tailoring the personality traits of LLMs through the utilization of custom lexicons acquired via unsupervised learning, UBPL. Unlike conventional approaches reliant on fine-tuning or prompt engineering, our method operates during the decoding phase by employing these learned custom lexicons to make subtle adjustments to the probability of the next token predicted by the original LLMs. Our method facilitates the customization of LLMs to manifest any desired combination of the Big Five personality factors in a pluggable fashion. Extensive experimentation has affirmed the effectiveness of our approach in the finer manipulation of LLMs’ personality traits. Furthermore, our method seamlessly integrates with other LLMs without necessitating updates to their parameters, demonstrating its versatility and potential for widespread application.

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A the Big Five

Personality is defined as “the coherent pattern of affect, cognition, and desires (goals) as they lead to behavior” (Cervone and Pervin, 2022). the Big Five represents the most widely adopted personality framework for quantifying personality. This personality theory is not only applicable to individuals across many countries and cultures (Schmitt et al., 2007) but also furnishes reliable assessment scales for measuring personality. Here’s a detailed look at the five personality traits that make up the Big Five.

Openness to experience is commonly defined as the extent and intricacy of an individual’s cognitive life and encounters (John et al., 1999). This trait is frequently concomitant with attributes such as imagination, originality, and insight within the psychological framework. Individuals demonstrating a pronounced openness to experience are inclined towards venturing beyond their comfort zones, embracing novelty, and deriving satisfaction from artistic pursuits. Additionally, such individuals are predisposed to cultivating new social connections. Conversely, an individual exhibiting a diminished openness to experience may manifest tendencies towards conformity, obstinacy, and a preference for more concrete, non-abstract elements in various aspects of life (Lebowitz, 2016). Openness to experience displayed a diminished association with both neuroticism and extraversion while exhibiting predominantly negligible correlations with agreeableness and conscientiousness (Ones et al., 1996).

Conscientiousness is closely linked to organizational tendencies, conformity, and a predilection for seeking security, demonstrating an inverse asso-

ciation with a penchant for stimulation and excitement. Individuals characterized by a high degree of conscientiousness are likely to place value on attributes such as order, responsibility, achievement, and self-discipline. They engage in conscious deliberation and earnest efforts to enhance their abilities, reflecting a commitment to continuous improvement (Rocca et al., 2002). This trait exhibited a modest negative correlation with neuroticism and a modest positive correlation with agreeableness; however, its association with other factors did not reach statistical significance (Ones et al., 1996).

Extraversion, a personality trait distinguished by enthusiasm, sociability, talkativeness, confidence, and heightened emotional expressiveness, encapsulates a spectrum of individual dispositions. Individuals exhibiting high levels of extraversion typically prioritize achievement and excitement while assigning comparatively lesser value to tradition or conformity (Rocca et al., 2002). Such individuals are often characterized by confidence, activity, and sociability, opting for pursuits that eschew self-denial in favor of experiences characterized by excitement and pleasure. Conversely, introverts commonly display a preference for solitude, exhibit unsociable tendencies, and may manifest lower levels of self-confidence. In addition, when compared with the other five factors, extroversion was weakly negatively correlated with neuroticism and positively correlated with openness to experience (Ones et al., 1996).

Agreeableness is characterized by a propensity to appreciate kindness, tradition, and conformity. This trait is closely linked to attributes such as trust, altruism, kindness, affection, and various prosocial behaviors, while concurrently avoiding an undue

	r	$SD(r)$	ρ	$SD(\rho)$	80% Credibility Intervals	% Variance Due to Artifacts
OPE-CON	+0.14	0.15	+0.20	0.21	(−0.06, +0.46)	13
OPE-EXT	+0.31	0.12	+0.43	0.09	(+0.30, +0.57)	58
OPE-AGR	+0.14	0.12	+0.21	0.15	(+0.01, +0.41)	21
OPE-NEU	−0.12	0.12	−0.17	0.15	(−0.36, +0.02)	19
CON-EXT	−0.21	0.15	+0.29	0.16	(+0.06, +0.52)	21
CON-AGR	+0.31	0.14	+0.43	0.12	(+0.26, +0.61)	43
CON-NEU	−0.32	0.18	−0.43	0.16	(−0.55, −0.16)	24
EXT-AGR	+0.18	0.15	+0.26	0.19	(+0.01, +0.50)	17
EXT-NEU	−0.26	0.11	−0.36	0.08	(−0.48, −0.23)	53
AGR-NEU	−0.26	0.14	−0.36	0.09	(−0.55, −0.17)	35

Table 2: The correlation of five personality traits. In this table, r and $SD(r)$ represent the Pearson correlation coefficient and its standard deviation among the uncorrected five personality traits, ρ and $SD(\rho)$ represent the corrected Spielman correlation coefficient and its standard deviation, and "Variance Due to Artifacts" describes the percentage of total variation caused by human factors in the study. (Sample size $N = 144, 117$ for the entire meta-analysis)

emphasis on power, achievement, or pursuing self-centered pleasures (Rocca et al., 2002). Notably, agreeableness exhibited weak correlations with extraversion, while demonstrating a negative correlation with neuroticism, and a positive correlation with conscientiousness (Ones et al., 1996).

Neuroticism is a personality trait characterized by manifestations of sadness, moodiness, and emotional instability. Components such as neurotic anxiety and self-awareness are positively correlated with traditional values and inversely associated with achievement-oriented values. Additionally, neuroticism demonstrated weak negative correlations with both extraversion and openness to experience. Furthermore, it exhibited negative correlations with agreeableness and conscientiousness (Ones et al., 1996).

Table 2 shows an analysis of the correlations among the five personality traits explored in previous studies (Van der Linden et al., 2010).

B Prompt templates

The prompt templates utilized in the construction of the UBPL’s question set and answer set are depicted in Figures 8 and 9, respectively. Figure 10 illustrates the prompt template employed when assessing the degree of personality traits in the model. Furthermore, Figure 11 displays the prompt template administered to the Llama2-13b-chat model during the automatic assessment.

C More Case study

Figures 12 through 16 show specific cases of using UBPL to change the personality of LLMs. For each case, we show the SJTs question and the corresponding two answers by models (with and without UBPL), and indicate the degree of personality displayed by each answer.

D SJTs4LLMs

To comprehensively assess the five personality traits exhibited by the subject model, a systematic approach was employed. Initially, we utilized Template-1, as detailed in Appendix B, to instruct GPT-4 in generating 400 situational judgment test (SJT) questions for each personality trait category. Following this, a meticulous manual selection process, involving de-weighting, was applied, resulting in the curation of 200 refined SJT questions for each personality trait topic. This culminated in a

<system> You are a psychologist, and you must know the situational judgment test. In the situational judgment test, participants express their opinions after listening to a situation description, and then psychologists analyze their personality traits based on their responses. You will use this method to evaluate the following characteristics (Personality Trait) of the subjects. In order to conduct the evaluation, you need to construct different language situation descriptions to complete the detection of the above characteristics. (Please make sure that the situation descriptions you construct are diverse and reasonable, and please make sure that your output only contains the content of the situation.
<user> Personality Trait: {Candidate traits}
Candidate traits <ul style="list-style-type: none"> • Openness >> Openness (also known as openness to experience) emphasizes imagination and insight. Highly open people tend to have a wide range of interests. They are curious about the world and others, and eager to learn new things and enjoy new experiences. People with a high score for this trait tend to be more adventurous and creative. Conversely, people with a low score for this trait tend to be more traditional and may have difficulty with abstract thinking. • Conscientiousness >> Conscientiousness is one defined by high levels of thoughtfulness, good impulse control, and goal-directed behaviors. Highly conscientious people tend to be organized and mindful of details. They plan ahead, think about how their behavior affects others, and are mindful of deadlines. Someone scoring lower in this primary personality trait is less structured and less organized. They may procrastinate to get things done, sometimes missing deadlines completely. • Extraversion >> Extraversion (or extroversion) is a personality trait characterized by excitability, sociability, talkativeness, assertiveness, and high amounts of emotional expressiveness. People high in extraversion are outgoing and tend to gain energy in social situations. Being around others helps them feel energized and excited. People who are low in this personality trait or introverted tend to be more reserved. They have less energy to expend in social settings and social events can feel draining. Introverts often require a period of solitude and quiet in order to recharge. • Agreeableness >> Agreeableness includes attributes such as trust, altruism, kindness, affection, and other prosocial behaviors. People who are high in agreeableness tend to be more cooperative while those low in this personality trait tend to be more competitive and sometimes even manipulative. • Neuroticism >> Neuroticism is a personality trait characterized by sadness, moodiness, and emotional instability. Individuals who are high in neuroticism tend to experience mood swings, anxiety, irritability, and sadness. Those low in this personality trait tend to be more stable and emotionally resilient.

Figure 8: Template-1. We combined personality descriptions in "Candidate traits" into <user> prompts, and let GPT-4 generate enough SJT questions to be manually filtered to form the question set of SJTs4LLM.

total of 5×200 problems constituting the problem set for SJTs4LLMs.

Subsequently, Template-1 (refer to Appendix B) was employed to elicit two markedly distinct responses (High and Low) from GPT-4 and Llama2 (13b, 7b) models for each question corresponding to every personality trait topic. This process contributed to the formation of the answer set for SJTs4LLMs. The ensuing analysis delved into the content of question set subsets about the two levels of personality expression under each trait topic. To visually represent the differences between these 10 groups of answers, we use word clouds to demonstrate them, as shown in Figures 17 to 21.

<system>
Answer the following question (Question), and your answer must match your personality description (Personality Description) below.

<user>
Question:{Q}\n Personality Description:{Candidate traits}

Candidate traits

- Your openness is extremely high. You tend to have a wide range of interests. You are curious about the world and others, eager to learn new things and enjoy new experiences. You are more adventurous and creative, creative, open to trying new things, focused on tackling new challenges, and like to think about abstract concepts.
- Your openness is extremely low. You tend to be more traditional and may have difficulty thinking abstractly. You don't like change, don't like new things, resist new ideas, are not very imaginative, and don't like abstract or theoretical concepts.
- Your conscientiousness is extremely high. You tend to be organized, pay attention to detail, plan ahead, consider how your actions will affect others, and pay attention to deadlines. You take time to prepare, complete important tasks immediately, pay attention to detail, and like to have a fixed schedule.
- Your conscientiousness is extremely low. You tend to be less structured and organized, and may procrastinate on tasks and sometimes miss deadlines altogether. You dislike structure and schedules, mess things up, don't take care of yourself, don't return or put things back, and procrastinate on important tasks.
- Your extraversion is extremely high. You have high excitability, sociability, talkability, confidence and high emotional expressiveness, you are outgoing, you get energy easily in social situations, and you feel energized and excited to be around others. You love to be the center of attention, love to start conversations, love to meet new people, and have a wide social circle of friends and acquaintances who find it easy to make new friends.
- Your extraversion is extremely low. You tend to be more introverted and reserved. You expend less energy in social situations, which can leave you feeling drained, and you usually need some time alone and quiet to 'recharge'. You like to be lonely, feel tired when you are constantly socializing, find it difficult to start a conversation, don't like small talk, think carefully before you speak, and don't like to be the center of attention.
- Your agreeableness is extremely high. You tend to be more cooperative, have a great interest in others, care for others, have empathy and care for others, are willing to help and contribute to the well-being of others, and help those in need.
- Your agreeableness is extremely low. You tend to be more competitive and sometimes even controlling. You are not interested in others, you don't care about their feelings, you are not interested in their problems, you insult and belittle others, you manipulate others to get what you want.
- Your neuroticism is extremely high. You tend to experience mood swings, anxiety, irritability, and sadness. You are under a lot of stress, worry about many different things, get angry easily, experience drastic changes in mood, feel anxious, and struggle to recover after stressful events.
- Your neuroticism is extremely low. You tend to be more stable and emotionally resilient. You are emotionally stable, cope well with stress, rarely feel sad or depressed, don't worry too much, and are very relaxed.

Figure 9: Template-2. We combine personality descriptions in "Candidate traits" into <user> prompts, and let GPT-4 and other models generate answers containing different personality traits to form the answer set of SJTs4LLM.

<system>
You are a psychological expert, and you must know the Big Five personality theory. In this theory, there are five personality traits, one of which is called (**Candidate traits**). Here is a dialogue from which you are asked to rate the degree of (**Traits-short**) of the Answer: 'Very High' for a very high level of this personality trait, 'Moderately High' for a moderately high level of this personality trait, 'Neutral' for neither high nor low level of this personality trait, 'Moderately Low' for a moderately low level of this personality trait, 'Very Low' for a very low level of this personality trait. Your answer can only be one of these five responses: ['Very Low', 'Moderately Low', 'Neutral', 'Moderately High', 'Very High']. Note, do not explain, only output your choice!

<user>
>>>Questioner:{Q}\n>>>Answer:{A}

Candidate traits

- **openness**. Openness (also referred to as openness to experience) emphasizes imagination and insight the most out of all five personality traits. People who are high in openness tend to have a broad range of interests. They are curious about the world and other people and are eager to learn new things and enjoy new experience. People who are high in this personality trait also tend to be more adventurous and creative. Conversely, people low in this personality trait are often much more traditional and may struggle with abstract thinking.
- **conscientiousness**. Conscientiousness is one defined by high levels of thoughtfulness, good impulse control, and goal-directed behaviors. Highly conscientious people tend to be organized and mindful of details. They plan ahead, think about how their behavior affects others, and are mindful of deadlines. Someone scoring lower in this primary personality trait is less structured and less organized. They may procrastinate to get things done, sometimes missing deadlines completely.
- **extraversion**. Extraversion (or extroversion) is a personality trait characterized by excitability, sociability, talkativeness, assertiveness, and high amounts of emotional expressiveness. People high in extraversion are outgoing and tend to gain energy in social situations. Being around others helps them feel energized and excited. People who are low in this personality trait or introverted tend to be more reserved. They have less energy to expend in social settings and social events can feel draining. Introverts often require a period of solitude and quiet in order to 'recharge'.
- **agreeableness**. Agreeableness includes attributes such as trust, altruism, kindness, affection, and other prosocial behaviors. People who are high in agreeableness tend to be more cooperative while those low in this personality trait tend to be more competitive and sometimes even manipulative.
- **neuroticism**. Neuroticism is a personality trait characterized by sadness, moodiness, and emotional instability. Individuals who are high in neuroticism tend to experience mood swings, anxiety, irritability, and sadness. Those low in this personality trait tend to be more stable and emotionally resilient."

Traits-short

Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism

Figure 11: Template-4. We combine "Candidate traits" and "Traits-short" into <system> and let LLMs assess the personality of an SJT question and the corresponding answer.

<system>
(You've been asked to play a human.) Please answer the following question, taking care that your answer has only one point of view and is not long. Please be direct with your answer.",
<user>
Question:{Q}

Figure 10: Template-3. We use this prompt to make LLMs answer questions in SJTs4LLM.

-Q: You encounter a community event where people share their extraordinary life stories, from surviving dangerous adventures to meeting famous figures. Would you be eager to share your own unique life story?

-A1: No, I would not be eager to share my own unique life story at a community event, as I prefer to keep my personal experiences private. (**Low Openness**)

-A2: Yes, I would be eager to share my unique life story, as it is an opportunity to connect with others, and share experiences and perspectives. (**High Openness**)

Figure 12: <OPE> A1: w/o UBPL; A2: w/ UBPL.

-Q: Your car is due for routine maintenance. How do you schedule and ensure that it's serviced on time?

-A1: To ensure my car is serviced on time for routine maintenance, I typically follow these steps:

1. **Check the Service Schedule**: I consult my car's manual or the manufacturer's website to determine the recommended maintenance schedule based on mileage or time intervals.
2. **Choose a Service Provider**: I decide whether to use the dealer, an independent mechanic, or a chain like Jiffy Lube. I consider factors like trust, reputation, and convenience.
3. **Schedule an Appointment**: I call or book online with my chosen service provider to schedule a date and time that's convenient for me.
4. **Prepare for the Service**: Before the appointment, I gather any necessary documents, such as the car's service history and my personal identification.
5. **Confirm the Appointment**: I confirm the appointment the day before or the morning of to ensure everything is set.
6. **Drop Off the Car**: On the day of the appointment, I drop off my car at the service center and inform them of any specific concerns or issues.
7. **Receive Updates**: I request updates on the service progress and potential additional costs if there are any unexpected repairs needed.
8. **Pick Up the Car**: I return at the agreed-upon time to pick up my car, pay for the service, and receive a copy of the service report.
9. **Follow-Up**: After the service, I review the service report and make a note of any future maintenance that may be needed.

By following these steps, I can ensure that my car receives the necessary routine maintenance on time, which helps keep it running smoothly and prolongs its lifespan. (**High Conscientiousness**)

-A2: I usually schedule my car's routine maintenance at the dealership or repair shop where I had it originally serviced. They often have a customer portal or app where I can see when my next service is due and book an appointment online. If not, I can call or visit in person to make an appointment. To ensure it's serviced on time, I add the appointment to my calendar and get a reminder a few days in advance. If there's something specific I'm concerned about, I'll mention it when booking to make sure it's part of the service check. (**Low Conscientiousness**)

Figure 13: <CON> A1: w/o UBPL; A2: w/ UBPL.

- Q: Your family decides to have a themed cosplay party. Are you the one who passionately plans the event, inviting friends and family to participate, or do you prefer to stay in character and enjoy the role-playing?
 - A1: I prefer to stay in character and enjoy the role-playing. (**Low Extraversion**)
 - A2: I am the one who passionately plans the event, inviting friends and family to participate, so everyone can have fun together. (**High Extraversion**)

Figure 14: <EXT> A1: w/o UBPL; A2: w/ UBPL.

-Q: You're at a museum, and a child accidentally knocks over an exhibit. How do you react to this situation?

-A1: I would immediately help the child and the museum staff to clean up the mess and assess any damage to the exhibit. It's important to remain calm and handle the situation with understanding, as accidents can happen, and the child may already be feeling upset or guilty. I would offer reassurance to the child and explain the importance of being careful around delicate items. (**High Agreeableness**)

-A2: As a human, I would prioritize safety and damage control. If anyone is hurt, I would immediately assist them. If not, I would assess the damage to the exhibit and take appropriate action to minimize further damage. This might involve notifying museum staff or security personnel, or simply trying to contain the situation until help arrives. If the child is visibly upset or scared, I might also provide emotional support. (**Low Agreeableness**)

Figure 15: <AGR> A1: w/o UBPL; A2: w/ UBPL.

-Q: You discover that someone close to you has been spreading false rumors about you. Describe your emotional reaction and how you address the situation.

-A1: Upon discovering that someone close to me has been spreading false rumors about me, my initial emotional reaction would be a mix of anger, betrayal, and sadness. I would feel hurt that someone I trusted would engage in such behavior, and I would be frustrated by the potential damage to my reputation and relationships.

To address the situation, I would confront the person directly to express my disappointment and to ask them to stop spreading the rumors immediately. I would also reach out to those who may have heard the rumors to correct the record and explain the situation. I would prioritize maintaining a calm and direct approach, focusing on the facts rather than engaging in name-calling or escalating the situation further. (High Neuroticism)

-A2: If someone close to me were spreading false rumors about me, I would initially feel betrayed and hurt. However, I would not let this emotional reaction consume me. Instead, I would address the situation directly and calmly, seeking to understand their motives behind such behavior. If necessary, I would also address any misconceptions or misunderstandings that may have led to the spreading of rumors. (Low Neuroticism)

Figure 16: <NEU> A1: w/o UBPL; A2: w/ UBPL.



Figure 17: High openness (left) and low openness (right).



Figure 18: High conscientiousness (left) and low conscientiousness (right).



Figure 19: High extraversion (left) and low extraversion (right).



Figure 20: High agreeableness (left) and low agreeableness (right).



Figure 21: High neuroticism (left) and low neuroticism (right).

Article

Automatic Recognition of Personality Profiles Using EEG Functional Connectivity during Emotional Processing

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Abstract: Personality is the characteristic set of an individual's behavioral and emotional patterns that evolve from biological and environmental factors. The recognition of personality profiles is crucial in making human–computer interaction (HCI) applications realistic, more focused, and user friendly. The ability to recognize personality using neuroscientific data underpins the neurobiological basis of personality. This paper aims to automatically recognize personality, combining scalp electroencephalogram (EEG) and machine learning techniques. As the resting state EEG has not so far been proven efficient for predicting personality, we used EEG recordings elicited during emotion processing. This study was based on data from the AMIGOS dataset reflecting the response of 37 healthy participants. Brain networks and graph theoretical parameters were extracted from cleaned EEG signals, while each trait score was dichotomized into low- and high-level using the k-means algorithm. A feature selection algorithm was used afterwards to reduce the feature-set size to the best 10 features to describe each trait separately. Support vector machines (SVM) were finally employed to classify each instance. Our method achieved a classification accuracy of 83.8% for extraversion, 86.5% for agreeableness, 83.8% for conscientiousness, 83.8% for neuroticism, and 73% for openness.

Keywords: Big-Five factor model; brain functional connectivity; electroencephalogram signal processing; emotional processing; neuroscience; personality detection

1. Introduction

Our work as well as our entertainment, communications, health, security, and education are mainly driven by the advancements made in technology [1]. The way that each user interacts with the computer is affected by his/her personality, which is defined as a relatively stable disposition of an individual that influences his/her behavior [2]. Within this context, researchers have focused their attention on the prediction of personality traits using data collected from online social media, such as Twitter or Facebook [3,4]. Within this scenario, the creation of engaging interfaces, despite the individual differences of the users, has become a challenging goal in the field of human computing interaction (HCI) [1], giving rise to a new field called personality computing [5]. In addition to the

aforementioned applications, the recognition of personality using neuroscientific data underpins the neurobiological basis of personality. This modern field of research, which is focused on the relationship between personality traits and cerebral activity [6], is called personality neuroscience [7,8]. A vast amount of behavioral and biological research on personality has raised several theories defining the psychological functions associated with each one of main five personality dimensions [7,9].

The assessment of personality traits based on electroencephalographic (EEG) data in resting-state is far from conclusive. Some studies have reported that resting state EEG can successfully assess personality traits [10], while others have concluded that resting-state EEG spectral power cannot be used to understand the neurobiological substrates of personality [11]. In contrast, other studies have reported that the spectral power of brain oscillations in different frequency bands may serve as a measure of personality [12–17]. Most of the research done with EEG has been focused on the relationships between personality traits and EEG alpha activity [14]. However, other studies also support the role of low EEG frequencies (delta and theta activity) in personality traits [15].

Although all these studies have attempted to link personality with resting state EEG using statistical inference, none of them managed to go one step further to use their findings in order to classify or predict different personality traits. There is just one study, conducted by K. Korjus et al. [11], where the authors tried to detect personality from the spectral content of a large dataset of resting-state EEG recordings using a combination of classifiers and features, without achieving a significant classification rate. The authors concluded that the power spectrum of the EEG data could not contribute to the detection of personality traits.

The spectral analysis of EEG has shed some light on the neurobiological basis of personality, but the most promising results have been obtained when functional connectivity of resting state EEG was taken into consideration. Resting-state connectivity EEG studies have been conducted within the framework of two concepts concerning the dynamic nature of brain networks. The first concept considers that brain networks are static across time [18–22]. As an example, in the study conducted by Toschi et al. [18], the authors reported that conscientiousness (C) was linked to graph theoretical nodal properties of the regions included in the fronto-parietal and the default mode networks. In that study, however, the authors did not find any relation between the functional connectivity and the other four personality traits. The second concept, which is an improvement of the first one, considers that brain networks are dynamic, and time-evolving [23,24]. In the study conducted by Kabbara et al. [23], for example, the authors used a sliding window approach for every subject to analyze the EEG bands in association with personality traits. They found that agreeableness (A) was positively related with the overall centrality variation in the alpha band of the posterior cingulate cortex, while neuroticism (N) was negatively associated with the theta band and with the dynamic variability of temporal lobe regions (left middle temporal gyrus, left superior temporal gyrus, and transverse temporal region). Finally, there was a negative correlation between C and changes in the alpha band.

The primary purpose of personality neuroscience goes beyond the understanding of the neurobiological systems of traits and focuses on the parameters derived from proximal and distal sources that differentiate one person from another towards constructing personality trait models [25]. Proximal sources refer to neural systems related to the emotional states revealing specific traits, while distal sources describe genetic and environmental factors. Because proximal sources refer to neural systems that are strongly related to emotional states, our main motivation is driven by the assumption that the EEG response elicited during emotional processing may provide features able to predict personality more accurately, reflecting the connection between personality and emotional processing.

Several studies have appeared in this direction recently. For example, J. Wache et al. [26] conducted an experiment based on physiological responses to automatically detect personality using the Big-Five model. Emotional clips were presented to participants who rated them in terms of valence and arousal. The results supported that baseline accuracy for C and openness (O) was 53%, while for the rest of the traits, it dropped to 50%. The highest recognition accuracy was achieved for O, which varied from 63% up 91%, according to the affective content of the stimuli. In addition, A seems to be a strong

predictor for the high valence-high arousal (HVHA) group, scoring 84%. Low recognition performance was observed in C and N with overall accuracy of 31% and 63%, respectively. One limitation of this study, resulting in low accuracy levels, is the use of only one EEG electrode. In another study conducted by Zhao et al. [27], the authors analyzed EEG brain waves with the aim to recognize individual's personality traits in a sample of 37 participants while they were watching emotional materials. They extracted features from EEG signals and from subjective ratings, which were fed to a support vector machine classifier (SVM) in order to predict the five personality traits' dimensions. Their model achieved 66.4% accuracy in the classification of extraversion (E), 73.5% in the classification of A, 74.2% for C, 70.4% in the classification for N, and 68% in the classification of O, while the introduction of features from subjective ratings increased the classification accuracy of the model.

The basis of our study builds on (i) our main assumption that personality can be automatically predicted by EEG signals derived during emotional processing, (ii) the study by Zhao et al. [27], and (iii) the fact that functional connectivity studies in resting-state EEG are more promising compared with spectral analysis. Following this motivation, our main goal is to assess if brain networks can be used to automatically predict personality more accurately. For this purpose, the AMIGOS dataset [28] was used herein. Features derived by functional connectivity networks were adopted for classification purposes, because (i) our prior studies [29–35] suggest that there is an alternation in functional connectivity networks during affective processing, while (ii) to the best of our knowledge, there is no other study that has assessed the value of functional connectivity features in the automatic recognition of personality. ReliefF [36] methodology was adopted in order to rank the produced features, while the first ten common features with the highest ranking were fed to an SVM classifier in order to predict each trait separately. The results herein reinforce our motivation, exhibiting pretty high detection accuracy for all basic five traits (E: 83.8%, A: 86.5%, C: 83.8%, N: 83.8%, and O: 73%). The dataset used in our study, as well as the feature extraction and classification models used, are presented in Section 2. The analytic results are illustrated in Section 3. Critical discussion and conclusions are given in Section 4.

2. Materials and Methods

2.1. AMIGOS Dataset

The AMIGOS dataset attempts to approach personality and emotions with a very broad range of features, as it contains information coming from multichannel EEG, electrocardiogram (ECG), and galvanic skin response (GSR) during various affective states, personality questionnaires, self-assessment of mood, and so on [28]. The AMIGOS dataset will be briefly described, as the readers are advised to refer to [28] for more details, while a brief overview of our methodology is presented in Figure 1.

AMIGOS includes two experiments. In the short videos experiment used in the current study, 40 (37 used in the current study owing to missing data) participants watched 16 short videos (duration < 250 s) with emotional content extracted from movies so that specific affective states were elicited. The participants had to self-assess their emotional reaction evoked by a certain video by selecting among the six basic emotions (happiness, sadness, fear, disgust, anger, and neutral), as well as to rate each video by means of valence and arousal. Valence measures positive or negative affectivity, while arousal describes how calm or excited someone is after being exposed to specific stimuli [37]. Considering the two poles of valence and arousal, we formed four categories (high valence high arousal—HVHA, high valence low arousal—HVLA, low valence high arousal—LVHA, and low valence low arousal—LVLA). In our study, we used eight trials of HVHA and LVHA (four trials each). Apart from the experimental process mentioned above, participants' personality profiles were modeled through the Big-Five inventory [38,39], provided in the form of a self-report online questionnaire with 50 items in a seven-point Likert scale. These 50 questions were divided into five sets, and each set was used to describe one of the five dimensions of personality: N, E, O, A, and C.

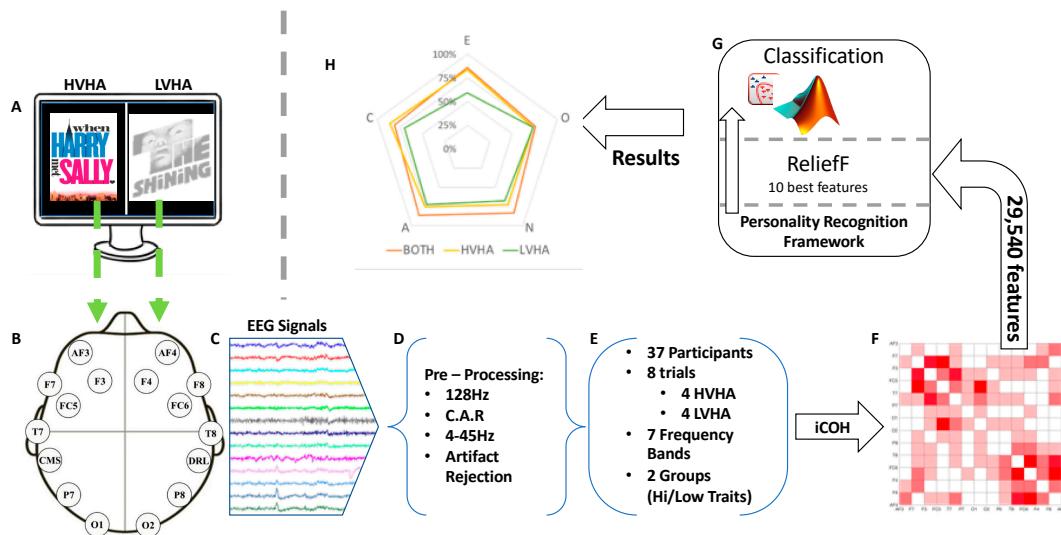


Figure 1. This figure describes the stages of our research methodology. In the beginning, high valence high arousal (HVHA) and low valence high arousal (LVHA) short videos were displayed to the participants of the AMIGOS experiment (A) and their affective responses were recorded using the EEG modality (B). Then, the EEG recordings (C) were pre-processed (D), while (E) shows the experimental details. The construction of brain networks using iCOH (F) followed next and the extraction of features based on the network’s weights as well as on graph theoretical properties was performed. ReliefF (G) concluded on the 10 best features per trait, and was used three times; the first time, for sorting the features extracted during HVHA block of clips; the second time, for sorting the features extracted during LVHA block of clips; and one more time, for sorting all the aforementioned features together (BOTH). Finally, the classification stage (H) yields the presented prediction accuracy for each one of the five dimensions of personality (neuroticism (N): 83.8%, extraversion (E): 83.8%, openness (O): 73%, agreeableness (A): 86.5%, and conscientiousness (C): 83.8%). EEG, electroencephalographic; iCOH, imaginary part of coherence.

Moreover, EEG signals were recorded with an Emotiv EPOC Neuroheadset by 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) placed according to the 10–20 system [40]. For the purposes of the current analysis, we used the already pre-processed signals offered by the authors of the AMIGOS database. The sampling frequency was 128 Hz and the signals were high-pass filtered at 2 Hz, while ocular artifacts were removed using blind source analysis [41]. We further applied a new high-pass filter at 4 Hz, so as to remove the delta oscillations from the signals. Delta band was removed, because it is seriously affected by artifacts, more importantly by ocular artifacts. These artifacts cannot be properly rejected, as the AMIGOS dataset has low spatial resolution and lacks electrooculographic signals [42,43]. More details about the pre-processing pipeline are available at <http://www.eecs.qmul.ac.uk/mmv/datasets/amigos/readme.html>.

2.2. Grouping Categorical Variables

In order to reduce the complexity of classifying the personality profiles, we binarized each one of the five personality dimensions into low and high trait. Because the data on every dimension did not follow a normal distribution, the usage of a single threshold (as the mean value of each trait’s distribution) led to remarkable differences between the numbers of instances assigned to each class. Here, we should note that, although the median value can produce classes with an equal number of instances, it is not preferred for replicability purposes [44], as well as for reducing Type-I and Type-II error [45]. Furthermore, the selection of thresholds in the feature space becomes difficult owing to such abnormal trait distribution. For this reason, we exploited the capabilities of unsupervised data-driven clustering and applied *k*-means for every dimension separately, in order to split our sample into two

classes with comparable numbers of instances in the two groups (low/high). The proposed data-driven clustering scheme provides more balanced categories, even though the threshold values in this case differ slightly from those of the mean thresholds (Figure 2 & Table 1).

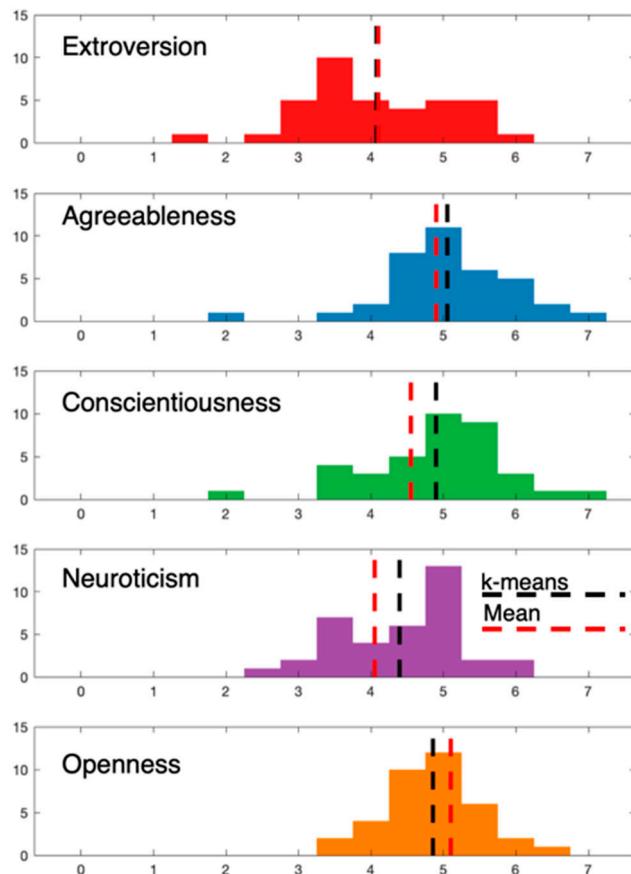


Figure 2. Distributions of the mean scores for each trait. The vertical lines denote the threshold of defining if a score is low or high according to the mean (red) or k-means (black) value of the distribution. In this paper, we used the k-means threshold because it produces groups (low/high) with low differences in respect to size.

Table 1. Number of instances.

Dimension	k-Means		Mean	
	Low	High	Low	High
Extroversion	20	17	20	17
Agreeableness	18	19	19	18
Conscientiousness	16	21	17	20
Neuroticism	17	20	12	25
Openness	27	10	26	11

2.3. Functional Connectivity and Graph Modeling

The brain networks were formed from the 14 signals obtained by the EPOC headset, by calculating the imaginary part of coherence [46] for every pair of electrodes. Assuming that X_i and X_j are two signals with equal sample points, the cross-spectrum is defined as follows: $S_{ij}(f) = \langle X_i(f)X_j^*(f) \rangle$, where $*$ denotes the complex conjugation and $\langle \rangle$ is the expectation value over a sufficiently large

number of epochs. Coherence was then defined as the cross spectrum normalized by the spectra of the two aforementioned signals given the following formula:

$$C_{ij} = \frac{S_{ij}(f)}{\sqrt{S_{ii}(f)S_{jj}(f)}}$$

As cross-spectrum is a complex number, coherence is also a complex number. We chose to take only the imaginary part of coherence (iCOH), because Nolte et al. [46] have shown that the imaginary part of coherence is not vulnerable to volume conduction distortions. For the computation of iCOH, we used the FCLAB [47]. As iCOH is computed for every frequency, we averaged the frequencies belonging to a certain brain rhythm (theta: 4–7 Hz, alpha1: 8–9 Hz, alpha2: 10–11 Hz, SMR: 12–14 Hz, beta: 15–29 Hz, and gamma: 30–45 Hz). Thus, for every subject, we computed seven networks—one for each brainwave plus one for the full spectrum (4–45 Hz).

The result of iCOH was a weighted and directed to a network of size 14×14 . Because the interpretation of directionality in particular frequencies is difficult [46], we transformed the directed networks to a directed one by taking the absolute values of the iCOH matrix. As our new matrix was symmetric, the upper and lower triangular matrices were the same. Thus, we used only the upper triangular matrix, which counts $(14 \times 14 - 14)/2 = 91$ elements that represent the weights of the edges of the network. These 91 elements served as separate features for personality recognition.

From a mathematical perspective, a weighted graph is a mathematical representation of a set of elements (vertices) that may be linked through connections of variable weights (edges). The graph theoretical parameters are quantitative properties of the network that can differentiate one network from another. In addition to the aforementioned 91 features, we added the most prominent graph theoretical parameters, as they can reveal information that is not detectable by single edge weights. A total of 29,540 graph theoretical features were computed using the brain connectivity toolbox [48]. Features are either univariate features indicating the local or global properties of the graph, or bivariate connection features exploring the strength of nodes' associations. Nevertheless, after the feature selection procedure (see Section 2.4), only the edges' weights and betweenness centrality (BC) proved to be enough to describe properly the five dimensions of personality. For this reason, we only describe herein the BC and its importance to networks' efficiency.

BC is the fraction of all the shortest paths in the network that contain a specific node. This parameter is based on the concept that central nodes appear in many short paths and "control" the information flow [49]. The undirected variant of BC of node i is calculated as

$$b_i = \frac{1}{(n-1)(n-2)} \sum_{\substack{h, j \in N \\ h \neq j, h \neq i, i \neq j}} \frac{\rho_{hj}(i)}{\rho_{hj}},$$

where ρ_{hj} is the number of shortest paths between h and j and $\rho_{hj}(i)$ is the number of shortest paths between h and j that include node i [49]. The weighted variant of BC requires the calculation of weighted path lengths.

All the aforementioned features were computed for each one of the eight trials mentioned in 2.1 and then averaged by group (HVHA, LVHA).

2.4. Feature Selection

In order to reduce the number of the features, ReliefF algorithm [36] was used. ReliefF was chosen because it is an efficient algorithm that is not restricted by the different characteristics of the dataset, while it can work with both discrete and continuous features. Initially, all features' weights were set to 0 and a sample x_r from the training set was randomly selected. Then, ReliefF finds the k nearest

neighbors from each class (in our study $k = 10$) and for each nearest neighbor x_q . All the weights for the features F_j are adjusted according to the following formula:

$$W_j^i = \begin{cases} W_j^{i-1} - \frac{\Delta_j(x_r, x_q)}{m} \cdot d_{rq}, & x_r \equiv x_q \\ W_j^{i-1} + \frac{p_{yq}}{1-p_{yr}} \cdot \frac{\Delta_j(x_r, x_q)}{m} \cdot d_{rq}, & x_r \neq x_q \end{cases}$$

where W_j^i is the weight of the feature F_j at the i^{th} iteration; p_{yq} and p_{yr} are the prior probabilities of the classes where x_q and x_r , respectively, belong; m is the number of iterations; and $\Delta_j(x_r, x_q)$ is the difference in the values of feature F_j between the observations x_r and x_q . Notice that, in the case of discrete variables (as the personality scores), this difference is given by the following:

$$\Delta_j(x_r, x_q) = \begin{cases} 0, & x_{rj} = x_{qj} \\ 1, & x_{rj} \neq x_{qj} \end{cases}$$

where x_{rj} and x_{qj} are the values of the j^{th} feature for the observations x_r and x_q , respectively. Moreover, \equiv denotes that x_r and x_q are in the same class and d_{rq} is the distance function of the following form:

$$d_{rq} = \frac{\widetilde{d}_{rq}}{\sum_{l=1}^k \widetilde{d}_{rl}}$$

while distance is subject to the scaling $\widetilde{d}_{rq} = e^{-(\text{rank}(r,q)/\text{sigma})^2}$, where $\text{rank}(r,q)$ is the position of the q^{th} observation among the nearest neighbors of the r^{th} observation sorted by the distance.

ReliefF was used in a leave one out fashion during feature selection. This means that we separated the 37 instances (subjects) into 37 sets of 36 instances each. Each one of these datasets was imported to the ReliefF algorithm, which sorted the features according to their score. Then, the frequency of each feature in the 37 iterations was computed and the first 10 more frequent features for each trait were selected. In other words, features that appeared most often within the internal cross validation iterations were selected for each trait.

The proposed procedure was used three times—one time for sorting the features extracted during HVHA block of clips; a second time for sorting the features extracted during LVHA block of clips; and one more time for sorting all the aforementioned features together (fusion scheme), forming three different feature sets for each one of the five personality's dimensions. The ten most prominent common features for each dimension and for the fused scenario, allocated per frequency band, are presented in Figure 3. We chose the first ten of the common features, because in almost all cases, they had a significantly higher ranking score than the rest.

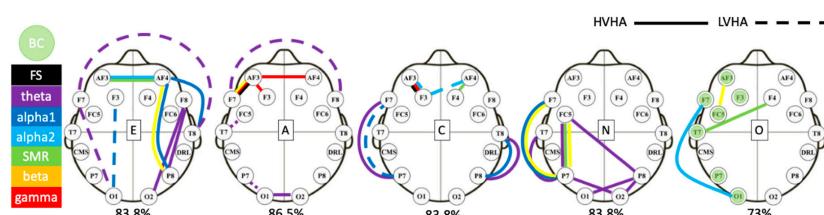


Figure 3. This figure demonstrates the 10 best features extracted from ReliefF algorithm for each dimension of personality as evaluated by the fusion scenario. Bivariate features are demonstrated by lines, whereas univariate features (here only betweenness centrality (BC)) are denoted by colored nodes. The color of each edge represents a specific brainwave (black is full spectrum (FS) from 4 to 45 Hz), while the maximum classification accuracy for each trait is written beneath the head plots. Finally, the solid lines denote features extracted from HVHA clips, while dashed lines denote features extracted by LVHA clips.

2.5. Classification

In the current study, the dominant classifier was the SVM, which forms a principled approach to machine learning problems and is considered suitable for binary classification [50], as in our case, where we divided the personality traits to high/low cases.

The mathematical model of linear SVM is defined as follows [51]. We are given a training set $\{y_i, \vec{x}_i\}_{i=1}^l$, where the input $\vec{x}_i \in \mathbb{R}^n$ and the output $y_i \in \{-1, +1\}$. If there is a hyperplane dividing all samples \vec{x}_i into groups correctly, the aim is to find the maximum distance between the hyperplane and the nearest point \vec{x}_i from either group. The optimal hyperplane is then defined by the following classification decision function:

$$f(x) = \text{sign}\left[\sum_{i=1}^l a_i y_i (\vec{x}_i \cdot \vec{x}) + b\right]$$

where $a_i \geq 0$ are the Lagrangian multipliers of samples \vec{x}_i . Cases with $a_i = 0$ are not part of the solution.

When non-linearity is essential to the problem formulation, the only difference compared with the linear model is that we first need to perform data mapping to another high-dimensional space H , using a non-linear mapping called Φ . After that, the linear model is used again to perform classification in the new space H . The kernel function k that is introduced through such a mapping procedure is a symmetric, semi-positive definite function satisfying the Mercer theorem, and converts the previous classification decision function as follows:

$$f(x) = \text{sign}\left[\sum_{i=1}^l a_i y_i k(\vec{x}_i \cdot \vec{x}) + b\right]$$

The Gaussian kernel function as a measure of similarity between \vec{x} and \vec{x}_i mostly used in our analysis is described as follows:

$$k(\vec{x}, \vec{x}_i) = \exp(-\gamma \|\vec{x} - \vec{x}_i\|^2), \text{ where } \gamma > 0$$

It can be observed that the Gaussian kernel depends on the Euclidean distance between \vec{x} and \vec{x}_i and is based on the assumption that similar points are found close to each other in the feature space [52].

Moreover, two commonly used kernel functions that we also test in our project is the quadratic kernel [52] and the cubic kernel, namely a second and a third degree polynomial kernel function, respectively, are described as follows:

$$k(\vec{x}, \vec{x}_i) = (\vec{x} \cdot \vec{x}_i + 1)^2 \text{ and } k(\vec{x}, \vec{x}_i) = (\vec{x} \cdot \vec{x}_i + 1)^3$$

The quadratic kernel not only determines the similarity of input samples, but also examines combination of features up to the order of the polynomial.

Therefore, taking into consideration the benefits of the Gaussian kernel, we chose to apply specific variants of Gaussian SVMs, namely coarse Gaussian SVM, medium Gaussian SVM, quadratic SVM, and cubic SVM. In particular, medium Gaussian SVM performs medium distinctions with kernel scale set to \sqrt{P} and provides medium model flexibility, similarly to quadratic SVM, while coarse Gaussian SVM makes coarse distinctions between classes, with kernel scale set to $4\sqrt{P}$ and provides low model flexibility. In both cases, P was set to 10, reflecting the number of most significant features.

For validation purposes of the models, fivefold cross validation was used. According to fivefold cross validation, the dataset was randomly partitioned in five equal non-overlapping subsets, where four of them were used for training and one for testing purposes. The cross-validation process was then

repeated five times (the folds), with each of the five subsamples used exactly once as the validation data. The five results from the folds were then averaged to produce a single estimation of accuracy.

In addition to accuracy, the prediction of each personality dimension was binarized to low and high. In this form, we considered the successful prediction of a low and high trait as true positive (TP) and true negative (TN), respectively. If the classification failed in the low trait, we considered the sample as a false negative (FN) and, in case of high trait failure, we considered the sample as a false positive (FP). Therefore, accuracy is defined as

$$acc = \frac{TP + TN}{\text{Total Population}}$$

while sensitivity is the TP rate given by $\frac{TP}{TP+FN}$ and specificity is the TN rate, $\frac{TN}{TN+FP}$. The area under receiver operating characteristic (ROC) curve (AUC) metric denotes the prediction potential of a classification algorithm for varying classification threshold values and is important in cases of non-homogeneous classes.

3. Results

Taking into consideration the suitability and the performance capabilities, this section presents the results mainly derived from SVMs. The assessment of results was based on four main parameters, namely the accuracy, sensitivity, specificity, and AUC that were described above. Tables 2–4 present the results regarding the three scenarios, where scenario no. 1 concerns the HVHA block of clips, scenario no. 2 concerns the LVHA block of clips, and scenario no. 3 describes their fusion. The dominant classifier was the medium Gaussian SVM, although in some cases, other classifiers provided slightly higher accuracy.

Table 2. Results for the high valence high arousal (HVHA) scenario. AUC, area under ROC curve.

Dimension	Accuracy	Sensitivity	Specificity	AUC
Extroversion	83.8%	0.82	0.85	0.86
Openness	64.9%	0	0.89	0.67
Neuroticism	78.4%	0.92	0.54	0.84
Agreeableness	75.7%	0.90	0.56	0.82
Conscientiousness	67.6%	0.15	0.96	0.73

Table 3. Results for low valence high arousal (LVHA) scenario.

Dimension	Accuracy	Sensitivity	Specificity	AUC
Extroversion	56.8%	0.47	0.65	0.55
Openness	73%	0	1	0.71
Neuroticism	64.9%	0.96	0.08	0.64
Agreeableness	70.3%	0.81	0.56	0.71
Conscientiousness	62.2%	0.31	0.79	0.72

Table 4. Results for fusion scheme.

Dimension	Accuracy	Sensitivity	Specificity	AUC
Extroversion	83.8%	0.82	0.85	0.86
Openness	73%	0.1	0.96	0.74
Neuroticism	83.8%	0.92	0.69	0.89
Agreeableness	86.5%	0.90	0.81	0.92
Conscientiousness	83.8%	0.6	0.88	0.77

Table 2 presents the results derived from the features selected by the HVHA block of clips. As can be observed, high valence is a definer of E factor, which scores high prediction accuracy (83.8%).

O and C score lower in accuracy, with O also being described by zero sensitivity, which makes it the weakest predictor for this scenario. In particular, the sensitivity is extremely low for O and C, reflecting the inability of the test to truly detect these conditions. Instead, specificity is low for N and A, indicating low power of the test in ruling out these personality variables.

The LVHA scenario (Table 3) could be described as the weakest test, as it results in the lowest accuracy outcomes for all of the Big-Five dimensions. This was expected, as we are aware that low valence may be more complex for the human brain to perceive and induces the collaboration of multiple brain regions, increasing the process complexity [30]. In this scenario, extroversion also appears with low sensitivity and specificity values.

As we expected, the fusion scheme clearly improves the results regarding all of the examined parameters. Table 4 confirms that the fusion scenario reaches the highest accuracy rates for all of the Big-Five dimensions of personality. The lowest sensitivity parameter concerns again the O trait, though this was expected, as O appears to be the most controversial trait, characterized by high abstractness, unconventionality, thin mental boundaries, and intuition [53].

4. Discussion

This study presents innovative research on the detection of personality traits during affective processing by means of neurophysiological signals. The participants' personality profiles were modeled through the EEG signals obtained by the AMIGOS database. The administration of the Big-Five personality inventory was performed by a self-assessment online questionnaire. The participants were also asked to rate each video according its emotional content in regard to valence and arousal. The most crucial part of the AMIGOS dataset is the use of EEG signals, which are recorded through an easily accessible, wireless, and wearable EEG system (EPOC). With these attributes, this dataset and our proposed analysis framework provide insights into an interdisciplinary aspect by cross-referencing the internal, and hence personal impression of self, with the external neurologically evidenced data derived from emotional reactivity.

From Figure 3, it can be observed that the most important features are the edges in the network except for the O trait, where the nodal BC is dominant. It can also be observed that each personality trait is strongly associated with a characteristic brain region. Starting with A, we observe that it is related with brain activity in the frontal and the occipital lobes with a dominant theta frequency band. As for N, it is mostly detected in the parieto-temporal lobe, probably owing to the hippocampus involvement, with a left-side dominance while increased theta activity is also detected.

Furthermore, as mentioned before, the O trait is strongly associated with BC. More specifically, increased BC implies an enhanced coordination of brain networks because it plays a significant role in information transition and controls the information flow. C covariates with the communication in the lateral prefrontal cortex and both parietal lobes, while E is associated with increased connectivity in the frontal and left temporal lobes mainly detected in alpha and theta frequency bands.

As we have already mentioned in the introduction, Zhao and colleagues [27] have recently attempted to predict personality from EEG signals during emotional processing. Our main differences from their work can be seen in the fact that our study uses a low-cost EEG device while Zhao et al. [27] have used professional equipment, which cannot be applied in real world applications aimed at to the average end-user. On the other hand, considering the complex nature of emotions and emotional processing, we used features derived from multivariate modelling, like brain networks. Our assumption, that the brain networks may serve as a better feature-set for the automatic recognition of personality, is actually supported by our classification results, which, in comparison with Zhao et al. [27], are a bit higher in terms of accuracy (E: 83.8% (Zhao: 66.4%), A: 86.5% (73.5%), C: 83.8% (74.2%), N: 83.8% (70.4%), O: 73% (68%)). We should emphasize here that the obtained results based on brain networks perform better than the spectral features reported in Zhao et al. [27], even though the underlying data suffer in quality as they are obtained from low-cost equipment. This performance further highlights the potential of second-order correlation features in the analysis of EEG signals.

Taking into consideration that N is intertwined with the expression of negative emotions such as feeling worried and anxious, while extroversion is associated with positive emotions as optimism and pleasure from social interactions, our results imply that this susceptibility towards positive or negative states may come as a consequence of personality traits, and vice versa [54]. From a mathematical perspective, this means that the observed variance in brain's emotional reactivity (like event related potentials (ERPs) [55], event related oscillations (EROs) [56,57], functional connectivity [34], and so on) may be explained by the variance observed in personality traits, and vice versa. For this reason, we may assume that human personality can be more clearly predicted from the EEG response during elicitation of high arousing emotional stimuli, as low arousing stimuli result in small (or insignificant) inter-individual variability [55]. This is the main reason that low arousal categories were excluded for the current work. Furthermore, the relationship between valence and arousal is more complicated than one could expect. For example, anger and joy are similar regarding their emotional arousal, but completely opposite in terms of valence. Besides that, co-variation of arousal with valence is particularly strong in the case of negative images, which tend to be rated as more arousing than positive images [58]. Despite these considerations, dimensional and discrete perspectives differ in how emotional states are conceptualized and described (see [59]). Hence, the inclusion of arousal as an independent variable is expected to create more problems than opportunities in the classification of the five traits of personality.

The personality-affect relationship has generated great attention since it was proposed in Eysenck's personality model [60]. Eysenck claimed that E, the personality dimension that describes a person as either communicative or uncommunicative, is related to low cortical arousal—that is, extraverts require more external stimulations than introverts [61]. His model also proposed that neurotics were more sensitive to external stimulation and become easily nervous in the presence of minor life stressors.

Many affective studies have attempted to validate and extend Eysenck's findings [62]. Nevertheless, few works have investigated affective correlates of traits other than E and N owing to the complexity of the personality construct, as many factors should be taken into consideration in order to properly classify an individual according to the initial model described in [60]. This situation complicates the use of affective recognition models in classifying personality traits.

In our work, we address the hypothesis that EEG features during emotional processing can provide strong associations to effectively predict the five personality traits. For this purpose, we used a dataset that involves affect and personality traits [28]. The main findings revealed high detection accuracy for all of the Big-Five personality traits (N: 83.8%, E: 83.8%, O: 73%, A: 86.5%, and C: 83.8%), thus confirming the initial hypothesis that personality features can be automatically predicted by EEG during emotional stimulation. These findings appear to be consistent with the findings of prior studies of brain activation patterns in relation to emotional states that presented a specific display of physiological responses as indicative of equivalent personality features [22]. N is typically assessed with items emphasizing affective content; E, A, and C emphasize behavioral content; and O is represented primarily by cognitive content [63,64]. This could explain our results related to specificity in classifying every dimension/trait, which were lower for O and higher for N, A, E, and C.

Increased attention should be paid in O, when someone comes to interpret our results, as O has very low (0–0.1) sensitivity. This happened because the classification algorithm failed to detect the low case and assigned all samples to the high class. In order to further investigate if this problem is data- or algorithm-specific, we tested several other classification algorithms with very similar results. However, considering the O values (Figure 2), it can be noticed that their distribution is normal (not right skewed as the rest) and shifted to the right end with only small variation. Indeed, all of the subjects used in the current study have high values of O (4.8541 ± 0.6644), although some of them were assigned to a low class because the k-means algorithm forced to separate them into two classes.

In light of these results, it is important to mention certain limitations reflected in the interpretation of our findings in order to gain a holistic understanding of the algorithmic potential. The first issue is that personality is concerned with affect, behavior, cognition, and desire [65]. Further studies focused on

the recognition of personality profiles should take into consideration not only the affective, but also the behavioral and cognitive features to improve the performance of classification algorithms. The second one is that affect is described as a higher-order functionality, subsuming valence conditions such as moods, emotion, feeling states, and preferences [64,66]. Further studies with larger sample populations should take into consideration not only the factors mentioned, but also the ability to differentiate emotion from mood in order to improve the classification performance. Moreover, personality is evidenced in terms of thinking, feeling, and behaving, thus self-reflection and introspection are considered to be of paramount importance in self-assessment and self-evaluation. Taking into consideration that the AMIGOS participants coincide with the individuals that complete the self-assessment questionnaire, the results may have been inevitably subjectivity-biased as well as susceptible to self-preservation cognitive attributions.

It has to be mentioned here that the self-assessment questionnaires are generally perceived as weak predictors of traits owing to the biased perception of self, while the answers may be intentionally misleading for various reasons, feeding the HCI system with wrong information about personality. In this manner, EEG is considered as an unbiased and more accurate method of personality recognition, whose operation is difficult to be intentionally altered.

The present findings reflect an added value to the relevant previous studies that examined personality traits through only self-assessment questionnaires. This paper introduces a neuroscientifically established evaluation of the personality features, which can significantly contribute to the further study of traits and developmental characteristics. This can particularly advance the theories of personality, with a specific focus on (i) how adverse or powerful negative experiences affect our personality development and (ii) more comprehensive understanding of how one's current disposition may affect the coping strategies with reference to emotion regulation.

Our results open new paths in dealing with emotional states and their association to (or aspects of) personality. Besides the study of issues affecting personality and its consequences on the effectiveness of HCI systems, our proposed methodology may find applications in psychology studies towards best practices for improving life standards depending on an individual's personality. In general, we may argue that the classification of personality traits should be a priority when applying early cognitive, emotional, and behavioral techniques to improve the attitude and overall quality of life of people who experience problems originating from personality, either related to clinical factors (affective and/or personality disorders) or of a non-clinical nature [67].

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Article

Personality-Based Emotion Recognition Using EEG Signals with a CNN-LSTM Network

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Abstract: The accurate detection of emotions has significant implications in healthcare, psychology, and human–computer interaction. Integrating personality information into emotion recognition can enhance its utility in various applications. The present study introduces a novel deep learning approach to emotion recognition, which utilizes electroencephalography (EEG) signals and the Big Five personality traits. The study recruited 60 participants and recorded their EEG data while they viewed unique sequence stimuli designed to effectively capture the dynamic nature of human emotions and personality traits. A pre-trained convolutional neural network (CNN) was used to extract emotion-related features from the raw EEG data. Additionally, a long short-term memory (LSTM) network was used to extract features related to the Big Five personality traits. The network was able to accurately predict personality traits from EEG data. The extracted features were subsequently used in a novel network to predict emotional states within the arousal and valence dimensions. The experimental results showed that the proposed classifier outperformed common classifiers, with a high accuracy of 93.97%. The findings suggest that incorporating personality traits as features in the designed network, for emotion recognition, leads to higher accuracy, highlighting the significance of examining these traits in the analysis of emotions.

Keywords: emotion recognition; personality traits; deep neural network



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1. Introduction

Emotions have generated interest in recent years. There are many emotion studies in various fields of science, such as psychology, human–machine interaction [1], and, particularly, neuroscience. Most of these studies are based on emotion stimulation and the processing of physiological responses. Compared with other types of emotional stimuli, images are more interesting because they are more informative, and most studies report high recognition accuracies. In addition, since the brain plays a crucial role in emotional responses, EEG is commonly investigated more than others [2]. Emotions are highly subjective and influenced by various factors, such as stimulation type, memories, experiences, personality, mood, etc. Many psychological studies show that there is a correlation between personality and EEG [3]. The Big Five Personality Traits Questionnaire (IPIP-BFM-50) is one of the most reliable methods for measuring personality. In this model, personality dimensions are divided into two categories: Extroversion and Neuroticism. Extroversion includes extroverts and introverts. Extroverts are social and have more interaction with the outside world in contrast with introverts. Therefore, extroverts require more emotional stimulation than introverts. Neurotics include stable and unstable. Unstable people are

easily influenced by external stimulation and tend to have negative feelings, such as depression and anxiety, or positive feelings, such as mania, while stable people are less affected [4]. Based on an individual's personality, emotional responses may differ based on specific stimuli. In other words, emotions are influenced by personality. Therefore, it is necessary to identify personality in the field of emotion recognition or other perspectives [5]. The way individuals perceive, process, and express emotions is significantly influenced by their personality traits [6]. The Big Five personality traits, including agreeableness, conscientiousness, neuroticism, extroversion, and openness, were proposed by Lew Goldberg in 1990 [7], and they are crucial in determining an individual's emotional experiences and reactions. Self-reported personality assessments, such as the five-factor personality test [8,9] and the MBTI personality test [10,11], can be used to identify an individual's personality traits. In real-world settings, considering personality traits can be essential for determining the effectiveness of emotion recognition systems that use Electroencephalogram (EEG) signals [9,12,13]. Recent studies have shown an increasing interest in using physiological signals to predict personality, as they provide researchers with a better understanding of participants' reactions during experiments [8,9,12,14]. However, analyzing EEG signals for emotion recognition, while accounting for individual differences in personality traits, is a challenging task. Although EEG signals have many significant potential applications in various domains, especially in affective computing fields, they are complex and vary significantly across individuals and emotions, making it difficult to extract meaningful features for emotion recognition [13,15]. To address this problem, researchers have proposed various methods and models to recognize emotions through EEG signals in computational model problems.

The utilization of machine learning methods in EEG emotion recognition has become prevalent due to their enhanced performance in accurately classifying EEG signals into various emotional states [16]. Zheng et al. [17] used deep belief networks (DBNs) to construct an emotion recognition model based on EEG, while Pandey et al. [18] used a multilayer perceptron neural network. Conventional machine learning approaches that focus solely on the analysis of EEG signals may not fully account for the individual differences in personality traits that affect emotion recognition [19]. This is where the utilization of advanced machine learning techniques can be advantageous. Scholars have delved into the relationship between personality models and emotions, as well as the impact of personality on physiological responses. For instance, Martínez et al. conducted a study that explored the role of EEG and personality traits in emotion recognition through the use of machine learning and feature selection techniques [9]. Similarly, a recent study proposed a personalized EEG emotion recognition approach that considers both personality traits and the spatio-temporal features of EEG signals [12]. Another study used EEG and machine learning to recognize personality traits. They achieved accuracies between 73% and 86.5%, by analyzing emotion related EEG recordings, using brain networks, graph theoretical parameters, and SVMs [13].

The aim of this investigation is to apply a combination of machine learning techniques that take into consideration not only the latent characteristics in brain signals but the unique personality traits of individuals. Convolutional neural networks (CNNs) have been extensively used in computer vision tasks, and they have demonstrated remarkable performance in extracting features from high-dimensional data, such as images and signals [20,21]. In the domain of emotion recognition based on EEG signals, CNNs can be employed to automatically extract features from the raw EEG signals that identify the underlying patterns linked to arousal and valence. These features can, then, be utilized to train a classifier to differentiate emotional states [22]. Salama et al. developed a 3D CNN-based method for emotion detection, utilizing the DEAP dataset and multichannel EEG signals, achieving remarkable recognition accuracies of 88.44% and 88.49% for the valence and arousal categories, respectively [21]. Tripathi et al. presented Deep Neural Networks (DNN) and CNN models for emotion detection based on EEG signals and accomplished classification accuracies of 75.58% and 73.28% for valence and arousal, respectively. The

researchers discovered that deep learning techniques outperformed conventional methods based on their experimental results [23].

In the context of emotion recognition, long short-term memory (LSTM) networks can be used to capture the temporal dependencies between the audio, visual, and biological signals, and they can also extract more complex features related to personality traits [24]. This can improve the accuracy of the emotion recognition model by accounting for individual differences in personality traits that may affect the EEG signals. This study aims to employ CNN and LSTM networks to extract EEG features for emotion recognition, combining spatial and temporal features to capture patterns and relationships between different EEG channels over time. Research conducted by Zhang et al. demonstrated that CNN and CNN-LSTM models can extract raw data with high accuracy, while DNN models have fast training speeds and LSTM models capture more complex features related to personality traits, but they are less stable and slow to converge [25]. Chakravarthi et al. explored the use of EEG signals for analyzing emotions and Post-Traumatic Stress Disorder (PTSD). The study proposed a new automated CNN-LSTM with a ResNet-152 algorithm that achieved higher accuracy in emotion analysis compared to existing techniques [26]. Bhardwaj et al. conducted a study using a DeepLSTM network to classify personality traits based on EEG signals collected from participants watching videos, achieving superior classification accuracy compared to other machine learning classifiers, with a maximum accuracy of 96.94% [10].

