Wearable heart rate variability and atrial fibrillation monitoring to improve clinically relevant endpoints in cardiac surgery—a systematic review

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Background: This systematic review aims to highlight the untapped potential of heart rate variability (HRV) and atrial fibrillation (AF) monitoring by wearable health monitoring devices as a critical diagnostic tool in cardiac surgery (CS) patients. We reviewed established predictive capabilities of HRV and AF monitoring in specific cardiosurgical scenarios and provide a perspective on additional predictive properties of wearable health monitoring devices that need to be investigated.

Methods: After screening most relevant databases, we included 33 publications in this review. Perusing these publications on HRV's prognostic value, we could identify HRV as a predictor for sudden cardiac death, mortality after acute myocardial infarction (AMI), and post operative atrial fibrillation (POAF). With regards to standard AF assessment, which typically includes extensive periods of unrecorded cardiac activity, we demonstrated that continuous monitoring via wearables recorded significant cardiac events that would otherwise have been missed.

Results: Photoplethysmography and single-lead electrocardiogram (ECG) were identified as the most useful and convenient technical assessment modalities, and their advantages and disadvantages were described in detail. As a call to further action, we observed that the scientific community has relatively extensively explored wearable AF screening, whereas HRV assessment to improve relevant clinical outcomes in CS is rarely studied; it still has great potential to be leveraged.

Conclusions: Therefore, risk assessment in CS would benefit greatly from earlier preoperative and postoperative AF detection, comprehensive and accurate assessment of cardiac health through HRV metrics, and continuous long-term monitoring. These should be achievable via commercially available wearables.

Keywords: Wearables; heart rate variability (HRV); stress; atrial fibrillation (AF); cardiac surgery (CS)

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Introduction

This systematic review aims to shed light on the prognostic potential of heart rate variability (HRV) metrics and improving atrial fibrillation (AF) diagnosis in cardiac surgery (CS) patients considering the pivotal role of AF, HRV assessment, and current development of continuous health monitoring methods via wearables.

CS patients with an impaired cardiovascular system are particularly prone to preoperative and postoperative life-threatening complications such as arrhythmias, strokes, and sudden cardiac death (1-4). Continuous monitoring of AF are common risk factors and complications after CS.

Tools to better predict and eventually prevent associated adverse events (AEs) are thus clearly needed (5,6). The pivotal role of continuous assessment of AF and HRV has been described: commonly available wearables with integrated single-lead electrocardiogram (ECG) and photoplethysmography (PPG) can provide easily accessible continuous data. Alterations in the HRV pattern provides an early marker of compromised health (7-11). In the 1970s, decreases in HRV were first associated with increased mortality and increased incidence of cardiac arrhythmias in patients after myocardial infarction (12). In more recent studies, reduced HRV has been found to independently predict all-cause mortality and sudden cardiac death in patients with acute and chronic heart failure (13,14). Given that research on HRV as a biomarker for AF prediction and other cardiac AEs is still in its early stages—and standard AF monitoring still consists mostly of singular heart rate measurements—we emphasize the importance of continuous data collection to drive both the improvement of AF detection and the progression of HRV as an early marker for AEs in CS.

In brief, frail CS patients may undergo pre-, peri, and post-interventional complications, most commonly AF, which is often subclinical and may be overlooked. Continuous monitoring today via wearables (e.g., Apple, Fitbit, and Samsung watches) can improve patient outcomes. They have already received the CE mark and FDA approval to report sinus rhythm, AF, and inconclusive (15). Moreover, HRV assessments via wearables could predict complications such as post-operative atrial fibrillation (POAF) or sudden cardiac death sudden cardiac death. This systematic review aims to describe the current state of continuous monitoring through wearables in CS patients and outline an outlook of future potential highlighting AF detention and risk evaluation with HRV.

The number of conduced cardiac surgeries per year range from 0.5 per million in low- and lower-middle income countries (average 107±113 per million) to 500 in the upper-middle-income countries (average 107±113 per million). Outside the industrialized world, CS is insufficiently accessible for more than 6 billion people. Therefore, a population ranging from 1.6 to 500 billion per year would benefit from improved AF monitoring and HRV assessments. Obviously, this benefiting population would further increase as worldwide access to CS improves because low-income and middle income countries are still on their way to fully meet their needs (16). We present this article in accordance with the PRISMA reporting checklist (available at https://mhealth.amegroups.com/article/view/10.21037/mhealth-23-19/rc).

Highlight box

Key findings
- Risk assessment in cardiac surgery (CS) would benefit greatly from earlier atrial fibrillation (AF) detection, comprehensive and accurate assessment of cardiac health through heart rate variability (HRV) metrics, and continuous long-term monitoring. These should be achievable via commercially available wearables.

What is known and what is new?
- CS patients are prone to witness complications such as AF, arrhythmias, and strokes.
- Today's wearables (e.g., Apple, Fitbit, and Samsung watches) can easily provide continuous monitoring of CS patients to improve outcomes.

What is the implication, and what should change now?
- In addition to the application in the general population, screenings via wearables in fragile CS patients should be improved. Hereby, AF diagnosis as well as heart health assessment through HRV measurements should be addressed.

Methods

Search strategy

A focused query of the most popular databases (PubMed, Scopus, and Web of Science) was conducted on the 28th of October 2022. There was no restriction on date or language for publication selection. The following keyword combination yielded 33 results: ((Wearable) AND (Cardiac Surgery) AND (Heart Rate Variability)) OR ((Wearable) AND (Cardiac Surgery) AND (Atrial Fibrillation)).

Among the 33 results, there were nine articles that focused on postoperative monitoring, three articles that focused on preoperative assessment and screening, five reviews, two meta-analyses, and five results of low relevance. One publication was removed prior to screening because the study did not focus on CS patients. In addition, nine results were excluded because of a lack of focus on patients or applicability to CS. The focus in the studies excluded from the analysis was on the cognitive load on the team during surgery from HRV assessment, the influence of specific drugs, implantable devices, and specific brands of devices (17-26). *Figure 1* shows the PRISMA flow diagram for the selection of outcomes

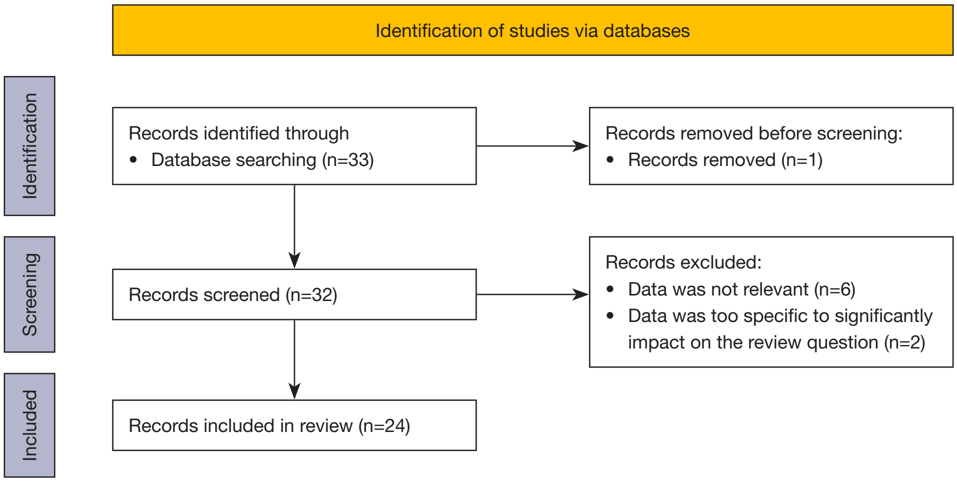


Figure 1 The PRISMA flow chart indicates the process of research, screening, and inclusion of records for this review.

included in this review.

