The Influence of Language on Personality Traits: A Multi-modal Study Among Chinese-English Bilinguals

Xinyi Liu[1], Mingxi Lu[2], and Ran Tao[2]
[1]Department of Linguistics and Modern Languages, The Chinese University of Hong Kong
xinyi.liu@link.cuhk.edu.hk
[2]Research Centre for Language, Cognition, and Neuroscience, Department of Chinese and Bilingual Studies, The Hong Kong Polytechnic University
mency.lu@polyu.edu.hk; ran.tao@polyu.edu.hk

Abstract

Personality is a stable trait, but it may be influenced by the language in use, as bilingual speakers may internalize different experiences and values when acquiring these languages. This study investigated the effect of language on neuroticism in Chinese-English bilinguals using a multi-method approach combining self-report questionnaires, behavioral data-based assessments, and electroencephalography (EEG) recordings. Thirty Chinese-English bilingual students completed the Big Five Inventory (BFI) in both languages, responded to questions, and underwent EEG recording during the tasks. The results showed no significant differences in neuroticism scores between the Chinese and English versions of the BFI. However, behavioral data analysis using artificial intelligence (AI) revealed higher neuroticism scores in Chinese responses than in English. EEG analysis indicated differences between languages in the theta and alpha bands during the writing phase. These findings suggest that language may have a more pronounced effect on the implicit expression of personality traits, as reflected in language use and neural activity patterns, but not explicit self-reports. This study contributes to the understanding of the complex relationship between language and personality in bilinguals and highlights the potential of AI-based methods for personality prediction through text analysis.

1 Introduction

Personality is usually considered a relatively stable structure that maintains consistent qualities and behaviors over time and across different situations (Boeree, 2006). However, the concept of personality stability intersects interestingly with the Sapir-Whorf theory's proposition that language influences personality. This theory, based on the preliminary concepts of Edward Sapir (1921) and Benjamin Lee Whorf (1956) and further developed by Roger Brown and Eric Lenneberg, argues that there is a deterministic or influential relationship between language and thought. Within this theoretical framework, two hypotheses are distinguished: the strong hypothesis posits that language shapes and defines one's way of thinking, whereas the weak hypothesis views language as a factor that influences thought (R. Brown, 1976; R. W. Brown & Lenneberg, 1954; Bugelski, 1970). Although the strong hypothesis of Sapir-Whorf and Wittgenstein's arguments has largely failed to gain recognition in the field of psycholinguistics (Ahearn, 2021; Pinker, 2015), the influence indicated by the weak hypothesis has been confirmed in multiple research areas, including studies on the perception of color (Athanasopoulos, 2009; Winawer et al., 2007), space (Majid et al., 2004), time (Boroditsky, 2001; Casasanto, 2008), and new vocabulary (Barner et al., 2009).

Learning a new language involves adopting a different way of thinking, as language potentially influences identity, cognition, and personality. This idea challenges the notion that personality is stable, suggesting that language can dynamically influence thoughts, perceptions, and interactions. Further exploration of language and personality relationships is warranted to understand this complex dynamic.

1.1 Culture Frame Shifting (CFS)

Culture Frame Shifting is a compelling theoretical explanation for the phenomenon of personality change when using different languages. CFS refers to the shift in values and attributions of bicultural individuals (people who have internalized two cultures) when exposed to different cultural stimuli (Y. Hong et al., 2000). Some studies have suggested that CFS can affect personality traits

(Ramírez-Esparza et al., 2006; Rezapour & Zanjirani, 2020), emotional expressions, attribution styles (Kreitler, 2018), and cognitive processes related to cultural evolution (Gabora et al., 2008; Gabora & Smith, 2018). Regarding bicultural individuals, specific cultural symbols can trigger cultural values and attributes. For example, a series of studies have shown that when Chinese-American bicultural individuals are exposed to American icons (e.g., the White House & Lincoln), their American cultural knowledge network is activated; when exposed to Chinese icons (e.g., the Forbidden City & Confucius), their Chinese cultural knowledge network is also activated (Y. Y. Hong et al., 1997; Kemmelmeier & Winter, 2008). Moreover, in attribution tasks, participants placed less emphasis on external social factors when primed with American culture than with Chinese culture (Y. Hong et al., 2000).

Bilinguals exhibit different personality traits when using different languages, suggesting that language activates specific cultural frameworks (Ramírez-Esparza et al., 2006; Rezapour & Zanjirani, 2020). Ronzani's (2023) study on bilingual students confirms this, showing cultural frame switching (CFS) affects personality and leads to adaptation to the second language's culture. Participants' English proficiency also influenced self-descriptions, with only one Canadian resident describing himself as "polite." To adapt, they imitate local behavioral and linguistic patterns in the media. The degree of bicultural identity integration (BII) moderates the impact of CFS (Benet-Martínez et al., 2002). However, Bender et al. (2022) found similar response patterns in bicultural and monocultural participants, indicating that the CFS mechanisms may be more complex.

