

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

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

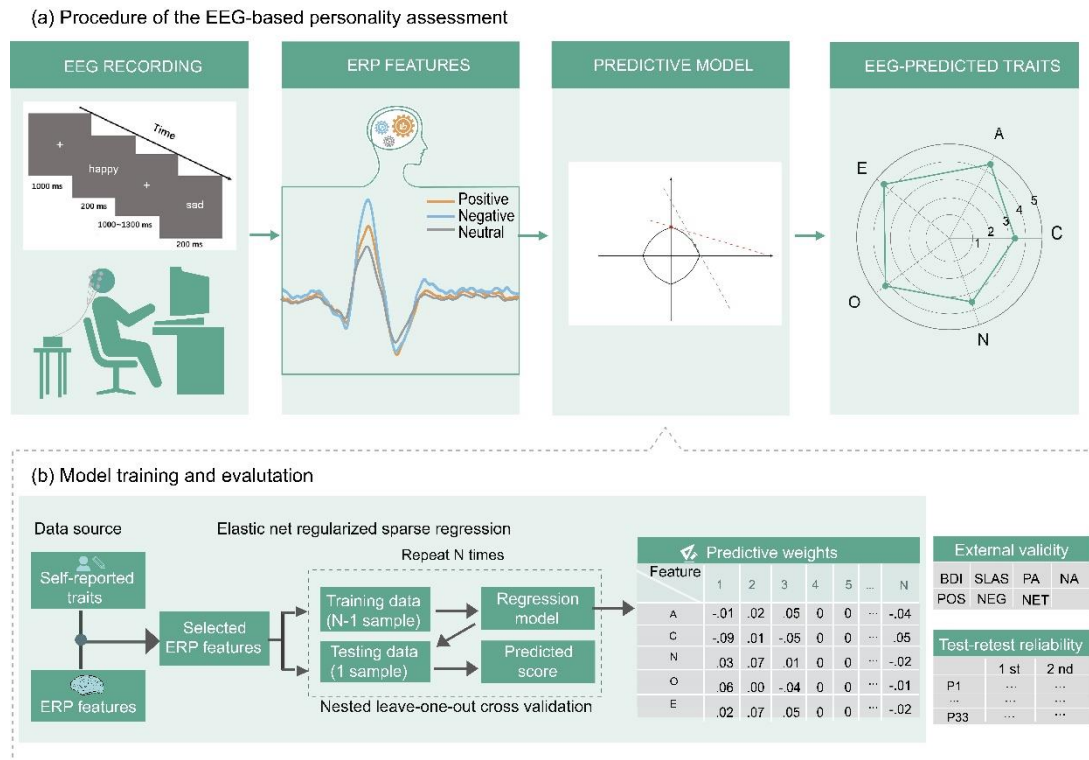
50 psychologists and neuroscientists to investigate the neurobiological basis of  
51 personality(R. Jiang et al., 2018; Korjus et al., 2015; Nostro et al., 2018). Despite the  
52 fact that consensus has not been reached for many traits, broadly speaking, the  
53 available data do suggest that there 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.

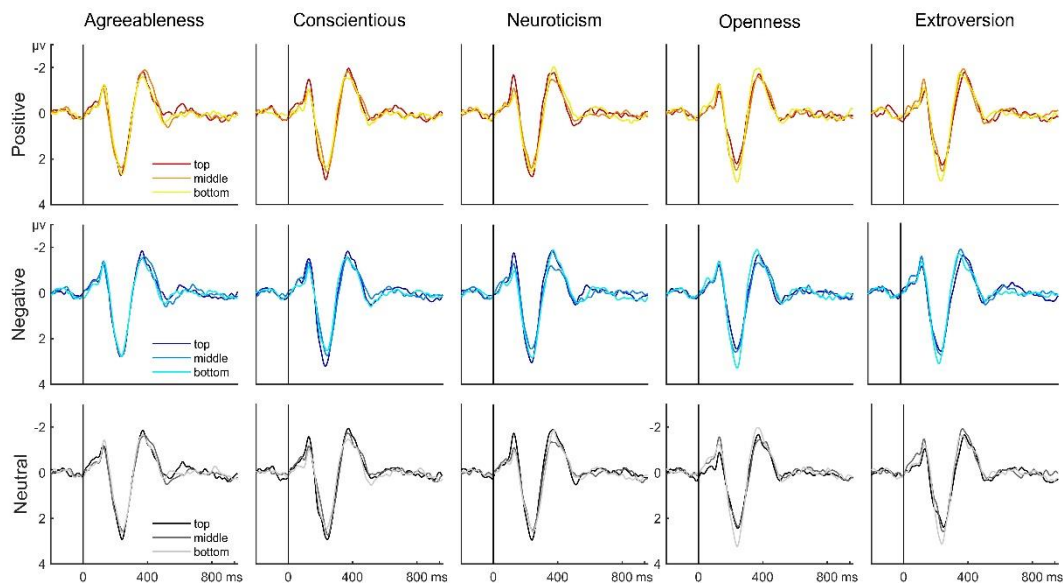
## 106 Results

## 107 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  $97.19 \pm 5.04\%$  and  
111 the mean response time was  $522 \pm 166$  ms, indicating that participants were attentive  
112 during the task.