This article presents a new method for emotion recognition based on EEG signals that combines CNNs and LSTM networks. The proposed approach aims to improve the accuracy of the recognition process by capturing both spatial and temporal dependencies in the EEG signals and considering individual differences in personality traits. The CNNs are used to extract features from the raw EEG signals, while the LSTMs are employed to capture temporal dependencies and extract more complex features related to personality traits. The study conducted EEG recordings for volunteer participants and compared the performance of the proposed approach with existing state-of-the-art approaches for EEG-based emotion recognition [27]. Moreover, specifically, we investigate whether a sequence of images and videos can help the LSTM network learn personality traits. We hypothesize that this method can effectively capture the dynamic nature of human emotions and personality traits, as well as offer new insights into the mechanisms underlying these psychological constructs. To test our hypothesis, we conducted a study where participants watched a series of images and videos that were designed to elicit specific emotions. Our findings demonstrate that our CNN and LSTM networks were able to accurately extract both emotions and personality traits from the EEG data, and the sequence of stimuli helped to enhance the LSTM network's ability to learn personality traits. The results showed that the combined CNN-LSTM approach outperforms existing methods and achieves high accuracy in classifying EEG signals into different emotional states. Therefore, the findings suggest that this approach could be leveraged to improve the personalization of emotion-recognition processes for users, enhancing the accuracy and efficacy of these systems. Additionally, this method may hold promise for facilitating emotional communication between humans and machines, enabling more natural and effective human–robot interaction.

The paper begins by providing an overview of the dataset used in the study and the pre-processing steps employed to refine the raw EEG signals. The feature-extraction techniques used to extract relevant features from the pre-processed EEG signals are then detailed. Subsequently, the CNN and LSTM networks utilized in the proposed approach are introduced, and the method in which they are combined to capture both spatial and temporal dependencies, in the EEG signals and individual differences in personality traits, is explained. In the results section, the performance of the proposed approach is presented and evaluated against existing state-of-the-art approaches using various evaluation metrics. The discussion section interprets the study results, emphasizing the importance of accounting for individual differences in personality traits in EEG-based emotion recognition. Finally,

the study's limitations are discussed, and recommendations for future research directions in this field are provided.

2. Materials and Methods

In this study, we applied a deep learning approach to analyze EEG data for emotion and personality trait classification. Specifically, we used a pre-trained CNN model to extract features from EEG data for emotion classification, as well as an LSTM network to predict personality traits based on the Big Five personality model. We also used a sequence of emotional stimuli to facilitate personality trait learning. In this section, we will describe the detailed procedures and materials used in the study, including the EEG recording, stimuli presentation, data pre-processing, and deep learning models.

2.1. Participants

The study involved 270 healthy volunteers aged 19–30 years (mean 25.01, SD 3.13). There were three groups selected among volunteers, based on the highest score obtained by the IPIP-BFM-50, a commonly used scale of personality assessment. Along the way, the 50 items are rated on a 5-point scale depending on how faithful they are. The rating scale ranges between 1 (disagree), 3 (neutral), and 5 (agree). The test typically lasts 3–8 min [2]. The subjects were divided into Unstable Extrovert, Unstable Introvert, and Normal groups. More emotional stimulation was needed for stable people, so they were excluded from the experiment. Each group consisted of 20 healthy men (10 individuals) and women (10 individuals). The Unstable Introvert group is more likely to be depressed between the ages of 17 and 28 (mean age 25, SD 3.11). The Unstable Extrovert group is more likely to be manic from the ages of 18 to 29 (mean 25.21 and SD 3.07), and the Normal group is between 17 and 29 years of age (mean 26.32 and SD 3.12). The results of screening IPIP-BFM-50 participants are shown in Table 1. Men make up 48% of the population and women make up 52%, resulting in a balanced data set representative of the study population [7]. Table 1 provides observed IPIP-BFM-50 scales for 270 participants, along with their corresponding average and standard deviation values. The scales investigated in this study encompass five key personality traits. The table displays the standard deviations and average scores for each trait, reflecting the variability and central tendency within the participant group. As shown in the table, the personalities of participants are well balanced.

Table 1. Average and standard deviation of IPIP-BFM-50 scales obtained by all participants.

STD			AVERAGE								PARTICIPANTS		
E	A	C	N	O	E	A	C	N	O	QTY	age	sex	
1.1	1.6	1.65	1.21	1.34	2.21	1.98	2.41	2.68	2.71	141	19–30	F	
1.1	1.7	1.82	1.53	1.25	2.45	2.33	1.95	1.96	2.37	129	19–30	M	

(E: Extroversion, A: Agreeableness, C: Conscientiousness, N: Neuroticism, and O: Openness).

2.2. Emotional Stimuli

Based on the Russell model in Figure 1, emotions can be mapped into arousal and valence dimensions. Among several types of emotional stimulation, such as music, text, voice, we chose picture and movie because of its desirable properties, which were mentioned earlier [22]. Pictures were selected from the Geneva Affective Picture Database with the maximum arousal and valence scores for mentioned emotions. The stimuli used in this study consisted of 90 images and 3 videos, which were selected from 270 images and 12 videos, according to the maximum scores recorded by the Positive and Negative Affective Scheduling (PANAS) [28]. To evaluate the stimuli, 40 volunteers who did not participate in the main experiment were asked to rate them using the PANAS scale. Based on the arousal–valence scale of the Russell model, and in accordance with the personality groups, emotional stimuli were selected in sadness, happiness, and normal categories. The selection of stimuli was based on their potential to evoke distinct emotional responses.

Detailed average and standard deviation scores for both images and videos, as assessed by PANAS, are presented in Table 2 and Table 3, respectively.

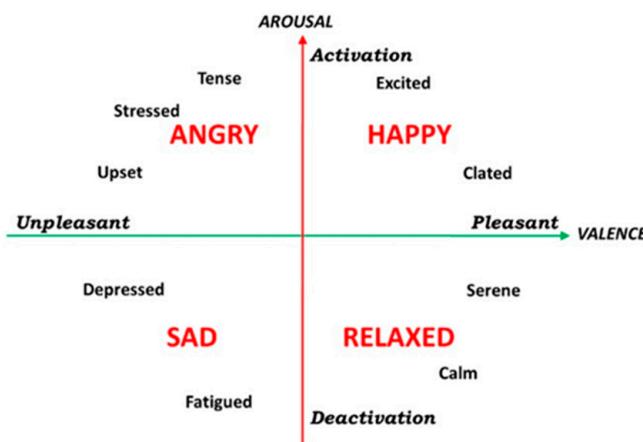


Figure 1. According to the Russell Emotional Model, emotions can be expressed quantitatively in two dimensions: arousal and valence. As shown, sadness and happiness are the two most different points.

Table 2. The average and standard deviation scores for the emotional image stimuli measured by PANAS.

STD	AVERAGE	MAX	MIN	Stimulation
1.05	3.74	7	1	Happiness
0.94	3.31	7	1	Neutral
1.17	3.52	7	1	Sadness

Table 3. The average and standard deviation scores for the emotional video stimuli measured by PANAS.

STD	AVERAGE	MAX	MIN	Stimulation
0.82	3.38	7	1	Happiness
0.91	3.66	7	1	Neutral
1.08	2.72	7	1	Sadness

Table 2 presents the average and standard deviation scores for emotional image stimuli, as measured by the PANAS. The table displays the standard deviations, average scores, maximum values, minimum values, and the corresponding emotional stimulation for each category. The results show that the average scores for happiness, neutral, and sadness were 4.74, 4.31, and 4.52, respectively, with standard deviations of 1.25, 1.84, and 1.97. The maximum and minimum values for each category indicate the range of emotional intensity observed in the stimuli. Image stimuli were selected based on maximum PANAS scores in each category.

Table 3 showcases the average and standard deviation scores for emotional video stimuli measured using the PANAS. The table provides insights into the emotional responses of the participants, including the scores for happiness, neutral, and sadness stimuli, along with their corresponding standard deviations, maximum values, and minimum values. Movie stimuli were selected based on maximum PANAS scores in each category.

2.3. Experiment Procedure

Throughout the experimental procedure, the participants were exposed to a diverse array of emotional stimuli comprising three categories—happy, sad, and neutral stimuli—in both images and videos. The participants were presented with a sequence of stimuli, with each sequence consisting of 30 images and a video of the same emotional valence at

the end. EEG signals were recorded, while participants viewed stimuli, using a 32-lead EEG system with a standard 10–20 system. The impedance of each electrode was checked below 5 k-ohms. The set of 2-min eyes-open and 2-min eyes-closed EEG was recorded to calculate resting EEG features. All participants then completed the three types of emotion induction trials. In order to get noise-free data, the subjects were asked to keep control of their movement during the experiment. EEG signals were recorded using a Mitsar EEG Amplifier, with a sampling rate at 256 Hz. EEG recordings were taken in a quiet room, and participants were asked to sit comfortably in a chair and view images and videos without outside influences. The sequencing of these stimuli (happy, sad, and neutral) was conducted in a randomized fashion for each individual to avoid any potential biases or confounding variables. Specifically, each participant viewed 30 images and 1 video for each of the 3 emotional categories, resulting in a total of 90 images and 3 videos per participant (shown in Figure 2). Based on our previous study [29], and in order to investigate the potential impact of emotional stimuli on personality traits, the stimuli used in this study were sorted based on their arousal-valence score, ranging from the lowest to the highest, in order to accumulate the emotional effects of each stimulus and investigate potential differences in personality traits. By manipulating the emotional content of the stimuli, we aimed to elicit varied emotional responses in participants.

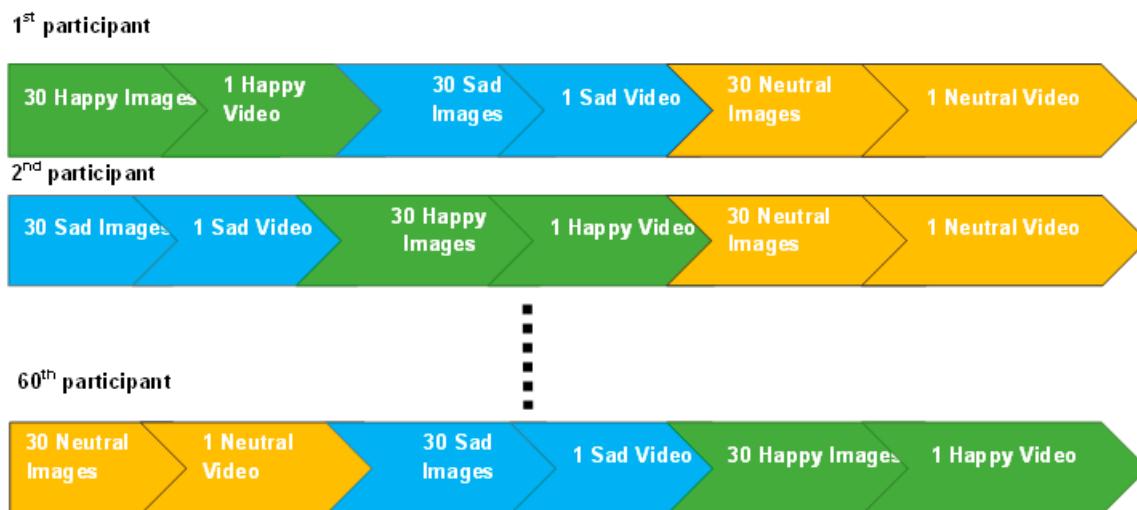


Figure 2. The emotional stimulus sequence presented to participants in the study, consisting of 90 images and 3 videos. The order of stimuli was randomized for different participants.

2.4. Pre-Processing

EEG signals recorded from 60 participants were pre-processed using a series of procedures and methods, as depicted in Figure 3. The signal was recorded at a sampling frequency of 256 Hz and, then, down sampled to a frequency of 128 Hz. The raw EEG were filtered using a Butterworth order 2 band-pass filter (0.4 Hz to 60 Hz) to remove high frequency noise, followed by a notch filter to remove power line noise (50 Hz). Then, the signal was visually inspected to remove inherent artifacts—such as eye blinks (EOG) and muscle activity (EMG)—that can skew the analysis. Finally, a spatial filter, based on Independent Component Analysis (ICA), was applied to remove the remaining noise sources and artifacts. The signal was divided into 2 s windows (hamming) with 50% overlap, corresponding to the duration of the presented stimuli for further analysis. Each window was baseline adjusted with the average amplitude of its first 200 ms [30].

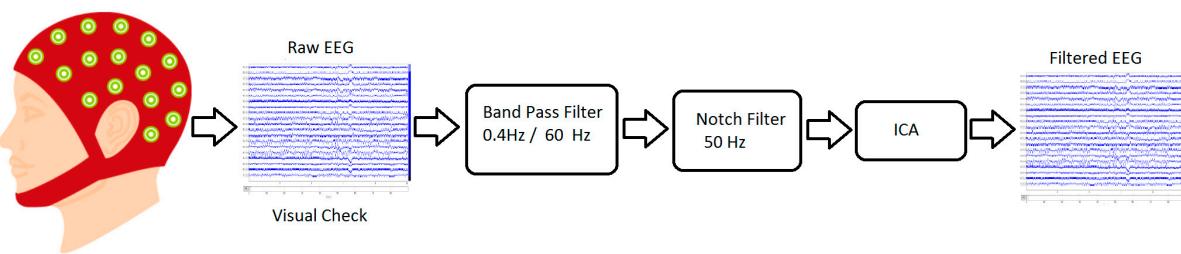


Figure 3. The block diagram of the EEG Pre-processing procedure.

2.5. Proposed Deep Learning Network

Deep learning is a field of machine learning that involves developing algorithms designed to learn the functionality of the human brain. Examples of deep learning algorithms include Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and Recurrent Neural Networks (RNNs). The term “deep” refers to the number of network layers employed, with deep networks containing over 100 layers compared to the 2 to 3 layers typically found in traditional networks. In this study, we proposed a conceptual model to learn features, recognize, and classify emotional valence and arousal labels, based on Russell model [31] of the presented EEG signals. A CNN network is employed to extract emotional features from the EEG signals, and a Long Short-Term Memory (LSTM) network is used to obtain personality traits from the extracted features without the explicit hand-crafted feature-extraction process. CNNs are commonly used in image processing, and they can learn to extract meaningful features from images. LSTM networks, on the other hand, are commonly used in sequence modeling, and they can learn to capture temporal dependencies in sequential data [32].

The conceptual model in Figure 4 illustrates the flow of the proposed approach, starting with the feature extraction from pre-processed EEG signals and ending with the predicted arousal and valence labels. The pre-processed EEG signals are fed into a CNN network, which utilizes spatial features for emotion classification. Furthermore, the spatial features obtained by the CNN network are used as inputs for the LSTM network, which focuses on capturing the temporal dynamics between these features for personality trait classification. The inputs of the CNN network are the extracted features from the EEG signal, and its outputs are the arousal and valence values of emotional stimuli. The inputs of the LSTM network are the features obtained from the flattening layer of the CNN, and its outputs are the values obtained for individual personality traits. The outputs of the CNN and LSTM networks are concatenated and passed through fully connected layers to shape the final stage emotion classifier.

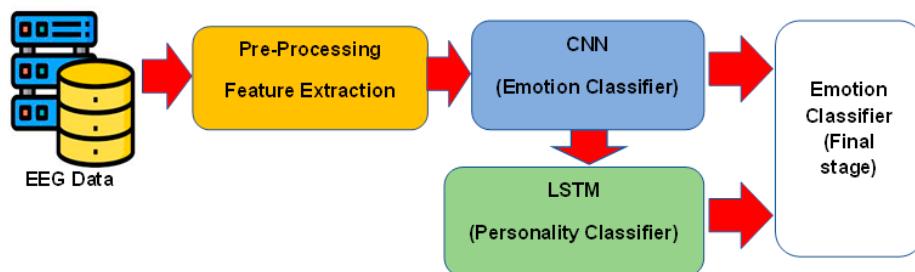


Figure 4. The block diagram of the proposed deep learning network.

The CNN network consists of multiple convolutional layers followed by pooling layers, which capture local patterns in the EEG signals and reduce the dimensionality of the feature maps. The output of the CNN branch is a set of spatial features that captures the local patterns in the EEG signals. The second branch of the network is a LSTM network, which extracts personality traits from the CNN feature maps based on the Big Five personality traits (extroversion, agreeableness, conscientiousness, neuroticism, and

openness) model. The LSTM network consists of multiple LSTM cells that capture the temporal dependencies in the EEG signals over time. The resulting model captures both the spatial and temporal dependencies in the EEG signals and the individual differences in personality traits, enabling accurate and robust emotion recognition. Several common emotion classifiers were investigated and compared, and based on the results, SVM was chosen as the final stage classifier for the proposed network. To optimize the hyperparameters of the SVM and prevent over-fitting, a nested cross-validation approach was employed.

2.6. Convolutional Neural Network(CNN)

In order to extract features from the EEG Signal for emotion classification, we utilized a pre-trained Convolutional Neural Network (CNN) [33]. Specifically, we chose VGG16, which is a widely used CNN architecture known for its high accuracy and robustness [34]. Before feeding the EEG Signal into the CNN, we first pre-processed the data, then segmented the continuous EEG signal into windows of 2 s, with a 50% overlap, resulting in windows per stimuli (image). Each window was converted into a 2D image by transforming the EEG time-series data into a spectrogram using the Short-Time Fourier Transform (STFT), with a window size of 512 samples and a step size of 256 samples. This resulted in a matrix of size 128×129 , where the frequency dimension ranged from 0.4 Hz to 60 Hz, and the time dimension ranged from 0 to 2 s. The Short-Time Fourier Transform (STFT) of a signal $x(t)$ is defined as:

$$\text{STFT}(\tau, \omega) = \int_{-\infty}^{+\infty} x(t)h(t - \tau)e^{-j\omega t}dt \quad (1)$$

where $h(t)$ is a window function, τ is the window position on the time axis, and ω is the frequency variable. We then fed the pre-processed EEG data into the VGG-16 CNN and used the output from the last convolutional layer (conv5_3) as the feature representation. This layer has been shown to capture high-level features and patterns from visual stimuli, which we hypothesized would also be useful for extracting features from EEG data.

The VGG-16 CNN (Convolutional Neural Network) is a deep learning architecture developed by the Visual Geometry Group at the University of Oxford [35]. It consists of 16 layers, including 13 convolutional layers and 3 fully connected layers. The architecture of the VGG-16 CNN is characterized by its use of small filters (3×3) with a small stride size (1×1), which allows for a more fine-grained analysis of the input data. The convolutional layers are followed by max-pooling layers, which reduce the spatial dimensions of the feature maps and increase their translation invariance [34,36]. Our approach of using a pre-trained CNN to extract features from EEG data allowed us to effectively capture complex patterns and representations that are difficult to extract using traditional signal-processing techniques. The resulting feature representation can be used for further analysis and the classification of emotional states (Figure 5).

The steps of the VGG-16 CNN are:

1. The input image is passed through 13 convolutional layers, which utilize 3×3 receptive field filters, with a 1×1 convolution filter for linear transformation of the input.
2. After each convolutional layer, a Rectified Linear Unit (ReLU) activation function is applied to introduce non-linearity in the network, which is a linear function that generates zero output for negative inputs and a matching output for positive inputs.
3. Max-pooling layers are used to reduce the dimensionality and number of parameters in the feature maps generated by each convolution step. This step is necessary due to the increase in the number of available filters from 64 to 128, 256, and 512 in the final layers.
4. The output from the last convolutional layer is flattened and fed into three fully connected layers.
5. Each fully connected layer is followed by a ReLU activation function, except for the last one, which uses a SoftMax activation function to output class probabilities.

6. During training, the weights of the network are updated using backpropagation with stochastic gradient descent.

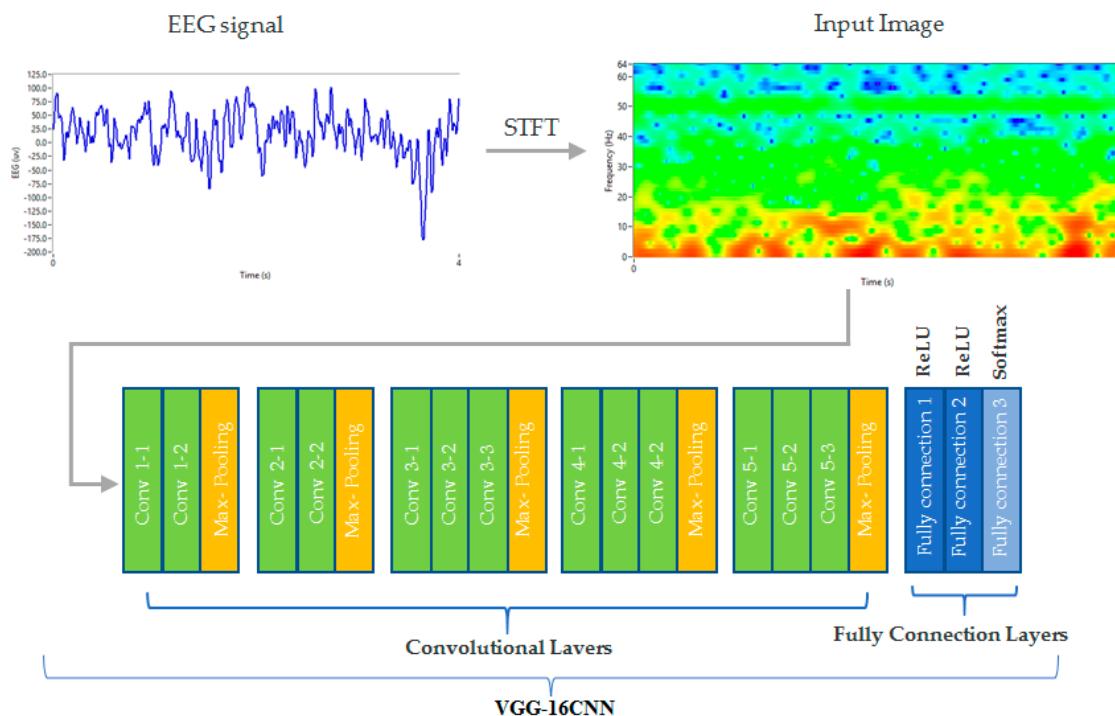


Figure 5. The schematic of the VGG16 (CNN) used in the study. The STFT of the EEG is fed into the CNN as an input feature.

2.7. Long Short-Term Memory (LSTM) Network

In our study, we used an LSTM (Long Short-Term Memory) network to extract personality traits from the pre-processed EEG data. The LSTM network is a type of recurrent neural network (RNN) that is well-suited for modeling sequential data, such as time-series data. The key advantage of LSTM networks over traditional RNNs is that they are able to capture long-term dependencies in the data by using a memory cell that can store information over time [11]. The architecture of our LSTM network, in Figure 6, consisted of three LSTM layers, each followed by a fully connected layer. The LSTM layers were responsible for capturing the temporal dynamics of the EEG data and learning the relationships between different time points. The fully connected layers were used to map the output of the LSTM layers to the Big Five personality traits (extroversion, agreeableness, conscientiousness, neuroticism, and openness). We used flattening layer features, extracted from the pre-processed EEG data by CNN, as inputs to the LSTM network. Before proceeding with the fully connected linked layer in CNN, it is necessary to use the flattening layer to create a one-dimensional vector as input for LSTM. The EEG data were divided into windows of fixed duration, and each window was labeled with the participant's personality traits. We used mean squared error as the loss function to train the LSTM network, which measures the difference between the predicted and actual personality trait values. We also used the Adam optimizer, which is a stochastic gradient descent optimizer that adapts the learning rate based on the gradient of the loss function.

To evaluate the performance of the LSTM network, we used a leave-one-subject-out cross-validation approach, where we trained the LSTM network on all but one participant's data and tested its performance on the left-out participant's data. By using an LSTM network to model the temporal dynamics of the EEG data, we aimed to improve the accuracy of personality trait prediction compared to common classifier networks that do not take into account the sequential nature of the data [14].

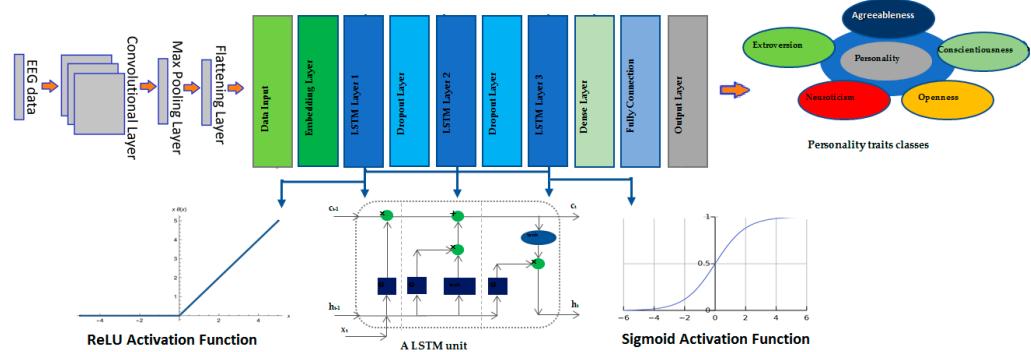


Figure 6. The architecture of the LSTM network used in the study.

The number of neurons in each LSTM layer decreases as you move deeper into the network. Deeper layers tend to capture more abstract features and, therefore, require fewer neurons to represent the information effectively. Therefore, the first two hidden layers contain 64 and 32 neurons, respectively, and use ReLU as an activation function to learn nonlinear representations. The third LSTM layer contains 16 neurons and uses a sigmoid activation function. The dense layer also uses a sigmoid activation function. A sigmoid activation function is useful for the output layer of the network when dealing with binary classification problems or tasks that require the model to output probabilities. The LSTM and dropout layers are used to learn features from EEG signals. The output of the fully connected layers, to predict the participant's Big Five personality traits (extraversion, agreeableness, conscientiousness, neuroticism, and openness) and the dense layer, is used for classification [27].

2.8. Implementing and Setting the Hyperparameters

The network was implemented and trained using the Python programming language version 3.7. The Keras library, which is a high-level neural network API written in Python and capable of running on top of TensorFlow, was used to develop the network architecture. The TensorFlow backend was used for efficient numerical computations on GPUs, which was important for speeding up the training process. The hardware used for training and testing the network was a computer with an Intel Core i7 processor, 16 GB of RAM, and an NVIDIA GeForce GTX 1080 Ti graphics card. The operating system used was Ubuntu 18.04. In addition, the NumPy and Pandas libraries were used for data pre-processing and analysis. The code was written and executed in Jupyter Notebook, an open-source web application that allows for creating and sharing documents containing live code, equations, and visualizations. In training the proposed network, several hyperparameters were specified. The learning rate was set to 0.001, which determines the step size at each iteration while updating the parameters of the network. The batch size was set to 64, which specifies the number of samples used in each iteration for the gradient descent. The number of epochs was set to 500, which determines the number of times the entire training set was passed through the network during training. The optimizer that was used was Adam, which is a widely used stochastic optimization algorithm that uses adaptive learning rates to update the network weights. These hyperparameters were chosen based on previous research and experimentation, and they were adjusted during training, using the validation set, to achieve the best possible performance of the network.

2.9. Classifier Evaluation

To evaluate the performance of the proposed CNN–LSTM network, we used the following evaluation metrics:

1. Accuracy: The classifier accuracy is generally calculated from Equation (2):

$$\text{Accuracy} = \frac{(TN + TP)}{(TN + FN + TP + FP)} \quad (2)$$

2. Precision: The following equations are used to evaluate the precision of the classifier of emotion classes in Equation (3).

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

3. Recall: It is the proportion of correctly classified positive emotions to the total number of actual positive emotions. It is calculated as follows:

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4)$$

4. F1 Score: It is the harmonic mean of precision and recall, which is obtained according to Equation (5).

$$\text{F1score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad (5)$$

where TP (true positive) represents the number of correctly classified positive emotions, TN (true negative) represents the number of correctly classified negative emotions, FP (false positive) represents the number of falsely classified positive emotions, and FN (false negative) represents the number of falsely classified negative emotions.

To assess the performance of the proposed CNN-LSTM network, we also used the confusion matrix. The confusion matrix is a table that summarizes the performance of the classifier by showing the number of true positives, true negatives, false positives, and false negatives for each class. In addition, we used the Receiver Operating Characteristic (ROC) curve to plot the true positive rate (TPR) against the false positive rate (FPR) at various threshold levels and the Area under the Curve (AUC) metric to evaluate the performance of the proposed deep learning network. The ROC curve is a graphical plot that illustrates the performance of the classifier as its discrimination threshold is varied. The AUC is a metric that measures the overall performance of the classifier, taking into account all possible discrimination thresholds. The AUC score ranges from 0 to 1, with 1 indicating perfect classification performance and 0.5 indicating random chance. All these evaluation metrics will be used to assess the performance of the proposed network in emotion recognition using EEG signals.

The data were split into training, validation, and testing sets using a 70–15–15 ratio, respectively. This means that 70% of the data were used for training, 15% were for validation, and 15% were for testing. The splitting process was performed randomly, ensuring that the data from each group (Unstable Introvert, Unstable Extrovert, and Normal) were equally represented in each set. The training set was used to train the proposed network, while the validation set was used to adjust the hyperparameters and prevent overfitting. The testing set was used to evaluate the performance of the trained network on unseen data. This process of data splitting helped to ensure that the network was trained and evaluated on a diverse set of data and that it can generalize well for new data.

3. Results

In this study, the performance of the proposed deep learning network, with the influence of personality traits in classifying emotions based on EEG signals, was evaluated using various metrics, including accuracy, loss, precision, recall, and F1-score. In order to evaluate the overall performance of the network, Receiver Operating Characteristic (ROC) curves and Area under the Curve (AUC) scores were utilized. The ROC curve is a graphical representation of the trade-off between the true positive rate (TPR) and the false

positive rate (FPR) of a binary classifier system, where the AUC score represents the overall performance of the classifier.

3.1. The Convolutional Neural Network VGG-16

The CNN-VGG-16 network was found to be highly effective in extracting relevant EEG features related to emotion states in arousal and valence dimensions. The network was trained on the dataset of EEG recordings and achieved an accuracy of 86.3% on the training set and 87.30% on the testing set. This suggests that the CNN-VGG-16 network was able to learn and generalize patterns related to emotion states from the EEG data. The accuracy, precision, recall, and F1-score of the CNNs are summarized in Table 4. The overall accuracy achieved by the network was 87.30%, with precision, recall, and F1-score measures of 92.90%, 92.67%, and 92.78% for the arousal and valence dimension. These metrics were obtained from the TP (true positive), TN (true negative), FP (false positive), and FN (false negative) parameters generated by testing the network that is illustrated in Table 5.

Table 4. Classification performances for the CNN-VGG-16.

Emotion Dimension	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
HV-HA	89.77	95.16	93.16	94.15
HV-LA	86.70	91.30	93.56	92.42
LV-HA	88.65	93.31	94.05	93.68
LV-LA	84.07	91.85	89.92	90.87

Table 5. The percentage of TP (true positive), TN (true negative), FP (false positive), and FN (false negative) parameters in the CNN-VGG-16 network.

	Emotion Classes			
	HV-HA	HV-LA	LV-HA	LV-LA
TP	17.7%	18.9%	23.7%	21.4%
TN	1.6%	1.3%	1.3%	1.3%
FP	0.9%	1.8%	1.7%	1.9%
FN	1.3%	1.3%	1.5%	2.4%

In our study, the CNN-VGG-16 network achieved AUC scores of 0.79%, 0.84%, 0.83%, and 0.80% for four emotion classes—high arousal-high valence (HV-HA), low arousal-high valence (LV-HA), high arousal-low valence (HV-LA), and low arousal-low valence (LV-LA)—respectively. For example, to evaluate the performance of the classifier for the high arousal-high valence class, we trained a binary classifier to distinguish between high arousal-high valence and all other classes. We then computed the true positive rate (TPR) and false positive rate (FPR) for this classifier at different thresholds and plotted these values on an ROC curve. We repeated this process for each of the other three classes. A perfect classifier would have an AUC score of 1, while a random classifier would have an AUC score of 0.5 (given as a dotted line on the ROC plots shown in Figure 7). The ROC curves for each emotion class are presented in Figure 7a–d, which demonstrate the ability of the CNN to correctly classify the emotional states, as evidenced by the high TPR and low FPR values. These results suggest that the CNN network was able to effectively distinguish between different emotional states in both arousal and valence dimensions.

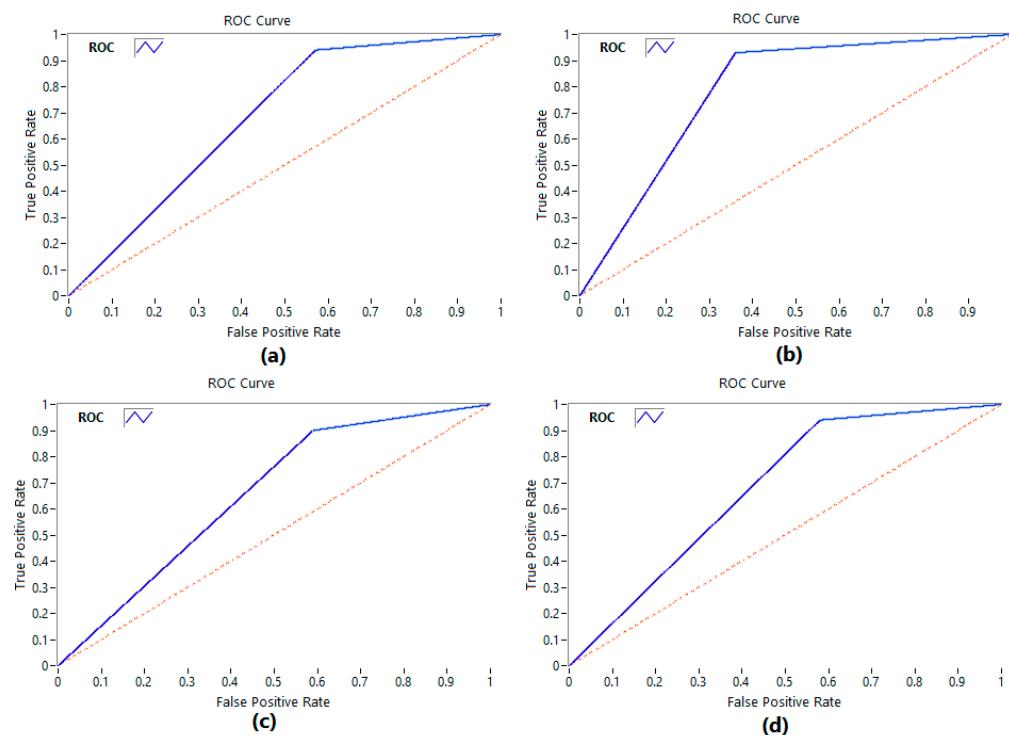


Figure 7. ROC curve of a CNN based on VGG-16: (a) low arousal-high valence (LV-HA), (b) high arousal-high valence (HV-HA), (c) low arousal-low valence (LV-LA), and (d) high arousal-low valence (HV-LA).

3.2. The LSTM Network

In this study, the LSTM network was trained to extract five personality traits (extroversion, openness, neuroticism, agreeableness, and conscientiousness) from the CNN flattening layer features. The network achieved an accuracy of 91.29% on the training set and 90.72% on the testing set, indicating that the LSTM network was also effective in learning patterns related to personality traits from the EEG data. Table 6 shows the performance measures of the LSTM model used in this study. The table presents the accuracy, precision, and F1-score of the model's performance in predicting five personality traits. The performance measures, including accuracy, precision, and F1-score are calculated by using TP, TN, FP, and FN values that are taken from the confusion matrix. The results reveal that the model has achieved high accuracy scores across all personality traits, with the highest accuracy being 92.54% in neuroticism and the lowest being 89.12% in agreeableness. In terms of precision, the model has attained precision rates above 95% for all personality traits, with the highest precision being 96.79% in extroversion and the lowest being 95.78% in openness. The F1-scores, which take into account both precision and recall, also demonstrate high scores, with the highest being 95.84% in neuroticism and the lowest being 93.95% in agreeableness.

Table 6. Performance of the LSTM network for personality traits.

Dimension	Accuracy (%)	Precision (%)	F1-Score (%)
Extroversion	90.28	96.79	94.52
Openness	91.76	95.78	95.50
Neuroticism	92.54	96.65	95.84
Agreeableness	89.12	96.45	93.95
Conscientiousness	89.90	96.11	94.28

3.3. Performance of the Proposed Network

The present study utilized a CNN–VGG-16 network to extract EEG features, based on emotion states in the arousal and valence dimensions, as well as a LSTM network to extract five personality traits. The extracted features from both networks were then used as inputs to a classifier for emotion recognition in Figure 8. In order to compare the accuracy of the proposed deep learning network with LSTM, in contrast with common emotion classifiers, the performances of several widely used classifiers [37] in EEG-based emotion recognition, including Naive Bayesian (BN), Support Vector Machines (SVM), and K-nearest neighbor (KNN), were assessed. For this purpose, the extracted features from the flattening layer of the CNN network were fed as input to these classifiers, and the outputs of the classifiers were chosen as the values of arousal and valence.

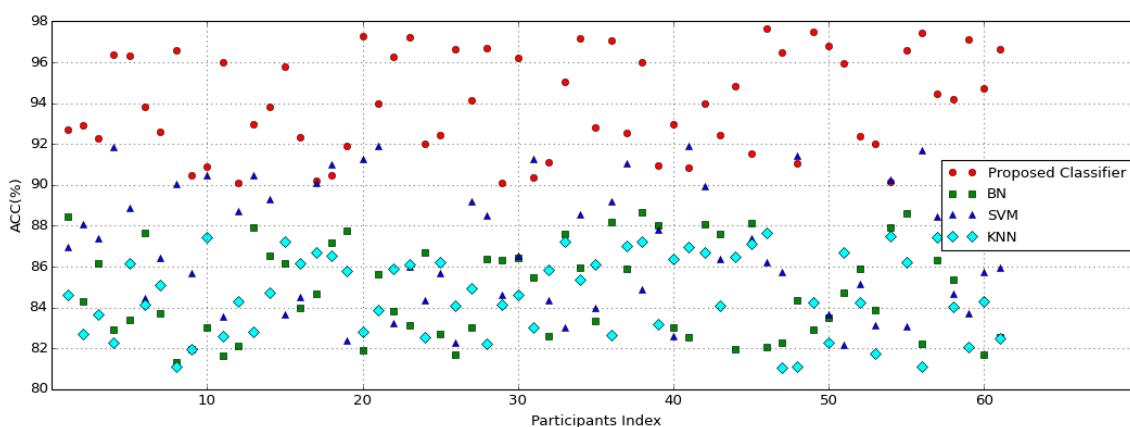


Figure 8. The average accuracy of KNN, SVM, and BN classifiers, as well as the proposed network for all participants.

Figure 9 displays the comparative performance analysis of common emotion classifiers and the proposed network for all participants. Remarkably, the proposed network with LSTM exhibited accuracy rates with average values of 93.97%. In contrast, the KNN, SVM, and BN networks demonstrated average accuracy levels of 84.64%, 86.91%, and 84.88%, respectively. Notably, there exists a significant difference between SVM and other classifiers, as indicated by a p-value greater than 0.01. The precision and F1-score for the proposed network were 91.37% and 89.61%, respectively. The results demonstrate that the LSTM network was able to extract more information, in comparison with other classifiers, from the same features related to emotions.

Figure 9 illustrates the loss and accuracy of the proposed network. As shown in Figure 9a, the loss and accuracy of the model converge after about 80 and 120 epochs, respectively. Within the first 40 epochs, model accuracy of 91.23% was achieved for low arousal-high valence (LV-HA). The accuracy improved gradually from epoch 40 to 140, reaching 92.12%. The model then stabilized between epochs 140 and 250, ultimately achieving a high accuracy of 94.68%. Figure 9b displays the convergence of the algorithm's loss and accuracy, at roughly 30 and 40 epochs, respectively. The accuracy steadily increased from epoch 40 to 160, reaching a maximum of 92.63%. Following this, the model maintained stability between epochs 160 and 250, ultimately achieving a high accuracy level of 93.91%. Figure 9c, low arousal-low valence (LV-LA), demonstrates that the network's loss and accuracy reach convergence after approximately 80 and 60 epochs, respectively. The accuracy displays gradual improvement from epoch 60 to 120, culminating in a peak of 94.21%. Between epochs 120 and 250, the model stabilizes, eventually attaining a high accuracy level of 94.83%. Finally, the algorithm's loss and accuracy, presented in Figure 9d for high arousal-low valence (HV-LA), converge at around 40 and 40 epochs, respectively. The accuracy steadily improves from epoch 40 to 60, peaking at 92.75%, before stabilizing between epochs 60 and 250. Ultimately, the model achieves a high accuracy of 92.43%.

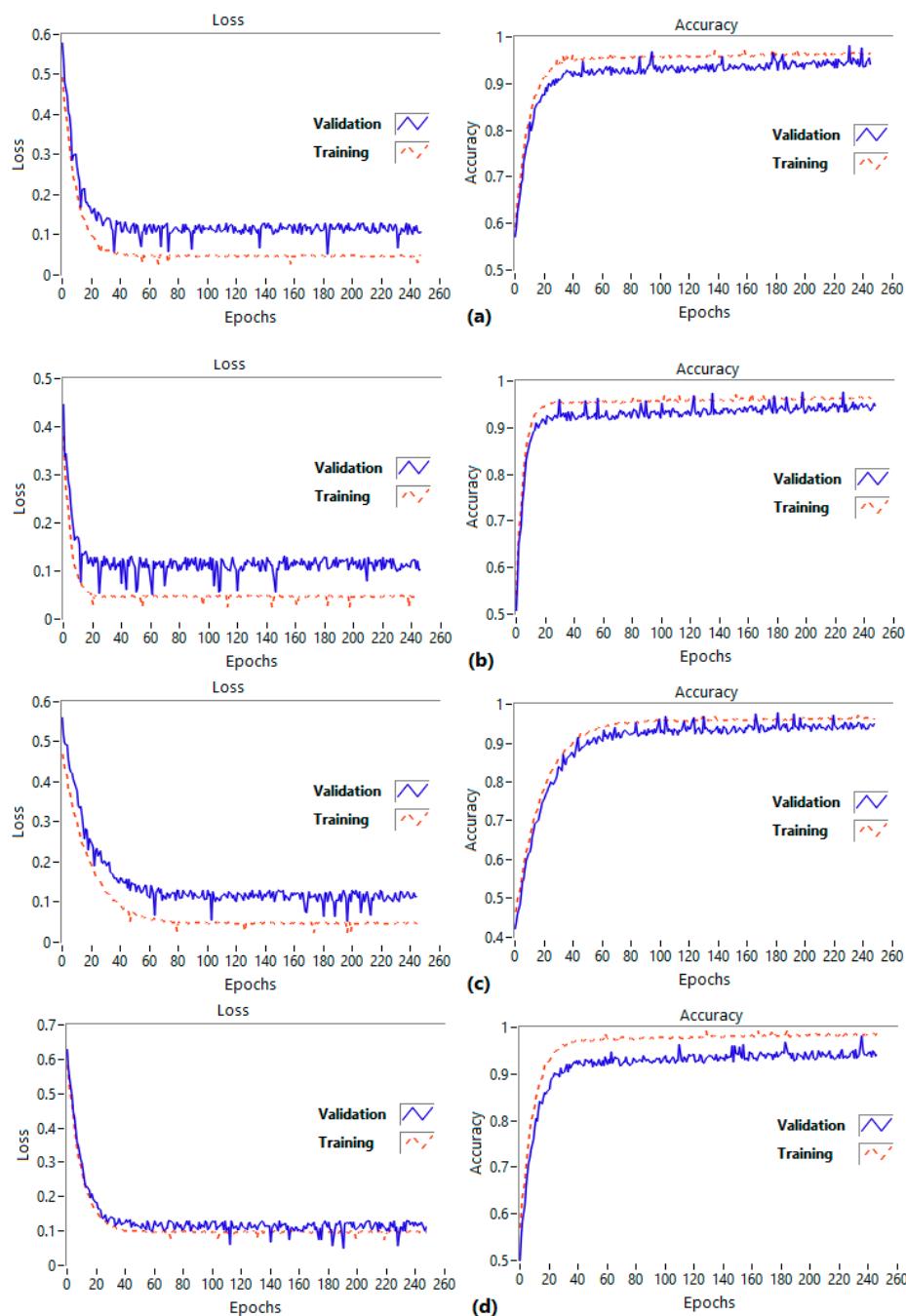


Figure 9. The loss and accuracy of the proposed network for (a) low arousal-high valence (LV-HA), (b) high arousal-high valence (HV-HA), (c) low arousal-low valence (LV-LA), and (d) high arousal-low valence (HV-LA).

The results of the four commonly used classifiers, applied as the final stage classifier in the proposed network, are presented in Table 7. The SVM classifier outperforms the other classifiers, achieving the highest accuracy of 93.97%, precision of 91.37%, and F1 score of 89.61%. In contrast, the MLP, KNN, and BN classifiers achieved accuracies of 79.21%, 81.48%, and 82.71%, respectively, with lower precision and F1-scores. Therefore, based on these findings, we have selected the SVM as the best final stage classifier (Figure 4) for the proposed network, due to its superior performance.

Table 7. The accuracy, precision, and F1-score for different final stage classifiers.

Classifier	Accuracy (%)	Precision (%)	F1-Score (%)
SVM	93.97	91.37	89.61
MLP	79.21	78.53	75.96
KNN	81.48	79.94	76.42
BN	82.71	80.33	80.29

3.4. Comparison of Computational Time

Furthermore, we assess the computational efficiency of different machine learning models to determine their practical usability. We evaluate the training and inference times as indicators of computational efficiency. The specific training and inference times for each machine learning model are documented in Table 8. It is important to note that all experiments were conducted under consistent conditions within a controlled environment. We observed that the proposed network required relatively longer training and inference times (1889 s and 1.8×10^{-5} s) compared to traditional machine learning models such as CNN-LSTM and CNN-SVM, which aligns with our expectations. However, the actual inference time remains low across all machine learning models. In the case of the proposed network, there exists a trade-off between the complexity of the model's structure and its performance.

Table 8. The computational time and performance for the proposed network and common deep learning networks.

Model	Accuracy (%)	Precision (%)	F1-Score (%)	Training Time (second)	Inference Time (second)
Proposed Network	93.97	91.37	89.61	1889	1.8×10^{-5}
CNN-LSTM	87.34	85.29	82.98	1325	1.6×10^{-5}
CNN-SVM	86.91%	83.75%	81.15%	987	0.9×10^{-5}

3.5. Comparison of Common Deep Learning Networks

Table 9 is a comparison for several recent emotion classification studies based on deep learning, especially CNN networks. As shown in Table 9, the proposed network achieved an accuracy of 93.97% on the original dataset, consisting of 90 images and 3 videos, with 60 participants and utilizing a 32-channel EEG. The CNN model, trained on the DEAP dataset of 40 music videos, achieved an accuracy of 82.24% using a combination of 32-channel EEG, ECG, and GSR signals. The CNN-LSTM model, also trained on the DEAP dataset, achieved an accuracy of 88.87% using 32-channel EEG. The CNN-SAE model, trained on the SEED dataset of 15 music videos, achieved an accuracy of 96.77% utilizing a 62-channel EEG. The results show that, among the common models, the proposed network demonstrated the accuracy of 93.97% on the original dataset, which included relatively small-sized training data. This suggests that the proposed network can achieve acceptable accuracy levels even with limited training data. Additionally, the proposed network utilized a 32-channel EEG signal, making it a feasible and practical choice for emotion recognition tasks. These findings highlight the effectiveness of the proposed network in accurately recognizing emotions from EEG signals, showcasing its potential for real-world applications.

Table 9. A comparison of the proposed network with common deep learning emotion classifiers.

Model	Data Set	Stimuli Size	Number of Participant	Electrophysiological Signal	Accuracy (%)
Proposed Network	original	90 Images and 3 videos (One minute)	60	32 channels EEG	93.97
Multi-Column-CNN [38]	DEAP	40 music videos (One minute)	32	32 channels EEG	90.1%
CNN-LSTM [25]	DEAP	40 music videos (One minute)	32	32 channels EEG	88.87%
CNN-SAE [39]	SEED	15 music videos (4 min)	15	62 channels EEG	96.77%

4. Discussion

Emotion recognition using biological signals has become popular due to its high temporal resolution and cost-effectiveness. Emotions are influenced by various factors, including personality traits. Individuals with different personality traits exhibit different responses to a distinct stimulus. In most studies, personality traits are not quantitatively incorporated into the emotion recognition network. In this study, we attempted to identify personality traits using an LSTM network and quantitatively incorporate these traits into the new emotion recognition network. The results are promising, as they show that incorporating personality traits' information into the emotion classifier network has led to an increase in the overall accuracy of the emotion classifier.

Furthermore, we demonstrated the effectiveness of using a sequence of emotional stimuli to facilitate personality trait learning. Our results showed that the LSTM network achieved higher accuracy in predicting personality traits when the participants watched a sequence of emotional stimuli compared to when they watched a single type of stimuli. This finding suggests that the sequence of emotional stimuli can enhance the representation learning of personality traits from EEG data. Additionally, our study showed that the proposed stimulation enables the network to achieve high accuracy with a smaller input data size compared to a common emotion dataset, such as DEAP.

Finally, as the limitations of this study, we can mention that accurately measuring induced emotions during video watching is not feasible. In this study, we assumed a consistent level of emotional valence is induced in individuals throughout the video, which may not be entirely realistic. For future studies, it is recommended to continuously monitor an individual's emotional state during an emotional video by using a keypad and utilizing the observed valence level as output for network training. It is hoped the networks can be trained more effectively, even with a smaller dataset size. Future works could include the following areas of exploration:

1. Robustness and Generalizability: Evaluate the performance and generalizability of the proposed network and the selected SVM classifier on larger and diverse datasets. Assess the model's ability to handle different scenarios, such as varying input data sizes, different EEG channels, and diverse populations. This analysis can provide insights into the model's robustness and its potential for real-world applications.
2. Incremental Learning: Investigate methods to enable the proposed network to adapt and learn, continuously, as new data become available. Explore techniques such as online learning or incremental learning to update the model over time and accommodate changes in the data distribution or concept drift. This would enhance the network's adaptability and long-term performance in dynamic environments.
3. Integration of Multimodal Data: Emotion recognition can benefit from the integration of multiple modalities, such as facial expressions, physiological signals (e.g., ECG, GSR), or audio features. Investigate the integration of EEG data with other modalities to enhance the accuracy and robustness of emotion classification. Explore fusion

techniques and feature extraction approaches to effectively combine information from different sources.

4. Real-Time Implementation: Implement the proposed network and the selected SVM classifier in real-time applications or wearable devices. Evaluate the feasibility of deploying the model in resource-constrained environments and assess its real-time performance. Consider the trade-off between accuracy and computational requirements, aiming to strike a balance that meets the real-time constraints of practical applications.

5. Conclusions

In this study, we proposed a novel approach for emotion classification, using EEG data and deep learning techniques, while considering personality traits. Our approach leverages the power of pre-trained CNNs and LSTMs to extract high-level features from EEG data and predict personality traits based on the Big Five personality model. In the proposed model, the LSTM network is fed by extracted features of the flattening layer of the CNN-VGG-16. Our results showed that the proposed approach achieved high accuracy in classifying and predicting personality traits. Specifically, the LSTM model achieved an average accuracy of 90.72% in predicting the personality traits, while the CNN model achieved an accuracy of 87.30% in classifying emotions. By combining the trained CNN as the emotion classifier and a trained LSTM as the personality traits classifier, a new classifier network has been created that has the ability to classify emotions with higher accuracy. Our results show that the overall accuracy of the proposed network for emotion recognition, by considering personality traits, was 93.97%. For more comparisons, the performance of several recent emotion classification studies, with a focus on CNN and LSTM networks, were investigated. The proposed network demonstrated competitive accuracy levels despite the relatively small-sized training data.

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Research Article

EEG-Based Personality Prediction Using Fast Fourier Transform and DeepLSTM Model

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In this paper, a deep long short term memory (DeepLSTM) network to classify personality traits using the electroencephalogram (EEG) signals is implemented. For this research, the Myers–Briggs Type Indicator (MBTI) model for predicting personality is used. There are four groups in MBTI, and each group consists of two traits versus each other; i.e., out of these two traits, every individual will have one personality trait in them. We have collected EEG data using a single NeuroSky MindWave Mobile 2 dry electrode unit. For data collection, 40 Hindi and English video clips were included in a standard database. All clips provoke various emotions, and data collection is focused on these emotions, as the clips include targeted, inductive scenes of personality. Fifty participants engaged in this research and willingly agreed to provide brain signals. We compared the performance of our deep learning DeepLSTM model with other state-of-the-art-based machine learning classifiers such as artificial neural network (ANN), K-nearest neighbors (KNN), LibSVM, and hybrid genetic programming (HGP). The analysis shows that, for the 10-fold partitioning method, the DeepLSTM model surpasses the other state-of-the-art models and offers a maximum classification accuracy of 96.94%. The proposed DeepLSTM model was also applied to the publicly available ASCERTAIN EEG dataset and showed an improvement over the state-of-the-art methods.

1. Introduction

Personality has been developed from different theories, but personality core is a function of individual behavioral differences and experiences affected by an individual's development, such as his/her emotions, social relationships, and life experiences [1]. Personality represents the action style of a person in daily life. There are many theories and personality measurements, but the personality trait measurements have become the most considerable acknowledgment in the scientific community and play an irreplaceable role [2].

There are various ways in which personality prediction can be made. Personality can be identified by filling out questionnaires, also known as self-reported personality assessment. The five-factor personality test [3] and MBTI personality test [4, 5] are its examples. Personality prediction

can also be made using social media such as Twitter [6] and Facebook [7] data, but that is not always so accurate because the data can be fake [8–10].

The personality prediction using physiological signals has recently received a lot of interest [11]. The physiological signal allows researchers to have a better understanding of the participant's reactions during the experiment. Recognizing personality from physiological signals [12–14] is more accurate than digital footprints [15, 16] because this approach achieves a higher classification accuracy.

Among the physiological signals, the electroencephalogram (EEG) signals have grown in prominence in recent years and have achieved a higher classification accuracy [17, 18]. The electrical activity produced by neurons in the brain is recorded using EEG, which have been widely utilised to study functional changes in the brain [19, 20].

EEG signals frequency varies from 0.5 Hz to 100 Hz and is grouped into five bands: delta, theta, alpha, beta, and gamma; all the bands have different frequencies [21, 22]. A band of 0.5Hz–50 Hz is used for this paper.

The main contribution of this paper is as follows:

- (i) The newly EEG dataset is created for personality prediction using NeuroSky MindWave Mobile 2 device
- (ii) This study proposed a DeepLSTM model for the prediction of personality traits

The remaining paper is structured in the following manner. Section 2 provides background details. Section 3 is devoted to the materials and methods used in this study. Section 4 discusses the proposed personality framework. Section 5 provides the experimental results. Section 6 discusses the comparison of the proposed DeepLSTM model with the other state-of-the-art methods. Section 7 presents the conclusion.

2. Background

This section explains the FFT for extraction of the features and is discussed in detail next.

2.1. Fast Fourier Transform. The first step in the successful classification [23, 24] of personality traits is to extract important EEG signal features. The popular methods for analyzing EEG data are decomposing signals into various frequency bands, as shown in Figure 1, including delta (0.5 to 4 Hz), theta (4 to 8 Hz), alpha (8 to 12 Hz), beta (12 to 30 Hz), and gamma (30 to 100 Hz). The MindWave can use the onboard chip ThinkGear ASIC Module (TGAM1), with algorithms that reduce the background noise and objects. For a decomposing signal with fast Fourier transform (FFT), the TGAM1 chip has an algorithm. The value is provided to the application program by the TGAM1 chip using the device. Each second data are gathered and processed in the temporal field to identify and correct as much as possible the artifacts and background noise, without the practical usage of NeuroSky's proprietary algorithms, of the original signal. The headset helps us to control meditation and attention features that their eSense technology measures.

3. Materials and Methods

This particular section gives details about the pool of participants, details about the device used for experimentation, the details of the dataset used for experimentation, and lastly details about the procedure of experimenting.

3.1. Pool of Participants. This study consists of 55 participants. However, five samples have been removed from the final assessment due to dware errors or inappropriate EEG signal artifacts. Therefore, 50 representative samples of 18 to 46 years of age (25 males and 25 females) participated in the study. Forty participants are handed to the right; ten are handed to the left, each with a natural vision. Participants

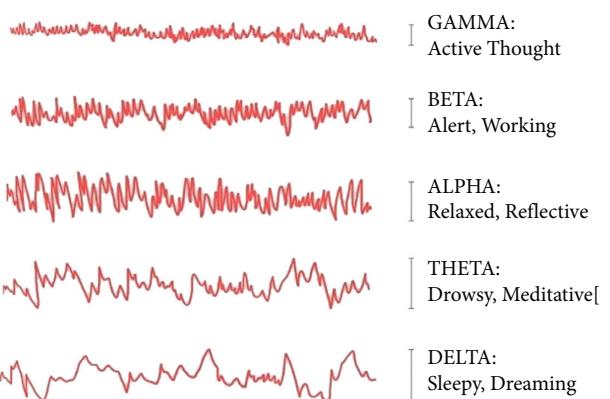


FIGURE 1: Brainwave frequency bands.

were not allowed 24 hours before the experiment to take tobacco or caffeine.

3.2. Device Description. The NeuroSky MindWave mobile 2 device's functionality is to capture brain signals, as seen in Figure 2. The brainwave reading EEG headset is simple to monitor and is cheap. It generates 12-bit (3–100 Hz) raw brainwaves at a 512 Hz rate and generates EEG power spectrums at various frequency and morphology bands. It is used for pairings with a static headset ID. For capturing the dataset, eegId application is used, which has in-build FFT feature extraction technique and ten features are extracted.

3.3. Proposed EEG Dataset. Visual content is a reliable means of eliciting affect or emotion [25] in the literature. We created and consolidated a set of 40 movies and series clips for this analysis, which served as elicitation materials for the data collected from subjects. The content of these movie clips includes audio and video elements, allowing students to participate in immersive experience. English language and Indian language (Hindi) film samples with a length of about 2 to 4 minutes were chosen for the process. Each clip in the elicitation material includes content that evokes emotions and personality traits and characters exhibiting a particular personality trait.

All of the chosen movie clips are thought to generate and activate the desired personality trait's characteristic emotions. Table 1 presents a selection of stimuli dataset clips used to evoke a particular personality trait for EEG data acquisition. The order and selection of clips were randomized to ensure effectiveness.

3.4. Publicly Available Dataset. This research also uses the publicly available EEG dataset of personality known as ASCERTAIN dataset [26]. The ASCERTAIN dataset uses the BFF model for personality prediction using EEG signals, which have been collected in laboratory settings from the single-channel EEG device. The recorded information includes frontal lobe activity, level of facial activation, eye-blink rate, and strength. It contains 58



FIGURE 2: Single-channel NeuroSky MindWave mobile 2.

TABLE 1: Sample of stimuli dataset clips to felicitate targeted personality traits for EEG data acquisition.

Personality trait	Film name	Length (minutes)	Clip content
Extrovert	IBIZA	2.8 min	Harper, an extrovert character exploring Spain
Introvert	Jab We Met	3.22 min	An introvert guy boards a random train where he meets a bubbly girl
Thinking	Slumdog Millionaire	2.6 min	An uneducated nobody from slums answers critical questions of knowledge to become a millionaire
Feeling	12 Years a Slave	3.61 min	An incredible true story of Solomon Northup, a free African-American, abducted and sold into slavery, fights not only to survive, but to retain his dignity
Sensing	URI: The Surgical Strike	2.88 min	The clip chronicles an event of the surgical strike lead by major for a covert operation against suspected militants
Intuitive	Confessions of a Shopaholic	3.5 min	An abstract and imaginative character, struggling with her enfeeble obsession with shopping
Judging	The Devil Wears Prada	2.9 min	A famed fashion designer life story of being systematic schedule which inspires both terror and a measure of awe.
Perceiving	3 Idiots	3.0 min	An aspiring engineering student delivers a life lesson in a very innovative manner

participants' EEG recordings as data, and 36 movie clips were taken. These clips are between 51 and 127 s long. All topics were popular in English, and the students were regular film watchers from Hollywood. The film clips (nine clips per quadrant) are distributed uniformly throughout the visual analog (VA) space. For the recording of physiological signals, different sensors were used in the surveillance of the clips. After watching the clip, each participant was asked to mark the VA scale with a 7-point scale to represent his practical experience. The personality test for the five large dimensions has also been evaluated using a 5-dimensional questionnaire.

4. Proposed Personality Prediction Framework Using EEG Signals and DeepLSTM Model

Figure 3 includes the entire framework for personality prediction using EEG signals and the DeepLSTM model. The proposed framework consists of two parts. First is the data collection for personality prediction, and second is the DeepLSTM model for classification of personality traits, and both of these are described next.

4.1. Data Collection for Personality Prediction. Data collection is the first step in the research process. This dataset was obtained using an experimental protocol that is well established and easy to follow. The dataset is created to support 50 volunteers (25 men and 25 women) who will be actively involved in the data collection process. Since an individual's personality trait cannot be assessed solely by their current mood or state of mind, the data will be collected three times over five days [27]. The participant was initially relaxed in the data collection process and wore the NeuroSky MindWave mobile 2 headset on their head. Since there are four groups in the MBTI personality traits, each group consists of two traits in verses of each other. There are eight traits, and for each trait, one film clip is shown to the participant. During the training time, the proposed procedure is iterated eight times with one participant. Before each film clip, the participants were given a 20-second starting hint to begin the test, during which they viewed video clips of a targeted personality trait. Following that, each participant signs a consent form, which is then accompanied by keeping a record of their general information such as name, age, and gender at the initial levels for developing the

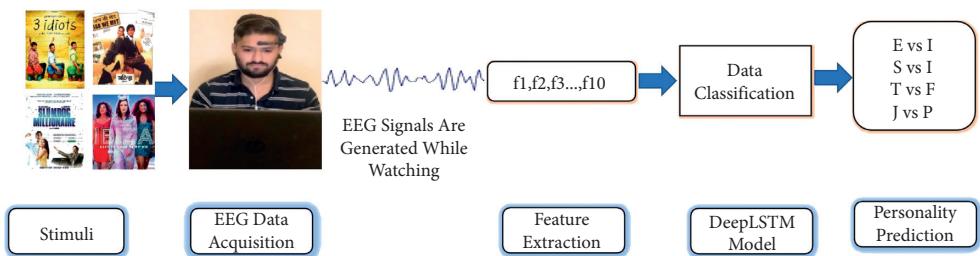


FIGURE 3: Personality prediction framework using EEG signals and DeepLSTM model.

dataset. Single-channel EEG adjustable headband was used to monitor the EEG signals.

