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Original Research

Validation of Short-Term and Ultra-Short-Term Heart Rate Variability Measurement Based on Photoplethysmogram Using Commercial Mobile Application

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ABSTRACT

Heart rate variability (HRV) is a valuable tool for assessing autonomic function and diagnosing cardiovascular diseases. Electrocardiography (ECG) is considered the gold standard for HRV measurements. Photoplethysmography (PPG), a simpler and more convenient method has emerged as an alternative to ECG for HRV measurement. As a result of this technique, many mobile applications have been developed that claim to perform real-time HRV in short periods ranging from 10 seconds to 1 minute. However, HRV requires at least 5-mintues for accurate measurements. Therefore, this study aims to investigate the validity of short-term (5 min) and ultra-short-term (<5 min) HRV measurements obtained through a commercially available smartphone app (Camera Heart Rate Variability app) and compared to a traditional PPG sensor (Shimmer3 GSR+). PPG signals were collected from 16 healthy participants and pre-processed to eliminate noise and reduce motion artifacts. A total of 12 HRV features were then extracted using time-domain analysis (TA) and frequency-domain analysis (FA). Next, HRV features were compared using correlation analysis. TA features using Camera HRV app (meanHR, AVNN, RMSDD, pNN50) showed significant correlation ($r > 0.7$) at a minimum duration of 0.5-minute, while SDNN required 1 minute. FA features (VLF, LF, LFnu, HFnu) required a minimum duration of 2 minute, while (HF, LF/HF, TP) required 3 minutes. In conclusion, Camera HRV app is suggested to be a valid surrogate to traditional PPG sensors and has the potential to be used in various fields.

INTRODUCTION

Heart Rate Variability (HRV) refers to the variation in time between each heartbeat. This variation reflects the balance between the sympathetic and parasympathetic branches of the autonomic nervous system (ANS) (Acharya et al., 2007; Huynh et al., 2019). HRV is thought to be an important indicator of the heart's ability to respond and adapt to changing circumstances and respond quickly to unpredictable stimuli (Acharya et al., 2007). Hence, a heart rate that is intricate and continually fluctuating is a sign of well-functioning regulatory systems that can promptly adjust to unforeseen environmental and psychological stressors (Mccraty & Shaffer, 2015). Moreover, HRV data yields linear and non-linear parameters. These parameters are obtained through HRV analysis, which allows for the assessment of the overall cardiac health and the ANS state responsible for regulating cardiac activity (Acharya et al., 2007).

Recently, HRV has gained increasing attention, especially in clinical settings. One of the most significant applications of HRV in clinical practice is to determine the risk stratification (Ernst, 2017). According to Ernst (2017), multiple studies have

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demonstrated strong links between reduced HRV and the possibility of experiencing sudden cardiac arrest. Furthermore, reduced HRV has been shown to be a predictor of various health outcomes, including cardiovascular disease, diabetes, mental disorders, and cognitive impairments (Pham et al., 2021). Thus, regular monitoring of HRV could be beneficial for identifying and monitoring individuals who are vulnerable to critical health problems (Huynh et al., 2019).

Traditionally, HRV measurements have been conducted in clinical or laboratory settings using Electrocardiography (ECG), which is regarded as the gold standard for HRV measurement (Nelson & Allen, 2019). However, ECG has significant drawbacks to be used for daily HRV monitoring, including the need for additional devices and direct contact with the skin through electrodes, which are not available or convenient for most people or public community (Huynh et al., 2019). Moreover, recent advances in mobile technology have enabled the development of mobile applications that can measure HRV based on the Photoplethysmography (PPG) principle.

PPG is a non-invasive method of measuring the blood volume changes in the microvascular tissue that occurs with each heartbeat. It works by using a light source and a sensor to measure the amount of light that is absorbed or reflected by the blood vessels. The use of PPG technology as a substitute for heart rate monitoring has become more widespread in recent times, primarily because of its straightforward operation, the comfort it provides to the user, and its cost-effectiveness (Tamura et al., 2014). However, PPG-based monitoring techniques face a significant challenge in accurately tracking PPG signals during daily activities and light exercises due to motion artifacts (Sviridova & Sakai, 2015). Additionally, environmental noise can also impact signal acquisition, leading to decreased accuracy in HRV estimation (Zhang et al., 2015).

