

Wearable Photoplethysmography Devices

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Abstract

The wearables market has expanded greatly in recent years, with wrist-worn devices now widely used. Smart wearables provide opportunity to monitor health and fitness in daily life. Wearables such as fitness bands and smartwatches routinely monitor the photoplethysmogram (PPG) signal, an optical measure of the arterial pulse wave which is strongly influenced by the heart and blood vessels. This Chapter presents a comprehensive overview of the state-of-the-art of wearable photoplethysmography devices. It summarises: (i) key considerations in the design of wearable PPG devices; (ii) the physiological parameters that can be estimated from wearable PPG signals; (iii) commercially available devices; and (iv) potential applications in health and fitness monitoring.

Index Terms

blood volume pulse, cardiovascular, fitness, health monitoring, photoplethysmogram, pulse wave, sensor, signal processing, smartwatch, wearables, wellbeing, wristband

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1. INTRODUCTION

The growing use of smart wearables which measure the photoplethysmogram (PPG) provides a wealth of opportunities to monitor health and fitness in daily life. Wearables are becoming more widely used, ranging from fitness bands to smart rings. It has been estimated that by 2022 there will be over 1 billion wearables globally [1], and annual spending on wearables will exceed \$80 billion [2]. The growth in wearables is expected to be increased further by their potential for remote monitoring during the COVID-19 pandemic [3]–[5]. Initially, most wearables were used for electrocardiogram (ECG) or activity monitoring, whereas nowadays many smart wearables include a PPG sensor. Early examples of PPG-based wearables include the Mio Alpha (Mio Global, Canada) and Schosche myRhythm (Schosche Industries, CA, USA) devices [6], both of which appeared in early 2013.

The PPG signal is an optical measure of arterial blood volume. In wearable devices it is typically measured by shining a light on to the skin, and measuring the amount of light reflected back from the skin. The resulting signal is dominated by a pulse wave due to the change in blood volume with each heartbeat (see Fig. 1). Many consumer devices use the PPG for heart rate (HR) monitoring. As well as the heart, the PPG is also influenced by the vascular, respiratory and autonomic nervous systems. Consequently, a range of physiological parameters can be estimated from the PPG, which in the future could facilitate extensive, unobtrusive health monitoring.

1.1. Overview

This chapter provides a comprehensive overview of the state-of-the-art of wearable PPG-based devices, and highlights areas for future research to realise their full potential. It covers the following aspects of wearable photoplethysmography devices:

Hardware configurations: Wearable photoplethysmography devices are now widely available in a variety of hardware configurations. Section II summarises key hardware considerations: measurement site, sensor design, and the optional acquisition of simultaneous signals. When designing wearable devices it is important to consider the hardware configuration in the context of the device’s intended application, as different configurations are most suitable for different applications.

Physiological parameters: Several physiological parameters can be estimated from wearable PPG signals, although only a minority of these are currently provided by wearables. Section III summarises these parameters, describing the techniques used to estimate them, and highlighting pressing areas for future work in order to refine them for use in wearables in daily life.

Commercially available devices: A wide range of PPG-based wearables are now commercially available. Section IV provides an overview of the devices, focusing on their form factors, functionality.

Applications: Wearable PPG devices could potentially be used for applications in health and fitness monitoring. Section V presents several applications, including the background to each application, the PPG-based approaches used for each application, and areas for future work.

The chapter concludes that PPG-based wearables hold great promise for monitoring health and fitness in daily life, with several potential applications. However, further work is required to ensure that the full potential of wearables is realised, as outlined in Section VI.

1.2. Recommended reading

This Chapter builds on a recent review of wearable photoplethysmography for cardiovascular monitoring [7], which provides complementary information on: the origins of the PPG signal, PPG signal processing techniques, PPG-derived parameters, clinical applications, and an in-depth discussion of future research directions.

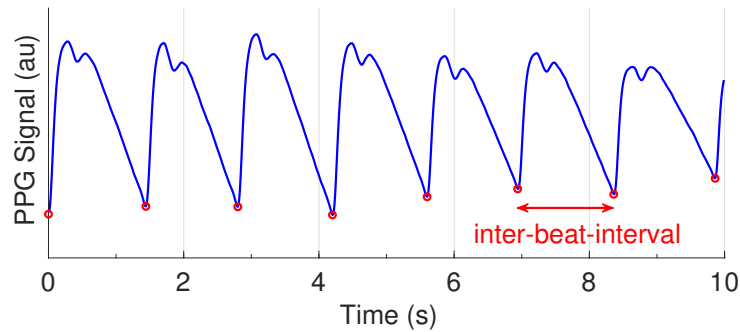


Fig. 1. The PPG signal: An example of a PPG signal acquired in daily life, with red circles indicating individual pulse waves corresponding to heart beats. Signal acquired at the finger, and measured in arbitrary units (au).

Source: [8] under [CC BY 4.0](#). Data from the PPG Diary Pilot Study 1 dataset [9].

2. HARDWARE CONFIGURATIONS FOR WEARABLE PHOTOPLETHYSMOGRAPHY DEVICES

Wearable photoplethysmography devices are now widely available in a variety of hardware configurations. This Section outlines important factors in hardware design. These factors should be considered alongside the intended application, as the hardware configuration can influence the utility of the acquired PPG signal for estimating physiological parameters. Herein, wearables are defined as devices which attach to (and can be detached from) the body, acquire physiological measurements, and are physically disconnected from the external environment [10].

2.1. Measurement site

Wearable PPG devices can acquire PPG signals at a range of anatomical sites. The choice of PPG measurement site can influence both the utility of the acquired PPG signals, and the user acceptability of the wearable device. The shape of PPG pulse waves differs between sites [11], [12], as shown in Fig. 2 (a). This may affect the utility of the pulse wave for physiological parameter estimation using pulse wave analysis. The pulse arrival time (PAT, the time delay between ventricular contraction and PPG pulse wave arrival) is greater at sites further from the heart such as fingers or toes [11], which may influence the utility of PAT measurements. Finally, the form of devices naturally differs between measurement sites, ranging from wristbands to armbands, earbuds to glasses, and therefore the choice of site may influence user acceptability. Fig. 3 shows several examples of PPG-based wearables worn as a headband, armband, and wrist watches.

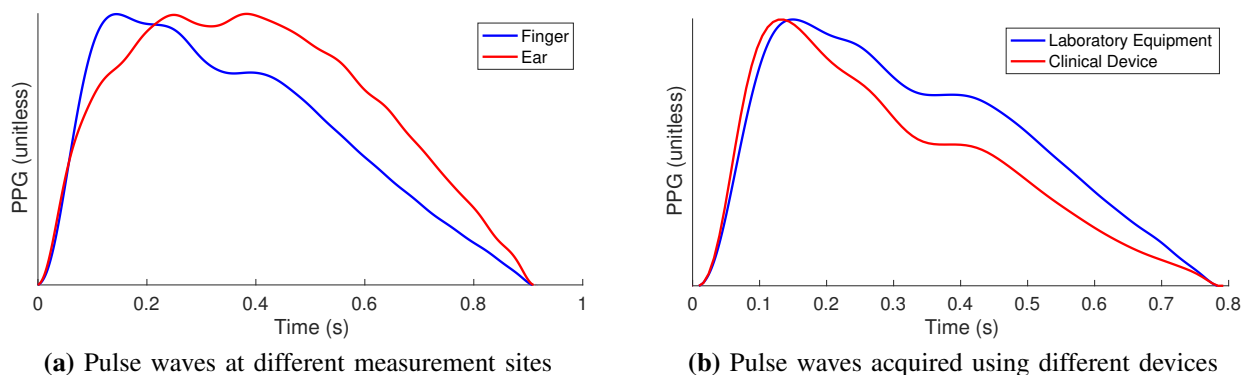


Fig. 2. The influence of hardware configuration on PPG pulse wave measurements: Examples of the influence of hardware configuration on PPG pulse wave shape. (a) shows a comparison of finger and ear pulse waves; (b) shows a comparison of pulse waves acquired using laboratory equipment and a clinical monitor. Signals were recorded simultaneously from a young healthy subject (and subsequently time-aligned by pulse onset).

Source: [13] under [CC BY 4.0](#). Data from the Vortal dataset [14].



Fig. 3. Wearable photoplethysmography devices: Examples of wearables which measure the photoplethysmogram (PPG) signal, shown from above and the sensor side (below).

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The following measurement sites are suitable for wearable devices:

2.1.1. Finger: Smart rings are now commercially available which acquire PPG signals at the finger [16]. The PPG sensor can be placed on the underside of the finger in order to obtain a reflectance PPG signal from as close as possible to the main arteries in the finger. Pulse oximeters typically acquire transmission PPG signals at the finger, and much research has been conducted using PPG signals acquired at the finger [17], particularly as the PPG signals in the widely used MIMIC Database [18] are mostly measured at the finger.

2.1.2. Wrist: Fitness bands and smartwatches acquire PPG signals at the wrist. The PPG sensor is typically housed within the same unit as the display, and typically acquires reflectance signals at the upper wrist. The major arteries of the wrist are located on the lower wrist, centimetres from the typical measurement site, indicating that the PPG signal at the upper wrist likely originates from the microvasculature rather than the major arteries. Indeed, PPG signals acquired close to the major arteries of the wrist have been found to have much higher signal-to-noise ratios than those acquired at the upper wrist [19]. The shape and amplitude of PPG pulse waves has been observed to differ between the finger and wrist [20]. Nonetheless, wrist PPG devices mounted on the upper wrist can provide accurate HR measurements [21].

2.1.3. Arm: Armbands can be used to acquire reflectance PPG signals at the upper arm [22], [23], although this approach is not yet widely used in consumer devices. The arm may be less susceptible to motion artifact than more peripheral sites such as the finger or wrist [24].

2.1.4. Ear: The ear has the potential advantage of being less prone to motion artifact [25]. Wearable PPG devices at the ear can take several forms. Firstly, earring sensors can be used to obtain PPG signals from the earlobe [25]. Secondly, sensors have been applied to the skin immediately behind the ear using a wrap around ‘ear cup’ system [26]. Thirdly, earbud sensors can be used to obtain PPG signals at the inner ear [27], [28], with the potential advantages that this site is less prone to vasoconstriction than peripheral sites [29], and that noise can be removed through simultaneous acquisition of PPGs using an earbud in each ear [27].

2.1.5. Chest: Chest-worn devices, potentially attached via a chestband or adhesive patch, can acquire PPG signals [30]. The chest is an ideal location for acquiring electrocardiogram and seismocardiogram signals, indicative of

heart activity.

2.1.6. Face: Smart glasses have been designed to acquire PPG signals at either the nose bridge [31] or the temple [32]. It may be beneficial to acquire PPG signals at the temple during exercise as HRs derived from PPG signals at the temple can be more accurate than those acquired at the wrist [33].

2.2. Sensor design

There are several options to consider when designing a PPG sensor for a wearable device, all of which can influence the utility of the measured PPG signal. This is demonstrated in Fig. 2 (b), which shows PPG pulse waves acquired simultaneously from adjacent fingers on the same hand using two different devices: the pulse wave shape differs, indicating that the hardware configuration could influence parameters extracted from the pulse wave shape. These hardware options are now considered in turn.

2.2.1. Transmission and reflectance photoplethysmography: Wearable PPG devices use either transmission or reflectance photoplethysmography. In transmission photoplethysmography light is shone onto an extremity (e.g. finger, toe or earlobe), and the amount of light transmitted through the extremity is measured using a photodetector on the opposite side. Consequently, transmission photoplethysmography can only be used at limited anatomical sites where a photodetector can be placed opposite the light emitting diode (LED), such as the finger, toe or earlobe. In reflectance photoplethysmography light is shone onto the skin, and the amount of light reflected back is measured using a photodetector positioned close to the emitting LED. Reflectance photoplethysmography can be used at additional sites such as the wrist, arm or chest. It has been observed that reflectance photoplethysmography provides a higher signal-to-noise ratio at the fingertip than transmission photoplethysmography, indicating that the reflectance mode should be used in wearables [34].

Further details of transmission and reflectance photoplethysmography are provided elsewhere in this book: see Chapter 2 "Light Tissue Interaction in PPG" and Chapter 3 "PPG Technology" for details.

2.2.2. PPG wavelength: The wavelength of light used to acquire signals affects the resulting PPG measurement [35]. Wearable devices typically use infrared (longest wavelength), red, or green (shortest wavelength) light. The longer the wavelength of transmitted light, the greater the depth to which the light penetrates into the body [36], so green light penetrates less deeply than red and infrared light [37]. Consequently, red or infrared light is typically used for transmission photoplethysmography. In contrast, green light has been found to provide a higher signal-to-noise ratio than red or infrared light in reflectance photoplethysmography [34], [38], and to be more robust to changes in temperature [39]. Indeed, Apple Watches equipped with LEDs of multiple wavelengths (green, red and infrared) can switch between using infrared light for HR monitoring at rest, and green light during exercise [40]. The wavelength of light can also influence the shape of the acquired PPG waveform (see Fig. 1 of [41]). The wavelength of light has been investigated as a factor in ensuring that PPG sensors perform well across different skin types [38]. Reassuringly, research to date has found the performance of certain PPG-based wearables not to be affected by skin type [42], [43].

2.2.3. Multiple PPG signals: Recently, PPG sensors have been designed to acquire multiple PPG signals at a single site in order to reduce the influence of noise or provide additional physiological information. Multiple PPG signals acquired at a single site can be used to assess signal quality by assessing the level of similarity between the signals. Multiple PPG signals can also be used for noise reduction by: identifying the highest quality signal and discarding the others; extracting a composite signal as a sum of the individual signals weighted according to their quality [19]; or using multichannel decomposition to extract significant signal components by exploiting information from all of the signals [44]. Multiple PPG signals of different wavelengths can be used to obtain PPG signals corresponding to different levels of the vasculature, such as the capillaries, arterioles and arteries, which can be used to estimate parameters such as the arteriolar pulse transit time (PTT) [41]. In addition, it has been proposed that an infrared PPG signal can serve as a reference motion signal in order to reduce the influence of tissue deformation on green PPG signals [45].

