Happiness at Your Fingertips: Assessing Mental Health with Smartphone Photoplethysmogram-Based Heart Rate Variability Analysis

Article *in* Telemedicine and e-Health · February 2020

DOI: 10.1089/tmj.2019.0283

Shiguang Ni
Tsinghua University

Happiness at Your Fingertips: Assessing Mental Health with Smartphone Photoplethysmogram-Based Heart Rate Variability Analysis

Ivan Liu, PhD(c),[1] Shiguang Ni, PhD,[2] and Kaiping Peng, PhD[1,3]

[1]Data Science and Information Technology Research Center, Tsinghua-Berkeley Shenzhen Institute, Tsinghua University, Shenzhen, China.
[2]Graduate School at Shenzhen, Tsinghua University, Shenzhen, China.
[3]Department of Psychology, Tsinghua University, Beijing, China.

Abstract

Background: *Heart rate variability (HRV) provides essential mental health information for clinical diagnosis, telemedicine, preventive medicine, and public health; however, the lack of a convenient detection method limits its potential.*
Objective: *This study aims to investigate the feasibility and credibility of smartphone photoplethysmogram (PPG)-based HRV analysis for mental well-being and health assessment.*
Methods: *Data were collected from 93 students and university employees in Shenzhen, China. Forty-six percent were male, and the average age was 23.71 years ($\sigma = 4.33$). An app recorded a 4-min video of their fingertips and converted the frames into five HRV measures, including the root mean square of successive differences (rMSSD), standard deviation of the normal-to-normal (NN) intervals (SDNN), percentage of successive NN intervals differing by ≥50 ms (pNN50), log high-frequency (HF) HRV, and log low-frequency (LF) HRV.*
Results: *The data verify the positive relationship between mental well-being and HRV measures. Participants with higher Satisfaction With Life Scale (SWLS) scores have a higher rMSSD ($p = 0.047$), SDNN ($p = 0.009$), log HF ($p = 0.02$), and log LF ($p = 0.003$). Participants who suffer from depression have lower log HF ($p = 0.048$) and log LF ($p = 0.02$). Participants in the high-anxiety group have lower pNN50 ($p = 0.04$) and log HF ($p = 0.03$).*
Conclusions: *The results of this study validate the feasibility of using the smartphone PPG by demonstrating similar results to previous findings. Our data also support the theorized positive link between mental health and HRV.*

Keywords: *smartphone photoplethysmogram, heart rate variability, subjective well-being, mental health, anxiety, depression, telemedicine*

Introduction

BACKGROUND

Having a happy life is the ultimate goal for many people. Happier people have higher incomes, more stable marriages, and better health.[1,2] Maintaining a positive mental state enables us to build resilience against mood disorders.[3,4] Studies also link mental health to physical health; positive psychological constructs, including positive affect,[5] well-being,[6] optimism,[7] and vitality,[8] are associated with superior cardiovascular outcomes[9,10] and better immune functioning.[11,12]

When compared to immediate emotional responses (e.g., laughter, anger),[13] however, an individual's long-term mental state is less evident.[14] Traditionally, psychiatrists and psychological researchers relied on self-reported questionnaires to assess mental health, which had limitations and posed research challenges.[15] People tend to present favorable images of themselves,[16] and the inattentiveness of some participants reduces the validity of the results.[17] To overcome these difficulties and obtain objective results, practitioners and researchers are increasingly evaluating physiological variables, such as heart rate variability (HRV).

Heart rate variability. At any time, a person's heart rate (HR) indicates the balance of multiple physiological systems such as the cerebral cortex, autonomic nervous system (ANS), endocrine system, and baroreflex. By observing HR variations, researchers can obtain an insight into physiological information that would otherwise be difficult to capture. Studies have linked HRV to health-related variables, such as age, sex,[18] body mass index,[19] and exercise habits.[20] Reduced HRV has also been shown to reflect decreased regulatory capacity[21] and to predict health problems, including heart attack[22] and renal impairment.[23]

The literature has also recognized the mind/heart relationship,[24] through which the sympathetic nervous system (SNS), which is part of the ANS, accelerates the HR when the mind perceives threats, and the parasympathetic nervous system (PNS), also part of the ANS, counterbalances the SNS when the mind relaxes. Since the ANS is modulated by the prefrontal cortex activities,[25] which are associated with attention,[25,26] decision-making, social behavior,[27,28] and emotional modulation,[24,29] many mental activities also have an impact on HRV measures. Within the normal range, higher levels of HRV are generally considered a marker of one's superior capacity for self-control and adaption to the environment.[30]

There are several benefits of using HRV in assessing mental health. First, cardiac equipment can capture HR information noninvasively, and it is cost-effective compared with other methods such as functional magnetic resonance imaging. Second, evidence has connected HRV to psychological variables, and the literature has laid a strong foundation for further investigations. Third, unlike many single-purpose physiological measures, HRV consists of multiple indicators with different psychological interpretations. Finally, not only can HRV be observed, it can also be controlled.[31] The possibility of controlling HRV in a research design (e.g., by running or breathing control[32,33]) provides more flexibility in psychological research than other observation-only methods.

Nevertheless, as an objective and informative approach to assessing mental health, HRV has not received the appropriate attention from psychologists. One of the main reasons for this is the lack of a convenient HRV detection method. Usually, researchers measure HRV using an electrocardiogram (ECG); however, the high cost and immobility limit its potential in psychological studies. One of the advances in information technology that may help to resolve these difficulties is smartphone photoplethysmography (PPG), which is gaining prominence.[34,35]

Smartphone PPG. PPG is an optical method that uses sensors to monitor microvascular blood volume changes in the tissue. Smartphone PPG detects heartbeats by taking videos of the fingertips with the inbuilt camera and converting them into a pulse waveform[36,37] (*Fig. 1*). Fiducial point detection algorithms then determine heartbeat points based on the pulse wave contour. Studies indicate that the average heart rate obtained by smartphone PPG is compatible with those generated by the gold standard ECG.[38] The accuracy of using smartphone PPG in HRV analysis has also been validated by various studies.[34,39–42] The main reason for using smartphone PPG, opposed to other wearables, is the low equipment requirement. A camera is an integral part of modern smartphones, which makes them ideal alternatives when ECG or other devices are not accessible.