1.2 Measurement of Personality

In the field of personality assessment, self-report questionnaires are mainstream tools that consist of multiple statements or words for self-reflection. Participants were asked to rate their level of agreement with these descriptions in order to assess their personality traits. The Big Five framework is the most widely used and extensively applied personality measurement model, encompassing the following five dimensions: agreeableness, conscientiousness, neuroticism, openness, and extraversion. Currently, various tools are available to assess the Big Five dimensions, with representative ones including NEO-Personality-Inventory Revised (NEO-PI-R) (Costa & McCrae, 2008), the NEO Five Factor Inventory (NEO-FFI) (McCrae & Costa, 2004), and the Big-Five Inventory (BFI) (John, 1990; John & Srivastava, 1999). Among them, the BFI is concise, easy to understand, has broad applicability and cross-cultural validity, and is supported by numerous studies. So far, self-report questionnaires remain the most used method for personality assessment. However, owing to the subjectivity of self-reports, the results of self-report questionnaires may be influenced by social desirability.

With technological advancements, it is now possible to gain insights into individuals' personality traits by analyzing their behavioral data. For example, personal text messaging characteristics or social media behavior can be used to predict the Big Five personality traits. Gjermunds et al.'s (2020) meta-analysis provides strong evidence of the effectiveness of this analytical approach, confirming moderate correlations between the Big Five traits and text analysis indicators across multiple studies. This highlights the robustness of the relationship between language use and personality and supports the potential use of various computational methods, such as latent semantic analysis (LSA) (Kwantes et al., 2016), artificial neural networks (ANN) (Suhartono et al., 2017; Yoong et al., 2017), and transformer models (Vasquez & Ochoa-Luna, 2021) in personality analysis through text. However, although this research method can reduce participants' direct involvement to a certain extent and lower the possibility of data fabrication, such an analysis often requires a large amount of data to train language models, which is time-consuming and labor-intensive. Moreover, data fabrication may still exist, as individuals may shape an image inconsistent with their true selves when sending text messages or on social media platforms because of social expectations, personal desires, or other reasons.

To avoid social desirability bias, physiological and biological indicators such as EEG provide more reliable personality measures, as neural data are difficult to manipulate. Compared with other physiological methods (fMRI), EEG has the advantages of low cost and high portability, with a more stable relationship to personality. For example, neuroticism is reflected in higher left hemisphere activation (Bono & Vey, 2007). Studies have decoded personality traits, particularly agreeableness, from resting-state EEG frequency powers (Jach et al., 2020). Predicting extraversion, agreeableness, and conscientiousness was better when using positive emotional stimuli, whereas neuroticism was better classified from negative emotions (Zhao et al., 2018; Li et al., 2020). Overall, EEG shows promise for reliable and objective personality assessments.

1.3 Current Study

Neuroticism is a fundamental personality trait characterized by emotional instability, anxiety, moodiness, and negative emotionality. It is highly relevant to mental health and well-being, as higher levels of neuroticism are associated with a greater risk of developing various psychological disorders, including depression and anxiety (Lahey, 2009). Focusing on neuroticism allows for a deeper understanding of how language influences the expression of personality traits that are closely linked to mental health outcomes. By examining neuroticism specifically, this study aims to shed light on the potential impact of language on emotional regulation and psychological well-being in bilingual individuals.

The present study aims to address two key research gaps in the literature on language and personality: (1) investigating the language effect on neuroticism using text responses and EEG and (2) identifying neuroticism with an artificial intelligence (AI) model. Therefore, we employ a multi-method approach that combines self-report questionnaires, behavioral data-based assessment, and EEG recordings to examine the influence of language on personality, specifically neuroticism, among Chinese-English bilinguals. We hypothesize that language will influence the personality expression of second language users, as reflected in their language use (e.g., the degree to which personality-related vocabulary is used in different language contexts) and EEG responses (e.g., the contrast of neural activity patterns associated with neuroticism traits when using different languages). To test these hypotheses, we recruited thirty Chinese-English bilinguals from the Hong Kong Polytechnic University to participate in questionnaire assessments, behavioral experiments, and EEG experiments.

The findings of this study are expected to contribute to our understanding of the complex interplay between language, culture, and personality, and to inform the development of culturally sensitive approaches to personality assessment and intervention.

2 Method

2.1 Participants

Thirty Chinese-English bilingual students (9 male, 21 female) from the Hong Kong Polytechnic University, aged between 19 and 30 years, were recruited to participate in this study. Participants were randomly assigned to either the behavioral experiment group (3 males, 14 females) or the EEG experiment group (6 males, 7 females). All participants were native Chinese speakers who had taken a standardized English proficiency test (IELTS 6 or TOEFL 80). The mean age of the participants was 23.73 years (SD = 2.41), and the mean age of English acquisition was 6.77 years (SD = 2.63). All participants were right-handed, as assessed by the Edinburgh Handedness Inventory (Oldfield, 1971), and had no psychological or neurological disorders. Participants also had normal or corrected-to-normal vision. The study protocol was approved by the Human Subjects Ethics Sub-committee of the Hong Kong Polytechnic University.