Currently, smartphone-based PPG application is gaining more popularity for HRV measurements due to its convenience and user-friendliness when compared to the traditional ECG method (Huynh et al., 2019; Nelson & Allen, 2019). Many commercial mobile applications claim to do HRV analysis in ultra-short-term (UTS) periods ranging from 10 seconds to 1 minute, whereas the standard short-term (UT) HRV analysis requires at least 5 minutes (Pecchia et al., 2018). Therefore, uncertainties arise surrounding the use of such applications, primarily because of the lack of reliable statistical tests used in studies or clear guidelines from professional bodies (Pecchia et al., 2018). Additionally, the use of PPG for monitoring is restricted by several factors that can influence measurements, including finger pressure, skin tone, light levels, and movement, resulting in inaccurate readings (De Ridder et al., 2018; Hassan et al., 2017). Thus, the reliability and practicality of using smartphone-based PPG will be affected by these factors. Moreover, there is still limited research on the validation of accuracy and reliability of HRV measurements using PPG mobile applications (Pagaduan et al., 2019).'Therefore, this paper aims to contribute to the investigation of the validity of HRV measurements obtained particularly through a 3rd party commercial mobile application (Camera Heart Rate Variability) and compared with a laboratory standard PPG Acquisition device (Shimmer3 GSR+).

MATERIALS AND METHOD

This study employed a systematic approach to collect and analyze PPG signals from healthy subjects. The method section describes the data acquisition process, including the criteria for participant selection and the detailed procedures that were used in the experiment. Additionally, it describes the pre-processing technique applied to the PPG signals and elaborates on the HRV features selected for analysis in this study.

Participants

PPG signals were collected from a total of 16 healthy subjects with no previous medical records of autonomic or cardiovascular diseases. Two of those participants were excluded due to poor signal quality. Thus, data from 14 subjects (9 males and 5 females) with an average age of (mean ± SD, 22 ± 0.88) were used in this study. Prior to the data acquisition, this study received ethical approval from Universiti Teknologi Malaysia Research Ethics Committee (UTM REC) with the approval number (UTMREC-2023-42).

Procedure

The PPG signals were recorded using a Shimmer3 GSR+ unit and Camera Heart Rate Variability app. The Shimmer3 GSR+ unit is a wrist-wearable device that can be used for capturing PPG data using an optical pulse probe. The Camera HRV app (Version 5.0.6) is a smartphone application available on both android and apple stores, that allows the measurements of short-term and ultra-short-term HRV data using the smartphone camera.

Prior to the recording, the Shimmer unit was securely placed around the wrist, while an optical pulse probe was wrapped around the index finger of the left hand of each participant followed by a 5-minute of rest in a sitting position. After that, the participants were asked to place their right-hand index finger on the camera lens of an iPhone XR. Different hands were used due to participants having trouble holding the mobile in the same hand, causing constant movement and motion artifacts. The PPG signals from the shimmer unit and the Camera HRV app were recorded simultaneously for 5 minutes. The participants were instructed to relax, breathe at a default rate (10 breaths per minute) according to the breathing bar provided by the app, and remain still in a sitting position during that period. After the recordings, the raw data was exported as a CSV file to be analyzed in MATLAB and segmented into (0.5, 1, 2, 3, 4, and 5-minute) lengths. The complete procedure is shown in Figure 1.

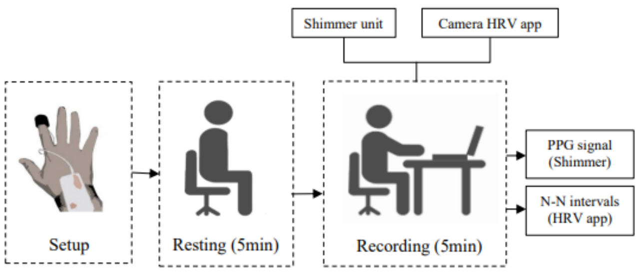

Fig 1 The procedures that were carried out during the recording session.

Signal Pre-processing

The recorded PPG signals were then pre-processed to extract HRV using MATLAB software (Figure 2). This was only required for the raw PPG data obtained from the Shimmer device, as the Camera HRV app already provides computed N-N intervals.