OBJECTIVE

This study aims to investigate the feasibility and credibility of using smartphone PPG in mental well-being and health assessment. By developing an app (*Heartily Happy*, henceforth the App, publicly available on Google Play App Store;

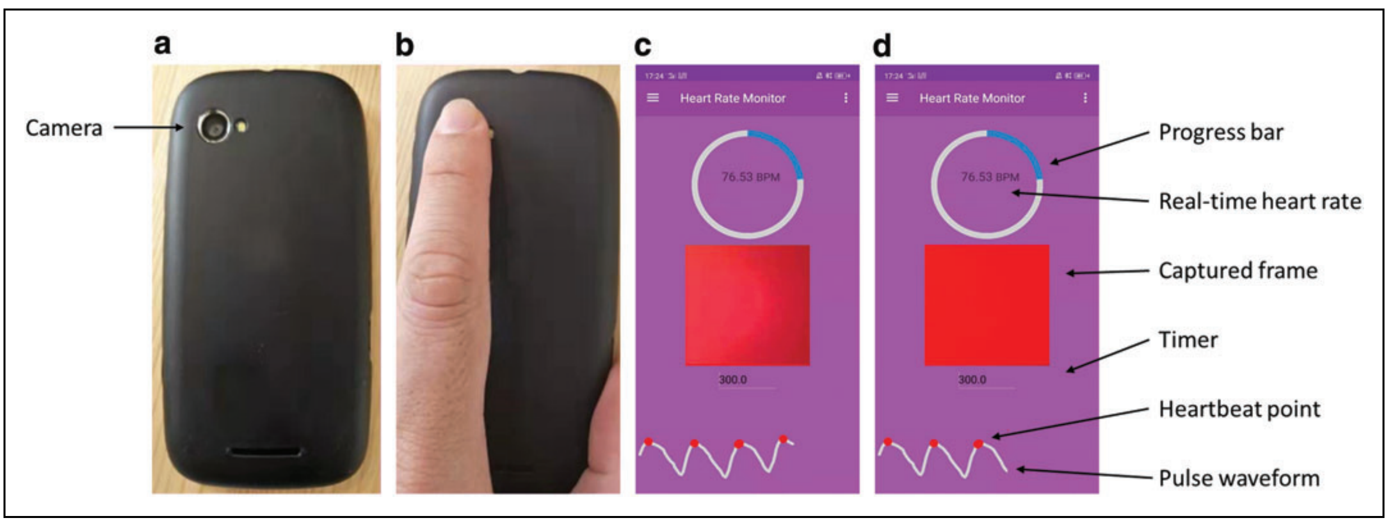

Fig. 1. Using a smartphone camera to take fingertip blood volume information and to convert the image into a waveform. **(a)** A smartphone with an embedded camera. **(b)** The smartphone camera is covered by the index finger. **(c)** A screenshot of the App in capturing videos of the fingertip at the systole phase. When the heart contracts, blood is pushed into the peripheral circulation. The fingertip becomes darker due to light absorption in the hemoglobin. The color differences are converted into the pulse waveform by PPG. **(d)** When the heart relaxes, the captured frame becomes lighter. PPG, photoplethysmography. Color images are available online.

the iOS version is not yet available) based on PPG, we attempt to provide the first empirical evidence that smartphones can quantify HRV for psychological research and practice. The challenges of using smartphone PPG are also presented with suggestions for future work.

Materials and Methods

RECRUITMENT

Data were collected from 93 students and university employees in Shenzhen, China (age: mean [μ] = 23.71, standard deviation [σ] = 4.33; sex: 46% male). The study protocol was approved by the Ethics Board of the Department of Psychology at Tsinghua University, and written informed consent was obtained from all participants. Participants remained seated during a 5-min debriefing and then completed a questionnaire before data collection. They were asked to hold a smartphone (Mi-8 SE; Xiao-Mi, China) in their left hand and rest their forearm on the desk, while the App recorded a 4-min video (twice the 2-min minimum length required for all HRV measures used in this study[43]) of their fingertips. Each participant received 50 renminbi (about 7 USD) as compensation for participation.

MEASURES

Mental well-being and health measures. This study used five different measures to assess mental well-being and health. Subjective well-being was measured using the Satisfaction With Life Scale (SWLS)[44] and the Positive Affect and Negative Affect Schedule (PANAS).[45] As a subjective well-being assessment method, the SWLS contains five 7-point items measuring a person's cognitive assessment of life satisfaction. The Chinese-revision of the PANAS is an 18-item measure of trait-positive and trait-negative affect.[46] Nine of the items measure trait-positive affect (PANAS-P) and the other 9 items measure trait-negative affect (PANAS-N). The difference between the PANAS-P and PANAS-N determines the PANAS value. The Patient Health Questionnaire-9 (PHQ-9) is an instrument for the diagnosis of depression. Nine items are rated on a 4-point scale giving a symptom severity measure with five levels.[47] The Generalized Anxiety Disorder Scale-7 (GAD-7) is a 7-item instrument for the diagnosis of anxiety.[48] Each of the items is rated on a 4-point Likert-type scale.

HRV measures. There are three types of HRV measures: (1) time-domain, (2) frequency-domain, and (3) nonlinear measurements. The frequency-domain components of HRV consist of four frequency bands: high frequency (HF), low frequency (LF), very-low frequency (VLF), and ultralow frequency (*Table 1*). The vagal (PNS) modulation of HF, regulated by acetylcholine, peaks within 0.5 s and returns to baseline within 1 s. Therefore, HF indicates vagal modulation.[49,50] In contrast, the SNS is associated with norepinephrine, which increases HR after 4 s and returns to baseline after 20 s. Therefore, LF is associated with the SNS. Since this study only recorded videos for 4 min, the data could not be used to compute ultra and VLF.[43] The HF and LF values were log-transformed as they were not normally distributed.[31,51]

Table 1. Heart Rate Variability Measures

HRV MEASURES	DEFINITION
Time-domain	
SDNN	Standard deviation of the average NN intervals.
pNN50	Percentage of successive NN intervals that differ by more than 50 ms
rMSSD	Root mean square of successive NN interval differences
Frequency-domain	
HF	Absolute power of the high-frequency band (0.15–0.4 Hz)
LF	Absolute power of the low-frequency band (0.04–0.15 Hz)
VLF	Absolute power of the very-low-frequency band (0.0033–0.04 Hz)
ULF	Absolute power of the ultralow-frequency band (≤0.003 Hz)
Log HF	Log-transformed HF
Log LF	Log-transformed LF
Log LF/HF	Log-transformed ratio of LF to HF

HRV, heart rate variability; NN, normal-to-normal (beat-to-beat).