2.2.4. Sampling frequency: Wearable devices typically sample the PPG at between 50 and 100 Hz [46], [47]. However, studies have shown that HR can be estimated from PPG signals sampled at 9 Hz [48], pulse rate variability can be accurately assessed from PPG signals sampled at 25 Hz [49], respiratory rate can be accurately estimated using a sampling frequency of 16-18 Hz [14], [48], and generally PPG features can be accurately measured at sampling frequencies of at least 60 Hz [38]. Therefore, a relatively low sampling frequency may be acceptable for many applications.

2.2.5. PPG bandwidth: The bandwidth of PPG signals affects their potential utility for parameter estimation. It is beneficial to strongly filter PPG signals prior to HR estimation, using a narrow bandwidth corresponding to the range of plausible HRs such as 0.4-2.25 Hz [50]. This narrow range ensures that most irrelevant content is eliminated, such as low frequency variations due to respiration, and high frequency noise. Having a narrow range can assist with HR and SpO₂ estimation [51]. However, the frequency content of PPG signals outside of this narrow range is required for estimating other physiological parameters. A higher low-pass cut-off is required to preserve high frequency content so that fiducial points on PPG pulse waves can be accurately identified, which can be set as low as 5 Hz for detecting pulse troughs for inter-beat-interval calculation [52], but must be much higher (*e.g.* 20 Hz [53]) to locate fiducial points accurately enough to measure pulse wave features. Similarly, a lower high-pass cut-off of approximately 0.05 Hz may be required to ensure pulse wave features are faithfully reproduced [54], and that all respiratory content is preserved [55]. Consequently, wearable devices may need to apply different filters to the signal for different purposes.

2.2.6. Measurement frequency and battery life: PPG sensors consume substantial power which can reduce the battery life of wearables [56]. Therefore, rather than continuously monitoring PPG signals, it may be beneficial to turn on PPG sensors either intermittently, or only during periods of low activity. One approach to maintain PPG monitoring whilst reducing power consumption is to only activate the PPG sensor during periods of low activity, since PPG signals are typically of low quality during periods of high activity [8]. This can be achieved by using an accelerometer, which consumes much less power than a PPG sensor, to measure activity levels. Indeed, some wearables now adopt this approach [57]. An alternative approach is to turn off the PPG sensor after a high quality signal segment has been obtained, and to only turn it on again after a certain delay [58]. Such strategies will help ensure that PPG-based wearables are acceptable to users, without requiring too frequent battery charging.

2.2.7. LED driving schemes and power consumption: A key factor in determining the power consumption of a PPG sensor is the proportion of time for which the LED is illuminated [59]. Typically, the LED is duty-cycled, meaning the PPG signal is uniformly sampled by illuminating the LED at a regular sampling frequency [60]. Both the sampling frequency and the duration of time for which the LED is illuminated when taking each sample are a compromise between power consumption and signal fidelity (which influences the accuracy of derived parameters [59]). Alternative approaches have been proposed which use non-uniform sampling to reduce power consumption [60]. Firstly, compressive sampling can be used to reduce the number of samples per pulse wave and still maintain accurate analyses by exploiting the sparseness of the PPG pulse wave [61]. Secondly, windowing can be used to only sample the PPG at points of interest during the pulse wave, such as around the expected time of pulse wave peaks for inter-beat-interval analysis [60]. The appropriate scheme for driving an LED should be chosen with the intended analyses in mind.

2.3. Additional signals

Many wearable devices acquire additional signals which can be used with the PPG to provide improved physiological monitoring. Fig. 4 shows four additional signals which are commonly acquired by wearables, and are now described.

2.3.1. Electrocardiogram: The electrocardiogram (Fig. 4(a)) is a measure of the heart's electrical activity which can be measured by smart wearables either continuously or when activated by the user. The ECG can be monitored continuously between two skin electrodes measuring the potential difference caused by myocardial activity. The signal-to-noise ratio of the ECG tends to be higher when the separation of the electrodes in relation to the heart is greater. For instance, the signal-to-noise ratio is greater when the ECG is measured at the chest, or at two arms (providing a view across the heart), and significantly lower when measured with both electrodes on a single arm [65]. The ECG can also be acquired intermittently when activated by the user of a device (such as a smartwatch) which has one electrode constantly in contact with the skin (typically on the underside of the watch), and a second electrode which the user touches with their opposite hand [66]. An ECG can be recorded for as long as the user has their opposite hand on the device. The inclusion of ECG technology into PPG-based wearables could enhance the utility of the PPG-based wearables. For example, if an irregular heart rhythm is detected then the user could be prompted to record an ECG which could be used to confirm a diagnosis (such as atrial fibrillation). In addition, intermittent pulse arrival time (PAT) measurements could be obtained from simultaneous ECG and PPG measurements, which could be used for blood pressure (BP) estimation.

2.3.2. Accelerometry: Accelerometers measure static and dynamic acceleration. Due to their power efficiency and low price they are already used in the majority of wearables for step counting and recognising some activities (such as walking). Accelerometry signals (Fig. 4(b)) can also be used to improve parameter estimation from the PPG.

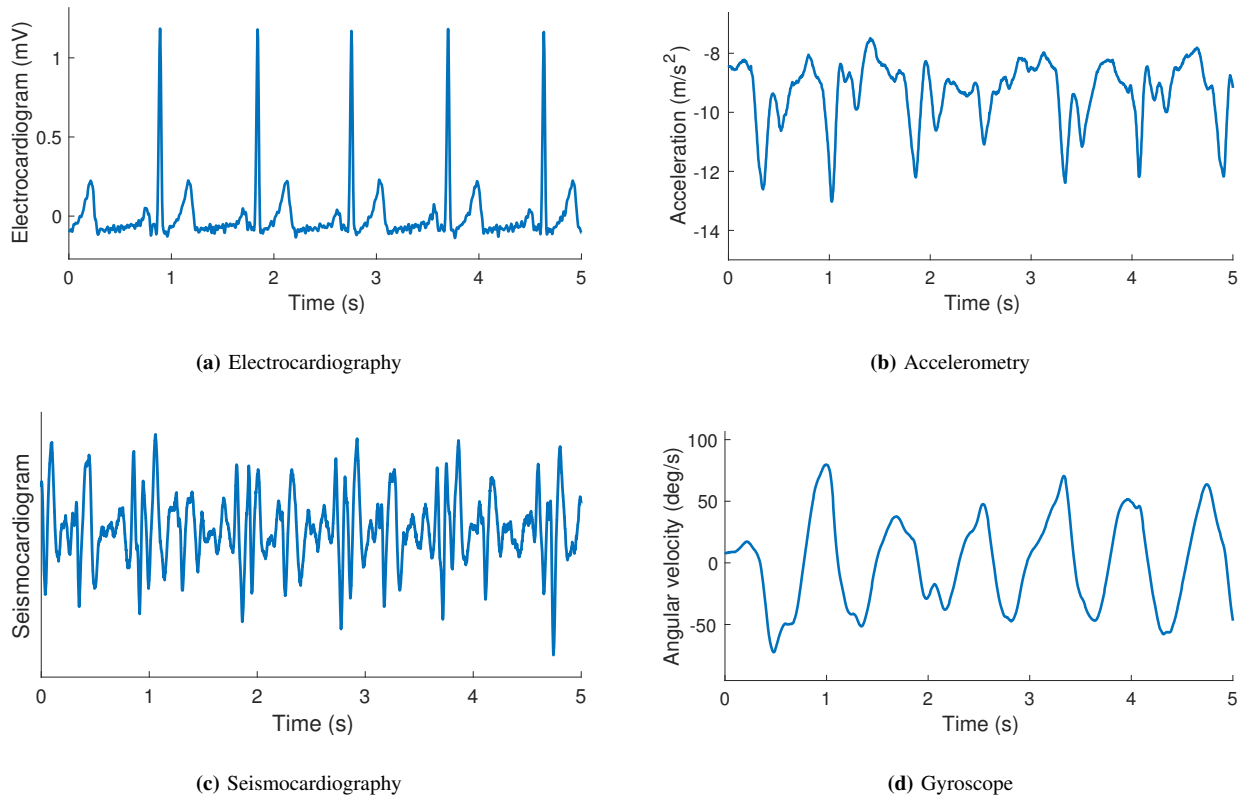


Fig. 4. Additional signals acquired by smart wearables: Smart wearables commonly acquire additional signals simultaneously with the PPG. This figure shows examples of: (a) an electrocardiogram (ECG) signal, a measure of the heart's electrical activity dominated by heart beats approximately once per second; (b) an accelerometry signal indicating the level of movement, and used for step counting; (c) a seismocardiogram signal, a measure of surface vibrations which is dominated by heart activity when acquired at the chest; (d) a gyroscope signal indicating rotation of the device.

Source: [13] under [CC BY 4.0](#). All signals from PhysioNet, reproduced under [ODC-BY 1.0](#). [62]. (a) and (c) are from the CEBS database [63]; (b) and (d) are from the Wrist PPG During Exercise database [64].

Firstly, accelerometry signals can be used to reduce noise in PPG signals by cancelling noise which is common to both accelerometry and PPG signals [67]. Secondly, accelerometry can be used to identify periods when activity levels are too high to estimate parameters reliably from PPG signals. Thirdly, accelerometry could be used to contextualise PPG-derived parameters according to the activity in which they were recorded, as accelerometry can be used to infer body position (*e.g.* lying or standing), and could be used to identify a wide range of activities of daily living [68].

2.3.3. Seismocardiography: The seismocardiogram (Fig. 4(c)) is a measure of surface vibrations acquired by an accelerometer in contact with the skin. It can be particularly informative when measured at the chest, where it is influenced by heart activity and can be used to identify the times of ventricular ejection [69]. Pulse transit time can be calculated from the PPG and the seismocardiogram [70], with potential utility for BP monitoring.

2.3.4. Gyroscope: Gyroscopes measure angular velocities around orthogonal axes and thus are suitable for capturing rotational movements. This feature can be used for adaptive motion artifact cancellation from PPG signals [71]. In addition, gyrocardiography was recently proposed as a noninvasive monitoring method for the assessment of cardiac mechanics [72].

It has also been proposed that skin conductance measurements could be used to assess the quality of contact between the skin and a wearable sensor [73]. Some wearables include a galvanic skin response sensor, which whilst commonly used to assess emotions, could also be used to assess skin contact, allowing PPG signals acquired during poor skin contact to be rejected.

3. PHYSIOLOGICAL PARAMETERS

Several physiological parameters can be estimated from the PPG, and potentially many of these could be integrated into wearables. At present, HR is the parameter most commonly estimated from the PPG by wearables. Other parameters such as BP and respiratory rate (RR) are provided by some wearables, whilst the many of the parameters proposed in the literature have not yet been incorporated into wearables. Techniques for estimating key physiological parameters from the PPG are now described.

Further details relating to some of the parameters are provided elsewhere in this book: see primarily Chapter 4 "PPG Signal Analysis and Synthesis", as well as Chapter 5 "PPG in Oxygenation", Chapter 9 "PPG in Autonomic Function", and Chapter 12 "PPG in Noninvasive Cuff-less BP Monitoring".

3.1. Heart rate (HR)

The PPG signal is dominated by pulse waves generated by the ejection of blood from the heart during each heartbeat. Consequently, most PPG-based wearables provide HR measurements. HR is typically estimated from the PPG in four steps [74]:

- 1) The PPG signal is band-pass filtered to eliminate frequency content outside of the range of plausible HRs.
- 2) Motion artifact is removed from the PPG, potentially with the aid of accelerometry signals.
- 3) An initial HR estimate is obtained by analysing the frequency spectrum of this processed PPG signal.
- 4) A tracking algorithm is used to track HR estimates over time, helping to eliminate erroneous HRs.

It is relatively straightforward to estimate HR from a high quality PPG signal in the absence of movement. However, the task is altogether more challenging during exercise which can cause substantial movement artifact in the PPG [75]. This is demonstrated in Fig. 5: at rest (upper row) the dominant peak in the PPG spectrum coincides with the dominant peak in the ECG spectrum, indicating the true HR. HR estimation is more challenging in this example during walking (middle row): whilst there is a spectral peak corresponding to the true HR at ≈ 1.4 Hz, care must be taken not to identify the peaks at lower frequencies as the HR. The interested reader is referred to [76] for further details of the signal processing techniques used to remove motion artifact from PPG signals and track HRs during motion.

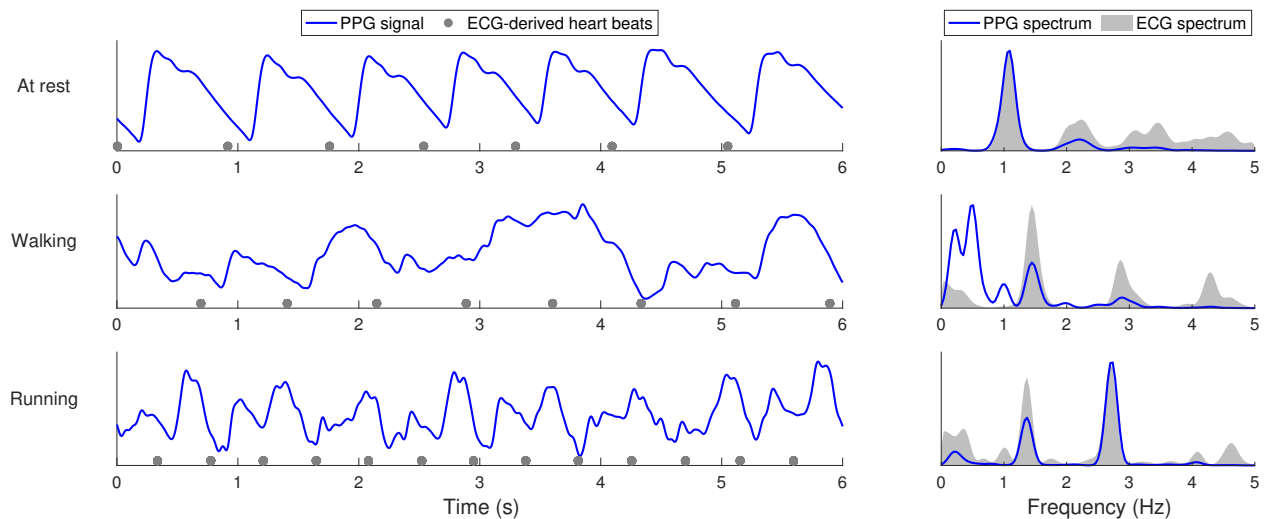


Fig. 5. PPG signals and corresponding frequency spectra: PPG signals acquired during rest, walking and exercise, shown alongside heart beats identified from a simultaneous chest ECG signal, and the corresponding frequency spectra of the PPG and ECG signals.