Study biases

Attrition-bias might have impact on the study outcomes because CS patients are often frail, elderly, and undergo an emotionally arousing situation. Therefore, probands with an impaired cardiovascular system and consequently a higher probability to develop arrhythmic events could be more likely to drop out of the studies or show incompliance wearing the wearable eventually impairing sufficient data collection. Intention-to-treat analysis that better preserves randomization than per-protocol-analysis was conducted in most included studies to mitigate attrition-bias. When reported by these studies, intention-to-treat-analysis was often applied in wearables studies for cohorts obligated to wear the device, whereas per protocol analysis was conducted for patients that did not undergo continuous monitoring in most cases.

There are other important biases of concern such as the risk of response bias in cardiovascular symptom reports. Additionally, reporting bias may impact on the study that we could assess for this review because positive results are more likely to be published than negative. This can substantially influence the findings of this systematic review.

Results

The burden of AF in CS

AF plays a crucial role in primary and secondary stroke prevention and is associated with a significant increase in morbidity and mortality (1,10). In North America, an estimated 12–20% of all ischemic strokes are due to AF (27,28). In patients with paroxysmal AF, the risk of stroke increases up to 5-fold, whereas the annual risk of suffering a cardiac-related stroke varies between 1–12%.

To accurately assess the individual stroke risk and thus evaluate the indication for anticoagulation, the 4S scheme is used in patients with AF according to current 2020 ESC guidelines (29). As outlined in *Figure 2*, the 4S scheme assesses the following parameters: (I) stroke risk, (II) severity of symptoms, (III) severity of AF burden, and (IV) severity of substrate. As part of the 2020 ESC Guidelines, the AF Better Care (ABC) pathway guides AF management (indicated by *Figure 3*). CS patients whose cardiovascular systems are often severely compromised will benefit from improved AF screening and continuous postoperative long-term monitoring.

Wearable health monitoring devices (wearables) are designed to be worn by patients in their everyday lives and can rely on increasingly accurate and sophisticated artificial intelligence supported measurement methods. This will take preoperative and postoperative AF screening to a new level. A key driver of this evolution is the ability to easily monitor heart rate non-invasively and continuously, which most clearly differentiates wearables from traditional AF screening methods. The predominant technical methods used in wearables for this purpose are PPG and single-lead ECG. It is therefore likely that wearables will not only enable earlier and more accurate AF detection before and after surgery, but, through their continuous long-term

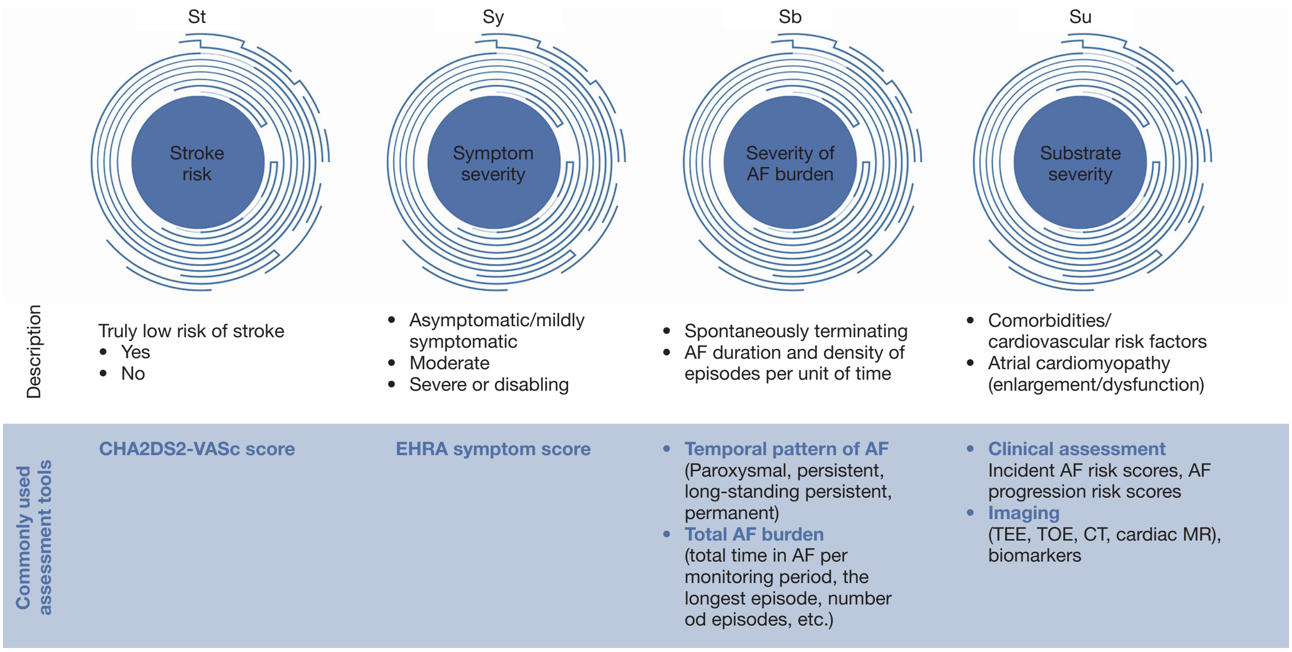


Figure 2 The 4S-AF scheme aims to outline a structured representation of AF management by relevant factors grouped into four AF-related domains (stroke risk, symptom severity, AF burden severity, substrate severity). CHA_2DS_2-VASc, congestive heart failure, hypertension, age ≥75 years, diabetes mellitus, stroke, vascular disease, age 65–74 years, sex category (female); EHRA, European Heart Rhythm Association; AF, atrial fibrillation; TEE, transesophageal echocardiography; TOE, transesophageal echocardiography; CT, computed tomography; MR, magnetic resonance.

