Correlational Analyses among Personality Traits, Emotional Responses and Behavioral States Using Physiological Data from Wearable Sensors

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***Abstract*—Mental health is crucial to the overall well-being of individuals, societies, and countries. In addition, personality traits, emotional responses and behavioral states caused by acute stress have a significant influence on mental health. However, correlations among personality traits, emotional responses, and behavioral states were analyzed only by manual reports in psychology. This might cause a problem in that data might not be objective. Therefore, the main purpose of this paper is to examine whether and how personality traits are associated with emotional responses and behavioral states using physiological data from wearable devices. In experiments, 38 male and female university graduates and undergraduates volunteered as participants, and each of them first completed a Big Five Inventory (BFI) questionnaire and then made a presentation in class, to get personality traits, emotional responses, and behavioral states, respectively. In the presentation, three wearable devices were used for emotional response data collection, including an Emotive Insight detecting electroencephalogram (EEG) data, a Spire Stone collecting respiration data and a Huawei Fit Watch to get the heart rate value. In detail, six attributes of emotional responses: focus, interest, relaxation, engagement, stress and excitement, and 8 attributes of behavioral states: smile, clench, blink, surprise, furrow, wink, breath, and heart rate were used to analyze the personality traits. As a result, correlational analyses have indicated associations among the personality traits, emotional responses, and behavioral states.**

Keywords-wearable sensors; personality traits; emotional responses; behavioral states; correlation.

I. INTRODUCTION

Mental health is crucial to the overall wellbeing of individuals, societies, and countries [1]. Body sensors can be applied to better monitor individual's psychological conditions. In addition, personality traits, which can be defined as habitual patterns of behavior and thought, have a significant influence on mental health. Correlation analysis between mental health and personality traits, using physical data from wearable sensors, is an interdisciplinary field spanning computer science and psychology.

In psychology, Penley and Joe [2] have proposed that there are strong associations among the personality traits, emotional responses and behavioral states. Unfortunately, their study was conducted only by analyzing the answers to specific questions, and thus might not be so objective.

In computer science, several studies have found that personality traits are related to many factors, such as text, nonverbal communication, social network, and physical behaviors. For example, in context detection, IBM has provided Personality Insights [3], a service that uses linguistic analytics to infer individuals' intrinsic personality traits, such as the Big Five model [4]. In addition, Gundogdu et al. [5] proposed that personality traits are related to social relationships by analyzing face-to-face interactions. What's more, personality traits are associated with physical activity, speech activity, and face-to-face time, was studied based on wearable sensors [6]. Besides these, with the development of sensors, such as EEG and Electrocardiogram (ECG), computing emotions become possible. More recently, ASCERTAIN [7] recognized personality traits by emotions using data collected by commercial sensors, like EEG, ECG, and Galvanic Skin Response (GSR), while participants were watching some affective movie clips. However, this work did not take a person's behaviors, such as smile and wink, into consideration.

Hence, this research aims to find out correlations among the personality traits, emotional responses and behavioral states using physiological data from wearable sensors. To the best of our knowledge, it is the first work to analyze associations among the three aspects of personality traits, emotional responses and behavioral states using wearable sensor data. A modified personalized mental health framework has been proposed to better monitor individuals' mental health, which has taken the personality traits into consideration.

The rest of this paper is organized as follows. Section II describes the personalized mental health framework. Section III explains data collection experimental details, which includes descriptions of participants, measurements of personality traits, and three wearable devices used for getting emotional responses and behavioral states. Section IV goes into correlational analyses among the personality traits, the emotional responses, and the behavioral states. The important findings of this study and necessary future work are depicted in the last section.