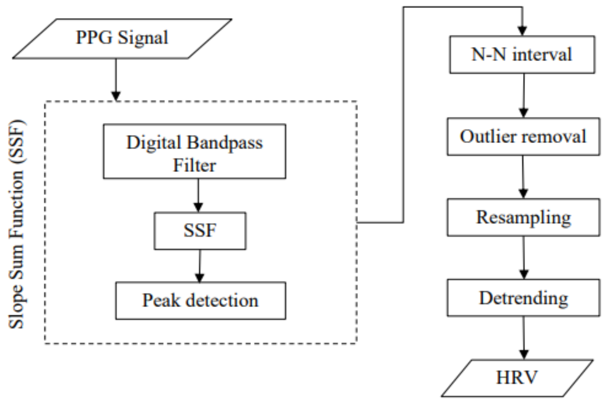

Fig. 2 Signal preprocessing algorithm.

Typically, the raw PPG signals are corrupted by noise and baseline drifting. Therefore, a digital bandpass filter formed by cascading a low pass and a high pass filter was used. The lowpass filter (LPF) reduces the random noise, such as the powerline interference at 50 Hz, and the high pass filter (HPF) reduces the motion artifcats (baseline drifting/abrupt) caused by finger movements, the gap of contact between the finger and the PPG sensors, or other reasons.

The next step was to detect the pulse peaks of the PPG signal by transforming the signal using Slope Sum Function (SSF). This technique is used to enhance the anacrotic (ascending phases) of the PPG waveform and suppresses the remainder of the waveform (Jang et al., 2014). The SFF value, at time i, is defined as:

$$SSF_i = \sum_{k=i-w}^{i} \Delta x_k,\ \ \Delta x_k = \begin{cases} \Delta s_k : & \Delta s_k > 0 \\ 0 : & \Delta s_k z \leqslant 0 \end{cases} \quad (1)$$

where, w represents the size of the analyzing window, and sk refers to the filtered PPG signal's length.

The N-N intervals obtained were then computed and passed through the outlier removal process. During this process, the removal of outliers might lead to the removal of data segments (Aimie-Salleh et al., 2018). Therefore, the lost segments were replaced using cubic spline interpretation. Then, the PPG signal was resampled at 800 Hz to increase the temporal resolution (Peng et al., 2015), using cubic spline interpolation. This process enables the generation of uniformly sampled signals (Aimie-Salleh et al., 2018), with better temporal resolution (Peng et al., 2015), making it more suitable for HRV frequency analysis. Moreover, the N-N intervals were then passed through a detrending process to overcome irregular trends. Before HRV parameters extraction, ectopic beats (irregular heartbeats) were removed and replaced by cubic spline interpolation. This is because HRV parameters only consider N-N intervals (regular heartbeats) (Peng et al., 2015).

HRV Features Extraction

This study focused on time and frequency domain analysis. The following Table 1 includes the HRV features that were computed. These features are adapted from the guideline provided by Task Force of The European Society of Cardiology (ESC) (Miranda Dantas et al., 2012) and existing literature of related studies.

Table 1 Selected HRV features

Domain	HRV features	No. of features
Time	meanHR, AVNN, SDNN, RMSDD, pNN50	5
Frequency	VLF, LF, HF, LFnu, HFnu, LF/HF, TP	7
	Total	12

Time-Domain Features

In this study, the time-domain features examined from the HRV signal were the meanHR, average of all normal-to-normal intervals (AVNN), Standard deviation of the normal-to-normal intervals (SDNN), Root mean square of successive differences between adjacent normal-to-normal intervals (RMSDD), and the percentage of normal-to-normal intervals that differ by more than 50 ms from the previous interval (pNN50). SDNN and RMSDD were computed using equations described in Eq. (2) and Eq. (3), respectively.

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}\left[RR_n - mean(RR)\right]^2} \quad (2)$$

where N is the total window length and RR is the normal-to-normal time interval.

$$RMSDD = \sqrt{\frac{1}{N-2}\sum_{n=3}^{N}\left[I(n) - I(n-1)\right]^2} \quad (3)$$

where N is the total window length.