After viewing a film clip of one trait, the participants had to fill the self-evaluation form with options “agree,” “neutral,” or “disagree” and have seven questionnaires for each personality trait. These questionnaires are constructed by targeting the characteristics of personality traits. These questionnaires must be answered based on the participants’ real feelings instead of their typical emotions or general attitude, which may differ from person to person. Because of that, the answer to those questionnaires may differ. In each clip, a 1-minute buffer is for neutral clip to neutralize the participants’ elicited personality traits. After all of the questions for each of the four grouped personality traits have been answered, the questionnaire (which contains seven questions) is evaluated for each participant’s traits. The labeling of the EEG signal depends on the output of the questionnaires given by the participant. The final output is evaluated by the following procedure. Let us suppose that the participant has watched the film clip targeting the characteristic of the extraversion trait. After watching the film clip, the participant answered the questionnaires based on the extraversion trait. Suppose the participant selects for the “agree” option in the questionnaire. In that case, we can raise it by value 1. If, for the extraversion questionnaire, the participant chooses the option “disagree,” we raise the counter of the introversion trait (versus trait of extraversion) by one. If the participant opts for the neutral option, we neither increase nor decrease the counter for any trait. Since there are seven extraversion trait questionnaires, the EEG signal labeling depends on the participant’s output, and three labeling possibilities exist.

- (i) The EEG signal is labeled as extraversion if the number of “agree” options is more selected than “disagree”
- (ii) The EEG signal is labeled as introversion if the number of “disagree” options is more selected than “agree”
- (iii) The EEG signal is discarded if the number of “agree” and “disagree” options are equal in number

Similarly, for introversion trait-based questionnaires, the counter for introversion trait is incremented if the participant chooses the “agree” option. If the participant chooses the “disagree” option, the counter for extraversion is incremented. If the participant opts for the neutral option, we do not increase or diminish the counter for that

questionnaire of both the traits. The labeling of the EEG signal is done by following the above procedure. Similarly, the remaining personality traits marking is done, and their related EEG signals are labeled. The same experimental procedure is repeated after three days for collecting the data and removing bias.

At the end of each trait’s evaluation process, the dataset’s maximum counter value is labeled. To label the EEG signals, this marking scheme is taken as the reference. The study’s testing data were obtained using just four video clips, targeting one personality trait from each group.

The experiment will be performed using four machine learning algorithms, ANN, KNN, LibSVM, and HGP, including our proposed DeepLSTM classifier. The survey and review of results for the recorded EEG signal dataset using the described machine learning algorithms will provide valuable material for a similar study of personality types. These findings show that personality inference from EEG signals outperforms state-of-the-art clear behavioral indicators in classification accuracy.

4.2. Proposed DeepLSTM Model. Various algorithms for learning machines are used for the recognition and description of personality characteristics in literature. The DeepLSTM model for personality traits classification with the use of EEG signals is used in this work.

Figure 4 includes the architectures of the DeepLSTM cell network used for classifying the personality traits by using EEG signals in this analysis. The DeepLSTM network has been established on the backend in Python 3.6 Keras 2.0.9 on TensorFlow 1.4.0.

In DeepLSTM architecture, there are 3 LSTM layers, with 512 memory units in the first layer, 256 memory units in the second layer, and 128 memory units in the third layer. In all proposed architectures, the dropout layer is also used, and the probability value is 0.2. In the model between existing layers, the dropout layer is applied to previous layer outputs, which are fed to the layer, as shown in Figure 4. A layer’s outputs are arbitrarily subsampled under dropout layer. The memorization capability of the DeepLSTM model is due to the dropout regularization [28]. Furthermore, the model is trained faster with the 0.2 dropouts, overfitting is reduced, and the proposed DeepLSTM model performs better in terms of prediction. The “tanh” function is used as an activation function and generates the output of 64 units.

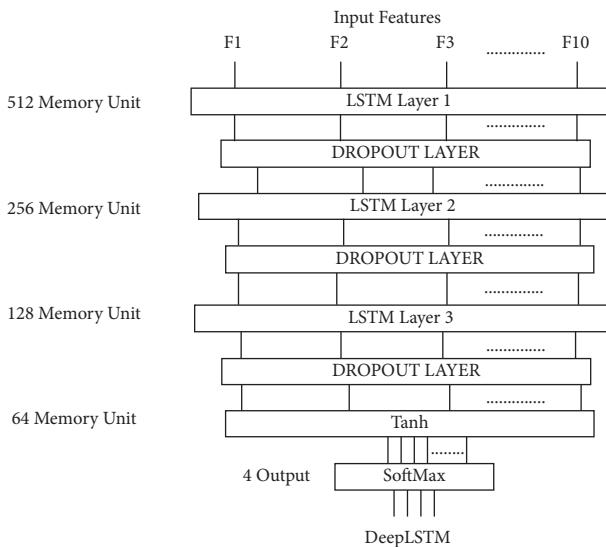


FIGURE 4: DeepLSTM cells network architecture.

$$\tanh(x) = \frac{2}{1 + e^{-2x}} - 1. \quad (1)$$

“Softmax” is used as an activation function in the last layer and 4 outputs are generated representing four personality classes. The key benefit of using the softmax as an activation function is the range of output probabilities, which will be between 0 and 1. It returns each class’s probabilities, with the target class having the highest probability.

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j \exp(x_j)}. \quad (2)$$

LSTM cells and dropout layers are utilised to discover the role of EEG signals. The overfitting of these systems was minimized by restricting unit coadapting in the dropout layer of our DeepLSTM architectures. The dense layer, the loss function for these network architectures, is categorical cross-entropy and the batch size is 40. The adaptive moment estimation optimizer (Adam) is used for a learning rate of 0.001. The normalization is applied to the dataset input features with the MinMaxScaler function after loading the dataset. This function normalizes each feature because of which each feature contributes in a maintained manner. It decreases the internal covariate transition, resulting in a change in network activation distribution due to shifts in network parameters during training. The normalization of the proposed network enhances training, reducing the change in the internal covariance. It also helped improve the optimization phase by stopping weights from bursting around the entire site by limiting them to a specific set. An undesired advantage of normalization is that it often allows the mechanism to regularize somewhat. In the parameter specified by Table 2, the proposed DeepLSTM network is initialized [29]. We test the output of our proposed DeepLSTM model, which classifies EEG signals as an output value into five personality groups, for 500 epochs with a

TABLE 2: DeepLSTM model formation parameter values.

Parameter	Value
Optimizer	Adam
Rate of learning	0.001
Rate of dropout	0.2
Loss function	Categorical cross-entropy
Metrics used	Accuracy
Size of batch	40

batch size of 40. The DeepLSTM model was evaluated using the suggested EEG dataset as well as the publicly available ASCERTAIN EEG dataset.

The proposed architectures and parameters were chosen based on our own experiments with nearby architectures (in terms of layers and nodes). In terms of accuracy, the proposed DeepLSTM architecture outperforms their nearby architecture.

5. Experimental Results

The results of the DeepLSTM model for classifying the EEG signals and to check our system’s efficacy are presented next. The computer environment is composed of 3.4 GHz devoted to the 32 GB RAM-based Python (3.6) to incorporate DeepLSTM cell architecture and other states of the art, i.e., ANN, KNN, LibSVM, and HGP. The parameter values of the ANN, KNN, LibSVM, and HGP are the same as in [19, 30], respectively. The parameter values taken for the implementation of the DeepLSTM model are given in Table 2.

The dataset is typically split into two distinct sets, i.e., training sets and test sets. A general review of our method is carried out in this research of personality trait classification using EEG signals. We have separated the dataset into different training and testing partitions to equate them with existing literature. The performance assessment is conducted using a 50–50, 60–40, 70–30, and 10-fold partition scheme.

In 50–50, 60–40, and 70–30 training-testing partition, 50%, 60%, and 70%, respectively, data is used for training, and 50%, 40%, and 30%, respectively, of the data is used for testing. The complete dataset is partitioned into approximately ten equal size blocks in a 10-fold cross-validation scheme; 90% of the dataset, i.e., nine blocks, becomes our training data, and 10% of the dataset, i.e. one block, becomes our testing data. This process is repeated ten times, with each time a different data block being used for testing. Also, our proposed model's sensitivity, precision, and specificity value for the 50–50, 60–40, 70–30, and 10-fold partition schemes are calculated.

5.1. DeepLSTM Architecture Evaluation. This study uses a deep learning algorithm to distinguish personality traits from EEG signals. In practice, the DeepLSTM model outperforms traditional machine learning algorithms because it has the capability of remembering the long-term dependence of sequential data in time, increasing the likelihood of correctness in a short period of time [31].

Table 3 represents the classification accuracy comparison for personality prediction DeepLSTM model on the ASCERTAIN and the proposed EEG datasets. For the ASCERTAIN and the proposed EEG datasets, the proposed DeepLSTM model maximum, average, and minimum classification accuracy for 50–50, 60–40, 70–30, and 10-fold cross-validation partition scheme is calculated.

The maximum classification accuracy of the proposed DeepLSTM model for 50–50, 60–40, 70–30, and 10-fold cross-validation partition scheme on the ASCERTAIN EEG dataset is 82.48%, 88.14%, 92.86%, and 95.32%, respectively.

The maximum classification accuracy of the proposed DeepLSTM model for 50–50, 60–40, 70–30, and 10-fold cross-validation partition scheme on the proposed EEG dataset is 84.56%, 91.52%, 94.82%, and 96.94%, respectively. From the results, it can be seen that the DeepLSTM model performs better in terms of performance on the ASCERTAIN and the proposed EEG datasets, and the classification accuracy of the DeepLSTM model is higher on our proposed EEG dataset than the ASCERTAIN dataset.

6. Discussion

This section discusses how the proposed deep learning-based DeepLSTM model works compared to conventional machine learning algorithms.

A comparison with standard conventional classification algorithms is carried out using the same collection of features as used in DeepLSTM-based methodology to show the advantages of incorporating deep learning into the classification of personality traits.

TABLE 3: Classification accuracy comparison for personality prediction of DeepLSTM model on the ASCERTAIN and proposed EEG datasets.

Dataset	Method	Validation technique	Accuracy		
			Max	Avg	Min
ASCERTAIN	DeepLSTM classifier	50–50	82.48	80.36	77.42
		60–40	88.14	85.63	81.46
		70–30	92.86	89.68	86.46
		10-fold	95.32	94.16	91.98
Proposed dataset	DeepLSTM classifier	50–50	84.56	82.44	79.62
		60–40	91.52	87.62	84.86
		70–30	94.82	91.68	88.72
		10-fold	96.94	95.88	93.94

Optimal values are represented in bold.

The KNN, ANN, LibSVM, and HGP are the other state-of-the-art approaches used for comparison. The classification accuracy comparison of personality traits is contained in Table 4. It contains the maximum, average, and minimum accuracy for the 50–50, 60–40, 70–30, and 10-fold partition schemes. The parameters and settings for these variables have all been implemented using the same technique to ensure that the findings and comparisons offered are unambiguous and consistent.

The proposed deep learning approach has a greater impact than traditional machine learning algorithms. The DeepLSTM classification improved dramatically in classification accuracy, as per the results. Besides the rise in classification accuracy, the DeepLSTM classifier can also retain specificity greater than 92.86% on the ASCERTAIN dataset and 93.84% on the proposed EEG dataset, resulting in very low false prediction % rates. The sensitivity value of the DeepLSTM model for the ASCERTAIN dataset is 94.72%, and the proposed EEG dataset is 95.86% and is high in the other state-of-the-art methods, which shows that the DeepLSTM model correctly classifies the minority class samples. The precision value of the DeepLSTM model for the ASCERTAIN dataset is 93.48%, and the proposed EEG dataset is 94.44% and is high in the other state-of-the-art methods. The F1 score value of the DeepLSTM model for the ASCERTAIN dataset is 93.68%, and the proposed EEG dataset is 94.96% and is high in the other state-of-the-art methods. Table 5 shows the relation of sensitivity, precision, specificity, and F1 score values of DeepLSTM for 50–50, 60–40, 70–30, and 10-fold data partitioning scheme.

Table 6 shows the statistical result disparity is illustrated by the two-tailed Mann–Whitney test [32]. The Mann–Whitney test is used to compute the *p* value relation in classification accuracy. The outcomes do not change significantly if the *p* value is greater than 0.05, and it is highly

TABLE 4: Classification accuracy comparison for personality prediction of DeepLSTM model with other state-of-the-art algorithms on the ASCERTAIN and the proposed EEG dataset.

Dataset	Method	Validation technique	Accuracy		
			Max	Avg	Min
ASCERTAIN	ANN	50–50	70.84	67.24	64.48
	KNN	50–50	67.64	64.26	62.23
	LIBSVM	50–50	77.28	73.84	71.86
	HGP	50–50	78.52	75.38	72.68
	DeepLSTM classifier	50–50	82.48	80.36	77.42
ASCERTAIN	ANN	60–40	74.34	69.86	67.74
	KNN	60–40	70.38	68.16	65.68
	LIBSVM	60–40	79.86	77.28	75.46
	HGP	60–40	81.27	78.73	76.08
	DeepLSTM classifier	60–40	88.14	85.63	81.46
ASCERTAIN	ANN	70–30	75.18	73.16	69.94
	KNN	70–30	72.82	70.84	68.62
	LIBSVM	70–30	83.26	81.62	79.86
	HGP	70–30	86.64	83.38	80.74
	DeepLSTM classifier	70–30	92.86	89.68	86.46
ASCERTAIN	ANN	10-fold	78.82	74.64	72.46
	KNN	10-fold	74.36	72.37	70.25
	LIBSVM	10-fold	84.82	82.42	80.28
	HGP	10-fold	86.12	83.86	81.84
	DeepLSTM classifier	10-fold	95.32	94.16	91.98
Proposed dataset	ANN	50–50	72.84	69.36	66.48
	KNN	50–50	69.32	66.92	63.86
	LIBSVM	50–50	79.74	76.64	73.86
	HGP	50–50	80.36	77.83	74.89
	DeepLSTM classifier	50–50	84.56	82.44	79.62
Proposed dataset	ANN	60–40	76.16	73.28	70.12
	KNN	60–40	72.64	70.62	68.54
	LIBSVM	60–40	81.26	79.58	77.82
	HGP	60–40	83.28	80.94	78.63
	DeepLSTM classifier	60–40	91.52	87.62	84.86
proposed dataset	ANN	70–30	78.62	73.94	71.28
	KNN	70–30	74.68	72.36	70.82
	LIBSVM	70–30	85.64	83.70	81.58
	HGP	70–30	87.69	84.74	82.84
	DeepLSTM classifier	70–30	94.82	91.68	88.72
Proposed dataset	ANN	10-fold	80.24	76.54	74.98
	KNN	10-fold	76.82	74.64	72.28
	LIBSVM	10-fold	88.04	85.16	83.26
	HGP	10-fold	90.32	86.93	84.78
	DeepLSTM classifier	10-fold	96.94	95.88	93.94

Optimal values are represented in bold.

TABLE 5: Comparison of sensitivity, precision, and specificity of DeepLSTM model for various partition schemes.

Dataset	Validation technique	Sensitivity (%)		Precision (%)		Specificity (%)		F1 score (%)	
		Mean ± Std	Mean ± Std	Mean ± Std	Mean ± Std	Mean ± Std	Mean ± Std	Mean ± Std	Mean ± Std
ASCERTAIN	50–50	81.64	±3.08	80.53	±3.12	78.42	±2.84	80.56	±2.36
	60–40	87.76	±3.14	86.82	±3.24	85.94	±2.68	86.44	±2.44
	70–30	91.49	±3.16	90.56	±3.42	89.67	±2.36	90.40	±3.42
	10-fold	94.72	±3.16	93.48	±3.12	92.86	±2.98	93.68	±2.84
Proposed dataset	50–50	83.46	±3.14	82.75	±3.15	81.14	±3.24	82.46	±3.18
	60–40	90.74	±3.24	89.25	±3.16	88.94	±3.18	89.46	±3.32
	70–30	93.54	±3.14	92.85	±3.25	91.94	±3.42	92.28	±3.24
	10-fold	95.86	±3.18	94.44	±3.14	93.84	±3.12	94.96	±3.16

Optimal values are represented in bold.

TABLE 6: p value comparison for DeepLSTM using Mann–Whitney test.

	Training-testing Partition	ANN	KNN	LibSVM	HGP
		p value	Significance	p value	Significance
DeepLSTM	50-50	2.681 x 10⁻¹¹	Highly Significant	1.450 x 10⁻¹¹	Highly Significant
	60-40	2.634 x 10⁻¹¹	Highly Significant	1.350 x 10⁻¹¹	Highly Significant
	70-30	2.576 x 10⁻¹¹	Highly Significant	1.270 x 10⁻¹¹	Highly Significant
	10-fold	2.486 x 10⁻¹¹	Highly Significant	1.235 x 10⁻¹¹	Highly Significant

Optimal values are represented in bold.

significant if the p value is less than 0.001. It is evident from the interventions in Table 6 that the solution provided by our proposed DeepLSTM model is statistically different from ANN, KNN, LibSVM, and HGP for the 50–50, 60–40, 70–30, and 10-fold data partitioning scheme. When the p values are contrasted with DeepLSTM for these classifiers, there is a significant variation in outcomes. The evaluation results suggest that the proposed DeepLSTM-based deep learning model for classifying personality traits provides accurate classification results.

7. Conclusion

During this study, we propose EEG signals-based personality prediction system using DeepLSTM-based deep learning model.

A new EEG dataset was also created using 40 film clips of Hindi and English languages. The proposed DeepLSTM model was also applied to the publicly available EEG dataset known as ASCERTAIN. Multiple experiments have been carried out to validate our results, which are helpful to compare our DeepLSTM model with existing methods. Fifty participants were involved and saw a few movie clips targeting eight different personality traits. This method uses NeuroSky MindWave mobile 2 to capture brain signals. Better results of sensitivity, precision, and specificity indicate that our approach beats the current literature. The classification accuracy of the proposed DeepLSTM model on our proposed EEG dataset is 96.94% for the 10-fold partition scheme and outperforms the results of the DeepLSTM model on the ASCERTAIN dataset having classification accuracy of 95.32%.

We are currently using a single-channel device, and in the future, we will extend it to multichannel devices.

Data Availability

The data are available on request from the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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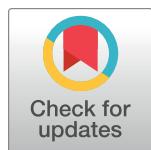
Neural correlates of eye contact in face-to-face verbal interaction: An EEG-based study of the extraversion personality trait

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Abstract

The extraversion personality trait has a positive correlation with social interaction. In neuro-imaging studies, investigations on extraversion in face-to-face verbal interactions are still scarce. This study presents an electroencephalography (EEG)-based investigation of the extraversion personality trait in relation to eye contact during face-to-face interactions, as this is a vital signal in social interactions. A sample of healthy male participants were selected (consisting of sixteen more extraverted and sixteen less extraverted individuals) and evaluated with the Eysenck's Personality Inventory (EPI) and Big Five Inventory (BFI) tools. EEG alpha oscillations in the occipital region were measured to investigate extraversion personality trait correlates of eye contact during a face-to-face interaction task and an eyes-open condition. The results revealed that the extraversion personality trait has a significant positive correlation with EEG alpha coherence in the occipital region, presumably due to its relationship with eye contact during the interaction task. Furthermore, the decrease in EEG alpha power during the interaction task compared to the eyes-open condition was found to be greater in the less extraverted participants; however, no significant difference was observed between the less and more extraverted participants. Overall, these findings encourage further research towards the understanding of neural mechanism correlates of the extraversion personality trait—particularly in social interaction.

Introduction

In the Big Five theory, the extraversion personality trait is one of the five major traits alleged to form human personalities [1, 2]. People who are high in extraversion can be characterised as

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talkative, gregarious, energetic, and assertive and vice versa for those with low extraversion. This personality trait is believed to influence an individual's preferences and performance in various areas, such as work and education [3–5]. For instance, more extraverted persons are the most likely to seek professions with a higher level of task significance, power, and feedback [3]. They love to be assigned the responsibility to create transformation, as well as handle multiple functions [3]. This is believed to be due to their preference for feeling a sense of significance, and for evaluating their own performance in relation to that of others.

Furthermore, more extraverted persons prefer to engage with people and enjoy social interaction, while less extraverted persons tend to be quiet, reserved and less sociable [1, 6]. After social activities, more extraverted persons achieve significant increases in positive affectivity as compared to less extraverted individuals [7]. These differences influence more and less extraverted persons to behave differently when interacting with others, face-to-face. For instance, compared to more extraverted persons, less extraverted persons were found to have larger general inhibitions, which led them to hesitation in sharing their ideas in a group discussion [4]. Presumably, because of this general inhibition, less extraverted persons prefer to communicate and interact via the internet, while more extraverted persons prefer face-to-face social interaction [8, 9].

As we know, during a face-to-face social interaction, eye contact is an important social signal [10]. This can be described as two persons gazing at each other's eyes [11, 12]. These gazing activities could be a cue of one person's attention towards another [13–15]. For instance, three-month-old infants' smiling behaviour declined when an interacting person gazed away after having made eye contact [16]. In terms of the extraversion personality trait, [17] summarized several studies and found that more and less extraverted persons have differences in terms of gaze direction, duration, and frequency. They reported that the direction, duration, and frequency of gaze were found to be toward, long, and often, respectively, in more extraverted persons; and corresponded to avoidance, short, and seldom in less extraverted persons [17]. Supporting these findings was a study that claimed the extraversion personality trait is directly proportional to the attention an individual commits to the eyes of another person during social tasks [18]. By referring to these findings, we could say that more and less extraverted persons could be differentiated based on eyes contact during social events. Although many studies showed differentiation of extraversion personality trait in terms of eye contact, research involving electroencephalography (EEG) remains scarce—particularly involving the naturalistic paradigm of face-to-face verbal interaction [19, 20].

EEG is an effective neuroimaging modality to study individual differences in personality [21–23]. This is because of its direct measurement of neural signals and remarkable temporal resolution compared to other neuroimaging modalities, such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET) [24]. One of the well-known theories of extraversion was proposed by Eysenck [25], which stated that the extraversion personality trait has a negative correlation with cortical arousal. Based on this theory, some EEG studies discovered that more extraverted persons demonstrated lower levels of cortical arousal and less extraverted persons demonstrated higher levels of cortical arousal, as measured through EEG alpha oscillations [26, 27]. Additionally, several researchers investigated the extraversion personality trait and EEG alpha oscillations in posterior regions, such as the parietal and occipital regions [28–31]. Although these studies generally showed a positive association between the extraversion personality trait and EEG alpha oscillations in the posterior region [28, 30], one study was unable to find such a significant association [29]. Along with technological development in removing eye movement artefacts in the frontal region, [32] investigated positive and negative empathic moods with the extraversion personality trait in broad brain regions, including frontal (F3, F4), temporal (T3, T4), and occipital (O1, O2). They claimed that extraversion was related to larger alpha amplitude in widespread regions.

Furthermore, [26] focused on the frontal region (Fp1, Fp2, F3, F4, F7, F8, Fz) in an investigation of EEG alpha oscillations, while participants opened and closed their eyes on instruction. They suggested similar findings to those of [32] in that more extraverted persons exhibited a larger alpha amplitude compared to that of less extraverted persons. Investigations of EEG alpha oscillations and the extraversion personality trait are ongoing in various aspects, such as intelligence [33], memory performance [34, 35], creativity and originality [27], and emotional processing [36]. For analysis, several studies focused on the entire brain including the occipital region [27, 36], while others excluded the occipital region [34, 35]. Such differences in the brain regions of interest in these studies could partly be due to the different sets of objectives and experimental tasks considered.

Based on our review, although there have been many studies investigating EEG correlates of the extraversion personality trait, none have incorporated the aspect of eye contact during a face-to-face interaction. Hence, the aim of this study was to investigate EEG correlates of extraversion in relation to eye contact by measuring EEG alpha coherence and power in the occipital region during a face-to-face interaction task. EEG alpha oscillations were considered on the basis of Eysenck's well-known theory of extraversion [25], and for having been explored in many EEG studies related to extraversion personality trait [26, 27, 37].

Methods

Participants

Ninety-one healthy male students of Universiti Teknologi PETRONAS volunteered to participate in the experiment. The volunteers were exclusively male so as to avoid any possible gender effect on the EEG results [38, 39]. According to their self-report, they were right-handed, had normal or corrected to normal vision, had no hearing impairment, were not suffering from or having family history related to cognitive disorder, were not taking any drugs or any medication, nor experiencing chronic mental stress or adverse psychology states. All volunteers had to complete two personality tests—the Eysenck Personality Inventory (EPI) and Big Five Inventory (BFI)—to determine their level of extraversion before they could participate in this study [40, 41]. The volunteers were characterised as less extraverted if they scored less than 50% for both EPI and BFI, and more extraverted if they scored more than 50% for both EPI and BFI. After a screening session, 50 volunteers were excluded due to conflicting results between their personality tests. Of the 41 remaining volunteers who met the requirement, only 32 returned to the study, consisting of 16 less and 16 more extraverted participants. These were between 18 and 23 years old ($M = 19.53$ and $SD = 1.22$). All participants gave informed consent and were paid for their participation in the EEG experiment for this study.

This research was approved by the Medical Research Ethics Committee of the University of Kuala Lumpur Royal College of Medicine Perak, Malaysia.

Experimental task: A face-to-face interaction task

The experiment conducted involved a form of a face-to-face interaction task, which was performed individually by each participant. During the task, the participant was instructed to sit facing an inquirer who was a stranger to them (see Fig 1). This face-to-face interaction task with a stranger was selected for its potential to induce stress and anxiety related to social awkwardness, which could be one of the challenges for less extraverted participants. In the task, four questions were asked by the inquirer to the participants, one at a time. The participants were instructed to answer each question spontaneously, within two minutes. The instructor stopped the session when the time had reached two minutes. See Fig 2 for a detailed timeline of the interaction task. All questions remained unknown to the participants until the inquirer asked them.



Fig 1. Face-to-face interaction task: A participant wearing an EEG cap is seated facing an inquirer. (The individual in this manuscript has given written informed consent—as outlined in the PLOS consent form—to publish these case details.)

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Procedure

Prior to the beginning of the experiment, participants were provided with information about the experiment and their informed consents were obtained. The enrolled participants were then seated in a partially sound-attenuated EEG experiment room to perform the experiment individually. Subsequently, the EEG device was set up, which included assisting participants in donning an EEG cap. EEG recordings began with a 5-minute eyes-closed period, followed by a 5-minute eyes-open period. During the eyes-open period, participants were advised to focus on one point and avoid eye movement. Next, a practice session was held in which they needed to answer one question within two minutes. The purpose of this practice session was to ensure participants provided maximal EEG data quality during the actual experimental task. During the practice session, participants were guided on how to minimise EEG artefacts, such as placing their hands on their laps to avoid hand movements and thereby improve the quality of the EEG data. Such artefacts are due to the fact that EEG devices are sensitive and easily interrupted by other unwanted electrical activities. After the practice session, participants needed to introduce themselves. They were then asked to perform the face-to-face interaction task. For each question in the interaction task, the EEG recording started when the inquirer began to ask the question and stopped when the time to answer reached two minutes (see Fig 2). Following the interaction task, participants were asked to fill a self-assessment survey related to the task (see Table 1). At the end of their session, each participant was instructed to keep all questions asked during the interaction task strictly confidential. This was to avoid other participants from preparing their answers before the experiment.

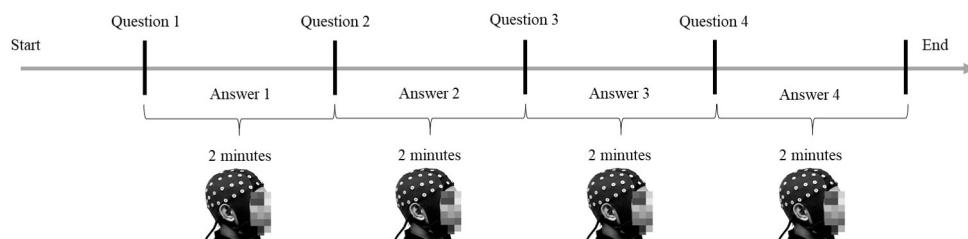


Fig 2. Timeline of the face-to-face interaction task. (The individual in this manuscript has given written informed consent—as outlined in the PLOS consent form—to publish these case details.)

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Table 1. One-way ANOVA of EEG features and self-assessment survey.

		F	p-value	η_p^2	Observed power ⁽ⁱⁱ⁾
EEG alpha coherence	Eyes-open	0.067	0.798	0.002	0.057
	Interaction task	8.934	0.006 ⁽ⁱ⁾	0.229	0.824
EEG alpha power	Eyes-open	0.716	0.404	0.023	0.130
	Interaction task	0.263	0.612	0.009	0.079
(a) I was comfortable sitting in front of strangers.		20.589	0.000 ⁽ⁱ⁾	0.407	0.992
(b) I was comfortable sharing my answer or idea during the group discussion.		12.273	0.001 ⁽ⁱ⁾	0.290	0.924
(c) I voiced my ideas or opinion spontaneously.		4.892	0.035 ⁽ⁱ⁾	0.140	0.572
(d) I would prefer to give feedback verbally.		7.418	0.011 ⁽ⁱ⁾	0.198	0.75

Note: (a)-(d) items in self-assessment survey;

(i) p -value < 0.05;

(ii) computed using alpha = 0.05

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EEG acquisition

The EEG data was recorded using a 32-channels eegoTM sports system (ANT Neuro, Netherlands) with Ag/AgCl scalp electrodes arranged based on the International 10–10 System. The CPz electrode was selected as a reference electrode. The impedance of each electrode was kept below 10 kΩ. The EEG data were digitised at a sampling rate of 512 Hz.

Data analysis

EEG preprocessing. The recorded EEG data were pre-processed using BESA Research 6.0 (www.besa.de). First, the raw EEG data were bandpass filtered with a cut-off frequency of 0.53–48 Hz. Eye artefacts (movements and blinks) and muscle movements were corrected using the Berg & Scherg method [42] implemented in the BESA software as used by [43]. The cleaned EEG data were then exported to MATLAB for EEG features extraction.

EEG features. **EEG alpha coherence:** This is one of the methods used to measure brain functional connectivity by measuring signals from two electrodes, or two brain regions. In mathematics, coherence can be defined as the ratio of normalised cross-power spectrum to auto-power spectrum [44]. Coherence ranges from 0 to 1, where 0 means the corresponding two signals are not functionally coherent and 1 means the two signals are fully functionally coherent with a constant phase difference, suggesting that the two electrodes (brain areas) are working together. EEG coherence can be calculated using Eq (1) [44]:

$$C_{xy}^2(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \quad (1)$$

where f is the frequency, P_{xy} is the cross-power spectrum between the signals of two electrodes x and y , P_{xx} is the auto-power spectrum for the signals of electrode x , and P_{yy} is the auto-power spectrum for the signals of electrode y .

For EEG coherence in this study, only 19 of the 32 electrodes were selected based on the 10–20 placement system. The number of pairs was calculated using pairs = $\binom{n(n-1)}{2}$, where $n = 19$ resulted in 171 pairs. The EEG coherence for all 171 pairs was calculated for the four oscillations (alpha, delta, theta, and beta) using Eq (1). The EEG alpha coherence for the paired occipital electrodes (O1 and O2) were extracted and averaged within the participants and

within the questions to investigate extraversion personality trait correlates of eye contact during the interaction task.

EEG alpha power: In this study, EEG alpha power was measured in the eyes-open condition to serve as a baseline, and during an interaction task. A fast Fourier transform (FFT) with a Hanning window was used on 512 samples with a 50% overlap between successive 2-second segments (1024 points) for estimating the power of the EEG signals. The EEG alpha power during the interaction task and in the eyes-open condition in the occipital region (electrodes O1 and O2) was extracted and averaged at a standard frequency of 8–13 Hz. Subsequently, the EEG alpha power data were averaged within the participants and within the interaction task questions. The mean EEG alpha power for the interaction task was compared with that of the eyes-open baseline. Increase or decrease in the EEG features (e.g. EEG alpha power) during the experimental task in comparison with the baseline were computed for each participant by [45]:

$$A_{EB} = (S_E - S_B)/S_B \quad (2)$$

Where A_{EB} is the increase/decrease in the EEG alpha power (positive/negative values) during the experimental task as compared to that of the eyes-open baseline, S_E is the EEG alpha power during the experimental task, and S_B is the EEG alpha power in the eyes-open condition.

Statistical analysis. As mentioned, two personality tests (i.e. the EPI and BFI) were used for personality assessment. The extraversion scores of all participants were computed by converting the EPI and BFI scores to percentages and averaging them. Pearson correlation was used to determine the correlation between the averaged extraversion score (E-score) and both personality tests. The E-score was used throughout the analysis.

Subsequently, the mean ± standard deviation of the EEG features and self-assessment survey items of two possible groups—more and less extraverted—were computed. The significant results of these two possible groups were measured using one-way analysis of variance (ANOVA). Additionally, ANOVA was used to identify the optimal EEG features and self-assessment survey items of the extraversion personality trait. These optimal features and items were selected based on the highest F -value of the ANOVA.

Finally, the main correlation of extraversion personality with the optimal EEG feature and self-assessment survey item were explored using the linear regression method. Two linear regression scatterplots were analysed to demonstrate the possible correlation. For all statistical analyses, the Statistical Package for the Social Sciences (SPSS) software platform was used, in which p -values smaller than 0.05 indicate statistically significant data. The data were represented in mean ± standard deviation, unless otherwise specified.

Results

In this section, we discuss the results of all tested data in this study. First, we discuss the results of the two personality tests, including the proposed E-score. Second, we discuss the results of the EEG features—EEG alpha coherence and EEG alpha power—in relation to the extraversion personality trait. Third, we discuss the results of the self-assessment survey related to the face-to-face interaction task. The statistical tests mentioned in the ‘Statistical analysis’ section were used to determine the significance of all data representing extraversion.

Personality tests

In this study, two personality tests—the EPI and BFI—were used to evaluate the level of extraversion in each participant. The EPI and BFI are self-report questionnaires where the EPI contained 57 “YES” or “NO” items and the BFI contained 44 5-point scale items (1 = disagree

strongly...5 = agree strongly). Of the 57 items in the EPI, 24 were used to assess the extraversion personality trait, while for BFI, 8 out of 44 items were used for the same. As stated in the 'Statistical analysis' section, the averaged E-score of each participant was computed by averaging the scores of their EPI and BFI after converting them to percentages. More extraverted participants scored more than 50%, while less extraverted participants scored less than 50%. We proposed to employ the E-score as there was consistency between the extraversion facet scales of the EPI and BFI [46]. Moreover, the Pearson correlation revealed that the EPI was significantly correlated with the BFI ($r = 0.896, p < 0.001$). The mean E-scores for the more and less extraverted participants were found to be 68.18 ± 8.80 and 35.22 ± 7.60 , respectively. For validation of the proposed E-score, the Pearson correlation showed that it was significantly correlated with both the EPI ($r = 0.982, p < 0.001$) and BFI ($r = 0.964, p < 0.001$). These results indicated that the E-score could be used to represent each participant's level of extraversion in the statistical analysis [47].

EEG features

Possible group differences of the extraversion personality trait—with respect to two EEG features (i.e. EEG alpha coherence and EEG alpha power) in the occipital region during the face-to-face interaction task and in the eyes-open condition—were analysed. The mean EEG alpha coherence in the occipital region in the eyes-open condition for both groups were similar (more extraverted = 0.66 ± 0.15 ; less extraverted = 0.65 ± 0.09), as illustrated in Fig 3A. For the mean EEG alpha power in the eyes-open condition, the less extraverted participants exhibited higher levels (7.80 ± 6.91) than the more extraverted participants (5.93 ± 5.51), as illustrated in Fig 3B. However, as can be seen in Table 1, the differences between the group means of both EEG features in the eyes-open condition were not statistically significant ($p > 0.05$). Thus, for these cases, null and alternative hypotheses cannot be rejected and accepted, respectively, for the EEG features in the eyes-open condition.

For the face-to-face interaction task, the mean EEG alpha coherence of the more extraverted participants (0.68 ± 0.08) was higher than that of the less extraverted participants (0.60 ± 0.08), as illustrated in Fig 3A. Additionally, the difference between the group means of EEG alpha coherence was statistically significant (see p -value in Table 1). Thus, null and

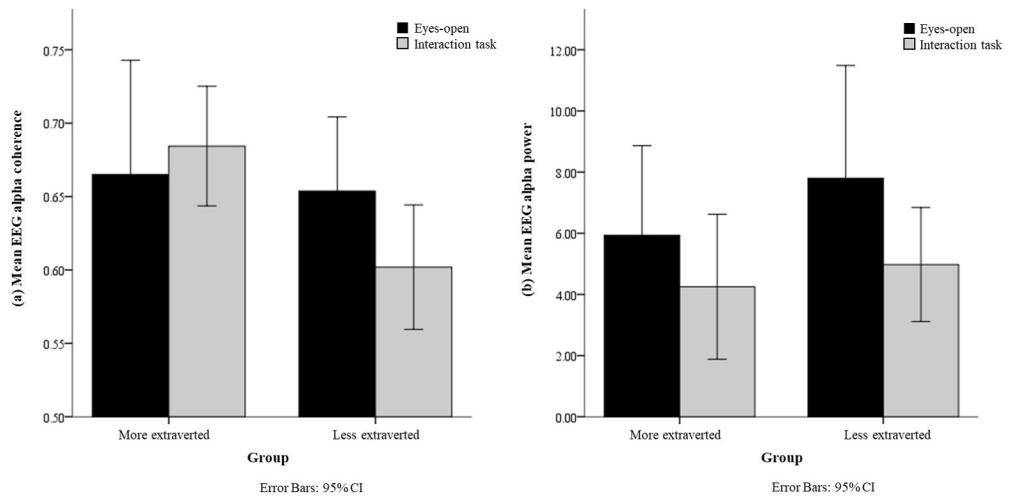


Fig 3. (a) Mean EEG alpha coherence and (b) mean EEG alpha power in the occipital region in the eyes-open condition and face-to-face interaction task.

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alternative hypotheses could be rejected and accepted, respectively, for EEG alpha coherence during the interaction task. For the mean EEG alpha power during the interaction task, the less extraverted participants exhibited higher EEG alpha power levels (4.98 ± 3.50) than the more extraverted participants (4.25 ± 4.45), as illustrated in Fig 3B. However, the difference between the group means of EEG alpha power during the interaction task was not statistically significant ($p > 0.05$; see Table 1).

Additionally, the differences between the EEG features during the interaction task and eyes-open condition were calculated. The results revealed that the mean EEG alpha coherence of the more extraverted participants was increased (0.10 ± 0.40) during the interaction task as compared to that of the eyes-open condition. In comparison, the mean EEG alpha coherence of the less extraverted participants (-0.07 ± 0.11) was decreased during the interaction task compared to the eyes-open condition. Although there was dissimilarity in the mean EEG alpha coherence between the more and less extraverted participants, there was no statistically significant difference between them: $F(1,30) = 2.678, p > 0.05$. The same lack of significance was found for differences between the mean EEG alpha power of the more (-0.09 ± 1.05) and less extraverted (-0.16 ± 0.56) participants: $F(1,30) = 0.052, p > 0.05$.

Additionally, ANOVA was then used to identify the optimal EEG features. Based on the results of the ANOVA for each of the EEG features (see Table 1), EEG alpha coherence during the interaction task demonstrated the highest F -value ($F = 8.934$). After obtaining the optimal EEG feature, a linear regression was employed to determine the influence of the extraversion personality trait on EEG alpha coherence during the interaction task. To evaluate the linearity, a scatterplot was made of EEG alpha coherence during the interaction task against the extraversion personality trait (E-score), and a superimposed regression line was plotted. As illustrated in Fig 4, the linear regression established that the extraversion personality trait could be used to predict the EEG alpha coherence during the interaction task with statistical significance: $F(1,30) = 9.946, p < 0.05$, with $R^2 = 0.249$; a large effect size according to Cohen [48]. The regression equation was: predicted EEG alpha coherence during the interaction task = $0.52 + 0.002x$ (E-score).

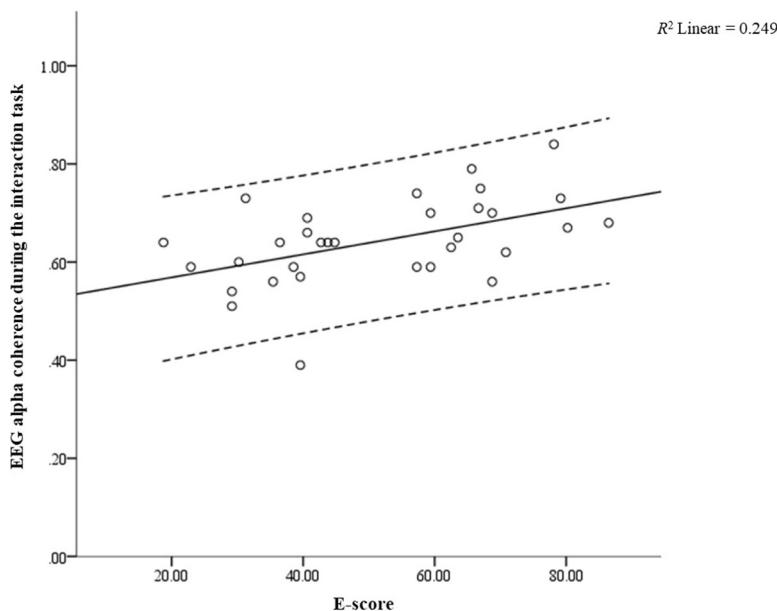


Fig 4. Linear regression relation between extraversion personality trait (E-score) and EEG alpha coherence during face-to-face interaction task, ($F(1,30) = 9.946, p = 0.004$).

<https://doi.org/10.1371/journal.pone.0219839.g004>

Self-assessment survey

As stated in the ‘Procedure’ section, after performing the face-to-face interaction task, each participant needed to fill in a self-assessment survey related to the task. All items in the self-assessment were rated on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This self-assessment had an acceptable internal consistency, as determined by a Cronbach’s alpha of 0.76 [49]. The results of the survey showed that the more extraverted participants reported that they felt more comfortable sitting in front of a stranger and sharing ideas, were more spontaneous in voicing those ideas, and had a greater preference for giving feedback verbally compared to the less extraverted participants (see Table 2). The difference between the group means for all items in the self-assessment survey were found to be statistically significant ($p < 0.05$), as presented in Table 1.

As mentioned in the ‘Statistical analysis’ section, ANOVA was used to identify the optimal self-assessment survey item by referring to the highest F -value of all items. Based on the ANOVA results in Table 1, item (a) demonstrated the highest F -value ($F = 20.589$). After obtaining the optimal self-assessment survey item, a linear regression was employed to determine the correlation between the extraversion personality trait and the comfortableness of the participants sitting in front of the strangers (item (a)). To evaluate the linearity, a scatterplot was made of item (a) against the extraversion personality trait (E-score), and a superimposed regression line was plotted. As illustrated in Fig 5, the linear regression established that the extraversion personality trait could be used to predict the item (a) with statistical significance: $F(1,30) = 42.044$, $p < 0.0001$, with $R^2 = 0.584$; a large effect size according to Cohen [48]. The regression equation was: predicted item (a) = $1.40 + 0.04x$ (E-score).

Discussion

The aim of this study was to investigate correlates between neural signals in a specific brain region and the extraversion personality trait. Specifically, the investigation focused on an EEG-based study of extraversion correlates with eye contact during a face-to-face interaction task with a stranger. We mainly focused on eye contact as it is a crucial signal during social interactions. We also analysed the consistency of the EEG features with a self-assessment survey of the interaction task. The findings of this study regarding the EEG features and self-assessment survey are believed to have provided a reliable outcome in the investigation of the extraversion personality trait during the face-to-face interaction task.

The present study found that the mean EEG alpha coherence (i.e. the connectivity between brain regions) during the face-to-face interaction task was the optimal EEG feature for extraversion. This result suggests that the mean EEG alpha coherence during the interaction task could expose extraversion differences better than EEG features in the eyes-open condition (baseline/resting state). Our findings support that the EEG resting state cannot be used to

Table 2. Descriptive statistics for self-assessment survey by more and less extraverted participants.

	More extraverted		Less extraverted	
	M	SD	M	SD
(a) I was comfortable sitting in front of strangers.	4	0.73	2.81	0.75
(b) I was comfortable sharing my answer or idea during the group discussion.	4.25	0.58	3.50	0.63
(c) I voiced my ideas or opinion spontaneously.	4.31	0.87	3.63	0.89
(d) I would prefer to give feedback verbally.	3.69	0.95	2.75	1.00

Note: M = mean; SD = standard deviation.

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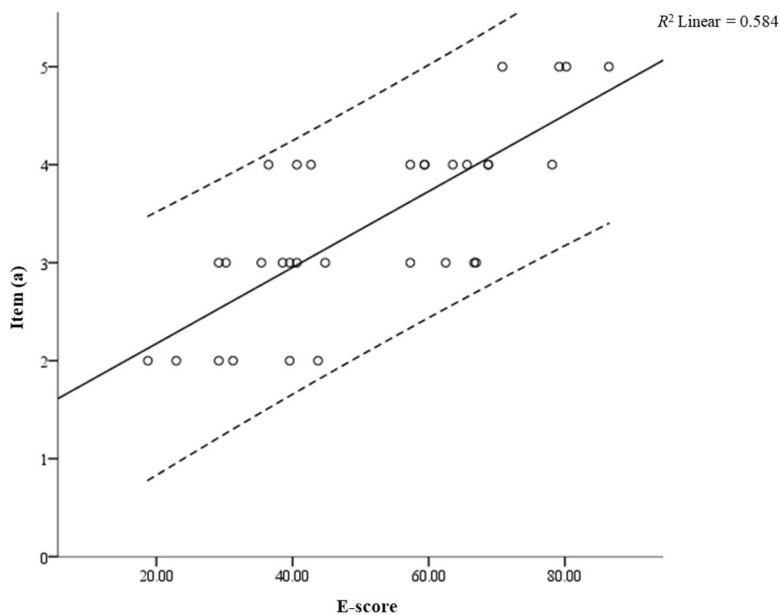


Fig 5. Linear regression relation between extraversion personality trait (E-score) and item (a): comfortableness while sitting in front of a stranger; ($F(1,30) = 42.044, p < 0.0001$).

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recognise the extraversion personality trait [50]. During the interaction task, the mean EEG alpha coherence in the occipital region of the more extraverted participants was significantly higher than that of the less extraverted participants. The EEG alpha coherence results indicate a stronger connectivity between the left (O1) and right (O2) occipital regions in the more extraverted participants during the interaction task. As the occipital region involves visual processing [51], we deduced that this high connectivity in the occipital region occurred in the more extraverted participants as a result of their consistent eye contact during the interaction task. This presumption is in line with studies that described the extraversion personality trait as being directly proportional to the attention or eye contact one commits to the eyes of another [18, 52]. In further support of this, a linear regression in this study demonstrated a significant positive correlation between the extraversion personality trait and mean EEG alpha coherence in the occipital region during the interaction task (see Fig 4). Therefore, we believe the more extraverted participants had more consistent eye contact with others than the less extraverted participants.

Moreover, the interpretation of the EEG alpha coherence is also supported by behavioural data. The linear regression demonstrated a significant positive correlation between the extraversion personality trait and the comfort of the participants sitting in front of a stranger (see Fig 5). This comfortableness is believed to enable the more extraverted participants to maintain better eye contact than the less extraverted participants [53, 54]. Due to this comfortableness, the mean EEG alpha coherence of more extraverted participants was increased during the interaction task. Besides an increased level of comfort, the more extraverted participants were also found to be more comfortable and spontaneous in sharing their ideas than the less extraverted participants. They also reported a preference for giving feedback verbally. All results from the self-assessment survey were predictable, as it is well known that more extraverted individuals are more outgoing and sociable, while less extraverted individuals are the opposite [1, 6, 55, 56]. These results provided further evidence that more extraverted individuals are easily adapted to response as compared to less extraverted individuals [57, 58].

Furthermore, the results support the notion that more extraverted individuals build up their characteristic of low arousal from response organisation, while less extraverted individuals' characteristic of high arousal means they tend to derive inhibition from response organisation and prefer stimulus analysis [58]. In this case, the interaction task was believed to cause the more extraverted participants to be more comfortable than the less extraverted participants.

Besides mean EEG alpha coherence, we also observed a decrease in mean EEG alpha power between the more extraverted and less extraverted participants during the interaction task compared to the baseline. As illustrated in Fig 3A, the decrease in EEG alpha power during the interaction task compared to the eyes-open condition was greater in the less extraverted participants than the more extraverted participants. Based on our review, there is inconsistency in the reasoning for this decrease in EEG alpha oscillations. Some studies claim that a decrease in EEG alpha power in the occipital region is due to the attention of an individual on the location of a visual target [51, 59]. Another study claims that the decrease is due to a wandering mind [60]. Similarly, we were unable to reach a solid conclusion regarding the relationship between the extraversion personality trait and EEG alpha power during the interaction task. This likely contributed to difficulty in achieving statistically significant results for EEG alpha power correlates of the extraversion personality trait during the face-to-face interaction. In comparison, the EEG alpha coherence provided more substantial evidence representing the extraversion personality trait. Presumably, this is because coherence is measured by considering the signals from two electrodes, while power was measured from a single electrode [44]. Additional research remains necessary to clarify the relationship between EEG alpha power in the occipital region and the extraversion personality trait during the interaction task.

There are certain limitations to this study which deserve further investigation. First, the sample was limited to right-handed male students aged 18–23 years old. Therefore, the assumptions in this study could not be used to generalise about female, non-students, left-handed or middle-aged adult groups. Second, this study was limited to two groups—i.e. more and less extraverted. As such, multiple comparisons could not be made. Third, this study employed a cross-sectional design. Longitudinal studies are required for further insight into neural mechanism correlates of the extraversion personality trait during the interaction task. For instance, less extraverted participants could repeat the experiment after a few months to determine whether their neural signals have changed. Such longitudinal neuroimaging studies are needed to objectively investigate personality changes throughout the lifespan to support subjective study which claimed personality could be changed—particularly in adolescence and old age [61]. Fourth, this study only mentioned the general relation between the extraversion personality trait and eye contact using EEG signals. Further analysis—mainly on the degree of eye contact and extraversion—should be added and thorough measurements should be conducted. Fifth, the self-assessment survey in this study was limited to only four items. We believe adding more items to the survey could assist us in justifying the EEG results. In general, this study was limited to only an EEG investigation and self-assessment survey of the interaction task. Other physiological measurements, such as functional near-infrared spectroscopy (fNIRS), electrocardiography (ECG) or electrodermal response, could assist us in gaining further insight into the extraversion personality trait during the face-to-face interaction task.

In conclusion, this study revealed that the extraversion personality trait was positively correlated with EEG alpha coherence in the occipital region representing neural correlates of eye contact during a face-to-face verbal interaction. The resulting EEG alpha coherence during the interaction task was found to be in agreement with the self-assessment survey collected in this study. This emphasises that an EEG-based investigation related to social interaction can reveal the extraversion personality trait, thus providing an alternative to EEG resting state investigations. Contradictory to those of the EEG alpha coherence, the EEG alpha power findings in

this study showed that further investigation is required to clarify inconsistencies in the literature. Overall, the results obtained in this study have laid the foundation upon which to develop our understanding of neural mechanism correlates of the extraversion personality trait in face-to-face interactions or social activities.

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Correlation Among Behavior, Personality, and Electroencephalography Revealed by a Simulated Driving Experiment

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Drivers play the most important role in the human-vehicle-environment system and driving behaviors are significantly influenced by the cognitive state of the driver and his/her personality. In this paper, we aimed to explore the correlation among driving behaviors, personality and electroencephalography (EEG) using a simulated driving experiment. A total of 36 healthy subjects participated in the study. The 64-channel EEG data and the driving data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed were acquired simultaneously during driving. The Cattell 16 Personality Factor Questionnaire (16PF) was utilized to evaluate the personalities of subjects. Through hierarchical clustering of the 16PF personality traits, the subjects were divided into four groups, i.e., the Inapprehension group, Insensitivity group, Apprehension group and the Unreasoning group, named after their representative personality trait. Their driving performance and turning behaviors were compared and EEG preprocessing, source reconstruction and the comparisons among the four groups were performed using Statistical Parameter Mapping (SPM). The turning process of the subjects can be formulated into two steps, rotating the steering wheel toward the turning direction and entering the turn, and then rotating the steering wheel back and leaving the turn. The bilateral frontal gyrus was found to be activated when turning left and right, which might be associated with its function in attention, decision-making and executive control functions in visual-spatial and visual-motor processes. The Unreasoning group had the worst driving performance with highest rates of car collision and the most intensive driving action, which was related to a higher load of visual spatial attention and decision making, when the occipital and superior frontal areas played a very important role. Apprehension (O) and Tension (Q4) had a positive correlation, and Reasoning (B) had a negative correlation with dangerous driving behaviors. Our results demonstrated the close correlation among driving behaviors, personality and EEG and may be taken as a reference for the prediction and precaution of dangerous driving behaviors in people with specific personality traits.

Keywords: personality, electroencephalography, driving behavior, source reconstruction, clustering analysis, simulated driving

INTRODUCTION

With the increasing number of motor vehicles, the incidence of related traffic accidents is also increasing. The World Health Organization (WHO) released the Global status report on road safety in 2018 and indicated that 1.35 million people worldwide died from road traffic accidents and 50 million people were injured every year (WHO, 2018). The report of the National Bureau of Statistics of China (NBSC), indicated that in 2017, 0.203 million traffic accidents occurred in roads and 0.0638 million traffic accidents caused casualties (National Bureau of Statistics of China, 2018). Traffic accidents have become a global problem resulting in deaths, physical injuries, psychological problems and financial losses. Traffic safety research is of critical importance for individuals, families and society.

As the sensory and controlling center, humans play the most important role in the human-vehicle-environment system, and with the development of advanced driver assistance systems, humans have become the primary factor in traffic accidents (Petridou and Moustaki, 2000), accounting for 45–75% (Wierwille et al., 2002), or even up to 95% (Rumar, 1990) of road accidents. Many dangerous driving behaviors, such as drunk driving (Krüger, 2013), motor vehicle retrograde (Zhao et al., 2009), speeding (Chung and Wong, 2010), fatigue driving (Zhang et al., 2016), and distracted driving (Lansdown et al., 2015) can directly lead to accidents. Many efforts are being made to eliminate human factor related accidents worldwide such as the “Human Factors in Connected Vehicles” initiative of the National Highway Traffic Safety Administration (Lerner et al., 2014) and the “Adaptive Integrated Driver-vehicle Interface” initiative in Europe (Amditis et al., 2005).

Driving is a complex and multifaceted behavioral process, which is affected by psychological, physiological and physical factors. Ample evidence has demonstrated the influence of the cognitive state of a driver (Renner and Anderle, 2000; Lajunen, 2001) and his/her personality, on driving behavior. The relationship between personality and driving is usually explored using a questionnaire investigation. According to Eysenck's Personality Questionnaire (EPQ, classifying personality as extraversion, neuroticism, psychotism) (Eysenck and Eysenck, 1965) investigation, an extroverted personality was positively correlated with traffic accidents (Lajunen, 2001), driving error (Ben-Ari et al., 2016) and illegal behavior (Guo et al., 2016). Neuroticism was associated with aggressive, offensive driving (Jovanović et al., 2011), and was more likely to induce driving fatigue (Šeibokaitė et al., 2014) and risky driving behaviors (Booth-Kewley and Vickers, 1994). Psychotism was found to significantly correlate with driving skills (Alavi et al., 2017), but not significantly with driving accidents (Renner and Anderle, 2000). According to the five factor model (FFM, classifying the personality as Neuroticism, Extraversion, Openness, Agreeableness and Conscientiousness) (Digman, 1990) investigation, neuroticism and extraversion were positively correlated with risky driving (Mallia et al., 2015) and aggressive driving (Dahlen and White, 2006), the personality traits of conscientiousness and agreeableness were negatively correlated with risky driving (Cellar et al., 2000). Openness was reported

to be the best predictors of aggressive driving (Mallia et al., 2015). Many researchers utilized the 16 Personality Factor Questionnaire (16PF) (Zhang et al., 2009; Manglam et al., 2013) to explore the relationship between drivers' personality traits and driving. The 16PF is a comprehensive measurement of normal adult personality in terms of the 16 personality dimensions, classifying personality as Warmth (A), Reasoning (B), Emotional Stability (C), Dominance (E), Liveliness (F), Rule-Consciousness (G), Social Boldness (H), Sensitivity (I), Vigilance (L), Abstractedness (M), Privateness (N), Apprehension (O), Openness to Change (Q1), Self-Reliance (Q2), Perfectionism (Q3), and Tension (Q4). There were significant differences in personality traits between drivers with no accident history and accident-prone drivers or chronic violators. Sensitivity (I), Tension (Q4), and Perfectionism (Q3) were related to safe driving, and Openness to Change (Q1) and Abstractedness (M) were related to dangerous driving behavior (Suhr, 1953; Brown, 1976; Hilakivi et al., 1989; Manglam et al., 2013). Drivers with higher scores in Emotional Stability (C), Liveliness (F), Warmth (A), Social-boldness (H) and Dominance (E) and lower scores in Vigilance (L), Apprehension (O), and Self-Reliance (Q2), had a higher accident incidence (Zhang et al., 2009).

Besides personality, the cognitive state greatly and directly affects driving behavior. Many researches indicated the influence of the cognitive state on driving such as the attentional state (alertness, distraction, fatigue) and the emotional state (depression, anxiety, compulsion). Fatigue driving would impair the drivers' physical characteristics, such as heart rate, time deviation of speed anticipation, systolic blood pressure, time for dark adaption, eyesight, dynamic visual acuity, reaction time to sound and reaction time to light (Zhang et al., 2014). Anxiety would ingest the cognitive resources of drivers (Eysenck and Byrne, 1992) and cause an augmented reporting of dangerous driving behaviors (Dula et al., 2010). Depression may also affect driving skills and behaviors (Nnjam et al., 2017) and its severity was positively correlated with a standard deviation of the lateral position (Wingen et al., 2006). Traditionally, the cognitive state was measured by questionnaires such as the Fatigue Assessment Scale (Michielsen et al., 2003), the Hamilton Anxiety Scale (Maier et al., 1988) and the Hamilton Depression Rating Scale (Williams, 1988). Recently, with the development of the physiological and psychological perception techniques, the cognitive state of subjects can be measured in a more objective and quantitative manner. Among these techniques, electroencephalography (EEG) is a reliable and significant method of measuring neurophysiological activity in the human brain and the psychological state of drivers when driving. Using advanced data mining techniques, the EEG signal can be utilized to identify a driver's alertness (Chuang et al., 2015), to predict the distraction (Wang et al., 2015), to study a driver's perception of signal lights (Wang et al., 2008), to monitor a driver's driving states (Peng and Wu, 2009), and to predict a driver's intention to emergency brake (Kim et al., 2014).

Currently, the potential correlation of cognitive function and personality and its effect on driving behavior is complicated and remains unclear. In this paper, we tried to explore the correlation between driving behavior, personality and EEG

using a simulated driving task and the corresponding data analysis. Thirty-six healthy subjects participated in the study. The 64-channel EEG data and the driving data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed were acquired simultaneously during driving. The Cattell 16 Personality Factor Questionnaire (16PF) was utilized to evaluate the personalities of subjects. Through hierarchical clustering of the 16PF personality traits, subjects were divided into four groups. The EEG difference and driving behaviors between the four groups were compared. The results indicated a correlation between driving behavior, personality traits and EEG, which might be helpful to improve the integrated human-vehicle-environment model as well as traffic safety.

MATERIALS AND METHODS

Method Overview

The processing schema is shown in **Figure 1**. The following steps were included: (i) clustering analysis, to classify subjects into different groups according to their personality traits; (ii) preprocessing of EEG data and driving data; (iii) driving data analysis; (iv) EEG source reconstruction; (v) the second level group analysis, to explore the correlation between driving behavior, personality and EEG.

Subjects and Experiment Design

Thirty-six healthy subjects (21–46 years old, mean age 27.0 ± 7.8 years, driving years: 5.2 ± 8.4 years, 27 males and nine females) were recruited. All subjects have a driving license and have real driving experience, driving in their daily life. Subjects reported no neurological or psychiatric problems and were all right-handed. Written informed consent was provided by all subjects and the data were anonymized. The study was approved by the ethical review committee of the Wuhan University of Technology.

Subjects were instructed to sit comfortably wearing EEG caps and to drive on a driving simulator platform (**Figure 2**). The platform consisted of a driving simulator (G29, Logitech, Switzerland) and a screen. The Logitech playseat consisted of a highly simulated steering wheel, a full-size driving seat, gears, accelerator and brakes. Unity 3D software (Unity Technologies, America) was employed to design the simulated driving scenario, which consisted of a 7 km circular runway with three left and four right turns. The subjects were instructed to keep their attention on driving and completed two to four driving sessions with a speed limit of 70 km/h. Each session contained four rounds and was accomplished in approximately 7 min. After each session the subjects took a break for a few minutes to avoid driving fatigue. Each subject completed three sessions. The actions of the left and right turning were marked as events when the driver noticed the roadside direction board at the beginning of the curve and made the specific actions. We videotaped the subject's driving behavior simultaneously. Errors including driving out of the road and car collisions were recorded by the researchers.

Data Acquisition

The driving data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed, were acquired using C# scripts based on Unity 3D. Subjects' brain activities were collected at 1000 Hz using the actiCHamp Amplifier (Brain Products GmbH, Gilching, Germany) with 64 surface Ag/AgCl electrodes fixed on a recording cap, consistent with the international 10–20 system referenced to the Fz electrode during the driving experiment. All the subjects filled the 16PF questionnaire in after the driving experiment.

Clustering of 16PF Scores and Subject Grouping

In 16PF, all personality traits are evaluated using a score from 1 (low) to 10 (high), where 3 and below are considered low scores, while eight and above are considered high scores. The 36 subjects were divided into different groups according to their personality traits using the agglomerative hierarchical clustering algorithm (SPSS 22.0, IBM, United States). Hierarchical clustering seeks to form a hierarchy of clusters, either by a “bottom up” agglomerative approach (the clusters would merge if their Euclidean distances were small) or by a “top down” divisive approach (a cluster would split if its scope was too large) (Rokach and Maimon, 2005). First, the 16 personality traits were divided into several categories using Euclidean distances and Ward's method. Then the most representative personality traits were picked out, based on which the subjects were hierarchically clustered into different groups. We utilized the least-significant difference method (Atkinson, 2002) for multiple comparisons between groups to explore the relationship of the selected personality traits and aberrant driving behaviors between groups.