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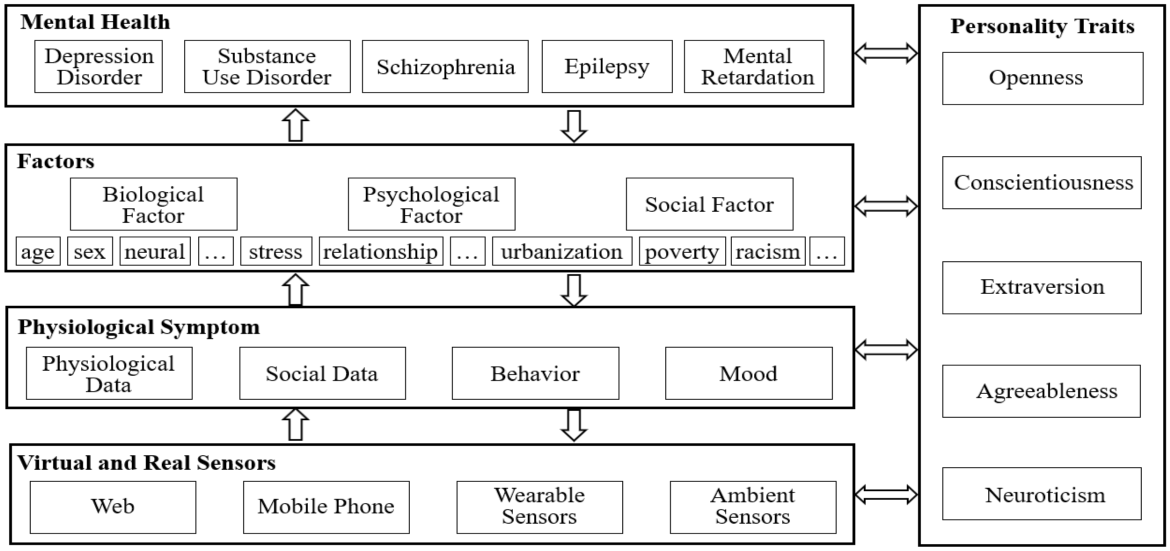

Figure 1. A personalized mental health framework.

II. PERSONALIZED MENTAL HEALTH FRAMEWORK

For better monitoring individuals' psychological conditions, a personalized mental health management framework was designed based on [8], shown in Fig. 1. In this personalized mental health framework, four layers are designed to transfer raw sensor data to mental health statements. In the first layer, raw data are collected from virtual or real sensors, for example, web browsing histories and accelerometers embedded in mobile phones. Then, the second layer aims to detect physiological symptoms, like the mood [9] and the behavior [8], based on these raw data. In the third layer, detailed factors are illustrated, which can be reported to professional doctors. Also, these data can be used to automatically detect psychological statements. On the other hand, this layer can be considered as a personal health log management layer. Finally, according to these factors, a mental health statement can be diagnosed by doctors or a mental health system. The key point of this framework is that personality traits were taken into consideration, which have an obvious influence on mental health. For example, an individual might get a stress notification sent by the traditional mental health system, because of a person's few number of activities. But, in case of an indoors loving person, with low openness value, maybe they enjoy time at home without many activities. In this situation, the traditional system will make a mistake because it did not take into account the personality traits. It is apparent that personality traits have associations with each layer, and this idea is assumed in this paper. Whether and how personality traits influence each layer is still ongoing study, not only in psychology but also in computer science. So, in this paper, we address these problems.

III. DATA COLLECTION

This section mainly explains data collection experimental details. It can be divided into four parts, participants to this study, an approach of measuring personality traits, three wearable devices, and attributes of emotional responses and behavioral states.

A. *Participants*

This research is composed of 38 university undergraduates and graduates. Each of them first completed a Big Five Inventory (BFI) questionnaire, and then took a presentation in class. When they were presenting, three wearable devices were equipped to record emotional responses and behavioral states.

B. *The Measure of Personality Traits*

The Big Five Model describes five personality traits: Openness (O), Conscientiousness (C), Extroversion (E), Agreeableness (A) and Neuroticism (N). In detail, personality traits are measured with a 44-item version of BFI questionnaire [10] and the range of O is [10, 50], C is [9, 45], E is [9, 45], A is [9, 45], and N is [8, 40].

C. *Wearable Devices*

Three devices are applied into this study. They are Emotive Insight, Spire Stone, and Huawei Fit watch.

