Quantitative Personality Predictions from a Brief EEG Recording — **Source link**

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Title: Quantitative Personality Predictions from a Brief EEG Recording

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Abstract

The assessment of personality is crucial not only for scientific inquiries but also for real-world applications such as personnel selection. However, most existing ways to quantify personality traits rely on self-reported scales, which are susceptible to biases such as self-presentational concerns. In this study, we propose and evaluate a novel implicit measure of personality that uses machine learning (ML) algorithms to predict an individual's levels in the Big Five personality traits from 5 minutes of electroencephalography (EEG) recordings. Results from a large test sample of 196 volunteers indicated that the personality scores derived from the proposed measure converged significantly with a commonly used questionnaire, predicted behavioral indices and psychological adjustment in a manner similar to self-reported scores, and were relatively stable across time. These evaluations suggest that the proposed measure can serve as a viable alternative to conventional personality questionnaires in practice.

Keywords: personality assessment, emotion words, event-related potentials, EEG, predictive model

1   Introduction

2   Over a hundred years of scientific inquiry into individual differences has identified

3   five overarching traits as the fundamental dimensions of personality: extraversion,

4   neuroticism, conscientiousness, agreeableness, and openness to experience(McCrae &

5   Costa, 2008; McCrae & John, 1992). These "Big Five" traits represent dispositional

6   differences in cognitive, affective, behavioral and motivational patterns, and can

7   predict important life outcomes such as psychological adjustment(Ozer & Benet-

8   Martinez, 2006). Given the importance of the Big Five traits, it is crucial to develop a

9   reliable measurement of them not only for academic research, but also for application

10   scenarios such as personnel selection.

11   Most applications of the Big Five model rely on self-reported scales which require the

12   respondents to read statements or adjectives which they judge in relation to their

13   personality and report their degree of agreement(Costa Jr & McCrae, 2008; Gosling,

14   Rentfrow, & Swann, 2003). These self-reported scales, whilst having the advantages

15   of straightforwardness and cost-effectiveness, are susceptible to biases such as social

16   desirability or self-presentational concerns. For example, a job applicant may

17   deliberately fake his/her responses to a personality questionnaire to show competency

18   for the position. This disadvantage limits the method's effectiveness in certain

19   application settings.

20   One way to tackle this problem is to use indirect measures that do not require the

21   participants to report a subjective assessment of their own personality but make

22   inferences from other sources of data such as observed behavioral patterns(Gawronski

23   & De Houwer, 2014). Throughout the history of personality science, there have been

24   multiple attempts to develop such measures. For example, psychoanalysts have used

3

25   the subjective interpretation of ambiguous inkblot patterns to probe one's unconscious

26   mind(E. Exner Jr, 2003; Rorschach, 1921). However, its validity has been an ongoing

27   issue of debate(Wood & Lilienfeld, 1999). A more recent example is the personality

28   measure based on the Implicit Association Test (IAT), which employs measures of

29   reaction time to assess the association strength between one's concept of self and the

30   concept of a trait(Schmukle & Egloff, 2005; Schnabel, Asendorpf, & Greenwald,

31   2008). These IAT-based measures have been demonstrated to have adequate

32   reliability and validity, although what they actually measure may be conceptually

33   distinct from explicit measures of personality(Dentale, Vecchione, & Barbaranelli,

34   2016).

35   In recent years, the introduction of machine learning techniques into psychological

36   science has opened up new possibilities for implicit personality measures(Bleidorn &

37   Hopwood, 2018). The machine learning approach to personality assessment focuses

38   on developing automated algorithms to predict one's personality from certain data

39   sources, and the algorithms are usually cross-validated to ensure their generality to

40   new samples. Recently, there have been reports of success in the application of this

41   approach on individual's digital footprints on social media websites(Settanni, Azucar,

42   & Marengo, 2018; Wald, Khoshgoftaar, & Sumner, 2012; Wu, Kosinski, & Stillwell,

43   2015). For example, Wu et al.(Wu et al., 2015) developed machine learning models to

44   predict one's levels on the Big Five traits from Facebook "Likes". The accuracy of

45   their model's predictions, evaluated against self-reported personality scores and

46   predictive validity for life outcome variables, was higher than the judgments made by

47   human informants.

48   Besides online behaviors, another type of data that may benefit from a machine

49   learning approach is neurophysiological data. It has been an ongoing endeavor for

50 psychologists and neuroscientists to investigate the neurobiological basis of

51 personality(R. Jiang et al., 2018; Korjus et al., 2015; Nostro et al., 2018). Despite the

52 fact that consensus has not been reached for many traits, broadly speaking, the

53 available data do suggest that there are stable patterns of intraindividual variance in

54 neural activities which correspond to dispositional differences at the behavioral level.

55 However, for the purpose of developing neural-based personality measures, the

56 existing studies are limited in two ways. First, many of the findings were obtained by

57 techniques such as functional magnetic resonance imaging (fMRI), which due to their

58 expensive costs and immobility, are not suitable in application settings. Second, most

59 of these studies took a correlational approach, in which the focused trait was

60 correlated with specific neural features. These correlations relied on in-sample

61 population inference and were not necessarily generalizable to out-of-sample

62 individuals(Dubois & Adolphs, 2016). In contrast, a predictive machine-learning

63 inspired framework would employ cross-validation techniques to ensure out-of-

64 sample generalizability, thus may be more desirable for application scenarios which

65 require accurate personality predictions from novel samples.

66 In the present study, we propose a novel machine learning-based assessment of the

67 Big Five personality traits using a brief electroencephalography (EEG) recording.

68 EEG is one of the most commonly used non-invasive neuroimaging techniques and is

69 especially suitable for application-oriented personality assessment due to its relatively

70 inexpensive and tolerable nature(Suzuki, Hill, Ait Oumeziane, Foti, & Samuel, 2018).

