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Review

How accurate is pulse rate variability as an estimate of heart rate variability? A review on studies comparing photoplethysmographic technology with an electrocardiogram

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ABSTRACT

Background: The usefulness of heart rate variability (HRV) as a clinical research and diagnostic tool has been verified in numerous studies. The gold standard technique comprises analyzing time series of RR intervals from an electrocardiographic signal. However, some authors have used pulse cycle intervals instead of RR intervals, as they can be determined from a pulse wave (e.g. a photoplethysmographic) signal. This option is often called pulse rate variability (PRV), and utilizing it could expand the serviceability of pulse oximeters or simplify ambulatory monitoring of HRV.
Methods: We review studies investigating the accuracy of PRV as an estimate of HRV, regardless of the underlying technology (photoplethysmography, continuous blood pressure monitoring or Finapresi, impedance plethysmography).
Results/conclusions: Results speak in favor of sufficient accuracy when subjects are at rest, although many studies suggest that short-term variability is somewhat overestimated by PRV, which reflects coupling effects between respiration and the cardiovascular system. Physical activity and some mental stressors seem to impair the agreement of PRV and HRV, often to an inacceptable extent. Findings regarding the position of the sensor or the detection algorithm are not conclusive.
Generally, quantitative conclusions are impeded by the fact that results of different studies are mostly incommensurable due to diverse experimental settings and/or methods of analysis.

1. Introduction

The term '*Heart rate variability*' *(HRV)* refers to the fact that the duration of cardiac cycles is not constant, but varies from one heartbeat to the next. The extent of variability is determined by digital processing of an electrocardiographic (ECG) signal. Because of their distinct profile, the R peaks of an ECG signal are suitable for automated detection by computer algorithms; hence the standard method to assess cardiac cycles is to place their limits at the R peaks. As a result, one obtains a time series of such consecutive *RR intervals*. Ectopic beats and arrhythmic events are usually not processed when determining HRV; only regular beats should be considered, which is why one often encounters the alternative term *NN intervals* ('normal to normal'). Analysis of HRV comprises the computing of meaningful parameters from RR interval time series called *HRV variables*. For a comprehensive presentation of the methodology see [1].

HRV has become a very useful tool in clinical diagnostics within the last decades. Reduced HRV is correlated with the risk of cardiac events like myocardial infarction and congestive heart failure [2,3], and with sudden cardiac death [4,5]. From the early 1980s on, the frequency domain HRV variables, gained from a power spectrum of the RR interval series, have been found to reflect autonomic cardiovascular control [6,7]. Physical fitness and social integration are both associated with reduced cardiac risk and enhanced HRV [8,9]. Treatment of psychiatric patients with tricyclic antidepressants seriously diminishes HRV, although there is ambiguity as to whether psychopharmacological treatment increases mortality [10]. Also, depression itself seems to influence autonomic control and HRV [11]. All in all, HRV seems to be a reliable and multifunctional parameter indicating cardiovascular and autonomic health as well as general psychic and somatic fitness.

Evaluation of HRV variables can be gained from sessions of various duration, up to Holter recordings lasting 24 h or more. However, short-term recordings of only a few minutes have been found to be comparably useful [12], and even ultra-short sequences of only 10 s seem to have reasonable diagnostic value [13].

Photoplethysmography (PPG) is a technique developed in the 1930s for monitoring blood volume changes in the micro vascular bed of tissue

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[14]. In more recent decades, progress in semiconductor technology and optoelectronics, as well as advancements in digital signal processing, have facilitated a renaissance of PPG, which today is probably the most widespread method used in clinical monitoring. Its basic principle requires a light source to illuminate subcutaneous tissue (typically an LED, i.e. a light emitting diode) and a photo detector with spectral characteristics matching those of the light source (e.g. a photodiode or phototransistor). Current PPG sensors use low-cost optoelectronic components operating in the domain of red and/or near infrared wavelengths.