## 113 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).



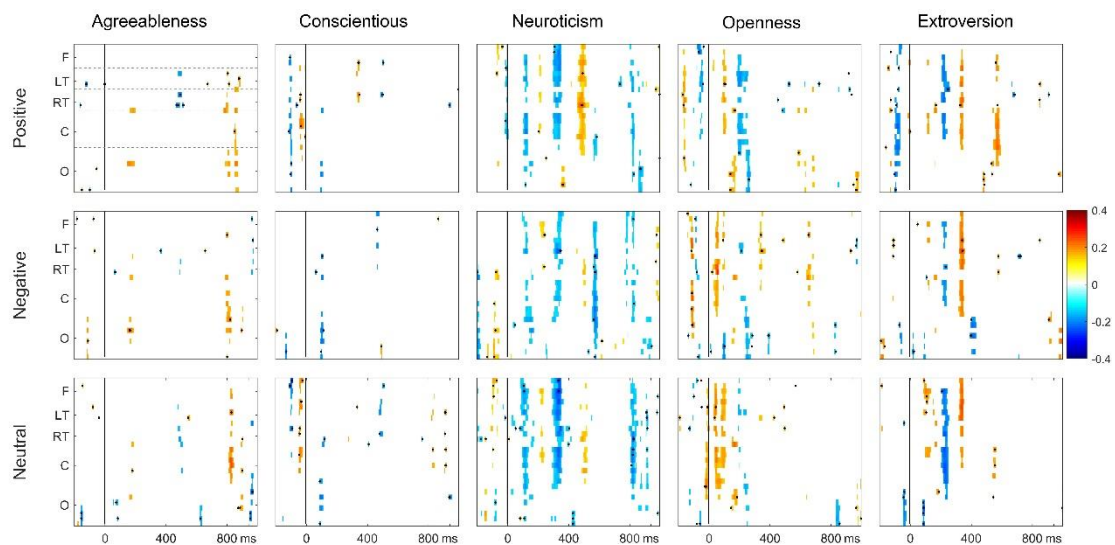
121 As a first step, we examined these components' correlation with personality. As  
122 shown in Fig. S1, there was only one significant correlation between LPC for positive  
123 words in the temporal area and self-reported scores for agreeableness ( $r = -.18, p$   
124  $< .05$ ). For conscientiousness, 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 ( $r = .15, p < .05$ ).

## 142 Predictive models of personality based on ERP responses

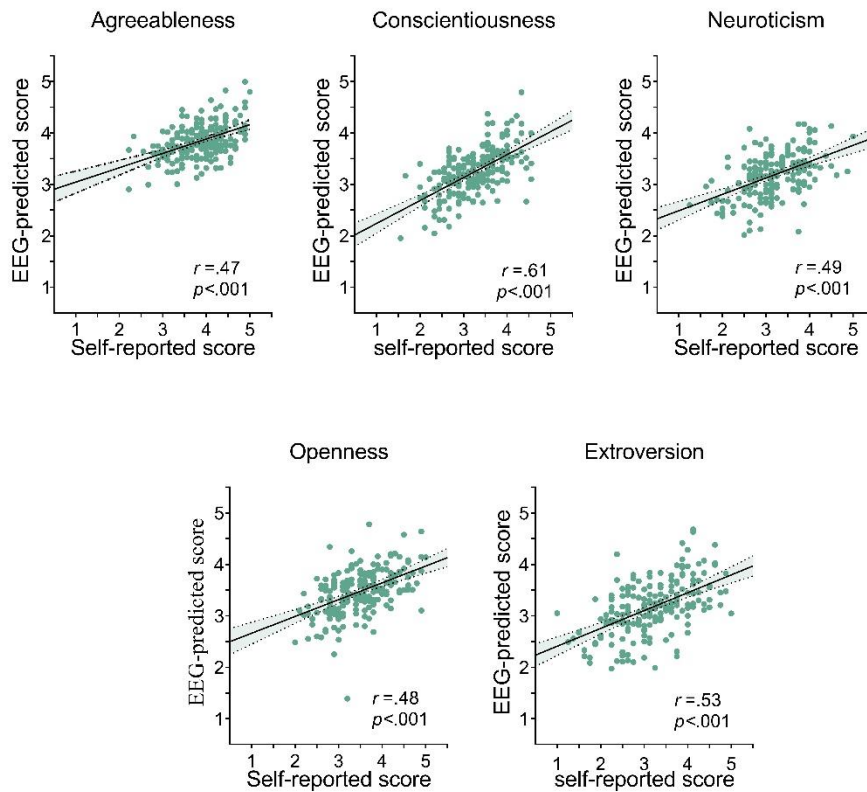
143 Participants' ERP responses elicited by the word stimuli were used as features to train  
144 five predictive models, one for each of the Big Five traits, using a nested cross-  
145 validation approach with elastic net regularized regression analyses. To assess the  
146 predictive models' performance, 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