71 The premise of the proposed measure is based on a large body of previous research

72 which shows that the Big Five traits are related to affective reactivity. For example,

73 extroverts were shown to be more likely to experience positive emotions(Lee Anna

74 Clark & Watson, 2008; John, Naumann, & Soto, 2008), while those scoring high on

75 neuroticism were more inclined to experience negative emotions(Lee Anna Clark &

76 Watson, 2008; John et al., 2008). Accordingly, studies of event-related potentials

77 (ERPs) have shown that personality affects one's neural response to emotional

78 stimuli(De Pascalis, Strippoli, Riccardi, & Vergari, 2004; Y. Lou et al., 2016; Speed

79 et al., 2015; Suzuki et al., 2018), and there are recent studies reporting distinct EEG

80 profiles by people with high versus low level of personality traits when viewing video

81 clips(Subramanian et al., 2018; Zhao, Ge, Shen, Wei, & Wang, 2018). However,

82 personality inferences finer than binary levels based on brain activities have not yet

83 been achieved. Our method aims to fill this gap by providing quantitative EEG-based

84 predictions of the Big Five traits.

85 In the proposed method, participants rapidly view a series of emotional words whilst

86 their brain activities are captured as EEG signals which are then fed to trained

87 machine learning algorithms as features to predict their scores on each of the Big Five

88 traits (Fig. 1A). We choose words as emotional stimuli because they are fast to

89 process, allowing the task to be brief (~ 5 mins) and offering flexibility in application

90 scenarios. To train the machine learning model for personality inference, and to

91 systematically evaluate its reliability and validity, we collected data from a large

92 sample of 196 young and healthy participants recruited from nearby universities (154

93 females, mean age = 21 years). Two-hundred double-character Chinese words were

94 briefly presented in a randomized order, including 60 positive words, 60 negative

95 words, 60 neutral words, and 20 name words. EEGs were simultaneously recorded

96 whilst participants viewed the words. ERPs evoked in response to the three types of

97 emotional words were extracted from the EEG recordings and used to train predictive

98 models with a nested cross-validation approach (Fig. 1). The performances of the

99 predictive models were evaluated using the correlations between EEG-predicted and

100   self-reported trait scores. Furthermore, the external validity of the measure was

101   evaluated by using the predicted traits scores to predict participants' behavioral
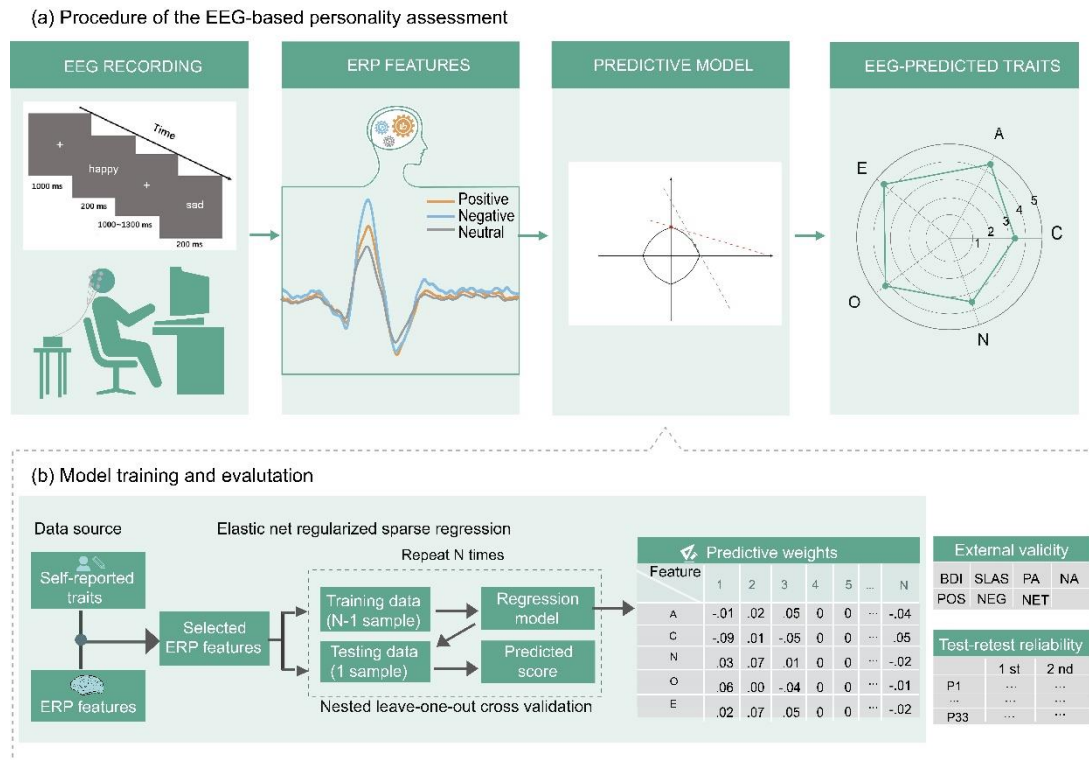

Fig. 1. Flow chart of the data collection and overview of the model training and evaluation. (*a*) The procedure of the personality assessment task. The participants perform the word attention task while their brain activity is recorded by a portable wireless EEG system. The event-related potential (ERP) responses to positive, negative and neutral words are used as features for implementing machine learning-based predictive models. The output of the models are the predicted scores for the Big Five traits. (*b*) The procedure of model training and evaluation. Elastic net regularized sparse regression is employed, with a nested leave-one-out cross-validation strategy for feature selection and model evaluation. The models' external validity and test-retest reliability are also assessed.

102   tendencies and life outcomes. Lastly, some of the participants completed the task

103   again 19-78 days later, and the correlations between the predicted scores of the two

104   time points were used to assess the test-retest reliability of the proposed EEG-based

105   measure.

106   **Results**

Behavioral results

108   The presentation of the emotional words was randomly intermixed with 20 common

109   Chinese name words. The participants were required to press a button when they

110   detected a name. The mean accuracy for responding to names was 97.19 ± 5.04% and

111   the mean response time was 522 ± 166 ms, indicating that participants were attentive

112   during the task.