Time-domain indices of HRV quantify the amount of variability in the beat-to-beat intervals. They are easy to compute but less related to ANS activities.[52] Low standard deviation of the normal-to-normal (NN) intervals (SDNN) is a robust predictor of adverse cardiovascular events and mortality[53] and is statistically related to LF.[43] Conversely, root mean square of successive differences (rMSSD) and percentage of successive NN intervals differing by ≥50 ms (pNN50) are associated with HF[43] and less affected by changes in breathing frequency.[54] Nonlinear measurements consider HR a chaotic process and techniques such as the Poincaré plot are used to describe the behavior of HR. The nonlinear measures of HRV also correlate with the time- and frequency-domain HRV measures.[43] Although nonlinear HRV measures have been well investigated, fewer studies have linked them to psychological phenomena.[55,56] Therefore, the current study did not include nonlinear measurements.

DATA CLEANING AND PREPARATION

The PPG data were visually inspected for errors, and artifacts were removed manually. Of the 93 valid samples, we excluded three outliers in the HRV measures (HF >1,200 or <30; LF >2,000 or <50) and two for problematic answers to the questionnaire. For statistical analysis, we divided the answers for each mental health measure into three groups: High (H > 67th percentile), Medium (M > 33rd percentile and $\leq$66th percentile), and Low (L $\leq$ 33rd percentile). Most participants were university students and relatively young; hence, we divided them into High (age >25 years) and Low (age ≤25 years) age groups. The differences between these groups were then analyzed using the one-tailed *t* test.

Results

Age was inversely related to the frequency- and time-domain HRV measures. Older people (group H) had significantly lower pNN50 (p = 0.02), SDNN (p = 0.004), and log HF scores (p = 0.02) (*Fig. 2*). They also had lower rMSSD (p = 0.08) and log LF (p = 0.06) scores, but the differences were only close to the significance level (p = 0.05). Female participants had significantly higher pNN50 (p = 0.011) and rMSSD (p = 0.005) scores. They also had higher SDNN (p > 0.15), higher log HF (p = 0.13), and lower log LF (p > 0.15) scores, with no significant associations.

The HRV measures separated participants from high to low in depression and anxiety groups. Both log HF (p = 0.048) and log LF (p = 0.02) were significantly lower in the high PHQ-9 group (*Fig. 3*). Differences were not significant for time-domain HRV measures, but they all showed the same tendency. Log HF (p = 0.03) and pNN50 (p = 0.04) were significantly lower in the high GAD-7 group. Although not statistically significant, the other HRV measures were also inversely related to the GAD-7 score.

HRV could also differentiate between people with different levels of subjective well-being (*Fig. 4*). Participants with higher SWLS scores had a higher rMSSD (p = 0.047), SDNN (p = 0.009), HF (p = 0.02), and LF (p = 0.003). The values of PANAS also supported the SWLS results. People with higher PANAS scores had higher pNN50, log HF, and log LF (p = 0.07) values. However, the differences were not statistically significant.

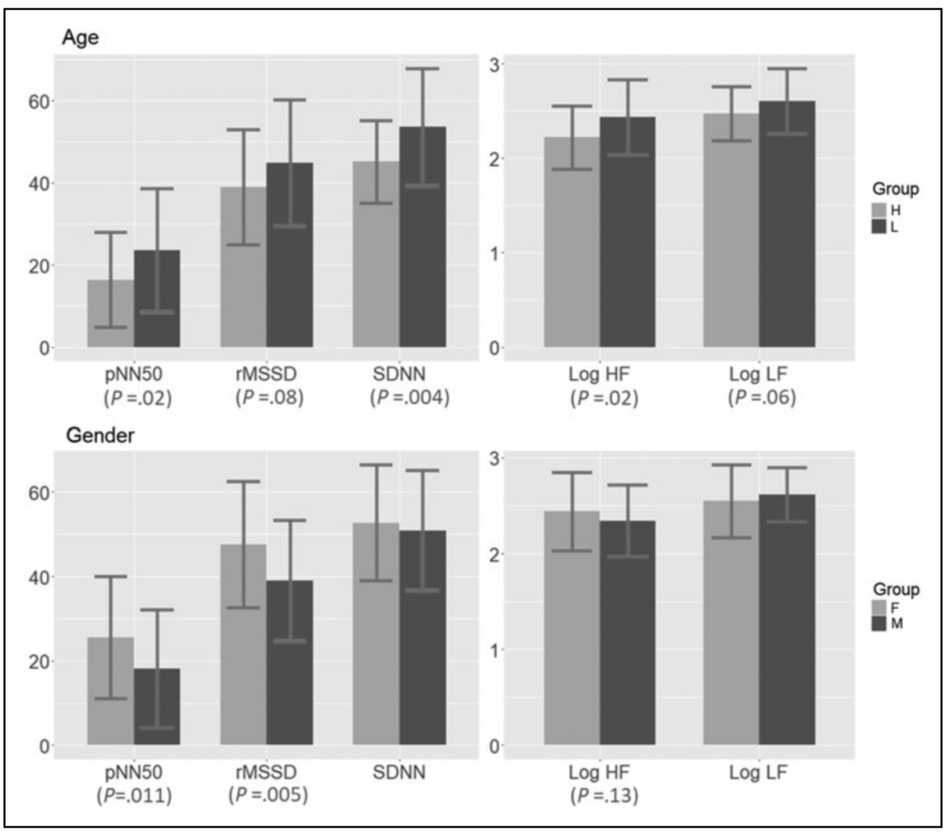

Fig. 2. HRV measures for participants with different age and gender. The *p*-values indicate the result of the one-tailed *t* test of the difference between the two groups. The error bars indicate the intervals of one standard deviation. HF, high frequency; HRV, heart rate variability; LF, low frequency; NN, normal-to-normal; pNN50, percentage of successive NN intervals differing by ≥50 ms; rMSSD, root mean square of successive differences.