Frequency-Domain Features

In this research, the autoregressive (AR) method employing Burg's estimation technique was used due to its ability to minimize both forward and backward prediction errors. The AR method has ability to generate a higher quality spectrum resolution and provides a smoother spectral components and accurate estimation of the power spectral density (PSD), even when dealing with short data samples such as ST and UST HRV measurements (Aimie-Salleh et al., 2018; Malik, 1996; Miranda Dantas et al., 2012). These advantages allow HRV frequency components to be easily identified and extracted. The power spectrum of the AR method, computed using Burg's estimation, can be expressed as follows:

$$P_{Burg}(f) = \frac{\hat{e}_p}{\left|1 + \sum_{l=1}^{p} \hat{a}_p(l)\, e^{-2jfl}\right|^2} \quad (4)$$

where êp represents the combined sum of forward and backward prediction errors (total least square error) and p represents the model order, and â (*l*) represents the order of the AR coefficient.

Statistical Analysis

Multi-length HRV parameters derived from the Shimmer and Camera HRV app were compared in three ways. First, between different durations of Camera HRV data and the 5-minute baseline data from Shimmer. Second, between different durations of Shimmer and its 5-minute baseline data. Third, between different durations obtained from the Camera HRV app and its 5-minute baseline data. This comparison was done using Pearson correlation coefficient. The Pearson correlation coefficient (r) measures the strength and direction of the linear relationship between two variables. The value of r ranges from -1 to 1, where 1 indicates a perfect positive linear relationship, -1 indicates a perfect negative linear relationship, and 0 indicates no linear relationship. In this case, Pearson's method can help determine if there is a consistent association between the two sets of HRV parameters. The HRV parameters measurability criterion was set to ($r > 0.7$, $p < 0.05$) where r is the Pearson's correlation coefficient and p is the statistical significance of the correlation. This criterion is commonly used to indicate a strong correlation (Baek et al., 2015). The statistical analysis was performed using Microsoft Excel.

RESULTS

This section presents the results and comprehensively discusses the findings. It begins with the signal pre-processing results of HRV from PPG using SSF algorithm. It then proceeds to showcase HRV feature extraction using AR spectral analysis method, followed by multiscale statistical analysis of the extracted time and frequency domain features between camera heart rate variability app the shimmer GSR3+. Lastly, the overall findings are discussed.

Signal Pre-processing

Figures 3 and 4 show the output of each pre-processing step in the HRV analysis, along with the resultant HRV.

From Figure 3, it can be seen that the N-N intervals were successfully detected using SSF algorithm, as validated by Jang et al (2014). Meanwhile, Figure 4 continued the process by generating an applicable and smooth HRV signal after outlier removal, resampling and detrending

HRV Features Extraction

A total of 12 features were selected for HRV analysis as presented in Table 1. These features were selected in this study based on their prevalence in the existing literature for ultra-short-term and short-term HRV analysis, where they have demonstrated acceptable results.

AR spectral analysis was performed for all data with an overall fixed order p=16, which was recommended by Boardman et al (2002), as the optimum fixed model order to allow accurate estimation of the PSD of N-N intervals resampled at 4 Hz. This selection is because the spectra at p=16 contained resolvable peaks and no spurious peaks or smearing compared to other orders. Figure 5 shows the PSD of a randomly selected subject from the data obtained using the Shimmer and Camera HRV app.

Statistical Analysis

The results of the correlation analysis using Microsoft excel between multi-length HRV features (5, 4, 3, 2, 1, and 0.5 minutes) obtained from the Camera HRV app and the standard 5-minute data from the Shimmer unit are provided in Table 2. Based on the findings, all features extracted from the mobile app produced similar results to the Shimmer unit for short-term (5-min) measurement. For ultra-short-term recordings (<5 min), both TA and FA features showed strong correlation ($r > 0.7$) and correlation significance ($p < 0.001$) for signal excerpts of 4 and 3 minutes. Furthermore, all time-domain HRV features showed consistent strong correlation coefficients and statistical significance ($r > 0.7$, $p < 0.001$) for varying signal excerpt lengths of 2, 1, and 0.5 minutes, except for SDNN, which only