Source: [13] under [CC BY 4.0](https://creativecommons.org/licenses/by/4.0/). Data from the Vortal dataset [77].

A recent meta-analysis of studies of the performance of wrist-worn devices for HR monitoring found summary mean absolute errors of 2.15 (95% confidence interval 1.84 to 2.46) bpm during rest, compared to 7.70 (6.32 to 9.07) during treadmill activities [21]. Similar reductions in performance with exercise were reported in [42], and

differences in performance between brands were reported in [42], [78]. Future assessments of performance will benefit from recent recommendations for determining the validity of devices [79].

A key parameter derived from HR measurements is the resting HR. Resting HR varies greatly between individuals, and is a marker of cardiovascular risk [80], [81]. Resting HR varies with age [82], circadian rhythms [83], and across seasons [81]. In the future wearables could be used to track an individual's resting HR over time, with changes in resting HR potentially providing valuable insight into their health [84].

3.2. Identifying an irregular pulse

PPG-based wearables provide opportunity to detect an irregular pulse in daily life. Irregular heart beats are typically identified from a PPG signal segment as follows [57]:

- 1) Individual pulse waves corresponding to individual heart beats are identified.
- 2) Inter-beat-intervals are calculated from consecutive pulse waves, using a fiducial point such as the systolic peak.
- 3) The irregularity of inter-beat-intervals is assessed statistically, using a technique such as a Poincaré Plot [85].
- 4) If the level of irregularity exceeds a threshold then the segment is deemed to contain an irregular pulse.

This can be performed using segments of 1 minute duration [57], although it is possible to use this approach with shorter segments to identify possible arrhythmias [86]. Irregular heart beats can occur in healthy individuals without being a cause for concern. However, an irregular pulse can also be caused by arrhythmias such as atrial fibrillation, in which case it is clinically useful to be aware of it. Consequently, it may be helpful to only raise an alert of an irregular pulse if it is observed consistently over multiple recordings (as performed by the Apple Watch [57]). Techniques to identify atrial fibrillation from the PPG have recently been reviewed in [87], [88].

3.3. Arterial oxygen saturation (SpO_2)

Arterial blood oxygen saturation is the proportion of haemoglobin in the blood which is carrying oxygen. It is widely used in clinical practice, and denoted as SpO_2 when measured using pulse oximetry. SpO_2 can be estimated from two simultaneous PPG signals of different wavelengths as follows [89]:

- 1) Identify individual pulse waves in the two PPG signals.
- 2) Calculate the normalised AC component for each signal (defined as the total intensity of light at the systolic peak divided by the total intensity at the pulse onset).
- 3) Calculate the ratio of the normalised AC components for each signal.
- 4) Estimate SpO_2 from an empirical relationship between SpO_2 and the ratio of normalised AC components (see also [90]).

This approach can be aided by the use of a heart-rate tuned comb filter [91]. However, it is difficult to obtain reliable estimates of SpO_2 in the presence of motion artifact. An alternative approach is used in Masimo pulse oximetry which is designed to be more robust during motion and poor tissue perfusion [92], although it is more computationally complex [91].

The accurate estimation of SpO_2 requires consideration of several aspects of wearable design. Firstly, PPG wavelengths should be carefully chosen by considering the absorption spectra of oxygenated and deoxygenated haemoglobin. Secondly, when using reflectance mode photoplethysmography, the spacing between the LED and photodetector in the PPG sensor should be positioned far enough apart to obtain sufficient signal quality [93]. Thirdly, it is important that good skin contact is maintained during SpO_2 measurements, noting that contact pressure might be influenced by body position [94]. There is potentially great benefit in monitoring SpO_2 , particularly to identify obstructive sleep apnea and as a potential indicator of COVID-19 [95].

3.4. Respiratory rate (RR)

RR, the number of breaths per minute, is used in clinical practice as a marker of illness. Much research has focused on developing algorithms to estimate RR from the subtle modulations to the PPG signal caused by breathing [55]. The three main modulations of the PPG due to breathing are baseline wander (BW), amplitude modulation (AM), and frequency modulation (FM) [77], [96], as illustrated in Fig. 6.

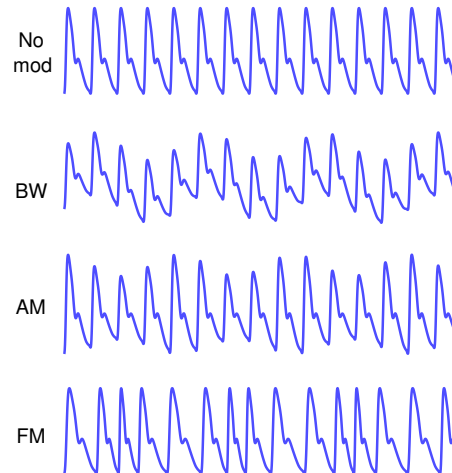


Fig. 6. The modulations of the PPG signal caused by breathing: baseline modulation (BW), amplitude modulation (AM) and frequency modulation (FM). Idealised modulations are compared to a signal with no modulation (No mod).

Source: [77] under [CC BY 3.0](#).

Respiratory rate can be estimated from the PPG by (see [77] for further details):

- 1) Identifying individual pulse waves.
- 2) Extracting pulse wave features indicative of a respiratory modulation, such as the amplitude of pulse waves (indicative of AM), or the inter-beat-intervals (FM).
- 3) Extracting a respiratory signal from the time series of features.
- 4) Estimating RR from the respiratory signal using either a time- or frequency-domain technique.
- 5) (optionally) Combining RR estimates derived from different respiratory signals.

There are challenges to estimating RR from wearable PPG signals, such as identifying the most appropriate respiratory signal(s) for use with the target population [14], only estimating RR when the respiratory modulations in the PPG are sufficiently strong [97], and avoiding erroneous detection of other low frequency phenomena rather than breathing [98]. Nonetheless, some wearables do now provide RR (see the Biostrap Evo). It could prove to be a helpful parameter for the detection and management of COVID-19 [95], [99].

3.5. Blood pressure (BP)

PPG-based wearables would be greatly enhanced if they could assess BP, since it is used for a wide range of clinical purposes. It may be feasible to assess BP from the PPG because it influences two aspects of the pulse wave: the shape of the pulse wave and the speed of its propagation from the heart to the periphery. A plethora of approaches to assess BP from the PPG have been proposed, mostly exploiting one or both of these phenomena. Firstly, BP can be assessed from the shape of the pulse wave and its derivatives [100] (see [101], [102] for lists of PPG features). Secondly, BP can be assessed from the pulse arrival time measured between a marker of cardiac contraction (such as the QRS complex of the ECG) and the subsequent PPG pulse arrival [11], [103]. Thirdly, BP can be assessed from the pulse transit time between PPG pulse waves measured closer to, and further away from, the heart [104]. Machine learning has been widely used to develop techniques to estimate BP from PPG-based measurement [105]. It is challenging to assess BP from the PPG because: changes in BP may have only a relatively small effect on the PPG; the nature of the effect of BP on the PPG is partially subject-specific; and, other cardiovascular properties (such as arterial stiffness) can cause similar changes to the PPG. Consequently, PPG-based devices may require calibration with reference BP measurements in order to monitor BP (see the Samsung Galaxy Watch3). In addition, manufacturers may decide to only assess changes in BP (or the direction of BP changes), rather than absolute values [106].

3.6. Sleep assessment

Wearables are extensively used for sleep assessment, based primarily on monitoring activity levels (actigraphy) [107]. PPG-based wearables which also include an accelerometer provide opportunity to enhance sleep assessment

through the inclusion of HR and PRV analysis. Indeed, consumer PPG-based wearables have been found to identify periods of wake and sleep with a performance similar to, or better than, research-grade actigraphy devices [107], [108]. Error rates vary considerably between PPG-based wearables [109]. Further research is required to determine whether sleep stages can be accurately classified using PPG-based wearables [110].

3.7. Energy expenditure (EE)

Energy expenditure (EE) is now measured by some PPG-based wearables. EE primarily consists of three components [111], [112]: basal (*i.e.* baseline) EE, the thermic effect of feeding, and energy expended from physical activity. The most important component to monitor is that relating to physical activity, since it accounts for the most variable portion. On the other hand, basal EE can be predicted from age, sex and height [112], and the thermic effect of feeding is relatively small. Energy expended from physical activity can be estimated from HR, which indicates the intensity of exercise [113], [114]. This is based on the assumption of a linear relationship between HR and oxygen consumption, which can be considered consistent for an individual performing submaximal activities [115]. However, the true relationship varies between individuals and between exercise types. Furthermore, care must be taken not to include periods of rest and light activity in calculations of energy expended from physical activity, since the relationship does not hold in these cases. The accuracy of EE estimates has been questioned [116], [117], and none of the wearables included in a recent systematic review were found to accurately estimate EE [78].

3.8. Maximal oxygen consumption

The maximum rate of oxygen consumption during exercise (denoted $\dot{V}O_{2\max}$) is an important marker of cardiorespiratory fitness [118]. Broadly, two approaches are taken to estimate $\dot{V}O_{2\max}$. The first consists of estimating $\dot{V}O_{2\max}$ from an individual's resting HR and maximum HR (the maximum possible HR for an individual, which can be estimated as a function of gender and age [119]). The second approach is based on the relationships between oxygen consumption and running speed, and between running speed and HR [120]. HR and speed measurements are obtained during exercise, and used to derive a relationship between HR and running speed for the individual. This relationship is then extrapolated to calculate a maximal running speed corresponding to the maximal predicted HR [120]. Finally, $\dot{V}O_{2\max}$ is estimated from the maximal running speed [120]. Devices such as Fitbits estimate $\dot{V}O_{2\max}$ from HR, speed (obtained via GPS), resting HR, and demographics [118]. Studies of the accuracy of $\dot{V}O_{2\max}$ estimates provided by PPG-based wearables have reported mixed results [116], [118], [121], [122]. In the future it will be important to assess whether this approach has utility in subjects who do not or cannot run [118].

3.9. Pulse rate variability (PRV)

PRV is the variability in inter-beat-intervals assessed from the PPG. PRV has several potential applications, including assessing mental stress levels, identifying sleep stages, and assessing cardiovascular health [123]. PRV is highly related to HR variability (HRV), the variability in inter-beat-intervals assessed from the ECG (the gold standard). However, PRV and HRV are not equivalent because they are caused by different physiological mechanisms [124]. A range of summary statistics can be used to quantify PRV and HRV from inter-beat-intervals [125]. The level of agreement between the PRV and HRV statistics is dependent on several technical factors. Firstly, PPG sampling frequency affects PRV measures [49], [126]. Secondly, interpolation of the PPG to higher sampling frequencies can improve agreement [126]. Thirdly, PRV has been found to agree more closely with HRV when calculated from the timings of particular fiducial points on the PPG (namely the middle-amplitude point, the apex point of the first derivative, and the tangent intersection point) [127]. In addition, agreement between PRV and HRV is dependent on several physiological factors [123]. Agreement tends to be higher when measurements are performed at rest than during exercise [124], [128]. In the future it will be important to determine the minimum duration of PPG signal required to accurately assess PRV so that it can be assessed during periods of low activity during daily living [129].

3.10. Arterial stiffness

Some PPG-based devices now offer an assessment of arterial stiffness (see Biostrap Evo's *Arterial Elasticity* and *Peripheral Elasticity* metrics). Such measurements are based on analysis of the shape of the PPG pulse wave. Several pulse wave features have been identified as potentially indicative of arterial stiffness [102], [130], based on similar physiological mechanisms to those exploited when assessing BP from a single pulse wave. Gold standard measurements of arterial stiffness are associated with cardiovascular events and all-cause mortality [131], as are features of the PPG pulse wave [132]. However, it is not yet clear how accurately arterial properties can be assessed from wearable PPG signals, and whether such measurements are indicative of cardiovascular risk.

4. COMMERCIALLY AVAILABLE DEVICES

This Section provides an overview of the wide range of commercially available PPG-based wearables. Many wearables are used alongside smartphone apps, which enable data storage, visualisation and analysis. Readers interested in apps for PPG-based wearables are referred to [133].

The consumer market for PPG-based wearables has exploded in recent years. Smartwatches, wristbands, smart rings, and ear buds are all widely available. Although not all consumer wearables use photoplethysmography, those which monitor HR invariably use photoplethysmography to do so, such as those shown in Fig. 7. The functionality of selected PPG-based wearables is summarised in Table I. This table provides an overview of the field, demonstrating the range of form factors taken by wearables, and parameters estimated by them. The list is by no means comprehensive: devices are shown from selected wearable manufacturers, and only one device is listed per manufacturer. Furthermore, the functionality of devices can be enhanced with software updates, or through use with additional apps. The interested reader is referred to [4], [134] for details of additional consumer devices. Devices which are not available to consumers are beyond the scope of this review (see for instance the CE-marked SOMNOtouch NIBP device [135] and the FDA-approved Biobeat watch [136]).