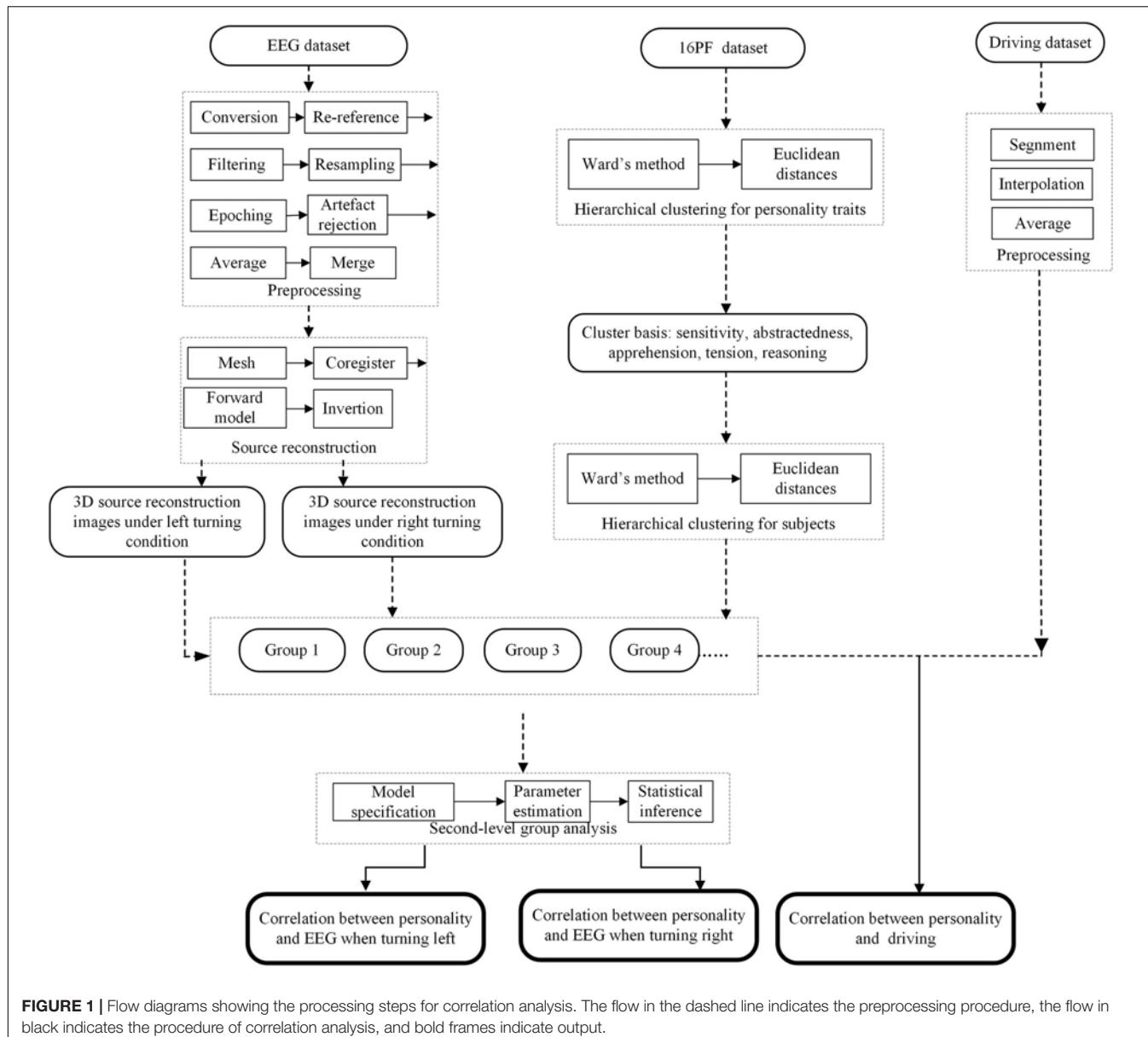
Analysis of the Driving Data

The steering wheel angle data with a peri-stimulus window of 0–10 s for all left and right turns of all the subjects were extracted. The relative increment of the steering wheel angle to the first angle at time 0 were calculated and the mean curves of each group of subjects under left and right turning conditions were then obtained. The least square estimate was performed to estimate the slope of two segments of the curves as an angular velocity for each group. Their characteristics were analyzed.

Analysis of EEG Data

The EEG signals were preprocessed with MATLAB (R2018a, MathWorks, American) and SPM12.¹ The preprocessed process included conversion, montage, filter, downsample, epoch, merge, removing artifacts and averaging. First, the raw EEG data were converted to the format available for Statistical Parameter Mapping (SPM). Then all channels of the data were re-referenced by subtracting from the reference channel (Fz). Next, the EEG signals were band-pass filtered in the range of 0.1–30 Hz, to selectively eliminate noise and down sampled to 200 Hz to reduce the sample size. Then, the EEG epochs with a peri-stimulus window of –100 to 1000 ms were extracted. Time 0 denoted the

¹<http://www.fil.ion.ucl.ac.uk/spm>



moment the subjects began to turn, which was determined by the time that the vehicle passed by the direction board. The artifacts were removed with the threshold for eye movements or muscular activity exceeding $100 \mu\text{V}$. The threshold was set at 0.2 for the bad channel, which would be excluded in the processing which followed. Robust averaging was performed to produce an event related potential (ERP) under two driving conditions (turning left and turning right), respectively.

The ERPs were utilized for source reconstruction, which was conducted to project 2D sensor data into a 3D brain space, to locate the exact anatomical structures of the brain activity (Litvak et al., 2011). Source space modeling, data co-registration, forward computation using the Boundary Element Method (BEM) (Jatoi et al., 2015), and inverse reconstruction using the Multiple Sparse Priors (MSP) algorithm, were performed. The time window of

inversion was set as -100 to 1000 ms, which was based on an empirical Bayesian approach. Finally, 3D images containing root mean square (RMS, unsigned) source estimates corresponding to two driving conditions (turning left and turning right) for each subject were obtained and then compared between the different groups using one-way analysis of variance (ANOVA, $P < 0.05$, family wise error (FWE) correction, extent threshold $k > 70$). Age, driving years and gender were utilized as the covariates.

RESULTS

Personality Traits and Clustering Results

Sixteen personality traits of all the subjects were all within the normal range and they were divided into three clusters



FIGURE 2 | Simulated driving platform. The subject has provided written consent for the publication of this image.

(Figure 3A), which were (i) Rule-Consciousness, Perfectionism, Emotional Stability, Social Boldness and Liveliness; (ii) Dominance, Privateness, Vigilance, Openness to Change, Self-Reliance and Warmth; (iii) Sensitivity, Abstractedness, Apprehension, Tension and Reasoning. The Euclidean distance between cluster (ii) and (iii) was the smallest, therefore, the personality traits in

these two clusters were utilized to conduct the second hierarchical clustering of the subjects. The subjects were divided into four groups according to the five personality traits in cluster (iii) (Figure 3B). Four groups had extremely significant differences in personality of Reasoning ($F = 18.852, P < 0.0005$), Apprehension ($F = 21.856, P < 0.0005$), and Sensitivity ($F = 7.092, P < 0.001$). Four groups had significant differences in personality of Emotional Stability ($F = 4.203, P = 0.013$), Dominance ($F = 2.934, P = 0.048$), Abstractedness ($F = 3.554, P = 0.025$), Perfectionism ($F = 6.144, P = 0.002$), and Tension ($F = 3.424, P = 0.029$, Table 1). The subjects were also divided into four groups according to the six personality traits in cluster (ii), but the ANOVA analysis revealed no significant difference between these groups. Accordingly, the subjects were grouped based on personality traits in cluster (iii). The pairwise comparison was conducted for these five personality traits between the four groups (LSD-*t* test, $P < 0.05$, Table 2). The group with significantly lower scores in Apprehension (O), Sensitivity (I), or Reasoning (B) than the other three groups was named as the Inapprehension group, Insensitivity group and Unreasoning group, respectively. The group with the highest scores in Apprehension (O) and who also had a significant difference to the Inapprehension group and Insensitivity group was named as the Apprehension group. As for the driving performance, the number of car collisions were significantly different between the four groups (ANOVA, $P < 0.05$) and the pairwise comparison indicated that the Unreasoning group had significantly more car collisions than the other three groups (LSD-*t* test, $P < 0.05$). The number of times driving out of the road between four groups were not significantly different, but the Unreasoning group drove out of the road

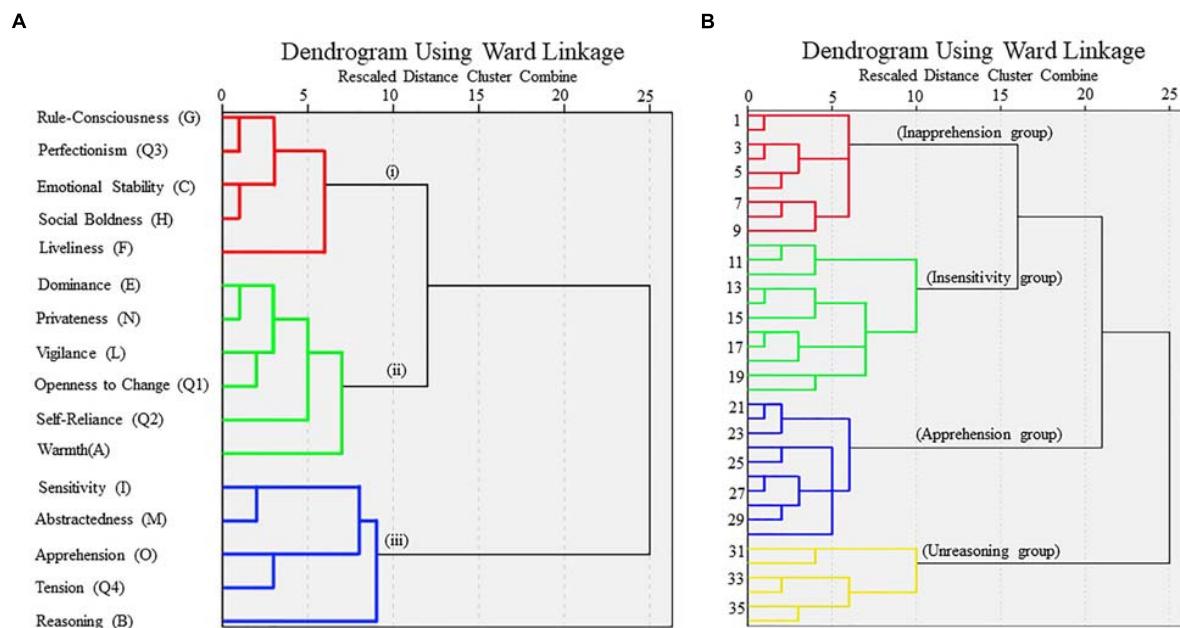


FIGURE 3 | Dendrograms from Hierarchical Clustering (Ward's method, Euclidean distance, SPSS 22.0). **(A)** Dendrogram from Hierarchical Clustering of Cattell 16 personality factors. **(B)** Dendrograms from Hierarchical Clustering of the subjects based on five personality traits [Sensitivity (I), Abstractedness (M), Apprehension (O), Tension (Q4), Reasoning (B)]. 36 subjects were clustered into four groups, from top to bottom, Inapprehension group, Insensitivity group, Apprehension group, and Unreasoning group.

TABLE 1 | The normalized 16PF personality traits and aberrant driving behaviors of the four groups of subjects ($\bar{x} \pm s$).

Feature	Total (n = 36)	Inapprehension group (n = 9)	Insensitivity group (n = 11)	Apprehension group (n = 10)	Unreasoning group (n = 6)	F	P
Warmth (A)	4.72 ± 1.86	5.67 ± 3.73	3.73 ± 1.49	4.70 ± 1.83	5.17 ± 2.14	2.121	0.117
Reasoning (B)	6.17 ± 2.20	7.67 ± 5.82	5.82 ± 1.66	7.30 ± 0.67	2.67 ± 1.86	18.852**	< 0.0005
Emotional Stability (C)	5.19 ± 1.58	5.11 ± 6.36	6.36 ± 1.43	4.30 ± 1.64	4.67 ± 1.37	4.203*	0.013
Dominance (E)	4.36 ± 1.38	4.56 ± 4.64	4.64 ± 0.92	3.40 ± 0.84	5.17 ± 1.47	2.934*	0.048
Liveliness (F)	5.78 ± 1.49	6.22 ± 5.73	5.73 ± 1.68	5.20 ± 1.62	6.17 ± 0.98	0.894	0.455
Rule-Consciousness (G)	5.19 ± 1.58	5.89 ± 5.64	5.64 ± 1.63	4.40 ± 1.51	4.67 ± 1.03	2.110	0.119
Social Boldness (H)	5.00 ± 1.33	5.44 ± 5.45	5.45 ± 1.21	4.30 ± 1.16	4.67 ± 1.63	1.958	0.140
Sensitivity (I)	6.44 ± 1.27	7.22 ± 5.27	5.27 ± 1.27	6.80 ± 1.03	6.83 ± 0.75	7.092**	< 0.001
Vigilance (L)	4.17 ± 1.18	3.89 ± 3.91	3.91 ± 1.38	4.40 ± 1.17	4.67 ± 0.52	0.813	0.496
Abstractedness (M)	7.08 ± 1.44	7.67 ± 6.18	6.18 ± 1.33	7.80 ± 1.32	6.67 ± 1.63	3.554*	0.025
Privateness (N)	4.42 ± 1.36	4.67 ± 3.91	3.91 ± 1.51	4.50 ± 1.27	4.83 ± 0.98	0.798	0.504
Apprehension (O)	6.64 ± 1.69	4.78 ± 6.09	6.09 ± 0.94	8.20 ± 0.92	7.83 ± 1.17	21.856**	< 0.0005
Openness to Change (Q1)	4.78 ± 1.24	5.11 ± 4.64	4.64 ± 1.29	4.50 ± 0.97	5.00 ± 1.79	0.470	0.705
Self-Reliance (Q2)	4.97 ± 1.59	5.44 ± 4.64	4.64 ± 1.36	5.40 ± 2.01	4.17 ± 1.47	1.196	0.327
Perfectionism (Q3)	5.86 ± 1.36	6.89 ± 6.27	6.27 ± 1.1	4.90 ± 0.74	5.17 ± 1.33	6.144**	0.002
Tension (Q4)	5.89 ± 1.62	5.33 ± 5.09	5.09 ± 1.58	6.60 ± 1.26	7.00 ± 2.10	3.424*	0.029
Times of driving out of the road	5.17 ± 6.55	3.33 ± 3.74	4.64 ± 3.78	3.10 ± 3.07	8.17 ± 5.78	2.374	0.089
Times of car collision	5.86 ± 4.48	4.11 ± 2.37	5.09 ± 4.74	5.50 ± 5.28	10.33 ± 2.16	3.049*	0.043
Driving Time (s)	416.24 ± 53.47	420.13 ± 51.96	430.18 ± 46.38	405.08 ± 43.60	403.40 ± 84.11	0.503	0.683

*P < 0.05, **P < 0.01.

TABLE 2 | Multiple Comparisons of five personality traits and aberrant driving behaviors between groups.

Feature	Group	Insensitivity	Apprehension	Unreasoning
		group	group	group
Reasoning (B)	Inapprehension group	0.006**	0.568	0.000**
	Insensitivity group	–	0.020*	0.000**
	Apprehension group	–	–	0.000**
Sensitivity (I)	Inapprehension group	0.000**	0.380	0.480
	Insensitivity group	–	0.002**	0.006**
	Apprehension group	–	–	0.951
Abstractedness (M)	Inapprehension group	0.017*	0.826	0.156
	Insensitivity group	–	0.008**	0.470
	Apprehension group	–	–	0.103
Apprehension (O)	Inapprehension group	0.007**	0.000**	0.000**
	Insensitivity group	–	0.000**	0.002**
	Apprehension group	–	–	0.489
Tension (Q4)	Inapprehension group	0.716	0.070	0.039*
	Insensitivity group	–	0.025*	0.016*
	Apprehension group	–	–	0.602
Times of driving out of the road	Inapprehension group	0.471	0.899	0.028*
	Insensitivity group	–	0.383	0.090
	Apprehension group	–	–	0.019*
Times of car collision	Inapprehension group	0.601	0.469	0.007**
	Insensitivity group	–	0.822	0.017*
	Apprehension group	–	–	0.030*

LSD-t test. *P < 0.05, **P < 0.01.

significantly more times than the Inapprehension and Apprehension group ($LSD-t$ test, $P < 0.05$). The other comparisons revealed no significance. There was no significant difference in driving time between the four groups.

Driving Features

The steering angles of four groups are shown in **Figure 4** and the detailed data are listed in **Table 3**. There seemed to be two obvious peaks in each curve and the least square estimate was performed to estimate the slope of two segments of the curves, which represented the mean angular velocities. The turning process can be formulated in two steps, i.e., (i) rotating the steering wheel toward the turning direction, modulating the head direction and entering the turn and then (ii) rotating the steering wheel back and leaving the turn.

In the first step, under a left turning condition, the absolute angular velocity was Unreasoning group > Apprehension group > Inapprehension group > Insensitivity group; the absolute angular velocity was Unreasoning group > Inapprehension group > Apprehension group > Insensitivity group. In the second step, under the left turning condition, the absolute rotation angle was Unreasoning group > Apprehension group > Inapprehension group > Insensitivity group; the absolute angular velocity was Unreasoning group > Apprehension group > Insensitivity group > Inapprehension group.

In the first step, under the right turning condition, the absolute angular velocity was Unreasoning group > Apprehension group > Inapprehension group > Insensitivity group; the absolute angular velocity was Unreasoning group > Insensitivity group > Inapprehension group > Apprehension group. In the second step, under the right turning condition, the absolute rotation angle was Insensitivity group > Apprehension group > Unreasoning group > Inapprehension group; the absolute angular velocity was Unreasoning group > Inapprehension group > Apprehension group > Insensitivity group. Under the left turning condition, the two times needed to finish the two steps of turning were Inapprehension group > Apprehension group > Insensitivity group > Unreasoning group; under the right turning condition, the two times needed to finish the two steps of turning were Apprehension group > Inapprehension group > Unreasoning group > Insensitivity group.

EEG Features

EEG Source Reconstruction Results of All Subjects

Electroencephalography source reconstruction results of all the subjects under the two driving conditions are shown in **Figure 5** and the details are listed in **Table 4**. Under the left turning condition, the bilateral temporal gyrus, frontal gyrus and the occipital gyrus were activated. Under the right turning condition, the bilateral temporal gyrus and frontal gyrus were activated. No different activation was found between the two conditions.

EEG Source Reconstruction Results of Four Groups

The EEG source reconstruction results of the four groups are shown in **Figure 6** and the details are listed in **Table 5**. When turning left, in the Inapprehension group, the left inferior occipital gyrus, and right middle temporal gyrus,

inferior temporal gyrus, precuneus, middle frontal gyrus and the precentral gyrus were activated; in the Insensitivity group, the left middle occipital gyrus, middle frontal gyrus, inferior frontal gyrus, calcarine and right middle frontal gyrus and the inferior frontal gyrus were activated; in the Apprehension group, the left superior parietal gyrus, middle temporal gyrus, middle frontal gyrus, and right superior frontal gyrus, supramarginal gyrus and the middle temporal gyrus were activated; in the Unreasoning group, the left postcentral gyrus, superior temporal gyrus, middle temporal gyrus, rolandic operculum, and right precentral gyrus, inferior occipital gyrus, calcarine, middle frontal gyrus and the postcentral gyrus were activated.

When turning right, in the Inapprehension group, the left and right superior frontal gyrus were activated; in the Insensitivity group, the left middle and inferior temporal gyrus, superior frontal gyrus, supplementary motor area, and right middle, inferior and superior frontal gyrus were activated; in the Apprehension group, the left and right inferior, middle and superior frontal gyrus, and the left middle temporal gyrus were activated; in the Unreasoning group, the left postcentral gyrus, paracentral gyrus, precentral gyrus, and right superior frontal gyrus, supplementary motor area, paracentral gyrus, and the precentral gyrus were activated.

Intra- and Inter-Group Comparison of EEG Source Reconstruction Results

An Intra-group comparison of the EEG source reconstruction indicated that there was a right turning > left turning activation difference in the left precentral gyrus (peak voxel at $[-36 -8 50]$, $t = 5.14$, 479 voxels) in the Unreasoning group. There was no other intra-group activation difference between the two conditions.

Results of the inter-group comparison are shown in **Figure 7** and the details are listed in **Table 6**. Under the left turning condition, the Inapprehension group had stronger activity in the left inferior occipital gyrus compared to the Apprehension group. The Unreasoning group had stronger activity in the left superior temporal gyrus compared to the Insensitivity group, and in the right occipital pole and left central operculum compared to the Apprehension group.

Under the right turning condition, the Unreasoning group had stronger activity in the left postcentral gyrus, precentral gyrus, paracentral lobule, and right precentral gyrus, superior frontal gyrus, and the supplementary motor area compared to the Insensitivity group, and in the left postcentral gyrus, precentral gyrus, paracentral lobule, and right superior frontal gyrus, precentral gyrus and the paracentral lobule compared to the Apprehension group, and in the left postcentral and postcentral gyrus compared to the Inapprehension group, the Apprehension group had stronger activity in the left superior temporal gyrus compared to the Insensitivity group.

DISCUSSION

In this study, 36 healthy subjects participated in a simulated driving experiment. The 64-channel EEG data and the driving

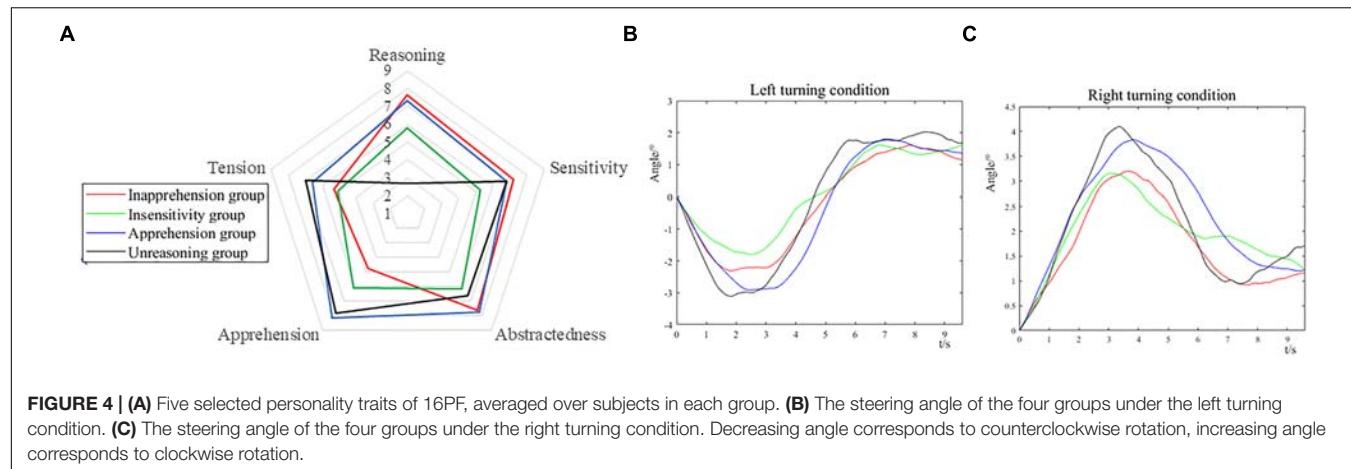


TABLE 3 | Driving feature of the four groups under the left turning and right turning conditions.

Task	Group	First step			Second step			Total time (s)
		Rotation angle (°)	Angular velocity (°/s)	Time (s)	Rotation angle (°)	Angular velocity (°/s)	Time (s)	
Turning left	Inapprehension group	-2.2994	-1.3501	1.8653	1.6087	0.8264	5.9474	7.8127
	Insensitivity group	-1.7948	-0.7109	2.4376	1.6079	0.8331	4.3304	6.7680
	Apprehension group	-2.9016	-1.2506	2.3969	1.7668	1.3112	4.5966	6.9935
	Unreasoning group	-3.1045	-1.8599	1.8039	1.7705	1.4134	3.9998	5.8037
Turning right	Inapprehension group	3.1981	0.9666	3.645	0.9218	-0.6762	4.0448	7.6898
	Insensitivity group	3.1531	1.1263	3.0507	1.8565	-0.4698	3.2049	6.2556
	Apprehension group	3.8346	1.0625	3.8502	1.2045	-0.5894	5.5171	9.3673
	Unreasoning group	4.0992	1.3732	3.3372	0.9489	-0.9293	4.0661	7.4033

data, including the real-time position of the vehicle, the rotation angle of the steering wheel and the speed were acquired simultaneously during driving. Through hierarchical clustering of the 16PF personality traits, the subjects were divided into four groups, i.e., the Inapprehension group, Insensitivity group, Apprehension group and the Unreasoning group, named after their representative personality trait. The driving data, the occurrence of aberrant driving behaviors and EEG source reconstruction results were compared between the four groups. The Unreasoning group had the highest occurrence of car

collisions and the highest angular velocity during turning. For the subjects as a whole, the bilateral frontal and temporal gyrus were activated under the left turning and right turning conditions and no difference was detected between the two conditions. An intra-group comparison of the EEG source reconstruction indicated right turning > left turning activation in the left precentral gyrus in the Unreasoning group. An inter-group comparison indicated stronger activation of the temporal gyrus under the left turning condition and motor areas under the right turning condition in the Unreasoning group. Several other areas were also detected in the inter-group comparison, such as the inferior occipital gyrus (Inapprehension group > Apprehension group) and the superior temporal gyrus (Apprehension group > Insensitivity group).

Correlation Between Personality and Driving

As shown in Tables 1–3, the number of car collisions were significantly different between four groups and were the highest in the Unreasoning group. The number of times driving out of the road were not significantly different between the four groups but were also the highest in the Unreasoning group. As for the performance in turning (Figure 4 and Table 3), the whole turn could be formulated into two steps, i.e., rotating the steering wheel toward the turning direction, modulating the head direction and entering the turn, and then rotating the steering

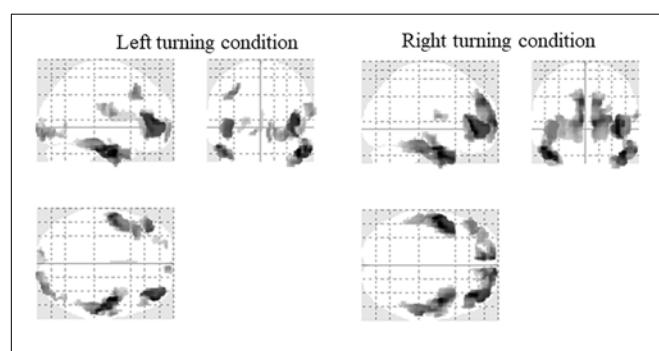


TABLE 4 | Activation of all the subjects under the left turning and right turning conditions.

Task	Anatomy	Peak location			t	Cluster size (Voxels)
		x	y	z		
Turning left	Inferior temporal gyrus	46	-6	-32	7.58	827
	Middle frontal gyrus	46	46	6	7.12	733
	Middle temporal gyrus	-54	-8	-26	6.90	508
	Inferior frontal gyrus, triangle part	-40	40	-2	6.43	220
	Inferior frontal gyrus, orbital part	-40	40	-4	6.39	156
	Inferior occipital gyrus	30	-94	-12	5.89	369
	Middle frontal gyrus	-36	22	40	5.85	169
	Rolandic operculum	62	-6	14	5.55	247
	Supramarginal gyrus	60	-18	24	5.26	95
Turning right	Middle temporal gyrus	-54	-8	-26	8.48	881
	Inferior frontal gyrus, triangle part	38	40	-4	8.20	708
	Inferior frontal gyrus, triangle part	40	34	8	7.79	399
	Superior frontal gyrus, medial part	-6	52	32	7.43	984
	Superior frontal gyrus, medial part	12	66	6	7.33	528
	Middle temporal gyrus	50	-4	-26	7.09	435
	Superior frontal gyrus	18	60	6	6.74	221
	Inferior frontal gyrus, orbital part	-46	38	-10	6.18	339
	Rolandic operculum	62	-6	14	5.77	81
	Frontal gyrus, orbital part	12	62	-8	5.52	86

SPM12, ANOVA, $P < 0.05$, FWE-corrected for the left turning and right turning, extent threshold $k > 70$. The location is in MNI coordinates.

wheel back and leaving the turn, which was in accordance with previous research (Xiong, 2010; Vesel, 2015). The Unreasoning group had the greatest absolute angular velocity in the two

turning steps under the two driving conditions and the greatest rotation angle of the steering wheel in most circumstances (except in the second step of right turning). The total time of left turning of the Unreasoning group was the shortest, and second shortest in right (longer than Insensitivity group). Generally speaking, the greater rotation angle and higher angular velocity in turning corresponded to the more intensive modulation of the steering wheel, and were closely related with accidents (Vesel, 2015). These results indicated the worst driving performance and the most intensive driving action for the Unreasoning group. In the other three groups, the Inapprehension group had the lowest, but not significantly different, number of times of driving out of the road and there seemed to be no obvious difference in the turning performance between them.

People with a high Reasoning (B) score are intelligent, good at abstract thinking, and can learn quickly and correctly (Hilakivi et al., 1989; Manglam et al., 2013), while those with a low Reasoning (B) score are less intelligent, unable to handle abstract problems, think slowly and are suitable for trivial works (Hilakivi et al., 1989; Manglam et al., 2013). People with a high Sensitivity (I) score are sensitive, aesthetic, careful, dependent and lack confidence, while those with a low Sensitivity (I) score are utilitarian, objective, unsentimental, tough minded, careless, independent, realistic, decisive and confident, mature and are able to face reality (Zhang et al., 2009; Shi et al., 2017). People with a high Abstractedness (M) score are abstract, imaginative, absent minded, impractical, absorbed in ideas, imaginative, inattentive to things and careless, while those with a low Abstractedness (M) score are grounded, practical, prosaic, solution oriented, steady, conventional and serious (Zhang et al., 2009; Shi et al., 2017). People with a high Apprehension (O) score are apprehensive, self-doubting, worried, guilt prone and insecure, while those with a low Apprehension (O) score are confident, pretentious, smug and easily adapt to the environment (Brown, 1976; Hilakivi et al., 1989). People with a high Tension (Q4) score are tensive, highly energetic, impatient, driven, frustrated, over wrought, nervous, frustrated and often in a passive situation, while those with a low Tension (Q4) score are relaxed, placid, tranquil, torpid,

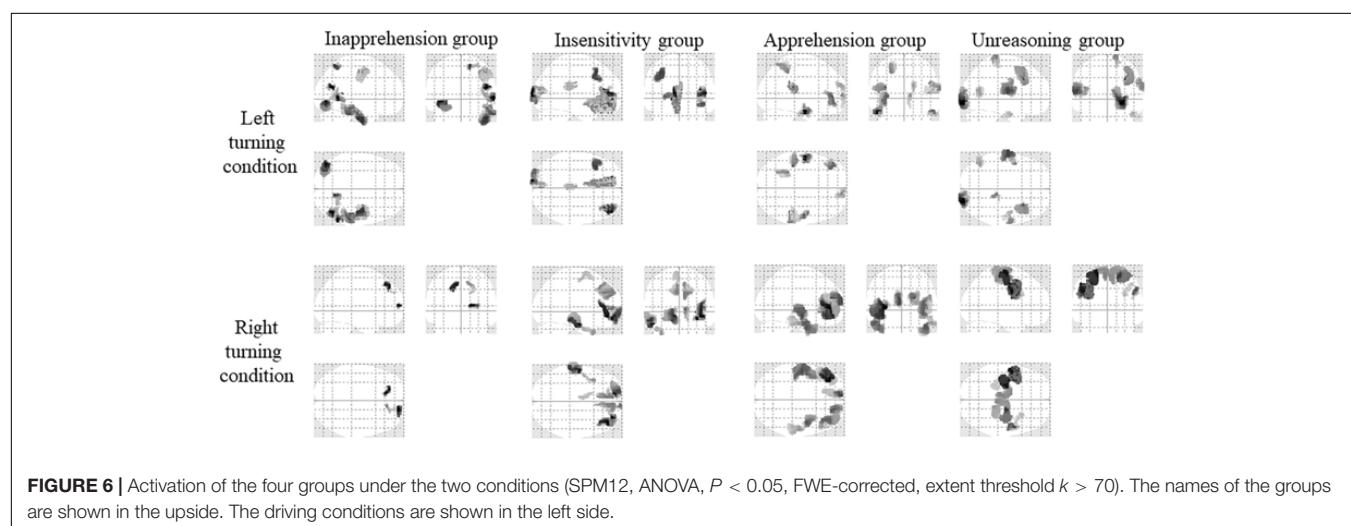


FIGURE 6 | Activation of the four groups under the two conditions (SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$). The names of the groups are shown in the upside. The driving conditions are shown in the left side.

TABLE 5 | Activation of the four groups under the left turning and right turning conditions.

Task	Group	Anatomy	Peak location			t	Cluster size (Voxels)
			x	y	z		
Turning left	Inapprehension group	Middle temporal gyrus	46	-68	20	6.46	468
		Inferior occipital gyrus	-42	-80	-6	6.33	572
		Inferior temporal gyrus	46	-16	-36	5.81	771
		Precuneus	14	-60	60	5.81	623
		Middle frontal gyrus	46	0	54	4.89	75
		Precentral gyrus	56	-2	46	4.67	134
	Insensitivity group	Middle occipital gyrus	-12	-102	8	5.70	639
		Middle frontal gyrus	46	48	6	5.47	383
		Middle frontal gyrus	-36	20	46	5.26	380
		Inferior frontal gyrus, orbital part	42	44	-12	5.16	305
		Calcarine	-8	-102	-2	5.03	314
		Middle frontal gyrus, orbital part	-2	54	-4	4.85	663
Turning right	Apprehension group	Middle temporal gyrus	-54	-10	-26	6.40	354
		Middle temporal	52	-14	-24	5.55	214
		Parietal operculum	-38	-32	18	5.52	323
		Middle frontal gyrus	-34	40	2	5.43	439
		Superior frontal gyrus, medial part	12	60	4	5.20	284
		Supramarginal gyrus	46	-40	26	5.15	489
	Unreasoning group	Superior parietal gyrus	-28	-44	48	5.15	435
		Inferior occipital gyrus	26	-98	-8	6.84	610
		Calcarine	18	-104	0	6.04	548
		Postcentral gyrus	-60	-12	14	6.01	466
		Superior temporal gyrus	-60	-12	12	6.00	477
		Middle frontal gyrus	32	18	36	5.90	885
Turning right	Inapprehension group	Postcentral gyrus	12	-32	76	5.45	366
		Rolandic operculum	-64	-4	8	5.27	70
		Middle temporal gyrus	-44	-62	8	5.08	322
		Precentral gyrus	48	-6	-28	4.71	71
		Superior frontal gyrus	18	60	10	5.15	137
		Superior frontal gyrus	-12	36	48	5.02	148
	Insensitivity group	Superior frontal gyrus	12	38	48	4.63	80
		Middle temporal gyrus	-52	-14	-24	6.00	192
		Middle frontal gyrus, orbital part	32	52	-14	5.93	445
		Superior frontal gyrus, orbital part	-12	56	-8	5.81	300
		Inferior frontal gyrus, triangle part	40	36	8	5.67	404
		Inferior temporal gyrus	-60	-30	-18	5.54	607
Turning right	Apprehension group	Superior frontal gyrus, medial part	-6	44	34	5.00	550
		Superior frontal gyrus, medial part	12	54	32	5.00	621
		Superior frontal gyrus	16	52	32	4.95	81
		Supplementary motor area	-4	-8	58	4.59	190
		Inferior frontal gyrus, triangle part	-34	40	4	8.07	649
		Middle frontal gyrus, orbital part	-38	44	-4	7.39	750
	Unreasoning group	Inferior frontal gyrus, triangle part	-40	32	10	7.35	927
		Superior frontal gyrus, medial part	-6	64	14	6.73	988
		Middle temporal	-46	-20	-4	6.49	333
		Middle frontal	44	40	6	6.41	700
		Inferior frontal gyrus, triangle part	40	34	10	6.38	569
		Middle frontal gyrus, orbital part	40	44	-6	6.36	461
		Superior frontal gyrus	16	52	22	6.05	142

(Continued)

TABLE 5 | Continued

Task	Group	Anatomy	Peak location			t	Cluster size (Voxels)
			x	y	z		
Unreasoning group		Postcentral gyrus	-54	-6	46	7.09	916
		Precentral gyrus	-50	-4	32	6.83	350
		Precentral gyrus	-24	-14	68	6.83	816
		Superior frontal gyrus	22	-12	62	6.30	561
		Precentral gyrus	52	0	36	6.14	716
		Paracentral lobule	-6	-24	60	5.41	242
		Paracentral lobule	4	-30	58	5.31	576
		Supplementary motor area	8	-12	68	5.19	75

SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$. The location is in MNI coordinates.

patient, insensitive and sometimes unresponsive (Manglam et al., 2013; Yan, 2016). Previous 16PF research indicated that Social Boldness (H), Perfectionism (Q3), Dominance (E), Emotional Stability (C), Warmth (A) and Liveliness (F) were protective factors related to safe driving (Zhang et al., 2009; Sun, 2013; Yan, 2016; Shi et al., 2017), while Tension (Q4), Openness to Change (Q1) Abstractedness (M), Vigilance (L), Apprehension (O), Self-reliance (Q2), and Sensitivity (I) were risk factors related to dangerous driving behaviors (Suhr, 1953; Zhang et al., 2009; Shi et al., 2017).

The Unreasoning group had higher Tension (Q4) and Apprehension (O) scores and lower Reasoning (B) scores (Table 2), and were tense, highly energetic, impatient, less intelligent and were unable to handle abstract problems (Manglam et al., 2013; Yan, 2016). According to our results, together with the driving performance of the four groups, we speculated the positive correlation of Apprehension (O) and Tension (Q4) with dangerous driving and a negative correlation of Reasoning (B) with dangerous driving.

Correlation Between EEG and Driving

We first analyzed the source reconstruction results of all the subjects. Under the left turning condition, the bilateral temporal gyrus, frontal and the occipital gyrus were activated. Under the right turning condition, the bilateral temporal gyrus and frontal gyrus were activated. No different activations were found between the two conditions. Then, the source reconstruction results of each group of subjects were analyzed and activation in the frontal gyrus was found in all groups. The temporal gyrus was detected in most groups and motor areas (precentral gyrus and postcentral gyrus) were strongly activated in the Unreasoning group. The occipital gyrus was activated in the Inapprehension group, Apprehension group and the Unreasoning group under the left turning condition. The activation of the Inapprehension group under right turning condition was restricted in the superior frontal gyrus.

To fulfill the turning behavior, the subjects needed to notice the turning sign, decide the turning direction and then to manipulate the steering wheel, which consisted of a series of visual-spatial and visual-motor processes. The brain regions

related with vision, attention and motion, including the pre-supplementary motor area, the superior parietal and lateral occipital cortices and the cerebellum would be activated (Spiers and Maguire, 2007; Calhoun and Pearson, 2012). The frontal gyrus was considered as an important area for visual attention (Corbetta and Shulman, 2002; Konen et al., 2004), decision-making (Volz et al., 2006; Glimcher et al., 2009), executive control (Christoff and Gabrieli, 2000; Koechlin and Summerfield, 2007; Posner et al., 2007), performance monitoring and adjustments (Ridderinkhof et al., 2004; Euston et al., 2012). The common activation of the bilateral frontal gyrus when turning left and right (Table 4 and Figures 5, 6) might be associated with these cognitive procedures. The occipital gyrus was activated in most groups only under the left turning condition. No significant difference was detected in the activations between the two turning conditions (FWE-corrected, $P < 0.05$, extent threshold $k > 70$). But if we applied a less conservative test ($P < 0.01$, uncorrected, extent threshold $k > 70$), left turning $>$ right turning activation could be detected in the superior frontal (peak voxel at $[-6 62 10]$, $t = 3.14$, 254 voxels; Supplementary Figure S1). As we described above, the frontal gyrus was involved in decision-making, executive control, performance monitoring and adjustments. The occipital gyrus played the important role in visual function (Lauritzen et al., 2009). Since motorists drive on the right-side in China, drivers are presumably accustomed to watching for traffic from both directions while turning left, which requires considerably stronger brain activity than with right turning (Schweizer et al., 2013; Oka et al., 2015). We speculated that the load of attention and visual information processing was more in left turning than right turning. It had been found that the superior temporal gyrus was an important structure in the pathway consisting of the prefrontal cortex and amygdala, which are all associated with social cognitive processes (Amanda et al., 2004; Callaghan et al., 2017). The stronger activation of the motor and sensorimotor areas in the Unreasoning group may relate with their more intensive movements, i.e., the greatest rotation angle and absolute angular velocity in turning (Tables 2, 3).

Some simulated driving studies investigated the underlying neural mechanisms of driving (Spiers and Maguire, 2007;

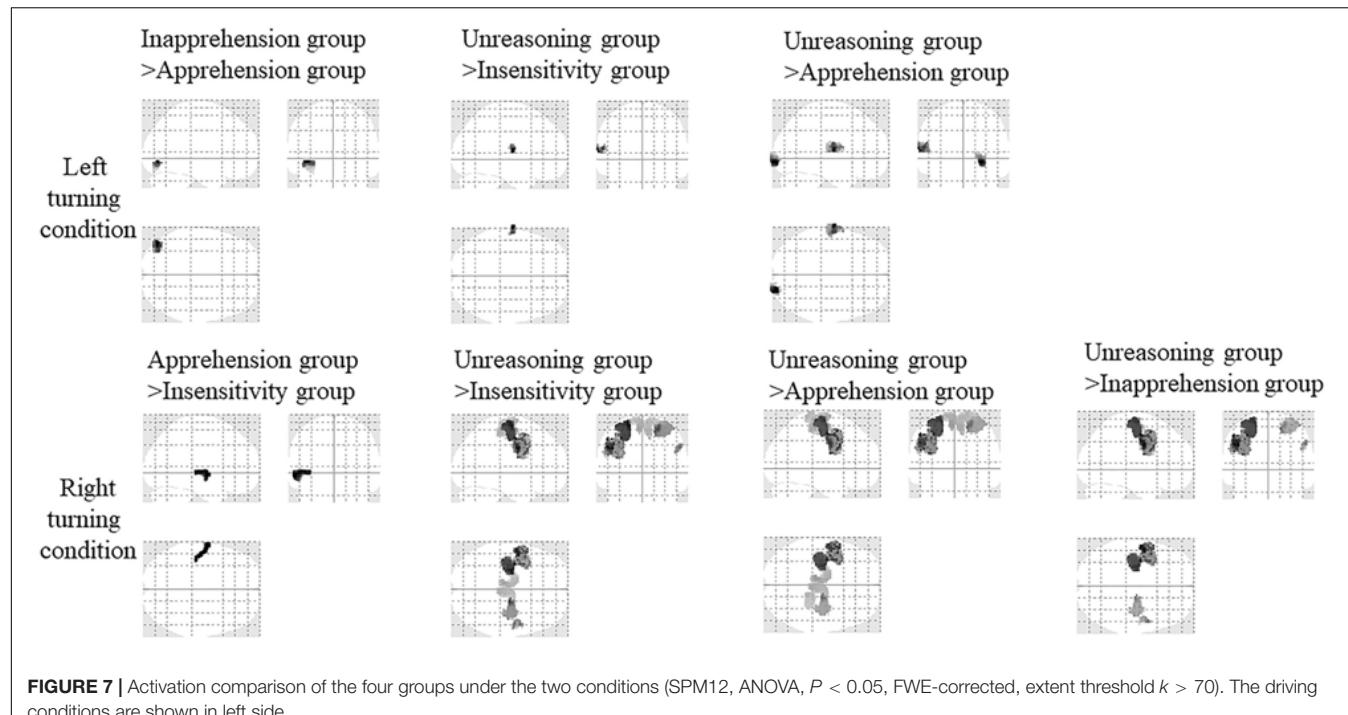


FIGURE 7 | Activation comparison of the four groups under the two conditions (SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$). The driving conditions are shown in left side.

TABLE 6 | Activation comparison among the four groups.

Task	Inter-group comparison	Anatomy	Peak location			Cluster size (Voxels)
			x	y	z	
Turning left	Inapprehension group > Apprehension group	Inferior occipital gyrus	-40	-80	-6	4.97
	Unreasoning group > Insensitivity group	Superior temporal gyrus	-66	-12	10	4.68
	Unreasoning group > Apprehension group	Inferior occipital gyrus	24	-96	-8	5.24
		Superior temporal gyrus	-66	-12	10	5.12
	Unreasoning group > Insensitivity group	Postcentral gyrus	-54	-6	46	6.11
	Unreasoning group > Apprehension group	Precentral gyrus	-52	-6	34	5.94
Turning right	Unreasoning group > Apprehension group	Superior frontal gyrus	34	-6	62	4.92
		Paracentral lobule	-6	-24	60	4.75
		Supplementary motor area	4	-30	56	4.67
	Unreasoning group > Apprehension group	Postcentral gyrus	-54	-6	46	6.65
		Precentral gyrus	-34	-8	48	6.18
		Paracentral lobule	-8	-24	60	4.97
		Superior frontal gyrus	22	-12	62	5.40
		Precentral gyrus	34	-24	68	4.88
		Paracentral lobule	6	-32	54	4.86
	Apprehension group > Insensitivity group	Superior temporal gyrus	-56	-8	-2	4.71
Unreasoning group > Inapprehension group	Postcentral gyrus	-54	-6	46	6.20	
	Precentral gyrus	-24	-14	66	5.68	

SPM12, ANOVA, $P < 0.05$, FWE-corrected, extent threshold $k > 70$. The location is in MNI coordinates.

Calhoun and Pearson, 2012; Schweizer et al., 2013; Oka et al., 2015). The brain regions related with goal direction, attention and motor planning, including the frontal gyrus (Spiers and Maguire, 2007), the superior parietal cortex and lateral occipital cortex (Oka et al., 2015), pre-supplementary motor area and

the cerebellum (Calhoun and Pearson, 2012) were activated. The higher activation of bilateral parietal lobe were positively correlated with good driving performance (Uchiyama et al., 2012), while the activity of the anterior cingulate were negatively correlated with good driving performance and was involved in

driving errors (Kan, 2011; Bledsoe et al., 2013). The inter-group comparison indicated that, under the left turning condition, the left superior temporal gyrus (Unreasoning group > Insensitivity group and Apprehension group) and right inferior occipital gyrus (Unreasoning group > Apprehension group) was detected (**Figure 5** and **Table 6**). The superior temporal gyrus is an important area in the pathway consisting of the prefrontal cortex and amygdala, which are all associated with social cognitive processes (Amanda et al., 2004; Callaghan et al., 2017). The occipital gyrus is mainly involved in visual information processing (Lauritzen et al., 2009) and was found to be coupled with the parietal gyrus in sustained attention (Lauritzen et al., 2009) and spatial attention (Garg et al., 2007; Weaver and Stevens, 2007). The Unreasoning group had the greatest absolute angular velocity in the two turning steps under the two driving conditions and the greatest rotation angle of the steering wheel under most circumstances. The total time of left turning in the Unreasoning group was the shortest, and of right turning the second shortest (longer than the Insensitivity group). Their driving style seemed to be the most intensive and more easily made errors. To fulfill the same turning task, the time of the Unreasoning group was generally shorter than the other groups, which meant that they needed to process the same amount of information but in a shorter time. From this viewpoint, we think that the cognitive load of the Unreasoning group to process the turning information was higher.

The cognitive load could affect driving negatively, undermining drivers' driving performance (Lee et al., 2007; Wijayanto et al., 2018). The increased cognitive load was associated with a common network comprising occipital cortices and parietal, thalamus, and the cerebellum (Tomasi et al., 2007). Among these areas, the occipital and parietal cortex are crucial in visual spatial attention functioning (Garg et al., 2007; Weaver and Stevens, 2007; Lauritzen et al., 2009). Visual spatial attention is a kind of attention, including a series of cognitive activities, such as visual searching, spatial area selection, attention switching and selective visual information processing in the useful field of view (Richardson and Marottoli, 2003; Wijayanto et al., 2018). Researches indicated that visual attention played an important role in predicting driving task performance, which is associated with a threefold increase in the risk of driving errors (Richardson and Marottoli, 2003). A higher load of visual spatial attention would diminish the sensitivity to the environment during driving and increase the risk of aberrant driving (Richardson and Marottoli, 2003; Lee et al., 2007), which is consistent with our results that the Unreasoning group are more likely to make errors and have poorer driving performance. Therefore, we speculated that the high occurrence of the aberrant driving behaviors and the intensive driving style in the Unreasoning group, were related with the higher load of visual spatial attention, when occipital areas played an important role.

Under the right turning condition, the Unreasoning group had stronger activity mainly in the bilateral postcentral gyrus, precentral gyrus and the paracentral gyrus compared to the other three groups (**Figure 7** and **Table 6**). The stronger activation of these motor and sensorimotor areas may relate with the more intense movement of the Unreasoning group, i.e., the

greatest rotation angle and absolute angular velocity in turning (Haseeb et al., 2007). Besides these areas, the superior frontal gyrus was also detected when comparing the Unreasoning group with the Insensitivity and Apprehension group. Considering the important role of the frontal gyrus in decision-making, executive control, performance monitoring and adjustments, its stronger activation here implied a higher load in these cognitive processes in the Unreasoning group compared to the other three groups. The Unreasoning group had the highest number of car collision with higher Apprehension (O) and Tension (Q4) scores and lower Reasoning (B) scores. We speculated that higher Apprehension (O) and Tension (Q4) and lower Reasoning (B) scores may cause dangerous driving and the superior frontal gyrus might play a very important role.

Limitations of the Study

There are some limitations that should be considered in future studies. First, the samples were biased in gender, age and driving years. A previous study found that age (Callaghan et al., 2017), gender (Adenzato et al., 2017) and driving years (Pekkanen et al., 2018) were significant factors affecting a human's cognitive and perceptive, decision making and spatial attention (Akamatsu et al., 2006). There were more male (75%) than female drivers in this study. The participant pool had relatively few and small personality differences. We compared the 16PF scores of the studied subjects and the national norm (Zhu and Dai, 1988) and found that the studied subjects had significantly different scores in Sensitivity (I), Abstractedness (M), Apprehension (O), perfectionism (Q3), Warmth (A), Dominance (E), Social Boldness (H), Vigilance (L), Privateness (N), and Openness to Change (Q1) (**Supplementary Table S1**). Second, the driving scenario was relatively complicated. The environment around the turns, and the parameters of the turns such as the radius and the length, were not exactly the same, which would affect the subjects' reaction and brain activity to some extent. A simpler and more comparable scenario might be helpful in a quantitative analysis and comparison. Third, different to real driving, simulated driving cannot induce exactly the same experience and performance of the subjects since there was no real risk of a collision or actual injury. Under these circumstances, the underlying cognitive process and behavior may be distorted to some extent. Additionally, one subject failed to accomplish the driving tasks due to driving sickness. How to transplant the experiment and analysis schema safely and effectively to the real driving, is worth studying further. The ERPs utilized for resource reconstruction were acquired throughout the whole driving process, therefore, the effect of driving duration could not be detected using our current schema, which is another limitation of this study. Generally, driving duration had a close relationship with driving behaviors (Otmani et al., 2005; Geden et al., 2018) and EEG features (Puspasari et al., 2017). The influence of driving duration on personality, EEG and driving behaviors warrants further research.

Our study is currently, to some extent, an exploratory work. All the subjects were clustered into four groups based on their personality traits and then a *post hoc* comparison of their driving behaviors and EEG characteristics were conducted. We hoped

to, and we did find a relationship between EEG, behavior and personality. If we could develop a large-scale study based on a larger sample size or if we could obtain the original data of the national norm, we might be able to extract all the typical and representative categories of the population, which can be applied as the standard and the new subjects could be classified based on this standard.

CONCLUSION

In this paper, we explored the correlation between driving behavior, personality and EEG using a simulated driving experiment. The subjects were clustered into four groups, i.e., the Inapprehension group, Insensitivity group, Apprehension group and the Unreasoning group, according to their personality traits, using the hierarchical clustering method. The turning process of the subjects can be formulated into two steps, rotating the steering wheel toward the turning direction and entering the turn, and then rotating the steering wheel back and leaving the turn. The bilateral frontal gyrus was found to be activated when turning left and right which might be associated with its function in attention, decision-making and executive control functions in visual-spatial and visual-motor processes. The Unreasoning group had the worst driving performance with highest number of car collisions and the most intensive driving action, which was related to a higher load of visual spatial attention and decision making, when the occipital and superior frontal areas played a very important role. Apprehension (O) and Tension (Q4) had a positive correlation, and Reasoning (B) had a negative correlation with dangerous driving behaviors. Our results demonstrate the close correlation between driving behavior, personality and EEG.

ETHICS STATEMENT

This study was carried out in accordance with the recommendations of the “Ethical Review Committee of the Wuhan University of Technology” with written informed

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consent from all subjects. All subjects gave written informed consent in accordance with the Declaration of Helsinki. The protocol was approved by the “Ethical Review Committee of the Wuhan University of Technology.” In this paper, we aimed to explore the relationship among personality traits, EEG and driving behavior, thus we needed to collect the electroencephalography signals of drivers during driving process. The whole experiment was completely harmless to the subjects.

AUTHOR CONTRIBUTIONS

FY and KG designed the data processing schema. YW, CD, and ML carried out the experiment. YW analyzed the data. LY and YW wrote the manuscript.

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SUPPLEMENTARY MATERIAL

The Supplementary Material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fpsyg.2019.01524/full#supplementary-material>

FIGURE S1 | Activation of all subjects under left turning > right turning condition (SPM12, ANOVA, $p < 0.01$, uncorrected, extent threshold $k > 70$).

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Article

Analysis of Personality and EEG Features in Emotion Recognition Using Machine Learning Techniques to Classify Arousal and Valence Labels

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Abstract: We analyzed the contribution of electroencephalogram (EEG) data, age, sex, and personality traits to emotion recognition processes—through the classification of arousal, valence, and discrete emotions labels—using feature selection techniques and machine learning classifiers. EEG traits and age, sex, and personality traits were retrieved from a well-known dataset—AMIGOS—and two sets of traits were built to analyze the classification performance. We found that age, sex, and personality traits were not significantly associated with the classification of arousal, valence and discrete emotions using machine learning. The added EEG features increased the classification accuracies (compared with the original report), for arousal and valence labels. Classification of arousal and valence labels achieved higher than chance levels; however, they did not exceed 70% accuracy in the different tested scenarios. For discrete emotions, the mean accuracies and the mean area under the curve scores were higher than chance; however, F1 scores were low, implying that several false positives and false negatives were present. This study highlights the performance of EEG traits, age, sex, and personality traits using emotion classifiers. These findings could help to understand the traits relationship in a technological and data level for personalized human-computer interactions systems.

Keywords: EEG; emotion recognition; human computer interactions; feature selection; machine learning; personality

1. Introduction

Emotions influence how people process information and make decisions, and they shape their behavior when they interact with their surroundings. When interactions between humans and systems occur, physical, cognitive, and social connections are integrated, including empathetic interactions to enhance users' experience in varied fields [1]. For new human-computer interaction (HCI) paradigms, in which systems are in constant contact with the users, it is important to identify and recognize users' emotional states to improve interactions between digital systems and the users with high recognition accuracy and provide a more personalized experience [2].

From an HCI perspective, it is important to find new ways in which systems can be more personalized to the user and to achieve better cooperation in fields like assistive and companion computing using physiological signals like electroencephalograms (EEG)—a useful tool that describe how cognition and emotional behavior are related at a physiological level [3–5]. Owing to the development of new technology and portable devices to measure EEG, the research is expanding beyond medical applications to areas like e-learning, commerce, entertainment, etc.

Research in emotion recognition using EEG as the main source of information has focused on how to achieve better performance and accuracy in the emotion identification and classification

process, considering different traits that are related on how emotions are managed and regulated. Demographic variables and personality characteristics are useful features to describe the relationship between emotional states and the individual characteristics related to behavior. Personality traits, age and sex are relevant to any computing area involving the understanding and predicting of human behavior [6,7]. From this, it is expected that demographic characteristics and personality traits will foster emotion recognition processes to achieve higher performance.

1.1. EEG and Emotion Recognition

Emotion is a psychological state that is accompanied by physiological changes that can lead to the modification of a person's expressions, which are observable and measurable manifestations and can be perceived and evaluated by others as evidence of an emotional state [8]. For the identification of emotional states by HCI systems, varied approaches are grouped under the term *emotion recognition*, which uses affective models (like discrete emotions labels or dimensional emotions scores; i.e., Russell's Affective Model [9]), and measurement methods to identify individuals' behavioral states, which are labeled as emotion or affective states. Emotion recognition can be examined by pattern extraction through machine learning techniques from signals like speech, body movement, and facial expressions, or physiological signals that describe individuals' behavior [10].

One of the physiological signals used for emotion recognition is EEG. EEG signals have gained increasing attention owing to its promise of potential applications in brain–computer interface (BCIs) for assistive technological solutions to overcome physical and speech disabilities. Emotion recognition using EEG signals focuses its development on two main application fields: first, medical applications designed to provide assistance, enhancement, monitoring, assessment, and diagnosis of human psychiatric and neurological diseases; and, second, non-medical applications designed to entertain, educate, and monitor emotional states in a commercial or personal context [11,12].

EEG signals are a powerful method for studying the brain's responses to emotional stimuli because its measurement equipment is noninvasive, fast, and inexpensive. EEG data lacks spatial resolution and requires several electrodes (around 8 to 128 depending on the experiment and the robustness of the equipment used) to be placed on the participant's head; however, it provides great time resolution, allowing researchers to study phase changes in response to emotional stimuli [13]. EEG signals are divided into specific ranges: delta (1–4 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (13–30 Hz), and gamma (> 30 Hz) bands. To analyze the signal contribution in each band, power spectral densities (PSD) and power spectral asymmetry (PSA) were used.

Regarding emotions recognition using EEG signals, some surveys revealed how EEG signals are related with emotional behavior and used varied methodologies and traits to classify arousal–valence space or discrete emotions [11,13,14]. The main findings revealed that EEG signals and emotions are related to the frequency analysis in different bands. For example, changes in alpha frequency band power and channel asymmetry between the front hemispheres of the brain are traits related to emotional activity: right frontal brain activation is associated with negative emotions, and greater left frontal activation is associated with positive emotions [15–17]. Furthermore, PSD have shown a frontal asymmetrical increase of theta and alpha activity related to the observation of pleasant (unpleasant) stimuli in the left (right) hemisphere [18,19]. Activity in the left frontal hemisphere is related to pleasant stimulus, and right frontal sites show EEG activations for unpleasant stimuli. Moreover, the scalp regions on the left frontal and pre-frontal areas are mostly activated when participants perceive pleasant content, and the right frontal lobe is more activated when people have been exposed to unpleasant content [18]. For discrete emotions, gamma frequency band is related to happiness and sadness [20], as are the alpha waves of the temporal lobe (left for sadness and right for happiness) [21]. However, a limitation with these techniques is that PSD and PSA are related to frontal activation, which can be related to other higher cognitive functions like concentration, planning, judgment, creativity, and inhibition [22].

1.2. HCI and Personality Traits

Personality is a behavior pattern that maintains over time and context, differentiating one person from other [23]. To measure and identify an individual's personality, there are a wide variety of psychometric tests that correspond to various psychological theories about behavioral patterns and innate characteristics. One of these theories is Eysenck's personality model, which posits three independent factors to describe personality: psychoticism, extraversion, and neuroticism (PEN) [24]. Another widely used personality model is the five factor model (FFM). Paul Costa and Robert McCrae [25] devised the FFM and the Neuroticism-Extraversion-Openness Five-Factor Inventory questionnaire. They posited that there are five personality traits: extraversion (social vs. reserved), agreeableness (compassionate vs. dispassionate and suspicious), conscientiousness (dutiful vs. easy-going), neuroticism or emotional stability (nervous vs. confident), and openness to experience (curious vs. cautious). These traits describe the frequency or intensity of feelings, thoughts, or behaviors of an individual compared with other people. From this model, individuals' personality is described through these traits in some varying degree. In contrast, Jeffrey Alan Gray built the Bio-psychological Theory of Personality (behavioral inhibition system (BIS)/ behavioral activation system (BAS)) [26]. This is a model of the general biological processes relevant to human psychology, behavior, and personality. This model describes the existence of two brain-based systems for controlling a person's interactions with their environment: the BIS and BAS.

The FFM is considered a standard in science; however, based on statistical analysis of the data, some researchers argue that the FFM should be expanded to include a sixth trait: honesty-humility. The HEXACO model of personality conceptualizes human personality considering this sixth dimension: honesty-humility (H), emotionality (E), extraversion (X), agreeableness (A), conscientiousness (C), and openness to experience (O). Although the HEXACO model has received growing support from scientists, the necessity of this sixth trait is still a matter of debate [27].

Emotion – personality relationships have been studied in psychology for a long time; however, their relationship in HCI is still under discussion. Some studies used varied kinds of behavioral data to identify emotional states, for example, using participants' text and annotation [28,29], identifying personal characteristics in voice and speech [30–32], body language [33,34], and also from digital footprints [35,36]. In the next section, we present some works that aimed to include personality information in different HCI applications.

1.3. Related Works

In [30], an approach to detect an user's interaction style in spoken conversation was presented. It combined emotional labeling of conversation-based affective speech corpus of 53 students from both sexes and International Personality Item Pool to measure personality for intelligent speech-based HCIs. Callejas-Cuervo and colleagues [37] proposed a system architecture where videogames can stimulate participants to extract characteristics that can correlate with information from emotion and personality traits, using electrocardiogram (ECG), galvanic skin response (GSR), electromyography (EMG) signals, and the PEN model together with Russell's affective model. Furthermore, in [28], the standard cognitive appraisal model (OCC emotion model) and the FFM personality model were combined in a natural language processing tools to analyze language for affect. In [38], researchers proposed an intensity-based affective model that incorporates the FFM for personality and the OCC model for affect, from predetermined answers related to image and labels; then, they performed personality processing and modeling to predict emotion.

Guo and Ma [35], proposed a modeling personality system from big data coming from different sources including participants' location, heartbeat rate, and browser data to describe person's conditions and activity to accurately identify participants' personality. They proposed a human model of four layers: state, pattern related to daily activity, emotions, and personality. Wei and colleagues [39] focused their attention on the "apparent personality analysis"—using short human-centered video sequences and developing an algorithm for recognizing personality traits from those videos — using

deep modal regression. In [40], emotion recognition and varied characteristics (i.e., personality traits, age, and sex) were used to create a car interphase that takes actions when it identifies an emotional reaction (neutral, panic/fear, frustration/anger, and boredom/sleepiness) in participants using GSR, temperature, and heart rate. At the time of the publication, one major concern was scenarios in which the emotion occurred, which the system could not identify. They noted that the incorporation of demographic characteristics and personality traits can enhance and increase the accuracy of emotion recognition; however, no data involving these were provided.

Robot interaction with people is another vast field of interest for emotion recognition and personality traits. Anzalone and colleagues [41] examined extraversion in human-humanoid interactions using nonverbal behavior (i.e., upper-body movements and interaction duration). Additionally, Bhin and colleagues discussed building an automated psychophysical personality data acquisition system for human-robot interaction under the premise that, to build more natural interaction between human and robots, systems need the ability to recognize the psychological state (i.e., personality) of users [42]. They proposed a system for personality recognition using nonverbal cues through a commercial webcam to record participants' body movement and facial expression, a microphone to record speech signals, a wristband (Microsoft Band or Empatica E4) to obtain physiological signals such as heart rate and body temperature, and the FFM (BFI-K-44) to measure personality.