2.2 Materials

Big Five Inventory. The Big Five Inventory (BFI) (John, 1990) is a 44-item self-report questionnaire that assesses the five dimensions of personality: agreeableness, conscientiousness, neuroticism, openness, and extraversion. Participants rated their agreement with self-descriptive statements using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). In this study, both the English and Chinese versions of the BFI were used. The English BFI has demonstrated good psychometric properties, with alpha reliabilities ranging from 0.75 to 0.90 and test-retest reliabilities ranging from 0.80 to 0.90. The Chinese BFI has also shown good reliability, with alpha reliabilities ranging from 0.79 to 0.87, and an average test-retest reliability of 0.84 (Li & Chung, 2020). The internal consistency between the Chinese and English versions of the BFI was found to be satisfactory.

Stimuli. Sixteen scenario questions were used as stimuli in this study, with eight texts in each language (Chinese and English). Among these, two questions were neutral and six were related to neuroticism, covering the six dimensions of neuroticism: anxiety, angry-hostility, depression, self-consciousness, impulsiveness, and vulnerability (Vittersø & Nilsen, 2002). To avoid bias, no emotional leading was included in any of the questions, and all questions were concluded with an open-ended prompt asking participants how they felt and what they would do in the given situation.

Each Chinese scenario contained approximately 150 words, whereas each English scenario contained approximately 80 words. This setting aimed to equalize reading time across languages. It is worth noting that there were no content differences between the Chinese and English scenarios, only language differences. See sample scenarios in the Appendix A.

2.3 Procedure

The study employed a scenario-reading and response task divided into Chinese and English sessions. To minimize sequence bias, participants were required to complete the experiment twice, with half starting with the Chinese session and the other half starting with the English session. There was a 4 to 10 days interval between sessions to avoid the influence of the previous session's content. The experimental procedure is illustrated in Figure 1.

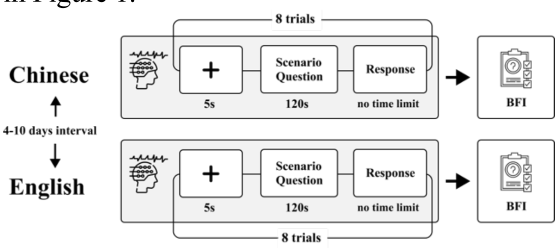

Figure 1: The experimental procedure. BFI: Big Five Inventory.

Each experiment consisted of eight trials. In each trial, participants saw a fixation cross (+) for 5,000 ms, followed by a scenario question presented in font size 36, Calibri font for English, and Microsoft YaHei for Chinese. The scenario question was displayed until the participant pressed the space bar to indicate that they had finished reading and were ready to proceed. The maximum duration for reading was 120 seconds. Then, the prompt "Please put in your thoughts..." appeared on the screen and participants were instructed to input their responses using the same language as the scenario question. Chinese responses were suggested to be around 70-80 characters, and English responses were 30-40 words, although this was not a strict requirement. Participants were encouraged to share their genuine reactions and actions, rather than what they thought they should do or what they expected.

After the experimenter explained the details, the participants voluntarily signed an informed consent form. Then, participants were fitted with an EEG cap, which took 40 minutes. The experiment was conducted in a soundproof room with two computers in front of the participant: Computer A was connected to the EEG recording system and presented the scenario questions, while Computer B, using a Python GUI, collected their responses. Participants then conducted a practice trial with a scenario that was not included in the formal experiment to familiarize themselves with the procedure. The presentation of stimuli and collection of behavioral responses were programmed using E-Prime. The order of the trials was randomized. After the experiment, participants were asked to fill out a Big Five Inventory questionnaire, covering four dimensions other than neuroticism, to prevent them from discerning the purpose of the experiment.

2.4 Analysis

BFI Analysis. Only eight items associated with neuroticism were calculated from the 44-item questionnaire (Items 4, 9, 14, 19, 24, 29, 34, and 39). Items 4, 14, 19, 29, and 39 were scored directly (e.g., a response of 5-strongly agree was allocated 5 points), whereas items 9, 24, and 34 were reverse-scored (e.g., a response of 5-strongly agree was allocated 1 point). The analysis employed raw scores rather than standardized scores. Upon aggregating these scores, a between-subjects t-test was conducted to examine potential differences in participants' scores when responding to the questionnaire in the Chinese versus English versions.

Behavioral Analysis. In this study, we used artificial intelligence (AI) models to analyze the participants' behavioral data. We employed the GPT-4 model, a state-of-the-art language model developed by OpenAI, known for its powerful natural language understanding and generation capabilities (OpenAI, 2023). GPT-4 is trained on a diverse range of internet text and leverages transfer learning. This allows the model to effectively analyze and score text responses in both Chinese and English.