There are two basic configurations used in PPG: *transmission mode*, where the perfuse tissue (like a fingertip or an earlobe) is placed between the source and the detector, and *reflection mode*, where the two electronic components are placed side-by-side near the skin, e.g. at the forehead. In both cases the detector registers small variations in the transmitted or reflected light, respectively, caused by changes in microcirculation. Major factors affecting the detected light intensity are blood volume, blood vessel wall movement and the orientation of erythrocytes [15].

Changes in a PPG signal arise from variations both in the path-length between source and detector and in the optical density of the blood. The signal can be decomposed into two parts [16]. The small pulsatile component, or AC component, arises from arterial blood pulsation; hence its oscillation parallels momentary cardiac activity. It is superimposed on the much larger DC component, where DC refers to direct current, suggesting a static behavior. However, the DC component is not entirely static, but includes variations slower than the heart rate due to venous volume fluctuations, vasomotor activity and thermoregulation. Changes in the intrathoracic pressure due to respiration cause fluctuations in the venous return to the heart, which in turn modulates cardiac output and blood pressure. Ventilation thus induces fluctuation of both AC and DC components, which enables one to monitor respiratory activity by filtering and processing a PPG signal appropriately [17,18].

PPG technology is a very versatile tool, and its usefulness in a wide range of clinical applications has been demonstrated. The most common one is pulse oximetry, which utilizes the difference of red and near infrared light absorption by oxyhemoglobin and reduced hemoglobin to estimate arterial blood oxygen saturation. Further applications include the estimation of cardiac output, the diagnosis of atherosclerosis, peripheral arterial occlusion and other peripheral vascular diseases, as well as the assessment of arterial compliance and aging, of endothelial and venous function, micro vascular blood flow and other functions [15]. Additionally, PPG offers a number of ways to assess cardiovascular autonomic function and skin vasomotor function. Due to this property, it is also a valuable instrument for monitoring nociception during general anesthesia [16]. For a comprehensive review on PPG and its clinical applications see [15].

Arterial blood pressure can also be estimated from a PPG, because the higher the pressure, the quicker the propagation of the pulse wave from the heart to the periphery. Therefore, the determination of pulse wave velocity or its reciprocal, pulse transit time (cf. Section 3.1 below) for each pulse cycle can serve as an approximation of continuous blood pressure (CBP) monitoring. However, estimators of systolic and diastolic blood pressure are only in moderate agreement with their directly measured counterparts, although this can be somewhat improved by including the amplitude of each PPG pulse wave in the analysis [19,20]. In order to provide a more reliable method for CBP monitoring, the Finapres™ (for FINger Arterial PRESsure) technology was introduced in the early 1980s. It is based on the dynamic vascular unloading of the arterial walls of the finger using an inflatable finger cuff [21]. The built-in PPG sensor is used as a control sensor to regulate cuff pressure for optimum CBP detection, but does not measure blood pressure directly.

Given that PPG is such a simple and ubiquitous technology in clinical indicated above, the signal can also be used to monitor the heart and respiratory rate of a patient, including instantaneous rates or cycle lengths. In principle, this would allow HRV variables to be determined as well from a PPG signal. Compared to the current standard of an ECG-based HRV analysis, this would involve certain benefits. In clinical situations where a pulse oximeter (PO) device is already at hand by default, being able to include HRV analysis in the monitoring process without requiring an ECG means a significant advantage. In addition, during magnetic resonance imaging (MRI), for example, ECG electrodes or other metal-containing sensors are not permitted, as they interfere with strong electromagnetic fields.

Another fact speaking in favor of PPG technology is that it is noninvasive, cost-effective and straightforward to use. Detecting the signal usually requires no more than attaching a single sensor to a finger or an earlobe, compared to at least three leads and Ag/AgCl electrodes required for an ECG. Furthermore, ECG electrodes often have to be applied to the chest, requiring the patients to undress—which can delay recordings and pose a problem for embarrassed patients. On the other hand, a major disadvantage of PPG technology is that the signal is susceptible to motion artifacts, which can impair the accuracy of the detected cardiac activity [15].

2. Scope of this review

The purpose of this review is to summarize the hitherto existing literature about the accuracy of estimating HRV and/or (instantaneous) heart rates from a continuously recorded pulse wave signal. All of the considered articles contrast the results of the latter with the gold standard of an ECG-based method.