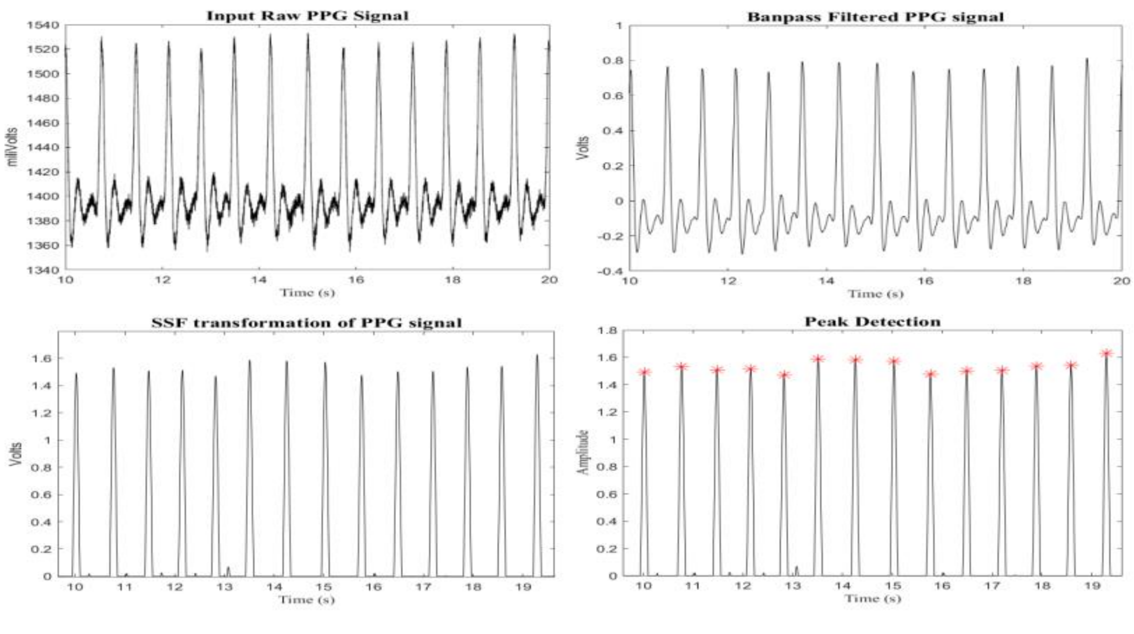

Fig. 3 The output of HRV pre-processing using SSF algorithm

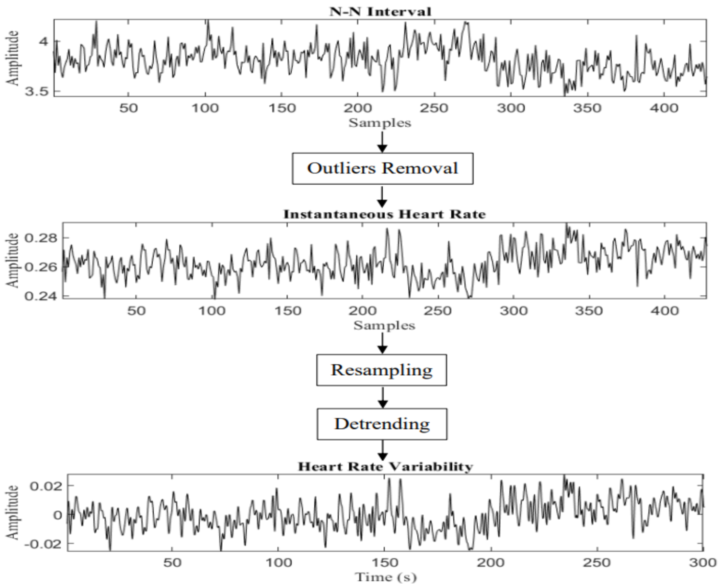

Fig. 4 The output of HRV pre-processing from N-N intervals

showed strong correlation in the 2-minute signal excerpt ($r = 0.8121$, $p < 0.001$). For frequency-domain features, only VLF and LF showed strong correlation for the 2-minute signal excerpt, while the remaining features exhibited no correlation for 2-minute data length. Moreover, none of the FA features displayed any correlation for 1 and 0.5-minute segments. In general, it can be observed that correlation exists between the two methods for HRV measurements, including short-term and ultra-short-term ones.

PPG, especially in mobile apps, can be affected by several factors, such as motion artifact and sampling rate (Li et al., 2018). Therefore, to further investigate how these factors and UST HRV measurements may affect each method independently, another correlation analysis was performed. The analysis was conducted by comparing multi-length HRV features from the Shimmer and Camera HRV app with their corresponding 5-minute original data separately. Table 3 summarizes the results from the correlation analysis.