Analyses of ERP responses

114   Averaged ERP responses to the word stimuli for participants with trait scores ranking

115   in the top, middle and bottom terciles are shown in Fig. 2 for each combination of trait

116   and word valence. The prominent ERP components elicited by the word stimuli

117   included two positive peaks at 200-300ms and 400-500ms, and two negative peaks at

118   100-200ms and 300-400ms, corresponding to the emotion related ERP components of

119   N100, P200, N400 and late positive complex (LPC)(Y. X. Lou et al., 2016; Williams
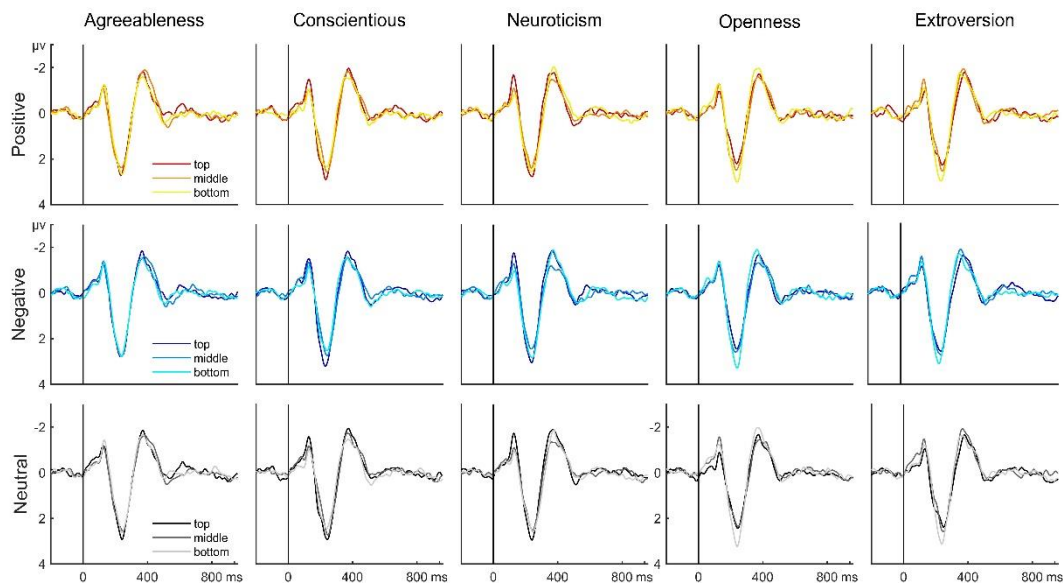
120   et al., 2006; M. Zhang, Ge, Kang, Guo, & Peng, 2018).

121   As a first step, we examined these components' correlation with personality. As

122   shown in Fig. S1, there was only one significant correlation between LPC for positive

123   words in the temporal area and self-reported scores for agreeableness ($r = -.18$, p

124   < .05). For conscientiousness, higher scores were associated with smaller LPC for

125   neutral words in the frontal and right temporal area ($r = -.15, -.15$, respectively, both p

126   < .05). For neuroticism, higher scores were associated with larger N100 for positive

127   words in the central area ($r = -.16$, p < .05), larger N100 for negative words in the left

Fig. 2. An overview of the event related potential (ERP) responses. The ERP waveforms show the average ERPs across all recording channels for the corresponding combination of trait (column) and word valence (row). The three waveforms within each subplot correspond to the ERPs averaged over the participants with the corresponding trait scores ranking in the top, middle and bottom terciles. Darker color refers to higher scores.

128   temporal area ($r = -.15$, p < .05), larger N100 for neutral words in the frontal, central,

129   left temporal ($r = -.16, -.17, -.17$, respectively, all p < .05), larger N400 for neutral

130   words in the frontal, central, left temporal and right temporal areas ($r = -.20, -.15,$

131    $-.15, .20$, respectively, all p < .05), larger LPC for positive words in the frontal,

132   central, left temporal and right temporal areas ($r = .15, .15, .17, .20$, respectively, all p

133   < .05). For openness, higher scores were associated with smaller P200 for positive

134   words in the central and left temporal area ($r = -.14, -.16$, respectively, both p < .05).

135   For extraversion, higher scores were associated with smaller N100 for positive words

136   in the central area ($r = .15$, p < .05), smaller P200 for positive words in the central,

137   left temporal and right temporal areas ($r = -.16, -.19, -.16$, respectively, all p < .05),

138   smaller N100 for neutral words in the frontal and central areas ($r = .18, .14$,

139   respectively, both p < .05), smaller P200 for neutral words in the central, left temporal

140   and right temporal areas ($r = -.21, -.18, -.18$, respectively, all p < .05), and smaller

141   N400 for negative words in the left temporal area ($r = .15$, p < .05).

## Predictive models of personality based on ERP responses

143 Participants' ERP responses elicited by the word stimuli were used as features to train

144 five predictive models, one for each of the Big Five traits, using a nested cross-

145 validation approach with elastic net regularized regression analyses. To assess the

146 predictive models' performance, correlations were calculated between pairs of EEG-

147 predicted and self-reported scores for each of the Big Five traits. Notably, important

148 ERP features retained as well as finally used for the sparse-regression-based trait

149 predictive models (see 'Feature selection and model training' in Methods) were

150 located not only within the time windows of these emotion related ERP components,

151 but also extended to the pre-stimulus periods (< 0 ms), as well as the late processing

152 stages (> 500 ms) (Fig. 3).

153
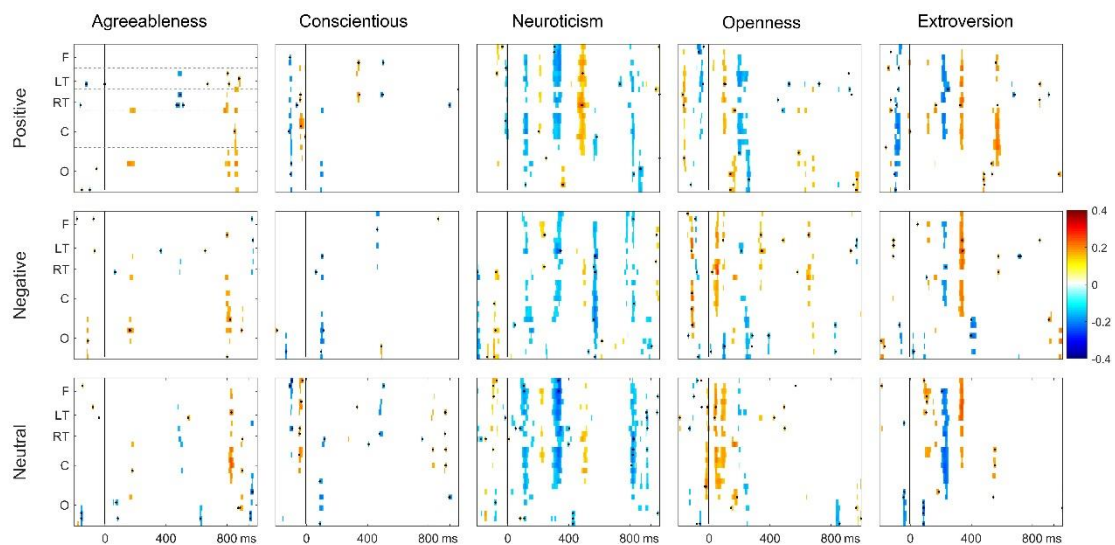
Fig. 3. ERP features used in the trait predictive models. The colored channel by time bins demonstrate the ERP features retained for model training (*p*-value < the optimal *p*-value threshold) and the black dots mark the bins that were finally used in the elastic net regularized sparse regression model. The colors show the bivariate Pearson correlation coefficients between the ERP features at the channel-time bin and the corresponding self-report trait scores. EEG channels array are Fp1/2, Fz, F3/4, F7, FC5, T3, CP5, F8, FC6, T4, CP6, FC1/2, Cz, C3/4, CP1/2, P3/4, Pz, PO3/4, Oz, O1/2, organized in five ROIs: frontal area (F), left temporal area (LT), right temporal area (RT), central area (C), occipital area (O). See 'Feature selection and model training' in Methods for details.

