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NEW THERAPIES FOR CARDIOVASCULAR DISEASE (AA BAVRY AND M MASSOOMI, SECTION EDITORS)

A Clinician's Guide to Smartwatch "Interrogation"

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Abstract

Purpose of Review Wearable technology is rapidly evolving and the data that it can provide regarding an individual's health is becoming increasingly important for clinicians to consider. The purpose of this review is to help inform health care providers of the benefits of smartwatch interrogation, with a focus on reviewing the various parameters and how to apply the data in a meaningful way.

Recent Findings This review details interpretation of various parameters found commonly in newer smartwatches such as heart rate, step count, ECG, heart rate recovery (HRR), and heart rate variability (HRV), while also discussing potential pitfalls that a clinician should be aware of.

Summary Smartwatch interrogation is becoming increasingly relevant as the continuous data it provides helps health care providers make more informed decisions regarding diagnosis and treatment. For this reason, we recommend health care providers familiarize themselves with the technology and integrate it into clinical practice.

Keywords Smartwatch · Apple Watch · Fitbit · Garmin · mHealth · Mobile ECG · HRV

Introduction

mHealth, or the use of mobile devices to support medical care and public health, is a rapidly changing landscape that can be challenging to keep up with. mHealth can involve the use of mobile applications, wearable sensors, and communication technologies. New devices are constantly being developed and released. Existing devices continue to be updated with new features. Software continues to evolve, pushing hardware to its limits. Major technology companies are marketing and advertising these devices more than ever, and across multiple platforms, from television to social media.

Broadly speaking, smartphones are perhaps the most widely used mHealth devices, given most people have one. While smartphones can record some data, such as step counts, flights climbed, and distance walked, that data can be limited as the phone needs to be on the user's body to record activity, which can lead to underestimation. The use of smartphones in clinical care has been discussed in a prior review and the automatically recorded health data is rather basic when compared to a smartwatch [1].

Statista reported 9 million smartwatch devices sold in 2016 and a staggering > 22 million units in 2019 [2]. Apple Watch has dominated the market share with around 50% over the past several years [3]. Other commonly used devices include Samsung, Fitbit, and Garmin. These data make it likely for a clinician to see several patients a day who are wearing a smartwatch, most likely an Apple Watch.

Given the prevalence of smartwatch use, patients sometimes seek medical care based on notifications received by their smartwatch. As clinicians, we deal with potential data overload, which may include false positives and false negatives. This can create an intimidating landscape for care providers as we try to incorporate data from wearable tech into clinical care. The aim of this review is to help inform care providers of the potential benefits of smartwatch interrogation in the clinical setting, reviewing the various parameters that can be monitored and how to interpret and apply the data in a meaningful way. Potential pitfalls and false positives and negatives will also be reviewed.

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There are innumerable websites and magazines with articles encouraging patients to purchase and use smartwatches to improve their health. However, there is a scarcity of literature guiding physicians on actual data and how to incorporate these devices into clinical care. This review seeks to help close this gap. There are several barriers that may prevent a physician from using smartwatch data clinically. These barriers include unfamiliarity with devices, skepticism regarding accuracy of data, lack of clinical trials, uncertainty in how to interpret the data, and lack of time in clinical encounters. The variety of devices and variance in proprietary features and metrics can further discourage physicians from learning to "interrogate" such devices.

The data on smartwatches may be used to assess a patient's current state of health and activity level, and that information may be used to help patients achieve optimal health. There are a plethora of metrics that can be assessed with a smartwatch and the key elements will be reviewed individually.

Energy Expenditure

Most smartwatches provide an assessment of active time, based on accelerometer use, as well as energy expenditure, based on calculations incorporating HR, accelerometer, age, weight, and gender. Active time can be a useful measure motivating patients to achieve an average of 30 min/day, as in the case of "closing the rings" on Apple Watch devices. It is our experience that sedentary patients often overestimate their activity, and this measure can help bring objectivity to the assessment while tracking improvement over time. The iOS Health App now identifies trends and notifies users of significant changes in fitness metrics. Energy expenditure is a more challenging metric to interpret as studies have shown that smartwatch algorithms often overestimate energy expenditure with wide error margins, up to 27% [4]. As such, energy expenditure is likely a less useful metric than many of the others which will be reviewed.

Step Count

Smartwatches estimate step counts using data from built-in accelerometers, which record tri-axial motion. Walking and running produces a sinusoidal plot created by arm motion and the impact of the feet on the ground, which can be discerned from other non-ambulatory motion. Sophisticated algorithms analyze these accelerometer plots to determine step counts and physical activity levels. The algorithms in the Apple Watch can even discern different swimming strokes based on accelerometer data.