Fig. 7. PPG-based wearable devices: Examples of wrist-worn devices which measure the PPG signal. (clockwise from top left) The Max-Health-Band, Oura Ring, Amazfit Bip, Samsung Gear Galaxy S2, and Apple Watch.

Sources: (clockwise from top left) [13] under [CC BY 4.0](#); cropped from image by Marco Verch ([CC BY 2.0](#)) - [link](#); cropped image from [137] under [CC BY 4.0](#); cropped from image by GEEK KAZU ([CC BY 2.0](#)) - [link](#); cropped from image by Pixels ([Pixabay License](#)) - [link](#); cropped from image by Luke Chesser ([CCO 1.0](#)) - [link](#).

4.1. Form factors

PPG-based wearables take a variety of form factors and can be attached to different parts of the body. As shown in Table I, the vast majority of PPG-based wearables are worn on the wrist, either as a watch (with a larger screen), a band (with a smaller screen), or a strap (without a screen). Other form factors have emerged more recently, such as finger rings, ear buds and ear wrap arounds, ankle socks, and arm sleeves. In addition, the Polar OH1 sensor is a disk-shaped sensor which provides the user with flexibility to mount it anywhere on the skin, and comes with an armband and swim goggle attachment. Potential users have expressed a preference for wrist-worn devices over other form factors [138]. Nonetheless, there are advantages to other measurement sites (see Section II-A), and use cases

TABLE I

THE FORM FACTORS AND FUNCTIONALITY OF SELECTED PHOTOPLETHYSMOGRAPHY-BASED WEARABLES.
 Definitions: *accel* - accelerometry; *HR* - heart rate; *irreg.* - irregular pulse detection; *SpO₂* - arterial oxygen saturation; *RR* - respiratory rate; *BP* - blood pressure; *VO_{2max}* - maximum rate of oxygen consumption; *ECG* - electrocardiogram; *temp* - temperature.

Source: Adapted from [4], [13] under CC BY 4.0.

Wearable	Form factor	Parameters from PPG					Params from PPG & accel.			Others			
		HR	irreg.	SpO ₂	RR	BP	sleep	calories	VO _{2max}	ECG	steps	elevation	temp
Apple Watch Series 6	wrist watch	✓	✓	✓	×	×	✓	✓	✓	✓	✓	✓	×
Withings Scanwatch	wrist watch	✓	✓	✓	✓	×	✓	✓	✓	✓	✓	✓	×
Samsung Galaxy Watch3	wrist watch	✓	×	✓	×	✓	✓	✓	?	✓	✓	×	×
Fitbit Sense	wrist watch	✓	×	✓	✓	×	✓	✓	✓	✓	✓	✓	✓
Garmin Forerunner 945	wrist watch	✓	×	✓	✓	×	✓	✓	✓	×	✓	✓	✓
Amazfit GTR 2e	wrist watch	✓	✓	✓	×	×	✓	✓	×	×	✓	✓	✓
Huawei Watch GT2 Pro (ECG)	wrist watch	✓	×	✓	×	×	✓	✓	✓	✓	✓	✓	✓
Fossil Gen 5	wrist watch	✓	✓	×	×	×	✓	✓	✓	×	✓	✓	×
WHOOP Strap 3.0	wrist strap	✓	×	×	✓	×	✓	✓	×	×	✓	×	×
Ava Bracelet	wrist strap	✓	×	×	✓	×	✓	×	×	×	×	×	✓
Biostrap Evo	wrist band	✓	×	✓	✓	×	✓	✓	×	×	✓	×	×
Oura Ring	finger ring	✓	×	×	✓	×	✓	✓	×	×	✓	×	✓
Jabra Elite Sport	ear buds	✓	×	×	×	×	×	✓	✓	×	×	×	×
Bodytrak	ear buds + case	✓	×	×	×	×	×	✓	✓	×	×	×	✓
Cosinuss Two	ear wrap around	✓	×	✓	×	×	×	×	×	×	×	×	✓
Owlet Smart Sock Baby Monitor 3	ankle sock	✓	×	✓	×	×	✓	×	×	×	×	×	×
AIO Sleeve 2.0	arm sleeve	✓	×	✓	×	×	✓	✓	×	✓	✓	×	×
Polar OH1 Sensor	armband OR goggles	✓	×	×	×	×	×	×	✓	×	×	×	×

in which other form factors are advantageous. For instance: a sock may be more suitable for monitoring babies (see Owlet Smart Sock); ear buds may provide more reliable fall detection than devices attached at peripheral sites such as the wrist (see Bodytrak); and, an arm sleeve can incorporate an ECG electrode on the chest (see AIO Sleeve), which is not possible with many other form factors. Additional form factors have been used in devices sold to industry rather than consumers directly: the Equivital eq02+ LifeMonitor takes the form of a chest belt with shoulder straps, and the Spire Health Tag attaches to clothing. Other form factors have been investigated in research too, such as incorporating PPG sensors into arm bands and glasses [22], [31]. Whilst the wrist form factor dominates the market at the moment, the finger ring may become increasingly popular as it shares many of the same characteristics. Other form factors are likely to be more suitable for specific use cases.

4.2. Functionality

Wearables estimate several physiological parameters from the PPG signal. The PPG is widely used for HR monitoring, as shown by HR being provided for all of the devices in Table I. Some devices also capture the ECG either on demand or continuously, from which HR can be obtained. Since PPG sensors can provide frequent or continuous monitoring without the need for additional electrodes, it is likely that photoplethysmography will remain the dominant method for HR monitoring in consumer wearables. The remaining PPG-derived parameters are less widely calculated, and the technology for estimating these parameters is still in the development phase in many cases. Some devices use the PPG to identify irregular heart beats which may indicate arrhythmias. This approach has been shown to have utility in the Apple Heart Study [57], and is likely to become more widely used as shown by the Huawei Heart Study [139], FitBit Heart Study [140], and work on detecting atrial fibrillation by other manufacturers [141]. SpO₂ has recently become more widely measured, and is now offered by several wrist-worn devices. SpO₂ measurement has been facilitated by devices incorporating LEDs of multiple wavelengths (such as the Apple Watch Series 6 using red, green and infrared light). RR and BP are more difficult to estimate reliably from PPG signals, and are not yet widely offered. Approaches to overcome the challenges of monitoring these parameters include: monitoring RR at night when there is likely to be less motion artifact (see the Withings Smartscan's *Respiratory Scan* function) [8], [142]; and calibrating BP estimates with a traditional cuff measurement

(see the Samsung Health Monitor App). In the future PPG-based wearables might routinely measure many or all of the mentioned parameters, in a similar way to the current widespread measurements of HR.

Wearables also estimate some parameters through analysis of both the PPG and other signals. Sleep can be identified and assessed using both activity levels from accelerometry signals, and HRs from PPG signals. Indeed, since most wearables incorporate an accelerometer, most of those listed in Table I assess sleep. Similarly, most of the wearables assessed calories burnt, which can be estimated from activity levels with (in some cases) the additional use of HRs. $\dot{V}O_{2\max}$ can be estimated from HRs acquired during both rest and exercise [118], and several of the listed wearables do estimate $\dot{V}O_{2\max}$.

Wearables also provide further parameters derived from other signals. The recent addition of an ECG sensor to some wrist-worn devices provides opportunity to complement PPG-based assessments with ECG signals which could potentially be used for diagnostics. For instance, on detecting an irregular heart rhythm from a PPG signal, the user could be prompted to take a short ECG recording which could then be clinically reviewed. The use of accelerometry to identify exercise, and barometers to identify stair climbing [143], provides complementary information which can be used in conjunction with PPG-derived HRs to assess fitness. Finally, several wearables measure temperature which, if closely associated with body temperature, may be a helpful marker of illness [144]. When measuring temperature, the ear bud form factor may be advantageous as temperature measured in the ear may agree more closely with core temperature than measurements at other measurement sites.

4.3. Marketing models

Several different marketing models have been used to commercialise wearables. In most cases the consumer pays for the device upfront, and any necessary apps are provided by the manufacturer without charge (for instance, Withings' *HealthMate* app). An alternative approach is to use subscription charges, and provide the wearable to subscribers (see WHOOP membership). In addition, a hybrid approach can be used in which additional data analytics and visualisation functionality is enabled with a subscription (see Biostrap's *Sleep Lab*).

4.4. Batteries

The way in which the battery is incorporated into the device affects its usage. Most PPG-based wearables contain built-in batteries and so must be removed from the body for charging, resulting in periods of downtime. For instance, the Apple Watch is charged using a magnetic charging cable, the Oura Ring is charged using a dock, and the Fitbit Charge is charged using a cable with clip attachment. In contrast, the Equivital eq02+ LifeMonitor and WHOOP Strap have interchangeable battery packs, virtually eliminating downtime due to battery constraints.

5. APPLICATIONS

A wide range of applications have been proposed for PPG-based wearables. These range from clinical applications to fitness and lifestyle monitoring. The reader is referred to [7] for a discussion of several clinical applications. A few additional applications are now discussed.

5.1. Menstrual cycle monitoring

The ability to monitor the menstrual cycle and predict ovulation is valuable for family planning. The data acquired by wearables could be used for this purpose, particularly when measured whilst asleep. Temperature measured at the finger using an Oura Ring has been found to be useful for menstrual cycle monitoring [145], and temperature measured in the ear canal has been found to be useful for predicting ovulation [146]. In addition, PPG-derived parameters including HR, PRV, RR and skin perfusion have all been found to be useful for predicting the fertility window [147], [148]. Potentially, such parameters could be used in combination to track the menstrual cycle.

5.2. Identifying orthostatic hypotension

Orthostatic hypotension is a prolonged drop in BP upon standing of at least 20 mmHg systolic BP, or 10 mmHg diastolic BP [149]. It is caused by a dysfunction of the autonomic nervous system, which would normally compensate for the reduction in BP when standing up due to gravity causing blood to pool in the lower body. In older adults, orthostatic hypotension is associated with an increased risk of falls [150], which in turn result in increased morbidity, mortality and healthcare costs [151]. Methods to identify orthostatic hypotension in daily life could potentially help prevent falls. It has been proposed that by estimating BP from the PPG, one could identify drops in BP indicative of orthostatic hypotension [152]. Accelerometry and gyroscope measurements from wearables could also be used to identify when a user stands following a prolonged period of lying down or sitting, which could be combined with PPG-based detection of drops in BP to identify possible orthostatic hypotension for further assessment.

5.3. Seizure detection in epilepsy

Epilepsy is one of the most common neurological disorders, affecting almost 1% of the population worldwide [153]. Patients are often required to keep a seizure diary outside the hospital in order to follow-up the disease and evaluate treatment. Reliable seizure detection might help optimise antiepileptic treatment, which could in turn reduce the risk of sudden unexpected death in epilepsy. Manual seizure diaries are unfortunately not highly reliable, thus there is a potential role for automated, preferably wearable, seizure detection devices. Some types of epilepsy affect the autonomic nervous system (*e.g.* temporal lobe epilepsy), and in turn the cardiovascular system. Temporal lobe seizures are often accompanied with a strong increase in HR, providing opportunity to detect this type of epilepsy through PPG-based HR monitoring [154], [155]. Another study has investigated cardiorespiratory effects of epilepsy by monitoring SpO₂ and found that 63%-73% of generalized convulsions and 20%-28% of focal seizures can be detected by using SpO₂ thresholds of 80%-86% [156]. Relatively little research has been conducted to date on using PPG-based wearables to detect seizures, although a planned multicenter study holds promise for providing new insights into the utility of PPG-based wearables for this application [157].

5.4. Anaesthesia and pain monitoring

Monitoring of painful stimulation is routinely used to assess the adequacy of analgesic medication for pain control during anaesthesia [158]. Pain causes sympathetic responses in the autonomic nervous system, and these are associated with morphological changes in the PPG [159]. Consequently, PPG-based devices may have utility for monitoring analgesia. The PPG-derived Surgical Plethysmography Index (SPI), calculated from the pulse wave amplitude and duration, has been proposed as an approach to assess analgesic state [160]. The SPI was integrated into the Aisys® Carestation device (GE Healthcare, Finland). The SPI does not appear to be valid in children [161], which may be due to both differences in blood vessel distensibility and baseline HRs in children versus adults. The autonomic nervous system state (ANSS) metric was introduced in [162], and is calculated from the same features of the PPG pulse wave as for the SPI. Additional approaches have been proposed in [163], which assessed the performance of a plethora of PPG pulse wave indices to assess postoperative pain, and [164], which used deep learning to classify pain level. Further details of methods for analgesia monitoring are provided in [158], including methods based on HRV and wavelet cardiorespiratory coherence [165], which could be suitable for implementation in PPG-based devices.

5.5. Chronic kidney disease monitoring

Chronic kidney disease (CKD) has a high global prevalence of 11 to 13% [166], [167], and advanced CKD may require frequent haemodialysis to replace lost kidney function. Consequently, interventions to delay the progression of CKD and improve outcomes are valuable. Cardiovascular diseases (CVDs) such as coronary artery disease (CAD), congestive heart failure, arrhythmias, and sudden cardiac death are the main causes of morbidity and mortality in patients with CKD [168]. These CVD pathologies impact haemodynamics and so could potentially be detected and monitored by PPG-based devices. In [169], the authors demonstrated the potential of dual wavelength (infrared and green) reflectance photoplethysmography to identify CAD in CKD patients. Differences were observed in the upslopes and downslopes of PPG pulse waves between CKD patients with and without CAD. In the future, such features could be adjusted to account for changes which occur with age. Specifically, in haemodialysis patients, an arteriovenous (AV) fistula in the arm significantly increases the steepness in blood volume change during systole compared with the arm without AV fistula. PPG-based monitoring may also be useful for detecting arrhythmias such as bradycardia and tachycardia, which are common in haemodialysis patients [170]. PPG-based monitoring might also be useful for preventing intradialytic hypotension [171] and for hypotension management [172], [173]. A recent review [174] identified only a few studies investigating the use of PPG-based monitoring in haemodialysis patients; however, they concluded that wearable health devices will enter clinical practice in the near future, including for haemodialysis patients.