We performed a search in PubMed and Embase for publications that matched at least one keyword in both of the following word groups:

1) *oximetr…/oxymetr…* or *plethysmogr…* or "*pulse wave*" or "*pulse applan…*"
2) *electrocard…* or *ECG* or "*rate variability*"

Here the ellipsis (…) indicates arbitrary completion of words, and quotation marks require the enclosed words to appear exactly in the specified order. The retrieved abstracts were then inspected for their thematic agreement with the topic of this review. Such selected articles and correspondingly eligible references cited therein were all included.

Most of the retrieved studies use a PPG signal to detect a pulse wave. However, some employ a Finapres™ system monitoring CBP or an impedance plethysmography system instead. The analysis techniques used to discern individual pulse cycles in these cases are similar to those utilized for PPG signals. Additionally, many of the findings therein complement those in PPG studies. For these reasons, all those references assessing the quality of results from non-PPG pulse waves are included in this review.

The main focus is on the question whether the ECG-based method of evaluating HRV can be replaced by a technique using a pulse wave. From now on the latter approach will be referred to as pulse rate variability (PRV), as it is based on the varying length of pulse cycles, not cardiac cycles. Heartbeats can be more accurately determined from an ECG; therefore we will henceforth use the term HRV mainly for ECG-derived heart rate variability.

It is clear that the methods used to determine the limits between adjacent pulse cycles affect the individual lengths of the latter and, hence, PRV results. The statistical techniques used to compare, say PRV and HRV, will likewise have an impact on the outcomes of an investigation. Section 3 outlines some important approaches used in analyses; additionally, Tables 1 and 2 summarize the most important abbreviations regarding HRV variables and HRV/PRV analysis.

A number of researchers were merely interested in the accuracy of

Table 1
Abbreviations of common HRV variables.

Time domain variables	
Mean NN, mean HR	Mean of all NN intervals. Mean HR is its reciprocal value, converted into beats per minute (bpm)
SDNN	Standard deviation of all NN intervals; measure of overall variability.
RMSSD	Root of mean of squared subsequent differences; measure of short-term variability.
SDSD	Standard deviation of subsequent differences (almost identical to RMSSD).
NN50/pNN50 (pNN10)	Number/percent of subsequent differences with an absolute value > 50 ms (or 10 ms).
Frequency domain variables (spectral domains according to Task force definitions [1])	
ULF	Ultra low frequencies (<0.003 Hz)
VLF	Very low frequencies (0.003–0.04 Hz)
LF	Low frequencies (0.04–0.15 Hz)
HF	High frequencies (0.15–0.40 Hz)
TP	Total power (sum contribution of all spectral domains)
Nonlinear variables	
SD1	Standard deviation of short diagonal axis in Poincaré plot
SD2	Standard deviation of long diagonal axis in Poincaré plot
ApEn	Approximate entropy
SampEn	Sample entropy

purposes; hence they did not concern themselves with individual heart or pulse cycles or HRV variables. However, some of them use analytical approaches that are interesting in context, while other investigations can be perceived as historical predecessors of the studies in the focus of this review. We thus summarize these results briefly in Section 4 and Table 3.

The central topic, compatibility of PRV with HRV, is treated in Section 5 and its subsections. We should note that the various findings are almost never comparable directly, since a variety of devices, analytical methods, experimental conditions etc. have been used. Therefore, we can present and contrast all results only descriptively, itemized in Tables 4 and 5.

A discussion and conclusions can be found in Sections 6 and 7.

3. Analytical methods

3.1. Pulse wave analysis

A typical pulse wave cycle can be subdivided into two parts (cf. Fig. 1). The *anacrotic* phase is the rising part of the pulse due to systole. Shortly after the QRS complex appears in the ECG, the ventricular systole generates a pulse wave travelling distally. In the arteries and arterioles this leads to a rapid increase in blood pressure and blood volume, i.e. a steep rise in the pulse wave. The subsequent decline corresponding to cardiac diastole is termed the *catacrotic* phase and is more prolonged than the anacrotic phase. Often it contains a secondary peak separated by the so-called dicrotic notch, an effect diminishing with ageing and increasing arterial stiffness [15]. This phenomenon is often attributed to the closure of the aortic valve [22], although recent findings suggest a causation by reflection of the pressure peak from small arteries in the trunk and lower limbs [23].