Physical inactivity is a major source of poor health and is a metric that is easily tracked with all smartwatches. Checking the step count on a patient's smartwatch can be clinically meaningful for risk stratification and for setting goals. This metric helps identify higher-risk patients as lower step counts are associated with higher mortality and insulin resistance. Studies suggest a step count < 5000/day to define "sedentary." [5] While step count absolute accuracy can vary between devices, trends are meaningful. Bringing attention to step counts can help patients to make changes and become more active [6]. Furthermore, the benefits of increased steps per day are continuous, meaning an increase in just 1000 steps a day is associated with lower mortality, especially those with lower baseline step counts [7, 8]. The AHA and CDC generally recommend a goal of 10,000 steps per day, but the average in the USA is only 3000–4000 steps a day (CDC.gov). A recent *JAMA* study showed that > 7000 steps a day was associated with lower mortality, compared to < 7000 steps per day [9••]. In a medical encounter, a clinician can check a patient's step count in a matter of seconds, quickly giving insight into a person's activity level and overall risk. This objective assessment of activity is important as patients sometimes tend to overestimate their level of activity. For those with lower step counts, a goal to increase by 2000 steps a day via a 10–20-min walk is an easily achievable and high-yield goal, and one that is easily monitored at follow-up. Most smartwatches display step data over daily, weekly, and monthly time frames while providing a daily average, which may be used to track overall progress (Fig. 1).

Heart Rate and Mobile ECG

Most smartwatches today are able to record pleth-based heart rate data. The accuracy of plethysmography-based HR data has been previously reviewed and validated against ECG, with smartwatch HR data typically being accurate within 10% of data obtained by ECG reference standard [10]. Apple Watch and Garmin devices were found to be the most accurate. Fitbit, while still fairly accurate, was found to sometimes underestimate HR [11]. As such, these data can be considered valid and useful. Smartwatch apps display HR over time in easy to interpret graphs (Fig. 2). A quick assessment of resting HR and HR range can be completed in < 1 min on the patient's smartphone. This can easily be incorporated into the outpatient visit. HR during exercise can be compared against age-related predicted maximums to gauge the level of exertion and/or chronotropic competence. For patients on AV nodal blockers, HR data can help better guide decisions on medication dose titration, as it provides a continuous source of data versus the snap-shot provided in the clinic, potentially decreasing the need for some face-to-face clinic visits when monitoring response to treatment.