1) *Emotive Insight*

Emotive Insight is a 5-channel mobile EEG headset that records a user's brainwaves and translates them into meaningful data. Six attributes of emotional responses, including focus, interest, relaxation, engagement, stress, and excitement, were recorded in real time. Each emotion contains 4 metrics: Min, Max, Raw and RawNorm values. In detail, Min, Max and Raw value are for scientific research and might be negative. RawNorm is scaled value deduced from the Raw, Min, and Max value to be bounded between 0 and 1. Besides emotional responses, this device also can recognize six attributes of behavioral states: smile, clench, blink, surprise, furrow and wink (left and right).

2) Spire Stone

Spire stone is a piece of equipment which supports continuous respiration sensing and real-time interventions. Respiration data can be considered as the seventh attribute of behavioral states.

3) Huawei Fit Watch

Although Huawei Fit is a smart piece of equipment, which can track sports activity, including sleep monitor, heart rate, and notification display, it is hard for developers to get real-time data. Thus, in this study, this device supports little. But for further study, the mobility of this device might give a hand. So, only heart rate can be considered as the eighth attributes of behavioral states.

D. Emotional Responses and Behavioral States

Due to associations among personality traits, emotional responses and behavioral states have a significant influence on mental health, it is very important to create a stressful scenario since it is strongly related with data quality. Therefore, a scenario of presentation in class was applied to this study according to [2].

Because of class time limitation, three classes of presentation were recorded respectively, and each class had 13, 13, and 12 student presentations, respectively. Each presentation was about 8 minutes and was composed of 5 minutes personal speech and 3 minutes of questions & answers. Besides personality traits, all emotional responses and behavioral states data were collected by wearable sensors.

Descriptions of six attributes of emotional responses are as follows.

- Interest measures on how much a person likes or dislikes something.
- Excitement captures the level of emotional arousal.
- Engagement measures how immersed a person is in what they are doing or experiencing.
- Focus is an ability to concentrate on one task and ignore distractions.
- Stress measures how comfortable a person is with the current challenge they are facing.
- Relaxation is an ability to switch off and reach a calm mental state.

As summarized, there are eight attributes of behavioral states that will be analyzed with personality traits.

- Smile: The possibility of smiling, ranged in [0, 1].
- Clench: The possibility of clench, ranged in [0, 1].
- Blink: The possibility of blink, ranged in [0, 1].
- Surprise: The possibility of surprised, ranged in [0, 1].
- Furrow: The possibility of a furrow, ranged in [0, 1].
- Wink left and wink right: Detecting wink activity, and the range is [0, 1].
- Breath: Number of breaths per minute, ranged in [10, 40], detected by Spire.
- Heart rate: Ranged in [30, 200], detected by Huawei Fit watch.

After data preprocessing, 90837 rows of data are extracted from raw and real-time data. On average, each participant contains 2390 rows of data, collected by Emotive Insight. Breath data are collected from the Spire server and heart rate data are got from Apple Health Kit.

IV. CORRELATIONAL ANALYSES

The Pearson Correlation Coefficient (PCC), which measures the linear relationship between two variables X and Y, is applied into this study [11]. Pearson correlation coefficient, noted as *r,* varies between -1 and +1 with 0 implying no correlation. Positive correlations imply that as x increases, so does y. Negative correlations imply that as x increases, y decreases. Equation (1) shows, n is the sample size, x_i and y_i are the single samples indexed with i and $\bar{x}$, $\bar{y}$ are the mean value of x and y.

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}. \quad (1)$$

To test the null hypothesis that the true correlation coefficients equal to 0, based on the value of the sample correlation coefficient *r*, permutation tests provide a direct approach to performing hypothesis tests and constructing confidence intervals. Here, p-value is desired to test the null hypothesis and it is the proportion of the *r* values generated in permutation test that are larger than the PCC that was calculated from the original data. In detail, $p <= 0.01$ implies strong evidences to reject null hypothesis, $0.01 < p < =0.05$ implies evidences to reject null hypothesis, $0.05 < p <= 0.1$ implies some weak evidences to reject null hypothesis, and $p > 0.1$ means no evidence to reject null hypothesis. Here, null hypothesis is that there is no correlation between two parameters *X* and *Y*.