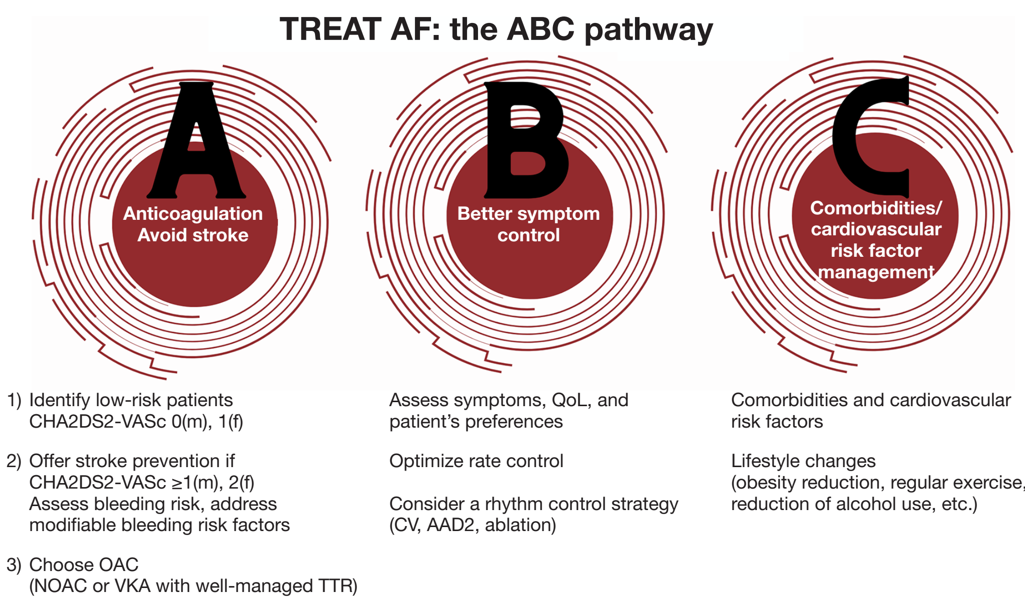


Figure 3 The ABC pathway aims to streamline an integrated approach to AF management. Hereby, three main pillars are outlined: "A" Avoid stroke (with Anticoagulants); "B" Better symptom management, with patient-centered decisions on rate or rhythm control; "C" Cardiovascular and Comorbidity risk optimization (29). AF, atrial fibrillation; ABC, Atrial fibrillation Better Care; OAC, oral anticoagulation; NOAC, new oral anticoagulation; VKA, vitamin K antagonists; TTR, time in therapeutic range; Qol, quality of life; CV, cardioversion; AAD2, antiarrhythmic drugs class 2.

monitoring of health data, will provide new and much deeper insights into the postoperative course of patients undergoing CS than ever before (30).

The physiological background behind HRV monitoring

The HR is the number of heartbeats per minute. The HRV expresses the physiological variations of time-intervals between successive heartbeats both at rest and during exercise (31). Although HRV has recently been widely implemented in medical and commercial applications, its scientific investigation is still in an early stage (32). HRV expresses neuro-cardiac function and is composed of heart-brain interactions and dynamic non-linear processes via the autonomic nervous system (ANS). Different interdependent regulatory systems operating on different time scales create HRV and enable us to properly adapt to an everchanging environment. Indeed, the HRV reflects ANS balance, the activity of the central nervous system, endocrine system, heart, gut, blood pressure (BP), and vascular tone (31,33). For instance, information about central nervous activity is reflected in higher levels of vagally-mediated HRV at regular heartbeat. These changes correlate to executive functions such as attention and emotional processing by the prefrontal cortex (1). On the contrary, afferent information produced by the intrinsic cardiac nervous system can influence frontocortical activity and thus affect higher-level functions (34,35). The heart rate itself is mainly regulated by the sympathetic and parasympathetic branches of the ANS. Thus, HRV is not only a relevant parameter for global cardiac health but is also an important indicator of the functional and cardiovascular integrity of the ANS. Often expressed in sympathetic hyperactivity, ANS impairment is linked to hypertonia, arrythmia, and other risk factors of cardiovascular deterioration. Consequently, early ANS assessment after pathological HRV measurements might be of particular importance in elderly and frail CS patients. We thus hypothesized that the extent of dysfunctional cardiac ANS integrity may not only provide essential insight into the optimal timing of the treatment, but might also be able to distinguish beneficial from futile regimens, thus ultimately providing a potential key factor for improved short- and long-term outcomes (36-38).

To understand the different HRV measurement methods and their correlation to either sympathetic or parasympathetic activity, we need to know the tendency of a healthy heart to have a strictly regular rhythm during high-frequency activity. The healthy heart shows lower HRV during physical exertion (strictly homogeneous rhythm) and higher HRV in relaxed mode (increasingly inhomogeneous rhythm). Physiological frequency fluctuations are most likely to be seen in the context of "respiratory sinus arrhythmia" (RSA).

The central ANS controls heart rate mainly via parasympathetic neuronal networks originating from the nucleus ambiguous of the medulla oblongata in synchronization with sympathetic nerve activity (superior cervical ganglia, ganglion stellatum, and thoracic ganglia) (39,40). Autonomic cardiac innervation is further modulated by various factors such as baroreceptors in the arcus aorticus and sinus caroticus or chemoreceptors in the glomus aorticum and caroticum. Best represented by the HF band (0.15–0.4 Hz) described below, the RSA forms the physiological heart rate pattern, which increases during inspiration and decreases during expiration (40,41). The baroreflex supports RSA and links heart rate, BP, and vascular tone. RSA fluctuations are mostly created through parasympathetic activation and inhibition (31). This can be illustrated by the example of a denervated heart, e.g., in the context of a heart transplantation where vagal tone is completely absent. As a result, the heart beats at an intrinsic rate averaging over 80 bpm at rest—this is significantly higher than a healthy heartbeat (42).

Our HR increases when we inhale followed by a BP rise about 4–5 seconds later (43). This BP rise is recognized by baroreceptors that consequently fire more rapidly. On the contrary, a rapid decline in BP recognized by these baroreceptors might activate vasocontraction to sustain sufficient perfusion. Expressed by the law of Hagen-Poiseuille [$Q = (\Delta P \times r4 \times \pi)/(8 \times \eta \times l)$], the arteriole-diameter adds most to peripheral resistance. BP is determined mainly by peripheral resistance and cardiac output, and thus the link between RSA, baroreflex, and vascular tone is unambiguous (31,43).

Healthy biological systems such as the cardiovascular system are characterized by temporal complexity. A decrease or increase in this complexity above a physiological threshold can be triggered by illness. Although increased HRV is associated with improved cardiac health in most cases, pathological conditions such as conduction disorders sometimes can lead to increased HRV, which in turn is associated with increased risk of death (31).

The different half-lives of norepinephrine and acetylcholine allow us to clearly assign certain frequency bands to sympathetic or parasympathetic activity. While the acetylcholine of the parasympathetic nervous system

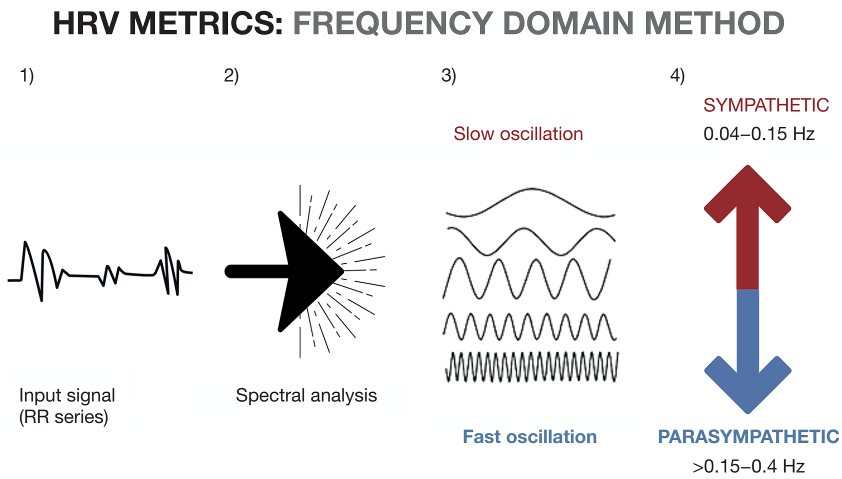


Figure 4 An ECG input signal is partitioned into different component bands by spectral analysis and the frequency domain method. Thereby, high frequency bands correlate with parasympathetic activity, while low frequency bands correlate with sympathetic activity (26). HRV, heart rate variability; ECG, electrocardiogram.