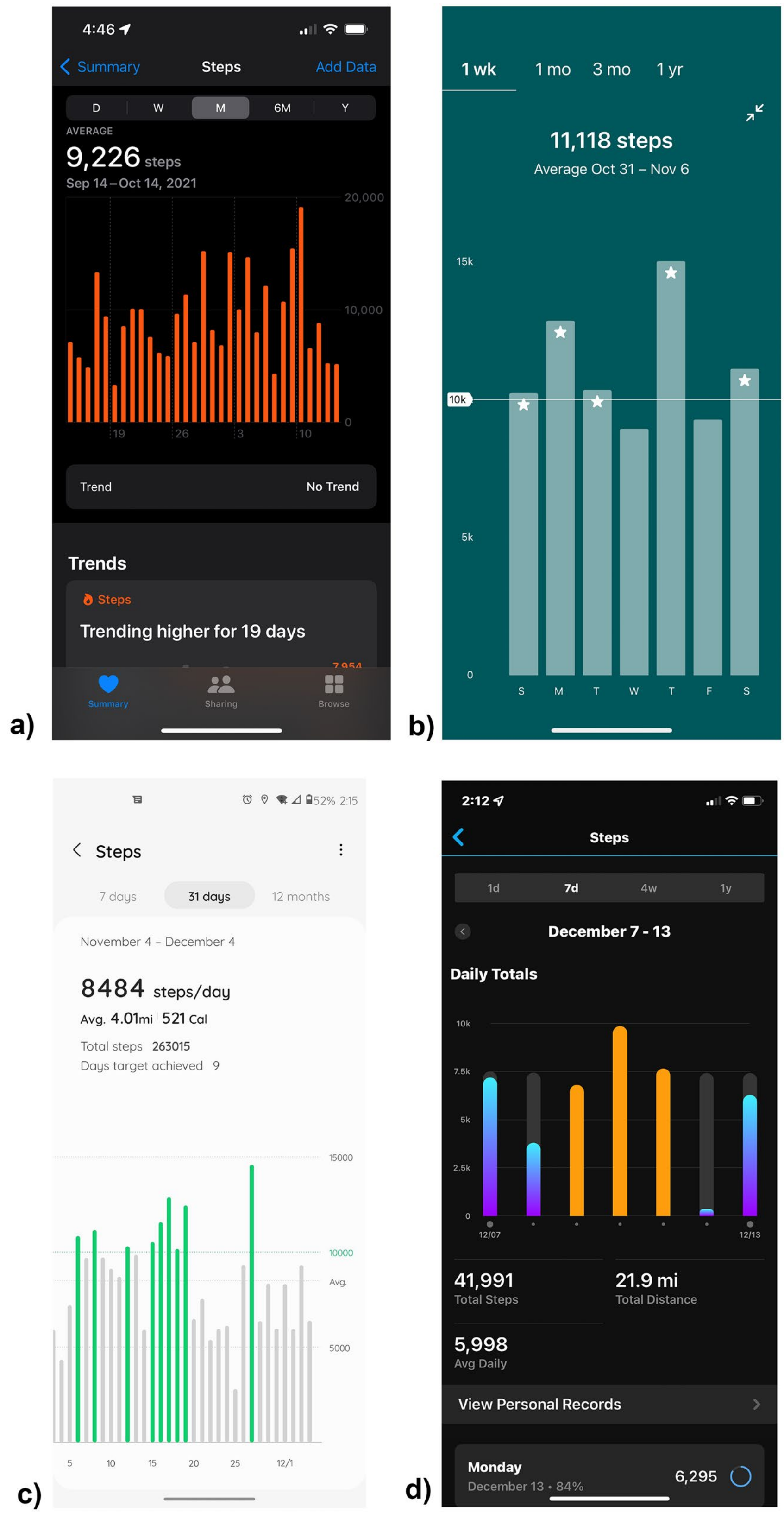


Fig. 1 Simple to interpret and trend step counts in Apple Health (**a**), Fitbit (**b**), Samsung Health (**c**), and Garmin (**d**). Current and prior data can easily be viewed and is automatically logged by wearing smartwatch