5.6. Biometric authentication

There is growing interest in new approaches to user authentication. PPG-based wearables provide opportunity to authenticate users based on analysis of their PPG signal, since PPG signals differ from one user to the next. Broadly, two approaches have been taken to identify an individual from their PPG signal: classification algorithms based on either pulse wave features [175]–[177] or deep learning frameworks [178]–[180]. The PPG can be transformed into the angle domain before feature extraction to reduce intra-subject variability [181], [182]. Time-frequency analysis has also been used to extract features without the need to identify individual pulse waves [183]. The main challenge is to reliably classify users in the presence of intra-individual variability. Consequently, it is helpful to train a system using data from one recording session, and assess its performance on data from the same individuals in a separate recording session [180]. Performance can also be assessed during situations which affect pulse wave morphology and variability, such as changes in emotions [181] and activities of daily living [176], [182]. PPG-based authentication could be used to provide access to confidential and sensitive information over the internet [180], or could act as a pre-cursor to existing authentication systems such as fingerprint scanning [179].

5.7. Health insurance

Some insurance providers are now offering rewards or discounts to policy holders who use a PPG-based wearable to track their exercise [184], [185]. In doing so, insurance providers can promote healthier lifestyles [186], personalise insurance premiums according to individual risk, and create personalised products based on users' data [187]. Indeed, many of the largest insurance companies in the USA offer self-tracking health and life insurance schemes [188]. However, concerns have been raised that the use of wearables in health insurance is not in keeping with the principles of solidarity, fairness and equality on which collective insurance schemes are based [188].

6. CONCLUSION AND FUTURE WORK

The growing use of PPG-based wearables provides opportunity to monitor health and fitness in daily life. The potential utility of wearables is directly linked to their design, with several form factors used in commercial devices. Several physiological parameters can be estimated from the PPG signal, which if incorporated in wearable systems, could provide a wealth of information on the cardiovascular, respiratory and autonomic nervous systems. Additional parameters and features have been incorporated into commercially available wearables over time, expanding their functionality and potential utility. Wearables may now, or in the future, have utility in a wide range of applications in clinical, health and fitness settings. However, much further work is required to realise the full potential of PPG-based wearables.

6.1. Areas for future work

Key areas for future work concerning PPG-based wearables include:

- 1) Identifying use cases for wearables in clinical practice, and assessing their cost-effectiveness for these use cases [189]. The detection of possible atrial fibrillation using PPG-based wearables is a promising initial use case, since the potential utility of devices for this purpose has been demonstrated [57], and there is an established treatment strategy (anticoagulation to reduce risk of stroke).
- 2) Assessing whether the use of wearables for behaviour change, such as prompting increased physical activity, is associated with improved health and wellbeing outcomes.
- 3) Harnessing the wealth of data provided by wearables for large-scale research [190], as achieved in the Apple Heart Study [57], Huawei Heart Study [139], and studies using data from Fitbit devices [191], [192].
- 4) Thorough evaluation of the limitations of wearables to ensure they are not used outside of their capabilities [193].
- 5) Ensuring that any clinical benefits of wearables are made accessible to all, noting the vast geographical discrepancies in the current use of wearables [1].

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REFERENCES

- [1] Cisco, "Cisco visual networking index (VNI) global mobile data traffic forecast update, 2017-2022 white paper," White paper (accessed 15 Mar 2021), 2019. <https://s3.amazonaws.com/media.mediapost.com/uploads/CiscoForecast.pdf>
- [2] Gartner, "Gartner forecasts global spending on wearable devices to total \$81.5 billion in 2021," Web page (accessed 15 Mar 2021), 2021. <https://www.gartner.com/en/newsroom/press-releases/2021-01-11-gartner-forecasts-global-spending-on-wearable-devices-to-total-81-5-billion-in-2021>
- [3] X.-R. Ding *et al.*, "Wearable sensing and telehealth technology with potential applications in the coronavirus pandemic," *IEEE Reviews in Biomedical Engineering*, vol. 14, pp. 48–70, 2021. <https://doi.org/10.1109/RBME.2020.2992838>
- [4] D. R. Seshadri *et al.*, "Wearable sensors for COVID-19: a call to action to harness our digital infrastructure for remote patient monitoring and virtual assessments," *Frontiers in Digital Health*, vol. 2, p. 8, 2020. <https://doi.org/10.3389/fgdh.2020.00008>
- [5] A. Tong *et al.*, "Research priorities for COVID-19 sensor technology," *Nature Biotechnology*, vol. 39, no. February, pp. 144–153, 2021. <https://doi.org/10.1038/s41587-021-00816-8>
- [6] J. Parak and I. Korhonen, "Evaluation of wearable consumer heart rate monitors based on photoplethysmography," in *Proc. IEEE EMBS. IEEE*, 2014, pp. 3670–3673. <https://doi.org/10.1109/EMBC.2014.6944419>
- [7] P. H. Charlton *et al.*, "Wearable photoplethysmography for cardiovascular monitoring: A review," [under review], 2021.
- [8] P. H. Charlton *et al.*, "Acquiring wearable photoplethysmography data in daily life: The PPG Diary Pilot Study," *Engineering Proceedings*, vol. 2, no. 1, p. 80, 2020. <https://doi.org/10.3390/ecea-7-08233>
- [9] P. H. Charlton, "PPG Diary Pilot Study 1 Data," Dataset, 2020. <https://doi.org/10.5281/zenodo.3268500>
- [10] P. H. Charlton, "Realising the potential of wearables," *IPEM Scope*, vol. 31, no. 1, pp. 50–53, 2021. <https://www.ipem.ac.uk/Portals/0/SCOPESPRING21FULLLRClowres.pdf#page=50>
- [11] J. Allen and A. Murray, "Age-related changes in peripheral pulse timing characteristics at the ears, fingers and toes," *Journal of Human Hypertension*, vol. 16, no. 10, pp. 711–717, 2002. <https://doi.org/10.1038/sj.jhh.1001478>
- [12] V. Hartmann *et al.*, "Quantitative comparison of photoplethysmographic waveform characteristics: Effect of measurement site," *Frontiers in Physiology*, vol. 10, p. 198, 2019. <https://doi.org/10.3389/fphys.2019.00198>
- [13] P. H. Charlton, "Wearable sensor images," Image, 2021. <https://doi.org/10.5281/zenodo.798234>
- [14] P. H. Charlton *et al.*, "Extraction of respiratory signals from the electrocardiogram and photoplethysmogram: technical and physiological determinants," *Physiological Measurement*, vol. 38, no. 5, pp. 669–690, 2017. <https://doi.org/10.1088/1361-6579/aa670e>
- [15] V. Marozas and P. H. Charlton, "Wearable photoplethysmography devices," Image, 2021. <https://doi.org/10.5281/zenodo.4601547>
- [16] H. Kinnunen *et al.*, "Feasible assessment of recovery and cardiovascular health: Accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG," *Physiological Measurement*, vol. 41, p. 04NT01, 2020. <https://doi.org/10.1088/1361-6579/ab840a>
- [17] M. Elgendi, "On the analysis of fingertip photoplethysmogram signals," *Current Cardiology Reviews*, vol. 8, no. 1, pp. 14–25, 2012. <https://doi.org/10.2174/157340312801215782>
- [18] A. E. Johnson *et al.*, "MIMIC-III, a freely accessible critical care database," *Scientific Data*, vol. 3, p. 160035, 2016. <https://doi.org/10.1038/sdata.2016.35>
- [19] Y. Khan *et al.*, "Organic multi-channel optoelectronic sensors for wearable health monitoring," *IEEE Access*, vol. 7, pp. 128 114–128 124, 2019. <https://doi.org/10.1109/ACCESS.2019.2939798>
- [20] S. Rajala, H. Lindholm, and T. Taipalus, "Comparison of photoplethysmogram measured from wrist and finger and the effect of measurement location on pulse arrival time," *Physiological Measurement*, vol. 39, p. 075010, 2018. <https://doi.org/10.1088/1361-6579/aac7ac>
- [21] Y. Zhang *et al.*, "Validity of Wrist-Worn photoplethysmography devices to measure heart rate: A systematic review and meta-analysis," *Journal of Sports Sciences*, vol. 38, no. 17, pp. 2021–2034, 2020. <https://doi.org/10.1080/02640414.2020.1767348>
- [22] Q. Zhang, D. Zhou, and X. Zeng, "Highly wearable cuff-less blood pressure and heart rate monitoring with single-arm electrocardiogram and photoplethysmogram signals," *BioMedical Engineering Online*, vol. 16, p. 23, 2017. <https://doi.org/10.1186/s12938-017-0317-z>
- [23] L. Barrios *et al.*, "Evaluating the accuracy of heart rate sensors based on photoplethysmography for in-the-wild analysis," in *ACM International Conference Proceeding Series*, 2019, pp. 251–261. <https://doi.org/10.1145/3329189.3329215>
- [24] Y. Maeda, M. Sekine, and T. Tamura, "Relationship between measurement site and motion artifacts in wearable reflected photoplethysmography," *Journal of Medical Systems*, vol. 35, no. 5, pp. 969–976, 2011. <https://doi.org/10.1007/s10916-010-9505-0>
- [25] M. Z. Poh, N. C. Swenson, and R. W. Picard, "Motion-tolerant magnetic earring sensor and wireless earpiece for wearable photoplethysmography," *IEEE Transactions on Information Technology in Biomedicine*, vol. 14, no. 3, pp. 786–794, 2010. <https://doi.org/10.1109/TITB.2010.2042607>
- [26] B. Bradke and B. Everman, "Investigation of Photoplethysmography Behind the Ear for Pulse Oximetry in Hypoxic Conditions with a Novel Device (SPYDR)," *Biosensors*, vol. 10, p. 34, 2020. <https://doi.org/10.3390/bios10040034>
- [27] Y. Tomita and Y. Mitsukura, "An earbud-based photoplethysmography and its application," *Electronics and Communications in Japan*, vol. 101, no. 1, pp. 32–38, 2018. <https://doi.org/10.1002/ecj.12019>
- [28] M. Masè, A. Micarelli, and G. Strapazzon, "Hearables: New perspectives and pitfalls of in-ear devices for physiological monitoring. A scoping review," *Frontiers in Physiology*, vol. 11, p. 568886, 2020. <https://doi.org/10.3389/fphys.2020.568886>
- [29] K. Budidha and P. A. Kyriacou, "The human ear canal: Investigation of its suitability for monitoring photoplethysmographs and arterial oxygen saturation," *Physiological Measurement*, vol. 35, no. 2, pp. 111–128, 2014. <https://doi.org/10.1088/0967-3334/35/2/111>
- [30] D. Marzorati *et al.*, "Chest wearable apparatus for cuffless continuous blood pressure measurements based on PPG and PCG signals," *IEEE Access*, vol. 8, no. 1, pp. 55 424–55 437, 2020. <https://doi.org/10.1109/ACCESS.2020.2981300>
- [31] Y. Zheng *et al.*, "A clip-free eyeglasses-based wearable monitoring device for measuring photoplethysmographic signals," in *Proc. IEEE EMBS. IEEE*, 2012, pp. 5022–5025. <https://doi.org/10.1109/EMBC.2012.6347121>