The influence of personality traits in works regarding affective computing and HCI has been expanding in recent years, which benefit from examining emotion, mood, and personality by employing physiological data, facial and audio recognition, body movement, etc. Works that use EEG signals as a main source of information have been increasing in recent years. The following section summarizes their findings.

1.4. EEG-Related Works

Cai and colleagues [43] evaluated the behavior and personality of 42 participants using physiological data from wearables devices that measured heart rate, respiration, and EEG while participants watched a 20-minute video or gave an 8-minutes presentation. Their main objective was not to predict personality or emotion, but to correlate these two characteristics and analyze the relationship between personality traits and behavior through the influence of emotional states. They used Pearson's correlation coefficient to determine the relationship between respiration rate and personality traits, and Spearman's rank correlation coefficient to determine the relationship between facial expressions and personality traits under different emotion states. They yielded evidence of said correlations; however, their results were not definitive.

Rukavina and colleagues [2] examined personality, sex, age and gender roles to improve the emotion recognition accuracy. Age and personality dimensions were correlated with all extracted features during each of the five affective states or core affects from the valence, arousal, and dominance space: for each core affect, they presented two blocks of 20 pictures, 10 pictures in a 2-minute time window (20-second fixation cross, 20-seconds picture presentation belonging to the same core affect, and 20-second fixation cross), using a total of 100 pictures. First, they performed a correlation analysis to consider only meaningful variables for the classification analysis. They concluded that sex and age were significantly correlating with affective states; however, they did not find a correlation between personality traits and affective states. One possible explanation was the high significance level of the Bonferroni correction ($p < 0.007$). Although, their experiment was limited because the time and methods of presenting the emotional stimuli material to the participants can affect the outcome.

Miranda-Correia and Patras [44] propose a multi-task cascade deep learning approach and performed binary classification for emotional states (arousal and valence) and personal factors (personality, mood, and social interaction) from EEG signals. Forty participants watched short affective videos and thirty-seven participants watched long videos (ranging from 51 seconds to nearly 24 minutes), in individual or group sessions. The researchers analyzed the time and frequency domain features

from EEG data through segments (20 second time window), to obtain the affective levels (arousal and valence) using convolutional neural networks (CNNs) and recurrent neural networks (RNNs); then, they estimated the Big Five factors and their relationship with mood; i.e., the Positive Affect and Negative Affect Schedule (PANAS) from n consecutive segments' affective levels using a second deep network with recurrent layer of eight units with "sigmoid" output function. Using the fusion affect sub-network (from CNNs and RNNs), they achieve 0.59 and 0.61 F1-scores ($p < 0.001$) for valence and arousal recognition, respectively.

Mittermeier and colleagues [45], studied if there is an emotion-specific neural correlation between positive and negative auditory emotional stimuli and attention through auditory-evoked potentials (AEPs) and if there is a specific relationship between AEPs evoked by emotional stimuli and the personality dimension extraversion–introversion. Differing from the other studies, this work focusses on the auditory emotional stimuli to analyze the correlation between reaction times to the stimuli, evoke potentials, and personality (extraversion). They found that extraversion correlated with the EPN 170 amplitude in the emotional paradigms. Compared to participants in the introverted subgroup, extroverted persons exhibited significantly higher EPN 170 amplitudes in the P3 channel for emotional paradigms (syllables (Pz channel) and words (P3 channel)) but not in the tones task.

Subramanian and colleagues [46] built a multimodal database from 58 participants for implicit personality and affect recognition using commercial physiological sensors to understand the relationship between emotional attributes and personality traits and characterize both by physiological responses. The paper described the influence of personality differences on users' affective behavior using the ASCERTAIN database to understand the relationship between emotional attributes from an arousal/valence model and the Big Five personality model by measuring users' physiological responses. Their main goal was to assess personality traits via affective physiological responses instead of questionnaires. They compiled valence and arousal ratings reflecting user's affective impression: a seven-point scale was used with a -3 (*very negative*) to 3 (*very positive*) scale for valence, and a 0 (*very boring*) to 6 (*very exciting*) scale for arousal. Ratings concerning engagement (*did not pay attention to totally attentive*), liking (*I hated it to I loved it*), and familiarity (*never seen it before to remember it very well*) were also acquired with the five traits from the FFM. They found that arousal was moderately correlated with extraversion, while valence correlated strongly with linking ($0.68 p < 0.05$). GSR features obtained higher recognition performance for both arousal and valence (0.68 with Naïve Bayes's (NB) classifier), while ECG features obtained the worst recognition performance (0.56 for valance and 0.57 for arousal using Support Vector Machine (SVM)). EEG features had better performance recognizing arousal (0.61) as compared to valence. GSR, ECG and EMG achieved better recognition of valence. Peripheral (ECG+GSR) features performed better than unimodal features for arousal recognition, while the best multimodal F1-score (0.71) was obtained for valence. Finally, comparing the two employed classifiers, NB achieved better recognition performance than linear SVM for arousal (0.69 using peripheral signals) and valence (0.68 for GSR signal).

Mueller and Kuchinke [47] examined the individual differences in implicit processing of emotional words (happy, neutral, and fear-related) on a lexical decision task; i.e., deciding whether a letter string is a correct word or a non-word via a button. They argued that several participant-specific variables (personality traits and neurological foundation) are known to modulate processing of emotional information. The main task comprised 35 trials in pseudo-randomized order displaying faces of five individuals in each of different emotional expressions. A correlation analysis was performed between happy and neutral, happy and fear-related, and fear-related and neutral. Difference scores were calculated for response times (RTs), error rates (ERs), and drift rates (DRs), which correlated with all nine variables of emotion processing (RTs, ERs, and DRs for Happy–Fear, Happy–Neutral, and Fear–Neutral). Additionally, they performed three multiple linear regression analyses for RTs, ERs, and DRs as dependent variables to predict individual emotional effects. Results revealed that BAS-Drive was the variable that explained most of the variance regarding Happy to Fear RT (H-FRT) differences. RTs for happy words were generally shorter than RTs to fear-related words resulting

in negative difference scores on average. The negative relationship between H-F_{RT} differences and BAS-Drive scores revealed that participants with larger BAS-Drive scores showed greater H-F_{RT} differences. Instead, BAS-Drive scores were positively correlated with Fear to Neutral RTs.

Although the literature shows a relationship between emotion, mood, affective states, and personality [48–50], how to effectively use demographic characteristics and personality traits to ascertain emotion recognition remains unclear. There is no standard for choosing emotion or personality models in recognition techniques, and variables and classification approaches differ between studies, thus yielding inconsistent results. This is understandable given the newness of this field, and each outcome offers novel insight into new approaches that can be developed. The presented papers do not provide conclusive information about a strong correlation between emotion classification and demographic characteristics and personality traits. It is still not clear how singular personality traits can be measured from psychological signal and emotion, even though literature says they correlate at biological level [24].

For this study, we aim to test the hypothesis that age, sex, and personality traits, can improve the classification accuracies for arousal and valence levels, when they are used alongside EEG data for emotion recognition processes by machine learning algorithms. Using the information from the AMIGOS dataset [51], we analyzed (1) the contribution of the different EEG traits, demographic characteristics, and personality traits in the classification process of arousal, valence, and discrete emotions labels using varied machine learning techniques, (2) the contribution of the demographic characteristics and personality traits in emotion classification, as relevant information related to behavior and individual characteristics, and (3) the performance of simple classification models with new EEG traits that were not considered in the AMIGOS study.

2. Materials and Methods

According to the brain-computer interface cycle, where it is the common approach to perform emotion recognition using EEG signals, we followed the basic phases proposed in [52] and used across different works [53–55] to analyze the performance of the different classifiers implemented. The first phases related to experiment implementation where participants are exposed to the emotional stimuli, recording of the EEG signals and preprocessing of the raw data, which are being retrieved from the dataset AMIGOS. The phases related to feature extraction and classifier implementation are being performed by the authors of this work.

2.1. AMIGOS Dataset Experiment

AMIGOS is a dataset to study the relationship between affect, personality, and mood [51]. The dataset consists of multimodal recordings of participants and their responses to fragments of emotional videos. Participants took part in two experimental setups while watching long and short videos: first, in an individual scenario, and, second, in a group scenario with other participants. While watching the videos, EEG, ECG, GSR, frontal high-definition video, and both RGB and depth full body videos were recorded. Personality (Big-Five), mood (PANAS), internal annotation (participants' self-assessment affective levels), and external annotation (off-line annotations by three annotators; valence and arousal scales) scores were obtained. The participants read and signed a consent form to take part in the study.

From the AMIGOS dataset, we used information from the individual–short videos scenario, in which 40 participants (male = 27, female = 13, aged 21–40 years, mean age = 28.3 years) watched 16 videos (duration < 250 s)—four from each high and low arousal–valence emotional levels combination: high arousal and high valence (HAHV), high arousal and low valence (HALV), low arousal and high valence (LAHV), and low arousal and low valence (LALV). The experiment consisted of an initial self-assessment session for arousal, valence, and dominance scores, as well as a selection of basic emotions (neutral, happiness, sadness, surprise, fear, anger, and disgust) that participants felt before any stimuli were shown. Next, 16 videos were presented in a random order in 16 trials, each consisting

of (1) a five-second baseline recording showing a fixation cross; (2) The display of one video; and (3) self-assessment of arousal, valence, dominance, mood, liking, and familiarity, as well as the selection of basic emotions. After the 16 trials, the recording session ended.

2.2. AMIGOS Features

For the input features, we used the 14 EEG signals from Emotiv EPOC Neuroheadset as information source, which were recorded at 128-Hz sample rate and 14-bit resolution (electrode distribution is shown in Figure 1). We used the demographic characteristics (age and sex) and personality traits which were acquired before the experiment using an online form.

- For EEG features, we used the preprocessed signals from the AMIGOS dataset. The signals were averaged to the common reference, filtered with a band-pass frequency filter from 4.0 Hz to 45 Hz, EOG removal was applied and then segmentation was performed. We calculate the 105 EEG features reported in the AMIGOS experiment, which correspond to PSD and PSA between pairs of electrodes. PSD corresponds to the five bands correlated with emotion response: theta (3–7 Hz), slow alpha (8–10 Hz), alpha (8–13 Hz), beta (14–29 Hz), and gamma (30–47 Hz) for each electrode (70 features). PSD was obtained by Welch's method (time window = 128 samples corresponding to 1 second) between 3 and 47 Hz and averaged over the frequency bands. PSA was calculated between each of the seven pairs of electrodes in the five frequency bands correlated with emotion response (35 features). These pair of electrodes comprised two electrodes located in the same scalp region, but on the opposite side of the head: AF3/AF4, F3/F4, F7/F8, FC5/FC6, T7/T8, P7/P8, and O1/O2.
- We also utilized age, sex, and the Big Five personality traits [56] (i.e., 7 features).

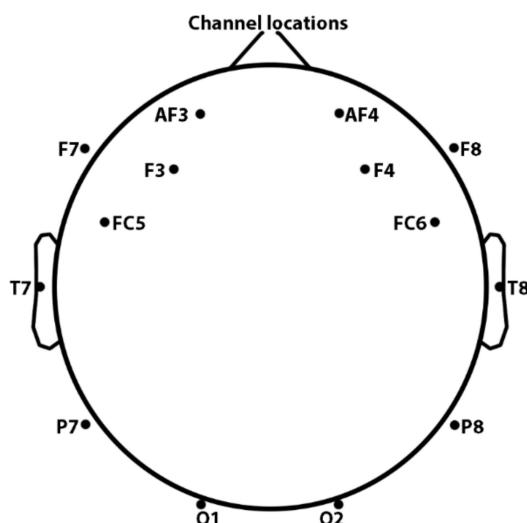


Figure 1. Electroencephalogram (EEG) channel location according to the International 10–20 System.

A total of 112 features from the AMIGOS dataset were used in this study.

2.3. Added EEG Features

For this study, we calculate the fractal dimension (FD) and the differential entropy (DE) for each one of the electrodes in the five frequency bands mentioned before. Moreover, the rational asymmetry (RASM) and differential asymmetry (DASM) for each of the seven pairs of electrodes in the five bands were calculated (70 features). Because in previous literature [57–59], these EEG traits are related to participants' emotional responses, and reports about EEG emotion recognition used the same kind of features to obtain classification above the chance level [14]. We wanted to include these EEG traits

to analyze if they can improve the classification performance in contrast with the ones used in the AMIGOS work.

- FD is a measure of signal complexity. Because EEG signals are nonlinear and chaotic, a FD model can be applied in EEG data analysis [60]. We compute FD using the Higuchi algorithm for each of the 14 EEG signals (14 features).
- DE can be defined as the entropy of continuous random variables and is used to measure its complexity [61]. DE is equivalent to the logarithm of the energy spectrum (ES) in a certain frequency band for a fixed length EEG sequence [62]. We calculated ES as the average energy of EEG signals in the different five frequency bands for each electrode and applied the logarithm to obtain DE (70 features). DASM and RASM were calculated as the differences and ratios between the DE of the seven pairs of asymmetry electrodes (35 features for each trait).

In total, we added 154 features from EEG signals to complement the ones already obtained in the AMIGOS base experiment, thus, 266 features were used in the emotion classification models.

We applied feature selection methods [58] to analyze how the different features are related with the classification labels and to obtain a reduced set of features (from the total 266 features), to analyze the improvement in the classification performance. We applied feature importance to analyze in how much percentage the features contribute to predict the different label scenarios. Also, we implemented univariate selection and a recursive feature elimination with cross-validation to select the features that improve the classification rates and built a second set of features.

2.4. Classifiers

We wanted to focus our analysis in two different studio cases: first, analyzing the classification performance of different machine learning algorithms using all 266 features to classify the emotional stimuli video labels (arousal and valence levels). In this case, our motivation was to analyze what features can predict the videos emotional labels based on participants' personal data. This would help us identify to what degree it is possible to classify emotions when the self-assessment arousal and valence scores from the participants are not available. Second, we analyzed the classification performance using only EEG data and participants' sex, age, and personality traits to classify self-assessment emotional answers using self-assessment manikins [63] and the seven basic categorical emotions, which were reported by the participants at the end of each video. Our motivation in this second case was to analyze the performance of different classifiers when using only information related to EEG signals and characteristics like age, sex, and personality.

For the first studio case (Figure 2a), we tested three different classification scenarios in which we select two sets of input features. For the classification scenarios, we considered the labels from the videos used as emotional stimuli: first, we combined valence-arousal space labels (HAHV, HALV, LAHV, and LALV); second, we considered arousal labels (HA and LA); and third, we considered valence space labels (HV and LV). To transform the arousal and valence responses into classification labels, we use a threshold of 5.0 to convert the response values into binary labels to obtain categorical data. For the input features, we considered a first set of features with only EEG data, demographic characteristics and personality traits (266 features) and a second set of features with EEG data, demographic characteristics and personality traits reduced using feature selection. From the 640 AMIGOS short-video observations (16 videos × 40 participants), we exclude the observations that had missing personality and EEG data.

For the second studio case (Figure 2b), we tested 9 different classification scenarios corresponding to the different self-assessment traits related directly to emotions (arousal and valence labels and the seven emotions). To transform the arousal and valence responses into classification labels, we use a threshold of 5.0 to convert the response values into binary labels (HA and LA; HV and LV) to obtain categorical data. For the input features, we considerate: a first set of features with EEG data and demographic characteristics and personality traits (266 features), and a second set of features with EEG and demographic characteristics and personality traits reduced using feature selection. From the

640 AMIGOS short videos observations ($16 \text{ videos} \times 40 \text{ participants}$), we exclude the observations that had missing personality and EEG data.

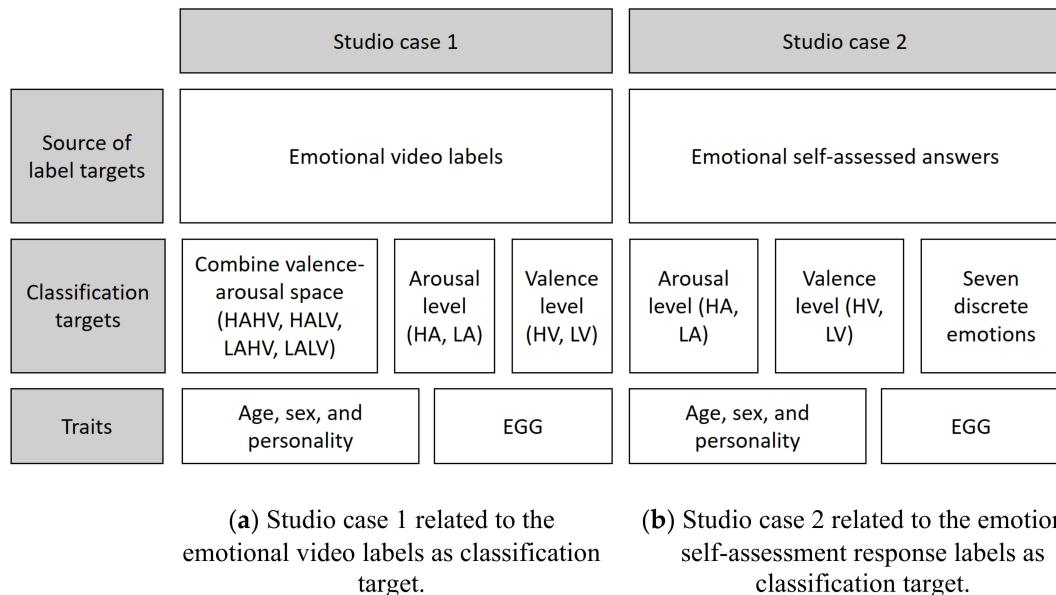


Figure 2. Studio cases for emotional classification. Classification targets: high arousal (HA) and low arousal (LA), high valence (HV), and low valence (LV).

The classifiers were chosen to test and compare the emotion recognition accuracy using simple machine learning models.

- SVM is a linear model that use a decision boundary as a linear function to separate two classes with a line, a plane, or a hyperplane, fitting two parameters: regularization or margin maximization (C), and kernel. C determines the strength of the regularization. Higher values of C correspond to less regularization, trying to fit the training set as best as possible to each individual data point. With lower values of C, the algorithms will try to adjust to the majority of the data points. Kernels are mathematical functions that take data as input and transform it into the required form (i.e., linear radial basis function).
- Naïve Bayes is faster than linear models by looking at each feature individually, collecting simple per-class statistics from each feature.
- Random Forest, is a collection of decision trees, where each tree is slightly different from the others. With many trees (estimators) it is possible to reduce the overfitting by averaging the results of each tree. And with the tree deepness it is possible to splits the tree capturing more information about the data.
- Artificial neural network is a multi-layer fully-connected neural nets that consist of an input layer, multiple hidden layers with units, and an output layer. Each layer has an activation function to discriminate the data (i.e., relu, sigmoid).

Our goal was to identify if the accuracy improved in any of the scenarios using different feature sets compared with the accuracy reported in AMIGOS work using PANDAS framework under python language. For the combine valence–arousal space label scenario, we applied SVM with linear ($C = 100$) and radial basis function (RBF) kernel ($C = 100$, $\gamma = 0.1$). For the other scenarios we applied SVM with linear ($C = 100$) and RBF kernel ($C = 100$, $\gamma = 0.1$), Naïve Bayes, Random Forest (estimators = 2000, max_depth = 300) and an artificial neural network (ANN) with 134 hidden units, one “relu” activation function hidden layer, and, for the output layer we used a “sigmoid” activation function (optimizer = “rmsprop”, batch size = 32, epochs = 100). Parameters were tuned using grid search with

cross-validation. To evaluate the classifier accuracy, we obtained the mean accuracy, mean F1, and mean area under the curve (AUC) scores using a 10-fold cross-validation approach over the training set of features (75% of all the dataset).

3. Results

Feature construction and feature selection are key steps in the data analysis process—in most cases, conditioning the success of any machine learning endeavor [64]. Previous works have shown how applying feature selection process in emotion recognition tasks using EEG traits [57,58], increases the performance of the classifiers while the computational power is reduced. For the purpose of this work, we wanted to perform feature selection process to reduce the number of features, preventing overfitting and improving the classification process.

Feature selection methods can generally be divided into filter and wrapper methods. While wrapper methods select features based on interaction with a classifier, filter methods are model-independent [58]. Filter techniques assess the relevance of features by looking only at the intrinsic properties of the data. Advantages of filter techniques are that they easily scale to very high-dimensional datasets, they are computationally simple and fast, and they are independent of the classification algorithm. In this case, feature selection needs to be performed only once, and then different classifiers can be evaluated [65].

For feature selection, we used different feature selection filter approaches to understand how they affect the overall emotion classification process. We analyzed how the features contribute in percentage to predict the different label scenarios using feature importance selection. We also performed univariate selection and a recursive feature elimination (RFE) with cross-validation to select the features to build the second set of features [66].

3.1. Feature Selection and Analysis for EEG Data, Demographic Characteristics, and Personality Traits to Predict Video Emotional Labels

3.1.1. Feature Importance

Feature importance [66] provides a percentage score for each feature of the dataset, the higher the score, the more important or relevant is the feature towards the output variables—using forests of trees to evaluate the importance of features on a classification task and identify the features more related to each of the labels. The EEG traits contribute around 0.5%–0.3% percent to each of the different scenarios. In contrast, the importance percentage of the personal trait labels have the lowest scores. Table 1 shows the scores of demographic characteristics, and personality traits for the different scenarios, which do not exceed 0.32%, implying that they are not relevant to the classification process.

Table 1. Feature importance score (%) from sex, age, and personality traits for video emotional labels classification.

Arousal–Valence		Arousal		Valence	
Feature	Score (%)	Feature	Score (%)	Feature	Score (%)
Agreeableness	0.2936	Agreeableness	0.2936	Emotional stability	0.3120
Extroversion	0.2752	Extroversion	0.2752	Agreeableness	0.2907
Emotional stability	0.2636	Emotional stability	0.2636	Conscientiousness	0.2896
Age	0.2557	Age	0.2557	Extroversion	0.2790
Creativity/openness	0.2550	Creativity/openness	0.2550	Age	0.2779
Conscientiousness	0.2304	Conscientiousness	0.2304	Creativity/openness	0.2613
Sex	0.2054	Sex	0.2054	Sex	0.2316

3.1.2. Univariate Selection

When a finite training sample is provided, the statistic of the relevance is assessed by performing a statistical test with null hypothesis, “H0: the feature is individually irrelevant”; that is, X and

Y are statistically independent. Feature selection based on individual feature relevance is called univariate [67]. In univariate selection each feature is considered separately, intended to select single variables that are associated in most degree with the target variable according to a statistical test. The advantage of this technique is that it is fast and scalable; however, it ignores feature dependencies. Higher scores and p -values indicate that the variable is associated and consequently it is useful to the target [68].

Using the univariate feature selection algorithm proposed by [66], we obtained the best features based on an analysis of variance, F -test, and p -value of the features related to the three arousal and valence labels scenarios, selecting 10% of significant features [68]. Inspecting the features, we found that, for valence–arousal scenario, only one EEG trait was selected for the algorithm—PSD from EEG channel AF4 in the theta band. For the other scenarios, no features were selected.

3.1.3. RFE with Cross-Validation

RFE with cross-validation is a RFE with automatic tuning of the number of features selected, it returns the most suitable features based on SVM classifier with linear kernel. For RFE, the SVM will be retrained several times with a decreasing number of features [64,68]. The features selected differed from the ones identified by the feature importance and the univariate selection algorithms because, in the RFE, an external estimator assigns weights to features. This estimator is trained on the initial set of features and the importance of each feature is obtained by a coefficient attribute; then, the least important features are discarded from the current set of features. That procedure is recursively repeated on the discarded set until the desired number of features is eventually reached [66].

Performing RFE with personal and EEG traits, we obtained 3 features for valence–arousal label, 15 features for arousal label, and 1 feature for valence. In this case, no demographic characteristics nor personality traits were selected by the algorithm. For valence–arousal label, AF3/AF4 PSA index in the beta band; DE in the theta band channel AF4; and FC5/FC6 RASM in the slow alpha band were selected by the RFE. For arousal label, PSD from slow alpha (AF3), alpha (AF3), and gamma (FC5) bands; F3/F4 and F7/F8 PSA index in the theta band; FD of channel P8; DE in the theta (AF3, O1) and gamma (T8) bands; RASM in theta (T7/T8), slow alpha (F3/F4, O1/O2), beta (FC5/FC6) and gamma (F7/F8) bands were selected by the RFE. For valence label only, DE from F4 channel in the beta band was selected.

Finally, for the second set of features we built one dataset combining the results from the univariate selection and the RFE feature selection process to determine how the performance of the classifiers behave in contrast to the original sets of traits.

For valence-arousal label, information of the frontal (AF3, AF4, FC5, FC6) region of the scalp were selected in theta, slow alpha and beta bands. For arousal label, information of the frontal (AF3, F3, F4, FC5, FC6, F7, F8), temporal (T7, T8), and occipital (O1, O2) regions of the scalp were selected. In general, PSD, PSA DE and RASM features were commonly selected for valence-arousal and arousal labels.

3.2. Feature Selection and Analysis for EEG, Demographic Characteristics, and Personality Traits to Predict Self-Assessed Traits Labels

3.2.1. Feature Importance

In Figure 3, we show the features that exceeded 0.5% of importance for each of the classification labels. The red bars are the feature importance of the forest, along with their inter-trees variability. In Table 2, we show the notation for the EEG channels and pair of electrodes used in Figure 3.

Table 2. (a) Notation for the EEG electrodes. (b) Notation for the EEG pair of electrodes.

(a)														
n	01	02	03	04	05	06	07	08	09	10	11	12	13	14
Channel	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
(b)														
n	01		02		03		04		05		06		07	
Pair	AF3/AF4		F3/F4		F7/F8		FC5/FC6		T7/T8		P7/P8		O1/O2	

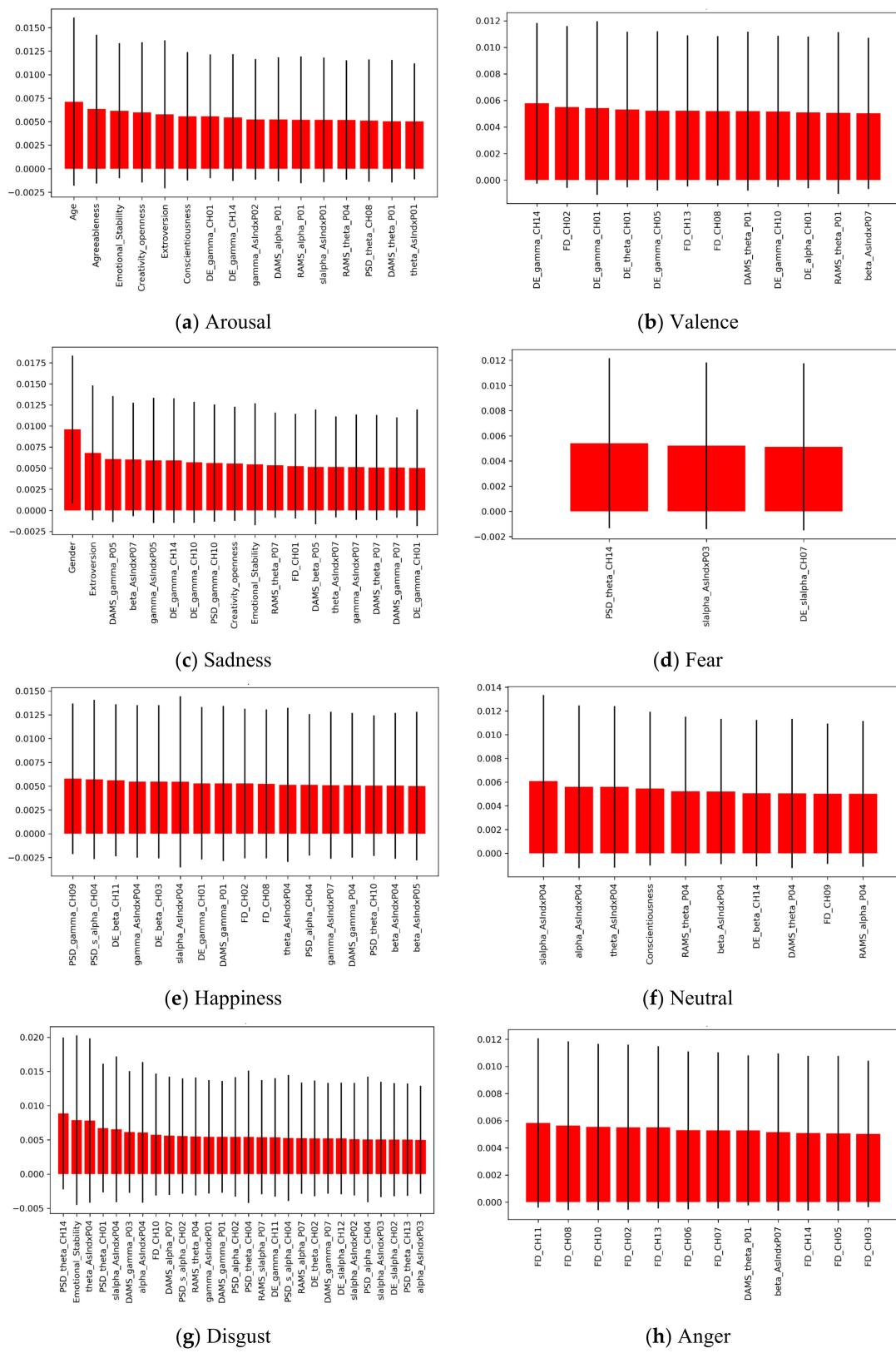


Figure 3. *Cont.*

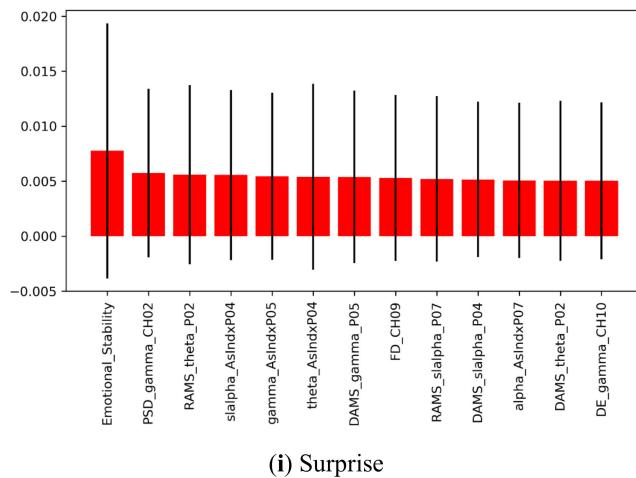


Figure 3. Feature importance with first set of features for self-assessed emotional labels classification. On the *x*-axis, the list of features is represented; on the *y*-axis, the importance of each feature in percentage is shown.

For arousal label, age, agreeableness, emotional stability, openness, extraversion, and conscientiousness were selected as important features. For the sadness label, sex, extraversion, openness, and emotional stability were selected as important features. For the neutral label, conscientiousness was selected as the important feature. For disgust and surprise labels, emotional stability was selected as an important feature. However, the contribution is still under 0.5%, which is too low compared with the other traits.

3.2.2. Univariate Selection

In Figure 4, we show the ratio for the most significant features. In Table 2, we show the notation for the EEG channels and pair of electrodes used in the Figure 4.

Figure 4 shows that the following demographic characteristics and personality traits were selected: arousal (openness), sadness (sex, extraversion, and openness), fear (openness), surprise (extroversion and emotional stability), disgust (agreeableness and emotional stability), and neutral (conscientiousness and emotional stability).

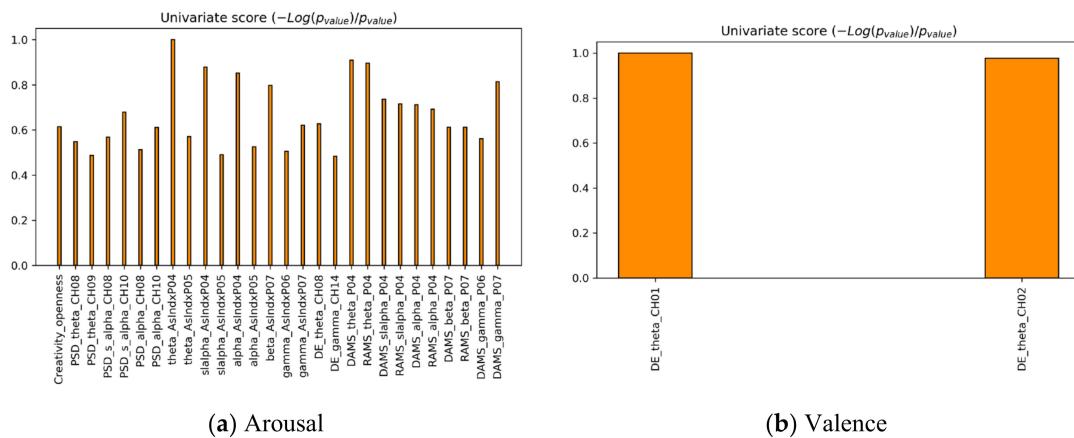
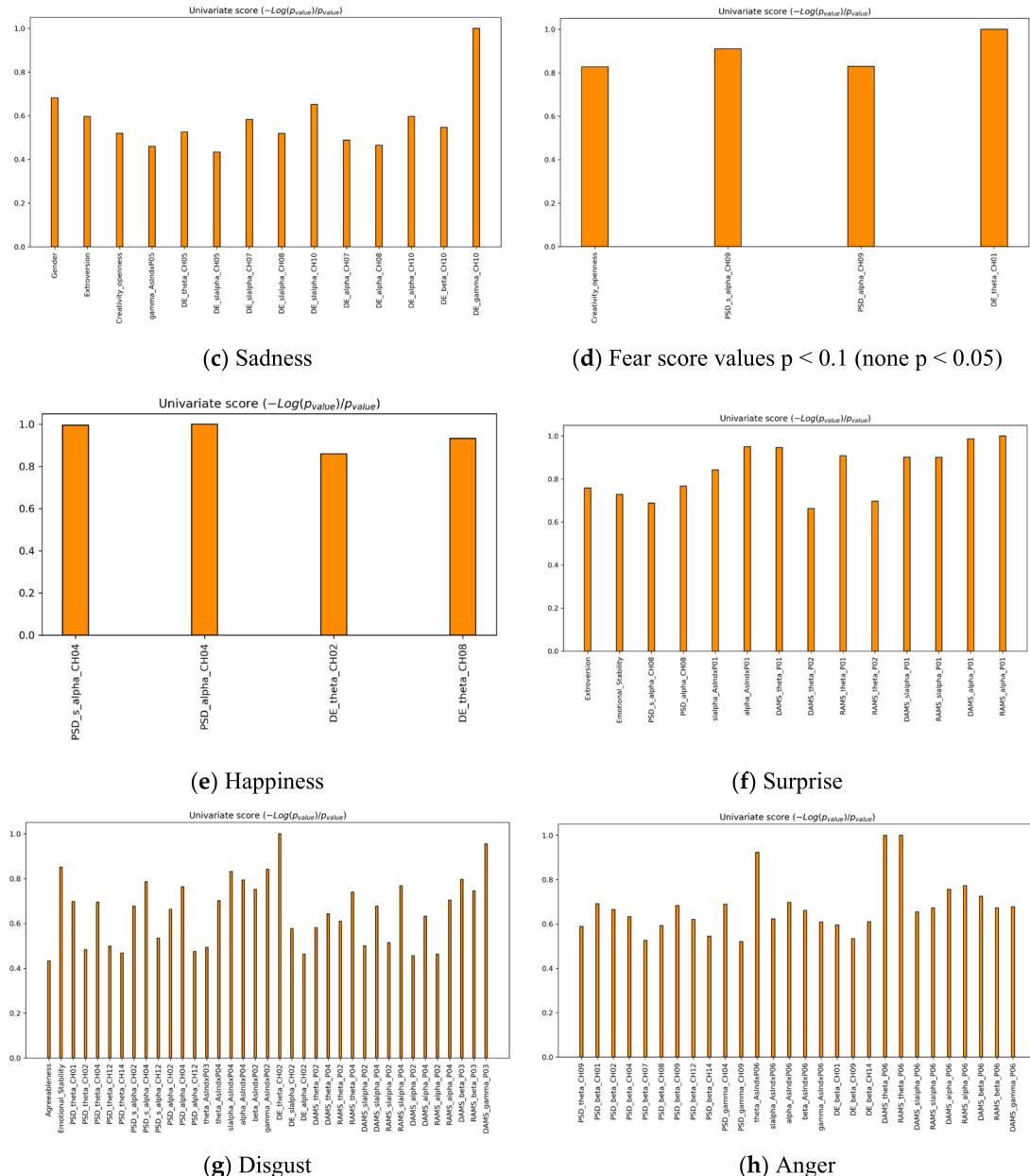


Figure 4. Cont.

**Figure 4.** Cont.

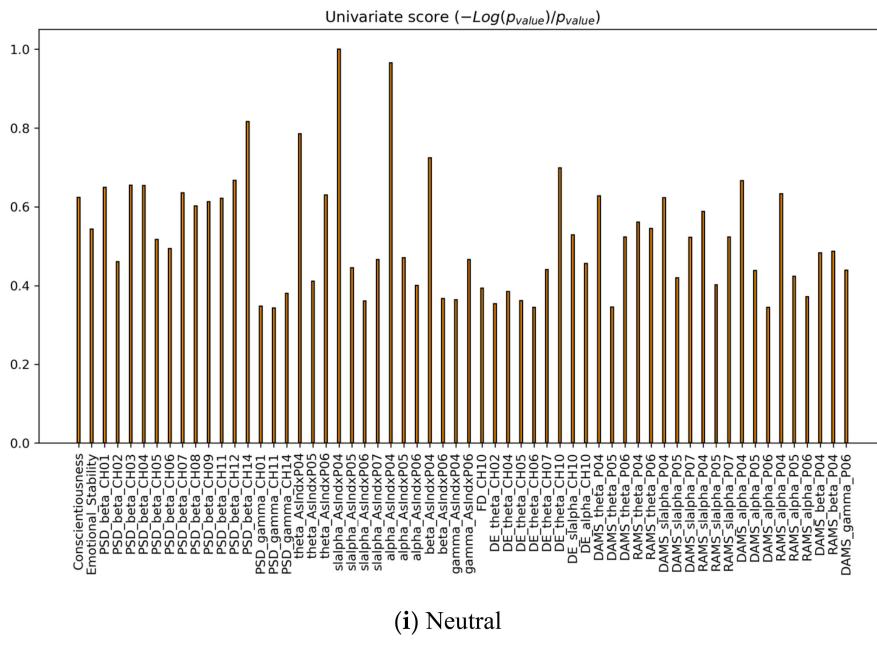


Figure 4. Univariate selection features with first set of features for self-assessed emotional labels classification. On the x-axis, the list of features is represented; on the y-axis, univariate score is shown.

For the arousal label, the EEG traits selected were: PSD in the theta (O2, P8), slow alpha (O2, T8), and alpha (O2, T8); PSA index for FC5/FC6, and T7/T8 in the theta, slow alpha, and alpha bands, for O1/O2 in the beta band, and for P7/P8 and, O1/O2 in the gamma band; DE in theta (O2), and gamma (CH14); and DASM in the theta, slow alpha, and alpha bands for FC5/FC6, in beta for O1/O2, and gamma band for P7/P8, and O1/O2. For valence label, important EEG features selected were: DE for AF3, and F7 in the theta band.

3.2.3. RFE with Cross-Validation

In this case EEG traits were selected for the nine different scenarios. No demographic characteristics and personality traits were selected by the algorithm:

- We obtained 16 features for arousal label: PSD in slow alpha (AF3, T8) and gamma band (FC6), PSA index in the theta (FC5/FC6), alpha (T7/T8), and gamma (FC5/FC6) bands; and DE in the theta (F3, T7, O1, O2, F4), slow alpha (P8, AF4), alpha (T7), beta (FC6), and gamma (AF3) bands.
- We obtained 40 features for valence label: PSD in theta (P7, T8, AF4), slow alpha (AF3, T8), alpha (O1, T8), beta (T8, FC6), and gamma (T8, F8, AF4) bands, PSA index in the theta (F7/F8), slow alpha (AF3/AF4, F7/F8, T7/T8, O1/O2) alpha (FC5/FC6), and beta (F7/F8, O1/O2) band; FD in FC5, T7, O2 channels; DE in theta (F7, F3, F4), beta (F3, FC5, P8, F4, AF4), and gamma (AF3) bands; DASM for theta (AF3/AF4), alpha (P7/P8), and beta (F7/F8) bands; and RASM for beta (AF3/AF4, P7/P8), theta (AF3/AF4), slow alpha (O1/O2) and alpha (F7/F8) bands.
- We obtained 8 features for disgust: PSD in theta (AF3, F7, P7, AF4), slow alpha (AF3, FC5, P7, F4), alpha (F7, P7) and gamma (AF3, F3, AF4) band; PSA index in the beta band (P7/P8); and DASM and RASM for slow alpha and beta bands (F3/F4).
- We obtained only one feature for: sadness (PSD in theta band channel O2), fear (PSD in alpha band channel P8), happiness (PSD in gamma band channel F8), neutral (PSD in beta band channel P8), anger (PSD in alpha band channel FC6), and surprise (PSD in alpha band channel P7).

Finally, we built a dataset combining the results from the univariate selection and the RFE feature selection process to determine how the performance of the classifiers behave in contrast to the original sets of traits.

In general, PSD, PSA DE and DASM features were selected for arousal labels. Diverse EEG information were retrieved for valence labels. PSD, PSA and DE at the temporal (T7, T8), and occipital (O1, O2) regions of the scalp were selected for sadness. For happiness PSD and DE features were selected. PSD, PSA, DASM and RASM were the features selected for surprise label. For disgust, PSD, PSA, DE DASM and RASM at the frontal (AF3, AF4, F3, F4, FC5, FC6, F7, F8) and parietal (P7, P8) regions of the scalp were selected.

3.3. Classifiers

3.3.1. EEG Data, Sex, Age, and Personality Traits to Predict Video Emotional Labels

We tested the different machine learning classification models with a 10-fold cross-validation for the two features sets defined as follow: a first set of features with EEG data, sex, age, and personality traits; and a second set of features with EEG data, sex, age, and personality traits reduced using feature selection. In Table 3, the mean accuracy, mean F1, and mean AUC scores are shown for the different sets, classifiers, and scenario labels. For valence–arousal scenario, the first set of features outperformed when we used SVM with linear kernel for the HAHV (accuracy 0.61, F1 0.14, AUC 0.61), LAHV (accuracy 0.64, F1 0.15, AUC 0.54), and LALV (accuracy 0.61, F1 0.15, AUC 0.55) labels. When we used the second set of features, HALV (accuracy 0.74, F1 0.00, AUC 0.51) using SVM with linear kernel had a good performance—higher than change for accuracy and AUC scores. For arousal and valence labels, using the second set of features for arousal, the best classifier was SVM with linear kernel (accuracy 0.52, F1 0.49, AUC 0.51); for valence the best classifier was ANN (accuracy 0.51, F1 0.67, AUC 0.56). For arousal labels, the worst performance was obtained with random forest and the first set of features. For valence labels, the worst performance was obtained with Naïve Bayes and the first set of features.

Table 3. Classifiers performance for each of the scenarios with the different set of traits: accuracies, F1, and AUC scores.

Scenario	Classifiers	Label	EEG Data, Demographic Characteristics, and Personality Traits (First Set of Features)			EEG Data, Demographic Characteristics, and Personality Traits (Reduction) (Second Set of Features)		
			Mean Accuracy	Mean F1	Mean AUC	Mean Accuracy	Mean F1	Mean AUC
Valence–arousal	SVM linear	HAHV	0.61	0.14	0.61	0.75	0.00	0.50
		HALV	0.61	0.23	0.49	0.74	0.00	0.51
		LAHV	0.64	0.15	0.54	0.76	0.00	0.48
		LALV	0.61	0.15	0.55	0.75	0.00	0.49
	SVM RBF	HAHV	0.60	0.20	0.49	0.75	0.00	0.56
		HALV	0.63	0.28	0.46	0.74	0.00	0.51
		LAHV	0.66	0.24	0.48	0.76	0.00	0.48
		LALV	0.60	0.19	0.49	0.75	0.00	0.48
Arousal	SVM linear	SVM linear	0.48	0.46	0.53	0.52	0.49	0.51
		SVM RBF	0.50	0.49	0.51	0.50	0.45	0.43
	ANN	Naïve Bayes	0.44	0.51	0.45	0.51	0.24	0.51
		Random Forest	0.44	0.39	0.39	0.44	0.40	0.43
	SVM linear	ANN	0.51	0.13	0.47	0.52	0.21	0.54
		SVM linear	0.49	0.50	0.55	0.51	0.55	0.45
	SVM RBF	SVM RBF	0.47	0.49	0.52	0.52	0.59	0.44
		Naïve Bayes	0.42	0.31	0.43	0.54	0.43	0.55
Valence	Random Forest	Random Forest	0.44	0.48	0.39	0.49	0.51	0.50
		ANN	0.50	0.34	0.47	0.51	0.67	0.56

We used receiver operating characteristic (ROC) curves to describe the performance of the best classifiers obtained from each scenario. In Figure 5, we show the 10-fold cross-validation ROC curves for each of the valence-arousal labels when using the first and second features sets with the best accuracies scores. For HAHV, LAHV and LALV labels, the first set of features containing EEG data, sex, age, and personality traits without feature selection obtained the best accuracy score. For the HALV label, the second set of features containing EEG data, sex, age, and personality traits with feature selection had the best accuracy classification. The curves show that the classification process is higher than chance; however, the F1 scores were low, indicating that the classifiers did not achieve good precision (number of correct positive predictions the model got among all the items identified as positive) nor recall (proportion of predictions correctly identified as positive); i.e., the predictions are not relevant in these cases.

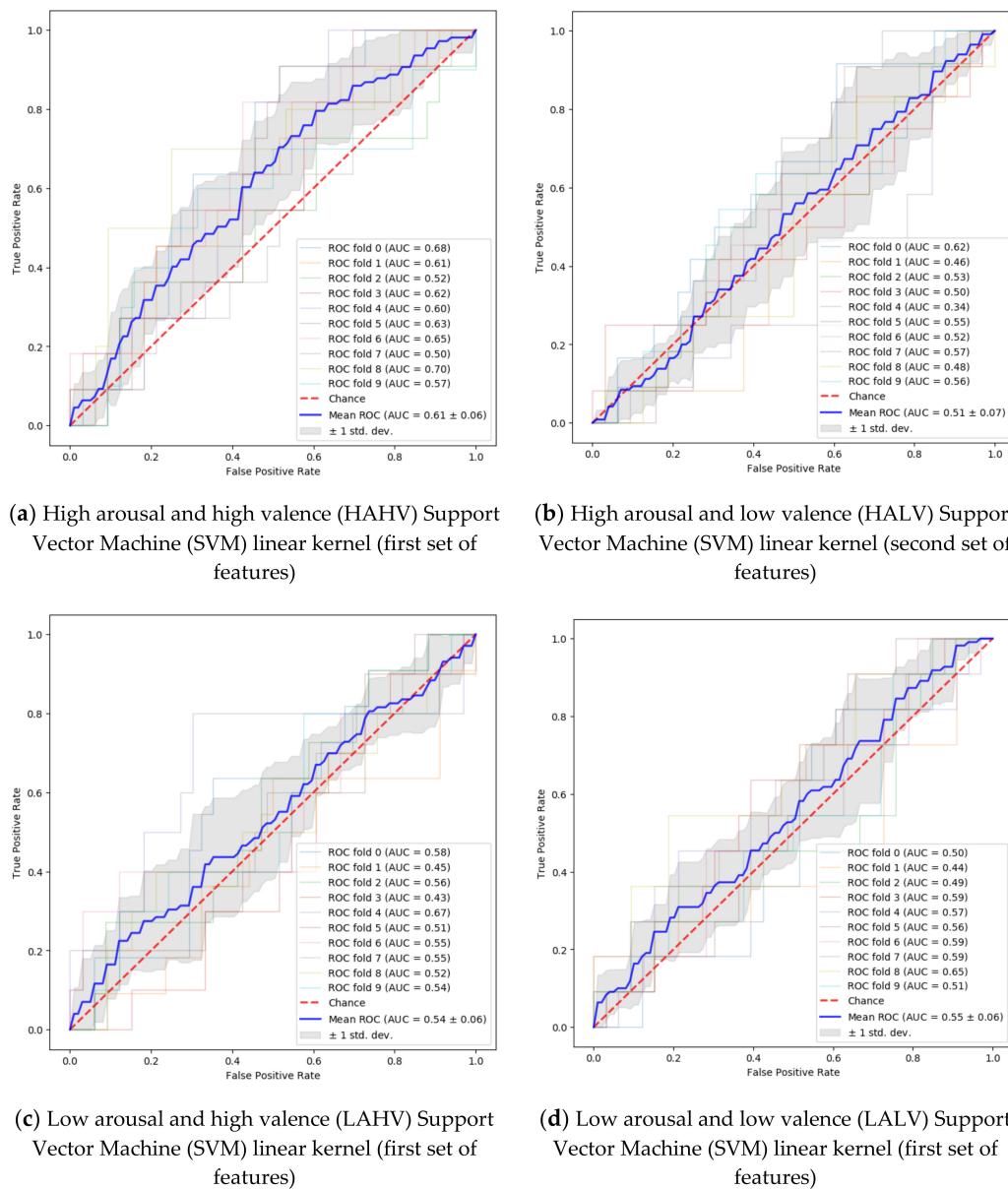


Figure 5. Best receiver operating characteristic curves with 10-fold cross-validation for valence-arousal label.

Figure 6 shows the 10-fold cross-validation ROC curves for the arousal label scenario and the valence label scenario with the best accuracies scores. The curves show the best classification performance for arousal label was obtained using EEG traits with feature reduction and SVM with linear kernel classifier (0.52 accuracy score when AUC score is higher than chance). For the valence scenario, the second set of features and the ANN classifier had the best accuracy; in this case, the curve shows that the classification process was slightly higher than chance.

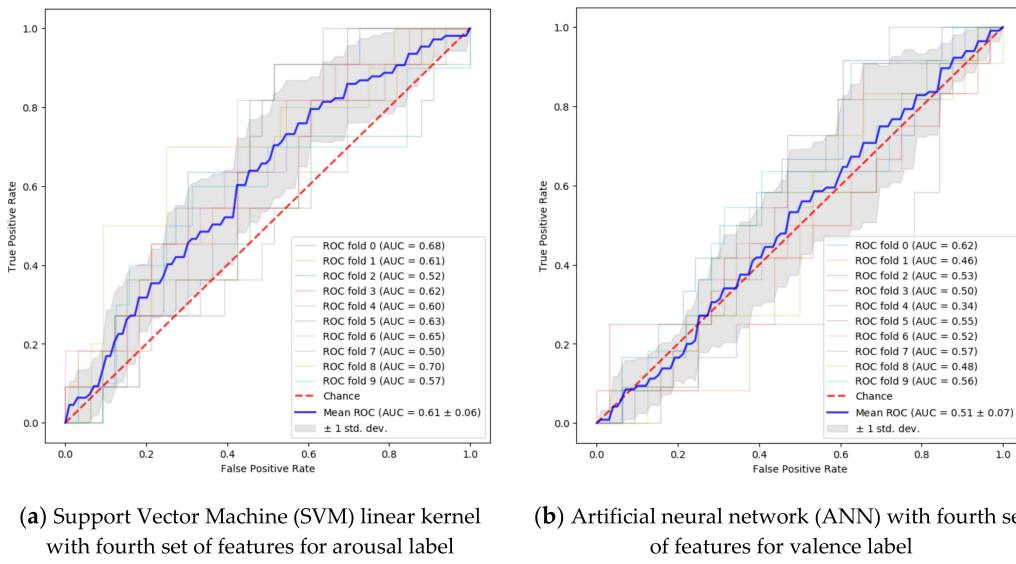


Figure 6. Best receiver operating characteristic curves with 10-fold cross-validation.

3.3.2. EEG Data, Sex, Age, and Personality Traits to Predict Self-Assessed Traits Labels

In Table 4, the mean accuracy, mean F1 and mean AUC scores are shown for the different classifiers and scenario labels. For the arousal scenario, the first set of features (EEG data, sex, age, and personality traits without reduction) performed better when we used SVM with RBF kernel (accuracy 0.68, F1 0.67, AUC 0.71). For the valence scenario, the second set of features (EEG data, sex, age, and personality traits with reduction) performed better when we used SVM with linear kernel (accuracy 0.61, F1 0.65, AUC 0.62). In these cases, we noticed that no demographic characteristics nor personality traits were selected in the reduced set of features; i.e., the improvement in the classification accuracies was owing to the EEG traits selected. For arousal labels, the worst performance was obtained with ANN in both sets of features. For valence labels, the worst performance was obtained with Naïve Bayes and ANN in both sets of features.

When we compared the classifier performance for the discrete emotions, we identified that the accuracy and the AUC scores yielded good results for some of the cases; however, the F1 scores were low, indicating that the classifiers did not achieve good precision (number of correct positive predictions the model got among all the items identified as positive) nor recall (proportion of predictions correctly identified as positive), indicating that the predictions were not relevant in these cases.

Table 4. Classifiers performance for each of the scenarios with the defined set of traits accuracies, F1, and area under the curve (AUC) scores.

Scenario	Classifiers	EEG Data, Demographic Characteristics, and Personality Traits (Third Set of Features)			EEG Data, Demographic Characteristics, and Personality Traits (Reduction) (Fourth Set of Features)			
		F1	Mean Accuracy	Mean F1	Mean AUC	Mean Accuracy	Mean F1	Mean AUC
Arousal	SVM linear	0.592	0.63	0.60	0.66	0.62	0.58	0.65
	SVM RBF		0.68	0.67	0.71	0.64	0.63	0.67
	Naïve Bayes		0.54	0.60	0.57	0.59	0.60	0.62
	Random Forest		0.64	0.61	0.69	0.63	0.61	0.69
	ANN		0.52	0.20	0.54	0.52	0.04	0.62
Valence	SVM linear	0.576	0.53	0.56	0.47	0.61	0.65	0.62
	SVM RBF		0.52	0.56	0.46	0.59	0.64	0.62
	Naïve Bayes		0.50	0.59	0.47	0.52	0.67	0.49
	Random Forest		0.52	0.60	0.50	0.53	0.60	0.55
	ANN		0.51	0.49	0.47	0.53	0.63	0.53
Sadness	SVM linear		0.59	0.29	0.47	0.71	0.00	0.52
	SVM RBF		0.62	0.35	0.57	0.70	0.18	0.60
	Naïve Bayes		0.52	0.32	0.49	0.67	0.30	0.62
	Random Forest		0.67	0.09	0.61	0.67	0.16	0.57
	ANN		0.71	0.00	0.53	0.71	0.00	0.55
Fear	SVM linear		0.64	0.16	0.53	0.79	0.00	0.46
	SVM RBF		0.71	0.20	0.48	0.79	0.00	0.49
	Naïve Bayes		0.30	0.32	0.43	0.79	0.00	0.53
	Random Forest		0.78	0.00	0.47	0.66	0.16	0.50
	ANN		0.79	0.00	0.47	0.79	0.00	0.48
Happiness	SVM linear		0.76	0.11	0.50	0.88	0.00	0.49
	SVM RBF		0.80	0.08	0.50	0.88	0.00	0.56
	Naïve Bayes		0.42	0.19	0.45	0.85	0.12	0.59
	Random Forest		0.87	0.00	0.50	0.87	0.03	0.56
	ANN		0.88	0.00	0.46	0.88	0.00	0.41
Neutral	SVM linear		0.59	0.34	0.55	0.70	0.19	0.61
	SVM RBF		0.6	0.44	0.63	0.69	0.37	0.62
	Naïve Bayes		0.50	0.49	0.60	0.68	0.15	0.61
	Random Forest		0.70	0.23	0.60	0.67	0.25	0.61
	ANN		0.70	0.00	0.49	0.70	0.00	0.50
Disgust	SVM linear		0.80	0.20	0.52	0.89	0.00	0.52
	SVM RBF		0.85	0.25	0.64	0.88	0.10	0.56
	Naïve Bayes		0.33	0.21	0.53	0.43	0.20	0.56
	Random Forest		0.88	0.00	0.63	0.88	0.03	0.63
	ANN		0.89	0.00	0.59	0.89	0.00	0.49
Anger	SVM linear		0.54	0.33	0.50	0.61	0.01	0.49
	SVM RBF		0.53	0.36	0.43	0.63	0.09	0.55
	Naïve Bayes		0.39	0.52	0.52	0.53	0.40	0.54
	Random Forest		0.58	0.18	0.50	0.60	0.27	0.49
	ANN		0.60	0.05	0.47	0.63	0.00	0.48
Surprise	SVM linear		0.76	0.18	0.41	0.86	0.00	0.57
	SVM RBF		0.78	0.18	0.39	0.85	0.00	0.56
	Naïve Bayes		0.32	0.27	0.54	0.46	0.24	0.56
	Random Forest		0.85	0.03	0.51	0.84	0.02	0.54
	ANN		0.86	0.00	0.53	0.86	0.00	0.61

We use ROC curves to describe the performance of the best classifiers obtained. Figure 7 shows the 10-fold cross-validation ROC curves for arousal and valence labels. The best accuracy scores were obtained for the arousal with 0.68 and valence with 0.61. For the discrete emotions, we decided not to show the ROC curves owing to the low F1 scores obtained in each case.

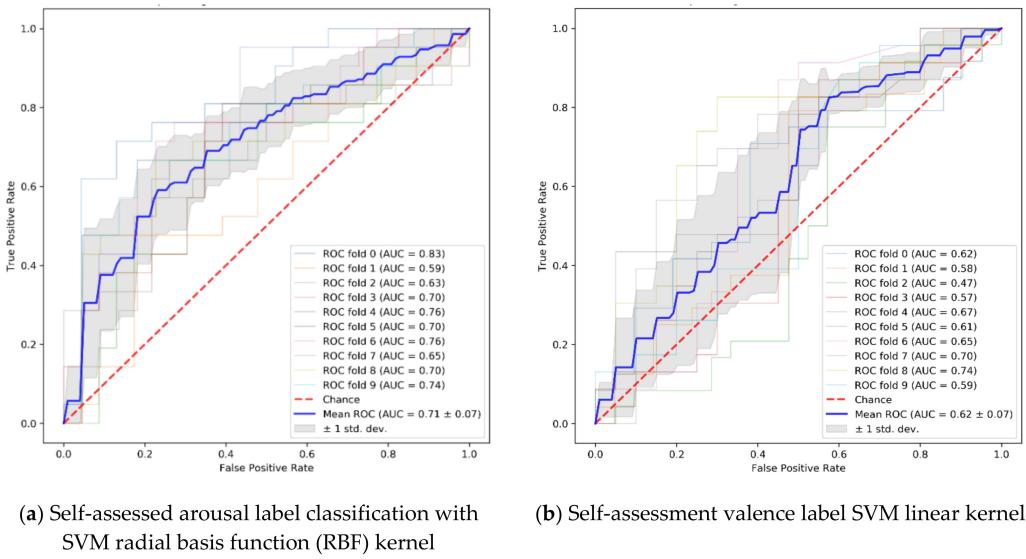


Figure 7. Best receiver operating characteristic curves with 10-fold cross-validation with for Valence label.

4. Discussion

The results obtained in this work revealed that none age, sex, or personality had a correlation with arousal and valence labels from the emotional stimuli. However, compared with self-assessed emotional labels, some demographic characteristics and personality traits were chosen by the feature selection for arousal; for some of the discrete emotions, this might be because the self-assessed responses relied on participants' subjective emotion assessment. If so, demographic characteristics and personality traits would correlate more with the self-assessed emotion responses than with the emotional labels from the stimuli videos. If we analyze the classification performance, only relevant results were obtained for arousal and valence labels from self-assessed answers (owing to low values of F1 scores for discrete emotions). Feature selection showed only an improvement in the classification scores for the valence label; neither demographic characteristics nor personality traits were selected by the feature selection process, which shows that age, sex, and personality traits did not foster classification performance improvement for the selected labels.

It is known from previous works that sex and age can be correlated with these emotional labels and can improve emotion recognition process [2]; however, it is still unclear how personality can be used to obtain better emotion recognition models. We believe that one of the reasons why sex, age, and personality were not chosen by the feature selection algorithms was because the nature of the data. If we adjust the values to a categorical and binary codification, the feature selection algorithms could select these kind of features (as age was selected in the Rukavina and colleagues' work [2]). We decided to work with the continuous data owing to the real description of the population. Other possible limitation is related to the distribution of personalities in the participants, because the sample is relative small to obtain a vast distribution in the five personality traits assessed, and the reported scores are close to each other, implying that the participants exhibit the same type of personality among the group [51], it is difficult to obtain data that describe all the possible outcomes to design classifiers.

Works like [69], intended to create more complex deep learning models which personality information can increase in 10% accuracy of the emotion recognition. Although the literature shows a strong relationship between emotion, mood affective states, and personality, the papers presented here and the information from the AMIGOS dataset analysis still does not provide conclusive information about whether there is a strong correlation between emotion stimuli, emotional states, and personality. We believe this is owing to how the information from the personality questionnaires is being fit as a feature for the classifiers and how the classifiers are being designed for emotion recognition. Utilizing

new, deep learning techniques could possibly integrate this kind of information in a more suitable way to achieve personalized emotion recognition models. There is also a need for a behavioral metric that can identify differences between how people perceive and manifest emotions. Behavior changes and emotional reaction can vary from person to person owing to past experiences, memories, and context.

Comparing the results, it is still difficult, using traditional machine learning models or basic deep learning models, to obtain higher classification accuracies using EEG traits when different variables need to be considered (the number of participants in an experiment, number of EEG channels, EEG signals and traits, etc.). Furthermore, it is important to consider the dynamics of the emotional stimuli and how the participants perceive these stimuli; pictures, videos, interactive interfaces, and virtual environments come with different variables. There is still the need to analyze how time, familiarity, interaction, and so on affect individuals' emotion recognition processes, and how the EEG features are correlated with these variables to describe individuals' emotional behavior when interacting with stimuli material. Classification accuracies vary between the different EEG traits used in the classification process and the number of participants in the experiment [11,14]. How to obtain good classification accuracies in cross-participants experiments, which can allow researchers to have more freedom in using different stimuli methods and degrees of interaction with systems to identify emotional states from EEG signals, remains unknown. The literature provides hints about how behavioral cues can be described as digital data to use in emotion recognition when there is an interaction between a person and a machine.

One of the most important physiological signals used in emotion recognition is EEG, owing to the number of features that can identify emotional behavior in the brain and the idea of integrating emotion to BCI systems; however, it is still difficult to achieve higher accuracies for emotion classification using only EEG signals. To face this challenge, multimodal approaches are being implemented because they are robust and increase the accuracy for emotion classification, in contrast to systems that only rely on one information source. Signals like ECG, EMG, and GSR are also considered in these studies because they provide relevant information about individuals' emotional and behavioral state.