is metabolized with a high turnover rate and a very short latency period, the norepinephrine of the sympathetic nervous system is metabolized much more slowly. Therefore, the parasympathetic influence on HRV occurs relatively fast and is associated with the high-frequency band. In contrast, the influence of the sympathetic nervous system correlates with the low frequency (LF), very low frequency (VLF), and ultralow frequency (ULF) bands. Consequently, high frequency (HF) metrics, which represent a rapid change in ANS influence on the heart are related to a dominant parasympathetic branch.

In summary, HF parameters, including the frequency range of RSA described above, are a clear indicator of parasympathetic function, whereas LF metrics represent mainly the sympathetic influence on the ANS (<0.15 Hz) (9,44). The assessment of HRV by quantifying the individual frequency components of a frequency spectrum using spectral analysis is shown in *Figure 4*.

An overview of most relevant HRV metrics

Information on HRV can be extracted through time-domain, frequency-domain, and non-linear metrics. The complexity and unpredictability of a series of heartbeats (R-R intervals) is assessed in non-linear measurements as shown in *Figure 5* (31). Time-domain parameters calculate the amount of HRV during monitoring periods ranging from 2 minutes to 24 hours (most relevant time domain metrics are displayed by *Figures 6,7*). Frequency-domain parameters quantify the amount of signal energy within the components of the frequency spectrum (31). Longer recordings better depict slower HRV fluctuations such as the circadian rhythm, and therefore are more prone to being influenced by environmental stimuli. Thus, these long-term recordings (~24 hours) cannot be directly compared with short- or ultrashort-term recordings. When calculating the variability of the R-R intervals, the indices in the time domain are expressed in original units or as the natural logarithm (Ln) of the original units to improve normal distribution of values (44-47).

According to the European Society of Cardiology and the North American Society of Pacing and Electrophysiology, frequency-domain measurements are divided by spectral analysis into four different frequencies: HF, LF, VLF, and ULF. The absolute or relative HRV power can be calculated within each band. The techniques that are used the most are the fast Fourier transformation or autoregressive modeling. The power describes the signal energy detected in each frequency band. Thus, absolute power is calculated as meter per second squared divided by cycles per second (ms^2/Hz), whereas relative power represents the proportion of a single frequency band to the absolute power of all low and HF bands measured in normal units (nu). Relative power enables easy HRV comparison between two patients, in case of large differences in total or specific band power (48).

Using 24-h recordings, the ULF band (≤0.003 Hz) quantifies fluctuations in R-R intervals within a period of

HRV METRICS: NON-LINEAR PARAMETERS

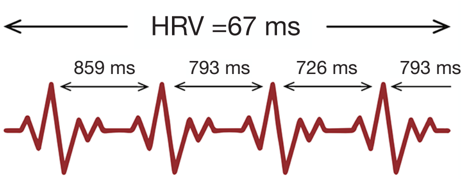
S (ms)	Area of the ellipse which represents total HRV
SD1 (ms)	Poincaré plot standard deviation perpendicular to the line of identity
SD2 (ms)	Poincaré plot standard deviation along the line of identity
SD1/SD2 (%)	Ratio of SD1-to-SD2
AnEn	Approximate Entropy, which measures the regularity and complexity of a time series
SampEn	Sample Entropy, which measures the regularity and complexity of a time series
DFAα1	Detrended fluctuation analysis, which describes short-term fluctuations
DFAα2	Detrended fluctuation analysis, which describes long-term fluctuations
D2	Correlation dimension, which estimates the minimum number of variables required to construct a model of system dynamics

Figure 5 Most relevant non-linear parameters for HRV assessment (26). HRV, heart rate variability.

HRV METRICS: TIME DOMAIN PARAMETERS

RR:
Interval between two heartbeats.
(R spikes in the QRS complex/ECG)

NN:
Interval between two heartbeats.
(emphasis on "normal" heartbeats)



SDRR (ms)
Standard deviation of the R-R intervals.

SDNN (ms)
Standard deviation of the N-N intervals.
The SDNN describes a median of the variability. It consists of parts from the sympathetic and parasympathetic nervous system.
The SDNN can be described as an overall variability or total power.

SDANN (ms)
Standard deviation of the average NN intervals for each 5 min segment of a 24 h HRV recording.
(higher values indicate increased parasympathetic activity)

rMSSD (ms)
Root mean square of successive RR interval differences.
(higher values indicate increased parasympathetic activity)

Figure 6 Most relevant time-domain parameters for HRV assessment (26). HRV, heart rate variability; ECG, electrocardiogram.

5 min to 24 h (10). Very slow acting biological processes affect the ULF band, and thus scientists assume that circadian rhythm may be the main driver of ULF alterations besides the body core temperature and certain metabolic events such as the renin-angiotensin system (49,50).

The VLF band (0.0033–0.04 Hz) measures rhythmical alternations within periods between 25 and 300 s. Requiring recording periods of at least five minutes, these recordings typically include 0–12 oscillating cycles. Overall, the VLF value may be most valuable in assessment of general cardiac health because low values on a 24-h VLF bands are associated with greater risk of AEs, and VLF power displays much stronger correlation with all-cause mortality than LF or HF bands. Furthermore, low power in the VLF band is related to low testosterone levels, high circulatory inflammation parameters, arrhythmic death, and post-traumatic-stress-disorder (11,44,51-55). Sympathetic impulse may modulate the amplitude and frequency of