Based on the results from Table 2, it was expected that the methods used should yield similar or better results when compared with their original 5-minute data. As expected, and based on the findings from Table 3, both measuring techniques showed strong correlations for ultra-short-term (UST) measurements for signal excerpts of 4 and 3 minutes across all

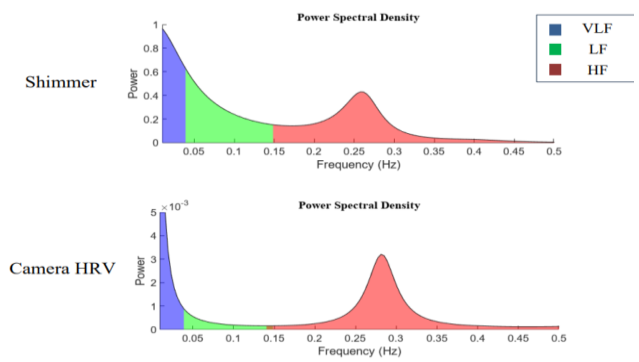

Fig. 5 PSD of a randomly selected subject

HRV features. For signal excerpts of 2 minutes, all TA and FA features extracted from the Shimmer met the measuring criteria ($r > 0.7$, $p < 0.05$) compared to the features from the Camera HRV app, where HF, LF/HF, and TP did not meet the criteria. Moreover, for signal excerpts of 1 and 0.5 minutes, all TA features exhibited strong correlation and correlation significance ($r > 0.7$, $p < 0.001$) for both techniques, except for SDNN, which only showed strong correlation for the Camera HRV app for signal excerpt of 1 minute ($r = 0.7038$, $p < 0.01$) and exhibited no correlation for Shimmer. For FA features, only HF showed strong correlation ($r = 0.8565$, $p < 0.001$) for 1-minute signal segment extracted from the Shimmer, while the remaining features displayed no correlation between the measuring techniques and their original 5-minute data, for signal excerpts of 1 and 0.5 minutes.

Overall, Table 3 summarizes the correlation analysis performed in this study between each measuring technique and their corresponding 5-minute original segment. Based on the results, it can be observed that correlation exists between Short-term (5 min) and ultra-short-term (<5 min) HRV measurements for both techniques.

DISCUSSION

This study intended to investigate if using PPG-based Camera HRV app is valid compared to standard 5-min excerpt from PPG-Shimmer for HRV measurements. Even though several studies reported that PPG provides an accurate and reliable alternative to ECG in the assessment of HRV at rest (Esgalhado et al., 2022; Lu et al., 2009; Sahroni et al., 2019; Selvaraj et al., 2008), there are several limitations for PPG-mobile phones for HRV measurement when compared with a more traditional and advanced system like Shimmer. One of the challenges is the sampling rate of mobile phones (i.e. 20-30 Hz), which is below the required sampling rate for HRV analysis of 250 Hz (Li et al., 2018). Another challenge is motion artifacts, especially since the standard HRV analysis requires at least 5 minutes, which is not feasible in everyday life as it requires remaining motionless for that period (Peng et al., 2015). Therefore, there have been many

Table 2 Correlation of multi-length HRV features of Camera HRV app with standard of 5-min Shimmer.

Features	Data Lengths (Minutes)					
	5	4	3	2	1	0.5
meanHR	**0.9999*** **	**0.9987*** **	**0.9948*** **	**0.9919*** **	**0.9878*** **	**0.9706*** **
AVNN	**0.9999*** **	**0.9985*** **	**0.9935*** **	**0.9894*** **	**0.9869*** **	**0.9701*** **
SDNN	**0.9787*** **	**0.9423*** **	**0.8736*** **	**0.8121*** **	0.6129*	0.5333*
RMSDD	**0.9612*** **	**0.9569*** **	**0.9409*** **	**0.9039*** **	**0.8874*** **	**0.8744*** **
pNN50	**0.9814*** **	**0.9791*** **	**0.9680*** **	**0.9191*** **	**0.9032*** **	**0.8615*** **
VLF	**0.9613*** **	**0.9547*** **	**0.8208*** **	**0.8073*** **	0.4446	0.3895
LF	**0.9851*** **	**0.9755*** **	**0.9127*** **	**0.8184*** **	0.3166	0.3748
HF	**0.9819*** **	**0.9729*** **	**0.9169*** **	0.5913	0.4460	-0.0278
LFnu	**0.9580*** **	**0.9596*** **	**0.8634*** **	0.6694**	0.4263	0.1583
HFnu	**0.9580*** **	**0.9595*** **	**0.8620*** **	0.6662**	0.4151	0.1405
LF/HF	**0.9625*** **	**0.9681*** **	**0.8325*** **	0.6488*	0.3346	0.1804
TP	**0.9524*** **	**0.9298*** **	**0.7301** **	0.491	0.3208	0.2048