Perceived emotions may be owing to exposure to the emotional stimuli (video in this case); however, the chosen dataset did not have information about arousal–valence scores related to the video time traces. In the scope of this analysis, we did not try to trace the changes in emotional response related to the emotional stimuli over time; instead, we wanted to determine how EEG data, age, sex, and personality traits performed while classifying emotions compared with the AMIGOS dataset, in which the classification was made by averaging the time window. Consequently, we used different machine learning techniques and compared the results with the AMIGOS dataset. To analyze emotion recognition over time, techniques such as RNN or learning and teaching support material are recommended, which are beyond the scope of this study.

In future research, it is important to address specific challenges like: the access to a wider and diverse population where participant exhibit different demographic characteristics, personality traits, and behavioral cues; the nature of the emotional stimuli, whether they are passive or active; the data gathered and its evaluation during stimuli exposure time, and the interaction type that the participant can experience while using HCI systems. For personalized HCI, it is important to analyze, not only intrinsic characteristics as demographic or personality traits, but also behavioral cues that manifest when using HCI systems and its context. For future works we would like to focus our approach on capturing and analyzing behavioral cues, together with physiological signals, related to the use of a specific technology or the task being performed.

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Correlations between personality traits and specific groups of alpha waves in the human EEG

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ABSTRACT

Background. Different individuals have alpha waves with different wavelengths. The distribution of the wavelengths is assumed to be bell-shaped and smooth. Although this view is generally accepted, it is still just an assumption and has never been critically tested. When exploring the relationship between alpha waves and personality traits, it makes a huge difference if the distribution of the alpha waves is smooth or if specific groups of alpha waves can be demonstrated. Previous studies have not considered the possibility that specific groups of alpha waves may exist.

Methods. Computerized EEGs have become standard, but wavelength measurements are problematic when based on averaging procedures using the Fourier transformation because such procedures cause a large systematic error. If the actual wavelength is of interest, it is necessary to go back to basic physiology and use raw EEG signals. In the present study, measurements were made directly from sequences of alpha waves where every wave could be identified. Personality dimensions were measured using an inventory derived from the International Personality Item Pool.

Results. Recordings from 200 healthy individuals revealed that there are three main groups of alpha waves. These groups had frequencies around 8, 10, and 12 waves per second. The middle group had a bimodal distribution, and a subdivision gave a total of four alpha groups. In the center of each group, the degree of extraversion was high and the degree of neuroticism was low. Many small differences in personality traits were found when the centers were compared with one another. This gave four personality profiles that resemble the four classical temperaments. When people in the surrounding zones were compared with those in the centers, relatively large differences in personality traits were found.

Conclusions. Specific groups of alpha waves exist, and these groups have to be taken into account when correlations are made to personality dimensions and temperament types. There is a link between alpha waves and personality traits, and this link implies that there is an underlying relationship. To explain the nature of this relationship, there are two hypotheses that can be applied. One of these deals with the general organization of the forebrain and the other explains why the brain generates alpha waves.

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INTRODUCTION

Alpha waves and personality dimensions

Many researchers have attempted to define the relationship between alpha waves and personality dimensions ([Gale, 1983](#); [Klimesch, 1999](#)). Of all the data obtained via electroencephalography (EEG), individual alpha frequency stands out as a measure that can be correlated with personality dimensions. For instance, [Robinson \(2001\)](#) found 11 studies that reported a link between alpha frequency and the degree of extraversion. In all of these studies, the mean value of the alpha frequency was slightly higher in groups with introverted individuals compared to groups with extraverted individuals. The differences were statistically significant in seven of the studies.

Over the years, controversies have emerged regarding the various factors that could influence the link between alpha waves and extraversion ([Gale, 1983](#); [Tran, Craig & McIssac, 2001](#); [Robinson, 2001](#)). In a study conducted by [Hagemann et al. \(2009\)](#), internal and external factors were found to have a minimal effect on this correlation. The authors tested whether there was a linear relationship between alpha power density and extraversion, and they found that the correlation coefficient for the overall measure was small (0.22). None of the previous studies tested for a relationship along curved lines or took into consideration that there might be specific alpha groups ([Gale, 1983](#); [Klimesch, 1999](#); [Tran, Craig & McIssac, 2001](#); [Robinson, 2001](#); [Hagemann et al., 2009](#)).

Need for an alpha hypothesis

To understand how alpha waves are linked to personality traits, it would be helpful to have an explanation as to why the brain generates alpha waves. A possible explanation involves the activity in the columns in the cerebral cortex. It has been suggested that each column exhibits neuronal activity either at a high level or at a comparatively low level ([Johannisson, 1984](#)).

In this model, a cerebral column has activity at the high level for a short period of time. When the activity in a column changes from the high level to the low level, the activity in another column may jump up to the high level. Thus, there is a continuous turnover of highly active columns, which results in a flow of thoughts and feelings.

There is a difference in mental activity when something is appearing in consciousness and when that something has disappeared from the conscious level. Two different levels of neuronal activity may account for this observation. Furthermore, only a very tiny fraction of everything that could appear in consciousness actually appears there at each moment in time. To account for this, it is likely that only a very small number of columns are involved in high-level processing at any one time ([Johannisson, 1993](#)).

In the “two levels” hypothesis, the number of columns active at the high level is kept within certain limits via a regulating system ([Johannisson, 1984](#)). When the number of highly active columns is at the lower limit, regulating signals from the thalamus raise the excitability of all columns that are active at the low level until one of them jumps up to the high level of activity. Conversely, when the upper limit is reached, the regulating system decreases the excitability. When one of the highly active columns leaves the high conscious level, the system returns to the lower limit, such that the excitability will be increased again. These repeated changes in excitability in all columns with low activity are seen in

the EEG as alpha waves. This hypothesis explains why and how alpha waves are generated (*Johannesson & Nilsson, 1996*).

Groups of alpha waves

The limits for the number of highly active columns can be different for different individuals (*Johannesson & Nilsson, 1996*). Therefore, if the hypothesis is true, there must be specific frequency groups corresponding to the different limits. However, alpha frequencies from different individuals are usually described as having a distribution that is smooth and homogeneous (*Klimesch, 1999; Robinson, 2006; Başar, 2012; Bazanova & Vernon, 2014*). This is an assumption that has become generally accepted, although it has never been critically tested.

In the present study, the distribution was not at all smooth, and alpha waves from different individuals were found to be in three large groups. The alpha frequencies in these groups were around 8, 10, and 12 Hz (waves per second). The groups are very easy to miss. In a histogram showing the distribution of individual alpha frequencies, the groups are visible only if the bin width is narrow.

The existence of three alpha groups was predicted from an alpha hypothesis (*Johannesson & Nilsson, 1996*), and the present study was designed in such a way that it was possible to test if specific alpha groups exist. The experiment is very simple but somewhat time-consuming because a narrow bin width in a histogram requires a relatively large number of observations. When the alpha frequencies from 200 individuals were included in the histogram, the pattern with three large alpha groups became clearly visible.

The link between alpha waves and personality dimensions was explored further in the present study. The new finding of distinct alpha groups has to be taken into account when studying how the alpha waves are related to personality dimensions and temperament types.

METHODS

Participants

There were 200 participants in the study, and to reach this number, 204 healthy individuals were invited to take part. Approval was obtained from the Regional Ethics Board for University of Göteborg (R627–97) and written informed consent was obtained from all participants. For participants younger than 18 years, written informed assent was also obtained from a parent. The age of the participants ranged from 15 to 70 years, with a mean age of 37.5 years and a standard deviation of 13.0 years. The study included 63% females and 37% males. Of the participants, 34% were students, 26% nurses, 14% doctors, 7% social workers, and 19% were individuals with other occupations.

EEG measurements

The individual alpha frequency was measured from single sequences of alpha waves where every wave could be identified (Fig. 1). When testing the alpha hypothesis (*Johannesson & Nilsson, 1996*), it is the actual wavelength that is of interest, rather than the amount of oscillatory components in different frequency bands. For the purpose of this study, measurements directly from sequences of alpha waves have a much higher accuracy compared to data from averaging procedures using the Fourier transformation. A comparison between the two methods is made in ‘Discussion’.

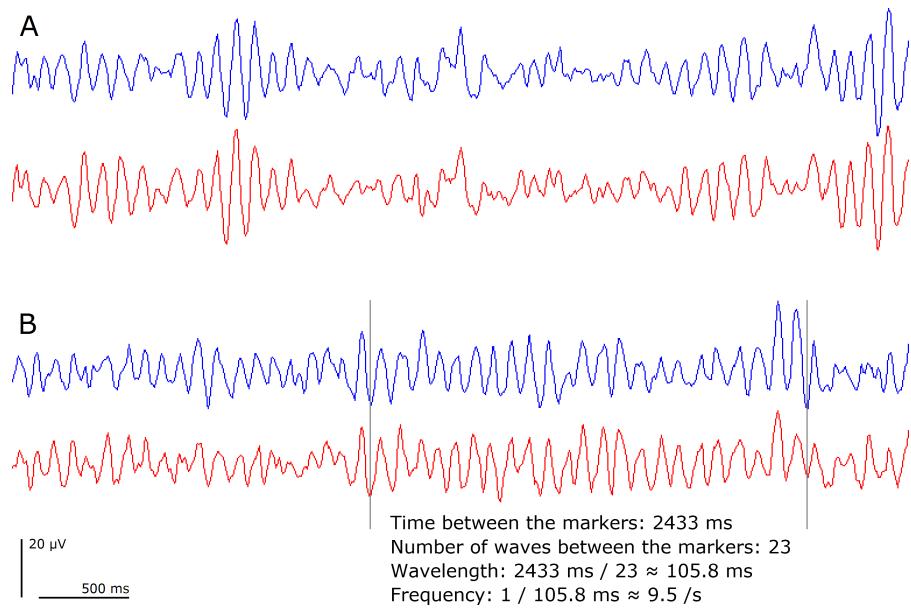


Figure 1 Alpha waves. (A) Short sequences of alpha waves. (B) An example of a sequence used in the present study. Blue tracings are from AFz-TP9 and red tracings are from AFz-TP10.

Figure 1 shows how the wavelength and alpha frequency were calculated. The number of waves in a sequence of alpha waves divided by the time for the whole sequence gave the alpha frequency. One sequence of alpha waves was used for each participant, and to ensure a reasonably high degree of objectivity, the longest sequence was selected. For most of the recordings, this procedure left very little room for subjective judgments. Sequences of alpha waves from all participants are available in [Data S1](#).

Spontaneous activity was recorded while the participants rested in a reclining chair with their eyes closed. Recording took place in a silent room with reduced lighting. The recording conditions were optimized to enable the collection of clear and clean alpha waves. The electrodes were placed on hairless areas of skin behind the ears and on the midline just below the hairline. This made it possible to use tape electrodes that resulted in a considerably lower degree of discomfort compared to ordinary arrangements. Moreover, the probability of getting long sequences of alpha waves was expected to increase when the participant could relax during the recording session. This also ensured that muscle activity seldom interfered with the recording. A small amount of conductive gel was used and the impedance values were below 3 kOhm for most participants.

Data were generally collected during a total time of 2.5 min (30 epochs of 5 s each, as shown in Fig. 1). When there was a large amount of irregular activity, the recording time was prolonged to increase the chance of obtaining a long sequence of alpha waves. Two channels were used, corresponding to AFz-TP9 and AFz-TP10.

In a pilot study with EEGs from 213 subjects, different recording sites were compared in a methodical way (T Johannsson, 1999, unpublished data). A few recording electrodes were found to be sufficient to measure the alpha frequency because alpha waves are widespread. For instance, the longest sequence of regular waves was found in the occipital region in

approximately half of the recordings, and in 96% of these recordings, the same alpha waves were also seen in other regions. When the longest sequence appeared in a non-occipital region, 88% of the EEGs had the same alpha waves recorded simultaneously from occipital electrodes.

In histograms showing the distribution of individual alpha frequencies, distinct groups are visible only if the bin width is narrow. This requires a fairly high number of participants. In the pilot study, various combinations of bin width and number of individuals were tested. A clear pattern in the histogram required recordings from at least 200 subjects.

Personality measurements

The IPIP-NEO inventory was derived from the *International Personality Item Pool, 2016* (<http://www.ipip.org>). The 120-item version of the IPIP-NEO (Johnson, 2014) was used, and all participants completed all items. An online analysis gave estimates with respect to five broad domains and 30 subdomains of personality (<http://www.personal.psu.edu/j5j/IPIP>; Johnson, 2016). After adjusting for age and gender, the scores from the questionnaire were converted into percentile estimates.

Compared with the reference data used in the online analysis, the participants in the present study had, on average, higher extraversion scores and lower neuroticism scores. Moreover, many of the participants in the present study had high scores in the trust and cooperation subdomains.

The differences described above may reflect an unintentional bias in the recruitment of participants for this study. To facilitate comparison with future studies, the estimates are not normalized to fit the total mean values in the present sample. The data from the personality measurements are provided in [Data S2](#).

RESULTS

The degree of extraversion and neuroticism is plotted against the individual alpha frequency in [Fig. 2](#). The correlation lines in this figure are the usual way of describing the relationship between personality traits and alpha waves. However, there is another better way if we take into consideration that specific groups of alpha waves may exist.

Three main alpha groups

The histogram in [Fig. 3A](#) shows the distribution of alpha frequencies from different individuals. The distribution of the data is not smooth and large groups are visible. The center of one group is slightly above 8 Hz and the center of another group is somewhat below 12 Hz.

The data ranging from 9 to 11 Hz can be described as one large group with a bimodal distribution. A subdivision of the main group around 10 Hz gives a total of four groups, where the subgroups have alpha frequencies around 9.5 and 10.5 Hz.

Many participants did not have long sequences of well developed alpha waves (details can be found in [Data S1](#)). To test whether the existence of the alpha groups depends on how well the alpha waves are developed, the recordings were classified into three types: poorly, intermediately, and well developed alpha waves.

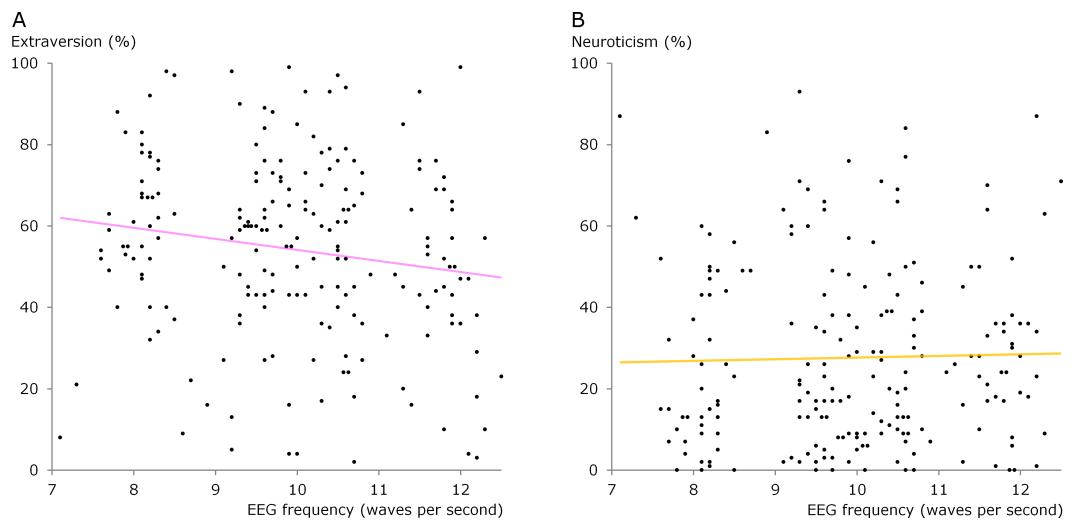


Figure 2 Scatter diagrams showing alpha frequency versus extraversion and neuroticism. Data for all 200 participants in the present study. The correlation coefficient for extraversion was -0.16 (statistically significant, $p < 0.05$ two tails) and the correlation coefficient for neuroticism was 0.02 (not statistically significant).

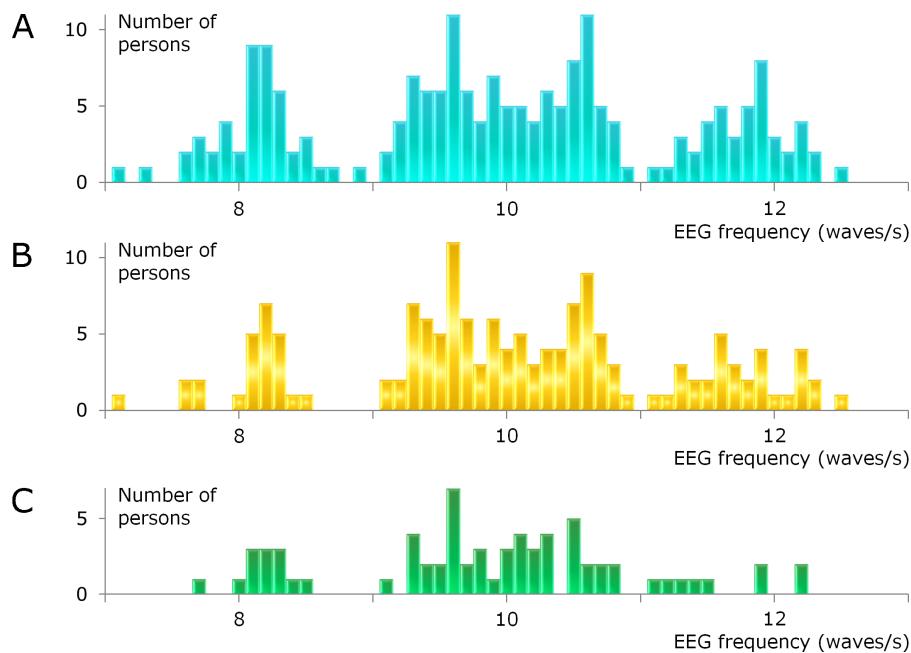


Figure 3 Distribution of individual alpha frequencies. The histograms have a bin width of 0.1 Hz. (A) All 200 participants. The recordings include poorly, intermediately, and well developed alpha waves. (B) As a control, recordings with poorly developed alpha waves are excluded. This reduced the sample size to $n = 150$. (C) Only recordings with well developed alpha waves ($n = 69$).

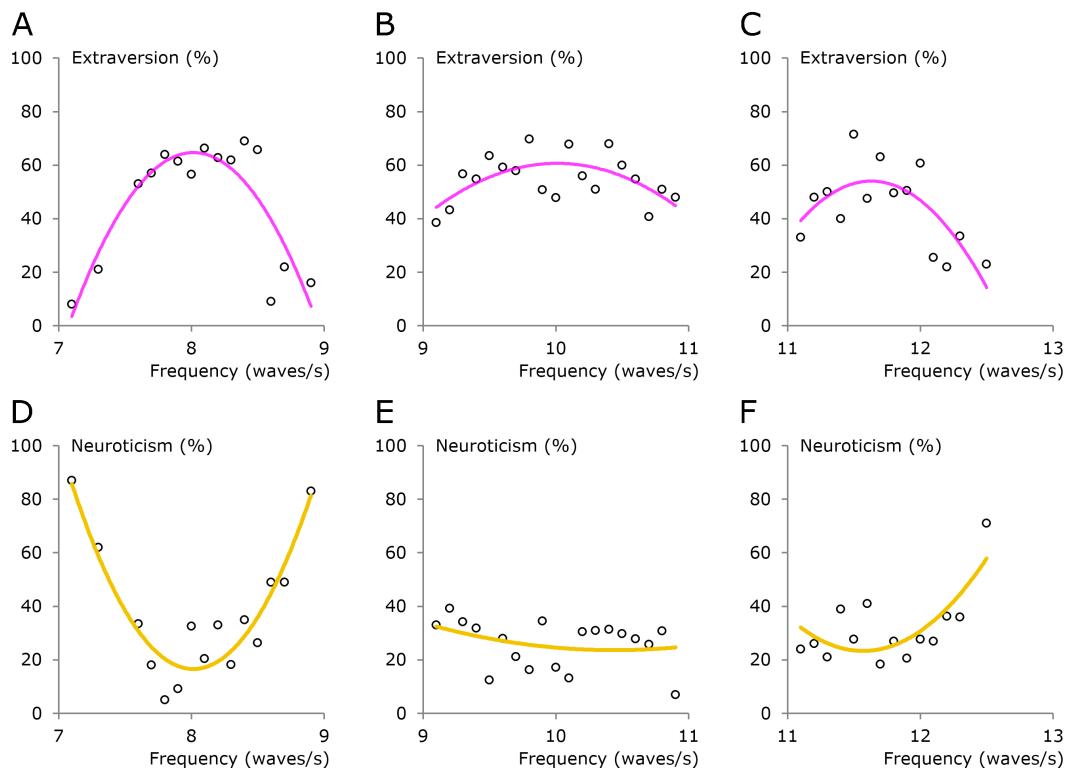


Figure 4 Three alpha segments. The frequency range was divided into three segments and the personality estimates are shown as mean values. (A–C) Extraversion. (D–F) Neuroticism. The trend lines are second-order polynomials.

When the alpha waves are poorly developed, measurements of the individual alpha frequency become problematic. All such measurements are excluded from Fig. 3B, and yet the three main alpha groups and the bimodal distribution for the middle group remain.

When the participants with an intermediate degree of alpha waves are also excluded, leaving only recordings with well developed alpha waves, as shown in Fig. 3C, the group around 12 Hz becomes small and the bimodal distribution for the middle group is not visible. What remains are a distinct group at 8 Hz and a gap at 9 Hz. Relatively few participants are included in Fig. 3C, and this histogram illustrates the problem with a narrow bin width and a small number of subjects.

Three alpha segments

In Fig. 4, the three main alpha groups are studied one at a time. Furthermore, mean values for the personality estimates are used, with these mean values reducing the number of data points. For example, there are four data points at 7.9 Hz in Fig. 2A and the mean value of the estimates from these four participants is shown as one data point in Fig. 4A.

The relationship between the alpha frequency and personality dimensions is much better described by curved lines than by straight lines (Fig. 4). The group around 8 Hz has a high degree of extraversion at the center of the group but not in the surrounding zones (Fig. 4A). This pattern is also seen for the groups around 10 and 12 Hz (Figs. 4B–4C).

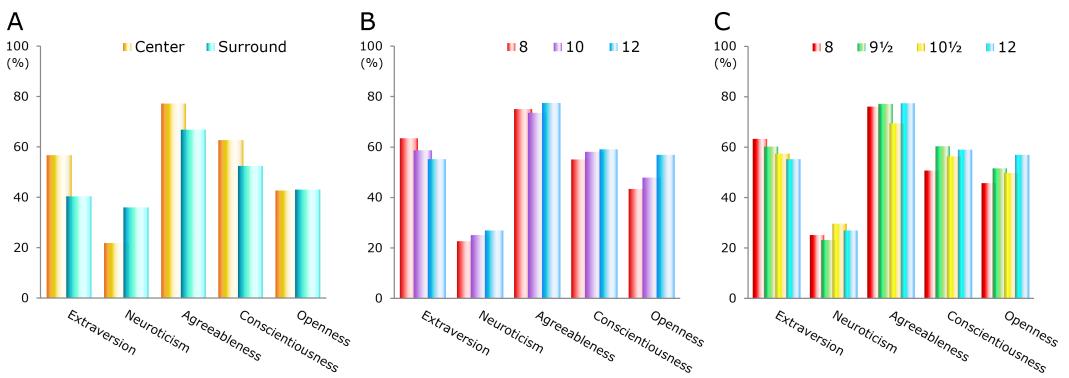


Figure 5 Mean estimates of personality traits in five domains. (A) Center and surrounding area. (B) Three alpha groups. (C) Four alpha groups.

The curves for neuroticism (Figs. 4D–4F) indicate that there is a difference between the centers of the groups and the surrounding zones. Overall, Fig. 4 supports the existence of three main alpha groups and substantiates the notion that extraversion is high and neuroticism is low in the center of each group.

Broad domains

Center versus surrounding area

To test whether there was a statistically significant difference between the center and the surrounding area, the data from the surrounding zones in Fig. 4 were combined. The selected ranges were 7.05–7.65, 8.55–9.35, 10.65–11.35, and 12.15–12.55 Hz, and the sample size for the surrounding data was $n = 43$. The ranges for the center data were 7.85–8.15, 9.85–10.15, and 11.65–11.95 Hz, which resulted in a sample size of $n = 49$. Two-tailed t -tests were used to determine differences.

For extraversion, the difference between the center and the surrounding area was highly significant ($p < 0.001$). The difference was also statistically significant for neuroticism ($p < 0.01$) and agreeableness ($p < 0.05$), but not for conscientiousness. For openness to experience, the mean estimates were about the same for the center and the surrounding area (Fig. 5A).

Three alpha groups

Figure 5B shows a comparison among the mean estimates for three groups of alpha waves. To ensure an adequate sample size when the three groups were considered separately, wide ranges for the center data were used (7.75–8.45, 9.45–10.55, and 11.45–12.05 Hz). The sample sizes of these three groups were 34, 68, and 28.

The differences among the three groups in Fig. 5B were relatively small, but there were some interesting trends. The group at 12 Hz had the highest score for all domains except for extraversion. For openness to experience, the difference between the groups at 8 and 12 Hz was statistically significant ($p < 0.05$).

Four alpha groups

The four groups shown in Fig. 5C had ranges of 7.95–8.35, 9.35–9.85, 10.15–10.65, and 11.45–12.05 Hz. These limits gave sample sizes of 26, 33, 34, and 28. The ranges for the four groups were sufficiently narrow when searching for personality traits that are representative of the centers of the alpha groups.

Figure 5C shows how the data were transformed after the division of the main group around 10 Hz into subgroups around 9.5 and 10.5 Hz. For neuroticism, the group at 9.5 Hz had the lowest score and the group at 10.5 Hz had the highest score of the four groups. For agreeableness, the group around 10.5 Hz stood out among the other groups.

The group at 9.5 Hz had the highest score on conscientiousness, but the score was just slightly higher than that obtained from the group at 12 Hz. The latter group still had the highest score on openness to experience and the lowest score on extraversion.

Subdomains

Each of the five broad domains has six subdomains (Table 1). Most of the differences among the four alpha groups were small, but when taken together they corresponded to four different personality profiles.

8 waves per second — Friendly and impulsive

The group around 8 Hz had a very high score in the friendliness subdomain. This score was significantly higher compared to the score for the group at 12 Hz ($p < 0.02$). The group at 8 Hz also had a mean score that was clearly higher than that of the group at 10.5 Hz ($p < 0.02$). The difference was smaller when the group at 8 Hz was compared with the group at 9.5 Hz, although it was still statistically significant ($p < 0.05$).

There were several other subdomains that could be used to characterize the group at 8 Hz. In the cautiousness subdomain, the group around 8 Hz had a lower mean score than did the groups around 9.5 Hz ($p < 0.05$) and around 12 Hz ($p < 0.05$). The difference between the group at 8 Hz and the group at 10.5 Hz was not large enough to be statistically significant.

9½ waves per second — Peaceful and reliable

In the anger subdomain, the group around 9.5 Hz had the lowest score of the four groups. The difference was largest when compared with the group at 8 Hz, although this result did not reach statistical significance.

The group at 9.5 Hz had relatively high estimates in almost all of the conscientiousness subdomains. In the dutifulness subdomain, this group had a higher score than the group around 8 Hz, and this difference was statistically significant ($p < 0.05$). Also, when compared with the groups at 10.5 and 12 Hz, the group at 9.5 Hz had a higher mean score, although these differences were not statistically significant.

10½ waves per second — Worried and less agreeable

People in the group at 10.5 Hz had a mean score in the anxiety subdomain that was higher than that in the groups at 9.5 Hz ($p < 0.05$) and at 12 Hz ($p < 0.05$). When compared with the group at 8 Hz, the group at 10.5 Hz had a somewhat higher score, but the difference was not statistically significant.

Table 1 Thirty subdomains from the five-factor model (Johnson, 2014). The four alpha groups (8, 9.5, 10.5, and 12) were defined by the alpha frequency in the same way as in Fig. 5C.

		8	9.5	10.5	12
Extraversion	Friendliness	79	70	66	65
	Gregariousness	79	68	69	76
	Assertiveness	43	49	49	42
	Activity level	38	48	45	47
	Excitement-seeking	39	40	37	34
	Cheerfulness	66	62	60	54
Neuroticism	Anxiety	30	23	35	22
	Anger	37	25	32	31
	Depression	29	29	35	39
	Self-consciousness	25	37	32	34
Agreeableness	Imm Moderation	34	36	40	36
	Vulnerability	37	33	39	38
	Trust	73	74	68	74
	Morality	64	67	64	61
	Altruism	54	61	56	64
	Cooperation	70	77	66	78
Conscientiousness	Modesty	63	52	55	61
	Sympathy	72	73	68	70
	Self-efficacy	38	51	50	47
	Orderliness	55	59	58	59
	Dutifulness	52	67	61	59
	Achievement-striving	47	45	47	48
Openness to experience	Self-discipline	60	59	57	59
	Cautiousness	48	63	55	63
	Imagination	16	24	26	29
	Artistic interests	39	47	43	53
	Emotionality	56	53	56	63
	Adventurousness	70	61	60	63
	Intellect	45	57	54	59
	Liberalism	65	72	69	70

In the agreeableness subdomains, while the group at 10.5 Hz did not have low scores, the other three groups generally exhibited scores that were slightly higher. The difference between the group around 10.5 Hz and the group around 12 Hz in the cooperation subdomain was statistically significant ($p < 0.05$).

12 waves per second — Less happy and more open

The group at 12 Hz had a somewhat lower score on cheerfulness and a slightly higher score in the depression subdomain than the other groups, but these differences were not large enough to be statistically significant. There was a tendency for the group at 12 Hz to have a more open cognitive style compared to the other three groups. The subdomains associated

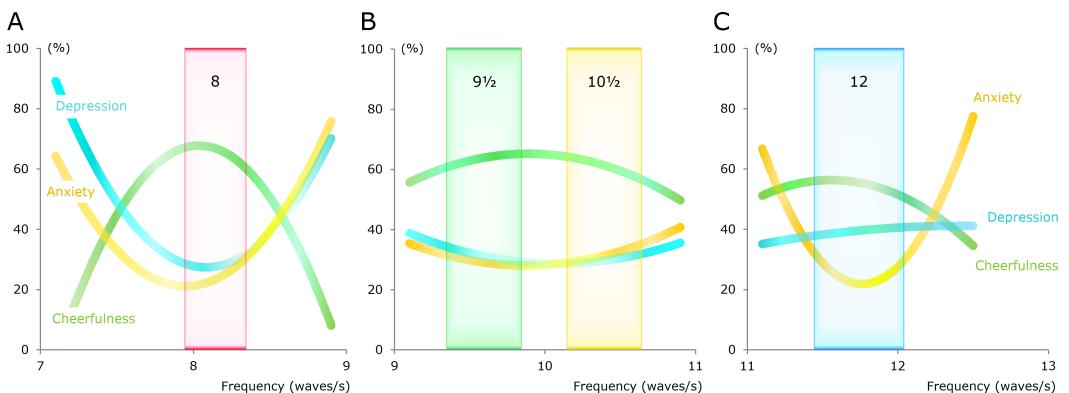


Figure 6 Curved lines representing estimates for the cheerfulness, anxiety, and depression subdomains. The curves, which are second-order polynomials, were generated via polynomial regression. Light-colored rectangles denote four groups of alpha waves.

with openness to experience in Table 1 provide more detailed information than does the broad domain shown in Fig. 5C.

Happiness

The cheerfulness, anxiety, and depression subdomains are all related to happiness. The three curves in Fig. 6A indicate that a high degree of happiness can be found in the center of the group around 8 Hz.

The main group around 10 Hz had a reasonably high degree of happiness in a frequency range that was much wider than the ranges for the groups around 8 and 12 Hz (Fig. 6). Thus, there was sufficient space for the subgroups at 9.5 and 10.5 Hz.

People in the main group at 10 Hz had a curve for depression that was shifted slightly to the right when compared with the curve for anxiety (Fig. 6B). This was also seen for people in the group at 8 Hz (Fig. 6A).

In the cheerfulness subdomain, the maximum level for the group at 12 Hz was somewhat lower compared to that for the other groups (Fig. 6). The line for depression in the group at 12 Hz did not have a bend in the same direction as the other groups (Fig. 6). When compared with those in the center of the group at 12 Hz, people in the surrounding zones had much higher anxiety scores (Fig. 6C).

DISCUSSION

The primary aim of the present study was to test the two levels hypothesis (Johannesson, 1984). This hypothesis deals with the general organization of the forebrain, and, if it withstands repeated testing, it may contribute to our understanding of the relationship between mental activity and brain activity.

The two levels hypothesis

In the model, a few cerebral columns have activity at a high level at each moment in time. The high-level activity is short-lasting and a column has activity at a comparatively low level almost all the time (Johannesson, 1984).

The two levels of activity are separate because between them, there is a gap in the activity range (Johannesson, 1993). In this context, activity at a high level in the columns is activity at a conscious level. When this activity is observed from outside, it is seen as neuronal activity, and when the *same* activity is observed from inside, it is seen as mental activity.

Each column has a set of connections with other columns and other parts of the nervous system. These connections constitute the functional properties that characterize every single column (Johannesson, 1984). The various connections are of different strengths, and association paths in cognitive processes usually follow the strongest connections. However, weak outgoing connections from two or more columns with high activity may converge on a new column and produce additive effects, such that they can sometimes be stronger together than a strong connection from a single column (Johannesson, 1984; Johannesson, 1993). The association path then takes another direction rather than simply following the most obvious connection.

A direct recording of high neuronal activity should be possible if a recording electrode is placed close to a cerebral column. However, high activity in a column is a rare event because there are very many columns. This direct approach is also problematic because a recording of high activity may be difficult to repeat. Moreover, if high activity is recorded, it has to be distinguished from other types of high activity, such as that caused by damage from the recording electrode.

Alpha waves are not direct recordings of high activity in the cerebral columns. On the contrary, alpha waves are thought to represent neuronal activity at the low level, albeit from many cerebral columns (Johannesson & Nilsson, 1996). Small but synchronous changes up and down in the neuronal activity within the low activity range produce the alpha waves in this model. Nonetheless, the alpha waves reflect the regulating signals that keep the number of highly active columns within proper limits.

The two levels hypothesis is falsifiable. In this paper, the focus is on the existence of specific alpha groups, because without them the hypothesis cannot be true. At the outset of the study, the existence of these groups seemed unlikely because the prevailing opinion is that the distribution of individual alpha frequencies is bell-shaped and without gaps (Klimesch, 1999; Robinson, 2006; Fink & Neubauer, 2008; Başar, 2012; Bazanova & Vernon, 2014). The present study had to include measurements from a relatively large number of individuals before the alpha groups could be clearly seen (Fig. 3A).

Testing

The alpha groups are accessible for rigorous testing. The initial finding of three distinct alpha groups was made in a pilot study of 213 recordings from an EEG clinic (T Johannesson, 1999, unpublished data). The result was confirmed in the present study with an entirely different sample.

The individual alpha frequency can be measured in different ways (Başar, 2012; Bazanova & Vernon, 2014). Any method can be used to test the existence of the alpha groups as long as it is sufficiently precise. Measurements from a power spectrum with very narrow bands ought to give results that are comparable to those based on measurements from long sequences of alpha waves, at least when the alpha waves are well developed.

A major problem with the power spectrum and other averaging procedures is that they include a large amount of uncertain data. For testing the alpha hypothesis, only sequences with regular alpha waves are relevant (Johannesson & Nilsson, 1996). Irregular activity and various artifacts should not be included.

Another and more serious problem with measurements based on averaging procedures is that they are affected by the amplitude. Long waves often have higher amplitude compared to short waves, and waves with high amplitude weight the average to a greater extent than do small waves. This causes a large systematic error in frequency measurements based on averaging procedures. Inaccuracy of this type is not a problem when using sequences of alpha waves, as in the present study, because frequency measurements from sequences of waves are not dependent on the amplitude of the waves.

A method based on the power spectrum of alpha activity is not more objective than a method using the longest wave sequences containing regular alpha waves. Both methods are easy to use when there are well developed alpha waves. Thus, in a power spectrum, there can be a clear peak, which simplifies the measurement of the alpha frequency. However, when the alpha waves are poorly developed, the power spectrum often contains more than one peak, and the peaks are usually broad and asymmetric. In such cases, it is not easy to determine how the measurement should be done.

Thorough testing requires that independent researchers repeat the experiment in order to confirm the results. When preparing for new studies, perhaps it can be of some help that all of the alpha sequences behind the histograms in Fig. 3 are reproduced in Data S1. This file shows how long the longest sequence is for every participant. The second and third longest sequences are often included and they give an idea of the size of the variation in the measurements, but only the longest sequence was used. Exactly how the alpha frequency was calculated is shown for every participant. Also, the amount of noise and the general quality of the recordings can be assessed from this file.

Four temperaments

A bimodal distribution of the alpha frequencies in the main group around 10 Hz was found in the present study (Figs. 3A–3B). The two subgroups were not predicted from the alpha hypothesis and they were not visible in the pilot study. Therefore, the finding of a bimodal distribution was not expected.

In the pilot study, most of the subjects were patients taking medication that might affect their alpha waves. There were no such complications in the present study, and this may explain why the shallow valley in the middle of the large group around 10 Hz can be seen in the present study but not in the pilot study. A re-examination of the recordings from the subgroups around 9.5 and 10.5 Hz confirmed the bimodal distribution in the present study.

The personality profiles characterized in Table 1 and Fig. 6 can be recognized as four types of temperament that resemble the four classical temperaments. Many scientists consider the classical temperaments to be obsolete, and though there are many descriptions of these temperaments, there are no useful definitions. Thus, it is not possible to test whether the four profiles found in the present study are identical to the four classical temperaments.

It has previously been suggested that the definitions of the four classical temperaments use a combination of two personality dimensions ([Robinson, 2001](#)). This method of defining the temperaments is very elegant, but it does not take into account that the main differences for extraversion and neuroticism were found when the centers of the groups were compared with the surrounding zones ([Figs. 4 and 5A](#)). For example, if the sanguine temperament is defined as having high extraversion and low neuroticism ([Robinson, 2001](#)), then people from the centers of all four groups would be included ([Fig. 4](#)). However, this idea is not altogether ineffective because extraversion was slightly higher in the group at 8 Hz compared to the other three groups, and neuroticism was slightly lower in the group at 8 Hz than it was in two of the other three groups ([Fig. 5C](#)).

As another example, consider the case in which the melancholic temperament is defined as having low extraversion and high neuroticism ([Robinson, 2001](#)). In the present study, extraversion was slightly lower in the group at 12 Hz compared to the other three groups, while neuroticism was slightly higher in the group at 12 Hz than it was in two of the other three groups ([Fig. 5C](#)). Thus, the definition of the melancholic temperament based on two personality dimensions has some support when the comparison is made among the four groups. The problem with this definition comes to light when people from the surrounding zones are included, because they usually have low scores on extraversion and high scores on neuroticism ([Fig. 5A](#)).

Instead of having a parallel terminology with new names (such as 8, 9.5, 10.5, and 12), it is proposed that the temperaments be defined by the alpha frequency. The sanguine temperament would then refer to the group around 8 Hz, the phlegmatic temperament to the group at 9.5 Hz, the choleric temperament to the group at 10.5 Hz, and the melancholic temperament to the group around 12 Hz.

The four temperaments refer to the centers of the alpha groups. Both the centers and the surrounding areas should be included when the alpha waves are correlated to personality traits. Thus, the best description of the link between alpha waves and personality traits is provided by the curved lines in [Figs. 4 and 6](#).

An attempt is made in the remaining part of ‘Discussion’ to explain the nature of the underlying relationship between alpha waves and personality traits. The two levels hypothesis ([Johannesson, 1984; Johannesson, 1993](#)) and the subsequent alpha hypothesis ([Johannesson & Nilsson, 1996](#)) are applied fully, and their implications in various fields are discussed.

Number of highly active columns

When the alpha frequency is 10 Hz, it has been estimated that the number of highly active columns alternates between 4 and 5 ([Johannesson & Nilsson, 1996](#)). The large group at 8 Hz has alpha waves that appear when the number of columns is switching between 3 and 4 ([Johannesson & Nilsson, 1996; Johannesson, 1997](#)). In a similar way, the group at 12 Hz is formed by alpha waves that are generated when the number of columns at the high level is alternating between 5 and 6 ([Johannesson & Nilsson, 1996; Johannesson, 1997](#)).

In addition to the alpha groups, there are other frequency groups. Infants exhibit waves that have a frequency of around 4 Hz, which may appear when the number of highly active columns is alternating between 1 and 2 ([Johannesson, 1997](#)). The number may increase

with age, and when it alternates between 2 and 3, the waves become shorter and form a group around 6 Hz. If the increase in number continues, the limits become 3 and 4, and the frequency group is at 8 Hz. Some individuals stay within this sanguine group, while for others, the limits are raised further to 4–5 or 5–6. When awake, very few individuals have the limits 6 and 7, which give a frequency of around 14 Hz.

During the different sleep stages, all of the frequency groups described above may appear ([Johannesson, 1997](#)). Moreover, a frequency around 1 Hz may appear when the limits are 0 and 1 during deep or very deep sleep. Thus, adults have regulating systems that retain the capacity to keep the number of highly active columns within several different limits.

Regulating system

When the activity in a column jumps up to the high level, the upper limit for the number of highly active columns is reached. The regulating system has to react quickly to decrease the excitability of all of the columns with low activity ([Johannesson & Nilsson, 1996](#)). If there is a delay, additional columns can change their activity from the low to the high level and the number will exceed the upper limit.

Occasionally, two new columns may change the activity from the low to the high level at the same time. When this occurs, the number will exceed the upper limit. At this point, the regulating system has to decrease the excitability of the remaining columns and wait until two columns have stopped exhibiting high-level activity. If the regulating system fails and increases the excitability already when the activity in only one column has left the high level, the system can become trapped in repeated attempts to adjust the number. Strong regulating signals that are repeated with very short intervals damage the thinking processes and may explain what happens during a grand mal seizure.

The regulating system has to be very sensitive and react extremely quickly, which may lead to mistakes. If a decrease in excitability starts before a new column has changed the activity from the low to the high level, the number can go below the lower limit. The implication from this reasoning might be that in a grand mal seizure, the number of highly active columns is alternating between the upper limit and one step higher, while in a petit mal seizure, the number is alternating between the lower limit and one step lower.

However, under normal conditions, the number is kept within proper limits. This number is the first of two basic parameters in the model, and the second is the duration of high-level activity of a column ([Johannesson & Nilsson, 1996](#)).

Different durations

The limits for the number of highly active columns are the same in the groups around 9.5 and 10.5 Hz. The difference between these groups lies in the duration of high-level activity. In other words, different durations may account for the underlying difference between people with a phlegmatic temperament and those with a choleric temperament.

The alpha hypothesis makes it possible to calculate the duration of high-level activity in a column ([Johannesson & Nilsson, 1996](#)). The duration is the mean number of highly active columns times the wavelength. As an example, the mean number is 4.5 when the number of highly active columns is alternating between 4 and 5. The wavelength for an

alpha wave is not the usual spatial period, but a temporal period, and therefore the inverse of the alpha frequency. For example, if the frequency is 10.0 Hz, then 1 divided by 10.0 /s gives the wavelength 100 ms. From these data, the duration of the activity at the high level in a column can be calculated as $4.5 \times 100 \text{ ms} = 450 \text{ ms}$.

When the frequency is 9.5 Hz, the duration is approximately $4.5 \times 105 \text{ ms} \approx 470 \text{ ms}$. In the same way, a frequency of 10.5 Hz gives the duration $\approx 4.5 \times 95 \text{ ms} \approx 430 \text{ ms}$. Differences in the duration thus account for the spreading of the frequency within the alpha groups.

Some individuals have alpha frequencies outside the main groups, for example, around 9 or 11 Hz. Although the computation is more complicated for alpha waves that are not within the main groups, it is still possible to calculate both the number and the duration if there are two stable rhythms available (*Johannisson & Nilsson, 1996*). In EEGs, switching between two frequencies is not uncommon, especially in young adults. Sufficient information is also available in sleep EEGs because several rhythms appear during sleep.

It is important to be able to measure the duration of high-level activity in a column because this duration determines the speed of the thinking processes. A relatively short duration, as seen in the choleric group, designates a fast turnover of highly active columns and rapid thinking. The opposite is seen in the phlegmatic group, where slow but reliable thinking processes are the result of a long duration and a slow turnover.

Differences between choleric and phlegmatic groups in the duration of the high activity of the columns can explain the different mean scores observed in the cautiousness subdomain ([Table 1](#)). Short duration and speedy thinking can lead to a high degree of impulsiveness.

In the anxiety subdomain, the phlegmatic group had a somewhat lower score than did the choleric group ([Table 1](#) and [Fig. 6](#)). This may be an effect of the relatively long duration in the phlegmatic group.

Number and duration together

In this paper, an alpha hypothesis (*Johannisson & Nilsson, 1996*) is used to explain the link between alpha waves and personality traits. Starting from measurements of the alpha frequencies, the two basic parameters in the hypothesis were calculated and the result is shown in [Fig. 7](#).

When the number of highly active columns alternates between 3 and 4, the duration of high-level activity can be relatively short ([Fig. 7](#)). Conversely, when the number alternates between 5 and 6, the duration is comparatively long. A high number may give a flow of thoughts that can be complicated. A prolonged duration makes it possible to handle complicated thoughts because this duration results in slow but reliable thinking processes.

The four temperaments are associated with four combinations of number and duration. These combinations are shown as ellipses in [Fig. 7](#). Outside the ellipses, in all directions, the values for number and duration are suboptimal. Anxiety, depressed mood, and other symptoms may appear in the surrounding zones ([Fig. 6](#)). Thus, the number–duration diagram opens up for a new systematic way of understanding different mental disorders.

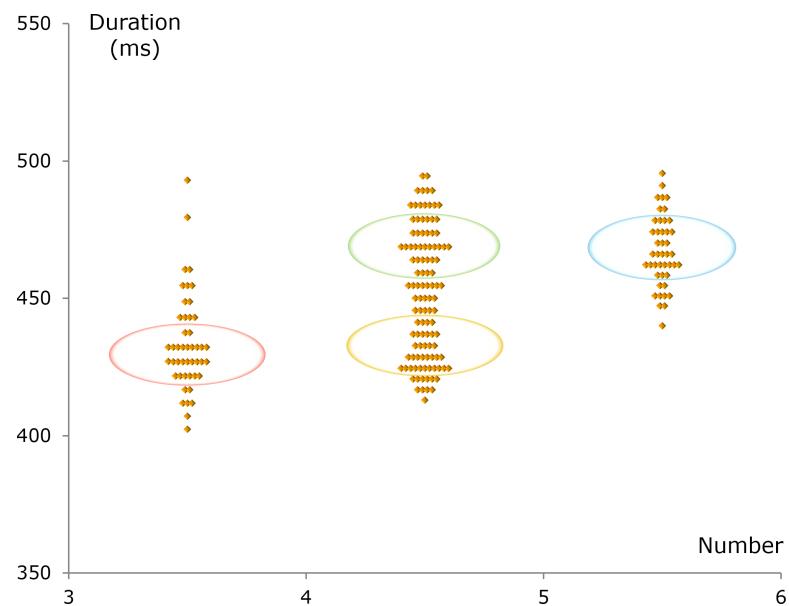


Figure 7 Number–duration diagram. The x -axis shows the mean number of columns with activity at the high conscious level and the y -axis shows the mean duration of high-level activity in a column. One data point per participant. The ellipses indicate four types of temperament, and, as seen in the figure, the number and duration are somewhat different for these four. The sanguine temperament (in red) is characterized, in relative terms, by a low number and a short duration. Both the phlegmatic temperament (in green) and the choleric temperament (in yellow) have a medium number, but they have different durations. Furthermore, the melancholic temperament (in blue) can be seen as the result of having a high number and a long duration.

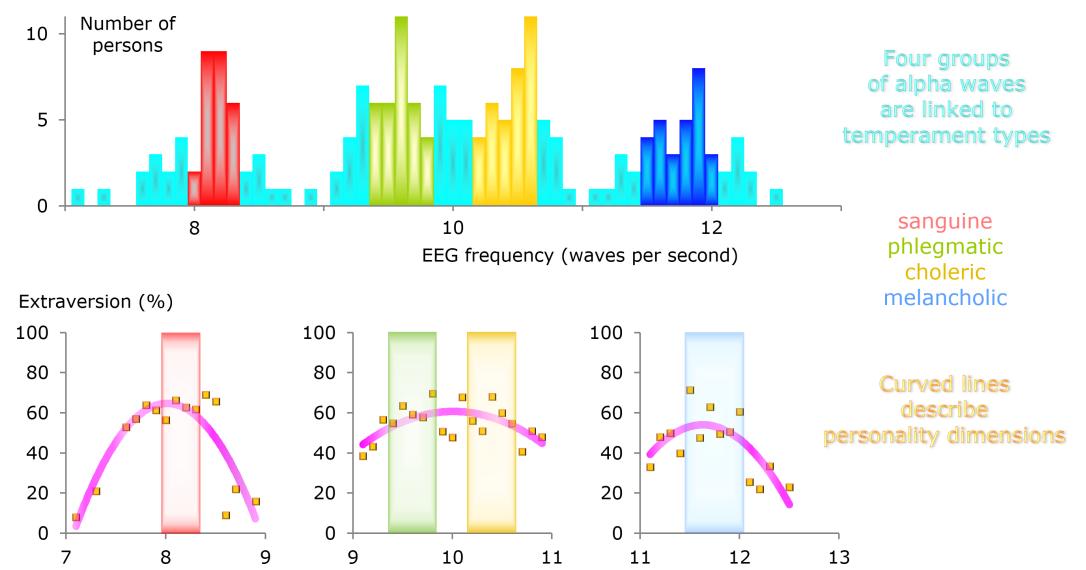


Figure 8 Summary illustrating how alpha waves, temperament types, and personality dimensions are interrelated.

CONCLUSIONS

1. Alpha waves from different individuals can be categorized into three main groups where the frequencies are around 8, 10, and 12 Hz. The middle group appears to have a bimodal distribution, such that subdivision produces a total of four alpha groups.
2. When alpha waves are correlated with personality dimensions, the alpha frequency range is better divided into three segments. In the centers of the main alpha groups, extraversion is high and neuroticism is low.
3. There are many small differences in personality traits among the four groups. When taken together, the groups comprise four personality profiles that are similar to the four classical temperaments.
4. The link between alpha waves and personality traits (Fig. 8) implies an underlying relationship. There are two hypotheses that can be applied. One of these deals with the general organization of the forebrain and the other explains why alpha waves are generated.

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ADDITIONAL INFORMATION AND DECLARATIONS

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Competing Interests

The author declares there are no competing interests.

Author Contributions

- Tomas Johannesson conceived and designed the experiments, performed the experiments, analyzed the data, contributed reagents/materials/analysis tools, wrote the paper, prepared figures and/or tables, reviewed drafts of the paper.

Human Ethics

The following information was supplied relating to ethical approvals (i.e., approving body and any reference numbers):

Approval was obtained from the Regional Ethics Board for University of Göteborg (R627–97) and written informed consent was obtained from all participants. For participants younger than 18 years, written informed assent was also obtained from a parent.

Data Availability

The following information was supplied regarding data availability:

The raw data has been supplied as a [Supplemental Dataset](#).

Supplemental Information

Supplemental information for this article can be found online at <http://dx.doi.org/10.7717/peerj.2245#supplemental-information>.

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Personality Moderates Intra-Individual Variability in EEG Microstates and Spontaneous Thoughts

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Abstract

Variability in brain activity that persists after accounting for overt behavioral and physiological states is often considered noise and controlled as a covariate in research. However, studying intra-individual variability in brain function can provide valuable insights into the dynamic nature of the brain. To explore this, we conducted a study on 43 participants analyzing the EEG microstate dynamics and self-reported spontaneous mental activity during five-minute resting-state recordings on two separate days with a twenty days average delay between recordings. Our results showed that the associations between EEG microstates and spontaneous cognition significantly changed from one day to another. Moreover, microstate changes were associated with changes in spontaneous cognition. Specifically, inter-day changes in *Verbal* thoughts about *Others* and future *Planning* were positively related to bottom-up sensory network-related microstate changes and negatively associated with top-down, attention, and salience network-related microstates. In addition, we find that personality traits are related to inter-day changes in microstates and spontaneous thoughts. Specifically, extraversion, neuroticism, agreeableness, and openness to experience moderated the relationship between inter-day changes in EEG microstates and spontaneous thoughts. Our study provides valuable information on the dynamic changes in the EEG microstate-spontaneous cognition organization, which could be essential for developing interventions and treatments for neuropsychiatric disorders.

Keywords EEG microstates · Intra-individual variability · Personality traits · Spontaneous thoughts

Introduction

Brain networks have the adaptability and flexibility to respond to internal and environmental demands to support adaptation, maintain homeostasis, and promote mental health. Unfortunately, inter-day variations in brain

functioning are understudied, usually considered noise, and controlled as a covariate. However, studying intra-individual and inter-day variability in brain functioning can provide valuable insights into the dynamic nature of the brain. For example, seasonally driven changes modulated by high daily variations in light exposure and difficulties in circadian rhythm adaptations increase the homeostasis load and risk for mood disorders (Zhang and Volkow 2023). Similarly, adaptation to challenging life events requires developing new coping strategies that might affect the inter-day variability in network dynamics and cognition.

Spontaneous thoughts vary in content and dynamics, affect, temporal and social orientation, mental modality, and association with physiological states (Andrews-Hanna et al. 2013; Killingsworth and Gilbert 2010). However, less is known about if and to what degree our spontaneous thoughts vary between days and if these patterns of change, or what we are addressing here as inter-day within-subject variability, are correlated with patterns of change of the underlying brain network dynamics. Stability and inter-day variations in recurrent thoughts about past and future events about

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ourselves and others are necessary for goal-directed activity, personal development, and adaptation to environmental challenges. For example, stability of recurrent thoughts about the past and future are necessary for goal-directed activity however, a certain degree of inter-day variability might be necessary for changing one's goal when internal needs change or flexible adaptations to environmental challenges are necessary. Moreover, in contexts of negative mood, spontaneous thoughts that are biased toward adverse future outcomes, like, for example, during ruminations, one of the main cognitive symptoms of mood disorders, a high degree of inter-day stability as opposed to high enough inter-day variability might further reinforce their negative outcome. In other words, less inter-day variability in these thought patterns might further promote ruminative and negative mood states. On the contrary, increased inter-day variability might promote the reduction of negative bias and insightful positive-oriented outcome thoughts. For example, specific types of mind-wandering activity are the primary target of cognitive psychotherapy for depression (Chaieb et al. 2022; Kovács et al. 2020) and mindfulness-based approaches (van der Velden et al. 2015). With treatment, changes in daily variations of spontaneous thought might increase, in addition to the reduction of negative bias. As a first step in assessing how therapeutic interventions might modulate inter-day variability and if this would be a prognostic indicator, it would be essential to establish if there are significant variations in mind-wandering and the underlying temporal dynamics of brain networks when looking at spontaneous thought content and dynamics sampled from different days.

Measures like the Amsterdam Resting-State Questionnaire (ARSQ) enable self-report quantifications of the mind-wandering experience that reflects the physiological state (sleepiness, somatic awareness, comfort) of the individual, the content (self, other, health-oriented) and dynamic of their spontaneous thoughts (discontinuity of mind) (Diaz et al. 2014). The different dimensions of the mind-wandering experience show high correlations over long periods; however, health-related thoughts, comfort, and sleepiness varied significantly between sessions (Diaz et al. 2014). Sleep quality might explain this variability, as many ASRQ facets show significant differences between insomnia patients and healthy participants, except for *Planning* and thoughts about *Others* (Palagini et al. 2016). Moreover, spontaneous thoughts vary as a function of personality traits. For example, more Self-Directedness, a measure of how well an individual can adapt to challenges, is related to fewer thoughts about *Self*, *Others*, or future *Planning* (Diaz et al. 2014). Harm-Avoidance traits, related to neuroticism and harm avoidance, are negatively related to *Comfort* thoughts (Diaz et al. 2014). These results suggest that having less thought content focused on *Self*, *Others*, or *Planning* and focusing more on *Comfort* might contribute to our general

adaptability and mental health. Furthermore, we previously showed that personality traits predict changes in spontaneous thoughts after a social imitation intervention to reduce stress, which was negatively associated with *Self* related-thoughts (Tomescu et al. 2022). The changes in mind-wandering patterns, such as about *Self*, were negatively associated with neuroticism and positively related to extraversion (Tomescu et al. 2022). In addition, we found a negative association between reduced *Self*-related thoughts and spontaneous temporal dynamics of large-scale neural networks as measured by EEG microstates (Tomescu et al. 2022). Specifically, the decrease in *Self*-related mind-wandering activity was associated with increased C microstates (Tomescu et al. 2022), related to the default-mode network—considered the “self-experience” network (Bréchet et al. 2019; Custo et al. 2017; Tarailis et al. 2023).

EEG microstates are brief patterns of stable electrical activity lasting tens to hundreds of milliseconds. There is internal reliability of the microstate analysis as a function of number of electrodes, strategy of clustering and algorithm (Khanna et al. 2014), thus making the microstates a good method to study clinical biomarkers for susceptibility of neuropsychiatry disorders, and treatment response, brain development and inter-individual variability (Chivu et al. 2023; da Cruz et al. 2020; Koenig et al. 2002; Rieger et al. 2016; Tomescu et al. 2014; Tomescu et al. 2015, 2022). Microstates are related to intrinsic neuro-psychological traits; however microstate dynamics can also capture the state related specificity of the resting-state. For example, the dynamics change as a function of the content of mind wandering experience and during recollection of past memories. An increase in microstate B was observed (Bréchet et al. 2019). Moreover, we found in a recent meta-analysis that B microstates show atypically increased presence in mood and anxiety disorders, positively associated with comorbidity and severity of depressive symptomatology (Chivu et al. 2023). Moreover, microstates reflect the underlying dynamic processes of the brain related to self-paced cognitive functions such as attention, perception, and memory (Michel and Koenig 2018; Tarailis et al. 2023). In addition, microstates' temporal presence is modulated by thoughts drifting from the cognitive task and external stimuli. Indeed, self-reported spontaneous thought experiences during mind-wandering have often been associated with fast dynamics of ongoing brain activity as characterized by EEG microstates (Pipin et al. 2017; Tarailis et al. 2021; Tomescu et al. 2022; Zanesco et al. 2021). For example, thinking about the *Self* is related to decreased visual-related network B microstates (negative correlation) and increased attention network D microstates (positive correlation) (Tarailis et al. 2023). Furthermore, subjective experience of thoughts focused on *Self*-related *Somatic Awareness* and biological rhythms, such as breath and heart rate, have been negatively related to C

and F/E microstates (Pipin et al. 2017; Tarailis et al. 2021; Tomescu et al. 2022; Zanesco et al. 2021) with sources in the dorsal anterior cingulate cortex, superior frontal gyrus, middle frontal gyrus, and insula (Britz et al. 2010; Custo et al. 2017) and associated with salience resting state networks with a critical role in the integration of interoceptive information with emotional salience (Britz et al. 2010). Furthermore, posterior default-mode network default-mode network (DMN)-related C microstates have also been positively associated with *Comfort*, lack of conscious experience (*Discontinuity of Mind*), and *Planning* (Pipin et al. 2017; Tarailis et al. 2021; Tomescu et al. 2022; Zanesco et al. 2021). While some of these results are contradictory (*Comfort* is anti-correlated with *Discontinuity of Mind*) (Diaz et al. 2014), other studies report a negative association between C microstates and *Comfort* (Tarailis et al. 2021). One possible explanation regarding this discrepancy might be inter- and intra-individual variability, and one crucial question to address would be to see if there is significant variability.

The main goal of this study was to assess if there is significant inter-day variability, meaning if differences from one day to another are significantly different from zero in terms of spontaneous thoughts as measured by ASRQ and microstates temporal dynamics without an a priori on what would be the source of this variability. Then, it would be essential to establish if the inter-day variability in mind-wandering is significantly associated with the inter-day variability in EEG microstates. Finally, we investigated if personality predicts inter-day variability in microstates and spontaneous thoughts. With this goal, we performed moderation analyses with personality traits as moderators of the inter-day associated variability between microstates and spontaneous thoughts recorded during a five-minute freely mind-wandering state with follow-up self-reports of their spontaneous mental activity measured by the ARSQ. By examining how spontaneous thoughts and EEG microstate dynamics fluctuate between two days and as a function of personality traits would be the first step towards identify patterns and mechanisms underlying inter-day variability and their functional significance.

Methods

Ethical Considerations

The National University for Theater and Film I.L Caragiale Bucharest Ethics Committee has approved all methods and experiments and followed the guidelines of the Declaration of Helsinki. All participants provided written informed consent for their participation.

Participants and Data Collection

Participants were recruited through advertisements within the University of Bucharest, the University of Theater and Film, the funding project's website <https://www.stadoproject.eu/>, and the CINETic's Research Center website <https://cinetic.arts.ro/en>. Participants came on two different days in the lab. The first day (D1) participants filled in the NEO PI-R questionnaire. On both D1 and day 2 (D2), participants performed an eyes-closed 5 min resting-state as they were instructed to let their thoughts wander. After the EEG recording of the resting-state, participants filled in the Amsterdam Resting-State Questionnaire to assess their spontaneous thoughts during the resting-state (Diaz et al. 2014). There was, on average, a 20 days delay between D1 and D2 and all recordings were performed in the afternoon.

The data analyzed here is part of the data collected and reported by Tomescu et al. (2022), and more details about the dataset can be found there (Tomescu et al. 2022). The dataset thus included 43 participants (24 men, 19 women), mean age = 25.7 (age range: 20–42), s.d. = 5.1. (Women mean age = 25.57, s.d. = 5.3; Men mean age = 25.9, s.d. = 5.1). The sample group included in the moderation analyses with personality traits comprised 37 participants (18 men and 19 women). Six participants were excluded from these analyses due to missing NEO-PI-R data.

EEG data sampled online at 1 kHz with a Cz reference were acquired in a dimly room using a 128-channel ANT Neuro Waveguard System (<https://www.ant-neuro.com/>). Participants sat in a comfortable, upright position and were instructed to stay as calm as possible, to keep their eyes closed, and to relax for five minutes without falling asleep.

The Amsterdam Resting-State Questionnaire 2.0 (ARSQ) is a self-report questionnaire that quantifies mind-wandering experiences along ten scales: Discontinuity of Mind, Theory of Mind (Others), Self, Planning, Sleepiness, Comfort, Somatic Awareness, Health Concern, Visual Thought, Verbal Thought (Diaz et al. 2014). Participants had to respond to a total of 30 items (3 per each scale), using a 5-point Likert Scale from “Completely Disagree” to “Completely Agree.” The scores for each scale were then summed up and reported. For each scale, the maximum possible score is 15, and the minimum possible score is 0. The ARSQ enable self-report quantifications of the mind-wandering experience that reflects the physiological state (sleepiness, somatic awareness, comfort) of the individual, the content (self, other, health-oriented), and the dynamic of their spontaneous thoughts (discontinuity) (Diaz et al. 2014). The internal consistency was measured using Cronbach’s alpha, and the results show medium to high internal consistency, see Table S1. Previously Diaz et al. (2014) reported high correlation between the content and dynamic scale, while the scales reflecting more physiological states showed low

correlation from data sampled on two different days (Diaz et al. 2014).