We established an API interface to connect to the gpt-4-0125-preview server and designed a prompt that divided the degree of neuroticism into five levels, increasing in severity from 1 to 5. Next, we let the AI model read each participant's responses to the senario questions and assign scores based on the level of neuroticism reflected in their answers (Table 1). To reduce the arbitrariness of AI scoring, we ran the prompt twice in both Chinese and English, meaning that for each answer (480 in total), we obtained four scores ($SD < 0.96$). We used the average of these four scores for subsequent calculations. In addition, we used the scores of responses to situational questions labeled as "neutral" as a reference to assess the accuracy of AI scoring. The results showed that only three responses were assigned a score of 2, while the rest were scored as 1 (indicating minimal neuroticism in the text), suggesting that the scores provided by the AI are highly accurate. It is worth mentioning that the AI did not assign a score of 5 (indicating extremely high neuroticism in the text) to any response. Through further testing, we found that AI only assigns a score of 5 when extreme words such as "suicide" or "die" appear in the text.

Responses	**Score**
I will feel so happy and surprised. So I will share this news with my best friend first, then I will check my timetable and make a plan. I will push myself to do things faster and seize the chance to see my idol!	1
Firstly, I think it is very common that people meet new individuals and begin their new exploration in their life. Therefore, personally, I felt happy for them if they have their more wonderful life. Because I will have mine as well in the future. Secondly, I will like the post they presented in the social media and wish them have a good time. Meanwhile, I will remember all the unforgetable things between us even though they or I have new friends in the future.	1
I feel very embrassed and guse that my colleague's polite smile is fake and they must mock me secretly. I will try my best to claim down and aviod other's sightline.	4
I feel so angry, he is cheating us! I don't believe professor believed him, because he cannot individually complete most of the tasks. I have to do some actions, I will find the evidence to prove my hard work.	4

Table 1: Neuroticism scores of examples responses scored by AI

NOTE: Score: average of four scores; Examples responses based on different scenario questions.

EEG Analysis. EEG data were analyzed using EEGLAB in MATLAB. Continuous EEG was preprocessed using the following steps: First, the sampling rate was downsampled to 100 Hz. The lowered sampling rate speeds up the data preprocessing and may not affect the result of the current analysis, as we focus on the spectrum between 1 and 50 Hz, for example, delta to gamma band. DC offset was removed. A high-pass filter of 1 Hz was applied to the continuous data. Bad channels were detected and replaced using spherical interpolation. ICA was applied to the EEG to identify non-brain signals. The independent component was automatically examined using the ICALabel function, and any component with a greater than 80% possibility of being a non-brain signal was removed from the data. After artifact correction, the continuous data were epoched to -1 to 10 s long ERPs relative to the onset of each reading and writing phase. These single-trial ERPs were entered into the spectrum power analysis, where the 1–50 Hz spectrum power of each trial was calculated relative to the pre-onset baseline for each channel.

Only the spectrum power of the Cz electrode was considered in the current report, as Cz is the most frequently studied channel in EEG studies. In future research, more electrodes will be considered with cluster-based multiple comparison corrections. Five frequency bands were selected for further analysis: delta (1-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12 – 30 Hz), and gamma bands (30-50 Hz) (Kumar & Bhuvaneswari, 2012). The spectral power of each frequency band was averaged across trials for the reading and writing phases separately in the two language sessions.

The frequency band average spectrum power was then entered into a three-way within-subject ANOVA to explore any differences between the two languages. The task phase (two levels: reading and writing), language in use (two levels: Chinese and English), and Frequency Bands (five levels: Delta, Theta, Alpha, Beta, and Gamma) served as within-subject factors. The Greenhouse-Geisser correction method was used when the assumption of sphericity was violated. A post-hoc analysis was applied when there was a significant main effect or interaction among the factors.

3 Results

3.1 BFI Results

The data reported here were collected from 30 participants, including 30 Chinese BFI questionnaires and 30 English BFI questionnaires. The analysis results showed that the neuroticism scores of the Chinese version of the questionnaire (M = 23.37, SD = 5.97) were higher than those of the English version (M = 22.70, SD = 5.73) (Figure 2), but the paired t-test results ($t(29) = 0.83$, $p = 0.41 > 0.05$) indicated that the difference between the two versions was not statistically significant, suggesting that the effect of language version on neuroticism scores was minimal. In addition, the correlation between the neuroticism scores of the participants' Chinese and English versions was compared ($r = 0.72$), pointing out that there was a high degree of consistency in measuring neuroticism dimensions across language versions.

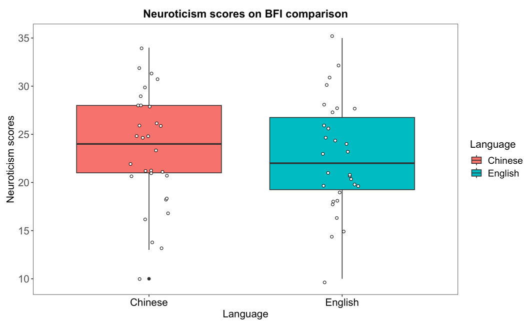

Figure 2: Boxplot of neuroticism scores from Chinese-English bilinguals on the BFI in both Chinese (orange) and English (blue) versions. No significant differences were observed between the languages.