164   The predictive models achieved significant correlations between the predicted and

165   self-reported trait scores (Fig. 4). Specifically, Pearson correlations for agreeableness,

166   conscientiousness, neuroticism, openness and extroversion were .47, .61, .49, .48,

167   and .53, respectively (all $p < .001$, $N = 196$).
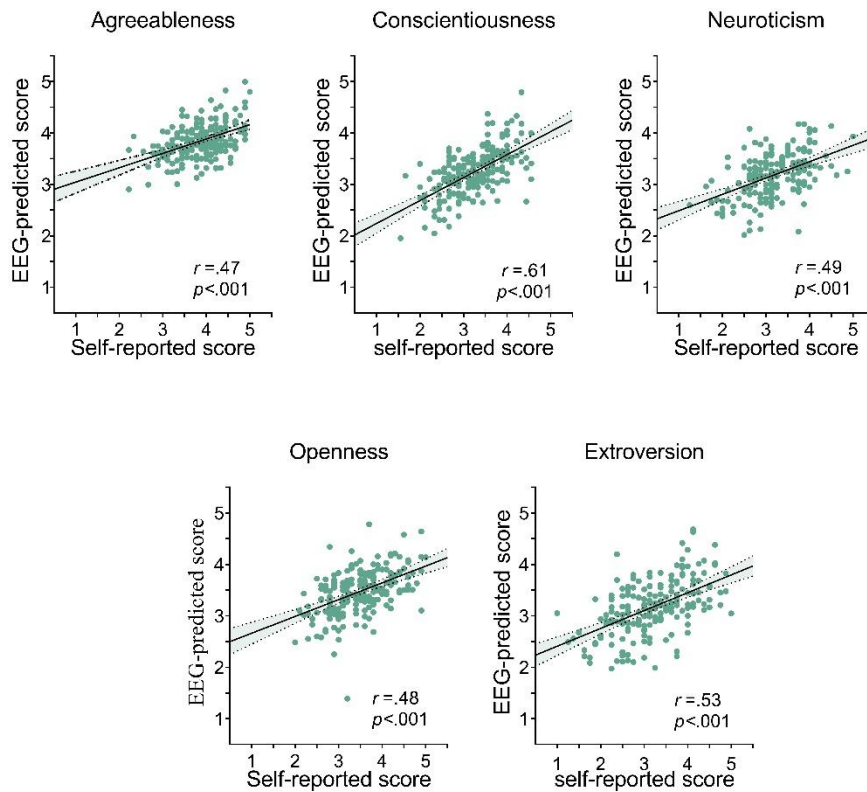
Fig. 4.   Scatterplots for the correlations between the predicted and self-reported trait scores. Each dot represents the scores from one participant (for each plot, $N = 196$). The predicted score for each dot was obtained by using a nested cross-validation approach with the predictive model trained with the remaining samples excluding the to-be-predicted sample.

170   For 127 of the 196 participants, the mean participant-wise absolute difference

171   between the predicted and self-reported scores (averaged over the absolute differences

172   from the five traits) were less than 0.5 on a 5-point scale (Fig. 5a, mean differences

173   across participants = 0.45±0.18). In addition, the histogram of the correlation

174   coefficients between the 5-dimensional EEG-predicted personality trait constructs and

175 the self-reported counterpart for each individual participant shows a clear tendency

176 towards high correlation values (Fig. 5b): 139 out of the 196 participants showed
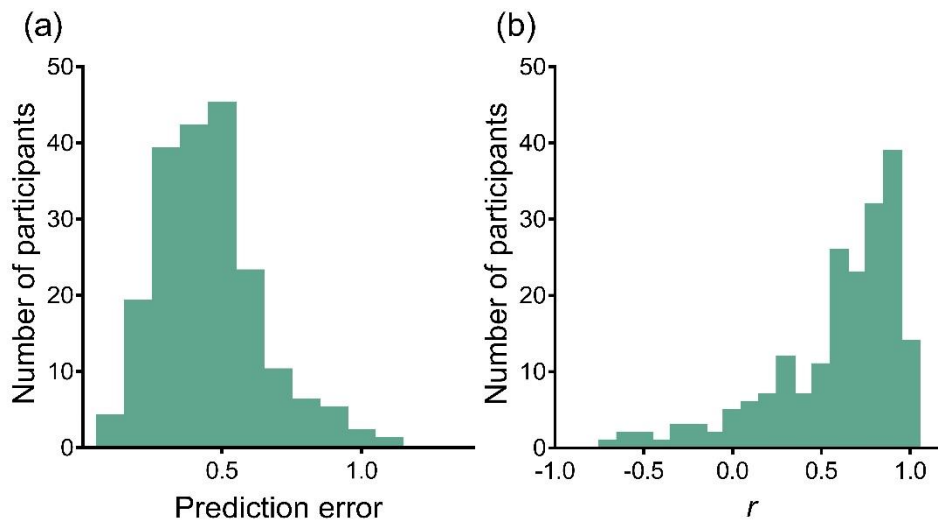

Fig. 5. Evaluation of the predicted scores. (*a*) A histogram of the participant-wise prediction errors (i.e. the mean absolute difference between the EEG-predicted scores and self-reported scores). (*b*) A histogram of the participant-wise correlations of the 5-dimension personality constructs between the EEG-predicted scores and self-reported scores.