154 **Fig. 3.** ERP features used in the trait predictive models. The colored channel by time  
155 bins demonstrate the ERP features retained for model training ( $p$ -value  $<$  the optimal  
156  $p$ -value threshold) and the black dots mark the bins that were finally used in the  
157 elastic net regularized sparse regression model. The colors show the bivariate Pearson  
158 correlation coefficients between the ERP features at the channel-time bin and the  
159 corresponding self-report trait scores. EEG channels array are Fp1/2, Fz, F3/4, F7,  
160 FC5, T3, CP5, F8, FC6, T4, CP6, FC1/2, Cz, C3/4, CP1/2, P3/4, Pz, PO3/4, Oz, O1/2,  
161 organized in five ROIs: frontal area (F), left temporal area (LT), right temporal area  
162 (RT), central area (C), occipital area (O). See 'Feature selection and model training'  
163 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  $p < .001$ ,  $N = 196$ ).



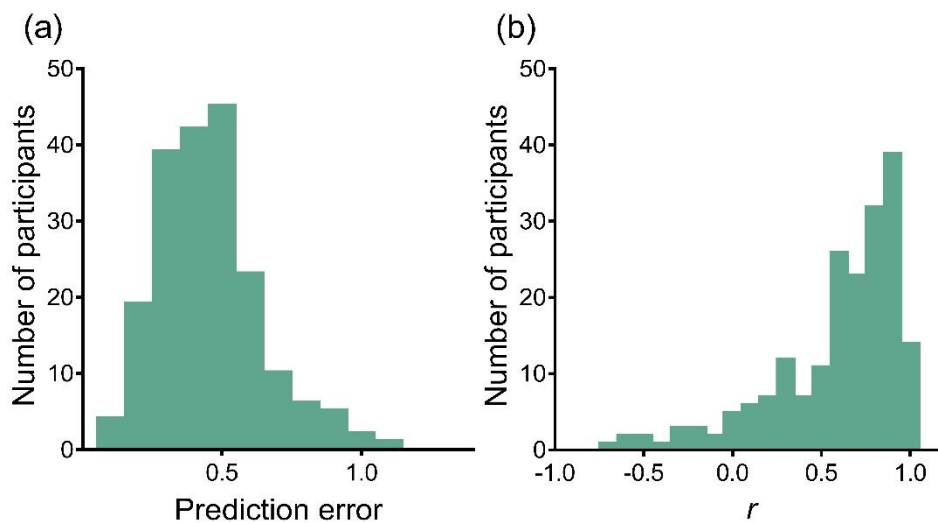
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**Fig. 4.** Scatterplots for the correlations between the predicted and self-reported trait scores. Each dot represents the scores from one participant (for each plot,  $N = 196$ ). The predicted score for each dot was obtained by using a nested cross-validation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

169

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 =  $0.45 \pm 0.18$ ). 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