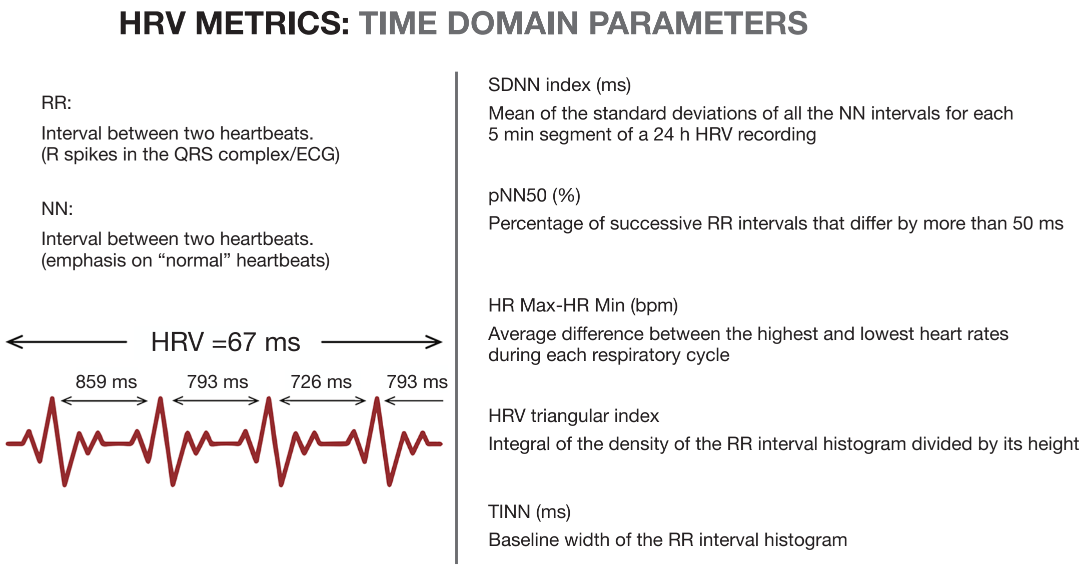


Figure 7 Additional time-domain parameters for HRV assessment (26). HRV, heart rate variability; ECG, electrocardiogram.

these oscillations, whereas parasympathetic modulations seem to be most influential on VLF power; parasympathetic blockage almost eradicates VLF power in general (56).

The LF band (0.04–0.15 Hz) requires recording periods of at least 2 minutes and predominantly reflects baroreceptor activity in resting conditions. That is why the LF band was originally called baroreceptor range. Influenced by both parasympathetic and sympathetic activity during normo-frequent breathing, vagally-mediated efferent respiratory influences are expressed particularly in the LF band during LF breathing (8.5 bpm) (55,57).

The HF band requires recordings over a minimum of 1 minute and previously has been called respiratory band (0.15–0.40 Hz). It is mostly influenced by normo-frequent breathing patters ranging from 9 to 24 bpm and reflects mostly parasympathetic activity (50). Total vagal blockage lowers LF power and completely irradicates HF oscillations. Remarkably, mitigated vagal inhibition is associated with morbidity, and low HF power correlates with mental stress, panic, and anxiety (58).

The LF to HF power ratio (LF/HF ratio) represents the ratio between the sympathetic nervous system (SNS) and the parasympathetic nervous system (PNS) activity. Total power is described by the sum of energy in every frequency band for 24 hours and the VLF, LF, and HF bands for short-term recordings (55). Ultimately, the unpredictability and intrinsic entropy of HRV are indexed by non-linear measurements (59) (*Figure 7*).

Potential of HRV metrics with wearables to improve clinically relevant endpoints

HRV has already been established as a helpful predictor in certain cardiac scenarios. On the one hand, HRV correlates with outcomes after acute myocardial infarction (AMI) (60,61). On the other hand, HRV-recorded vagal modulation predicts increased risk of sudden cardiac death (62). Thus, early diagnosis of these risks and subsequent implantable cardioverter defibrillator (ICD) implantation might be lifesaving. Moreover, in patients with hypertensive heart failure, root mean square of successive RR interval differences (rMSSD), and pNN50 (time-domain metrics outlined in *Figures 6,7*) were found to be independent predictors of the occurrence of AF along with traditional risk factors (age, hemodialysis, high PAC burden). Kim *et al.* concluded that abnormal autonomic cardiac regulation, represented by higher HRV in this study, is correlated with a higher risk of AF development (63). However, in CS, patients with a shorter PR interval and a decrease of the non-linear HRV parameter DFA1 could be identified as significant predictors of POAF (non-linear metrics are outlined in *Figure 5*) (64). In summary, further research is needed to realize the full potential of readily available HRV data in the face of a future in which a large proportion of people wear a continuous monitoring device. This is still true considering these findings on HRV metrics as predictors of mortality after myocardial infarction, risk of sudden cardiac death, and AF during CS as well as in patients with hypertension.

Table 1 A brief summary of e-certified wearable health monitoring devices and their capability to perform various measurements (69-71)

Company	Type	Biological measurement
Apple	Watch	ECG, HR, PA, sleep
Biobeat	Watch	HR, PA, cuff-less BP
Fitbit	Watch	HR, PA, sleep
Omron	Watch	HR, PA, cuff-less BP, sleep
Withings	Watch	ECG, HR, PA, sleep, SpO_2
iRhythm	Patch	ECG, HR
Preventice Solutions	Patch	ECG, HR
Corventis Inc.	Patch	ECG, HR
Bardy Dx	Patch	ECG, HR
BioTelemetry	Patch	ECG, HR
MediBioSense	Patch	ECG, HR
Global Instrumentation	Patch	ECG, HR
AliveCor	Wristband	ECG, HR
AliceCor	Mobile ECG	Single and 6-lead ECG, HR
Omron + AliveCor	Mobile ECG + BP	ECG, HR, BP
Zephyr	Chest strap	ECG, HR, PA, respiratory rate, skin temperature

ECG, electrocardiogram; HR, heart rate; PA, physical activity; BP, blood pressure; SpO_2, oxygen saturation.

AF diagnosis + HRV assessment with wearables

Similar to heart rhythm analysis with ECG, the current gold-standard of AF diagnosis, HRV metrics also derive from beat-to-beat (R-R) interval analysis (32). With respect to the 2020 ESC Guidelines, AF is diagnosed by either a 12-lead ECG or an at least 30 seconds recording of a single-lead ECG (65,66).

AF is defined as supraventricular tachyarrhythmia with uncoordinated electrical activity and inefficient contraction of the atrium and is characterized by irregular R-R intervals (with preserved integrity of atrioventricular conduction) and the absence of P waves in the ECG recording (24). AF is often associated with a ventricular rate of approximately 110–160 bpm, and AF can be further distinguished between the two types of rapid ventricular response and slow ventricular response constituting a ventricular rate of >100 and <60 bpm respectively (67). AF can often present as a subclinical phenomenon. In 18% of cases, AF is first detected at the time of stroke, thus highlighting the utility of using wearables for early detection (68). Currently available wearable health monitoring devices with CE mark and/or FDA approval are outlined in *Table 1* (30,69-71).

Compared to common chest-mounted devices such as a Holter ECG, watch-like continuous health monitoring devices are convenient and easy to integrate into the patient's daily routine (72). Despite the 2020 ESC guidelines, which for the first time have also addressed the diagnosis of AF using single-lead ESC, and the increasing use of wearable health monitoring devices by a broad mass of the population, further research is needed to perform screenings for silent AF in the general population and to reduce the associated morbidity and mortality. Currently, wearable health monitoring devices are seen more as medical advisors or detectors of rhythmic irregularities than as diagnostic tools (68).

Standards engineering methods in wearables: PPG + single-lead ECG

Single-lead ECG and PPG are the most common portable health monitoring devices. Therefore, this review focuses only on these two standard engineering methods.