- [32] F. Wahl, M. Freund, and O. Amft, "WISEglass: Smart eyeglasses recognising context," *BodyNets International Conference on Body Area Networks*, 2015. <https://doi.org/10.4108/eai.28-9-2015.2261470>
- [33] B. H. Olstad and C. Zinner, "Validation of the Polar OH1 and M600 optical heart rate sensors during front crawl swim training," *PLOS ONE*, vol. 15, no. 4, p. e0231522, 2020. <https://doi.org/10.1371/journal.pone.0231522>
- [34] K. Matsumura, S. Toda, and Y. Kato, "RGB and near-infrared light reflectance/transmittance photoplethysmography for measuring heart rate during motion," *IEEE Access*, vol. 8, pp. 80 233–80 242, 2020. <https://doi.org/10.1109/ACCESS.2020.2990438>
- [35] M. Elgendi *et al.*, "The use of photoplethysmography for assessing hypertension," *npj Digital Medicine*, vol. 2, p. 60, 2019. <https://doi.org/10.1038/s41746-019-0136-7>
- [36] R. R. Anderson and J. A. Parrish, "The optics of human skin," *Journal of Investigative Dermatology*, vol. 77, no. 1, pp. 13–19, 1981. <https://doi.org/10.1111/1523-1747.ep12479191>
- [37] A. N. Bashkatov *et al.*, "Optical properties of human skin, subcutaneous and mucous tissues in the wavelength range from 400 to 2000 nm," *Journal of Physics D: Applied Physics*, vol. 38, no. 15, pp. 2543–2555, 2005. <https://doi.org/10.1088/0022-3727/38/15/004>
- [38] B. A. Fallow, T. Tarumi, and H. Tanaka, "Influence of skin type and wavelength on light wave reflectance," *Journal of Clinical Monitoring and Computing*, vol. 27, no. 3, pp. 313–317, 2013. <https://doi.org/10.1007/s10877-013-9436-7>
- [39] Y. Maeda, M. Sekine, and T. Tamura, "The advantages of wearable green reflected photoplethysmography," *Journal of Medical Systems*, vol. 35, no. 5, pp. 829–834, 2011. <https://doi.org/10.1007/s10916-010-9506-z>
- [40] Apple Support, "Monitor your heart rate with Apple Watch," 2021. <https://support.apple.com/en-us/HT204666>
- [41] J. Liu *et al.*, "Multi-wavelength photoplethysmography enabling continuous blood pressure measurement with compact wearable electronics," *IEEE Transactions on Biomedical Engineering*, vol. 66, no. 6, pp. 1514–1525, 2019. <https://doi.org/10.1109/TBME.2018.2874957>
- [42] B. Bent *et al.*, "Investigating sources of inaccuracy in wearable optical heart rate sensors," *npj Digital Medicine*, vol. 3, no. 1, pp. 1–9, 2020. <https://doi.org/10.1038/s41746-020-0226-6>
- [43] B. Sañudo *et al.*, "Pilot study assessing the influence of skin type on the heart rate measurements obtained by photoplethysmography with the apple watch," *Journal of Medical Systems*, vol. 43, no. 7, 2019. <https://doi.org/10.1007/s10916-019-1325-2>
- [44] H. Lee *et al.*, "Wearable multichannel photoplethysmography framework for heart rate monitoring during intensive exercise," *IEEE Sensors Journal*, vol. 18, no. 7, pp. 2983–2993, 2018. <https://doi.org/10.1109/JSEN.2018.2801385>
- [45] Y. Zhang *et al.*, "Motion artifact reduction for wrist-worn photoplethysmograph sensors based on different wavelengths," *Sensors*, vol. 19, no. 3, 2019. <https://doi.org/10.3390/s19030673>
- [46] V. D. Corino *et al.*, "Detection of atrial fibrillation episodes using a wristband device," *Physiological Measurement*, vol. 38, no. 5, pp. 787–799, 2017. <https://doi.org/10.1088/1361-6579/aa5dd7>
- [47] O. Dur *et al.*, "Design rationale and performance evaluation of the Wavelet Health wristband: Benchtop validation of a wrist-worn physiological signal recorder," *JMIR mHealth and uHealth*, vol. 6, no. 10, p. e11040, 2018. <https://doi.org/10.2196/11040>
- [48] F. Wolling and K. Van Laerhoven, "Fewer samples for a longer life span," in *Proc. iWOAR*. New York, NY, USA: ACM, 2018, pp. 1–10. <https://doi.org/10.1145/3266157.3266209>
- [49] A. Choi and H. Shin, "Photoplethysmography sampling frequency: Pilot assessment of how low can we go to analyze pulse rate variability with reliability?" *Physiological Measurement*, vol. 38, no. 3, pp. 586–600, 2017. <https://doi.org/10.1088/1361-6579/aa5efa>
- [50] G. B. Papini *et al.*, "Photoplethysmography beat detection and pulse morphology quality assessment for signal reliability estimation," in *Proc. IEEE EMBS*. IEEE, 2017, pp. 117–120. <https://doi.org/10.1109/EMBC.2017.8036776>
- [51] N. Stuban and M. Niwayama, "Optimal filter bandwidth for pulse oximetry," *Review of Scientific Instruments*, vol. 83, no. 10, pp. 1–6, 2012. <https://doi.org/10.1063/1.4759491>
- [52] L. M. Eerikäinen *et al.*, "Comparison between electrocardiogram- and photoplethysmogram-derived features for atrial fibrillation detection in free-living conditions," *Physiological Measurement*, vol. 39, no. 8, p. 084001, 2018. <https://doi.org/10.1088/1361-6579/aad2c0>
- [53] J. Allen *et al.*, "Photoplethysmography assessments in cardiovascular disease," *Measurement and Control*, vol. 39, no. 3, pp. 80–83, 2006. <https://doi.org/10.1177/002029400603900303>
- [54] J. Allen and A. Murray, "Effects of filtering on multi-site photoplethysmography pulse waveform characteristics," in *Proc. CinC*, vol. 31, 2004, pp. 485–488. <https://doi.org/10.1109/cinC.2004.1442980>
- [55] P. H. Charlton *et al.*, "Breathing rate estimation from the electrocardiogram and photoplethysmogram: a review," *IEEE Reviews in Biomedical Engineering*, vol. 11, pp. 2–20, 2018. <https://doi.org/10.1109/RBME.2017.2763681>
- [56] J. Lee *et al.*, "A low-power photoplethysmogram-based heart rate sensor using heartbeat locked loop," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 12, no. 6, pp. 1220–1229, 2018. <https://doi.org/10.1109/TBCAS.2018.2876671>
- [57] M. V. Perez *et al.*, "Large-scale assessment of a smartwatch to identify atrial fibrillation," *New England Journal of Medicine*, vol. 381, no. 20, pp. 1909–1917, 2019. <https://doi.org/10.1056/NEJMoA1901183>
- [58] C. Orphanidou *et al.*, "Signal-quality indices for the electrocardiogram and photoplethysmogram: derivation and applications to wireless monitoring," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, no. 3, pp. 832–8, 2015. <https://doi.org/10.1109/JBHI.2014.2338351>
- [59] J. Prinable *et al.*, "A novel hardware implementation for detecting respiration rate using photoplethysmography," in *Proc. IEEE EMBS*. IEEE, 2017, pp. 726–729. <https://doi.org/10.1109/EMBC.2017.8036927>
- [60] J. Lee *et al.*, "A low-power photoplethysmogram-based heart rate sensor using heartbeat locked loop," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 12, no. 6, pp. 1220–1229, 2018. <https://doi.org/10.1109/TBCAS.2018.2876671>
- [61] V. R. Pamula *et al.*, "A 172 μW Compressively Sampled Photoplethysmographic (PPG) Readout ASIC with Heart Rate Estimation Directly from Compressively Sampled Data," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 11, no. 3, pp. 487–496, 2017. <https://doi.org/10.1109/TBCAS.2017.2661701>
- [62] A. L. Goldberger *et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals," *Circulation*, vol. 101, no. 23, pp. E215–20, 2000. <https://doi.org/10.1161/01.CIR.101.23.e215>

- [63] M. A. García-gonzález *et al.*, “A comparison of heartbeat detectors for the seismocardiogram,” in *Proc CinC. IEEE*, 2013, pp. 461–4. <https://ieeexplore.ieee.org/document/6713413>
- [64] D. Jarchi and A. Casson, “Description of a database containing wrist PPG signals recorded during physical exercise with both accelerometer and gyroscope measures of motion,” *Data*, vol. 2, no. 1, p. 1, 2016. <https://doi.org/10.3390/data2010001>
- [65] C. Beach *et al.*, “An ultra low power personalizable wrist worn ECG monitor integrated with IoT infrastructure,” *IEEE Access*, vol. 6, pp. 44 010–44 021, 2018. <https://doi.org/10.1109/ACCESS.2018.2864675>
- [66] N. Isakadze and S. S. Martin, “How useful is the smartwatch ECG?” *Trends in Cardiovascular Medicine*, vol. 30, no. 7, pp. 442–448, 2020. <https://doi.org/10.1016/j.tcm.2019.10.010>
- [67] M. Boloursaz Mashhadi *et al.*, “Heart rate tracking using wrist-type photoplethysmographic (PPG) signals during physical exercise with simultaneous accelerometry,” *IEEE Signal Processing Letters*, vol. 23, no. 2, pp. 227–231, 2015. <https://doi.org/10.1109/lsp.2015.2509868>
- [68] I. M. Pires *et al.*, “Pattern recognition techniques for the identification of activities of daily living using a mobile device accelerometer,” *Electronics*, vol. 9, no. 3, pp. 1–22, 2020. <https://doi.org/10.3390/electronics9030509>
- [69] A. Taebi *et al.*, “Recent advances in seismocardiography,” *Vibration*, vol. 2, no. 1, pp. 64–86, 2019. <https://doi.org/10.3390/vibration2010005>
- [70] J. Park *et al.*, “Cuffless and continuous blood pressure monitoring using a single chest-worn device,” *IEEE Access*, vol. 7, pp. 135 231–135 246, 2019. <https://doi.org/10.1109/ACCESS.2019.2942184>
- [71] A. J. Casson, A. Vazquez Galvez, and D. Jarchi, “Gyroscope vs. accelerometer measurements of motion from wrist PPG during physical exercise,” *ICT Express*, vol. 2, no. 4, pp. 175–179, 2016. <https://doi.org/10.1016/j.ict.2016.11.003>
- [72] M. Jafari Tadi *et al.*, “Gyrocardiography: A new non-invasive monitoring method for the assessment of cardiac mechanics and the estimation of hemodynamic variables,” *Scientific Reports*, vol. 7, no. 1, pp. 1–11, 2017. <https://doi.org/10.1038/s41598-017-07248-y>
- [73] M. Nystrom, “How optical heart rate monitoring works with Polar Precision Prime (TM),” 2021. <https://www.polar.com/blog/optical-heart-rate-monitoring-polar-precision-prime/>
- [74] D. Biswas *et al.*, “Heart rate estimation from wrist-worn photoplethysmography: A review,” *IEEE Sensors Journal*, vol. 19, no. 16, pp. 6560–6570, 2019. <https://doi.org/10.1109/jsen.2019.2914166>
- [75] Z. Zhang, Z. Pi, and B. Liu, “TROIKA: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise,” *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 2, pp. 522–531, 2015. <https://doi.org/10.1109/TBME.2014.2359372>
- [76] S. Ismail, U. Akram, and I. Siddiqi, “Heart rate tracking in photoplethysmography signals affected by motion artifacts: a review,” *Eurasip Journal on Advances in Signal Processing*, vol. 2021, no. 1, 2021. <https://doi.org/10.1186/s13634-020-00714-2>
- [77] P. H. Charlton *et al.*, “An assessment of algorithms to estimate respiratory rate from the electrocardiogram and photoplethysmogram,” *Physiological Measurement*, vol. 37, no. 4, pp. 610–26, 2016. <https://doi.org/10.1088/0967-3334/37/4/610>
- [78] D. Fuller *et al.*, “Reliability and validity of commercially available wearable devices for measuring steps, energy expenditure, and heart rate: Systematic review,” *JMIR mHealth and uHealth*, vol. 8, no. 9, pp. 1–23, 2020. <https://doi.org/10.2196/18694>
- [79] J. M. Mühlen *et al.*, “Recommendations for determining the validity of consumer wearable heart rate devices: expert statement and checklist of the INTERLIVE Network,” *British Journal of Sports Medicine*, pp. bjsports–2020–103 148, 2021. <https://doi.org/10.1136/bjsports-2020-103148>
- [80] M. Böhm *et al.*, “Resting heart rate: Risk indicator and emerging risk factor in cardiovascular disease,” *American Journal of Medicine*, vol. 128, no. 3, pp. 219–228, 2015. <https://doi.org/10.1016/j.amjmed.2014.09.016>
- [81] G. Quer *et al.*, “Inter- and intraindividual variability in daily resting heart rate and its associations with age, sex, sleep, BMI, and time of year: Retrospective, longitudinal cohort study of 92,457 adults,” *PLOS ONE*, vol. 15, no. 2, p. e0227709, 2020. <https://doi.org/10.1371/journal.pone.0227709>
- [82] R. Avram *et al.*, “Real-world heart rate norms in the Health eHeart study,” *npj Digital Medicine*, vol. 2, no. 1, 2019. <https://doi.org/10.1038/s41746-019-0134-9>
- [83] D. Morelli *et al.*, “A computationally efficient algorithm to obtain an accurate and interpretable model of the effect of circadian rhythm on resting heart rate,” *Physiological Measurement*, vol. 40, no. 9, p. 095001, 2019. <https://doi.org/10.1088/1361-6579/ab3dea>
- [84] J. Nauman *et al.*, “Temporal changes in resting heart rate and deaths from ischemic heart disease,” *JAMA*, vol. 306, no. 23, pp. 2579–2587, 2011. <https://doi.org/10.1001/jama.2011.1826>
- [85] U. Rajendra Acharya *et al.*, “Heart rate variability: a review,” *Medical and Biological Engineering and Computing*, vol. 44, no. 12, pp. 1031–51, 2006. <https://doi.org/10.1007/s11517-006-0119-0>
- [86] J. Lian, L. Wang, and D. Muessig, “A simple method to detect atrial fibrillation using RR intervals,” *The American Journal of Cardiology*, vol. 107, no. 10, pp. 1494–7, 2011. <https://doi.org/10.1016/j.amjcard.2011.01.028>
- [87] T. Pereira *et al.*, “Photoplethysmography based atrial fibrillation detection: a review,” *npj Digital Medicine*, vol. 3, no. 1, p. 3, 2020. <https://doi.org/10.1038/s41746-019-0207-9>
- [88] L. M. Eerikäinen *et al.*, “Atrial fibrillation monitoring with wrist-worn photoplethysmography-based wearables: State-of-the-art review,” *Cardiovascular Digital Health Journal*, vol. 1, no. 1, pp. 45–51, 2020. <https://doi.org/10.1016/j.cvdhj.2020.03.001>
- [89] J. P. de Kock and L. Tarassenko, “Pulse oximetry: Theoretical and experimental models,” *Medical and Biological Engineering and Computing*, vol. 31, no. 3, pp. 291–300, 1993. <https://doi.org/10.1007/BF02458049>
- [90] J. P. de Kock and L. Tarassenko, “In vitro investigation of the factors affecting pulse oximetry,” *Journal of Biomedical Engineering*, vol. 13, no. 1, pp. 61–66, 1991. [https://doi.org/10.1016/0141-5425\(91\)90046-A](https://doi.org/10.1016/0141-5425(91)90046-A)
- [91] L. Alkhoury *et al.*, “Heart-rate tuned comb filters for processing photoplethysmogram (PPG) signals in pulse oximetry,” *Journal of Clinical Monitoring and Computing*, no. 0123456789, 2020. <https://doi.org/10.1007/s10877-020-00539-2>
- [92] J. M. Goldman *et al.*, “Masimo signal extraction pulse oximetry,” *Journal of Clinical Monitoring and Computing*, vol. 16, no. 7, pp. 475–483, 2000. <https://doi.org/10.1023/A:1011493521730>
- [93] Y. Mendelson and B. D. Ochs, “Noninvasive pulse oximetry utilizing skin reflectance photoplethysmography,” *IEEE Transactions on*