Discussion

PRINCIPAL FINDINGS

Age and sex. The measures of HRV represent cerebral ability to maintain internal balance. This capability decreases with age, especially in those aged >40 years.[19] There is also evidence of a relationship between sex and HRV. Although the literature is inconsistent,[18] males usually have higher HRV values in long-term measures (i.e., LF and VLF)[19,57] and lower HRV in short-term measures (i.e., HF, rMSSD, and pNN50),[19,58] while SDNN results are inconclusive.[19]

Our data support the inverse relationship between aging and both time- and frequency-domain HRV measures, as expected. However, since the majority of the participants are younger

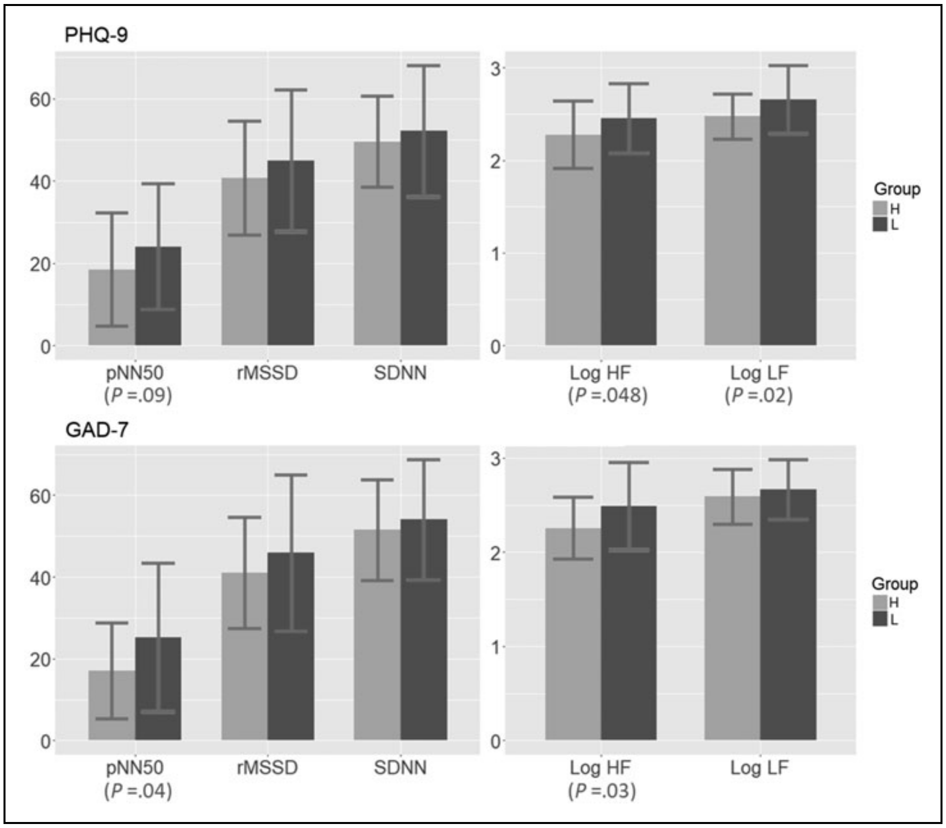

Fig. 3. HRV measures for participants with different levels of mood disorder. GAD-7, Generalized Anxiety Disorder Scale-7; PHQ-9, Patient Health Questionnaire-9.

than 40 years, the influence of aging is statistically significant but not as prominent as expected. Similar to previous studies, females have lower HRV in long-term measures and higher HRV in short-term measures. They also have higher SDNN, but the association is not significant.

Mood disorders. Anxiety and depression result from deficient self-regulation and emotional regulation abilities. When people cannot recover from daily distress, they suffer from long-term mood disorders. Since increased HRV is an indicator of superior executive function,[24,59] mood disorders are associated with lower HRV.[60–63] When a person is both depressed and anxious, the HRV reduces further.[64]

Data from this study provide empirical evidence of the use of smartphone PPG in assessing long-term mental problems such as anxiety and depression syndrome, which are inversely related to HRV. Random noise blurred the HRV differences, but the trend is clear and consistent, and the general directions are congruent with previous studies. However, since many of the previous findings were based on mentally ill clinic patients[65] and this study focused on healthy people, the HRV differences between people with and without depression and anxiety syndrome are not as distinct as expected.

Subjective well-being. In contrast with mental difficulties, the neural correlates underlying subjective well-being and trait positive affect are less prevalent in the literature.[66,67] Previous studies have linked positive emotions (anticipation enthusiasm, attachment love, nurturant love, amusement, and awe) to the patterns of HRV.[68] HRV correlates positively with trait-positive mood[69–72] and negatively with trait-negative mood.[73] However, one study noted that HRV should instead be quadratically related to positive emotions and that both high and low levels of positive emotion reduce HRV.[74]

Since prefrontal cortex activity is associated with long-term happiness (such as the traits of optimism, better psychological resilience, better social relationships, and fewer mental problems), and HRV is influenced by functions of the prefrontal cortex, we assume that there is a link between HRV and measures of subjective well-being. This study successfully demonstrates the feasibility of using smartphone PPG to assess trait-like happiness. Although the differences in a few measures are not statistically significant, our data provide strong evidence for the positive (but not the quadratic) relationship between mental well-being and HRV.