In bold: Pearson's correlation coefficient r > 0.7
Correlation significance (2-tailed): *p < 0.05; **p < 0.01; ***p < 0.001

mobile applications such as Camera HRV app that claim to do HRV analysis in ultra-short periods (<5 min).

A total of 12 HRV features were extracted from 14 healthy participants to investigate the validity of Camera HRV app for short-term and ultra-short-term HRV measurements. It is assumed that if measuring criteria is met, (r > 0.7, p < 0.05) then the ultra-short-term HRV feature is a good surrogate to the equivalent short-term HRV feature. Therefore, it can be deduced that TA features (meanHR, AVNN, RMSDD and pNN50) are all valid surrogates to the standard 5-min HRV duration across all lengths. SDNN required at least 2 minutes to be computed reliably using Shimmer and 1 minute using the Camera HRV app. These results align with the findings of a study conducted by Baek et al (2015), where a correlation coefficient of (r > 0.7) was achieved with a 0.5-minute duration for meanHR, AVNN, RMSDD, pNN50 and 1 minute for SDNN when comparing multi-length durations with the standard 5-min data of PPG signals.

Moreover, all FA features are valid surrogates to the standard 5-min HRV duration for Shimmer at a minimum duration of 2 minute, with the exception of HF which showed strong correlation at 1 minute, which was also reported by Baek et al (2015), as the minimum duration required for HF. In contrast, (VLF, LF, LFnu, HFnu) displayed strong correlation and said to be good surrogate at a minimum duration of 2 minute, while (HF, LF/HF, TP) required at least 3 minutes. Kim et al (2021), reported similar results for FA features at rest, where (VLF, LF, LFnu, HFnu) showed strong correlation at a minimum duration of 2 minute, LF/HF required at least 3 minutes, while TP and HF were the exception, with a strong correlation at 0.5-minute duration. These inconsistencies for TP and HF could be attributed to the different spectral analysis methods used.

Overall, both techniques provided similar results for HRV in ST and UST measurements. However, inconsistencies between the two methods, especially for FA features, could be due to

Table 3 Correlation of multi-length HRV features of Camera HRV app and Shimmer unit with their original 5 min data.

Features	Data Lengths (Minutes)									
	4^s	**4^c**	**3^s**	**3^c**	**2^s**	**2^c**	**1^s**	**1^c**	**0.5^s**	**0.5^c**
meanHR	**0.9983*** **	**0.9941*** **	**0.9937*** **	**0.9941*** **	**0.9907*** **	**0.9909*** **	**0.9848*** **	**0.9867*** **	**0.9626*** **	**0.9694*** **
AVNN	**0.9976*** **	**0.9924*** **	**0.9916*** **	**0.9924*** **	**0.9873*** **	**0.9878*** **	**0.9827*** **	**0.9854*** **	**0.9563*** **	**0.9683*** **
SDNN	**0.9741*** **	**0.9216*** **	**0.9029*** **	**0.9216*** **	**0.8246*** **	**0.8708*** **	0.5648*	**0.7038** **	0.5466	0.5954
RMSDD	**0.9945*** **	**0.9830*** **	**0.9730*** **	**0.9830*** **	**0.9613*** **	**0.9572*** **	**0.9549*** **	**0.9614*** **	**0.8978*** **	**0.9155*** **
pNN50	**0.9957*** **	**0.9705*** **	**0.9706*** **	**0.9705*** **	**0.9394*** **	**0.9147*** **	**0.9367*** **	**0.9273*** **	**0.8963*** **	**0.8654*** **
VLF	**0.9961*** **	**0.9184*** **	**0.9323*** **	**0.9184*** **	**0.8349*** **	**0.9004*** **	0.5900*	0.5039	0.5862	0.4493
LF	**0.9963*** **	**0.9450*** **	**0.8942*** **	**0.9450*** **	**0.8335*** **	**0.8635*** **	0.4875	0.3396	0.6338*	0.3984
HF	**0.9980*** **	**0.9636*** **	**0.9887*** **	**0.9450*** **	**0.9778*** **	0.6545*	**0.8565*** **	0.5189	0.0340	-0.0027
LFnu	**0.9942*** **	**0.9223*** **	**0.9539*** **	**0.9223*** **	**0.8421*** **	**0.7178** **	0.6521*	0.4604	0.4038	0.2075
HFnu	**0.9941*** **	**0.9217*** **	**0.9548*** **	**0.9217*** **	**0.8410*** **	**0.7165** **	0.6490*	0.4541	0.3986	0.2060
LF/HF	**0.9910*** **	**0.8400*** **	**0.9026*** **	**0.8400*** **	**0.7478** **	0.6491*	0.4897	0.2668	0.2462	0.1633
TP	**0.9941*** **	**0.8670*** **	**0.9204*** **	**0.8670*** **	**0.9031*** **	0.6518*	0.6278*	0.4649	0.3150	0.3650