Corresponding to each RR interval (RRI) of the ECG, which is considered as the "true" instantaneous heart cycle length, there is an interval comprising a full pulse cycle length. We will henceforth denote it as PPI ("pulse to pulse interval"). Its exact location depends on the definition of its boundaries and the computer algorithm used to detect them [24]. The black disks in Fig. 1 highlight three possible alternatives. One can determine the beginning of the anacrotic or, alternatively, the catacrotic phase, i.e. the pulse foot or peak (marked with an "f" or "p" in the figure), as the respective boundary. This leads to different definitions of pulse intervals, as is indicated in the figure by PPI (f) and PPI (p). A third option is to use the maximum 1st derivative representing the steepest part of the upstroke as a boundary, indicated by the disk marked "d". In the existing literature researchers have utilized all of these methods as well as others (cf. Table 5); comparative studies on some approaches can be found in [25,26].

Depending on the pulse wave velocity and the vascular path from the heart to the location of the detector, there is a delay between each R peak and the onset of its corresponding pulse wave. The delay is usually termed pulse transit time (PTT) and is negatively correlated with blood pressure, arterial stiffness, and age [15]. As defined above, it ranges from an R peak to the next pulse foot or the beginning of systole; however, many studies employ a different definition of a PTT extending to the subsequent peak. The two cases are denoted as PTT (f) and PTT (p) in Fig. 1.

Deviations of the PPI from the RRI series can arise from two possible causes: 1) an inaccurate detection of pulse cycle boundaries due to hardware limitations, artifacts and/or noise, or 2) a physiological variability in PTT.

Table 2
Abbreviations of HRV and PRV phenomena used in the text.

Time intervals	
RRI	RR interval length(s) from an ECG
PPI	Pulse interval length(s) from a pulse wave signal
Frequencies/rates	
HR	Heart rate, determined by an ECG signal
PR	Pulse rate, determined by a pulse wave signal
IHR	Instantaneous heart rate (reciprocal of RRI)
IPR	Instantaneous pulse rate (reciprocal of PPI)
Result of analysis	
HRV	Heart rate variability, gained by analyzing RRI values

3.2. Heart and pulse rate variability analysis

In order to quantify the agreement of PPI and RRI series, researchers have mostly used one or more of the following three strategies:

a) Often one is only interested in the accuracy of the determined mean pulse rate (PR) compared to the mean heart rate derived from an ECG. This is usually sufficient when a PPG device is used for monitoring or telecare.
b) The focus of this review is on the reliability of PRV as a substitute for HRV. Most of the studies in this domain compare HRV variables for both the RRI and PPI series, which we will henceforth refer to as HRV and PRV variables. The most common HRV variables evaluated are time and frequency domain variables, which have been extensively standardized, but nonlinear variables are also used [1]. Abbreviations of the most commonly used HRV variables are listed in Table 1.
c) A number of authors also compare the RRI and PPI series directly, i.e. they compare the lengths of individual heart beats to the corresponding pulse cycles—or they do the same thing with the instantaneous heart (IHR) and pulse (IPR) rates, which are simply the reciprocal values of the cycle lengths.

Table 2 gives an overview of the respective quantities and their abbreviations used throughout the subsequent sections.

3.3. Statistical analysis

In all the studies considered in this review, quantities determined from an ECG and a simultaneously recorded pulse signal are compared. Data pairs are given where each pair comprises corresponding values measured by each method in question, respectively. In case

Table 3
Overview of studies on monitoring heart rate with PPG technology.