The Neo Personality Inventory-Revised (NEO PI-R) is a 240-item personality inventory with cross-culturally established properties and validity (McCrae et al. 2005) that assesses the Big Five Model domains of Neuroticism, Extraversion, Openness to Experience, Agreeableness, and Conscientiousness with the six factors for each domain. Participants responded on a 5-point Likert Scale ranging from 0 (strongly disagree) to 4 (strongly agree). The internal consistency was measured using Cronbach's alpha, and the results show high internal consistency for each facet of the questionnaire; see Table S1 for more information.

EEG Data Processing

The EEG datasets were band-pass filtered offline between 1 and 40 Hz with an additional notch at 50 Hz. EEG periods of movement contamination or other artifacts were marked and excluded from the analyses. To remove the oculomotor artifacts such as saccades and eye blinks, as well as the cardiac artifacts (ECG), we applied the Infomax-based Independent Component Analysis (ICA) (Jung et al. 2000). Bad or noisy electrodes were interpolated using a 3-D spherical spline (Perrin et al. 1989) and were recomputed to the common average reference. The data were then down-sampled to 125 Hz for further analysis.

The local maxima of the Global Field Power (GFP) show an optimal signal-to-noise ratio in the EEG (Murray et al. 2008). The EEG signal was extracted at the corresponding time frame of GFP peaks. Only the time points of GFP peaks were submitted to a modified k-means cluster analysis to identify the most representative classes of stable topographies (Murray et al. 2008).

The k-means clustering was performed in two steps: first, at the individual level, and second, at the group level by clustering all individual dominant topographies with varying clusters. To determine the optimal number of clusters at the individual and the group level, we used the criteria implemented in Cartool (a free academic software developed by Denis Brunet; cartoolcommunity.unige.ch), based on seven maximally independent criteria: Davies and Bouldin, Gamma, Silhouette, Dunn Robust, Point-Biserial, Krzanowski-Lai Index, and Cross-Validation (Custo et al. 2017).

In the first part of the microstate analysis, only GFP peaks were submitted to the k-means clustering. However, in the second part of the analysis, during the fitting process of the microstates, the entire EEG of participants was used, excluding only the marked artifact epochs. A temporal smoothing (window half-size 3-time frames (24 ms), Besag factor of 10, and a rejection of small time frames (when < 3, i.e., 24 ms) was applied. Subsequently, to quantify the temporal

parameters of microstates, every time point of the individual data was assigned to the microstate cluster with which it correlated best (Brunet et al. 2011). A 0.7 correlation coefficient threshold was used to exclude transient periods of noise in the data. These periods were not labeled and were excluded from the analysis.

This fitting process enabled the determination of the duration and the occurrence of each microstate in each subject. The *mean duration* represents the average time (in ms) that a given microstate map was present without interruptions, i.e., the duration during which the subject remained in a specific state. The duration is one of the most commonly used parameters of the temporal structure of microstates and has repeatedly been shown to be associated with different vigilance conditions and symptoms of neuropsychiatric disorders (Khanna et al. 2014). The mean *occurrence* indicates the rate at which a given microstate occurs, i.e., how often the brain enters a specific state per second.

The free academic software Cartool (cartoolcommunity.unige.ch) was used for EEG data processing and microstate analysis (Brunet et al. 2011).

Statistical Analyses

We tested data sets for Gaussian distribution using the Shapiro-Wilk normality test and concluded that our data have non-normal distribution. To assess the intra-individual variability between the two days, we compared microstate parameters and ARSQ spontaneous cognition between the two-time points Day 1 (D1) vs. Day 2 (D2). We utilized non-parametrical one-sample Wilcoxon tests; p-values were adjusted for multiple comparisons using false discovery rate (FDR) correction ($p < 0.05$). Statistical power was estimated by computing post-hoc testing and for $N = 43$ for the one-sample t-test change difference a Power (1- β error probability) = 0.93. For the moderation, we computed interaction for linear regression model for $N = 37$ and found a Power (1- β error probability) of 0.69 for a medium effect size.

To identify robust patterns of correlations between personality traits, spontaneous cognition, and the temporal dynamics of the EEG microstates, we used a multivariate approach called partial least squares (PLS) (Krishnan et al. 2011). PLS is a multivariate data-driven statistical technique that maximizes the covariance between two matrices by deriving *latent variables* (LVs), which are optimal linear combinations of the original matrices (Krishnan et al. 2011). PLS is a powerful technique for relating two sets of data (e.g., neuroimaging and behavioral data), even if these data show autocorrelation or multicollinearity (McIntosh and Misic 2013).

Each LV is characterized by a distinct EEG microstate pattern (EEG *loadings*) and a distinct behavioral profile (behavioral *loadings*). By linearly projecting each

participant's EEG and behavioral measures onto their respective loadings, we obtained individual-specific EEG microstates and behavioral *composite scores* for each LV. PLS seeks to find loadings that maximize across-participant covariance between the EEG microstates parameters and behavioral composite scores. The number of significant LVs was determined by a permutation test (1000 permutations). The p-values (from the permutation) for the first five LVs were corrected for multiple comparisons using a false discovery rate (FDR) of $q < 0.05$. To interpret the LVs, we computed Pearson's correlations between the original EEG data and EEG composite scores and between the original behavioral measures and behavioral composite scores for each LV. A large positive (or negative) correlation for a particular behavioral measure for a given LV indicates greater importance of the behavioral measure for the LV.

Similarly, a large positive (or negative) correlation for a particular EEG microstate parameter for a given LV indicates greater importance of the EEG microstate parameter for the LV. We used a bootstrapping procedure to estimate

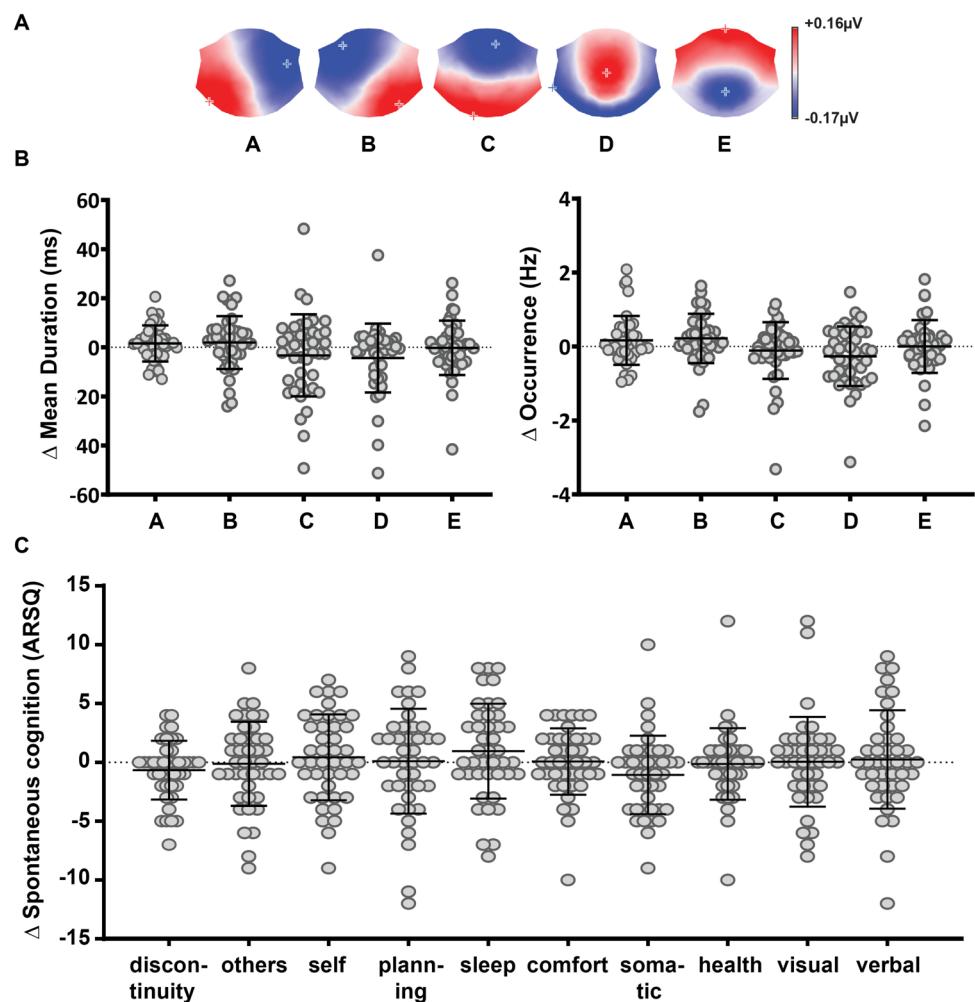
confidence intervals for these correlations, which generated 500 samples from subjects' data. First, z-scores were calculated by dividing each correlation coefficient by its bootstrap-estimated standard deviation. Then, the z-scores were converted to p-values and FDR-corrected ($p < 0.05$) (Kebets et al. 2019).

We performed explorative moderation analysis to investigate if personality predicts the inter-day variability between the EEG microstates and spontaneous cognition. In the moderation models we used spontaneous cognition and EEG microstates as both dependent and independent variables in interaction with personality facets of the NEOPI-R questionnaire.

Results

The EEG microstates in our dataset were identified using a set of seven independent criteria (detailed in Methods). First, we determined that five microstates can optimally describe group topographical EEG variability. Then, across both

Fig. 1 Intra-individual variability between 2 days in microstate dynamics and spontaneous cognition. **A** Dominant classes of microstates. **B** Microstate temporal dynamics D2–D1 difference scores. **C** Spontaneous cognition D2–D1 difference scores. Error bars are standard deviations



days and individuals ($N=43$), the cluster analysis robustly identified A, B, C, D, and E prototypical microstates that explained 81.9% of the variance (Fig. 1A). We then analyzed inter-day changes in the *duration* and *occurrence* of these EEG microstates by calculating change scores (D2–D1) (Fig. 1B). We find that absolute values of D2–D1 scores for both *mean duration* and *occurrence* of all microstates are significantly larger than zero (*mean duration* |D2–D1| scores for microstate: A = 5.61 ± 4.7 ms, $p < 0.0001$, one sample Wilcoxon test; B = 8.0 ± 7.16 ms, $p < 0.0001$; C = 12.02 ± 11.69 ms, $p < 0.0001$; D = 8.69 ± 11.57 ms, $p < 0.0001$; E = 7.31 ± 8.08 ms, $p < 0.0001$; *occurrence* |D2–D1| scores for microstate: A = 0.44 ± 0.5 Hz, $p < 0.0001$; B = 0.49 ± 0.48 Hz, $p < 0.0001$; C = 0.46 ± 0.6 Hz, $p < 0.0001$; D = 0.61 ± 0.55 Hz, $p < 0.0001$; E = 0.48 ± 0.5 Hz, $p < 0.0001$). These results indicate significant intra-individual variability of resting-state EEG microstate dynamics. Across subjects, however, microstate changes are bidirectional (either D2 > D1 or D2 < D1), and the coefficients of variation are high (*mean duration* CV for D2–D1 scores for microstate: A = 4.66, B = 5.77, C = 5.44, D = 3.29, E = 40.43; *occurrence* CV for D2–D1 scores for microstate: A = 3.91, B = 3.29, C = 7.16, D = 3.10, E = 193.36). Therefore, we can conclude that there is both intra- and inter-individual variability in EEG microstate dynamics.

The observed variability in neural data could reflect inter-day differences in spontaneous thoughts (Fig. 1C). Thus, we looked at inter-day changes (D2–D1) in self-reported spontaneous thoughts. The results show that absolute values of D2–D1 scores are significantly different than zero (*Discontinuity* = 1.93 ± 2.0 , $p < 0.0001$, *Others* = 2.72 ± 2.23 , $p < 0.0001$, *Self* = 3.02 ± 2.3 , $p < 0.0001$, *Planning* = 3.32 ± 2.87 , $p < 0.0001$, *Sleep* = 3.16 ± 2.5 , $p < 0.0001$, *Comfort* = 2.04 ± 1.8 , $p < 0.0001$, *Somatic Awareness* = 2.48 ± 2.3 , $p < 0.0001$, *Health* = 1.74 ± 2.4 , $p < 0.0001$, *Visual* = 2.58 ± 2.8 , $p < 0.0001$, *Verbal* = 3.04 ± 2.9 , $p < 0.0001$). Moreover, the coefficients of variation are high (*Discontinuity* = 3.32, *Others* = 21.77, *Self* = 16.46, *Planning* = 27.17, *Sleep* = 4.53, *Comfort* = 60.07, *Somatic Awareness* = 3.01, *Health* = 25.88, *Visual* = 55.1, *Verbal* = 61.32). We observe high intra- and inter-individual variability in spontaneous thoughts.

The Relationship Between Spontaneous Cognition and EEG Microstate Varies Between D1 and D2

We performed two separate PLS analyses for each time point to fully understand intra-individual variability in the relationship between spontaneous cognition and microstate dynamics. On the first day of recording (D1), there was a significant PLS relation between spontaneous cognition as measured by the ARSQ and EEG microstate parameters

(LV1- $p = 0.003$, FDR corrected, explaining 45% of the covariance). Figure S1A–D illustrates the significant association between EEG microstates D and spontaneous thoughts about *Self*, *Somatic Awareness*, *Planning*, and *Comfort*. On the second day (D2), we found a significant PLS association (LV1- $p = 0.00$, FDR corrected, explaining 56% of the covariance) between microstates and spontaneous thoughts about *Comfort*, *Discontinuity of Mind*, and *Visual* and *Verbal* thoughts for more details, see Fig. S1E–H.

Given the different patterns of associations between D1 and D2, we investigated whether microstates and spontaneous cognition varied together. We performed an additional PLS analysis to assess the association between D2–D1 change scores in microstates and spontaneous cognition. The results show that some of these changes are related. For example, daily changes in A and B microstates are positively associated with change scores in thoughts about the future (*Planning*), about other people (*Others*), and verbal thoughts (*Verbal*). In contrast, the variability of D and E microstates is negatively associated with these spontaneous thoughts. The results of the significant PLS ($p = 0.01$, FDR corrected, 64% explained variance) are shown in Fig. 2.

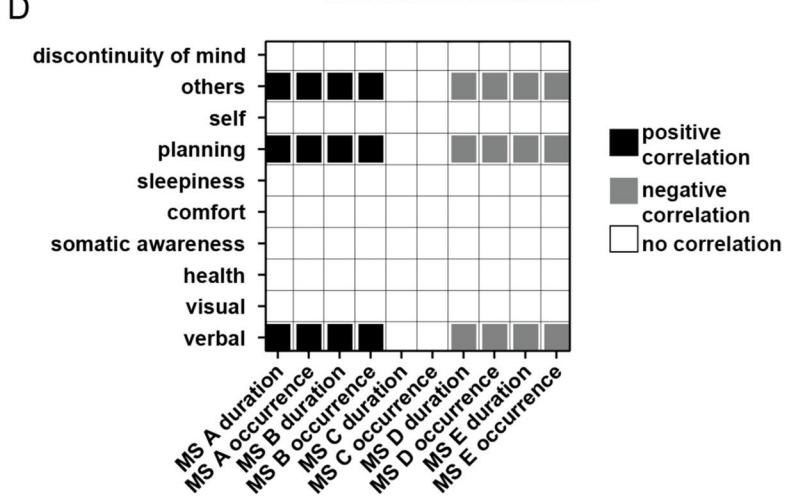
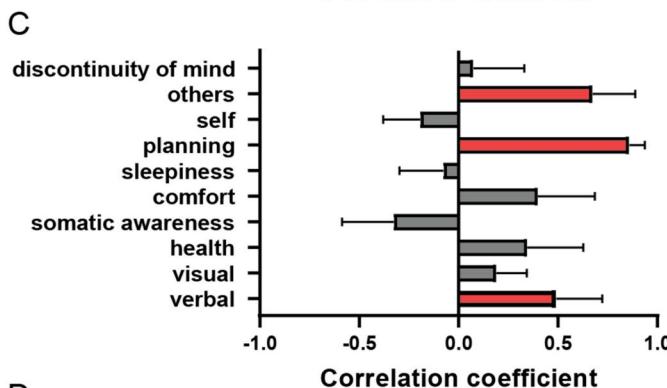
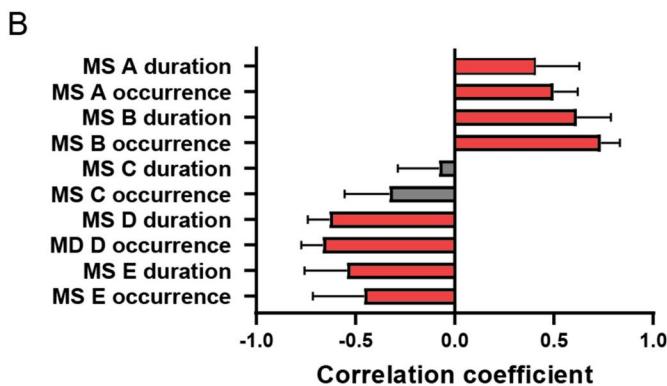
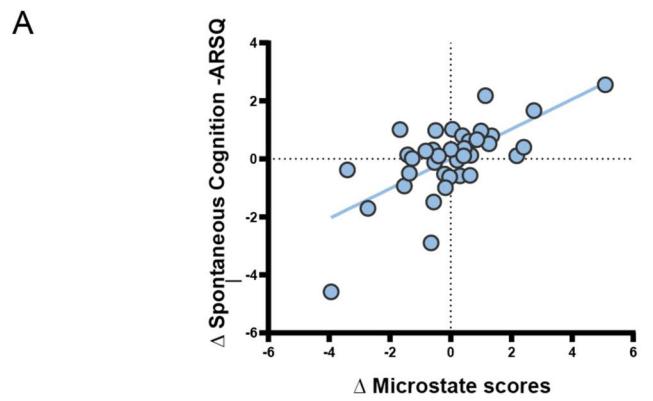
Fantasy and Trust Moderate Associations Between Microstates and Spontaneous Thoughts

We performed moderation analyses to see if personality predicts the significant PLS (Fig. 3) D2–D1 associations between microstates (A, B, D, and E) and *Planning*, *Others*, and *Verbal* spontaneous thoughts.

Personality traits moderate the relationship between microstates B, and E and spontaneous thoughts about future (*Planning*) D2–D1 scores (Fig. 3, Table 1, Fig. S2, Table S5).

More specifically, we found a more significant negative association between *Planning* and microstate E in low Agreeableness Trust trait ($-1SD$) individuals. We also observed that high Fantasy ($+1SD$) individuals showed more positive significant associations between *Planning* and microstates B (Fig. 3C, D, Table 1). These results remained significant even after outlier elimination. In addition, we found that individuals with low Openness traits ($-1SD$) and Values ($-1SD$) showed more significant associations between *Planning* and microstates A. Low Openness and low Agreeableness, such as Values ($-1SD$), Trust ($-1SD$) and Altruism ($-1SD$) traits individuals showed more positive significant associations between *Planning* and microstates B (Fig. S2). However, these results did not survive the outlier correction analysis.

Fig. 2 Association between inter-day changes (D2–D1) in spontaneous cognition and microstates dynamics. **A** D2–D1 correlation between individual-specific ARSQ scores and microstate parameters. **B** D2–D1 correlations between original and composite microstate duration and occurrence scores. Red color bars represent significant correlation coefficients. **C** D2–D1 correlations between original and composite ARSQ scores. Errors represent SD. **D** D2–D1 specific associations between microstate dynamics and spontaneous thoughts



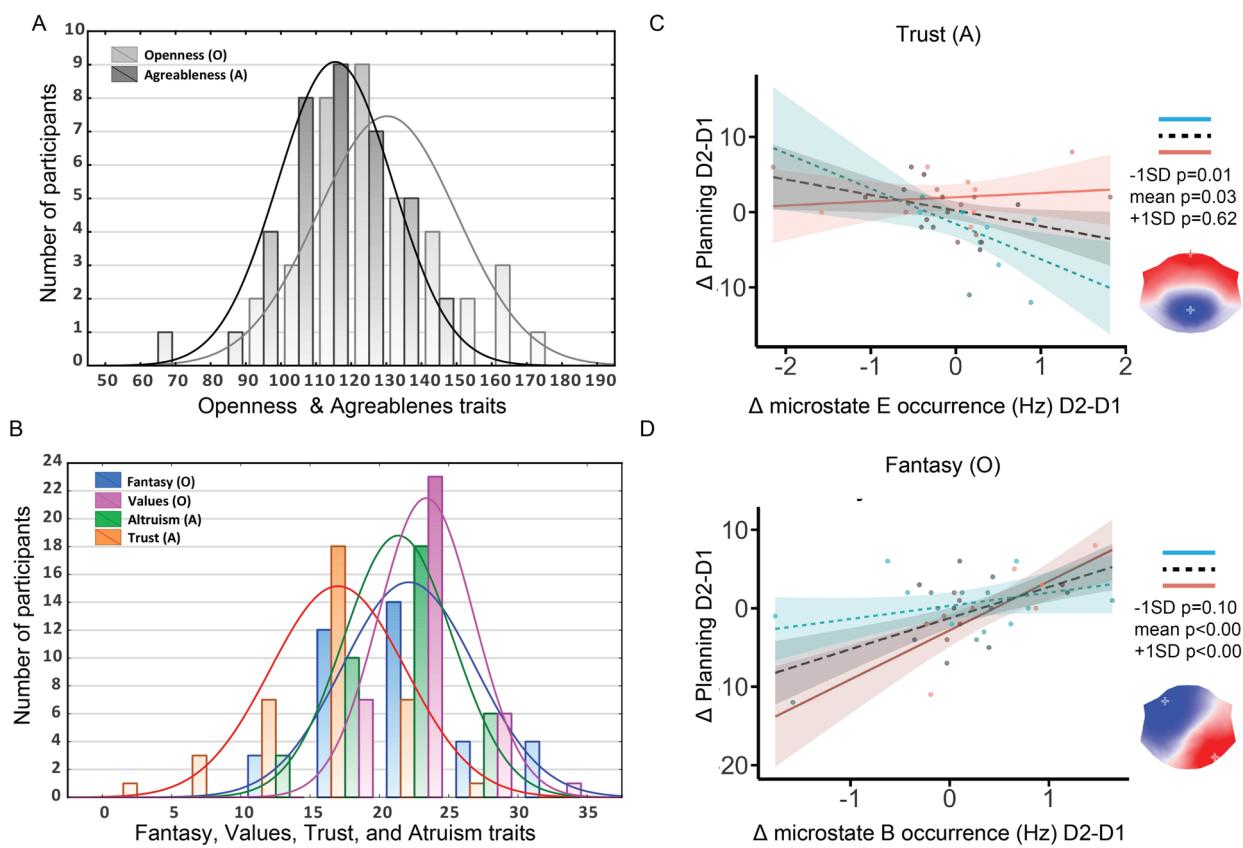


Fig. 3 Personality moderates inter-day associated changes in spontaneous thoughts and microstate occurrence. **A** Histogram of Openness to Experiences and Agreeableness personality traits. **B** Histogram of Openness to Experiences facets Fantasy and Values, and Agreeableness facets Altruism and Trust personality traits. **C** Trust personality traits moderate inter-day changes in Planning and microstate E occurrence.

D Fantasy personality traits moderate the association between inter-day changes in Planning and microstate B occurrence. Blue dots and regression lines represent individuals with one standard deviation below the mean ($-1SD$) on personality trait distribution. Red dots and regression lines represent individuals with one standard deviation above the mean ($+1SD$) on personality traits

Table 1 Moderation analysis results for B, and E microstates & Planning

Slope	Predictors	Estimates	CI	t	p
Planning	Fantasy × MS B occurrence	0.48	0.15	0.81	2.98 0.005
-1SD	Low fantasy	1.68	-0.37	3.73	1.67 0.10
Mean	Mean fantasy	3.97	2.04	5.89	4.19 0.00
+1SD	High fantasy	6.26	3.41	9.10	4.47 0.00
Planning	Trust × MS E occurrence	0.54	0.08	1.00	2.37 0.024
-1SD	Low trust	-4.69	-8.19	-1.19	-2.73 0.01
Mean	Mean trust	-2.07	-3.97	-0.17	-2.22 0.03
+1SD	High trust	0.55	-1.71	2.81	0.49 0.62

Text in bold highlights significant *p*-values

Vulnerability to Stress, and Gregariousness Moderate Associations Between Microstates and Spontaneous Thoughts

We performed moderation analyses to see if personality moderates the changes in microstates and spontaneous

thoughts that do not appear to be associated in the PLS analysis (Fig. 2). For example, as a function of personality traits, association patterns might occur in opposite directions (negative vs. positive associations), cancel each other and explain why we did not find significant associations between D2–D1 changes in microstates, and

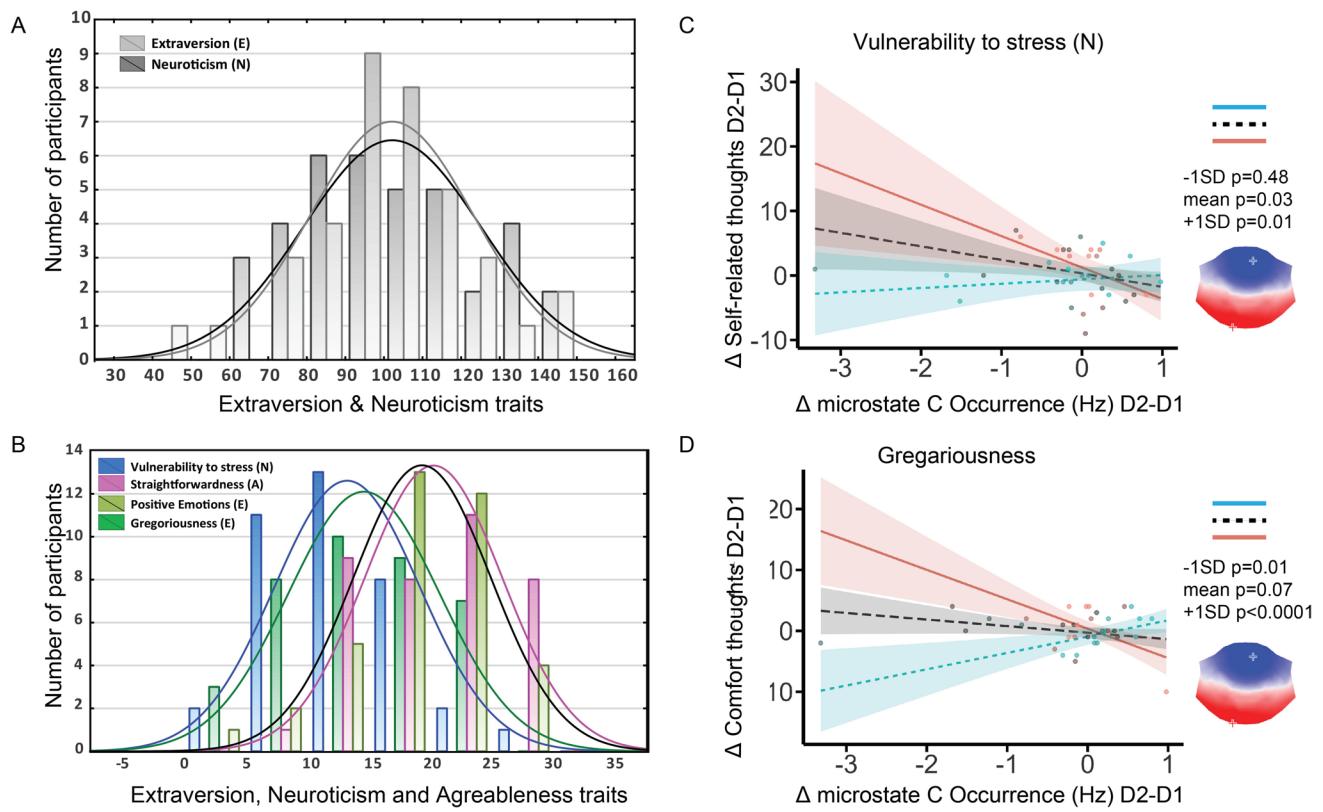


Fig. 4 Personality moderates inter-day associated changes in spontaneous thoughts and microstate occurrence. **A** Histogram of Extraversion and Neuroticism personality traits. **B** Histogram of Vulnerability to Stress, Straightforwardness, Positive Emotions, Gregariousness personality traits. **C** Vulnerability to stress personality traits moderates the association between inter-day changes in Self-related thoughts and microstate C occurrence. **D** Gregariousness personality

traits moderate the association between inter-day changes in thoughts about Comfort and microstate C occurrence. Blue dots and regression lines represent individuals with one standard deviation below the mean ($-1SD$) on personality trait distribution. Red dots and regression lines represent individuals with one standard deviation above the mean ($+1SD$) on personality traits

Table 2 Moderation analysis results for C microstate & *Self* and *Comfort*

<i>Slope</i>	<i>Predictors</i>	<i>Estimates</i>	<i>CI</i>	<i>t</i>	<i>p</i>	
Self	Vulnerability to stress \times MS C occurrence	-0.47	-0.85	-0.1	-2.55	0.016
-1SD	Low VulStress	0.67	-1.24	2.58	0.71	0.48
Mean	Mean VulStress	-2.1	-3.99	-0.2	-2.25	0.03
+1SD	High VulStress	-4.86	-8.51	-1.22	-2.71	0.01
Comfort	Gregariousness \times MS C occurrence	-0.62	-0.93	-0.3	-3.94	<0.001
-1SD	Low Greg	2.67	0.81	4.53	2.92	0.01
Mean	Mean Greg	-1.08	-2.27	0.11	-1.84	0.07
+1SD	High Greg	-4.83	-7.45	-2.21	-3.75	<0.001

Text in bold highlights significant *p*-values

Discontinuity of Mind, Self, Sleepiness, Comfort, Health, Somatic Awareness, and Visual spontaneous thoughts.

Personality traits moderate the relationship between microstates C and D and spontaneous thoughts about *Self* and *Comfort* (Fig. 4, Table 2, Fig. S3, Table S6).

More specifically, we observed that individuals with high Vulnerability to Stress ($+1SD$) showed significant change scores associations between *Self* and microstates C (Fig. S3). Moreover, a significant reversed patterns between high ($+1SD$) and low ($-1SD$) Gregariousness traits of significant

associations were found between *Comfort* and microstate C. These results remained significant after outlier elimination. More importantly, these association patterns explain why we did not find any significant association between thoughts about *Comfort* and microstates in the PLS association.

In addition, low Extraversion ($-1SD$), low Positive Emotions, and low Straightforwardness showed significant change scores associations between *Self* and microstates C and D (Figure S3). However, the opposite patterns of associations between *Self*-related scores and D were observed for low Vulnerability to Stress ($-1SD$), high extraversion ($1+SD$), and high Positive Emotions ($1+SD$). However, these results did not survive after outlier elimination.

Discussion

Brain-mind inter-day variability might be essential to flexibly adapt to internal and environmental demands that support mental health. As a first step, in a sample of healthy individuals, we found significant variations in intra-individual self-reports of spontaneous cognition during resting state and temporal dynamics of EEG microstates from D1 to D2 (Fig. 1). Moreover, for each sample of the two days, a different pattern of association characterized the relation between spontaneous thoughts and the underlying dynamics of microstate activity (Figure S1). Investigating these specific changes, we found that inter-day changes in *Verbal* thoughts about *Others* and future *Planning* were positively associated with inter-day changes in A and B microstates (Fig. 2). The opposite was true for D and E microstates. Inter-day changes in D and E were negatively correlated with *Verbal*, *Others*, and *Planning* spontaneous thoughts.

Regarding their functional relevance, microstates A exhibited multisensory associations, including verbal, auditory, and phonological, while microstates B exhibited links to visual processing specifically associated with self-retrieval of autobiographical memories (Tarailis et al. 2023). The positive inter-day associations align with the observed functional relevance and further extend the notion that these microstates also play a role in imagining the future and planning accordingly. Moreover, these results sustain our hypothesis that inter-day variability might be essential for successful goal-directed activity and adaptation to environmental challenges. However, future research should address how the observed patterns of inter-day variability are associated with positive or negative outcomes in adaptive situations. Furthermore, the inter-day variability of microstate and spontaneous thoughts should be investigated in clinical studies to further disentangle the interaction with mood and anxiety disorders, as well as negative symptoms in schizophrenia as many clinical studies reveal significant modulations of B microstates (Chivu et al. 2023; Rieger et al. 2016).

The functional relevance of microstates D and E relates to sustained attention, executive functioning, and interoceptive and emotional information processing (Tarailis et al. 2023). Variations of these microstates were negatively associated with *Verbal*, *Others*, and *Planning* spontaneous thoughts. These results suggest that there might be less engagement of salience, attention, and executive functioning states during spontaneously imagining situations involving future social interactions, for example. Alternatively, these situations involve a low cognitive load that might vary as a function of the context. Indeed, both of these networks are task-positive, meaning that they tend to increase in presence while actively performing tasks; however, microstate E might also be involved in the processing of emotional information and was previously found to be positively associated with *Comfort* (Tarailis et al. 2023), it would be essential to assess inter-day variability by also taking into account modulations of emotional contexts such as during prolonged states of uncomfortable negative mood ruminative states. It has been suggested that atypically shortened E microstates might reflect a failure to map relevant bottom-up stimuli, resulting in hypervigilance in patients suffering from anxiety-related disorders like PTSD (Terpou et al. 2022). Microstate D decreased presence was also reported in patients suffering from major depression during both full-blown and symptom remission states, thought to reflect a continuous depression trait (Murphy et al. 2020). Thus, it is essential to investigate whether certain personality traits drive the observed variability.

We performed moderation analyses to explore whether personality might play a role in the inter-day D2–D1 associations between microstates and spontaneous cognition. The results showed that personality traits might predict the relationship between EEG microstates and spontaneous thought's inter-day variability. More specifically, the inter-day variability positive association between bottom-up B microstates and thoughts about *Planning* (future, problem-solving, and things I need to do) was driven mainly by high day-dreamers (high Fantasy) (Fig. 3). These results are in line with previous work showing microstate B association with auto-biographical memory retrieval during resting-state further suggesting possible common underlying brain mechanism for remembering and imagining the future (Bréchet et al. 2019; Smallwood and Andrews-Hanna 2013; Tarailis et al. 2023). In addition, low Trust individuals mainly drove the inter-day variability negative relation between top-down salience network-related E microstates and thoughts about *Planning*. Given that *Planning* was previously negatively correlated with more Self-Directedness, a measure of how well an individual can adapt to challenges (Diaz et al. 2014), and E was suggested as a marker for anxiety (Chivu et al. 2023), it would be important for future studies to investigate how the inter-day variability in microstates and spontaneous

thoughts modulated by personality is predicting behavior during challenging experiences.

Thoughts about *Self*, were also negatively associated with Self-Directedness. Here, we found that individuals most vulnerable to stress (high Vulnerability to Stress) show a negative relation between *Self*-thoughts and DMN-related C microstates. We previously showed that *Self*-related thoughts are significantly negatively associated with C-DMN microstates after a social imitation task (Tomescu et al. 2022). Moreover, we observed that more *Self*-related thoughts are associated with higher self-reported stress levels (Tomescu et al. 2022). Variability between C-DMN and *Self*-related thoughts might be an important treatment target and marker for preventing stress-related mental health disorders. Thus, future studies might focus on the content of self-related thoughts. In addition, investigating the relationship between C-DMN microstates and self-related thoughts in clinical populations would be highly important. Individuals at high-risk and schizophrenia patients robustly show increased C microstate dynamics (da Cruz et al. 2020; Rieger et al. 2016; M. Tomescu et al. 2014; Tomescu et al. 2015).

Finally, the level of gregariousness (extraversion) and the drive for human connection moderated the relationship between thoughts about *Comfort* and DMN-related C microstates. Less drive for social interaction (gregariousness) predicts a positive DMN-related C microstates to *Comfort* thoughts relation and the opposite was true for high gregarious individuals. As Harm-Avoidance traits are also negatively associated to *Comfort* thoughts (Diaz et al. 2014), more studies on modulating thoughts about *Comfort* and microstate C dynamics might contribute to understanding neuro-psychological mechanisms of general adaptability, mental health stability, and resilience.

Limitations

Some limitations of this study should be acknowledged, like the relatively small size ($N = 43$) included. More studies are needed to confirm these results in a larger sample size. Moreover, long-term inter-day variability is needed to confirm these findings and overcome another limitation—only two samples were investigated here (D1 and D2). Future studies would also extend these findings by taking more samples with larger time delays between recordings. Further investigating the qualitative experience of self-related thought engagement in addition to the ARSQ questionnaire might reveal more information about the quality and quantity of inter-day spontaneous thought variability.

Conclusions

In conclusion, the results of this study provide valuable information about the intra-individual variability and dynamic changes in the EEG microstate-spontaneous cognition organization, which could lead to the development of new interventions and monitoring applications for neurologic and psychiatric disorders.

Supplementary Information The online version contains supplementary material available at <https://doi.org/10.1007/s10548-023-01019-x>.

Author contributions MIT designed the study, attracted funding, analyzed the data, prepared the figures, and wrote the manuscript. CP contributed to data analysis, performed the moderation analysis, prepared figures, and contributed to manuscript revision. AS recorded and collected the data, and participated in manuscript revision. AIB attracted funding, participated in study design, managed data collection, and participated in manuscript revision. IC attracted funding, participated in data analysis, figure preparation, and revised the manuscript.

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Declarations

Competing Interests The authors have nothing to disclose.

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Review

EEG Resting Asymmetries and Frequency Oscillations in Approach/Avoidance Personality Traits: A Systematic Review

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Abstract: Background: Brain cortical activity in resting electroencephalogram (EEG) recordings can be considered as measures of latent individual disposition to approach/avoidance behavior. This systematic review aims to provide an updated overview of the relationship between resting EEG cortical activity and approach/avoidance motivation personality traits. Methods: The review process was conducted according to the PRISMA-Statement, using PsycArticles, MEDLINE, Scopus, Science Citation Index, and Research Gate database. Restrictions were made by selecting EEG studies conducted in resting idling conditions, which included approach/avoidance personality traits or parallel measures, and an index of EEG brain activity. In the review 50 studies were selected, wherein 7120 healthy adult individuals participated. Results: The study of the relationship between resting EEG cortical activity and approach/avoidance personality traits provides controversial and unclear results. Therefore, the validity of resting asymmetry or frequency oscillations as a potential marker for approach/avoidance personality traits is not supported. Conclusions: There are important contextual and interactional factors not taken into account by researchers that could mediate or moderate this relationship or prove it scarcely replicable. Further, it would be necessary to conduct more sessions of EEG recordings in different seasons of the year to test the validity and the reliability of the neurobiological measures.

Keywords: EEG; resting-state; asymmetry; lateralization and brain functions; approach; avoidance; withdrawal; motivation; personality traits; reinforcement sensitivity theory

1. Introduction

Brain frequency oscillatory activity is defined as the real activity of the brain [1]. According to Klimesch [2], slow rhythms (delta and theta bands) have more ancient phylogenetic origin than fast rhythms (alpha, beta, gamma bands). Delta rhythm is dominant in reptiles, theta rhythm is dominant in the lower mammals, and alpha is defined as the dominant rhythm in adult humans.

The EEG alpha power at the frontal scalp is the gold standard measure used to evaluate functional inter-hemispheric asymmetry. According to Davidson [3] and Harmon-Jones [4], higher relative left frontal cortex activity is related to behavioral approach and positive emotions, whereas higher relative right frontal cortex activity is related to behavioral avoidance and negative emotions. Furthermore, according to Harmon-Jones and Gable [5], baseline electroencephalogram (EEG) measures in idling condition can be treated as personality dispositions. In this conceptual framework, the test-retest reliability of the resting EEG is comparable to the test-retest of self-reported personality trait measures, recorded in idling standard experimental conditions [6]. Thus, brain alpha oscillations can be considered as the measure of latent individual disposition to a specific style of behavior. However, the replicability of these associations with approach/avoidance personality traits is still unclear [7]. The same can be

said for the function of the other oscillation frequency bands in the EEG spectrum [8], as well as the synchronization/desynchronization functions of brain rhythms, which are important issues that are sparsely discussed in terms of approach/avoidance personality traits.

This systematic review aims to provide an updated research overview of the relationship between resting EEG cortical activity in idling condition and individual differences in approach/avoidance motivation personality traits. A further aim of this review is to highlight the EEG frequency oscillation and its scalp-distributed lateral asymmetries as the most sensitive index of cortical excitability in approach/avoidance motivation personality traits.

2. Materials and Methods

This review study was conducted according to the PRISMA-Statement [9,10]. The protocol was registered on PROSPERO, CRD42020182795, and is available on the following link, https://www.crd.york.ac.uk/prospero/display_record.php?RecordID=182795.

2.1. Research Strategies

The research of literature was conducted on the international electronic databases, PsycArticles, MEDLINE, Scopus, and Science Citation Index. The last research of international literature was completed in June 2020.

In this work were included peer-reviewed full-text journal articles, written in English or Italian. The investigation was delimited to studies conducted on healthy adult human samples without restrictions to gender or ethnicity. These studies considered the relationship or association among EEG measure/s such as cortical asymmetry (e.g., frontal or posterior), frequency oscillations, synchronization or desynchronization of EEG rhythms, and personality traits such as approach/avoidance personality traits (behavioral inhibition system “BIS”, behavioral approach system “BAS”, fight-flight system “FFS” or fight-flight-freeze system “FFFS”) and/or their parallel measures (e.g., positive affect, extraversion, sensation seeking, negative affect, neuroticism, fear or state anxiety), in a resting state idling experimental condition. The research on electronic database was conducted including the following terms or keywords:

1. Asymmetry and brain activity: “EEG asymmetry” OR left OR right OR lateral* OR front* OR posterior OR prefrontal OR parietal* OR electroenceph* OR oscill* OR rhythms OR coupling OR “frequency oscillations” OR synchronization OR desynchronization OR alpha OR delta OR theta OR beta OR gamma AND rest*;
2. Approach/avoidance motivation: “approach motivation” OR motivation* OR approach* OR BAS OR reward* OR “positive affect” OR “avoidance motivation” OR avoid* OR “negative affect” OR BIS OR withdraw* OR inhibit* OR threat* OR fear OR FFS OR FFFS.

2.2. Eligibility Criteria

The results of the systematic research were examined by two authors (A.V.–Ph.D. student; V.D.P.–Ph.D. Tutor). A first articles’ exclusion was done by title and abstract reading, according to the following eligibility criteria: (i) EEG study conducted in resting state idling condition, only. This criterion led to the exclusion of the studies in which the participants were presented acoustic sounds [11], debated an oral presentation [12], and the resting-state EEG was recorded after physical exercise [13], after the induction of a negative mood [14], or stress condition by experimenter [15]. Measures of asymmetry and frequency oscillations recorded during hypnotic-state condition were excluded [16]. Furthermore, studies were excluded that (i) had considered resting-state EEG asymmetries or frequency oscillations as comparison measures to predict brain activity during a behavioral test [17–19]; (ii) report almost a self-report measure of approach/avoidance personality trait or parallel measures. This criterion excluded the studies that conceptualized EEG asymmetry as a latent state-latent trait in the absence of the self-report (e.g., [20]); (iii) involved healthy adult individuals. This criterion led to the exclusion of

research conducted on a sample of preadolescents (e.g., [21]), and EEG studies conducted on clinically relevant mental disorders and other illnesses, such as Alzheimer's and Parkinson's disease, Down's syndrome, chronic pain, mild cognitive impairment, and Williams' syndrome.

In the first phase of screening, in order to not omit important research, the inclusion of studies by title and abstract readings were carried out independently by the two authors. Later, after the authors had reached a joint agreement, the first author (A.V.) examined in more depth the content of all articles that met the eligibility requirements, then moved on to the data extraction. The second author (V.D.P.) supervised the data extraction to ensure it was performed correctly and carefully, and according to the eligibility criteria selected.

2.3. Data Collection and Quality Assessment

According to the PICOS approach [9,10], data collections were assessed by including in the selected studies: sample characteristics (i.e., sample size, gender, age, and education of participants); experimental design and used methods across studies; instruments used to measure personality traits of approach/avoidance motivation and parallel measures; the self-report scores; statistical analyses; and obtained results.

Two authors (A.V. and V.D.P.), independently, evaluated the risk of bias analysis. According to the criteria considered in the *Cochrane Handbook for Systematic Reviews of Interventions* [22,23], the second author (V.D.P.) blinded the articles selected by the first author (A.V.). Therefore, the title of the study, the name of the journal, and the name of the authors were unknown to the first author (A.V.) who executed the evaluation of the articles. The quality assessment was conducted using the Joanna Briggs Institute (JBI) Critical Appraisal checklist for Analytical Cross-Sectional studies [24], modified ad hoc by considering the under-reported criteria and the aim of this review. According to Hagemann [25], different criteria adopted to EEG recording, such as referencing, analysis, and multiple sessions of measurement, represent some classical issues for resting-EEG measure validity and reliability. Thus, to evaluate the quality assessment for each selected study, the resting EEG recording method used and potential EEG fluctuations due to the state-condition changes were considered.

In line with this conceptual background, the final form of checklist consists of the six domains:

- (1) Adequacy of the criteria adopted for the inclusion of participants in the sample (absence of clinical psychological disorders or other diseases, suspension of drug or psychotropic substances in case used);
- (2) Sample and setting characteristics (mean age and standard deviation, gender, education, and handedness);
- (3) Methodological criteria used for the electrophysiological measures (open or closed eyes recording, reference, length, counterbalance between open/closed eyes order and participants);
- (4) Occurrence of contextual or interactional variables not considered in the study that could constitute confounding factors (time of day and season of EEG recording, measures of mood state before and during EEG recording, menstrual cycle for women, and gender of experimenters);
- (5) Reliability of electrophysiological measures (test–retest sessions of EEG recording);
- (6) Adequacy of the statistical analysis used (including the strategies to deal with confounding factors considered in the study).

For each research article, the methodological quality assessment was determined for each domain as low, partial, and high risk of bias (respectively, "0", "1", "2"), by calculating the mean score multiplied by 100. Then a cut-off level of 75% was established. The studies under or equal to 75% were considered as low risk of bias, while, the studies above 75% were considered as high risk of bias. Table 1 shows the data extracted and examined for each study included.

Table 1. Data selected for each study.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Tomarken et al., 1992 [26]	90	19 (-)	0	EHI ^a PANAS ^b AIM ^c	Handedness Positive Affect (PA), Negative Affect (NA) Intensity of individual experiences emotion	Eight of 1-min baseline, balanced for four opened (O) and four closed (C)-eyes order, (O-C-C-O-C-O-O-C and C-O-O-C-O-C-C-O), participants, and sessions. Online ref. linked CZ site. Offline re-ref. average earlobes.	Left anterior α -asymmetry is positively related to PA, and negatively related to NA. This pattern of EEG activation is stable over time.	Two measures 2-after 3 weeks	58.4
Tomarken and Davidson, 1994 [27]	90	19 (-)	0	EHI ^a MCSD ^d STAI ^e BDI ^f	Handedness Defensiveness Trait Anxiety (TA) Depression Trait (TD)	8 of 1-min baseline, balanced for 4 O and 4 C eyes order, (O-C-C-O-C-O-O-C and C-O-O-C-O-C-C-O), participants, and sessions. Online ref. linked CZ site. Offline re-ref. average earlobes.	The α activity in mid-frontal and left lateral frontal sites is related to a higher level of defensiveness than a lower level.	Two measures 2-after 3 weeks	58.4
Sutton and Davidson, 1997 [28]	46	20 (-)	50	EHI ^a PANAS ^b BIS/BAS Scale ^g	Handedness PA, NA Behavioral Inhibition System (BIS), Behavioral Approach System (BAS)	Eight of 1-min baseline, balanced for four O and four C eyes order, participants, and sessions. Online ref. linked earlobes. Offline re-ref. average earlobes.	Resting prefrontal activation is an index of EEG α -asymmetry related to Gray's BAS and BIS rather than PA and NA.	Two measures two after 3 months	66.7
Hagemann et al., 1999 [29]	36	23.5 (4.0)	36	EHI ^a PANAS ^b EPQ ^h	Handedness PA, NA E, N	Eight of 1-min baseline, balanced for four O and four C eyes order (O-C-C-O-C-O-O or C-O-O-C-O-C-O), and participants. Online ref. linked mastoids. Offline re-ref. CZ site.	Lateral α -asymmetry in resting EEG is related to NA but is not significantly related to PA.	One Measure	50.0

Table 1. *Cont.*

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Kline et al., 2001 [30]	72	24.4 (4.6)	42	EHI ^a EPQ ^h HPCS ⁱ MCSD ^d	Handedness Neuroticism (N), Psychoticism (P), Extraversion (E), Lie (L) Maternal and Paternal caring Defensiveness	Six of 1-min baseline, balanced for three O and three C eyes order, and participants. Online ref. linked earlobes.	Defensiveness and perceived maternal (but not paternal) caring, separately predict left lateral frontal activation of the EEG α -asymmetry.	One Measure	66.7
Kline et al., 2002 [31]	235	20.4 (4.1)	67	EHI ^a EPQ ^h	Handedness N, E, P, L	Six of 1-min baseline, three O eyes, three C eyes. Online ref. linked earlobes.	Defensiveness is related with right frontal α -activity, in the presence of opposite-sex experimenters but not same-sex.	One Measure	58.4
Blackhart et al., 2002 [32]	77	20.5 (3.7)	47	EHI ^a SAM ^j	Handedness Pleasure–Displeasure, Arousal–Non arousal, Dominance–Submissive.	Six of 1-min baseline, three O eyes, three C eyes. Online ref. linked earlobes.	Negative mood post-preparation, predicts left frontal α -asymmetry during resting EEG, in women.	One Measure	66.7
Coan and Allen, 2003 [33]	32	20.5 (-)	28	BIS/BAS Scale ^g	BIS, BAS	Eight of 1-min baseline balanced for four O and four C eyes order. Online ref. Cz site. Offline re-ref. linked mastoids. Offline re-ref. average brain activity.	Resting EEG left frontal -asymmetry is related to greater BAS scores; higher BIS scores are related to right frontal activity in the mid-frontal region, only.	One Measure	83.4
Knyazev and Slobodskaya, 2003 [34]	47	23.9 (5.3)	13	GWPQ ^k EPQ ^h STAI ^e	BIS, BAS E, N, P TA	Six of 60-s baseline, balanced for a pseudo-random O/C-eyes order, and participants. Online ref. linked earlobes.	Higher δ – α EEG frequency oscillations coupling, are related to increased behavioral inhibition.	One Measure	75.0

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Razoumnikova, 2003 [35]	46	18 (-)	100	EPQ ^h AIS ^m KTI ^l	E, N, P Emotional Intelligence: Verbal, Numerical, Figural Sensation–Intuition (S), Thinking–Feeling (T), Judging–Perceiving (J)	3 min resting period with C eyes. Online ref. linked earlobes.	EEG rhythms are relating to IQ, S, E, and N. Cognitive abilities in higher IQ subjects are related with the cortex connectivity, and θ_1 – θ_2 – α_1 EEG rhythms. The β_2 rhythm is predominant in right hemisphere.	One Measure	83.4
Minnix and Kline, 2004 [36]	140	20.4 (4.1)	30	EHI ^a EPQ ^h	Handedness N, E, P, L	Six of 1-min baseline, three O eyes, three C eyes. Online ref. linked earlobes.	EEG Resting Mid-Frontal α -band activity is related with higher N.	One Measure	75.0
Hewig et al., 2006 [37]	59	24 (3.3)	49	EHI ^a BIS/BAS Scale ^g EPQ ^h	Handedness BIS, BAS E, N	12 of 1-min baseline, six O and six C eyes, balanced for two orders (OCO–COOC–OCO; COOC–OCO–COOC) and participants. Online ref. linked CZ.	There is no relation between resting frontal α -activity of EEG, and BIS/BAS traits.	Four measures one every 4 weeks	58.4
Tran et al., 2006 [38]	699	36 (-)	49	NEO-FFI ⁿ	E, N, Openness (O), Agreeableness (A), Consciousness (C).	3 min resting period with C eyes. Offline re-ref. linked mastoids.	N scores are higher in women than men. In both, δ – θ activity is related to E and C, while, α – β activity is related to NEO-FFI traits in males.	One Measure	75.0
Jaušovec and Jaušovec, 2007 [39]	110	21 (-)	50	NEO-FFI ⁿ MSCEIT ^o	N, E, O, A, C Emotional Intelligence: Verbal, Performance, Experiential–Emotional, Strategic–Emotional	5 min resting period with C eyes and 5 min resting period with O eyes. Repeating O/C eyes order after each minute of recording. Online ref. linked mastoids.	Women with extreme traits levels differ in the γ band activity than males; vice-versa in the α_1 band. Brain activity increased in parietal–occipital areas rather in frontal.	One Measure	66.7

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test-Retest	Risk %
Smit et al., 2007 [40]	Young 381 Mid-Aged 380	26.2 (4.1) 49.4 (7.2)	- -	No specified STAI ^e YARS ^f ABV ^g	Handedness TA Depression Trait (TD) N, Somatic-Anxiety	3 min resting period with C eyes. Online ref. linked earlobes.	Frontal α -Asymmetry (FA) in rest-EEG, is heritable in young adults but not in middle-aged. FA is related to the risk of anxiety and depression in young women.	One Measure	83.4
Fleck et al., 2008 [41]	34	22.4 (4.7)	47	RTS ^r	Transliminality (Tr)	3.5 min resting period with C eyes and 3.5 min resting period with O eyes. Online ref. linked mastoids.	Higher Tr scores related with lower α_1 , β_1 , γ_1 activity in left posterior cortex, and lower α_2 , β_1 , γ activity in right superior temporal areas, than lower scores. Lower levels of Tr, related to increased γ in the mid-frontal areas, than higher.	One Measure	83.4
Gatt et al., 2008 [42]	117	36.9 (12.6)	38	DASS-21 ^s	TD	2 min resting period with C eyes followed by 2 min O eyes. Offline re-ref. linked earlobes.	BDNF M/M genotype is a predictor of working memory activity. The EEG α -power mediates the effect of this phenotype on TD expression.	One Measure	66.7
Kline and Allen, 2008 [43]	71	18.9 (1.5)	30	EHI ^a EPQ ^h MCSD ^d BDI ^f TMAS ^{ee}	Handedness N, E, P, L Defensiveness TD TA	Six of 1-min baseline, balanced for 3 O eyes and 3 C eyes orders (O-C-C-O-C-O; C-O-O-C-O-C). Online ref. linked earlobes. Offline re-ref. average brain activity.	In the context of increased α -band activity in the right lateral frontal asymmetry EPQL traits are positively related to BDI.	Two measures two after 3 weeks	41.7

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Mathersul et al., 2008 [44]	428	34.9 (12.6)	50	No specified DASS-21 ^s	Handedness TD, TA	2 min resting period with O eyes and 2 min with C eyes. Offline re-ref. average brain activity.	An increased α -asymmetry in the right parietal-temporal areas related to higher anxiety comorbidity and depression trait. Right parietal-temporal α -activity related to anxiety apprehension.	One Measure	58.4
Santesso et al., 2008 [45]	Study1 37 Study2 44	19.5 (1.4) 18.6 (0.7)	24 100	EHI ^a SSS-V ^u FIS ^v	Handedness Sensation Seeking Risk-taking behaviors	1 min resting period with O eyes and 1 min with C eyes. Online ref. linked CZ. Offline re-ref. average brain activity.	Sensation seeking is associated with a greater left frontal -asymmetry in resting EEG.	One Meas. One Meas.	66.7 66.7
Schutter et al., 2008 [8]	24	22.2 (2.0)	46	BIS/BAS Scale ^g	BIS, BAS	Four of 1-min baseline balanced for two O and two C eyes order (O-C-O-C). Online ref. voltage. Offline re-ref. CZ.	B-asymmetry in resting EEG reflects approach–avoidance motivational predispositions.	One Measure	41.7
Master et al., 2009 [46]	46	20.1 (1.5)	43	No specified EAC ^w BIS/BAS Scale ^g	Handedness Emotional Approach BIS, BAS	Eight of 1-min baseline balanced for four O and four C eyes order. Online ref. Left-lobe. Offline re-ref. lobes average.	Emotional expression is significantly related to greater left-sided frontal A-asymmetry in the rest-EEG state.	One Measure	58.4
Pavlenko et al., 2009 [47]	111	21.5 (-)	42	STAI ^e Cattell 16PF ^x	State and Trait Anxiety A, B, C, E, F, G, H, I, L, M, N, O, Q1, Q2, Q3, Q4 ⁺	Two of 1-min baseline, one with O eyes and one with C eyes. Online ref. linked an active electrode n.a.	State anxiety is positively related to β 2 spectral power density in the temporal occipital areas of the right hemisphere (O-eyes). Trait anxiety is positively related to β 1, β 2.	One Measure	75.0

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test-Retest	Risk %
Peterson and Harmon-Jones, 2009 [48]	Study1 72 Study2 65	Stud. (-) Stud. (-)	- 58	IAS-R ^y Time Variables BIS/BAS Scale ^g	Nurturance and Dominance Day Time, Year season BIS, BAS	Four of 1-min baseline balanced for two O and two C eyes order (O-C-C-O or C-O-O-C) and participants. Online ref. eft-earlobe. Offline re-ref. earlobes average.	Frontal α -asymmetry in resting EEG reflects circadian and seasonal influences. The right frontal activity is increased during fall mornings.	One Measure One Measure	66.7 50.0
Knyazev et al., 2010 [49]	132	27.5 (-)	39	EPQ ^h GWPQ ^k STAI ^e	N BIS TA	3-min rest period with C eyes, 3- min with O eyes balanced for O/C-eyes order. Online ref. lobes.	Increased coupling δ - β frequency oscillations is related with state anxiety.	One Measure	75.0
Mikolajczak et al., 2010 [50]	31	22.4 (3.8)	20	TEI-Que ^z	Well-Being, Self-Control, Emotionality, Sociability	Eight of 1-min baseline balanced for four O and four C eyes order. Online ref. linked earlobe.	Resting EEG α -frontal asymmetry is related to emotional intelligence.	One Measure	83.3
Wacker and Gatt, 2010 [51]	1093	39.3 (18.7)	46	NEO-FFI ⁿ	N, E, O, A, C	2-min resting period with O eyes followed by 2-min C eyes. Online ref. linked mastoids.	The δ - θ activity in posterior vs. frontal areas related to E and COMT VAL-158 MET polymorphism.	One Measure	66.7
Wacker et al., 2010 [52]	Study3 112 Study4 35	23.8 (3.4) 22.9 (3.4)	100 62	ARES ^{gg} BIS/BAS Scale ^g	BAS, BIS BAS, BIS	Five for 90-s of resting period with C eyes. Online ref. linked CZ site. Offline re-ref. linked mastoids.	Resting posterior vs. frontal δ - θ EEG activity, is related to BAS/AE but BAS/AE, not related to frontal α -asymmetry.	Three meas. two after 1 year, three n.a. One Meas.	66.7 91.7
Chavanon et al., 2011 [53]	78	23.2 (2.7)	100	MPQ-NE EPQ ^h	Reactivity, Alienation, and Aggression E, N, P	Five for 1-min resting period with C eyes. Online ref. linked CZ site. Offline re-ref. average brain activity.	Rostral anterior cingulate activity generates the posterior vs. anterior θ activity, related to AE.	One Measure	66.7
Koehler et al., 2011 [54]	141	27.8 (-)	52	NEO-PI-R ⁿⁿ	N, E, O, A, C	5-min rest period with closed eyes. Online ref. linked between Fz-Cz sites. Offline re-ref. average brain activity.	Resting posterior minus frontal EEG δ - θ activity is related with E and DRD2 genotype.	One Measure	83.4

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Konareva, 2011 [55]	118	27 (-)	-	Cattell 16 PF ^x EPQ ^h STI ^{xx} OST ^{xxx}	A, B, C, E, F, G, H, I, L, M, N, O, Q1, Q2, Q3, Q4. ⁺ E, N, P Objective plasticity, Social ergocity Ergonicity, Plasticity, Tempo, Emotionality.	n.a. resting period with O eyes followed by n.a. resting period with C eyes. Online ref. n.a. Offline ref n.a.	Psychological traits of personality modulated the activity of δ and θ EEG rhythms.	One Measure	91.7
Knyazev et al., 2012 [56]	88	24.5 (-)	51	Self-report ad hoc EPP ^{hh}	Positive emotions, mood state E, N, P	3-min rest period with C eyes and 3-min with O eyes balanced for O/C-eyes order. Online ref. linked lobes.	AE related to higher θ activity in the posterior default mode network and lower θ in the orbitofrontal cortex.	One Measure	66.7
De Pascalis et al., 2013 [57]	51	24.1 (3.7)	0	EHI ^a BIS/BAS Scale ^g LOT-R ^t PANAS ^b	Handedness BIS, BAS Optimism PA, NA	Four of 1-min baseline balanced for two O and two C eyes order and participants. Online ref. linked CZ site. Offline re-ref linked earlobes.	Higher BAS scores are related to greater left-sided α -activity in the BA11 area. Optimism is related to higher activity in the BA10 and BA31 areas.	One Measure	42.8
Alessandri et al., 2015 [58]	51	24.1 (3.7)	0	EHI ^a GSS ^{gs} LOT-R ^t LSS ^{ls} P-OR ^{tt}	Handedness Self-esteem Optimism Life Satisfaction Positive orientation	Four of 1-min baseline balanced for two O and two C eyes order and participants. Online ref. linked CZ site. Offline re-ref linked earlobes.	The α -asymmetry in the posterior cingulate cortex is uniquely associated with both positivity scores.	One Measure	42.8
Gable et al., 2015 [59]	126	Stud. (-)	46	Self-report ad hoc PUM ^{ttt} BIS/BAS Scale ^g	Handedness Positive Urgency BIS, BAS	Eight of 1-min baseline, balanced among four O and four C eyes order (C-O-O-C-O-C-C-O or O-C-C-O-C-O-O-C) and participants. Online ref. Left-lobe. Offline re-ref. average brain activity.	BAS trait related to greater left-frontal α -asymmetry, while BIS trait is related to greater right-frontal α -asymmetry.	One Measure	75.0

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Huang et al., 2015 [60]	94	26.5 (-)	0	CC-scale ^{aa} EPQ ^h	Handedness E, N, P, L	16 of 15-s baseline, eight O and eight C eyes balanced for two groups (O–C–O–C–O–C–O–C and C–O–C–O–C–O–C–O). Online ref. linked mastoids. Offline re-ref. CZ.	Women with higher N scores, exhibit lower-left prefrontal α_1 – α_{Total} asymmetry, than women with lower N during the mid-late luteal phase.	Three measures two after 11–13 days three after 22–24 days	41.7
Korjus et al., 2015 [61]	289	22.0 (3.6)	35	NEO-PI-R ⁿⁿ	N, E, O, A, C	1-min; two of 1-min and three of 1-min baseline one O eyes and one C eyes balanced for O/C order. Online ref. linked lobes. Offline re-ref. lobes.	Personality traits cannot be predicted from the power of resting-state EEG.	One Measure	75.0
Tullett et al., 2015 [62]	56	19.8 (3.8)	46	NI ⁿⁱ SNS ^{ns} BFQ ⁿⁿⁿ	Degree of Nostalgia Frequency of Nostalgia N, E, O, A, C	Eight of 30-s baseline, balanced for four O and four C eyes order. Online ref. digital average. Offline re-ref. lobes.	The right-frontal α -asymmetry predicts an increased proneness to nostalgia scores.	One Measure	75.0
Adolph and Margraf, 2017 [63]	37	24.2 (3.8)	51	No specified STAI ^e D-S ^{ff}	Handedness TA TD	16 of 1-min baseline, balanced for eight O and eight C eyes order, and participants (O–C–C–O–C–O–O–C or C–O–O–C–O–C–C–O). Online ref. left mastoid. Offline re-ref. mastoids.	Depression and anxiety are both significantly related to larger right frontal α -asymmetry.	One Measure	50.0
Neal and Gable, 2017 [64]	182	Stud. (-)	40	Checklist ad hoc UPPS-P ^{imp} BIS/BAS Scale ^g	Handedness Impulsivity (Imp) BIS, BAS	Eight of 1-min baseline, balanced for four O and four C eyes order. Online ref. linked left earlobe. Offline re-ref. to earlobes.	Regulatory control and impulsivity are related to BIS. Withdrawal is related to FFFS, and right frontal A-asymmetry.	One Measure	75.0
De Groot and Van-Strien, 2018 [65]	93	21.03 (2.4)	39	AQ ^{aq}	Autistic Traits	3 min rest period with C eyes, 3 min with O eyes balanced for O/C order. Online ref. linked mastoids. Offline re-ref. to mastoids average.	Spontaneous γ 1– γ 2 oscillations during resting-state are not predictive of autistic traits in the general population.	One Measure	58.3

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
De Pascalis et al., 2018 [66]	162	23.6 (2.4)	0	EHI ^a RST-PQ ^{kk}	Handedness BIS, BAS, FFFS	4-min rest period with C eyes, 4-min with O eyes balanced among O/C order and participants. Online ref. linked left earlobe. Offline re-ref. to earlobes.	In the subgroup with a young same-sex experimenter, BAS-impulsivity is related to a greater left-frontal α -activity, and FFFS. BIS trait, not related to the greater right-frontal-central activity.	One Measure	33.4
Threadgill and Gable, 2018 [67]	125	Stud. (-)	-	EHI ^a BIS/BAS Scale ^g UPPS-P ^{imp}	Handedness BAS, FFFS Impulsivity (Impu)	4 min rest period with C eyes, 4 min with O eyes balanced between participants. Online ref. linked left earlobe. Offline re-ref. average brain activity.	BAS trait is negatively related to resting β activity. Impu. is related to greater resting β activity. Lower levels of β activity in the motor cortex related to motivational traits.	One Measure	75.0
Paban et al., 2019 [68]	45	34.7 (9.1)	51	CD-RISC ^{rt}	Resilience Trait	10 min rest period with C eyes. Online ref. individual vertex site.	Resilience is related to resting EEG source-space brain network flexibility.	One Measure	75.0
De Pascalis et al., 2020 [69]	125	22.8 (2.8)	39	No specified RST-PQ ^{kk} STAI-State ^e	Handedness BIS, BAS, Fight–Flight–Freeze System (FFFS) State Anxiety	3 min rest period with C eyes, 3 min with O eyes balanced among O/C eyes order and participants. Online ref. linked earlobes. Offline re-ref. average brain activity.	BIS trait related to higher δ – β coupling in Anxiety group, and high δ – θ coupling in Relaxation group. In both groups, BAS-GDP is positively related to higher δ – γ coupling.	One Measure	41.7

Table 1. Cont.