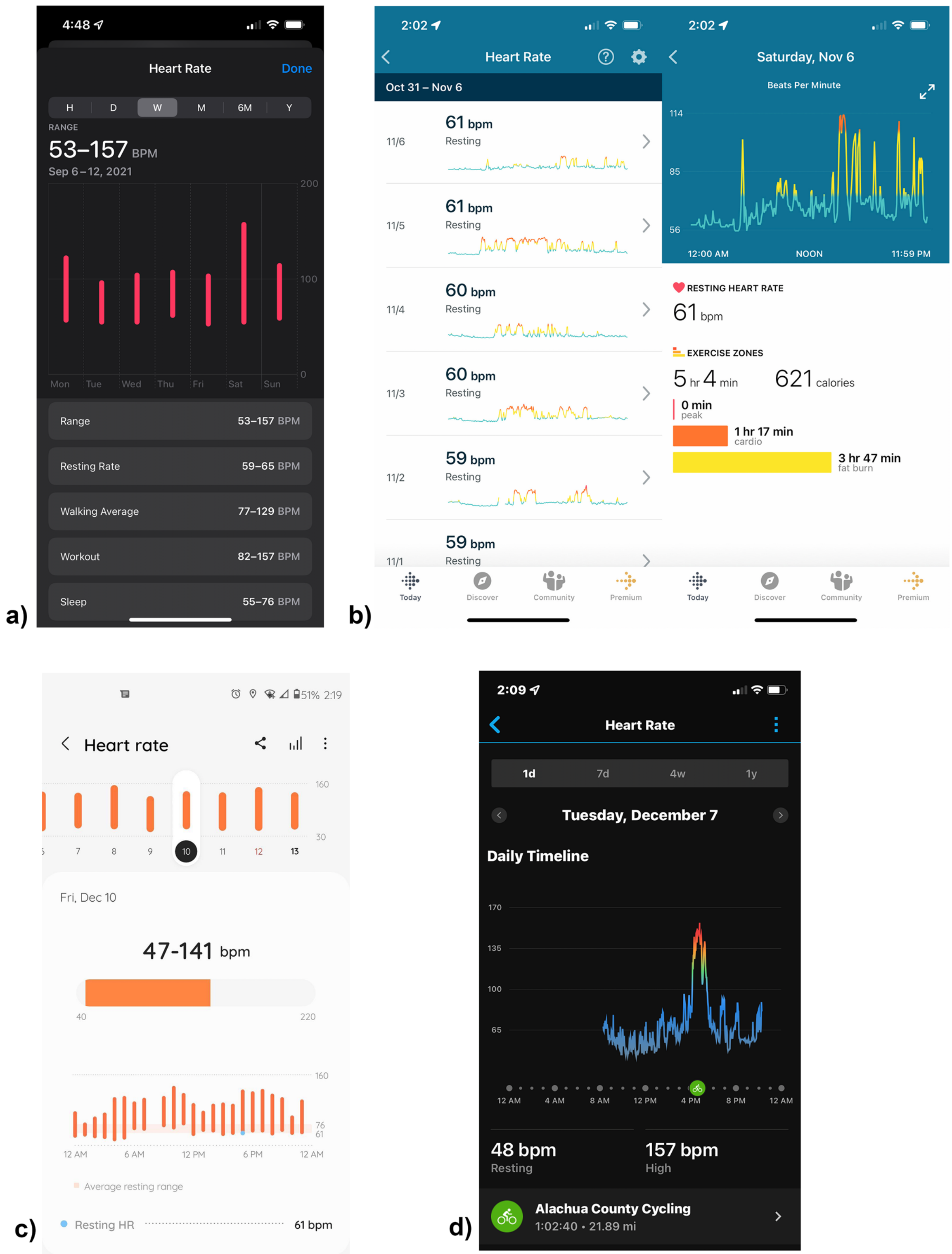


Fig. 2 Heart data in Apple Health (**a**), Fitbit (**b**), Samsung Health (**c**), and Garmin (**d**). Prior data can easily be viewed and timelines can be adjusted for long-term trends. Resting HR is shown in addition to the range

This is further validated by the fact that wrist-worn heart monitors have been shown to have better accuracy at rest than they do with activity, providing reassurance to the clinician that the average resting heart rates available for interpretation are a reliable source [12, 13].

The availability of such data by patients can lead to patient-driven visits for concerns over notifications. Patients may present with concerns over bradycardia detected by their smartwatch, which may at first seem frustrating to care providers; however, embracing the data can make it easy to deal with the situation. For example, Fig. 3 shows data from the Apple Watch of a patient who presented due to a low HR notification. The patient was asymptomatic and further review of the watch data showed a chronic resting rate of 45–50 bpm and the majority of low HRs were during the night. Furthermore, the walking average HR was normal, indicating chronotropic competence. As such, the patient was reassured and no further workup was pursued. In fact, the low HR zone was lowered to 40 bpm to reduce unnecessary notifications to the patient.

For patients with atrial fibrillation, HR data can provide insight into rate control, and indirectly, may help suggest paroxysms based on changes in baseline HR. For several years, the Apple Watch was the only device that provided background assessment of R-R variability on pleth-based HR as a method of screening for atrial fibrillation. Fitbit has now been approved by the FDA to roll out its own algorithm for background pleth-based irregular rhythm notifications, which is set to go live in May 2022. This feature of "irregular rhythm detection" needs to be enabled by users, as it is not on by default. Helping to educate patients about such features may help to increase early atrial fibrillation diagnoses, possibly helping to prevent strokes, which are a source of great morbidity and mortality related to atrial fibrillation. Apple is aiming to answer this important question via the Johnson & Johnson Heartline study, as the United States Preventative Services Task Force currently conclude that there is "insufficient evidence to assess the balance of benefits and harms of screening for atrial fibrillation" in asymptomatic adults [14]. While pleth-based screening of atrial fibrillation may produce false-positive results (ectopy, artifact, or misclassification of rhythm), this can be significantly reduced by having patients record single-lead ECG when notified of such an irregularity (Fig. 4). The topic of pleth-based irregular rhythm notifications and mobile ECG will be the focus of a future review.

Though the electronic interpretation of the tracing may incorrectly identify the rhythm, the tracings are of high fidelity and the rhythm may be adjudicated by a physician upon review during an outpatient visit. In fact, such visits are becoming more common, where patients present to discuss a potential abnormality detected by their smartwatch. This is just one reason that physicians need to embrace such devices