PPG measures pulsatile volumetric changes in microvascular blood flow during the cardiac cycle by

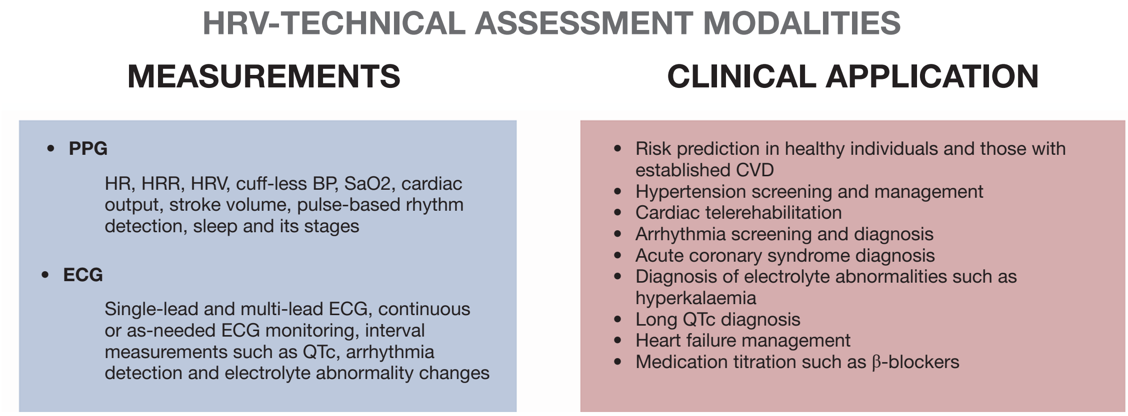


Figure 8 Clinical applications of ECG and PPG monitoring by wearable health monitoring devices (71). HRV, heart rate variability; PPG, photoplethysmography; HR, heart rate; HRR, heart rate recovery; BP, blood pressure; ECG, electrocardiogram; CVD, cardiovascular disease.

converting light absorbed or reflected by blood flow (typically LED or infrared light) within the sensor coverage area into waveforms and measurable signals (73). This amplitude of these waveforms marks the maximum of ventricular contraction during systole and resembles the R-peak in the ECG (68). Disadvantages of PPG measurements include the need for adequate BP, which is not the case, for example, when AF triggers peripheral malperfusion (74). Furthermore, PPG can only serve as an aid in the diagnosis of AF because, unlike the ECG, it is not considered a valid diagnostic method to date. A watch-type single-lead ECG can record the Einthoven I lead with the right index finger on the crown acting as the negative electrode and the watch on the left wrist acting as the positive electrode (75). The most relevant clinical applications of PPG and ECG in wearables are outlined in *Figure 8*. Consequently, the combination of screening by PPG and diagnosis by single-lead ECG could be a plausible solution to reduce undetected AF and related complications.

Pre-surgery

In addition to medical therapy, there are now additional minimal invasive treatment modalities such as left atrial appendage closure and radiofrequency catheter ablation that can both reduce thromboembolic risk and provide long-term freedom from AF (76,77). Earlier diagnosis of AF through continuous monitoring may thus allow these therapies to be applied at an early stage to prevent AEs (30,78,79). In a study of a population of 96 patients, Kim *et al.* compared continuous long-term measurement methods of a wrist-worn health monitoring device versus conservative, single-point screening methods with respect to the detection rate of AF (30). Paroxysmal arrhythmias often remain undetected during single-point screening using 12-lead ECGs and even Holter monitoring. In contrast, long-term continuous monitoring could detect 53% of all cardiac arrhythmias. Holter monitoring could only detect a significantly lower proportion at 28.1%. In conclusion, this study supports the potential of the wearable health monitoring device in early detection of AF as 24.9% of total cardiac events that have been missed without continuous measurement methods (30).

Periprocedural

Early detection of AEs in high risk-CS patients

Postoperative complications of CS are significantly associated with intrahospital mortality, but recognition of precursor events is often difficult leading to avoidable rescue failures (80-84). In addition, in most cases, signs of deterioration indicative of AEs occur up to 38 hours before the patient is transferred to the ICU (85-88). Therefore, efficient detection of these AE precursor events is critical to improve clinical outcomes.

To date, several wearable health monitoring devices have been tested for tracking vital signs in the hospital setting. However, the major obstacle to monitoring by wearables is the unacceptably high number of false-positive alarms. Therefore, machine learning systems were used to set more precise parameter thresholds for alerting. Approaching this end, Breteler *et al.* found that simultaneous increases in HR and RR and decreases in SpO_2 were associated with AEs during general and trauma surgery. Within the study population of 31 patients, 11 patients developed AEs, with AF as the most common cause in 20% (89). However, future studies incorporating larger study populations are needed to develop more precise vital sign warning patterns or algorithms for appropriate alerting systems. Similarly, other studies investigated the correlation between the new set AF and postoperative complications (90). Although a considerable number of studies have investigated the recording of vital signs to establish prognostic warning patterns, the number of studies evaluating continuous monitoring using wearable health monitoring devices in the hospital before and after surgery is limited (88,91-95). For example, continuous PPG monitoring could indicate a higher risk of cardiovascular events by assessing cardiac stress using measures such as ejection time index, subendocardial viability ratio, and evaluation of arterial stiffness by assessing pulse wave velocity (96,97).

In conclusion, the scientific community should further explore continuous monitoring by wearable health monitoring devices used in an in-hospital setting both to improve standard monitoring and to prevent serious postoperative complications.

Post surgery

POAF in CS patients

POAF is one of the most common AEs in CS patients within 30 days of discharge and is associated with a significantly increased risk of stroke (25–33% lifetime risk), heart failure, dementia, and death (98,99). In addition, according to the 2020 ESC guidelines, the decision to treat AF is based on the 4S regimen in which other cardiovascular deteriorations are relevant factors. Continued anticoagulation may lead to bleeding events and therefore must be weighed against the benefits of stroke prevention in each individual patient. However, early POAF diagnosis followed by pharmacological therapy could protect a significant proportion of CS patients from fatal strokes.

General risk for AF after CS

The incidence of POAF in coronary artery bypass grafting (CABG) and valve surgery patients is 20–30% and even up to 50%, respectively (28,100-105). To investigate the potential of continuous monitoring in CS, Funk *et al.* studied 302 patients undergoing CABG and/or valve surgery using wearable health monitoring devices during hospitalization and for an additional 14 days after discharge. The study reported that AF occurred in 42% of subjects with AF occurring after discharge in approximately 33% of these subjects. Of note, up to 70% of AF episodes were subclinical and were not associated with symptoms such as palpitations, fatigue, chest discomfort, or dyspnea. In addition, valve surgery and pulmonary hypertension, AF during index-hospitalization, and discontinuation of ß-blockers were found to be predictive of subsequent AF occurrence after discharge (106). By demonstrating a substantial degree of asymptomatic AF after discharge of CS patients, this study reinforced the importance of improved monitoring strategies with wearable health monitoring devices.