3.2 Behavioral Results

The neuroticism scores assigned by AI of participants' responses using the Chinese and English were compared. The results showed that the neuroticism score of the Chinese (M = 2.315, SD = 0.405) was higher than that of the English (M = 2.196, SD = 0.403) (Figure 3). Through paired t-test analysis, we found that this difference was statistically significant ($t(29) = 2.125$, $p = 0.042$), indicating that there was a significant difference between the Chinese and English when participants processed responses to the scenario questions.

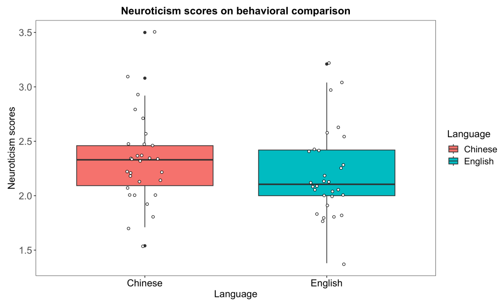

Figure 3: Boxplot of neuroticism scores from Chinese-English bilinguals on the behavioral results in both Chinese (orange) and English (blue) versions. Significant differences were observed between the languages.

However, for neuroticism scores, correlations between AI scores and BFI scores were not significant (Pearson's $r = 0.25$, $p = 0.171$ for Chinese language; $r = 0.10$, $p = 0.591$ for English language), implying that AI scores were not effective in predicting participants' personality traits. The results suggest that although the AI model is statistically different in its assessment of neuroticism scores across language, its validity as a personality predictor still needs to be improved.

3.3 EEG Results

The within-subject ANOVA revealed a main effect of Frequency Bands ($F(1.67, 20.09) = 348.99$, $ges = 0.894$, $p < 0.001$) and an interaction among language, frequency bands, and task phase ($F(2.40, 28.8) = 3.47$, $ges = 0.002$, $p = 0.037$). No other significant main effects or interactions were found (see Table 1 in the Appendix B). The main effect of the frequency bands was mainly contributed by the gradual lowering of the spectrum power from the delta to gamma bands. This trend is commonly seen in the spectrum power analysis of EEG, as a higher bandwidth tends to convey a lower power.

The Post hoc analysis of the three-way interaction revealed that only the writing phase of the tasks showed a language difference in the theta ($t = -2.258$, $p = 0.043$) and alpha ($t = -3.343$, $p = 0.006$) bands. No other frequency bands showed significant spectrum power differences between the languages during the writing task phase. No language difference was revealed in the reading phase on any frequency band (Table 2).

FB	Phase	Language	Power (dB)	SD
Delta	reading	Chinese	5.1	3.47
		English	5.1	2.31
	writing	Chinese	4.1	2.73
		English	5.0	2.81
Theta	reading	Chinese	-1.5	1.98
		English	-1.3	1.02
	writing	Chinese	-2.4	1.76
		English	-1.6	1.55
Alpha	reading	Chinese	-4.9	2.14
		English	-4.9	2.03
	writing	Chinese	-6.1	1.70
		English	-5.4	1.53
Beta	reading	Chinese	-9.4	2.86
		English	-8.5	3.08
	writing	Chinese	-9.7	2.57
		English	-9.1	2.70
Gamma	reading	Chinese	-18.4	3.18
		English	-17.2	4.51
	writing	Chinese	-18.1	3.24
		English	-17.0	4.00

FB	Phase	Language	t	p
Delta	reading	Chinese English	-0.088	0.932
	writing	Chinese English	-1.362	0.198
Theta	reading	Chinese English	-0.569	0.580
	writing	Chinese English	-2.258	0.043
Alpha	reading	Chinese English	-0.066	0.949
	writing	Chinese English	-3.343	0.006
Beta	reading	Chinese English	-1.374	0.195
	writing	Chinese English	-1.180	0.261
Gamma	reading	Chinese English	-1.266	0.230
	writing	Chinese English	-1.525	0.153

Table 2: Post-hoc analysis of the three-way interaction among language, frequency band, and task phase

NOTE: FB: frequency band; Phase: task phase; SD: standard deviation.

4 Discussion

The findings provide some interesting insights into the complex connections and interactions between language and personality.

The results of BFI analysis showed that there was no significant difference in neuroticism scores in the Chinese and English versions of the questionnaire ($p > 0.05$), and the correlation between the two was high ($r = 0.72$), indicating that language had little influence on the BFI neuroticism scores and the neuroticism measurements were highly consistent across different language versions. This supports previous research that BFI has cross-cultural validity and that self-reported personality traits tend to remain stable across language contexts (John & Srivastava, 1999). However, participants are likely to changing their responses based on perceived social expectations or personal desires, so self-report questionnaires may be affected by social expectation bias (Gjermunds et al., 2020).