- Biomedical Engineering*, vol. 35, no. 10, pp. 798–805, 1988. <https://doi.org/10.1109/10.7286>
- [94] F. Braun *et al.*, “Pulse oximetry at the wrist during sleep: Performance, challenges and perspectives,” in *Proc. IEEE EMBS*. IEEE, 2020, pp. 5115–5118. <https://doi.org/10.1109/EMBC44109.2020.9176081>
- [95] S. Richardson *et al.*, “Presenting characteristics, comorbidities, and outcomes among 5700 patients hospitalized with COVID-19 in the New York City area,” *JAMA*, vol. 323, no. 20, p. 2052, 2020. <https://doi.org/10.1001/jama.2020.6775>
- [96] H. Liu *et al.*, “Comparison of different modulations of photoplethysmography in extracting respiratory rate: From a physiological perspective,” *Physiological Measurement*, vol. 41, no. 9, pp. 0–14, 2020. <https://doi.org/10.1088/1361-6579/abaaf0>
- [97] D. A. Birrenkott *et al.*, “A robust fusion model for estimating respiratory rate from photoplethysmography and electrocardiography,” *IEEE Transactions on Biomedical Engineering*, vol. 65, no. 9, pp. 2033–2041, 2018. <https://doi.org/10.1109/TBME.2017.2778265>
- [98] P. H. Charlton, “Continuous respiratory rate monitoring to detect clinical deteriorations using wearable sensors,” 2017. <https://theses.eurasip.org/theses/829/continuous-respiratory-rate-monitoring-to-detect/>
- [99] D. J. Miller *et al.*, “Analyzing changes in respiratory rate to predict the risk of COVID-19 infection,” *PLoS ONE*, vol. 15, no. 12, p. e0243693, 2020. <https://doi.org/10.1371/journal.pone.0243693>
- [100] M. Hosanee *et al.*, “Cuffless single-site photoplethysmography for blood pressure monitoring,” *Journal of Clinical Medicine*, vol. 9, no. 3, p. 723, 2020. <https://doi.org/10.3390/jcm9030723>
- [101] W. H. Lin *et al.*, “Investigating the physiological mechanisms of the photoplethysmogram features for blood pressure estimation,” *Physiological Measurement*, vol. 41, no. 4, pp. 0–13, 2020. <https://doi.org/10.1088/1361-6579/ab7d78>
- [102] P. H. Charlton *et al.*, “Assessing mental stress from the photoplethysmogram: a numerical study,” *Physiological Measurement*, vol. 39, no. 5, p. 054001, 2018.
- [103] Chan *et al.*, “Multi-site photoplethysmography technology for blood pressure assessment: Challenges and recommendations,” *Journal of Clinical Medicine*, vol. 8, no. 11, p. 1827, 2019. <https://doi.org/10.3390/jcm8111827>
- [104] K. Welykholowa *et al.*, “Multimodal photoplethysmography-based approaches for improved detection of hypertension,” *Journal of Clinical Medicine*, vol. 9, no. 4, p. 1203, 2020. <https://doi.org/10.3390/jcm9041203>
- [105] C. El-Hajj and P. A. Kyriacou, “A review of machine learning techniques in photoplethysmography for the non-invasive cuff-less measurement of blood pressure,” *Biomedical Signal Processing and Control*, vol. 58, p. 101870, 2020. <https://doi.org/10.1016/j.bspc.2020.101870>
- [106] M. Radha *et al.*, “Estimating blood pressure trends and the nocturnal dip from photoplethysmography,” *Physiological Measurement*, vol. 40, no. 2, p. 025006, 2019. <https://doi.org/10.1088/1361-6579/ab030e>
- [107] D. M. Roberts *et al.*, “Detecting sleep using heart rate and motion data from multisensor consumer-grade wearables, relative to wrist actigraphy and polysomnography,” *Sleep*, vol. 43, no. 7, pp. 1–19, 2020. <https://doi.org/10.1093/sleep/zsaa045>
- [108] J. M. Lee *et al.*, “Comparison of wearable trackers’ ability to estimate sleep,” *International Journal of Environmental Research and Public Health*, vol. 15, no. 6, 2018. <https://doi.org/10.3390/ijerph15061265>
- [109] M. E. Rosenberger *et al.*, “Twenty-four hours of sleep, sedentary behavior, and physical activity with nine wearable devices,” *Medicine and Science in Sports and Exercise*, vol. 48, no. 3, pp. 457–465, 2016. <https://doi.org/10.1249/MSS.0000000000000778>
- [110] O. Walch *et al.*, “Sleep stage prediction with raw acceleration and photoplethysmography heart rate data derived from a consumer wearable device,” *Sleep*, vol. 42, no. 12, pp. 1–19, 2019. <https://doi.org/10.1093/sleep/zsz180>
- [111] E. T. Poehlman, “A review: exercise and its influence on resting energy metabolism in man,” *Medicine and Science in Sports and Exercise*, vol. 21, no. 5, pp. 515–525, 1989. <https://doi.org/10.1249/00005768-198910000-00005>
- [112] S. Gerrior, W. Juan, and P. Basiotis, “An easy approach to calculating estimated energy requirements,” *Preventing chronic disease*, vol. 3, no. 4, p. A129, 2006. <http://www.ncbi.nlm.nih.gov/pubmed/16978504>
- [113] A. V. Kurpad *et al.*, “A simple method of measuring total daily energy expenditure and physical activity level from the heart rate in adult men,” *European Journal of Clinical Nutrition*, vol. 60, no. 1, pp. 32–40, 2006. <https://doi.org/10.1038/sj.ejcn.1602264>
- [114] Firstbeat Technologies Ltd., “An energy expenditure estimation method based on heart rate measurement,” 2012. https://assets.firstbeat.com/firstbeat/uploads/2015/10/white_paper_energy_expenditure_estimation.pdf
- [115] A. P. Hills, N. Mokhtar, and N. M. Byrne, “Assessment of physical activity and energy expenditure: An overview of objective measures,” *Frontiers in Nutrition*, vol. 1, p. 5, 2014. <https://doi.org/10.3389/fnut.2014.00005>
- [116] S. Passler *et al.*, “Validity of wrist-worn activity trackers for estimating VO₂max and energy expenditure,” *International Journal of Environmental Research and Public Health*, vol. 16, no. 17, 2019. <https://doi.org/10.3390/ijerph16173037>
- [117] L. M. Feehan *et al.*, “Accuracy of fitbit devices: Systematic review and narrative syntheses of quantitative data,” *JMIR mHealth and uHealth*, vol. 6, no. 8, 2018. <https://doi.org/10.2196/10527>
- [118] K. Klepin *et al.*, “Validity of cardiorespiratory fitness measured with fitbit compared to VO₂max,” *Medicine and science in sports and exercise*, vol. 51, no. 11, pp. 2251–2256, 2019. <https://doi.org/10.1249/MSS.0000000000002041>
- [119] R. J. Gibbons *et al.*, “ACC/AHA guidelines for exercise testing: a report of the American College of Cardiology/American Heart Association task force on practice guidelines (Committee on Exercise Testing),” *Journal of the American College of Cardiology*, vol. 30, no. 1, pp. 260–311, 1997. [https://doi.org/10.1016/S0735-1097\(97\)00150-2](https://doi.org/10.1016/S0735-1097(97)00150-2)
- [120] Firstbeat Technologies Ltd, “Automated fitness level (VO₂max) estimation with heart rate and speed data,” pp. 1–9, 2014. https://assets.firstbeat.com/firstbeat/uploads/2017/06/white_paper_VO2max_30.6.2017.pdf
- [121] J. Parak *et al.*, “Estimating heart rate, energy expenditure, and physical performance with a wrist photoplethysmographic device during running,” *JMIR mHealth and uHealth*, vol. 5, no. 7, pp. 1–14, 2017. <https://doi.org/10.2196/mhealth.7437>
- [122] K. A. Freeberg *et al.*, “Assessing the ability of the Fitbit Charge 2 to accurately predict VO₂max,” *mHealth*, vol. 5, no. 3, pp. 39–39, 2019. <https://doi.org/10.21037/mhealth.2019.09.07>
- [123] E. Mejia-Mejia *et al.*, “Pulse rate variability in cardiovascular health: A review on its applications and relationship with heart rate variability,” *Physiological Measurement*, vol. 41, no. 7, 2020. <https://doi.org/10.1088/1361-6579/ab998c>
- [124] K. Georgiou *et al.*, “Can wearable devices accurately measure heart rate variability? A systematic review,” *Folia Medica*, vol. 60, no. 1, pp. 7–20, 2018. <https://doi.org/10.2478/folmed-2018-0012>

- [125] F. Shaffer and J. P. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in Public Health*, vol. 5, p. 258, 2017. <https://doi.org/10.3389/fpubh.2017.00258>
- [126] S. Béres, L. Holczer, and L. Hejmel, "On the minimal adequate sampling frequency of the photoplethysmogram for pulse rate monitoring and heart rate variability analysis in mobile and wearable technology," *Measurement Science Review*, vol. 19, no. 5, pp. 232–240, 2019. <https://doi.org/10.2478/msr-2019-0030>
- [127] E. Peralta *et al.*, "Optimal fiducial points for pulse rate variability analysis from forehead and finger photoplethysmographic signals," *Physiological Measurement*, vol. 40, no. 2, 2019. <https://doi.org/10.1088/1361-6579/ab009b>
- [128] A. Schäfer and J. Vagedes, "How accurate is pulse rate variability as an estimate of heart rate variability?" *International Journal of Cardiology*, vol. 166, no. 1, pp. 15–29, 2013. <https://doi.org/10.1016/j.ijcard.2012.03.119>
- [129] L. Pecchia *et al.*, "Are ultra-short heart rate variability features good surrogates of short-term ones? State-of-the-art review and recommendations," *Healthcare Technology Letters*, vol. 5, no. 3, pp. 94–100, 2018. <https://doi.org/10.1049/htl.2017.0090>
- [130] E. Von Wowern *et al.*, "Digital photoplethysmography for assessment of arterial stiffness: Repeatability and comparison with applanation tonometry," *PLoS ONE*, vol. 10, no. 8, pp. 1–19, 2015. <https://doi.org/10.1371/journal.pone.0135659>
- [131] C. Vlachopoulos, K. Aznaouridis, and C. Stefanadis, "Prediction of cardiovascular events and all-cause mortality with arterial stiffness: a systematic review and meta-analysis," *Journal of the American College of Cardiology*, vol. 55, no. 13, pp. 1318–27, 2010. <https://doi.org/10.1016/j.jacc.2009.10.061>
- [132] N. Inoue *et al.*, "Second derivative of the finger photoplethysmogram and cardiovascular mortality in middle-aged and elderly Japanese women," *Hypertension Research*, vol. 40, no. 2, pp. 207–211, 2016. <https://doi.org/10.1038/hr.2016.123>
- [133] C. M. Sarwar *et al.*, "Mobile health applications in cardiovascular research," *International Journal of Cardiology*, vol. 269, pp. 265–271, 2018. <https://doi.org/10.1016/j.ijcard.2018.06.039>
- [134] A. Channa, N. Popescu, and N. ur Rehman Malik, "Managing COVID-19 global pandemic with high-tech consumer wearables: A comprehensive review," in *Proc. ICUMT*. IEEE, 2020, pp. 222–228. <https://doi.org/10.1109/ICUMT51630.2020.9222428>
- [135] J. Nyvad *et al.*, "The cuffless SOMNOtouch NIBP device shows poor agreement with a validated oscillometric device during 24-h ambulatory blood pressure monitoring," *Journal of Clinical Hypertension*, vol. 23, no. 1, pp. 61–70, 2021. <https://doi.org/10.1111/jch.14135>
- [136] N. van Helmond, S. S. Martin, and T. B. Plante, "Is cuffless blood pressure measurement already here?" *Journal of hypertension*, vol. 38, no. 4, pp. 774–775, 2020. <https://doi.org/10.1097/HJH.0000000000002344>
- [137] S. Passler, N. Müller, and V. Senner, "In-ear pulse rate measurement: A valid alternative to heart rate derived from electrocardiography?" *Sensors*, vol. 19, no. 17, 2019. <https://doi.org/10.3390/s19173641>
- [138] J. B. Prinable *et al.*, "Motivations and key features for a wearable device for continuous monitoring of breathing: A web-based survey," *JMIR Biomedical Engineering*, vol. 2, no. 1, p. e1, 2017. <https://doi.org/10.2196/biomedeng.7143>
- [139] Y. Guo *et al.*, "Mobile photoplethysmographic technology to detect atrial fibrillation," *Journal of the American College of Cardiology*, vol. 74, no. 19, pp. 2365–2375, 2019. <https://doi.org/10.1016/j.jacc.2019.08.019>
- [140] Fitbit, "What should I know about the Fitbit Heart Study?" 2020. https://help.fitbit.com/articles/en_US/Help_article/2451.htm
- [141] J. L. Selder *et al.*, "Assessment of a standalone photoplethysmography (PPG) algorithm for detection of atrial fibrillation on wristband-derived data," *Computer Methods and Programs in Biomedicine*, vol. 197, 2020. <https://doi.org/10.1016/j.cmpb.2020.105753>
- [142] N. Pradhan, S. Rajan, and A. Adler, "Evaluation of the signal quality of wrist-based photoplethysmography," *Physiological Measurement*, vol. 40, no. 6, pp. 0–11, 2019. <https://doi.org/10.1088/1361-6579/ab225a>
- [143] D. Sokas *et al.*, "Estimation of heart rate recovery after stair climbing using a wrist-worn device," *Sensors*, vol. 19, no. 9, p. 2113, 2019. <https://doi.org/10.3390/s19092113>
- [144] T. Mishra *et al.*, "Pre-symptomatic detection of COVID-19 from smartwatch data," *Nature Biomedical Engineering*, vol. 4, no. 12, pp. 1208–1220, 2020. <https://doi.org/10.1038/s41551-020-00640-6>
- [145] A. Maijala *et al.*, "Nocturnal finger skin temperature in menstrual cycle tracking: Ambulatory pilot study using a wearable Oura ring," *BMC Women's Health*, vol. 19, no. 1, pp. 1–10, 2019. <https://doi.org/10.1186/s12905-019-0844-9>
- [146] L. Luo *et al.*, "Detection and prediction of ovulation from body temperature measured by an in-ear wearable thermometer," *IEEE Transactions on Biomedical Engineering*, vol. 67, no. 2, pp. 512–522, 2020. <https://doi.org/10.1109/TBME.2019.2916823>
- [147] B. M. Goodale *et al.*, "Wearable sensors reveal menses-driven changes in physiology and enable prediction of the fertile window: Observational study," *Journal of Medical Internet Research*, vol. 21, no. 4, 2019. <https://doi.org/10.2196/13404>
- [148] M. Shilaih *et al.*, "Pulse rate measurement during sleep using wearable sensors, and its correlation with the menstrual cycle phases, a prospective observational study," *Scientific Reports*, vol. 7, no. 1, pp. 1–7, 2017. <https://doi.org/10.1038/s41598-017-01433-9>
- [149] R. Freeman *et al.*, "Orthostatic Hypotension: JACC State-of-the-Art Review," *Journal of the American College of Cardiology*, vol. 72, no. 11, pp. 1294–1309, 2018. <https://doi.org/10.1016/j.jacc.2018.05.079>
- [150] A. Gangavati *et al.*, "Hypertension, orthostatic hypotension, and the risk of falls in a community-dwelling elderly population: The maintenance of balance, independent living, intellect, and zest in the elderly of boston study," *Journal of the American Geriatrics Society*, vol. 59, no. 3, pp. 383–389, 2011.
- [151] C. A. Pfortmueller, G. Lindner, and A. K. Exadaktylos, "Reducing fall risk in the elderly: risk factors and fall prevention, a systematic review," *Minerva Medica*, vol. 105, no. 4, pp. 275–81, 2014. <http://www.ncbi.nlm.nih.gov/pubmed/24867188>
- [152] A. Mol *et al.*, "Multimodal monitoring of cardiovascular responses to postural changes," *Frontiers in Physiology*, vol. 11, p. 168, 2020. <https://doi.org/10.3389/fphys.2020.00168>
- [153] S. P. Murphy, N. E. Ibrahim, and J. L. Januzzi, "Heart failure with reduced ejection fraction: A review," *JAMA*, vol. 324, no. 5, pp. 488–504, 2020. <https://doi.org/10.1001/jama.2020.10262>
- [154] J. van Andel *et al.*, "Using photoplethysmography in heart rate monitoring of patients with epilepsy," *Epilepsy and Behavior*, vol. 45, pp. 142–145, 2015. <https://doi.org/10.1016/j.yebeh.2015.02.018>
- [155] K. Vandecasteele *et al.*, "Automated epileptic seizure detection based on wearable ECG and PPG in a hospital environment," *Sensors*, vol. 17, no. 10, pp. 1–12, 2017. <https://doi.org/10.3390/s17102338>