LIMITATIONS AND SUGGESTIONS FOR FUTURE WORK

Difficulties in ensuring measurement accuracy of smartphone PPG. While smartphone PPG may be accurate in a controlled environment, it may not be robust enough in real-world situations.[75] When users measure their HR with smartphones outside of the laboratory environment, slight hand movements or ambient light changes can corrupt the PPG signals. Although an app user can retake a failed measurement, this might not be feasible in some research settings. The low-frame (sampling) rate of the smartphone camera is another limitation in using smartphone PPG. While the sampling rate can be as high as 1,000 Hz for medical equipment,[76] the smartphone camera usually samples at about 10–30 Hz.[42] The instability of the frame rate worsens acquisition performance.[75,77] Since the

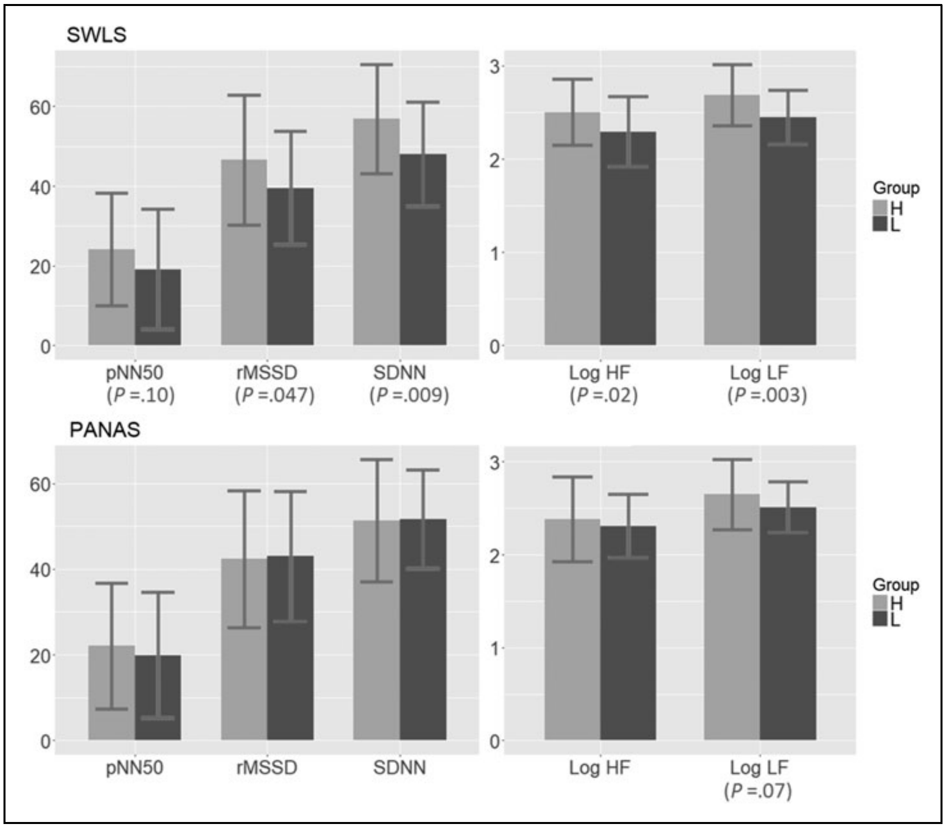

Fig. 4. HRV measures for participants with different levels of subjective well-being. PANAS, Positive Affect and Negative Affect Schedule; SWLS, Satisfaction With Life Scale.

influence of low-frame rate is still inconclusive,[31,42,78] it warrants further investigation.

Difficulties in reaching statistical significance in psychological studies. The results from the current study suffer from low signal-to-noise ratios. Our findings are mostly consistent with our expectations, but the sizeable random error has a devastating effect on statistical power. In addition to the randomness caused by the data collection process, the HRV measures are also severely affected by many physiological and psychological factors such as age, sex, exercise, sleep quality, time of day, and breathing.[43,79] Even the same emotional stimuli can trigger different physiological responses in different people or the same people in a different context.[80] Furthermore, various medications,[81,82] physical therapies,[83] and psychotherapies[84] have been reported to influence HRV levels, and the true baseline for comparison is obscure without strictly controlling these factors. Therefore, it is difficult to reach the level of statistical significance when a study compares HRV among different people.[31]

Possible solutions include focusing more on the within-group than between-group design if possible, as this can effectively reduce the randomness caused by individual differences.[31] Also, multiple measurements per individual can be taken. The easy-to-use interface and cost-effectiveness of smartphones can assist researchers in collecting more data for better comparison. Another strategy to reduce randomness is increasing the sample size,[30] especially when conducting between-subject psychophysiological comparisons.[85] Finally, lenient inclusion/exclusion criteria may have majorly contributed to the random noise in the current sample, which future study designs can avoid.

Smartphone PPG as the new research paradigm. Smartphone PPG presents unprecedented opportunities for researchers and practitioners to overcome research limits and to explore its possibilities: First, with the high penetration rate, smartphones enable psychologists to reach a broader population. Since the external validity of a theory is built upon the representativeness of its research participants, future work should take advantage of the low cost and wide availability of smartphone PPG. Second, smartphone HRV enables researchers to collect real-time feedback. Psychologists usually collect retrospective experiences that are susceptible to recall bias and possible memory distortions.[86] With smartphone PPG, researchers can gather HRV measures at any time and place, even shortly after the participants have experienced an extraordinary event. Third, using smartphones makes long-term HRV tracking easier. A person's mental state is ever-changing, and the real-life psychological response can be dramatically different from the feelings expressed in the laboratory. By collecting HRV measures periodically and over a long period of time, researchers can obtain more representative real-world data of a person.

Conclusions

The current study validates the feasibility of the proposed approach by its consistency with the results from similar studies. This study contributes to the literature in the following ways. First, the study pioneers the use of the smartphone app (without extra wearables) in assessing long-term mental well-being and psychological problems. The results validate the feasibility of this novel approach and provide psychologists with the confidence to include smartphone-based HRV assessment in their research design. Second, the current study extends the psychophysiological understanding of the heart/mind relationship by collecting data from a different perspective. Our data support the inverse relationship between mental disorders and HRV and the less-investigated positive link between subjective well-being and HRV. Third, the difficulties and potentials of using smartphone PPG in psychological studies are discussed. Future work should further explore the applications of smartphone PPG based on our suggestions. Finally, the publicly available app is designed to automatically process the detected signals, generate HRV measures, and store historical records. Users and researchers can easily export and share the HRV information for research or diagnosis.