Study	N = number of subjects × T = duration of records	Device(s) used	Position of sensor	Experimental conditions	Methods of pulse detection and analysis	Results
Adults						
Altemeyer et al. (1986) [31]	(Monitored patients during operation, ages 25–84) $N = 19$	Biox III, and Nellcor N-100 pulse oximeters	Index or middle finger	Both normal respiration and inhalation of hypoxic gas mixture.	Auto-detection method of monitoring devices.	"Good agreement" with ECG-determined HR, not quantitatively specified.
Atlasz et al. (2006) [37]	(Healthy, ages 22.2 ± 1.9) $N = 35 \times T = 10$ min	Self-made reflection PPG sensor	Fingertip	5 min supine rest, 5 min standing	Peak counting? (not exactly specified) Statistics: ANOVA/t-test	No significant differences between HR from PPG and ECG.
Lindberg et al. (1992) [34]	(Males, ages 20–30) $N = 11 \times T = 10$ min	Self-made PPG sensor	Left forearm	Supine rest	Manual counting of PPG peaks	Exact agreement with HR from ECG, when signal clean
Nakajima et al. (1996) [35]	(Males, ages 22–34) $N = 11 \times T = 20$ min	Self-made PPG sensor	Earlobe	Ergometer: sitting + Exercise (30–130 W)	Band-pass filtering PPG signal, then zero-crossing count. Take median of 10 consecutive HRs.	PPG and ECG determined heart rates "agreed well", maximum $\|\Delta HR\| = 10$ bpm
Kornowski et al. (2003) [36]	(Cardiac patients vs. healthy controls, ages 43 ± 18) $N = 144$	Medic4All wristwatch telecare system	Wrist (sensor worn like a watch)	Rest on chair, evaluation of up to 10 intervals of 30 s for each patient, respectively.	Band-pass filtering PPG signal, finding mean HR by autocorrelation analysis.	PCC of 0.95, Bland-Altman analysis says 95% CI: $\Delta HR = -0.1 \pm 6.5$ bpm
Vogel et al. (2007) [38]	$N = 1$, T not specified, additionally 6 h of data from the "MIT-BIH normal sinus rhythm database"	Self-developed IN-MONIT system, using both red and infrared LEDs	Inside auditory canal	Not specified	a) Peak detection by threshold algorithm, reciprocal median pulse interval → mean HR. b) Looking for freq. with max. power in FFT spectrum. Analysis by PCC and mean ± SD of difference.	Spectral method and infrared light both more reliable. Results in this case: PCC = 0.92, $\Delta HR = -0.6 \pm 1.3$ bpm (mean ± SD)
Neonates						
Barrington et al. (1988) [32]	(Lung or cardiorespiratory disease) N = 22 × T = 3 min	Roche Medical Electronics 634	"Gently restrained" limb	Comparison of HR detected from PPG- and ECG-based monitors.	Auto-detection method of monitoring devices. Test for $\|\Delta HR\| > 10$ bpm	Depending on condition, 11.9–29% of HR values found unreliable ($\|\Delta HR\| > 10$ bpm)
Johansson et al. (1999) [33]	$N = 6$ (4 preterm) × $T = 8$ h	Self-made PPG sensor, connected to HP 66S monitor	Lateral side of left thigh	Continuous monitoring during 8 h	High-pass filtering PPG signal, then zero-crossing count. Evaluation of 30 s epochs and binary classification.	PPG recorded 1.1% (±0.7%) false negative and 0.9% (±0.6%) false positive beats, as compared to ECG.
Kamlin et al. (2008) [39]	$N = 55 \times T = 3$ min	Masimo Radical PO monitor	Right hand/wrist	Experimenters reading HR displayed by PPG and ECG monitors from video.	Auto-detection method of monitoring devices. Bland-Altman analysis of ΔHR	95% CI: $\Delta HR = -2 \pm 26$ bpm
Olsson et al. (2000) [41]	$N = 10$ (preterm) × $T = 30$ min	Siemens photo diode SFH2030 (940 nm)	Leg, buttock and interscapular back	Rest in incubators	Manual elimination of motion artifacts. Visual analysis of PPG charts, manual counting of PPI. PCC of PR vs. HR	Buttock: PCC = 0.999 Leg: PCC = 0.995 Back: PCC = −0.134 (sic!)
Singh et al. (2008) [40]	$N = 30 \times T = 3$ min	Masimo Radical PO monitor	Right hand	Experimenters reading HR displayed by PPG and ECG monitors from video.	Auto-detection method of monitoring devices. Bland–Altman analysis of ΔHR	95% CI: $\Delta HR = -0.4 \pm 12$ bpm