- [156] D. M. Goldenholz *et al.*, “Long-term monitoring of cardiorespiratory patterns in drug-resistant epilepsy,” *Epilepsia*, vol. 58, no. 1, pp. 77–84, 2017. <https://doi.org/10.1111/epi.13606>
- [157] E. Bruno *et al.*, “Remote assessment of disease and relapse in epilepsy: Protocol for a multicenter prospective cohort study,” *JMIR Research Protocols*, vol. 9, no. 12, 2020. <https://doi.org/10.2196/21840>
- [158] B. G. Lim, “Nociception monitoring tools using autonomic tone changes for intraoperative analgesic guidance in pediatric patients,” *Anesthesia and Pain Medicine*, vol. 14, no. 4, pp. 380–392, 2019. <https://doi.org/10.17085/apm.2019.14.4.380>
- [159] I. Korhonen and A. Yli-Hankala, “Photoplethysmography and nociception: Review Article,” *Acta Anaesthesiologica Scandinavica*, vol. 53, no. 8, pp. 975–985, 2009. <https://doi.org/10.1111/j.1399-6576.2009.02026.x>
- [160] M. Huiku *et al.*, “Assessment of surgical stress during general anaesthesia,” *British Journal of Anaesthesia*, vol. 98, no. 4, pp. 447–455, 2007. <https://doi.org/10.1093/bja/aem004>
- [161] J. H. Park *et al.*, “Comparison of Surgical Pleth Index-guided analgesia with conventional analgesia practices in children: A randomized controlled trial,” *Anesthesiology*, vol. 122, no. 6, pp. 1280–1287, 2015. <https://doi.org/10.1097/ALN.0000000000000650>
- [162] M. P. Paloheimo, S. Sahanne, and K. H. Uutela, “Autonomic nervous system state: The effect of general anaesthesia and bilateral tonsillectomy after unilateral infiltration of lidocaine,” *British Journal of Anaesthesia*, vol. 104, no. 5, pp. 587–595, 2010. <https://doi.org/10.1093/bja/aeq065>
- [163] Y. L. Yang *et al.*, “Postoperative pain assessment indices based on photoplethysmography waveform analysis,” *Frontiers in Physiology*, vol. 9, p. 1199, 2018. <https://doi.org/10.3389/fphys.2018.01199>
- [164] H. Lim *et al.*, “A deep neural network-based pain classifier using a photoplethysmography signal,” *Sensors*, vol. 19, no. 2, 2019. <https://doi.org/10.3390/s19020384>
- [165] C. J. Brouse *et al.*, “Monitoring nociception during general anesthesia with cardiorespiratory coherence,” *Journal of Clinical Monitoring and Computing*, vol. 27, no. 5, pp. 551–560, 2013. <https://doi.org/10.1007/s10877-013-9463-4>
- [166] B. Bikbov *et al.*, “Global, regional, and national burden of chronic kidney disease, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017,” *The Lancet*, vol. 395, no. 10225, pp. 709–733, 2020. [https://doi.org/10.1016/S0140-6736\(20\)30045-3](https://doi.org/10.1016/S0140-6736(20)30045-3)
- [167] N. R. Hill *et al.*, “Global prevalence of chronic kidney disease: a systematic review and meta-analysis,” *PLOS ONE*, vol. 11, no. 7, p. e0158765, 2016. <https://doi.org/10.1371/journal.pone.0158765>
- [168] L. Di Lullo *et al.*, “Chronic kidney disease and cardiovascular complications,” *Heart Failure Reviews*, vol. 20, no. 3, pp. 259–272, 2015. <https://doi.org/10.1007/s10741-014-9460-9>
- [169] T. Saritas *et al.*, “Non-invasive evaluation of coronary heart disease in patients with chronic kidney disease using photoplethysmography,” *Clinical Kidney Journal*, vol. 12, no. 4, pp. 538–545, 2019. <https://doi.org/10.1093/ckj/sfy135>
- [170] P. R. Roberts *et al.*, “A systematic review of the incidence of arrhythmias in hemodialysis patients undergoing long-term monitoring with implantable loop recorders,” *Kidney International Reports*, vol. 6, no. 1, pp. 56–65, 2021. <https://doi.org/10.1016/j.ekir.2020.10.020>
- [171] L. Sormmo *et al.*, “Noninvasive techniques for prevention of intradialytic hypotension,” *IEEE Reviews in Biomedical Engineering*, vol. 5, pp. 45–59, 2012. <https://doi.org/10.1109/RBME.2012.2210036>
- [172] V. R. Nafisi and M. Shahabi, “Intradialytic hypotension related episodes identification based on the most effective features of photoplethysmography signal,” *Computer Methods and Programs in Biomedicine*, vol. 157, pp. 1–9, 2018. <https://doi.org/10.1016/j.cmpb.2018.01.012>
- [173] F. Sandberg *et al.*, “Prediction of hypotension in hemodialysis patients,” *Physiological Measurement*, vol. 35, no. 9, pp. 1885–1898, 2014. <https://doi.org/10.1088/0967-3334/35/9/1885>
- [174] J. P. Kooman *et al.*, “Wearable health devices and personal area networks: Can they improve outcomes in haemodialysis patients?” *Nephrology Dialysis Transplantation*, vol. 35, pp. II43–II50, 2020. <https://doi.org/10.1093/ndt/gfaa015>
- [175] A. Reit Kavsaolu, K. Polat, and M. Recep Bozkurt, “A novel feature ranking algorithm for biometric recognition with PPG signals,” *Computers in Biology and Medicine*, vol. 49, no. 1, pp. 1–14, 2014. <https://doi.org/10.1016/j.combiomed.2014.03.005>
- [176] T. Zhao *et al.*, “TrueHeart: Continuous authentication on wrist-worn wearables using PPG-based biometrics,” in *Proc. IEEE INFOCOM*. IEEE, 2020, pp. 30–39. <https://doi.org/10.1109/INFOCOM41043.2020.9155526>
- [177] A. Al Sidani *et al.*, “Comparison between K-nearest neighbor and support vector machine algorithms for PPG biometric identification,” in *Proc. ICABME*. IEEE, 2019. <https://doi.org/10.1109/ICABME47164.2019.8940333>
- [178] L. Everson *et al.*, “Biometricnet: Deep learning based biometric identification using wrist-worn ppg,” in *Proc. IEEE ISCAS*. IEEE, 2018, pp. 1–5. <https://doi.org/10.1109/ISCAS.2018.8350983>
- [179] D. Biswas *et al.*, “CorNET: Deep learning framework for PPG-based heart rate estimation and biometric identification in ambulant environment,” *IEEE Transactions on Biomedical Circuits and Systems*, vol. 13, no. 2, pp. 282–291, 2019. <https://doi.org/10.1109/TBCAS.2019.2892297>
- [180] D. Y. Hwang *et al.*, “Evaluation of the time stability and uniqueness in PPG-based biometric system,” *IEEE Transactions on Information Forensics and Security*, vol. 16, pp. 116–130, 2021. <https://doi.org/10.1109/TIFS.2020.3006313>
- [181] A. Sarkar, A. L. Abbott, and Z. Doerzaph, “Biometric authentication using photoplethysmography signals,” in *Proc. IEEE BTAS*. IEEE, 2016, pp. 1–7. <https://doi.org/10.1109/BTAS.2016.7791193>
- [182] Y. Cao *et al.*, “PPGPass: Nonintrusive and secure mobile two-factor authentication via wearables,” in *Proc. IEEE INFOCOM*. IEEE, 2020, pp. 1917–1926. <https://doi.org/10.1109/INFOCOM41043.2020.9155380>
- [183] U. Yadav, S. N. Abbas, and D. Hatzinakos, “Evaluation of PPG biometrics for authentication in different states,” in *Proc. ICB*. IEEE, 2018, pp. 277–282. <https://doi.org/10.1109/ICB2018.2018.00049>
- [184] R. Wiegard *et al.*, “Analysis of wearable technologies’ usage for pay-as-you-live tariffs: recommendations for insurance companies,” *Zeitschrift für die gesamte Versicherungswissenschaft*, vol. 108, no. 1, pp. 63–88, 2019. <https://doi.org/10.1007/s12297-019-00431-2>
- [185] Vitality, “Activity tracking,” 2021. <https://www.vitality.co.uk/rewards/partners/activity-tracking/>
- [186] S. Park, K. Chung, and S. Jayaraman, “Wearables: Fundamentals, advancements, and a roadmap for the future,” *Wearable Sensors: Fundamentals, Implementation and Applications*, pp. 1–23, 2014. <https://doi.org/10.1016/B978-0-12-418662-0.00001-5>
- [187] S. Tedesco, J. Barton, and B. O’Flynn, “A review of activity trackers for senior citizens: Research perspectives, commercial landscape

- and the role of the insurance industry,” *Sensors*, vol. 17, no. 6, 2017. <https://doi.org/10.3390/s17061277>
- [188] S. Krüger and N. Ní Bhroin, “Vital signs: Innovations in self-tracking health insurance and social change,” *The Journal of Media Innovations*, vol. 6, no. 1, pp. 93–108, 2020. <https://doi.org/10.5617/jomi.7836>
- [189] A. Singhal and M. R. Cowie, “The role of wearables in heart failure,” *Current Heart Failure Reports*, vol. 17, no. 4, pp. 125–132, 2020. <https://doi.org/10.1007/s11897-020-00467-x>
- [190] W. K. Lim *et al.*, “Beyond fitness tracking: The use of consumer-grade wearable data from normal volunteers in cardiovascular and lipidomics research,” *PLoS Biology*, vol. 16, no. 2, pp. 1–18, 2018. <https://doi.org/10.1371/journal.pbio.2004285>
- [191] J. M. Radin *et al.*, “Harnessing wearable device data to improve state-level real-time surveillance of influenza-like illness in the USA: a population-based study,” *The Lancet Digital Health*, vol. 2, no. 2, pp. e85–e93, 2020. [https://doi.org/10.1016/S2589-7500\(19\)30222-5](https://doi.org/10.1016/S2589-7500(19)30222-5)
- [192] A. Natarajan *et al.*, “Heart rate variability with photoplethysmography in 8 million individuals: a cross-sectional study,” *The Lancet Digital Health*, vol. 2, no. 12, pp. e650–e657, 2020. [https://doi.org/10.1016/S2589-7500\(20\)30246-6](https://doi.org/10.1016/S2589-7500(20)30246-6)
- [193] M. Lang, “Beyond Fitbit: A critical appraisal of optical heart rate monitoring wearables and apps, their current limitations and legal implications,” *Albany Law Journal of Science and Technology*, vol. 39, p. 39, 2017. <https://heinonline.org/HOL/P?h=hein.journals/albnyst28&i=45>