Contrary to the results of BFI, the behavior data analysis based on AI scores showed that there was a significant difference in neuroticism scores ($p = 0.042$) when participants responded to scenario questions in both Chinese and English. Participants showed higher levels of neuroticism in the Chinese responses compared to the English responses. This finding is consistent with the cultural frame Shift (CFS) theory, which suggests that language can serve as a powerful clue to activate specific cultural frames and influence personality expression (Ramírez-Esparza et al., 2006; Rezapour & Zanjirani, 2020). The difference in neuroticism scores between the two languages may be due to the adaptation of subjects to the second language culture (Ronzani, 2023). The low correlation between the AI's neuroticism score and the BFI score reveals the limitations of using AI-model text analysis for personality prediction. Although AI-model scoring methods can reduce subjectivity and social bias in assessments compared to humans, their validity and credibility as predictors of personality still need to be improved.

EEG analysis showed that participants showed differences between different languages only in the writing phase and showed differences in the use of Chinese and English in the theta band ($t = -2.258$, $p = 0.043$) and the alpha band (-3.343, $p = 0.006$). This finding is consistent with the results of the two previous analyses of this study, in which there were no personality differences in the perception phase

(BFI analysis) and only in the expression phase (typed response analysis) were personality differences observed. Higher theta and alpha power in English writing conditions may reflect the increased cognitive load and attention demands associated with using a second language (Kumar & Bhuvaneswari, 2012). However, it is important to note that the current EEG analysis is limited to the Cz channel, which may influence the conclusions reached to some extent.

The differences between BFI results and behavioral with EEG results suggest that language may have a more pronounced effect on the implicit expression of personality traits. This finding is consistent with previous research in which, with the same BFI questionnaire in English and in Spanish, the results for English-speakers and Spanish-speakers differed from the results for English-Spanish bilinguals, with significant differences in neuroticism scores for the former, but not for the latter (Ramírez-Esparza et al., 2006). Language use and neural activity can measure personality without participants being fully aware of it, revealing more implicit aspects of personality (Jach et al., 2020; Li et al., 2020). The implicit expression of personality through language use may be influenced by the activation of specific cultural frameworks associated with each language (Y. Hong et al., 2000).

The findings suggest that language may influence the implicit expression of personality traits, as reflected in language use and neural activity patterns, even if explicit self-reports remain stable across languages.

However, the study has limitations. Firstly, the small sample size (n=30) may limit generalizability, requiring larger, more diverse samples in future. Secondly, we focused only on native Chinese-English bilinguals, the results may be affected by language proficiency, necessitating extension to native English-Chinese bilinguals and other multilinguals to investigate language's influence on personality expression. Third, although we attempted to use BERT models for text-based personality prediction. The limited training data leading to overfitting, so the existing GPT-4-0125-preview model was used instead. In addition, we did not compare the AI-assigned neuroticism scores with ratings from human experts. In future research, we plan to include human expert ratings to evaluate the validity of AI-based personality assessments.

5 Conclusion

This study innovatively combined multiple research methods, including self-report questionnaires, scenario question reading and response task, and EEG recordings, to investigate the influence of language on neuroticism in Chinese-English bilinguals. The findings suggest that language may have a greater impact on the implicit expression of personality traits (e.g., responses to scenario questions and neural activity patterns) compared to explicit self-reports. This finding is consistent with previous research that language use and neural activity can measure implicit aspects of personality that individuals may not be fully aware of. It is also consistent with cultural frame shifting (CFS) theory, demonstrating that language is a powerful cue to activate specific cultural frames and influence personality expression.

It is worth noting that this study explored the use of AI models to predict neuroticism through text in behavioral data analysis. Although the validity and credibility of this approach still need improvement, it provides new ways for future research on language and personality. Future studies should investigate the impact of language on other dimensions of personality using larger and more diverse samples and continue to develop and refine AI-based personality prediction methods.

Acknowledgment

This study has been supported by an internal grant from The Hong Kong Polytechnic University [Project No P0048115].

References

Ahearn, L. M. (2021). *Living language: An introduction to linguistic anthropology* (Third edition). John Wiley & Sons.

Athanasopoulos, P. (2009). Cognitive representation of colour in bilinguals: The case of Greek blues. *Bilingualism: Language and Cognition*, *12*(1), 83–95. https://doi.org/10.1017/S136672890800388X

Barner, D., Inagaki, S., & Li, P. (2009). Language, thought, and real nouns. *Cognition*, *111*(3), 329–344. https://doi.org/10.1016/j.cognition.2009.02.008

Bender, M., Yue, X., & Chasiotis, A. (2022). *Autobiographical Memory and Cultural Frame Switching*. https://doi.org/10.31234/osf.io/u8r3s

Benet-Martínez, V., Leu, J., Lee, F., & Morris, M. W. (2002). Negotiating Biculturalism: Cultural Frame Switching in Biculturals with Oppositional Versus Compatible Cultural Identities. *Journal of Cross-Cultural Psychology*, *33*(5), 492–516. https://doi.org/10.1177/0022022102033005005

Boeree, C. G. (2006). Personality theories: An introduction. *Psychology Department*, 1–7.