177 correlations higher than .5 (average correlation $r = .59 \pm .37$). The high correlation

178 values indicate that these five predictive models together can reliably reflect the

179 relatively high and low of the participants' personality scores.

External validity

181 After the task, a subsample of the participants also completed one or two sets of

182 measures for assessment of external validity. First, a subsample of the participants

183 completed questionnaires for indices of psychological adjustment, including life

184 satisfaction (SLAS, $N = 135$), positive affects (PA, $N = 111$), negative affects (NA, N

185 $= 111$), and symptoms of depression (BDI, $N = 111$), which have been shown to be

186 predicted by personality scores in previous studies(Cloninger, Svrakic, & Przybeck,

187 2006; González Gutiérrez, Jiménez, Hernández, & Puente, 2005; Larsen & Ketelaar,

188   1991; Strickhouser, Zell, & Krizan, 2017). Second, 60 participants also watched a

189   series of emotional video clips and rated the valence of each clip. The averaged

190   valence ratings for the positive (POS), negative (NEG), and neutral (NET) clips were

191   used as measures of their affective responses to emotional stimuli. For each of the

192   seven indices, two separate regression models were built using the EEG-predicted and

193   self-reported trait scores, and external validity was assessed using the regression

194   model fitting R values.   For the four indices of psychological adjustment as well as
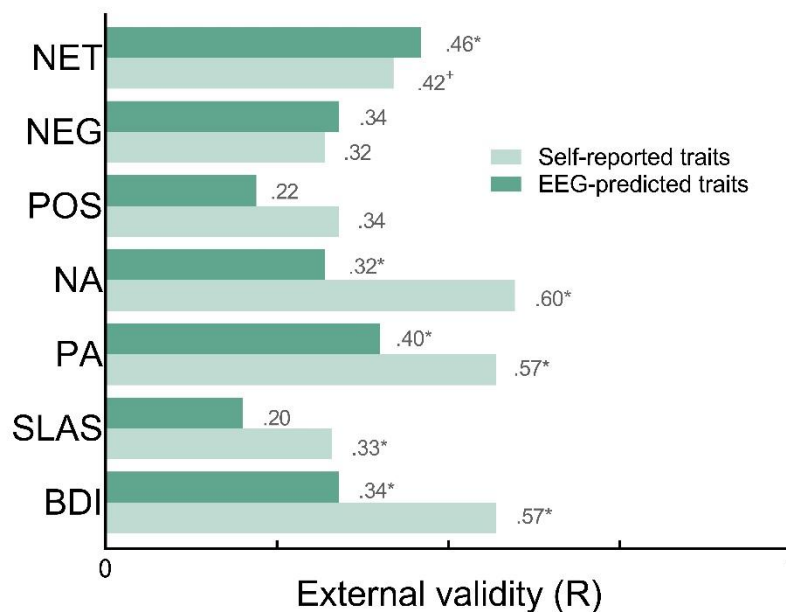

Fig. 6.   External validity of the EEG-predicted and self-reported trait scores. The dark green and light green bars show the predictive powers of EEG-predicted and self-reported trait scores for a certain behavior or life outcome index as reflected in regression model fitting r values. NET, NEG, POS are participants' ratings of the valence of neutral, negative and positive video clips, NA and PA are self-reported scores of negative and positive affects; SLAS is the self-reported score of Satisfaction with Life Scale; BDI is the self-reported score of Beck Depression Inventory. See Table S2 for detailed results.

195   the valence rating for positive video clips, the self-reported trait scores achieved

196   higher predictive power than the EEG-predicted trait scores. However, for the

197   experienced emotional valences the neutral and negative video clips, the EEG-

198   predicted scores were able to achieve slightly higher predictive powers than self-

199   reported scores (Fig. 6).

13

Test-retest reliability

Temporal correlations were calculated for each of the predicted and self-reported trait scores from the subsample of the participants (N = 33) who completed the task for a second time 19-78 days later. The self-reported trait scores showed adequate to good test-retest reliability (r = .86, .67, .65, .76 and .79 for agreeableness, conscientiousness, neuroticism, openness and extroversion, respectively). The predicted scores' test-retest reliability, except for neuroticism, were lower than the self-reported scores (r = .51, .31, .67, .50 and .58 for agreeableness, conscientiousness, neuroticism, openness, and extroversion, respectively). A closer look at the data suggested that the extremely low reliability of conscientiousness was largely due to two outliers. After these two were excluded, the reliability increased to .65. Participant-wise analyses revealed that the average of the mean score

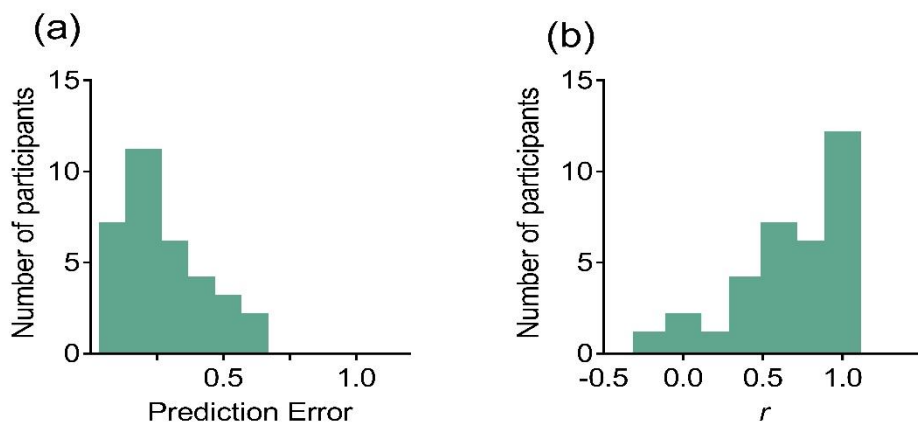**Fig. 7.** Evaluation of the test-retest reliability. (*a*) A histogram of the participant-wise test-retest errors across two data collections. (*b*) A histogram of the participant-wise correlations of the scores of the 5-dimension personality constructs between the two data collections.

difference over the five traits was 0.27 ± 0.15, and the average 5-dimension construct-based correlation was .67 ± .31 (Fig. 7).