Measurement method: ^{S} Shimmer device; ^{C} Camera HRV app
In bold: Pearson's correlation coefficient r > 0.7
Correlation significance (2-tailed): *p < 0.05; **p < 0.01; ***p < 0.001

serval reasons. A possible reason is the sampling rate of the smartphone used (iPhone XR) of approximately 30 Hz. Even though Camera HRV app implemented cubic spline interpolation at 180 Hz, which greatly improves the signal's resolution and has been employed in many studies to overcome this limitation (Peng et al., 2015), it is still below the minimum required sampling rate of 250 Hz for HRV analysis. Moreover, Shimmer, being sampled at 1024 Hz for this study, provides a much higher resolution for PSD analysis compared with the Camera HRV app.

Another factor could be the AR model order used. In PSD estimation, the accuracy of the results is significantly dependent on the model order that is chosen (Aimie-Salleh et al., 2018). In this study, an approach suggested by Boardman et al (2002), to use a fixed order of (p=16) was implemented instead of using prediction criteria to determine the optimal order, which may have influenced the results between the two methods.

Motion artifacts are another complicated issue when dealing with PPG signals, especially for smartphones where any slight finger movement may affect the quality of the signal compared to a traditional PPG sensor such as Shimmer which can be wrapped and secured around the finger. During data collection, even though participants were told to remain still during the 5-min recording period, some movement still occurred, causing motion artifacts.

Despite that, Camera HRV app showed strong correlation and correlation significance for HRV measurement compared with Shimmer across different lengths. Therefore, Camera HRV app is a good surrogate to traditional PPG sensors for short-term and ultra-short-term measurements. Overall, to compute all HRV features using camera HRV app reliably, a minimum duration of 1 minute is recommended for TA features and at least 3-minute duration for FA features.

CONCLUSION

Heart rate variability is a well-established indicator of autonomic nervous system functioning and has been linked to numerous health-related outcomes. Traditional ECG method for HRV measurements involves using skin electrodes, which are not practical for everyday use. In contrast, mobile-based PPG apps only require placing a finger on the camera lens, establishing them as simple, cost-effective, and suitable for daily life. Additionally, standard HRV analysis typically takes around 5 minutes, which can be challenging to remain still for that period. Hence, there is a growing interest in using ultra-short-term HRV recordings with mobile phones to monitor an individual's health and well-being in their daily life. In this research, it is presumed that short-term (5 min) and ultra-short-term (<5min) HRV features from the Camera HRV app is a valid surrogate to the Shimmer if they maintain a high correlation ($r < 0.7$, $p < 0.05$). Therefore, it can be deduced that Time-domain features (i.e. meanHR, RMSDD, AVNN, pNN50) are a valid surrogate across all signal excerpts in correlation to the Shimmer, while SDNN required a minimum duration of at least 1 minute. On the other hand, all frequency-domain features showed significant correlation across excerpts equal and longer than 3 minutes. In general, to compute ultra-short-term HRV features reliably using Camera HRV app, at least 1 minute for TA features and 3 minutes for FA features is recommended. In the future, more participants can be recruited to obtain more accurate results, and prediction criteria can be used to determine the optimal AR order.

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