values, in case b) they are HRV and PRV variables. In both approaches they are determined from detected cardiac cycles within the identical epoch of simultaneously recorded signals. In case c) the values under investigation consist of the time series of the detected cardiac cycle lengths themselves. Since each PPI belongs to an RRI, namely the one beginning directly before and separated only by PTT, one can also arrange them in pairs here. Whatever the case, one has a number of paired results derived from ECG and pulse signals.

In order to assess the agreement of data pairs from two methods of measurement, the correct statistical approach is not obvious. Often researchers use Pearson's correlation coefficient (PCC); however, it quantifies linear correlation, not agreement. As examples to illustrate this, one can envisage situations where the second method either consistently overestimates values by an additive constant (location shift) or a multiplicative factor (scale shift) or both, which still yield a perfectly linear correlation. Aside from this, results of two techniques measuring the same data will almost always be linearly correlated. In addition, PCC tends to be greater, if the range of the true quantity in the sample with a wide range of data, a highly significant correlation is almost guaranteed. The arguments speaking against PCC apply even more to Spearman's rank correlation coefficient, which was used in one of the studies [27] summarized in this review.

Testing the equality of the mean, e.g. by Student's t-test, is another insufficient way to verify agreement. It is merely able to detect whether the lack of accuracy of a method (i.e. its bias) is significantly worse than its lack of precision.

In order to cure the shortcomings of the mentioned analyses, several approaches have been proposed. An example is the concordance correlation coefficient, a more suitable recast of the PCC [28]. Most of the studies cited in this review, however, either simply itemize mean and standard deviation of the differences between ECG and pulse measures, or make use of the approach suggested by Bland and Altman [29]. In the latter, one plots the differences between the two methods versus the average as the best estimator of the true value. Even when one technique is considered as the gold standard, the average values should be plotted at the abscissa

Table 4
Survey of studies on the accuracy of PRV compared to HRV. For analysis methods and results cf. Table 5.