Discussion

14

215   Our results for the first time demonstrate the feasibility of combining machine

216   learning and EEG recordings to make indirect yet fairly accurate quantitative

217   predictions about an individual's personality. The correlations between the predicted

218   and self-reported scores (.47-.61) were comparable to previous studies using digital

219   footprints as input features(Wu et al., 2015). Furthermore, the EEG-predicted scores

220   could significantly predict several indices of psychological adjustment, even though

221   their predictive powers were lower than those of the self-reported scores. The better

222   performances of the self-reported trait scores might be partially attributed to the fact

223   that psychological adjustment was also measured with self-reported scales, and

224   common-method bias may have inflated the correlations among them(Podsakoff,

225   Mackenzie, Jeong-Yeon, & Podsakoff, 2003). For outcomes like affective responses

226   to video clips, the EEG-predicted trait scores achieved slightly better predictive

227   powers than the self-reported scores, demonstrating their usefulness in predicting real-

228   world affective experiences. While producing results comparable to self-reported

229   measures, the proposed method does not require the participant to report his/her own

230   personality explicitly, thus is less susceptible to faking. Also, the task is brief in time

231   and has been tested with a portable EEG system, making it useful for application-

232   oriented personality assessment.

233   Even though we primarily focused on developing a new method for personality

234   assessment, a closer look at the correlation between personality and the temporal and

235   spatial patterns of standard ERP features may also shed some light into the question of

236   the neurophysiological basis of personality. Firstly, in general, extroversion and

237   neuroticism were associated with more ERP components, which is consistent with the

238   previous finding that these two traits more closely connect to emotions(L. A. Clark,

239   2005; L. A. Clark, Watson, & Mineka, 1994; Watson, Clark, & Harkness, 1994).

240   Secondly, there were significant correlations between ERP responses for positive

241   words in the temporal area and self-reported scores for agreeableness and openness.

242   These results are consistent with previous studies reporting that these two traits are

243   associated with positive affects(Holtgraves, 2011; Letzring & Adamcik, 2015; Ready

244   & Robinson, 2008), and that agreeableness is closely associated with the temporal

245   regions responsible for social information processing(DeYoung et al., 2010; B. W.

246   Haas et al., 2015; Haas, Ishak, Denison, Anderson, & Filkowski, 2015). Finally, for

247   conscientiousness, we observed a diminished LPC for neutral words for the

248   participants with higher conscientiousness scores, which may support the hypothesis

249   that conscientiousness reflects a tendency to inhibit impulses and feel

250   calmness(Fleming, Heintzelman, & Bartholow, 2016; John et al., 2008). Nonetheless,

251   these correlations were generally weak in magnitude (.15-.21), making it difficult to

252   make accurate individualized inferences. The machine learning approach, on the other

253   hand, simultaneously took multiple neural features into considerations and produced

254   more reliable individualized predictions. Furthermore, the cross-validation techniques

255   used in the development of the predictive algorithm ensures greater out-of-sample

256   generalizability(Dubois & Adolphs, 2016), thus could be more useful for application

257   purposes such as personnel selection.

258   It might also be worthwhile to examine the predictive performances of models using

259   ERP responses from only a single condition (positive, negative or neutral words). In

260   general, these models' performances were sub-par compared to models using data

261   from all three conditions (Fig. S2). With single condition models, the best performing

262   condition for extroversion was the positive condition. This is consistent with previous

263   studies which have found that extroverts are more closely associated with positive

264   emotions(Canli et al., 2001; Lucas, Le, & Dyrenforth, 2008; Srivastava, Angelo, &

16

265   Vallereux, 2008; L. Wang, Shi, & Li, 2009; Yuan, He, Lei, Yang, & Li, 2009; Yuan

266   et al., 2012). For openness and neuroticism, the models in three conditions had similar

267   performance. This is also consistent with previous studies which have suggest that

268   both dimensions are associated with the processing of stimuli of various

269   valences(John et al., 2008),(Bartussek, Becker, Diedrich, Naumann, & Maier, 1996;

270   Gray, 1981). In the models for conscientiousness and agreeableness, there was better

271   performance in the neutral condition. These results are consistent with the definition

272   of the two dimensions, which are less related to emotional reactivity(John et al.,

273   2008). Even though we designed the measure based on the Big Five's relationship

274   with the processing of emotional stimuli, the predictive weights of the neutral features

275   suggest that non-affective processes may also contribute to the predictive models'

276   performances.

277   Interestingly, when taking a closer look at the temporal aspects of feature selection,

278   there were selected features from the pre-stimulus period for all the predictive models.

279   The nature of pre-stimulus ERP components has long been a topic of discussion.

280   While the ERP signals recorded before the onset of stimuli have traditionally been

281   considered as "baseline" and not included in data analysis, there is emerging evidence

282   to suggest that there are functional implications for pre-stimulus activity(Falkenstein,

283   Hoormann, Christ, & Hohnsbein, 2000; Lazzaro, Gordon, Whitmont, Meares, &

284   Clarke, 2001). The inter-trial variability of the pre-stimulus activity has been

285   repeatedly been reported as being related to one's cognitive states(Bode et al., 2012;

286   Ikumi, Torralba, Ruzzoli, & Soto-Faraco, 2019; Lou, Li, Philiastides, & Sajda, 2014;

287   Polich & Kok, 1995). As the mean amplitude of the pre-stimulus period was

288   subtracted before the analysis, our results suggest a possible contribution from the

289   fluctuation of the baseline activity rather than its absolute amplitude. In addition, our

290   study found associations between the inter-participant variability of the baseline ERP

291   responses and one's trait scores. Therefore, our findings extend existing findings by

292   suggesting that baseline activity might provide information about one's dispositional

293   tendencies. However, it should be noted that the above discussions based on feature

294   selection are mostly speculative. More theoretical and empirical works are needed to

295   clarify the psychological and neural mechanism.

296   The test-retest reliabilities for agreeableness, openness, and extroversion of the

297   proposed EEG measure were in the range of .5-.7. While these results were generally

298   lower than the self-reported counterpart (in the range of .7-.8), our findings are

299   comparable, if not better, than the existing studies on the stability of ERP responses(Ip

300   et al., 2018; Segalowitz & Barnes, 1993). According to previous studies, the reliability

301   of EEG and ERP was affected by various variables, such as age of

302   participants(Alperin, Mott, Rentz, Holcomb, & Daffner, 2014), recording

303   intervals(Sandman & Patterson, 2000), state and other factors(Ip et al., 2018;

304   Segalowitz & Barnes, 1993). In our study, one possible source of error may have been

305   if the EEG cap aligned slightly differently between the two data collection sessions.