Author Disclosure Statement

No competing financial interests exist.

Funding Information

This study was funded by the Humanities and Social Sciences Foundation of China Ministry of Education [18YJAZH065], the RD program of Shenzhen [JCYJ20170307153032483, JCYJ20170817161546744], Shenzhen Key Research Base of Humanities and Social Sciences, and the Interdisciplinary Research Project of Graduate School of Shenzhen of Tsinghua University [JC2017005].

REFERENCES

1. Layous K, Nelson SK, Lyubomirsky S. What is the optimal way to deliver a positive activity intervention? The case of writing about one's best possible selves. *J Happiness Stud* **2013;**14:635–654.
2. Lyubomirsky S, King L, Diener E. The benefits of frequent positive affect: Does happiness lead to success? *Psychol Bull* **2005;**131:803–855.
3. Keyes CL. Mental health as a complete state: How the salutogenic perspective completes the picture. In: Bauer GF, Hämmig O, eds. *Bridging occupational, organizational and public health.* Dordrecht, The Netherlands: Springer, **2014:** 179–192.
4. Whiteford HA, Degenhardt L, Rehm J, et al. Global burden of disease attributable to mental and substance use disorders: Findings from the Global Burden of Disease Study 2010. *Lancet* **2013;**382:1575–1586.
5. Brummett BH, Boyle SH, Siegler IC, et al. Ratings of positive and depressive emotion as predictors of mortality in coronary patients. *Int J Cardiol* **2005;** 100:213–216.
6. Boehm JK, Lyubomirsky S, Sheldon KM. A longitudinal experimental study comparing the effectiveness of happiness-enhancing strategies in Anglo Americans and Asian Americans. *Cogn Emot* **2011;**25:1263–1272.
7. Giltay EJ, Kamphuis MH, Kalmijn S, Zitman FG, Kromhout D. Dispositional optimism and the risk of cardiovascular death: The Zutphen Elderly Study. *Arch Intern Med* **2006;**166:431–436.
8. Kubzansky LD, Thurston RC. Emotional vitality and incident coronary heart disease: Benefits of healthy psychological functioning. *Arch Gen Psychiatry* **2007;**64:1393–1401.
9. Kim ES, Smith J, Kubzansky LD. Prospective study of the association between dispositional optimism and incident heart failure. *Circ Heart Fail* **2014;**7: 394–400.
10. Seldenrijk A, van Hout HP, van Marwijk HW, et al. Depression, anxiety, and arterial stiffness. *Biol Psychiatry* **2011;**69:795–803.
11. Cohen S, Doyle WJ, Turner RB, Alper CM, Skoner DP. Emotional style and susceptibility to the common cold. *Psychosom Med* **2003;**65:652–657.
12. Steptoe A, Wardle J, Marmot M. Positive affect and health-related neuroendocrine, cardiovascular, and inflammatory processes. *Proc Natl Acad Sci U S A* **2005;**102:6508–6512.
13. Lakens D. Using a smartphone to measure heart rate changes during relived happiness and anger. *IEEE Trans Affect Comput* **2013;**4:238–241.
14. Kemp AH, Krygier J, Harmon-Jones E. Neuroscientific perspectives. In: Calvo R, D'Mello S, Gratch J, Kappas A, eds. *The Oxford handbook of affective computing.* Oxford, UK: Oxford University Press, **2015:**38–53.
15. Baumeister RF, Vohs KD, Funder DC. Psychology as the science of self-reports and finger movements: Whatever happened to actual behavior? *Perspect Psychol Sci* **2007;**2:396–403.
16. Van de Mortel TF. Faking it: Social desirability response bias in self-report research. *Aust J Adv Nurs* **2008;**25:40–48.
17. Fleischer A, Mead AD, Huang J. Inattentive responding in MTurk and other online samples. *Ind Organ Psychol* **2015;**8:196–202.
18. Umetani K, Singer DH, McCraty R, Atkinson M. Twenty-four hour time domain heart rate variability and heart rate: Relations to age and gender over nine decades. *J Am Coll Cardiol* **1998;**31:593–601.
19. Antelmi I, De Paula RS, Shinzato AR, et al. Influence of age, gender, body mass index, and functional capacity on heart rate variability in a cohort of subjects without heart disease. *Am J Cardiol* **2004;**93:381–385.
20. Sandercock GR, Bromley PD, Brodie DA. Effects of exercise on heart rate variability: Inferences from meta-analysis. *Med Sci Sports Exerc* **2005;**37: 433–439.
21. McCraty R, Shaffer F. Heart rate variability: New perspectives on physiological mechanisms, assessment of self-regulatory capacity, and health risk. *Glob Adv Health Med* **2015;**4:46–61.
22. Nolan RP, Jong P, Barry-Bianchi SM, Tanaka TH, Floras JS. Effects of drug, biobehavioral and exercise therapies on heart rate variability in coronary artery disease: A systematic review. *Eur J Cardiovasc Prev Rehabil* **2008;**15: 386–396.
23. Brotman DJ, Bash LD, Qayyum R, et al. Heart rate variability predicts ESRD and CKD-related hospitalization. *J Am Soc Nephrol* **2010;**21:1560–1570.
24. Thayer JF, Hansen AL, Sausrose E, Johnsen BH. Heart rate variability, prefrontal neural function, and cognitive performance: The neurovisceral integration perspective on self-regulation, adaptation, and health. *Ann Behav Med* **2009;** 37:141–153.
25. Hansen AL, Johnsen BH, Thayer JF. Vagal influence on working memory and attention. *Int J Psychophysiol* **2003;**48:263–274.
26. Hjortskov N, Rissén D, Blangsted AK, et al. The effect of mental stress on heart rate variability and blood pressure during computer work. *Eur J Appl Physiol* **2004;**92:84–89.
27. Eisenberg N, Fabes RA, Murphy B, Maszk P, Smith M, Karbon M. The role of emotionality and regulation in children's social functioning: A longitudinal study. *Child Dev* **1995;**66:1360–1384.
28. Porges SW. The polyvagal perspective. *Biol Psychol* **2007;**74:116–143.
29. Geisler FC, Vennewald N, Kubiak T, Weber H. The impact of heart rate variability on subjective well-being is mediated by emotion regulation. *Pers Individ Dif* **2010;**49:723–728.