Bono, J. E., & Vey, M. A. (2007). Personality and emotional performance: Extraversion, neuroticism, and self-monitoring. *Journal of Occupational Health Psychology*, *12*(2), 177–192. https://doi.org/10.1037/1076-8998.12.2.177

Boroditsky, L. (2001). Does Language Shape Thought?: Mandarin and English Speakers' Conceptions of Time. *Cognitive Psychology*, *43*(1), 1–22. https://doi.org/10.1006/cogp.2001.0748

Brown, R. (1976). Reference in memorial tribute to Eric Lenneberg. *Cognition*, *4*(2), 125–153. https://doi.org/10.1016/0010-0277(76)90001-9

Brown, R. W., & Lenneberg, E. H. (1954). A study in language and cognition. *The Journal of Abnormal and Social Psychology*, *49*(3), 454–462. https://doi.org/10.1037/h0057814

Bugelski, B. R. (1970). Words and things and images. *American Psychologist*, *25*(11), 1002–1012. https://doi.org/10.1037/h0030150

Casasanto, D. (2008). Who's Afraid of the Big Bad Whorf? Crosslinguistic Differences in Temporal Language and Thought. *Language Learning*, *58*(s1), 63–79. https://doi.org/10.1111/j.1467-9922.2008.00462.x

Costa, P. T., & McCrae, R. R. (2008). The Revised NEO Personality Inventory (NEO-PI-R). In G. Boyle, G. Matthews, & D. Saklofske, *The SAGE Handbook of Personality Theory and Assessment: Volume 2—Personality Measurement and Testing* (pp. 179–198). SAGE Publications Ltd. https://doi.org/10.4135/9781849200479.n9

Gabora, L., Rosch, E., & Aerts, D. (2008). Toward an Ecological Theory of Concepts. *Ecological Psychology*, *20*(1), 84–116. https://doi.org/10.1080/10407410701766676

Gabora, L., & Smith, C. M. (2018). *Two Cognitive Transitions Underlying the Capacity for Cultural Evolution*. https://doi.org/10.48550/ARXIV.1811.10431

Gjermunds, N., Brechan, I., Johnsen, S., & Watten, R. G. (2020). Personality traits in musicians. *Current Issues in Personality Psychology*, *8*(2), 100–107. https://doi.org/10.5114/cipp.2020.97314

Hong, Y., Morris, M. W., Chiu, C., & Benet-Martínez, V. (2000). Multicultural minds: A dynamic constructivist approach to culture and cognition. *American Psychologist*, *55*(7), 709–720. https://doi.org/10.1037/0003-066X.55.7.709

Hong, Y. Y., Chiu, C. Y., & Kung, T. M. (1997). Bringing culture out in front: Effects of cultural meaning system activation on social cognition. *Progress in Asian Social Psychology*, *1*, 135–146.

Jach, H. K., Feuerriegel, D., & Smillie, L. D. (2020). Decoding personality trait measures from resting EEG: An exploratory report. *Cortex*, *130*, 158–171. https://doi.org/10.1016/j.cortex.2020.05.013

John, O. P. (1990). The "Big Five" factor taxonomy: Dimensions of personality in the natural language and in questionnaires. In *Handbook of personality: Theory and research.* (pp. 66–100). The Guilford Press.

John, O. P., & Srivastava, S. (1999). The Big Five Trait taxonomy: History, measurement, and theoretical perspectives. In *Handbook of personality: Theory and research, 2nd ed.* (pp. 102–138). Guilford Press.

Kemmelmeier, M., & Winter, D. G. (2008). Sowing Patriotism, But Reaping Nationalism? Consequences of Exposure to the American Flag. *Political Psychology*, *29*(6), 859–879. https://doi.org/10.1111/j.1467-9221.2008.00670.x

Kreitler, S. (2018). The meaning profiles of anxiety and depression: Similarities and differences in two age groups. *Cognition and Emotion*, *32*(7), 1499–1513. https://doi.org/10.1080/02699931.2017.1311248

Kumar, J. S., & Bhuvaneswari, P. (2012). Analysis of Electroencephalography (EEG) Signals and Its Categorization–A Study. *Procedia Engineering*, *38*, 2525–2536. https://doi.org/10.1016/j.proeng.2012.06.298

Kwantes, P. J., Derbentseva, N., Lam, Q., Vartanian, O., & Marmurek, H. H. C. (2016). Assessing the Big Five personality traits with latent semantic analysis. *Personality and Individual Differences*, *102*, 229–233. https://doi.org/10.1016/j.paid.2016.07.010

Li, W., Hu, X., Long, X., Tang, L., Chen, J., Wang, F., & Zhang, D. (2020). EEG responses to emotional videos can quantitatively predict big-five personality traits. *Neurocomputing*, *415*, 368–381. https://doi.org/10.1016/j.neucom.2020.07.123

Li, R., & Chung, H. (2020). 中文版簡式「五大人格量表」BFI 的發展. 測驗學刊, *67*(4), 271–299.