306   Thus, the positions of the electrodes may have deviated slightly, introducing

307   additional noise into the predictive models. In addition, a systematic evaluation and

308   control of the participant's general cognitive state should have been conducted, as it

309   could substantially affect the emotional ERP responses(Jiang et al., 2017). Further

310   studies are necessary to elucidate these issues, especially focusing on the participants

311   with low test-retest reliabilities.

312   As a final, but note-worthy comment, while the present study was conducted using a

313   wet electrode based EEG system, recent advances in EEG recording techniques on

314   electrode materials and designs, hardware improvements and system optimization

18

315 have shown the potential to greatly improve the usability of EEG devices to a general

316 user population(Lühmann, Wabnitz, Sander, & Müller, 2017; Siddharth, Patel, Jung,

317 & Sejnowski, 2018; F. Wang, Li, Chen, Duan, & Zhang, 2016). The proposed EEG

318 based personality measure is expected to be readily applicable in many practical

319 scenarios, serving as a promising alternative to conventional personality

320 questionnaires in the near future.

Materials and Methods

Participants

323 One hundred and ninety-six young participants (154 females, mean age = 21 years,

324 range 18-28 years) from Tsinghua University and China Women's University took

325 part in the study. All of them had normal or corrected-to-normal vision. Informed

326 consent was obtained from all participants. The study was conducted in accordance

327 with the Declaration of Helsinki and approved by the local Ethics Committee of

328 Tsinghua University.

Materials

330 One hundred and eighty double-character Chinese words were employed as the

331 stimuli, including 60 positive-emotion words, 60 negative-emotion words, and 60

332 neutral-emotion words (see Table S2 for the full list). All words were selected from

333 the Chinese Affective Words System(Y. N. Wang, Zhou, & Luo, 2008; Q. Zhang, Li,

334 Gold, & Jiang, 2010). According to their valence, we choose the top 20 most pleasant

335 adjectives, nouns and verbs as positive-emotion words (mean valence rating

336 7.43 ± 0.16 on a 9-point Likert scale), the top 20 least pleasant adjectives, nouns and

337 verbs as negative-emotion words (mean valence 2.38 ± 0.21), the median 20 pleasant

19

338   adjectives, nouns and verbs as neutral words (mean valence 5.52±0.71). In addition,

339   20 double-character common Chinese names were selected as non-emotional stimuli

340   for the behavioral task.

341   The Chinese version of the Big Five Inventory (BFI)(Carciofo, Yang, Song, Du, &

342   Zhang, 2016) was used to measure participants' personalities. The questionnaire is a

343   5-point Likert scale including 44 items, 8 measures of extraversion, 9 measures of

344   agreeableness, 9 of measures conscientiousness, 8 measures of neuroticism and 10

345   measures of openness. The internal consistency coefficients were good for every

346   dimension in the current study (alpha: extraversion = .89, openness = .85, neuroticism

347   = .84, conscientiousness = .82, agreeableness = .79).

Experimental procedure

349   The experiment was carried out in a regular laboratory environment without any

350   electrical shielding. There was ambient illumination from ceiling lights. The stimuli

351   were displayed on a 22-inch LCD monitor (DELL, USA) with a 60 Hz refresh-rate.

352   The participants sat in a comfortable chair approximately 60 cm away from the

353   monitor screen.

354   The participants first filled in the BFI questionnaire prior to the start of the

355   experiment. The main experiment consisted of 200 trials (Fig. 1). Within each trial,

356   one double-character Chinese word was presented for 200 ms, followed by an inter-

357   trial interval of a random length in the range 1000-1300 ms. All words were presented

358   in white against a black background. Words were presented in the center of the

359   computer screen, with a size of 1.5° by 2.0° (horizontal by vertical, measured in visual

360   angle) per character and a 0.75° center-to-center distance between the characters. The

361   order of the presentation was randomized for each participant. The participants were

362 asked to focus on the words and press the Down Arrow key on the computer keyboard

363 when they detected a Chinese name. The duration of the EEG recording was about 5

364 minutes per participant (excluding the EEG preparation time). Presentation of the

365 stimuli and collection of the behavioral responses were programmed in MATLAB

366 (The Mathworks, USA) using the Psychophysics Toolbox 3.0 extensions(Brainard,

367 1997; Kleiner et al., 2007; Pelli, 1997).

EEG recordings

369 A portable wireless EEG amplifier (NeuSen.W32, Neuracle, China) was used for data

370 recording at a sampling rate of 250 Hz. EEG data were recorded from 28 electrodes

371 positioned according to the international 10-20 system (Fp1/2, Fz, F3/4, F7/8, FC1/2,

372 FC5/6, Cz, C3/4, T3/4, CP1/2, CP5/6, Pz, P3/4, PO3/4, Oz, O1/2) and referenced to

373 linked mastoids with a forehead ground at AFz. Electrode impedances were kept

374 below 10 kOhm for all electrodes throughout the experiment.

EEG preprocessing

376 All EEG data analyses were performed using MATLAB with the Fieldtrip

377 toolbox(Oostenveld, Fries, Maris, & Schoffelen, 2011). The continuous EEG data

378 were first band-pass filtered at 1-30 Hz. Artifacts due to eye movement, muscle

379 movement, and other possible environmental noises were removed using independent

380 component analysis (ICA). On average, 1-3 artifact related independent components

381 (ICs) per participant were manually identified and excluded. The remaining ICs were

382 then back-projected onto the scalp EEG channels to reconstruct the cleaned EEG data.

383 EEG data were then segmented into 1.2-sec trials from 200 ms pre-stimulus to 1000

384 ms post-stimulus. Trials with non-emotional stimuli (i.e., Chinese names) were

385 excluded from further analysis. Trials with peak-to-peak voltage changes exceeding

386 ±150 mV in any recording electrode were also rejected to avoid possible artifact

387 contamination. On average, the number of rejected trials per participant was less than

388 10. The artifact-free trials were then averaged for each emotional category (i.e.,

389 positive, negative and neutral) and baseline corrected using the average of the 200 ms

390 pre-stimulus data, resulting in three ERP waveforms per participant.