30. Kemp AH, Quintana DS. The relationship between mental and physical health: Insights from the study of heart rate variability. *Int J Psychophysiol* **2013;**89: 288–296.

31. Laborde S, Mosley E, Thayer JF. Heart rate variability and cardiac vagal tone in psychophysiological research—Recommendations for experiment planning, data analysis, and data reporting. *Front Psychol* **2017;**8:213.

32. van der Zwan JE, de Vente W, Huizink AC, Bögels SM, de Bruin EI. Physical activity, mindfulness meditation, or heart rate variability biofeedback for stress reduction: A randomized controlled trial. *Appl Psychophysiol Biofeedback* **2015;**40:257–268.

33. Krygier JR, Heathers JA, Shahrestani S, et al. Mindfulness meditation, well-being, and heart rate variability: A preliminary investigation into the impact of intensive Vipassana meditation. *Int J Psychophysiol* **2013;**89: 305–313.

34. Plews DJ, Scott B, Altini M, et al. Comparison of heart-rate-variability recording with smartphone photoplethysmography, Polar H7 chest strap, and electrocardiography. *Int J Sports Physiol Perform* **2017;**12:1324–1328.

35. Li KHC, White FA, Tipoe T, et al. The current state of mobile phone apps for monitoring heart rate, heart rate variability, and atrial fibrillation: Narrative review. *JMIR Mhealth Uhealth* **2019;**7:e11606.

36. Jonathan E, Leahy MJ. Cellular phone-based photoplethysmographic imaging. *J Biophotonics* **2011;**4:293–296.

37. Pelegris P, Banitsas K, Orbach T, Marias K. A novel method to detect heart beat rate using a mobile phone. *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* Buenos Aires, Argentina: IEEE, **2010:**5488–5491.

38. De Ridder B, Van Rompaey B, Kampen JK, Haine S, Dilles T. Smartphone apps using photoplethysmography for heart rate monitoring: Meta-analysis. *JMIR Cardio* **2018;**2:e4.

39. Bánhalmi A, Borbás J, Fidrich M, et al. Analysis of a pulse rate variability measurement using a smartphone camera. *J Healthc Eng* **2018;**2018:4038034.

40. Ferrer-Mileo V, Guede-Fernandez F, Fernández-Chimeno M, Ramos-Castro J, García-González MA. Accuracy of heart rate variability estimation by photoplethysmography using an smartphone: Processing optimization and fiducial point selection. *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* Milan, Italy: IEEE, **2015:** 5700–5703.

41. Huang R-Y, Dung L-R. Measurement of heart rate variability using off-the-shelf smart phones. *Biomed Eng Online* **2016;**15:11.

42. Peng R-C, Zhou X-L, Lin W-H, Zhang Y-T. Extraction of heart rate variability from smartphone photoplethysmograms. *Comput Math Methods Med* **2015;** 2015:516826.

43. Shaffer F, Ginsberg JP. An overview of heart rate variability metrics and norms. *Front Public Health* **2017;**5:258.

44. Diener ED, Emmons RA, Larsen RJ, Griffin S. The satisfaction with life scale. *J Pers Assess* **1985;**49:71–75.

45. Watson D, Clark LA, Tellegen A. Development and validation of brief measures of positive and negative affect: The PANAS scales. *J Pers Soc Psychol* **1988;**54: 1063–1070.

46. Qiu L, Zheng Z, Wang Y-F. Revision of the positive affect and negative affect scale. *Chin J Appl Psychol* **2008;**14:249–254.

47. Kroenke K, Spitzer RL, Williams JB. The PHQ-9: Validity of a brief depression severity measure. *J Gen Intern Med* **2001;**16:606–613.

48. Spitzer RL, Kroenke K, Williams JB, Löwe B. A brief measure for assessing generalized anxiety disorder: The GAD-7. *Arch Intern Med* **2006;**166: 1092–1097.

49. Appelhans BM, Luecken LJ. Heart rate variability as an index of regulated emotional responding. *Rev Gen Psychol* **2006;**10:229–240.

50. Berntson GG, Bigger JM, Eckberg DL, et al. Heart rate variability: Origins, methods, and interpretive caveats. *Psychophysiology* **1997;**34:623–648.

51. Chalmers JA, Heathers JAJ, Abbott MJ, Kemp AH, Quintana DS. Worry is associated with robust reductions in heart rate variability: A transdiagnostic study of anxiety psychopathology. *BMC Psychol* **2016;**4:1–9.

52. Oweis RJ, Al-Tabbaa BO. QRS detection and heart rate variability analysis: A survey. *Biomed Sci Eng* **2014;**2:13–34.

53. Hillebrand S, Gast KB, de Mutsert R, et al. Heart rate variability and first cardiovascular event in populations without known cardiovascular disease: Meta-analysis and dose–response meta-regression. *Europace* **2013;**15: 742–749.

54. Penttilä J, Helminen A, Jartti T, et al. Time domain, geometrical and frequency domain analysis of cardiac vagal outflow: Effects of various respiratory patterns. *Clin Physiol* **2001;**21:365–376.

55. Melillo P, Bracale M, Pecchia L. Nonlinear heart rate variability features for real-life stress detection. Case study: Students under stress due to university examination. *Biomed Eng Online* **2011;**10:96.

56. Dimitriev DA, Saperova EV, Dimitriev AD. State anxiety and nonlinear dynamics of heart rate variability in students. *PLoS One* **2016;**11:e0146131.

57. Jensen-Urstad K, Storck N, Bouvier F, et al. Heart rate variability in healthy subjects is related to age and gender. *Acta Physiol Scand* **1997;**160:235–241.

58. Moodithaya S, Avadhany ST. Gender differences in age-related changes in cardiac autonomic nervous function. *J Aging Res* **2012;**2012:679345.