Wearables on the rise for POAF screening

Patch-based POAF screening

To investigate POAF screening by continuous monitoring methods, another study investigated a patch-based wearable health monitoring device applied after hospital discharge following CS. The results showed that continuous monitoring improved POAF detection by 17.9% in 336 CS patients for 30 days after CS compared with usual care (12-lead ECG screening) (107). The inclusion criteria were the absence of preoperative AF and a CHA2DS2-VASc score of greater than or equal to four. In addition, patients who reported AF of >24 h duration during hospitalization were excluded. A total of 19.6% of all patients monitored with the wearable health monitoring device met the criteria for intention to treat whereas only 1.7% of patients monitored with the 12-lead ECG were estimated to need treatment (absolute difference: 17.9%). Based on the inclusion criteria, the risk of stroke in patients diagnosed with POAF is estimated to be 1.3% and would meet the threshold for oral anticoagulation as described above (29). Notably, the relevant AF duration in this study was set at ≥6 minutes, and a substantial 73.3% were diagnosed in the first week after surgery. Consequently, continuous monitoring by wearable health monitoring devices for as little as one week would greatly improve postoperative surveillance and reduce future stroke events.

PPG-based POAF screening

Because of the practicality of wrist PPG monitoring, it can be easily used for screening POAF. Its predictors include nonlinear HRV parameter DFA1 mentioned above; it is seen in the long-term monitoring in CS patients (64). Today, guidelines call for 12-lead ECG recording at 3 and 6 months after index surgery followed by annual follow-ups. In contrast to continuous PPG screening, the major disadvantages of single time point measurements by 12-lead ECG are the non-detection of short AF episodes in measurement-free periods, the need for strong compliance, the cost to patients and healthcare providers, and the impossibility of detection during periods of mobilization (108). In terms of future improvements, continuous monitoring using PPG to monitor arrhythmias could be recommended in addition to standard procedures. Thus, wearable long-term monitoring could detect recurrence of AF or other arrhythmias and eventually lead to better treatment outcomes.

Immediate AF diagnose through machine learning

To diagnose paroxysmal AF even earlier, researchers are trying to improve PPG through machine learning. To develop the algorithms, the investigators provided CS patients with an Apple Watch (109). Thus, 80 patients underwent telemetry monitoring, 12-lead ECG screening, and continuous heart rate monitoring using Apple Watch in training mode over a 14-day period after CS in 2021 and 2022. Regarding the accuracy of the data, small black spots in the detection of AF could be compensated by the applied machine learning model GBDT (Gradient Boosting Decision Tree) and reached an accuracy of 0.94 (sensitivity: 0.909, specificity 0.838). This accuracy rate of the improved PPG system of the Apple Watch is comparable to similar wearable health monitoring devices, which generally achieve an accuracy rate of >0.9 (110-112). The investigators ultimately did not achieve their goal of establishing a more accurate diagnosis of AF. However, precisely distinguishing AF from other arrhythmias under perioperative conditions caused by various cardiac irregularities is inherently complex.

One of the major impediments to continuing progress on the development of an immediate diagnostic tool of AF may be related to the nature of PPG that derives its electronical impulses from pulse pressure curves propagating through the cardiovascular tree. In addition to the substantial cardiac changes and altered physiological processes immediately after CS complicating diagnosis, the compromised cardiovascular system often causes inadequate pulse pressure and intravascular volume, thus making accurate monitoring by PPG difficult (74,113-115). To address the question of whether a device other than the Apple Watch could provide more accurate data, Inui *et al.* compared the metric accuracy of the Apple Watch 3 and Fitbit, which showed slightly higher accuracy of 75% and 30%, respectively, when comparing pulse rate and heart rate (74). Therefore, techniques other than PPG could probably provide better support for more accurate AF detection in frail CS patients.

Algorithm-supported AF screening in a large population

Recently, the Fitbit Heart Study, published in September 2022 by Lubitz *et al.*, investigated on a novel PPG-based software algorithm aiming to detect irregular heart rhythms (IHR) in the general population to identify undiagnosed AF. The Study population (≥22 years) was monitored by using compatible wearable Fitbit devices and Android or iOS smartphones. In detail, 5-minute pulse windows (tachograms) were assessed, and subsequently participants revealing 11 consecutives irregular tachograms were identified as showing an IHR. These participants with an IHR were invited to a telehealth visit and received a 1-week ambulatory ECG patch monitor. Eventually, the first IHR detection with the ECG patch monitoring was assessed as a predictor for AF as the primary outcome. Results displayed 4,728 IHR in a total of 455,699 enrolled participants representing 1% (4%, 2,070 participants, in the ≥65-year-old). AF was present in 340 (32.2%) of the 1,057 participants who received the ECG patch monitor and in 221 participants of the 225 participants with another IHR during ECG patch monitoring resulting in a positive predictive value of 98.2%. In conclusion, the combination of algorithm-supported AF screening with Fitbit wearables in a large population exhibited a high positive predictive value and may be a strong tool for decreasing undiagnosed AF in the general population (116).

HRV as predictive value in CS

CS is known to alter the ANS system in several ways. First, anesthesia (e.g., propofol) increases sympathetic nerve activity, thus resulting in relaxation of peripheral vessels (117). Second, the pain stimulus, unless adequately suppressed by analgesics, induces an increase in heart rate due to the release of catecholamines resulting in an increase in LF and VLF power. The latter can also be induced by intravenous application by anesthesia (118). In addition, recovery of cardiac activity after cardioplegia affects the ANS. A variety of postoperative complications are related to ANS instability, and thus HRV may play a critical role in detecting ANS imbalances in the future and thus improve the prevention of complications in the early and late postoperative period.

HRV after AMI

Today, guidelines for treatment after AMI rely heavily on the left ventricular ejection fraction (LVEF) to decide between further treatment options such as implantation of an ICD or optimized pharmacological therapy. LVEF is often preserved after a myocardial infarction and revascularization (119,120). Therefore, the following additional metrics are needed to refine treatment options. Wolf *et al.* discovered that patients with a more pronounced HRV had a lower mortality rate after AMI than patients with a less pronounced HRV (12). In addition, other studies found significant associations between patients with decreased HRV and subsequent myocardial infarction and/or higher risk of sudden cardiac death (121). Consequently, the majority of the scientific community recognizes HRV as a strong marker of arrhythmogenic death and postulates its superiority versus ejection fraction-based metrics (94,122,123).

Decreased HRV often occurs because of increased sympathetic activity—adrenergic activity correlates with electrical instability. This is readily exemplified by AMI-induced myocardial necrosis, which exhibits increased sympathetic activity and drives malignant arrhythmias. Changes in HRV are also observed in patients with chronic heart failure, which is characterized by overactivation of the sympathetic nervous system. Furthermore, relevant correlations between HRV impairment and disease severity have been found especially a correlation between the LF/HF ratio and the risk of AEs, as well as a correlation between the LF parameter and right ventricular dysfunction could be described. Consequently, HRV could be used in addition to standard metrics, such as LVEF, in important decision-making and patient selection to improve clinical outcome (32,94,124-127).

Post-CABG

It is well known that coronary artery bypass leads to a significant reduction in HRV, which recovers in most patients after approximately two months. Versus HRV deterioration after AMI, HRV reduction after CABG is even more pronounced and is not caused by necrosis but is rather related to the use of the heart-lung machine, cardioplegia, anesthesia, and cardiac manipulation. Notably, due to the extreme adrenergic release during both on- and off-pump grafting, CABG invariably leads to a reduction in HRV immediately after the procedure (128,129). However, revascularization apparently outweighs ANS irritation, although HRV does not recover in every patient as shown by long-term follow-up. The prognostic value of HRV in the context of CABG is controversial. The results of the CAST (Cardiac Arrythmia Suppression Trial) suggest that there is no association between HRV recovery and clinically relevant endpoints or mortality. However, HRV metrics assessed by the nonlinear domain measurement method showed a particularly strong correlation between postoperative HRV reduction and the occurrence of AEs as well as the increase in mortality (129,130). In conclusion, the scientific community should conduct additional research to determine whether the persistent decline in HRV in CABG patients has prognostic value and whether restoration of HRV could lead to prognostically favorable outcomes.