ERP component analysis

392 This research analyzed the potentials of the N100, P200, N400 and LPC components

393 across different sets of electrodes. The mean amplitude of all ERPs component was

394 calculated in five ROIs and four time windows (frontal area: Fp1/2, Fz, F3/4; central

395 area: FC1/2, Cz, C3/4, CP1/2; left temporal area: F7, FC5, T3, CP5; right temporal

396 area: F8, FC6, T4, CP6; occipital area: P3/4, Pz, PO3/4, Oz, O1/2; time windows:

397 100–140 ms for N100; 200–280 ms for P200; 320-400 ms for N400; and 460-540 ms

398 for LPC).

399 Pearson's correlations were computed between the mean amplitudes of N100, P200,

400 N400 and LPC components for different emotional words (positive, negative, neutral)

401 and self-reported scores, with uncorrected p-values reported.

Feature selection and model training

403 The processed data were used as features for building regression models for the

404 prediction of the five trait scores. The averaged multichannel ERP responses to

405 positive, negative and neutral words yielded 3 (emotion: positive, negative and

406 neutral) × 28 (EEG channels) × 300 (sample points comprising 1.2 s at a sampling

407 rate of 250 Hz) = 25, 200 features per sample (participant). As the feature dimensions

408 were much larger than the sample size (i.e., 196 participants), it was necessary to

409   perform feature selection for enhancing the stability and generalizability of the

410   regression models(Bermingham et al., 2015). Following previous neuroimaging

411   studies(Cui, Xia, Su, Shu, & Gong, 2016; R. T. Jiang et al., 2018; Rosenberg, Hsu,

412   Scheinost, Todd Constable, & Chun, 2018), we applied a nested leave-one-out cross-

413   validation (nested-LOOCV) strategy, including an outer and an inner loop. The

414   procedure was performed separately for each of the five traits.

415   The outer loop performed the overall evaluation of the models generated by the inner

416   loop. By leaving out one sample (participant) at a time, the remaining 195 samples

417   were used as the training set to build 196 regression models (with the self-reported

418   scores of one trait as the dependent variable). These regression models were then

419   applied to the left-out sample to obtain 196 predicted personality scores. The

420   Pearson's correlation coefficient between these predicted scores and their

421   corresponding self-reported scores was used to quantify the effectiveness of the

422   models. The model with the highest correlation coefficient was considered the best-

423   performing model for further analyses.

424   The inner loop focused directly on feature selection. Here all analyses were performed

425   using 195 samples from the training set as described in the outer loop procedure. The

426   features were initially selected by thresholding the features according to the p-values

427   of their bivariate Pearson correlations with the self-reported personality scores

428   (performed separately for each personality score). By varying the p-value threshold

429   from .01 to .15 with a step of .01, different numbers of features were retained and

430   used for a series of regression analyses. Considering the possible occurrence of a high

431   feature dimension problem in these conditions, a sparse regression analysis method

432   was employed, using elastic net regularization with the alpha parameter set to

433   0.75(Zou & Hastie, 2005). All models were first evaluated using the outer loop, and

434   the optimal *p*-value was subsequently decided. The changes of cross-validated

435   correlation coefficients as a function of the *p*-value thresholds is shown in Figure S3.

436   The optimal *p*-values for the five personality models were .03, .02, .08, .05 and .02 for

437   Agreeableness, Conscientiousness, Neuroticism, Openness and Extroversion

438   respectively. Correspondingly, 74, 56, 90, 90, and 70 features on average were

439   retained for the 196 predictive models of the five traits, respectively.

440   The procedure is also briefly illustrated in Fig. 1 (lower panel). The LASSO method

441   was implemented using the Statistics and Machine Learning Toolbox provided by

442   MATLAB (The MathWorks, USA).

Evaluation of the predicted scores

444   Firstly, the model performance was assessed by correlating the predicted trait scores

445   with the self-reported scores (Fig. 4), computing prediction errors (the mean absolute

446   difference between the predicted and self-reported scores for each trait, Fig. 5a) and

447   computing participant-wise correlations (the correlations of the 5-dimension

448   personality constructs between the EEG-predicted scores and self-reported scores,

449   Fig. 5b).

450   Secondly, the external validity of the measure was assessed by comparing the

451   predictive power of the predicted scores to the self-reported scores (Fig. 6). A

452   subsample of participants completed a number of self-reported measures of indices of

453   psychological adjustment, including the Satisfaction with Life Scale(Xiong & Xu,

454   2009) (N = 135), Beck Depression Inventory(Shek, 1990) (N = 111), and Positive and

455   Negative Affects Scale(Huang, Yang, & Li, 2003)   (N = 111). Another sixty

456   participants watched 28 emotional videos including 12 positive clips (i.e., amusement,

457   joy, inspiration, and tenderness), 12 negative clips (i.e., anger, disgust, fear, and

458   sadness) and 4 neutral clips, all of which were selected based on standardized emotion

459   ratings from three established emotional video datasets(Hu et al., 2017; Liu et al.,

460   2018; Schaefer, Nils, Sanchez, & Philippot, 2010). After watching each of the clips,

461   participants reported their experienced emotional valence of the video. The average

462   valence of all positive (negative/neutral) clips was calculated as the final indices of

463   positive (negative/neutral) experiences. The information of the video clips is provided

464   in Table S3.

465   Finally, to assess the test-retest reliability of the models, 33 participants participated

466   in the experiment twice, with a time interval of from two weeks to two months (mean

467   interval 41 days, range 19-78 days). Correlations were computed between the

468   predicted scores from the two data collection sessions. The test-retest reliability of

469   self-reported scores was calculated in the same way. Meanwhile, prediction errors (the

470   mean absolute differences between the predicted scores from the two data collection

471   sessions, Fig. 7a) and participant-wise correlations (the correlations between the

472   predicted scores from the two data collection sessions, Fig. 7b) were also computed.

Acknowledgements

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Contributions

D.Z. and F.W. developed the study concept and design. W.L. and C.W. developed the study stimuli. W.L., C.W., X.H., and J.C. collected the data. W.L. analyses and interpreted the data under the supervision of D.Z.. W.L. drafted the manuscript. S.F., X.H., and J.C. discussed the results and commented on the manuscript. D.Z. and F.W. provided critical revisions.

Competing interests

The authors declare no competing interests.

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