Thus, 38 students' personality trait values are shown in Fig. 2. Each person has 5 dimensions: Openness Conscientiousness, Extraversion, Agreeableness, and Neuroticism. In correlational analyses, mean values of emotional responses and heart rate, sum values of smile, clench, blink, surprise, furrow, wink left and right, and breath were analyzed with personality traits. Table I presents meaningful Pearson correlation coefficients between each dimension of Big Five and the mean values of six attributes emotional responses.

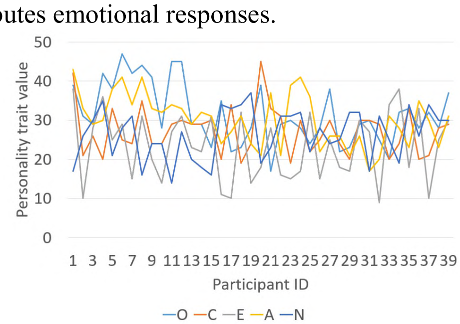

Figure 2. Personality values of participants.

TABLE I. CORRELATIONS BETWEEN THE BIG FIVE AND EMOTIONAL RESPONSES

Emotional Responses	Big Five Dimensions				
	O	*C*	*E*	*A*	*N*
EngagementRaw	0.07	-0.04	0.08	0.20	**0.43****
FocusRaw	0.13	-0.03	-0.04	0.07	**0.49***
InterestMax	-0.09	**0.37***	-0.07	**-0.49****	**-0.56****
InterestMin	0.13	**-0.37***	0.02	**0.42****	**0.56****
InterestRaw	-0.13	**0.34***	-0.02	-0.24	-0.25
ShortTermExcitementRaw	0.13	-0.03	-0.04	0.07	**0.49***
StressMin	-0.29	0.17	0.04	-0.02	**-0.32***

Note. *p<0.05, **p <0.01

Table II presents meaningful PCC between each dimension of Big Five and the sum value of smile, clench, blink, surprise, furrow, wink left and right, breath and heart rate. Some meaningful results will be shown as follows.

- Openness (O): Openness was positively associated with wink.
- Conscientiousness (C): Conscientiousness is most associated with interest. In addition, the smaller sum value of smile and wink, the more conscientious.
- Extraversion (E): Extraversion has little influence on emotional responses and behaviors.
- Agreeableness (A): The smaller range of interest value, the more agreeable. Besides, agreeableness is most relevant to behaviors. The greater sum value of blink, wink, and breath, the more agreeable. In addition, agreeableness is negatively relevant with clench and heart rate.
- Neuroticism (N): N is most relevant to emotional responses. The easier engaged, focused, interested, and excited, the more neurotic. In addition, neuroticism was negatively correlated with stress. For behaviors, the more blink and greater heart rate, the more neurotic.

TABLE II. CORRELATIONS BETWEEN THE BIG FIVE AND BEHAVIORS

Behavioral States	Big Five Dimensions				
	O	*C*	*E*	*A*	*N*
Smile	0.23	**-0.34***	0.15	-0.06	-0.0
Clench	-0.10	-0.12	-0.05	**-0.34***	-0.24
Blink	0.10	-0.29	0.22	**0.34***	**0.40***
Wink Left	**0.35***	**-0.36***	0.25	**0.37***	0.27
Wink Right	0.07	-0.23	-0.08	**0.33***	0.29
Breath	-0.21	0.26	0.29	**0.60***	0.08
Heart Rate	-0.10	-0.08	0.11	**-0.53***	**0.49***

Note. *p<0.05, **p <0.01

V. CONCLUSIONS AND FUTURE WORK

To summarize, our correlational analyses in this study revealed two main points. The first one is that Neuroticism (N) is most related to emotional responses and this conclusion is also supported by previous psychological researches. Secondly, agreeableness is most related to behaviors. But there are still some problems in this work, such as unstable connection of the Emotive Insight. In detail, sometimes participant's movement or hair might not guarantee a high quality of connection. Based on these two conclusions, further work is needed on how personality traits are associated with emotional responses and behavioral states.

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