Majid, A., Bowerman, M., Kita, S., Haun, D. B. M., & Levinson, S. C. (2004). Can language restructure cognition? The case for space. *Trends in Cognitive Sciences*, *8*(3), 108–114. https://doi.org/10.1016/j.tics.2004.01.003

McCrae, R. R., & Costa, P. T. (2004). A contemplated revision of the NEO Five-Factor Inventory. *Personality and Individual Differences*, *36*(3), 587–596. https://doi.org/10.1016/S0191-8869(03)00118-1

Oldfield, R. C. (1971). The assessment and analysis of handedness: The Edinburgh inventory. *Neuropsychologia*, *9*(1), 97–113. https://doi.org/10.1016/0028-3932(71)90067-4

Pinker, S. (2015). *The language instinct: How the mind creates language* ([New] edition). Penguin.

Ramírez-Esparza, N., Gosling, S. D., Benet-Martínez, V., Potter, J. P., & Pennebaker, J. W. (2006). Do bilinguals have two personalities? A special case of cultural frame switching. *Journal of Research in Personality*, *40*(2), 99–120. https://doi.org/10.1016/j.jrp.2004.09.001

Rezapour, R., & Zanjirani, S. (2020). Bilingualism and Personality Shifts: Different Personality Traits in Persian- English Bilinguals Shifting Between Two Languages. *Iranian Journal of Learning and Memory*, *3*(10). https://doi.org/10.22034/iepa.2020.230347.1169

Ronzani, A. (2023, June). *A study of cultural frame-switching in international students*. https://hdl.handle.net/20.500.12880/5302

Suhartono, D., Ong, V., Rahmanto, A. D. S., Williem, N. G. N., Nugroho, A. E., Andangsari, E. W., & Suprayogi, M. N. (2017). *Personality Prediction Based on Twitter Information in Bahasa Indonesia*. 367–372. https://doi.org/10.15439/2017F359

Vasquez, R. L., & Ochoa-Luna, J. (2021). Transformer-based Approaches for Personality Detection using the MBTI Model. *2021 XLVII Latin American Computing Conference (CLEI)*, 1–7. https://doi.org/10.1109/CLEI53233.2021.9640012

Vittersø, J., & Nilsen, F. (2002). The conceptual and relational structure of subjective well-being, neuroticism, and extraversion: Once again, neuroticism is the important predictor of happiness. *Social Indicators Research*, *57*(1), 89–118. https://doi.org/10.1023/A:1013831602280

Winawer, J., Witthoft, N., Frank, M. C., Wu, L., Wade, A. R., & Boroditsky, L. (2007). Russian blues reveal effects of language on color discrimination. *Proceedings of the National Academy of Sciences*, *104*(19), 7780–7785. https://doi.org/10.1073/pnas.0701644104

Yoong, T. L. C., Ngatirin, N. R., & Zainol, Z. (2017). *Personality Prediction Based on Social Media Using Decision Tree Algorithm*. https://api.semanticscholar.org/CorpusID:202727282

Zhao, G., Zhang, Y., Ge, Y., Zheng, Y., Sun, X., & Zhang, K. (2018). Asymmetric hemisphere activation in tenderness: Evidence from EEG signals. *Scientific Reports*, *8*(1), 8029. https://doi.org/10.1038/s41598-018-26133-w

Appendix A. Sample scenarios used in the experiment

Scenarios	**Property**
It's been a few weeks since you last saw your friends, so you decide to organize a weekend gathering, hoping to reconnect and strengthen your friendships. You carefully plan the details of the event, including each person's favorite food and drinks, and even prepare some interactive games to ensure a lively atmosphere. After sending out the invitations, most of your friends reply quickly, but one friend you are particularly looking forward to seeing hasn't responded. At this moment, how do you feel? What would you do?	Neuroticism
After finishing your classes for the day, you step out of the building and see the sun slowly setting on the horizon. A friend messages you on WeChat, asking if you're free to try a newly opened restaurant tonight. You quickly go through your pending assignments and scheduled plans in your mind and realize that there's nothing particularly urgent for the evening. You gladly accept your friend's invitation, deciding to spend a pleasant evening with a few close friends and temporarily put aside the pressures of your studies. At this moment, how do you feel? What would you do?	Neutral

Table 2: Sample scenarios used in the experiment

Appendix B. Result table of three-way within-subject ANOVA on spectrum power analysis

Effect	df	MSE	F	ges	p.value
language	1, 12	13.34	2.13	0.016	0.171
freqband	1.67, 20.09	25.18	348.99	0.894	<.001
phase	1, 12	6.79	1.98	0.008	0.185
language:freqband	1.74, 20.92	4.7	0.68	0.003	0.496
language:phase	1, 12	1.26	1.43	0.001	0.256
freqband:phase	1.74, 20.88	2.4	2.15	0.005	0.147
language:freqband:phase	2.40, 28.8	0.39	3.47	0.002	0.037

Table 2: Result table of three-way within-subject ANOVA on spectrum power analysis

NOTE: df: degrees of freedom; MSE: Mean Squared Error; ges: generalized eta squared; freqband: frequency band; phase: task phase.