59. Park G, Van Bavel JJ, Vasey MW, Egan EJ, Thayer JF. From the heart to the mind's eye: Cardiac vagal tone is related to visual perception of fearful faces at high spatial frequency. *Biol Psychol* **2012;**90:171–178.

60. Carney RM, Blumenthal JA, Stein PK, et al. Depression, heart rate variability, and acute myocardial infarction. *Circulation* **2001;**104:2024–2028.

61. Duarte J, Pinto-Gouveia J. Positive affect and parasympathetic activity: Evidence for a quadratic relationship between feeling safe and content and heart rate variability. *Psychiatry Res* **2017;**257:284–289.

62. Friedman BH. An autonomic flexibility–neurovisceral integration model of anxiety and cardiac vagal tone. *Biol Psychol* **2007;**74:185–199.

63. Nemeroff CB, Goldschmidt-Clermont PJ. Heartache and heartbreak—The link between depression and cardiovascular disease. *Nat Rev Cardiol* **2012;**9: 526–539.

64. Kemp AH, Quintana DS, Felmingham KL, Matthews S, Jelinek HF. Depression, comorbid anxiety disorders, and heart rate variability in physically healthy, unmedicated patients: Implications for cardiovascular risk. *PLoS One* **2012;**7: e30777.

65. Kemp AH, Quintana DS, Gray MA, et al. Impact of depression and antidepressant treatment on heart rate variability: A review and meta-analysis. *Biol Psychiatry* **2010;**67:1067–1074.

66. Kong F, Hu S, Wang X, Song Y, Liu J. Neural correlates of the happy life: The amplitude of spontaneous low frequency fluctuations predicts subjective well-being. *Neuroimage* **2015;**107:136–145.

67. Urry HL, Nitschke JB, Dolski I, et al. Making a life worth living: Neural correlates of well-being. *Psychol Sci* **2004;**15:367–372.

68. Shiota MN, Neufeld SL, Yeung WH, Moser SE, Perea EF. Feeling good: Autonomic nervous system responding in five positive emotions. *Emotion* **2011;**11:1368–1378.

69. Geisler FC, Kubiak T, Siewert K, Weber H. Cardiac vagal tone is associated with social engagement and self-regulation. *Biol Psychol* **2013;**93:279–286.

70. Kok BE, Fredrickson BL. Upward spirals of the heart: aAtonomic flexibility, as indexed by vagal tone, reciprocally and prospectively predicts positive emotions and social connectedness. *Biol Psychol* **2010;**85:432–436.

71. Oveis C, Cohen AB, Gruber J, et al. Resting respiratory sinus arrhythmia is associated with tonic positive emotionality. *Emotion* **2009;**9:265–270.

72. Wang Z, Lü W, Qin R. Respiratory sinus arrhythmia is associated with trait positive affect and positive emotional expressivity. *Biol Psychol* **2013;**93: 190–196.

73. Sloan RP, Schwarz E, McKinley PS, et al. Vagally-mediated heart rate variability and indices of well-being: Results of a nationally representative study. *Health Psychol* **2017;**36:73–81.

74. Kogan A, Oveis C, Carr EW, et al. Vagal activity is quadratically related to prosocial traits, prosocial emotions, and observer perceptions of prosociality. *J Pers Soc Psychol* **2014;**107:1051–1063.

75. Garcia-Agundez A, Dutz T, Goebel S. Adapting smartphone-based photoplethysmography to suboptimal scenarios. *Physiol Meas* **2017;**38: 219–232.

76. Kok BE, Coffey KA, Cohn MA, et al. How positive emotions build physical health: Perceived positive social connections account for the upward spiral between positive emotions and vagal tone. *Psychol Sci* **2013;**24:1123–1132.

77. Jiang WJ, Wittek P, Zhao L, Gao SC. Adaptive thresholding with inverted triangular area for real-time detection of the heart rate from photoplethysmogram traces on a smartphone. *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC).* Chicago, IL: IEEE, **2014:**3212–3215.

78. Sun Y, Hu S, Azorin-Peris V, Kalawsky R, Greenwald SE. Noncontact imaging photoplethysmography to effectively access pulse rate variability. *J Biomed Opt* **2012;**18:061205.

79. Steptoe A, Dockray S, Wardle J. Positive affect and psychobiological processes relevant to health. *J Pers* **2009;**77:1747–1776.

80. Stemmler G, Heldmann M, Pauls CA, Scherer T. Constraints for emotion specificity in fear and anger: The context counts. *Psychophysiology* **2001;**38: 275–291.

81. Zuanetti G, Latini R, Neilson JM, Schwartz PJ, Ewing DJ. Heart rate variability in patients with ventricular arrhythmias: Effect of antiarrhythmic drugs. *J Am Coll Cardiol* **1991;**17:604–612.

82. Elghozi J-L, Girard A, Laude D. Effects of drugs on the autonomic control of short-term heart rate variability. *Auton Neurosci* **2001;**90:116–121.

83. Routledge FS, Campbell TS, McFetridge-Durdle JA, Bacon SL. Improvements in heart rate variability with exercise therapy. *Can J Cardiol* **2010;**26:303–312.

84. Garakani A, Martinez JM, Aaronson CJ, et al. Effect of medication and psychotherapy on heart rate variability in panic disorder. *Depress Anxiety* **2009;**26:251–258.

85. Heathers JA. Smartphone-enabled pulse rate variability: An alternative methodology for the collection of heart rate variability in psychophysiological research. *Int J Psychophysiol* **2013;**89:297–304.

86. Takayanagi Y, Spira AP, Roth KB, et al. Accuracy of reports of lifetime mental and physical disorders: Results from the Baltimore Epidemiological Catchment Area study. *JAMA Psychiatry* **2014;**71:273–280.

Address correspondence to:
Shiguang Ni, PhD
Graduate School at Shenzhen
Tsinghua University
Shenzhen 518057
China

E-mail: ni.shiguang@sz.tsinghua.edu.cn

Received: November 11, 2019
Revised: January 1, 2020
Accepted: January 2, 2020
Online Publication Date: February 27, 2020