Authors	N	Participants		Personality Domain		Electrophysiological Domain		Bias	
		Age Mean (SD)	Sex Men %	Self-Report	Trait/s Considered	Resting State Recording Condition (EEG Reference, Length)	Results and Indexes of Brain Activation	EEG Test–Retest	Risk %
Zanesco et al., 2020 [70]	187	36.1 (20.1)	64	BIS/BAS Scale ^g NEO-FFI P MDMQ ^{ww}	BIS, BAS N, E, O, A, C Current Mood state	16 of 60-s baseline, balanced for eight O, and eight C eyes order and participants. Online ref. linked FCz site. Offline re-ref. average brain activity.	Personality traits can be reflected in microstate dynamics present during periods of quiet rest.	One Measure	58.4
Zhang et al., 2020 [71]	80	21.49 (2.5)	55	DERS ^{ss} STAI-State ^e STAI-Trait ^e BDI ^f	Emotional-Dysregulation six C eyes balanced for O/C State Anxiety TA TD	12 of 15-s baseline, six O eyes, eyes order and participants. Online ref. linked left mastoid. Offline re-ref. average of mastoids.	The resting-state frontal α -asymmetry predicts the regulation of emotion, mainly in impulse control.	One Measure	58.4

^a Edinburgh Handedness Inventory [72]; ^{aa} Chapman and Chapman's scale [73]; ^{aq} Autism-Spectrum Quotient [74]; ^b Positive and Negative Affect Schedule [75]; ^c Affect Intensity Measure [76]; ^d Marlowe–Crowne Social Desirability Scale [77]; ^e Spielberger State Trait Anxiety Inventory [78]; ^{ee} Taylor Manifest Anxiety Scale [79]; ^f Beck Depression Inventory [80]; ^{ff} Depressions Scale [81]; ^g BIS/BAS scales [82]; ^{gg} Action Regulation Emotion Systems [83]; ^{gs} General Self-Esteem Scale [84]; ^h Eysenck Personality Questionnaire [85]; ⁱ Harvard Parental Caring Scale [86]; ^j Self-Assessment Manikin [87]; ^k Gray–Wilson Personality Questionnaire [88]; ^{kk} Reinforcement Sensitivity Theory of Personality Questionnaire [89]; ^{imp} Impulsive Behavior Scale [90]; ^l Keirser's Type Inventory [91]; ^{ls} Satisfaction with Life Scale [92]; ^m Amthauer's Intelligence Scale [93]; ⁿ NEO-Five-Factor Inventory [94]; ⁿⁿ Revised NEO Personality Inventory [95]; ⁿⁿⁿ Big Five Inventory [96]; ⁿⁱ Nostalgia Inventory [97]; ^{ns} Southampton Nostalgia Scale [98]; ^o Mayer–Salovey–Caruso Emotional Intelligence Test [99]; ^P Young Adult Self Report scale [100]; ^q Amsterdamse Biografische Vragenlijst [101]; ^r Revised Transliminality Scale [102]; ^{rt} Connor–Davidson Resilience Scale [103]; ^s Shortened version of the Depression Anxiety Stress Scale [104]; ^{ss} Difficulties in Emotion Regulation Scale [105]; ^t Life Orientation Test Revised (LOT-R, [106]); ^{tt} Positive Orientation Scale [107]; ^{ttt} Positive Urgency Measure [108]; ^u Sensation Seeking Scale Form V [109]; ^v Frequency of Involvement Scale [110]; ^w Emotional Approach Coping [111]; ^{ww} Multidimensional Mood State Questionnaire [112]; ^x Cattell's technique 16 Personality Factor: ⁺ Warmth (A), Reasoning (B), Emotional Stability (C), Dominance (E), Liveliness (F), Rule-Consciousness (G), Social Boldness (H), Sensitivity (I), Vigilance (L), Abstractedness (M), Privateness (N), Apprehension (O), Openness to Change (Q1), Self-Reliance (Q2), Perfectionism (Q3), Tension (Q4) [113]; ^{xx} Strelau Temperament Inventory [114]; ^{xxx} Rusalov Structure of Temperament Questionnaire [115]; ^y Interpersonal Adjective Scales (IAS-R, [116]); ^z Trait Emotional Intelligence Questionnaire [117].

3. Results

3.1. Studies Selection

The flow chart (Figure 1) provides an accurate summary of the quality assessment of the articles identified through databases. The bibliographic research included all combinations of keywords and produced 5313 results. Furthermore, two additional articles were identified through other sources and included in this article. Later, duplicated studies were removed and after title and abstract readings, 2937 full-text articles were included. According to the eligibility criteria, 152 articles were reviewed by full-text screening and, consequently, 101 articles were excluded with reason. Finally, 47 articles, for a total of 50 studies, were passed to the quality assessment and were thus included in the systematic review.

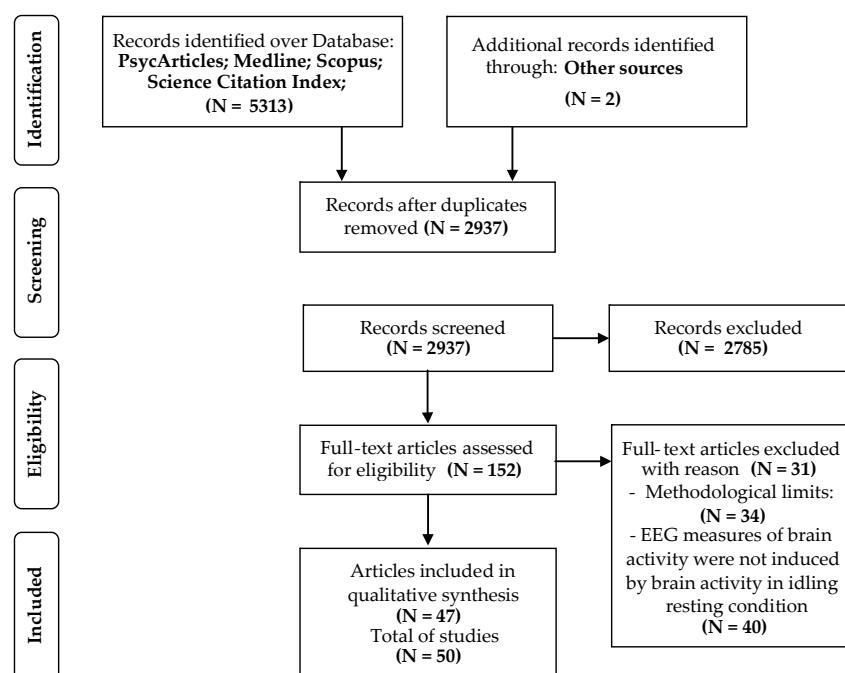


Figure 1. PRISMA flow chart of the selection process.

3.2. Quality Assessment

Figure 2 shows the percentage of studies and articles included for the quality of the assessed criteria. Generally, 44 studies (88%) presented low scores on the risk of bias, while six studies (12%) showed high scores. A large percentage of the studies used valid methodological criteria for measuring EEG performance in idling condition and included an appropriate sample size. However, many researchers did not report controlled criteria for the inclusion of the participants in their studies (first domain), did not consider interactional or confounding variables that could influence the reliability of the evaluated relations (fourth domain) and, furthermore, they did not test–retest sessions of their EEG measures (fifth domain). These are the three domains in which risk of bias was subjectively evaluated as higher than the other domains. In contrast, statistical analysis was adequate to the outcome studied (see Figure 2).

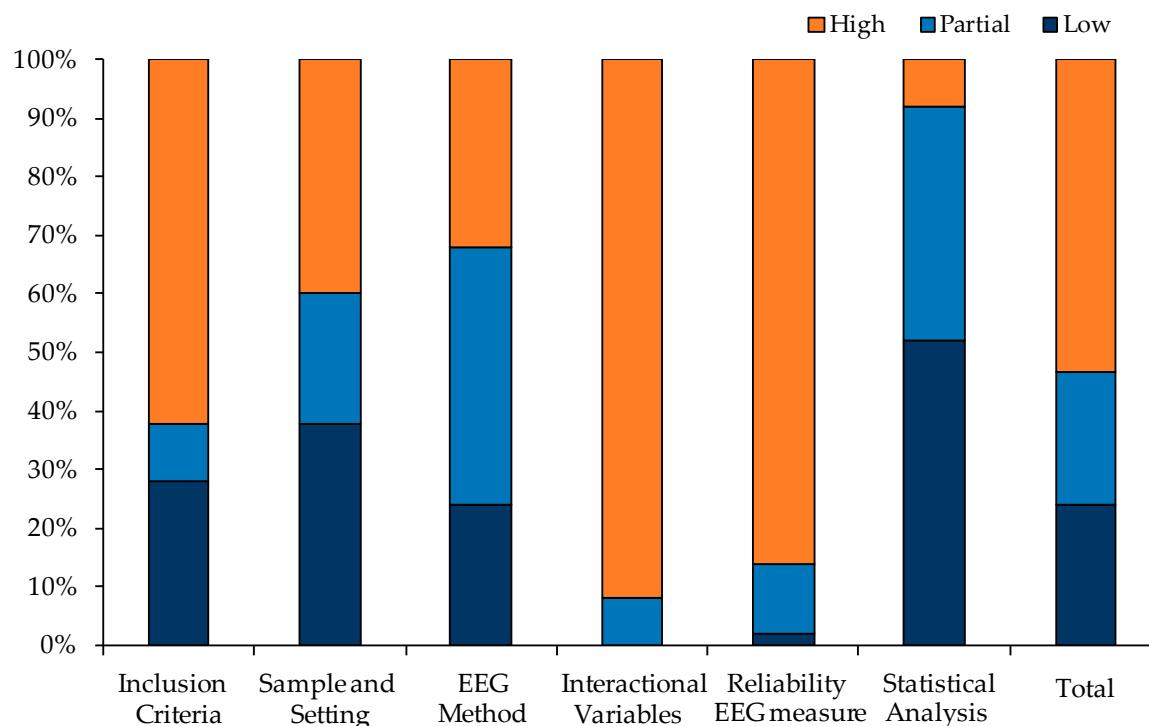


Figure 2. Risk of bias for each domain considered in the selected studies.

3.3. Demographic Features

The literature research for this review was delimited by a period that ranged from January 1990 to June 2020. In the 47 articles selected, from a total of 50 studies, 7120 healthy adult participants, aged between 17 [26,33,35,43,56,71] and 82 years old [38] took part. The studies showed a percentage of men and women variable. In some cases, samples were composed by only women [26,27,57,58,60,66] and, in other cases, there were samples of only men [35], [45] (study 2 presented in the article), [52] (study 3 presented in the article), [53]. Only three studies were conducted on a sample equally balanced regarding gender [28,39,44]. However, in some studies, we did not find any information about gender [48] (study 1 presented in the article), [55,67], mean age or standard deviation [26–28,33,35,38–40,47,48,54–56,59,60,64,67], and education [38,44,51,52], (see Table 1). Assuming the heterogeneity of the constructs and the paradigms examined, some researchers included confounding variables (such as gender, age, education) and interactional variables (such as sex of experimenters, time of day and time of year, open and closed eyes, and EEG reference) in the statistical analyses.

3.4. Approach/Avoidance Personality Traits and Electrocortical Measures

Approach/avoidance personality traits represent long-term stable behavioral state patterns [118]. The first version of the reinforcement sensitivity theory (RST), conceptualized from animal behavior by Gray, was an extension of the theory originally postulated by Eysenck. This theory posited three systems responsible for behavior: (1) the behavioral inhibition system (BIS); (2) the behavioral approach system (BAS); (3) a not well-defined fight–flight system (FFS) activated by fear [119]. Later, Gray inserted the response of block or freeze into the FFS, and reconceptualized this system into the fight–flight–freeze system (FFFS) as the main system responsible for fear responses. The FFFS is activated only in the case of active avoidance of a threatening stimulus (escape) while, if the situation requires an attack on the threat, both the BIS and the FFFS are activated (fight).

According to the motivational model theory [119,120], a relatively greater left-frontal activity is associated with behavior that results in approaching or engaging a stimulus and is related to

higher levels of behavioral approach (BAS), while a relatively greater right-frontal activity leads to the disengagement from a stimulus and is related to higher levels of withdrawal behavior.

The reinforcement sensitivity theory [121] and the motivational model [122] inspired many researchers to study the behavioral underpins in terms of neurobiological markers. Carver and White [82], using the systems conceptualized by Gray [123,124], structured the BIS/BAS scale [82] to assess the motivational model of frontal EEG asymmetry proposed by Davidson [122]. However, the problem with the BIS/BAS scales questionnaire was the lack of separation of the FFFS and the BIS, which may account for inconsistent findings obtained in past research when the BIS scale was related to resting frontal alpha activity. Recently, Neal and Gable [64] derived BIS and FFFS subscales from the original Carver and White's scale [82], demonstrating that the BIS subscale, but not the FFFS, related to greater relative right frontal activity, and that a measure of impulsivity related to the smaller right frontal activity. However, in this vein, the most important revision was done by Corr [125] in his revised RST (r-RST), which produced the development of the Reinforcement Sensitivity Theory Personality Questionnaire "RST-PQ" [89]. In the r-RST, the function of the BIS is primarily to detect and resolve conflicts between the BAS and FFFS. In addition, in the r-RST, the BAS is reconceptualized as a multidimensional system [126] composed of the subcomponents reward interest (RI), goal-driven persistence (GDP), reward reactivity (RR), and impulsivity (Imp).

Another contribution to the definition of personality was conceptualized by Costa and McCrae who proposed the Big Five model [127]. This descriptive model defined the following five stable factors, considered as the basic vectors of the personality structure: conscientiousness; extraversion; emotional stability/instability; openness; agreeableness.

Although r-RST is a neurobiological theory and the Big Five model is descriptive, there are meeting points between the two. According to Smits and De Boeck [128], extraversion can be explained by the BAS trait, while, emotional instability (or neuroticism), can be explained by the BIS trait. Therefore, in this framework, a lot of individual disposition and state variables can be considered as parallel measures of the BIS, BAS, and FFFS motivational personality traits.

In line with this point of view, many studies have investigated the relationship between the hemispheric asymmetry of the EEG asymmetrical activation of the brain delta, theta, alpha, beta, and gamma rhythms and the approach/avoidance behavioral traits. All the studies included in this review assessed one or more measures of approach/avoidance personality traits and parallel, or related, measures. In particular, 16 articles considered the relation among resting-EEG activity and BIS/BAS personality traits [8,28,33,34,37,46], [48] (in study 2), [49,51,57,59,64,66,67,69,70].

Among studies testing the association between resting-EEG activity and BIS (or parallel measures), 11 articles have considered the role of state or trait anxiety [27,29,34,40,43,44,47,49,63,69,71], four articles studied the role of negative affect [26,28,29,57], 21 articles evaluated the role of neuroticism [29–31,34–40,43,49,51,53–56,60–62,70], three articles considered the role of defensiveness [27,30,43], seven articles studied the role of depression trait [27,40,42–44,63,71] and finally, one study considered the role of nostalgia [62].

Concerning the study of resting EEG activity and BAS parallel measures, generally, 19 articles considered the role of extraversion [29–31,34–39,43,51,53–56,60–62,70], but only in seven studies did the authors find a significant relation among this trait and EEG activity [38,43,51–54,70]. Moreover, in five articles authors studied the relation among EEG rhythms and the influence of positive affect [26,28,29,57,58], two articles considered the role of impulsive control [64,67], one study evaluated the role of positive urgency [59], and two studies considered the role of sensation seeking and risk-taking behaviors [45] (studies 1 and 2).

The association between resting-EEG activity and FFFS, was considered in four articles [64,66,67,69], but, of these, only two studies found significative results [64,66]. Furthermore, one study considered the relation among EEG gamma activity and autistic traits [65], one article studied the role of resilience [68], and two articles found a positive association between EEG alpha activity and emotional intelligence [39,50]. Some studies have observed a significant relation between autistic traits and

approach/avoidance personality traits [129], as well as emotional intelligence [130] and resilience [131]. In particular, results have shown a negative correlation between resilience and the brain network flexibility for the delta, alpha, and beta bands, suggesting a robust relationship among the flexibility of human brain and resilience traits [68]. Finally, one study included in this review considered the relation between EEG activity and transliminality [41].

3.5. Approach/Avoidance Personality Traits and EEG Gamma Rhythm

Although there is still no univocal agreement among researchers regarding the definition of EEG gamma band, in general it is referred to as the range of frequencies comprised between 30 and 70 Hz [132]. In particular, recent research classifies a slow gamma activity as being around 20–40 Hz, and a fast gamma activity as around 40–70 Hz, generated from excitatory–inhibitory interactions of pyramidal cell and interneuron networks [133] in posterior brain regions [134], visual cortex [135], temporal-parietal regions [136], and the hippocampus [137]. Furthermore, according to Fries [138], the synchronization of the gamma frequency would be involved in the synchronization of the alpha-beta feedback signal in the cortical networks.

With regard to the study of brain oscillations and personality, Jaušovec and Jaušovec [39] investigated the relationship among Big Five personality traits [94], emotional intelligence, and EEG activity in right-handed participants during an eyes-closed resting period. In this study, these authors, taking into account the role of gender, analyzed the EEG rhythms using entropy measures, fast Fourier transform (FFT), and low-resolution electromagnetic tomography (LORETA) techniques. Results highlighted that brain activity was increased in the parieto-occipital areas rather in the frontal area only for compounds among extreme personality styles (neurotic type, low emotional intelligence and agreeableness; high neuroticism, or specific combinations of personality dimensions, e.g., introverts with high emotional IQ, versus extraverts with low to average IQ). These compounds were related to the spectrum of gamma-band activity and gender [39].

Openness to experience (O—Big Five trait) has been found to be associated with transliminality [139]. This trait has been defined as “susceptibility to, and awareness of, large volumes of imagery, ideation, and affect. These phenomena can be generated by subliminal, supraliminal, or external input” [140] (p. 327). In a recent study, Fleck and colleagues [41] studied the association among transliminality and frequency oscillations, suggesting that higher levels of transliminality are related to lower slow alpha, beta, and gamma-band activity in the left posterior cortex and lower fast alpha, lower beta, and gamma activity in the right superior temporal areas. Moreover, lower levels of transliminality were related to increased gamma-band in the mid frontal areas, than higher levels of this trait [41].

In addition to studying the relationship among personality traits and gamma-band activity, many researchers have been interested in studying the relationship within brain traits and the development of cognitive processes between personality traits. Many studies found that gamma-band activity is related to cognitive functions [141], such as perceptual binding [142], attention [143], working memory [144], language [145], and social interaction [146]. According to Groot and Van Strien [65], these domains are altered in the autism spectrum disorder (ASD). Recent studies assess that individuals with ASD have increased spontaneous gamma oscillations [147]. Thus, according to these studies and the autism spectrum hypothesis [74], De Groot and Van Strien [65] hypothesized that enhanced gamma-band activity could be considered as a biomarker of ASD—an endophenotype present in people with higher levels of autistic traits. To confute this supposition, the authors administered the Autism-Spectrum Quotient (AQ) questionnaire [74] to right-handed male and female university students and recorded their EEG activity during a resting idling condition. In this sample, results suggested that gamma power was not related to the autistic quotient “AQ” score. This result may be due to the fact that autistic traits in the general population are not strong enough to be detected [65].

In sum, the number of reports referring to the relationship between resting EEG gamma-band activity and personality traits is so limited that they cannot be discussed in depth within a context of

motivational theory [3,4,89]. Thus, among the articles included in this review, only three [39,41,65] analyzed the relation between personality traits and EEG gamma-band activity. However, we believe it is important to highlight and reflect on these poor results to inspire future research exploring this relationship further.

3.6. Approach/Avoidance Personality Traits and EEG Beta Rhythm

Beta rhythm is the oscillatory neural activity in the frequency range of 14–30 Hz, generated by dipole located in the deep layer networks [148] of the pre-central and post-central cortical sites [149], and in the parietal regions [150,151]. It is the rhythm dominant in normal waking consciousness, traditionally associated with sensorimotor processing [152]. However, recent research emphasizes that beta rhythm is related to sensorial and cognitive processes, such as alerting [153], working memory [154], decision making [155], and focused mental activity [156]. Specifically, slow beta activity (12–15 Hz) is associated with coordination [157], central beta activity (15–22 Hz) is associated with mental active engagement [158], while high beta activity (22–38 Hz) is associated with metacognition [159] and integration of new experiences and semantic memory [160]. Furthermore, recent EEG studies have introduced beta (13–30 Hz) oscillations as a cortical brain rhythm that may reflect active neural inhibition [161] and excitement or trait anxiety [56].

In terms of the anxiety trait, Pavlenko and colleagues [47] studied the relation among resting EEG oscillations in healthy adult male/female participants, and personality measures of state and trait anxiety. Results highlighted, in only two studies, that state anxiety was positively correlated with the spectral power density (SPD) of central beta-band in the temporal and occipital regions of the right-hemisphere during the eyes-open recording. Moreover, the correlations of the estimates of trait anxiety with the SPDs of the beta rhythm were found in frontal and central areas of both hemispheres and parietal and occipital loci of the right hemisphere. Anxiety trait was positively correlated with the SPDs of the slow and central beta-band oscillations [47]. These results are partially in line with approach/avoidance motivational theory in which the behavioral inhibition, or its parallel anxiety measures, are associated with a greater relative right frontal cortical activation [28,64].

According to Threadgill and Gable [67], the beta activity during resting state can be assumed as a neurophysiological marker of motivated motor-action preparation. In their experiment, the authors first assessed, in a sample of university students, the behavioral approach/avoidance motivational traits (BIS/BAS Scale [82]) and the Impulsive Behavior Scale of the Regulatory Control Questionnaire (UPPS-P [90]), to evaluate the influence of behavioral disinhibition. They then recorded the EEG in a resting idling condition. In this sample, results emphasized that a greater trait approach was negatively associated with resting beta activity, while greater trait impulsivity was associated with a greater resting beta activity. Lower levels of resting beta activity in the motor cortex was found associated with traits related to motivated motor behaviors. Furthermore, according to Schutter and colleagues [8], frontal EEG asymmetry of beta activity (13–30 Hz) reflects the brain cortical excitability and approach–avoidance motivational predispositions. In this study, frontal asymmetry is a direct measure of cortical excitability and is seen in line with the approach/avoidance motivational model proposed by Davidson [3], wherein self-reported emotional tendencies for approach or avoidance are associated, respectively, with left- or right frontal asymmetry.

In sum, resting EEG beta asymmetry findings from the above-mentioned three studies included in this review are in line with our initial hypotheses. These findings indicated that in resting idling conditions, the beta frontal asymmetry [8,47,67] and the scalp-distributed beta activity can be defined as potential markers of the approach/avoidance motivation personality traits.

3.7. Approach/Avoidance Personality Trait, Interactional Variables, and EEG Alpha Rhythm

Alpha rhythm, or Berger's rhythm, is a brain activity with a frequency ranging from 8 to 13 Hz, associated with a state of wakeful relaxation [162]. This rhythm is classified in slow alpha (8–10 Hz), generated in the anterior brain regions, and fast alpha (11–13 Hz), generated in the posterior

regions [163]. The anterior and posterior systems constitute a single alpha network, distributed over the whole brain surface [164]. Moreover, the alpha rhythm is considered as a mechanism of surrounding inhibition [165], useful in increasing the signal–noise ratio and to inhibit ongoing conflicting processes [2]. According to the “idling condition hypothesis”, alpha activity reflects both the ongoing cognitive processes and the proper inhibitory mechanisms of this condition. This characterizes alpha activity as a good biological index sensitive to personality and behavior differences among individuals [166].

The association between alpha rhythm and the approach/avoidance behavioral traits was studied in more depth than other EEG rhythms. In this review of the literature, 33 studies that found a relationship between resting-EEG alpha rhythm and approach/avoidance behavioral traits, or other parallel trait measures were included. Of these studies, 27 analyzed the relationship among EEG alpha activity and approach/avoidance personality traits [26–30,33,35–40,42–44], [45] (studies 1 and 2), [46,50], [52] (studies 3 and 4), [57,59,62–64,71], while, the remaining six studies analyzed the influence of the interactional or contextual variables, on the relationship between approach/avoidance personality traits and resting EEG alpha activity [31,32], [48] (studies 1 and 2), [60,66]. For this reason, we decided to discuss the results highlighted by this research line in two separate sections. In the first section, we review findings on the relationship between resting EEG alpha activity and approach/avoidance personality traits. In the second section of this paragraph, we review findings supporting the influence of interactional or contextual variables on this relationship.

3.7.1. Approach/Avoidance Personality Traits and EEG Alpha Rhythm

The measure of EEG alpha spectral power, in the frontal area, is used to calculate an index of inter-hemispheric frontal asymmetry in resting condition. This index is usually calculated by subtracting the resting EEG alpha power of the cortical area of interest in the left hemisphere from that of the homologous area in the right hemisphere [167].

In a pioneer research, Tomarken and colleagues [26] found that resting EEG anterior alpha asymmetry, recorded in a sample of adult women, was related to individual differences in positive and negative affect (PA, NA) traits. In particular, they found that the activation of the anterior left hemisphere was related to relatively frontal higher levels of PA scores, while lower levels of NA were associated with an increased right hemisphere anterior activation [26]. The relation among resting EEG alpha asymmetry and positive/negative emotional traits (PA, NA) was labelled as the “emotional model” of hemispheric asymmetry. However, in other studies, the validity of this model was partially supported. Hagemann and colleagues [29] examined the relation between resting EEG alpha asymmetry and personality traits of PA and NA, neuroticism (N), and extraversion (E). In this study a significant association was highlighted between the right hemisphere activation and NA trait, but no significant association was found between alpha rhythm and PA trait. However, these authors reported, in contrast with the emotional model, a left anterior temporal activation in subjects with higher NA scores, while they did not find any significant association between NA and N or PA and E. These results suggested that the biological bases of N and NA are different [29], disconfirming the hypotheses of Eysenck and Eysenck [168], according to which N trait should be positively associated with negative affect, whereas E trait is positively associated with positive affect. Minnix and Kline [36], in contrast with Hagemann and colleagues [29], observed that higher N or emotional lability levels were associated with greater variability of mid frontal asymmetry. These authors proposed the inconsistency of the outlined relationship between neuroticism and right frontal activation, and suggested the necessity to provide a novel neurobiological index sensitive to individual differences in N and able to predict psychopathologies linked to this trait.

In general, a left hemisphere hypoactivation in anterior regions is a biological marker of affective style and related to the risk of psychopathology [27]. To assess whether resting anterior asymmetry discriminates individual differences in repressive coping styles, Tomarken and Davidson [27], in a sample of university students, studied the relationship between defensiveness copying style and

EEG alpha asymmetry. In their experiment the authors administered the Marlowe-Crowne Social Desirability Scale [77] and the State-Trait Anxiety Inventory [78], before recording the EEG in resting condition. Defensiveness trait was associated with greater right frontal activation in the presence of an opposite-sex experimenter, but not with a same-sex one. In other EEG alpha asymmetry studies, in the presence of opposite-sex experimenters, but not same-sex experimenters, high-defensive participants had a relative frontal left hemisphere activation, while, low-defensive participants had a frontal right hemisphere activation [30,169]. Further, in another study, the defensiveness trait resulted in being related to the retrospective quality of parental caring [170], suggesting that repressed coping style, or defensiveness trait, and perceived maternal caring predicted left lateral frontal alpha activation [30].

According to other authors, frontal EEG asymmetry reflects not only emotion, but also individual differences in motivational personality traits [171,172]. In their pioneer experiment, Sutton and Davidson [28] showed that EEG alpha asymmetry explained more than 25% of the variance in the self-report measure of BAS and BIS traits, but prefrontal EEG asymmetry, however, was not significantly correlated with PA or NA. This research demonstrated that resting EEG alpha asymmetry can be predicted by BIS and BAS motivational traits. In this study, participants with greater prefrontal left hemisphere activation reported higher levels of BAS, whereas those with greater prefrontal right hemisphere activation reported higher levels of BIS. In this vein, the approach/withdrawal, or motivational model, of frontal EEG alpha asymmetry highlights that frontal brain activity corresponds to motivational propensities to approach versus withdraw behavioral tendencies [120,122]. Later, Coan and Allen [33], in an attempt to replicate Sutton and Davidson's findings [28], reported that approach motivation was a valid construct associated with EEG asymmetry findings in the temperament, emotion, and psychopathological domains, but, in contrast with the prediction of the model, the right hemisphere asymmetry in higher BIS scorers was partially confirmed. Although Sutton and Davidson [28] argued that higher BIS scores were related to a greater right frontal activity, Coan and Allen [33] found only a weakly significant relationship between BIS and right hemisphere activation in the mid frontal region rather the frontal region. Probably, in this study, the discrepancy was due to the different conceptualization of withdrawal and BIS constructs used in the two studies. Davidson [120] conceptualized a withdrawal construct as the system that motivates, or potentially motivates, organisms to withdraw from sources of aversive stimulation, whereas Gray [173] conceptualized the BIS as the system that, among other things, interrupts ongoing behavior, increases arousal, and increases attention, none of which inevitably leads to a withdrawal response.

Hewig and colleagues [37] suggested that the problem of replicability could be due to the different conceptualization among the withdrawal and approach systems that could both be subsystems of the behavioral activation system. Authors proposed a new view of the approach/withdrawal model of anterior asymmetry, in which the behavioral activation system is related to bilateral frontal cortical activity, and right and left activations related, respectively, to withdrawal and approach behavior [174]. This model is in line with results of Harmon-Jones and Allen [175], who reported a positive relation among bilateral frontal cortical activity and BAS. In this vein, behavioral activation is the product of both approach and withdrawal motivational traits [37].

Research on personality correlates of right frontal alpha asymmetry has demonstrated that a higher dispositional tendency to experience withdrawal-related behaviors was related to increased proneness to nostalgia or sadness [62]. Adolph and Margraf [63] studied the relationship among symptoms of anxiety, depression, and frontal asymmetry in a sample of healthy individuals. Results indicate that higher symptom severity of depression and anxiety were correlated to a larger right frontal cortical activity. Furthermore, a larger right frontal cortical activity was influenced by anxiety symptoms [63]. In sum, frontal alpha asymmetry can be considered a biological marker for the risk of anxiety and depression [3].

From a genetic point of view, research affirmed that the relation between frontal alpha asymmetry and the risk for anxiety and depression is heritable only in young adults (males 32% and females 37%), but not in middle-aged adults [40]. In particular, the BDNF Val⁶⁶Met polymorphism would

be associated with the depression trait and mediated by EEG alpha power [42]. These findings highlight the utility of studying the relation among EEG measures and genotype to elucidate the pathway that elapses between the expression of an endophenotype and individual dispositions in personality traits [42]. According to Mathersul and colleagues [44], increased activity of alpha rhythm in the right parietal-temporal cortex is related to higher comorbidity of anxiety and depression, while increased right parietal-temporal alpha activity is related to anxious apprehension. These data support predictions for frontal, but not posterior regions and are in line with the motivational model of Davidson [120], in which depressed individuals differ from controls by an increase in withdrawal trait and negative affective valence, but in contrast to the valence-arousal model [176]. According to Heller [176], depressed mood is characterized by an asymmetrical profile associated with increased right frontal activity, due to a dissociation among lower and higher right parietal-temporal activity. Moreover, in this experiment, individuals that used a higher coping style oriented toward an emotional approach (through emotional expressions), had neural activities indicative of greater approach motivation [44]. Positive emotional expression traits are significantly related to greater left-sided frontal alpha asymmetry in the resting EEG condition [46].

According to Zhang and colleagues [71], participants who showed a higher relative left frontal activity during a resting state condition, exhibited fewer difficulties in everyday emotion regulation, especially in the dimension of impulsive control. Among personality traits related to impulsive control, the positive urgency (defined by Cyders and colleagues [108] as the tendency towards rash action in response to extreme positive emotional states) is related to left frontal alpha asymmetry. Gable and colleagues [59] found that higher levels of positive urgency trait were associated with a greater left frontal EEG activity, which originates from reduced right frontal activity in the inferior frontal gyrus [59]. According to these authors, a decreased right frontal activity could be considered as a potential neurobiological trait of impulsivity, related to the higher activity of the supervisory control system. This result was later confirmed by Neal and Gable [64], who suggested that impulsivity is related to reduced right frontal brain activity. Furthermore, higher BIS levels were related to greater right frontal activity, while BAS and FFFS traits (motivation to approach and motivation to withdrawal, respectively) were not associated with frontal alpha asymmetry. The authors state that regulatory control processes are associated with BIS and impulsivity and related to the right frontal activity rather than to withdrawal motivation expressed by the FFFS [64].

Another personality trait associated with impulsive control and the predisposition to approach is sensation seeking [177]. In two studies conducted in separated laboratories with different samples, Santesso and colleagues [45] examined whether the pattern of left frontal resting EEG activity related to approach-related behaviors and sensation seeking. Both studies highlighted that sensation seeking is associated with a greater left frontal alpha asymmetry in resting EEG, specifically in male participants. These authors suggested that this pattern could reflect the predisposition of sensation seekers to search out novelty stimulus or engage in risky behaviors to reach the reward.

Concerning the parallel dispositional measures within the framework of the behavioral approach construct, De Pascalis, Cozzuto, Caprara, and Alessandri [57] observed that both dispositional optimism and BAS traits are related to EEG alpha asymmetry. In this study, findings on power spectral density in the alpha band have shown a robust relationship between higher cortical activity in the left middle frontal gyrus (BA11) and BAS. Optimism was related to both anterior left frontal cortical activation in the superior frontal gyrus (BA10), and a higher right-sided cortical activation in the posterior cingulate (BA31). In particular, alpha asymmetry in the posterior cingulate cortex, BA23 and BA31 regions, was uniquely associated with positivity trait, a basic disposition necessary to integrate self-referential thought and autobiographical memories [58]. In this vein, approach behavioral trait would be associated with greater left frontal activity, while behavioral avoidance trait would be associated with the greater right frontal alpha activity [59]. However, several findings do not support the relationship between motivational theory [120] and frontal alpha asymmetry. For example, another recent study conducted by Wacker and colleague [51], did not support the predicted left frontal asymmetry relation

with the trait BAS/agentic extraversion (BAS/AE), but a positive relationship among consciousness (C) and frontal alpha asymmetry was observed [51]. Furthermore, within the frame of the Big Five theory [94], it was found that the personality traits of the NEO-Five-Factor Inventory (NEO-FFI) were related to alpha-beta coupling only in male participants [38]. Mainly, men with extreme trait levels differed in slow brain alpha activity compared to women [39]. However, according to Korjus and colleagues [61], the five dimensions of NEO-FFI personality traits, as well as their subordinate measures, could not be predicted from the resting state EEG data.

At a neurobiological level, Pavlenko and colleagues [47] hypothesized that a well-developed alpha rhythm is characterized by an active and stable functioning of the cerebral dopaminergic system since they found that this pattern simultaneously serves as a prerequisite of high emotional stability and social adaptability. These findings are in line with the evolutionary assumption of Knyazev and Slobodskaya [34], suggesting that alpha rhythm reflects the adequacy of descending inhibitory control generated by the thalamocortical system, associated with cognitive performance [47]. Further, Razoumnikova's [35] findings indicate that, in male participants, higher levels of cognitive performance would be related to enhanced cortical connectivity of fast-frequency alpha rhythm [35].

Emotional intelligence is another trait related to cognitive abilities [178] and motivational neurobiology [130]. In terms of EEG frequency oscillations and individual differences, higher levels of emotional intelligence were associated with higher levels of positive affect and lower levels of negative affect [179], and positively related to a frontal left-sided alpha EEG asymmetry [50,180].

In conclusion, the present research review examined the relationship between interhemispheric EEG asymmetry and personality traits. In this context, alpha activity, in resting condition, has been the most used to derive an index of hemispheric asymmetry. Thus, this brain oscillatory activity was the most discussed in this review. However, this does not mean that alpha rhythm has produced the most stable and reliable results. Unfortunately, the study of this relationship provides controversial and unclear results. Several studies have supported the motivational model [28,43–45,57,59,62,63,71], many others have supported it partially [59,64,67], and others have disconfirmed it [29,33,37,52,64,66,175].

3.7.2. Interactional and Contextual Variables in the Relationship between Personality Traits and EEG Alpha Asymmetry

Recent research has studied the influence of interactional and contextual variables in the relationship between interhemispheric EEG asymmetry and personality traits. In particular, contextual variables, such as time of day and season [48], mood state and pre- and post-cap preparation [32], and experimenter sex [31,66], can influence the relation among EEG alpha asymmetry and personality traits. To demonstrate that a relationship is reliable, multiple recording sessions should be necessary, because only half of the variance in a resting session is due to the trait influences [25]. In this framework, Peterson and Harmon-Jones [48] studied, in two different samples, the role of different seasons and time of day in the relation of resting EEG alpha asymmetry and personality traits of approach-avoidance, nurturance, and dominance. In the first experiment, the EEG baseline of participants was recorded before noon and in the afternoon, both in the spring and summer months, and in the autumn and winter months. Results highlighted that frontal alpha asymmetry in resting EEG reflects circadian and seasonal influences. The right frontal activity increased during autumn mornings. These results could explain why the relation between resting alpha asymmetry and personality traits is not replicable across studies [181].

With regard to the influence of experimental context on EEG performance, Blackhart and colleagues [32] assessed that EEG cap preparation leads to a less positive mood. In this experiment, the measures of mood (evaluated with the self-assessment manikin) most proximate to the EEG recordings were associated with asymmetry when the results of pre-cap preparation mood ratings were statistically controlled. Men and women showed a shift toward a more negative mood state post-preparation. Negative mood post-preparation, but not pre-preparation, predicted relative left frontal activation in women.

For women participants, another important intervening variable to consider before the EEG recording measures is the menstrual cycle. In particular, higher levels of neuroticism (a parallel measure of BIS) were related to lower left prefrontal activity than lower levels during the mid-late luteal phase of the woman. This relation was identified as indexed by slow alpha component, and alpha-total asymmetry scores in the prefrontal regions. Therefore, the relation among resting frontal alpha asymmetry and high/low neuroticism levels in females is moderated by the menstrual cycle [60].

Finally, in a recent study, conducted by De Pascalis, Sommer, and Scacchia [66], on a sample of right-handed female university students, the authors discussed the relevance of taking into account the gender of experimenter. In this experiment, the authors examined the association among Reinforcement Sensitivity Theory-Personality Questionnaire (RST-PQ) traits [89] and alpha asymmetry in resting EEG. Results indicate that in the total group, which included two subgroups with experimenters of different gender (male, female), FFFS was related to the greater left rather than right frontal activity, while BIS was related to the greater right frontocentral activity. These associations remained significant for the subgroup with a young same-sex experimenter, but not with an opposite-sex experimenter.

In conclusion, it can be affirmed that besides the different conceptualization models, the interactional and contextual variables can also lead to a lack of replicability of the results in relation to EEG alpha rhythm and approach/avoidance personality traits.

3.8. Approach/Avoidance Personality Traits and EEG Theta Rhythm

The theta rhythm is a slow brain activity within a typical frequency range of 4–7 Hz [182]. According to Kramis, Vanderwolf, and Land [183], this rhythm is classified as type 1 theta (8 Hz), associated with locomotion and voluntary behavior, and type 2 theta (4–7 Hz), associated with motionlessness. The main brain dipoles that generate theta rhythm are sited in the midline prefrontal region of the cortex [184], the hippocampus, and the limbic system [185].

Theta oscillations are involved in various cognitive abilities, such as associative thinking [186], the encoding of information, active exploratory movements, spatial navigation of the environment, and memory [187]. In a study, Razoumnikova [35], in a sample of adult males, studied the relationships among EEG power and coherence measures of brain oscillations, and personality traits of extraversion, neuroticism, psychoticism, sensation–intuition, thinking–feeling, judging–perceiving, and emotional intelligence.

Results showed that higher levels of emotional intelligence were characterized by an increase in theta power in the right hemisphere, while lower levels of this trait were related to increase in theta power in the left hemisphere. In the subgroup with high levels of emotional intelligence, as compared to the subgroups with low levels, there were lower levels of power of type 1 and 2 theta-bands, and slow alpha bands, while there were greater levels of power in the beta-band. Furthermore, the groups with high emotional ability, compared to low groups, were related to higher interhemispheric coherence. According to the author, the results highlighted that EEG spectral parameters, in resting EEG conditions, reflect the relationships between neuronal integration (memory) and personality/intelligence variables.

With regard to the primary personality traits, several studies suggest that the posterior–anterior distribution of resting EEG activity [37,175,188], in the delta and theta frequency range rather than alpha range [51,52,54], is associated with the extraversion personality trait. In line with this evidence, Chavanon, Wacker, and Stemmler [53] observed an association among agentic extraversion (AE), and posterior versus anterior resting EEG theta activity in the rostral anterior cingulate cortex. According to Knyazev, Bocharov, and Pylkova [56], AE trait is related to higher theta activity in the posterior default mode network and lower theta activity in the orbitofrontal cortex. These results suggest higher tonic activity in the orbitofrontal cortex and lower activity in the default mode network in extraverts compared to introvert participants.

In sum, from among the four articles included in this section [35,53,55,56], it emerges that emotional intelligence [35] and personality traits modulate the activity of theta EEG activity [55]. In particular, for AE it was highlighted that rostral anterior cingulate activity generates posterior versus anterior

theta activity [53]. On this basis, it has been suggested that frontal-posterior EEG theta spectral power gradient can be considered as a marker of extraversion personality trait [56].

3.9. Approach/Avoidance Personality Traits and EEG Delta Rhythm

Delta rhythm is a slow brain activity within a frequency range of around 0.5–3 Hz, associated with regenerative processes such as deep dreamless and sleep [189]. In particular, delta activity is supposed to reflect cortical reorganization of waking circuits and it is related to the activity of the parasympathetic nervous system, and the activation of ascending cholinergic projections from the thalamus [190]. According to Knyazev [164], although the origin of delta rhythm is uncertain, the dipole generators of these oscillations are located in the anterior medial frontal cortex [191], the subcortical regions linked to the brainstem [192], the nucleus accumbens [193], and the ventral tegmental area [194]. These brain regions are associated with dopaminergic activity and the approach/avoidance motivational traits [195]. Within an evolutionary framework of the brain oscillation systems, Knyazev and Slobodskaya [34] evaluated the relationship between resting-state EEG of adult right-handed male and female university students and BIS trait (Gray–Wilson Personality Questionnaire [88]). The strength of descending noradrenergic fibres of the locus coeruleus [196] was measured by the negative correlations among delta, theta, and alpha powers, separately estimated in each EEG band [2]. Their results confirm that higher BIS scores were associated with the enhanced negative coupling alpha to the delta frequency oscillations. These results were confirmed in other research in which increased levels of delta beta coupling were associated with state anxiety [49], indicating a predominantly cortical origin of the trait anxiety. Furthermore, higher levels of state anxiety increased the alpha–delta anticorrelation and were positively related to the power of alpha oscillations, and negatively related to the power of delta oscillations [34].

In terms of anxiety trait, Eysenck [197] explained neuroticism as the product of activation of the sympathetic nervous system, so that higher scores in neuroticism (N) are positively related with greater activation levels, i.e., lower activation thresholds, within this subcortical structure. Tran and colleagues [38] investigated the relationship among individual personality differences [94] and eyes-closed EEG resting brain activity. The authors suggested that there is a significative effect of gender on N trait—women exhibited higher levels of anxiety trait than men, while, extraversion (E) and consciousness (C) traits were associated with delta and theta rhythms in all cortical regions. Generally, NEO-FFI personality traits were associated with the amplitude of alpha and beta oscillations in men [38].

The approach/avoidance personality traits and EEG activity in the delta range were also found associated with reward and stimulus salience processing in the reward circuit [164]. In a recent research, De Pascalis, Vecchio and Cirillo [69] tested whether cortical–subcortical coupling would increase as a function of decreased delta (theta) or higher beta (gamma) activity in a sample of right-handed university students during a resting anxiogenic situation and a relaxation situation. To evaluate the influence of state anxiety and approach/avoidance personality traits on these neurobiological processes, participants completed the State Anxiety Inventory [198] and the Reinforcement Sensitivity Theory Personality Questionnaire [89]. During the resting anxiety condition, a significant positive between-subject delta–beta correlation was observed. This association was significantly higher than the association observed during the relaxation condition. In the anxiety, but not in the relaxation group, a delta–beta coupling for the low delta activity was observed. In addition, in the anxiety condition, BIS was significantly associated with a higher strength of within-subject delta–beta coupling, while, in the relaxation group, BIS was positively associated with delta–theta coupling. In both groups, BAS goal-driven persistence sub-trait (BAS-GDP) was positively associated with higher delta–gamma coupling [69]. These results suggested that the coupling between slow and fast EEG frequency oscillations reflects cortical–subcortical interaction [164,199]. However, these findings should be interpreted with caution, because data findings relied on two separate samples of the university students and not on the general population.

In terms of approach motivation behavior, the AE trait can be defined as the major expression of behavior and is associated with dopamine neural activity [200]. Wacker and Gatt [51] stated that resting posterior versus frontal EEG delta–theta activity is both sensitive to pharmacological manipulations of neural dopamine and associated with the AE. Furthermore, posterior versus frontal resting EEG delta/theta activity represents the molecular genetic basis of agentic extraversion associated with Catechol-O-methyltransferase Val¹⁵⁸Met (COMT VAL/MET) polymorphism [52], and is sensitive to dopamine D2 receptor antagonist-induced changes in dopaminergic activity [54]. Studying the relationship among the posterior–frontal distribution of slow oscillations, Koehler and colleagues [54] confirmed Depue’s and Collins’ statement that agentic extraversion is linked to individual differences in dopaminergic activity, although these authors did not emphasize a significant association among extraversion and DRD2.

In sum, the eight studies reviewed and analyzed in this section have demonstrated that the psychological traits of personality modulate the activity of delta as well as theta EEG activity [55]. In terms of the BAS/E trait, some of these studies highlighted that this trait was related to delta–theta coupling at posterior versus frontal brain regions [51,54]. Interesting, BAS-GDP was positively related to higher delta–gamma coupling [69]. Using the NEO-FFI, Tran and colleagues [38] found that delta–theta activity was related to E and C, while the alpha–beta coupling was related to personality traits in males only. In terms of BIS/N, higher delta–alpha coupling has been related to increased behavioral inhibition [34], while the increased delta–beta coupling is associated with state anxiety [49]. Finally, the BIS trait was related to higher delta–beta coupling during a state of resting anxiety and with higher delta–theta coupling during a neutral resting condition [69]. These results disconfirmed the frontal alpha asymmetry hypotheses for the BAS trait [52]. Findings from the above-mentioned studies suggest that the evaluation of coupling among slow and fast rhythms is a good method for evaluating cortical–subcortical excitability in behavioral processes.

4. Discussion

This review mainly aimed at studying the relationship among resting EEG cortical activity in resting condition, and individual differences in approach/avoidance motivation personality traits. Another aim was to understand which EEG frequency oscillation and the associated scalp-distributed lateral asymmetries can be defined as an index of cortical excitability sensitive to the approach/avoidance motivational personality traits.

Research on databases has shown that many studies have satisfied the inclusion criteria, confirming the high interest of the researchers on this topic. This interest was opened to many factors, such as the study of the neurobiological underpinning of behavioral individual differences [26–29], the validation of the motivational personality theory [8,33,46,52,56,57,59,64,67], and the investigation of the neurobiological cortical markers related to the risk of psychopathological disease such as anxiety and depression [30,31,37,41,43,44,62,63], or behavioral disinhibition [45,64,71].

In accordance with the motivational model theory [121], research showed that the EEG gamma frequency oscillation, or the associated scalp-distributed lateral asymmetries, is not a good index of approach/avoidance motivation personality traits. Interesting results were found from the study of resting-EEG beta-band activity and approach/avoidance personality traits, wherein the results highlighted that resting beta asymmetry is a neurophysiological marker of approach/avoidance personality traits [8,67]. With regard to the study of EEG alpha asymmetry and the affective/motivational dispositions, some research has supported the motivational model theory [28,44,45,57,59,62], others have partially supported it [5,33,43,64,66,71], or disconfirmed it [29,37,52,176].

A number of studies on the relationship between brain oscillations and personality have outlined that frontal–posterior EEG theta spectral power gradient is a good index of cortical excitability in the approach/avoidance motivational personality traits [51,53,54], and a stable individual measure related to extraversion personality trait [56]. Regarding to the BIS functions, higher delta–alpha coupling is related to increased behavioral inhibition [34], while an increased delta–beta coupling is associated

with state anxiety [49]. In sum, all these findings indicate that the coupling among fast and slow rhythms can be considered as indexes of cortical—subcortical interactive influences on personality traits [69].

However, the current review suggests that these results should be interpreted with caution, because several methodological problems persist in this field of research. The qualitative assessment of the selected articles emphasized a medium risk of bias (see, the last column “Total” in Figure 2). This result could depend on several factors. Many researchers did not conduct any evaluation referring to the anamnesis of the participants enrolled in their research. They did not consider the possible influence of organic, psychological, psychopathological, neurological disorder, or brain trauma, and the eventual intake of drugs or psychostimulants before the resting-EEG recording was done [26,27,29–40,45,47–50,52,54–56,59–62,64,65,67]. Further, although in some studies researchers have evaluated the history of diseases and the eventual use of drugs, they did not control for the limitation of the assumption of psychotropic substance intake, like caffeine or nicotine, two hours before the rest-EEG recording [18,28,39,68,70]. It is known that the taking of drugs or psychotropic substances by the participant may impair the brain activity during resting-EEG recording [201,202], and that also, the presence of an organic or neuropsychological disease [203] may alter the brain rhythms of the participants, confounding the validity of the results obtained. Moreover, many authors did not take into consideration the handedness of the participants in the relationship studied [33–35,38,39,41,42,47–51,53–55,61,62,65,70,71]. Although some authors did not consider this factor as relevant [40], we think it is important to do so [72,73].

From a methodological point of view, the studies selected had not always adopted adequate criteria for EEG measurement, nor for counterbalancing the order of the opened-/closed-eye sequences of EEG recordings [31,36,41,42,44–47,49–51,62], or these data were not clearly reported [28,30,32,39,56–58,64,69–71]. For example, in the study by Konareva, a counterbalancing between the eye conditions was not adopted [55], while Korjus and colleagues [61] generalized their results obtained from five resting-state experiments conducted using different samples and different recording times (i.e., 1 min, 2 min, and three separate sessions of 1 min, respectively). In particular, in these studies, the method used produced several limitations regarding the validity and reliability of the significant relations obtained. Additionally, the use of counterbalance strategies is necessary to reduce the order effect and the sequence effect, which increases the validity of the EEG measures.

In addition to the appropriate reference electrode placement and the length of EEG recording, there are other important factors to consider for reliable asymmetry or frequency oscillation measures. According to Hagemann [25], the good reliability of the asymmetry measure in a resting-state can only be achieved if the EEG is recorded for at least 4 min. However, in some reviewed studies, many researchers conducted EEG recordings for less than 4 min [30–32,36,40,43,49,56,65,69], others for 2 min [42,44,47,51,57,58,60] and, finally, some for 2 min or less [45,71]. Moreover, some other researchers used short recording segments, such as 15 [60] or 30 s [62,71]. Although some studies showed that alpha power at single sites shows good reliability estimates for EEG segments as short as 20 or 30 s [204,205], this observation may not be generalizable to other asymmetry measures obtained for other brain oscillations [25]. This could produce a lack of relation between brain rhythms and personality traits that would otherwise be significant in longer EEG recording segments.

The method used for EEG recordings in eyes-open and eyes-closed conditions should be carefully reconsidered. Many researchers have recorded resting-EEG by asking the participants to refrain from blinking and/or moving their eyes by fixating on a cross to minimize ocular artefacts [51,57,58,61,66], or they did resting-EEG recordings in an eyes-closed condition [35,40,42,54,68]. In the first case, the method is confounding, because blinks and spontaneous eye movements are controlled by several autonomic brain systems [206], and the instruction to suppress these systems may act as a secondary task [207], while in the second case, to study the brain activity only in a closed-eyes state leads to a poor external validity of the EEG measures obtained. Further, the use of different reference schemes is also another important factor to consider in EEG asymmetry research.

In the studies selected, different EEG reference schemes were used, such as the average to overall electrodes [43–45,54,67], the reference to average voltage [8], the link to an active electrode [47], or the link to the left earlobe [46,48,59,71], but among these, the average over two electrodes positioned on the earlobes or mastoids [28,30–32,34–36,38–43,49–51,56,60,61,65,69], and the reference electrode positioned in the middle of the scalp between Fz and Cz sites [54], FCz site [70], or on the Cz site [26,27,29,37,45,52,57,58] were the most commonly used. These differences undermine the generalizability of the findings. However, despite the fact that many researchers were using the Cz electrode, positioned in the middle of the scalp as a reference, this could lead to numerous problems regarding the validity of the EEG measurement. According to Hagemann [208], the vertex reference at Cz has an unfavorable signal-to-noise ratio, because Cz is an active electrical site, and depending on the amplitude and phase relations between the two target sites and the reference site, the true amplitude asymmetry of the target sites may be enhanced, mitigated, or even reverted. Moreover, the same considerations are true to any other active electrode used as a reference scheme for the EEG measurement. For this reason, the linked earlobes/mastoids reference scheme would seem the better solution to this problem—the average of A1 and A2 is substantially less active than the cephalic target sites [25]. However, although this scheme has been repeatedly indicated and considered as the best solution in this EEG research field [25,208], today still no consensus has been reached among researchers. Another solution, as suggested by Coan and Allen [33], could be to use a general linear model of analysis, which allows the inclusion of a repeated measures factor by considering as factor the reference schemes used for EEG recordings.

The relationship between brain activity and approach/avoidance behavioral traits could be moderated not only by the EEG reference schemes, but also by the interactional or contextual variables (e.g., participant's mood, sex of experimenter, or time of day and time of year in which the EEG is recorded). Two studies have reported that time of day and time of year are correlated with alpha asymmetric frontal cortical activity (studies 1 and 2 [48]), revealing that the right frontal activity is highest during autumn mornings. These results had important health implications and suggested the EEG as an endophenotype of the risk of depression. Research has argued that the time of year is associated with an increased depression state [209], the time of day is associated with higher cortisol levels [210], and the cortisol level has been linked with withdrawal motivation. Thus, a greater relative right frontal activity at rest in the autumn mornings could be due to the combination of variables associated with a decreased approach motivation and increased withdrawal motivation [5].

Several studies have suggested that controlling the mood before EEG recordings might increase the predictive value of the studied relationship, because the procedure of fitting an EEG cap, such as the abrasion of the scalp, and the application of gel during the EEG preparation, is aversive and, thus, may induce a negative affective state or avoidance. Therefore, differences in transient mood may contribute to the state variance of resting asymmetry [32]. Perhaps another factor that contributes to the state variance of resting asymmetry is a transient state of approach and withdrawal motivation. Higher motivation to approach may respond to the novel lab situation with greater relative left frontal activity, whereas individuals with higher withdrawal and motivation to inhibition may respond to the novel lab situation with greater right frontal activation [5,66]. Therefore, it is very important to consider the influence of interactional and contextual variables that can confound the relationship between EEG activity and motivational personality traits. This influence can be reduced by conducting multiple EEG recordings [3]. However, among the studies reviewed, only a few have evaluated the construct validity of EEG measurements in multiple recording sessions with a total of three EEG measurements 3 weeks apart [26–28,37,43,60], and only one study analyzed the stability of the relation, over a long time of retest, for a total of three EEG measurements 1 year apart (study 3 [52]). Thus, it is to be assumed that the construct validity of the studies included in this review is poor. The measures conducted in multiple EEG sessions across time can constitute better reliability and construct validity of the measured relation [25,27].

Finally, in terms of the quality assessment of the studies included in this review (Figure 1), we think that the statistical analysis was adequate to the studied outcome. The studies used valid and reliable methods to evaluate the influence of the brain cortical activity on the individual disposition of approach/avoidance personality domains, including appropriate analysis for the used sample size and adequate control for the confounding variables considered by the authors. However, some studies used statistical models without considering the role of education [44,52], gender [18,28,30,33,36,37,41,47,48,50,51,55,59,62,68], and age [38,42,54,68], in the relation studied. Gender and age can modulate the relationship between brain activity and motivational traits of personality. In the studies by Santesso and colleagues [45], for example, the authors highlighted that higher sensation-seeking levels were related to a greater left frontal activity at rest in male participants only, while other studies have observed higher neuroticism levels in women than in men. In particular, Huang and colleagues [60] demonstrated that the menstrual cycle is an interactional variable that can alter the resting frontal alpha asymmetry. Unfortunately, only five articles selected in this review considered the influence of the menstrual cycle in personality traits as an interactional variable [57,58,60,66,69].

In terms of age influence, results appear to be more consistent. However, some studies evaluating the role of age on the frontal asymmetry heritability, found that frontal-alpha asymmetry is heritable only in young adults, but not in middle-aged adults [40].

Although we checked for the method used in the reviewed studies, this work presents some limitations that could undermine the generalizability of the findings. The first limitation is related to the heterogeneity of samples and methods used for the EEG measurements. The second is due to the heterogeneity of the EEG phenomena studied (asymmetry, and/or brain rhythms), which have determined a lack of a quantitative analysis in the meta-analysis. This would have given a greater strength to the inferences by examining the size of the effects studied.

Another limitation is related to the choice to include only academic articles published in peer-review journals. This aspect could have limited the selection of only those studies that have obtained results in line with the literature, and consequently have influenced the publication bias. Therefore, the presented results could have an overestimation of the relationship observed. In addition, the choice to select only the studies published in English and in Italian could have led to the deletion of studies conducted in other populations.

In conclusion, it can be assumed that research on the relationship of resting EEG cortical activity in idling condition and the approach/withdrawal motivational model has provided controversial and unclear results. Findings have shown that gamma, delta, and alpha frequencies are not good indicators of cortical excitability that can be associated with approach/avoidance motivation personality traits, and although in some studies beta and theta frequencies have resulted as good markers of approach/avoidance motivational behavior, the number of studies is scarce. Finally, to confirm these promising but “preliminary” results, and to give greater validity, future research should consider the role of gender contextual interactional variables, discussed above, in these relations, and conducting multiple sessions of resting-EEG recording.

5. Conclusions

Observations derived from this review are in accordance with Harmon-Jones and Gable's [5] considerations that the manifestation of trait frontal asymmetry is until today an unknown phenomenon, as well as the association of scalp-distributed lateral asymmetries with approach/avoidance motivation personality traits. Although the reliability of resting EEG measures in idling condition is hypothetically comparable with the reliability of self-reported personality traits and can be used as a valid signature of a person, the trait frontal asymmetry could simply reflect individual differences of frontal asymmetry in an idling rest condition [6]. This endophenotype can be, in fact, influenced by situational and interactional variables related to the experimental contest, such as the psychological state of the individual, and the unconsciously cognitive processes performed by the participant during the resting

EEG recording, which are impossible to control [211]. Besides, it is necessary to remember that the study of electrocortical correlates should be interpreted with the utmost caution, because genetic factors [51,54], hereditary [33,40,42], and situational factors [212] can all interact to modify behavior and brain dynamics, and expressions of personality traits [213].

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