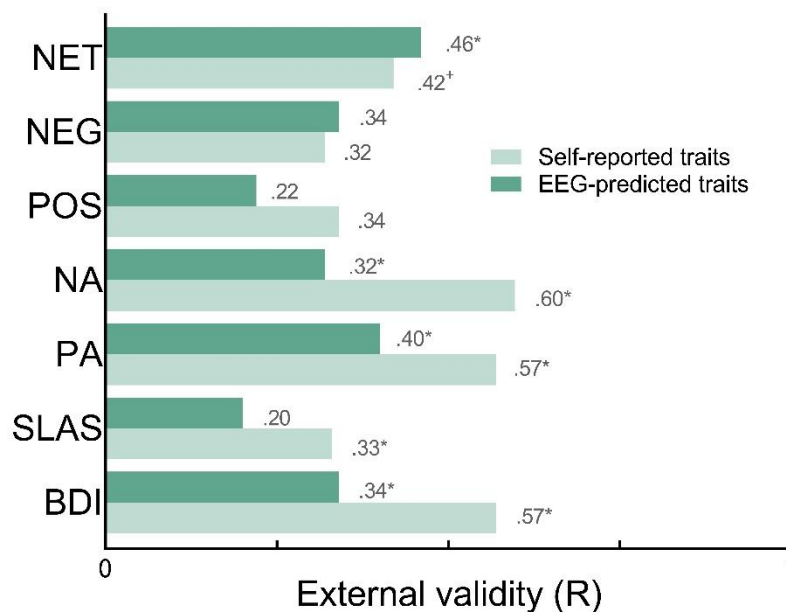
**Fig. 5.** Evaluation of the predicted scores. (a) A histogram of the participant-wise prediction errors (i.e. the mean absolute difference between the EEG-predicted scores and self-reported scores). (b) A histogram of the participant-wise correlations of the 5-dimension personality constructs between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

## 180 **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

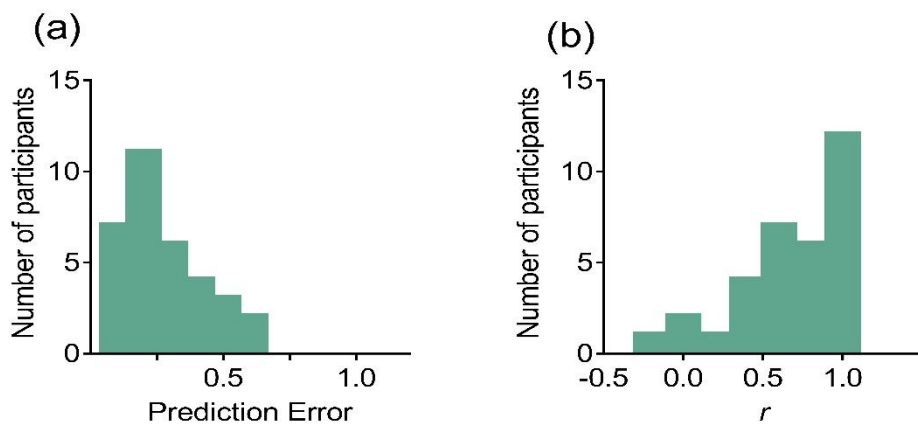


**Fig. 6.** External validity of the EEG-predicted and self-reported trait scores. The dark green and light green bars show the predictive powers of EEG-predicted and self-reported trait scores for a certain behavior or life outcome index as reflected in regression model fitting  $r$  values. NET, NEG, 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).

## 200 Test-retest reliability

201 Temporal correlations were calculated for each of the predicted and self-reported trait  
202 scores from the subsample of the participants ( $N = 33$ ) who completed the task for a  
203 second time 19-78 days later. The self-reported trait scores showed adequate to good  
204 test-retest reliability ( $r = .86, .67, .65, .76$  and  $.79$  for agreeableness,  
205 conscientiousness, neuroticism, openness and extroversion, respectively). The  
206 predicted scores' test-retest reliability, except for neuroticism, were lower than the  
207 self-reported scores ( $r = .51, .31, .67, .50$  and  $.58$  for agreeableness,  
208 conscientiousness, neuroticism, openness, and extroversion, respectively). A closer  
209 look at the data suggested that the extremely low reliability of conscientiousness was  
210 largely due to two outliers. After these two were excluded, the reliability increased  
211 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.

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

## 214 Discussion

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, &



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

315 have shown the potential to greatly improve the usability of EEG devices to a general  
316 user population(Lümann, 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.

## 321 **Materials and Methods**

### 322 **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.

### 329 **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  $7.43\pm 0.16$  on a 9-point Likert scale), the top 20 least pleasant adjectives, nouns and  
337 verbs as negative-emotion words (mean valence  $2.38\pm 0.21$ ), the median 20 pleasant

338 adjectives, nouns and verbs as neutral words (mean valence  $5.52 \pm 0.71$ ). 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).

## 348 **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  $1.5^\circ$  by  $2.0^\circ$  (horizontal by vertical, measured in visual  
360 angle) per character and a  $0.75^\circ$  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).

### 368 **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.

### 375 **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  $\pm 150$  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.

### 391 **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.

### 402 **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)  $\times$  28 (EEG channels)  $\times$  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).

#### 443 **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.

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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  
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### **Competing interests**

The authors declare no competing interests.

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