Study	N and type of subjects	Experimental posture or conditions	Number of records × duration	Device(s) used	Sampling rate	Position of sensor
Photoplethysmographic studies						
Chang et al. (2007) [104]	$N = 10$ (healthy men, ages 25–35)	Rest in chair	Not specified ('high quality' signals > 1 min)	Biopac MP30 + SS4L PPG sensor (860 nm)	250 Hz	Index finger
Charlot et al. (2009) [59]	$N = 9$ (healthy men, ages 26.3 ± 4.5)	3 sympathetic stimulations: orthostatic test, slow walk, bicycle exercise in supine pos.	9 × (10 + 20 + 20) min	Biopac PPG100C amplifier + MP150 + TSD123B transducer	1000 Hz	Left finger
Giardino et al. (2002) [52]	Exp. 1) $N = 16$ (healthy, ages 23–35)	Exp. 1) rest in chair	Exp. 1) 16 × 5 min	1) Beckman RM Dynograph	Exp. 1) 1000 Hz (downsampled to 10–100 Hz)	Left middle finger
	Exp. 2) $N = 10$ (healthy, ages 25–50)	Exp. 2) mental exercise tests	Exp. 2) 10 × 26 min	2) Flexcomp Biomonitoring System 1.5B	Exp. 2) 991 Hz	
Gil et al. (2010) [56]	$N = 17$ (healthy, ages 28.5 ± 2.8)	Tilt table: supine–head-up tilt–supine	17 × (4 + 5 + 4) min	Biopac PPG100C amplifier + TSD 200 transducer	250 Hz (interpolated to 1000 Hz)	Index finger
Hayano et al. (2005) [55]	$N = 30$ (healthy, ages 22–47)	Night sleep (otherwise no stable pulse detection by device)	30 × 6.0 ± 0.8 h of night sleep	DENSO "Prototype C"	20 Hz	Dorsal side of wrist
Khandoker et al. (2010) [105]	$N = 29$ (healthy, ages 51.3 ± 8.5) + 22 (OSA, ages 54.9 ± 16.3)	Night sleep	Night sleep records, 1724 × 2 min epochs used	Nellcor N-100 pulse oximeter	128 Hz (reconstructed at 2092 Hz)	Finger
Lu et al. (2008) [57]	$N = 10$ (healthy, ages 26 ± 7.5)	10 min in upright pos., 10 min in supine pos.	10 × (10 + 10) min	Nellcor MP506 pulse oximeter module	400 Hz	Not specified
Lu et al. (2009a) [58]	$N = 42$ (healthy, age 21 ± 3)	Semi-recumbent rest	42 × 7 min	Feedback Instruments PPG transmission sensor PS-2105	100 Hz	Left earlobe
Nilsson et al. (2007) [67]	$N = 48$ (healthy, ages 20–68)	Lying semi-erect in hospital bed	48 × 10 min	Various PPG sensors linked to a A/D converter in a PC	66 Hz	Index finger, medial forearm, wrist, shoulder, forehead
Rauh et al. (2004) [27]	$N = 44$ (healthy, ages 16–60)	Rest in chair; 3 min of spontaneous and controlled breathing, respectively	44 × 6 min	ADInstruments PowerLab410	400 Hz	Ear lobe
Selvaraj et al. (2008) [53]	$N = 10$ (healthy, ages 21–28)	Rest (not otherwise specified)	10 × 5 min	BIOPAC transducer TSD200	1000 Hz	Right middle finger
Shi et al. (2008) [54]	$N = 14$ (healthy, ages 25.8 ± 4.2)	Supine rest	14 × 10 min	ADInstruments ML305	1000 Hz	a) Left ear lobe b) Index finger
Wong et al. (2010) [65]	$N = 15$ (healthy, ages 23–38)	Supine rest	15 × 6 min 15 × 4 min 1 × 5 h of night sleep	Infrared PPG sensors (850 nm)	1000 Hz	a) Finger clip b) Contactless sensor in a mattress
Continuous blood pressure (CBP) studies						
Carrasco et al. (1998) [42]	$N = 10$ (healthy, ages 22.5 ± 1.6)	a) supine b) supine and controlled breathing c) standing d) exercise e) recovery	$N = 10$, a)–e) 5 min each → 50 × 5 min	Ohmeda Finapres 2300	Not specified: used IHR as provided by Finapres device	Middle finger
Constant et al. (1999) [43]	$N = 20$ (10 children with pace-maker and 10 controls, both aged 6–13)	a) supine b) orthostatic 1 min spontaneous, 4 min controlled breathing	a) 20 × 5 min b) 20 × 5 min	Ohmeda Finapres 2300	500 Hz	Right middle finger
Dawson et al. (1998) [44]	$N = 20$ (healthy, ages 22–75)	Supine rest	20 × 3 × 5 min	Ohmeda Finapres 2300	200 Hz	Right middle finger
McKinley et al. (2003) [46]	$N = 234$ (patients from multiple studies, various age ranges)	Supine or sitting rest, various physical or mental tasks	Various records, subdivided into 4 min epochs	Ohmeda Finapres 2300	500 Hz	Finger
Suhrbier et al. (2006) [47]	$N = 9$ (patients with dilated cardiomyopathy, ages 45.1 ± 7.3)	Supine rest	9 × 10 min	Colin-System	1000 Hz	Not specified
Impedance plethysmography (IP) studies						
Kristiansen et al. (2005) [48]	$N = 20$ (healthy, ages 19–51)	Rest in chair	20 × 10 s	Self-made handheld device	1000 Hz	Radial artery
Treo et al. (2005) [49]	$N = 40$ (hospital outpatients)	Supine rest. Supradiastolic and subsystolic occlusion, followed by release period.	40 × 5 min (randomly selected 40 × 30 s analyzed)	Biopac AcqKnowledge II	200 Hz	Radial artery

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