HRV in the context of heart valve procedures

To date, HRV reduction after cardiac valve surgery has not been found to have predictive value for long-term outcome or mortality. HRV deteriorated more after mitral valve compared to aortic valve surgery, which might be explained by the larger surgical accesses and the intensity of manipulation in mitral valve procedures. In addition, percutaneous procedures such as transcatheter aortic valve implantation (TAVI) did not cause significant worsening of HRV, whereas transapical procedures resulted in a mean reduction in HRV due to the higher invasiveness of the procedure (131).

Liu *et al.* investigated continuous monitoring after transcatheter aortic valve replacement (TAVR) by a smartwatch in 100 patients for 30 days after discharge. Cardiac events occurred in 34 patients, and four patients received pacemaker implantation as a result (132). Postoperative complications, such as conduction disorders occurring with latency can be life-threatening and must be detected at all costs in all patients. Continuous monitoring could certainly be helpful—especially in those patients who are scheduled for discharge the next day. In similar studies, a new diagnosis of AF was made in four patients—one of whom received anticoagulation as a result (133-135). We see that continuous monitoring beyond the hospitalized period is key to preventing late postoperative complications in the future.

PPG for HRV assessment

The biggest plus of PPG measurement for HRV monitoring

Table 2 Challenges of using wearables in today's clinical practice (71)

Theme	Challenges
Accuracy and validity	Inaccurate data is more harmful than no data
Meaningful use criteria and clinical evidence	Paucity of meaningful use criteria and robust clinical evidence; very few trials have examined the superiority of wearables for clinical outcomes compared with no wearables
Behavioral change	Enacting and maintaining behavioral change is difficult; some studies question the value of wearables in guiding behavioral change
Hardware cost and payment models	Wearables might emerge as a new health disparity; up to threefold difference in wearable use between high and low socioeconomic status
Data security and governance	Sensitive wearable data is subject to breaches; sharing wearable data for research or clinical purposes is difficult; unrealistic patient expectations for data handling
Data management	Data interoperability, provenance, and storage

is the convenience for the patient. The drawbacks of the PPG method include that HRV measurement is often compromised by low hypovolemia, that it varies significantly between subjects, and that there are numerous discrepancies between certain subset parameters. While some subset parameters can be adequately assessed by PPG (e.g., SDNN), most parameters belonging to the high-frequency band (LF/HF ratio) have not been adequately validated. One study even reported a measurement accuracy of only about 30% (136). Although PPG certainly has its drawbacks in terms of HRV assessment, PPG-equipped wearable health monitoring devices with sophisticated algorithms provide AF screening that is nearly comparable in quality to gold standard methods as demonstrated by the recent Huawei or Apple Watch study (96).

Overall challenges of wearables in a clinical practice are indicated by *Table 2*.

Discussion

Discussion on POAF monitoring via wearables

CS patients with a weakened cardiovascular system are vulnerable to AF and consecutive strokes; the 4S and ABC scheme of the ESC 2020 guidelines provide good guidance in the assessment and therapy (described in *Figures 2,3*). In addition, AF often occurs after discharge and in most cases presents without symptoms. For this reason, patients should be regularly evaluated for AF even after their hospitalization to benefit from earlier medical treatment such as anticoagulation, radiofrequency ablation, or atrial appendage closure. Consequently, the scientific and clinical community should make further efforts to explore and implement accurate, convenient, and affordable screening options via wearable health monitoring devices to promote AF and stroke prevention. These efforts would ultimately not only prevent serious complications but should also be undertaken in the interest of health care costs.

It is particularly important to note that POAF is not limited to the period of hospitalization because a significant percentage of AF has been detected by continuous monitoring using wearables after discharge. POAF is often described as a transient phenomenon attributable to pericardial inflammation, cardiac ischemia, hemodynamic alterations, and increased adrenergic state after surgery (137); however, conclusive studies examining periods after hospitalization of several weeks or even months are scarce. Therefore, the scientific community should investigate long-term monitoring through wearable health monitoring devices after CS, which have recently enabled and simplified this finding. Further research is needed to investigate the unexplored areas of POAF screening and potential therapeutic indications. Not only is post-discharge monitoring after CS rare, it remains unclear whether POAF in this specific setting should be classified as a transient phenomenon or a serious precursor of short- or long-term cardiovascular outcomes (138).

Furthermore, PPG-based recording of AF in the context of the compromised cardiovascular system after CS is complex because influencing factors such as blood volume and BP are often subject to considerable fluctuations and cannot be used for adequate assessment. Using machine learning methods, Hiraoka *et al.* developed an algorithm with an accuracy of 0.94 for AF detection in the study population of 80 patients (109). Consequently, future studies incorporating larger patient populations are needed to validate such findings in machine learning driven assessment in combination with PPG metrics of wearable health monitoring devices for AF detection in a postoperative setting.

Reduced HRV indicates a higher risk of arrhythmogenic death, adverse outcome after myocardial infarction, and severity of heart failure. Based on these current findings, HRV data may encompass a much broader range of predictive values in cardiac surgical patients, which the scientific community should further explore. However, the accuracy of HRV assessment as obtained by commercial wearable health monitoring devices is still uncertain. Despite the availability of remote and continuous HRV monitoring, ensuring accurate data delivery may be the major obstacle to overcome to realize the full potential of HRV as a prognostic tool to improve clinically relevant outcomes (32).

Bridging the gap between HRV assessment and postoperative AF in CS is important with an overall incidence 15% to 50% of patients undergoing CABG or heart valve surgery (139). One of the main causes of POAF is attributed to sympathetic hyperactivity, which is reflected by reduced HRV as a surrogate parameter. Therefore, HRV could be a valuable predictor for distinguishing between transient and long-lasting AF after CS. In terms of individualized patient care, understanding novel biomarkers such as HRV is essential. For example, HRV has been shown to be a valid surrogate parameter for treatment success of mesenchymal stem cell implantation after myocardial ischemia, as demonstrated by de Morais *et al.* The improvement in HRV after treatment was correlated with the decrease in infarct size and fibrosis (140).

Conclusions

In conclusion, the potential of HRV as a predictive value for AEs after CS is not just a hypothesis but has already been established as a validated predictor of AEs after myocardial infarction and the occurrence of sudden cardiac death. In addition, continuous monitoring of AF with wearable health monitoring devices has been shown to contribute to significant improvements in early detection. In addition, the researchers presented long-term monitoring of POAF as a promising option. The conclusion is that continuous monitoring with wearable health monitoring devices in CS patients should further explore HRV as a predictor to improve the detection of late-onset AF and, consequently, should be integrated into modern medical practice.

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Footnote

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