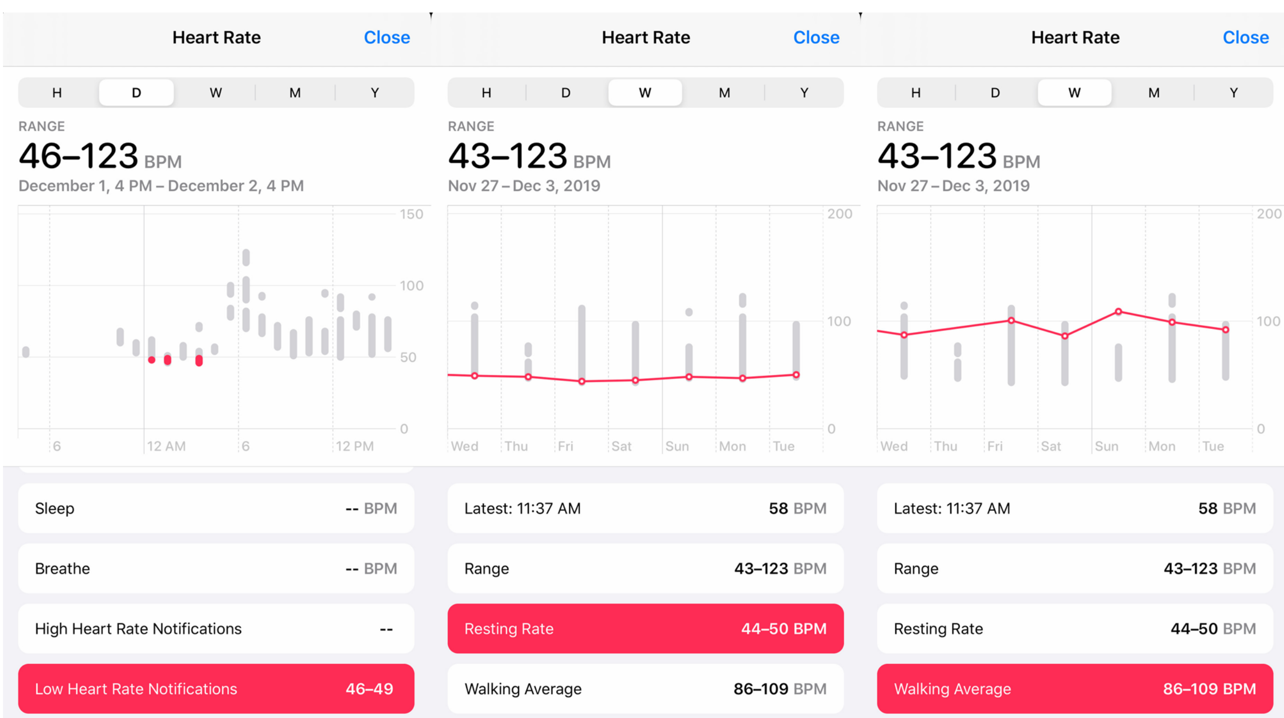


Fig. 3 Apple Health App data showing low heart rate notifications, but reassuring data with chronic, stable low baseline resting heart rate and walking HR > 100 bpm, suggesting reasonable chronotropic response

and become comfortable with finding and interpreting the data gathered by them.

Smartwatch ECG is a growing area as more and more devices are offering this feature of on-demand recording of a single-lead ECG. In addition to smartwatches, there are dedicated mobile ECG devices, such as Kardia, EMAY, Omron, and Eko. Given the number of devices and scope of this review, the highly relevant topic of patient-acquired ECG will be discussed separately in a future review, as there can be gray areas regarding atrial fibrillation screening and initiation of anticoagulation in patients with incidentally discovered atrial fibrillation.

While interpreting smartwatch data, it is also necessary to be able to recognize the false positive high and low spikes in heart rates that occur with daily use. During periods of changing heart rate devices can half count or double count until the photoplethysmography is accurately tracked. Apparent outliers in heart rates without clinical correlation likely do not require further evaluation, especially if data points reflect short periods in time which can be erroneous readings. This is certainly a weakness of smartwatches and misinterpretation or overinterpretation can lead to increased use of unnecessary downstream testing, as well as increased patient anxiety.

One study investigating the potential sources of these inaccuracies found that while most consumer wearables tend to be quite accurate at measuring heart rate both during rest and prolonged heart rate elevations, they vary widely in their response to activity changes. This study concluded that these devices tend to overestimate heart rates during low-intensity exercise, potentially as an engineered safety mechanism to prevent users from exceeding their maximum heart rate [15•]. This is an important bias for clinicians to consider while counseling patients with atrial fibrillation using smart wearables, as unnecessary follow-up expenditure could result if overreliance on these devices becomes commonplace without taking the patient's clinical picture and activity changes in context. This is supported by a retrospective study performed in patients with atrial fibrillation, which showed that atrial fibrillation patients with wearable devices utilized more follow-up health care, without a significant difference in pulse rates compared to patients not using wearable devices [16].

VO2 Max

Most smartwatches, including Apple, Samsung, Fitbit, and Garmin, can estimate VO2 max, which is the maximum volume of oxygen that an individual can extract from inhaled

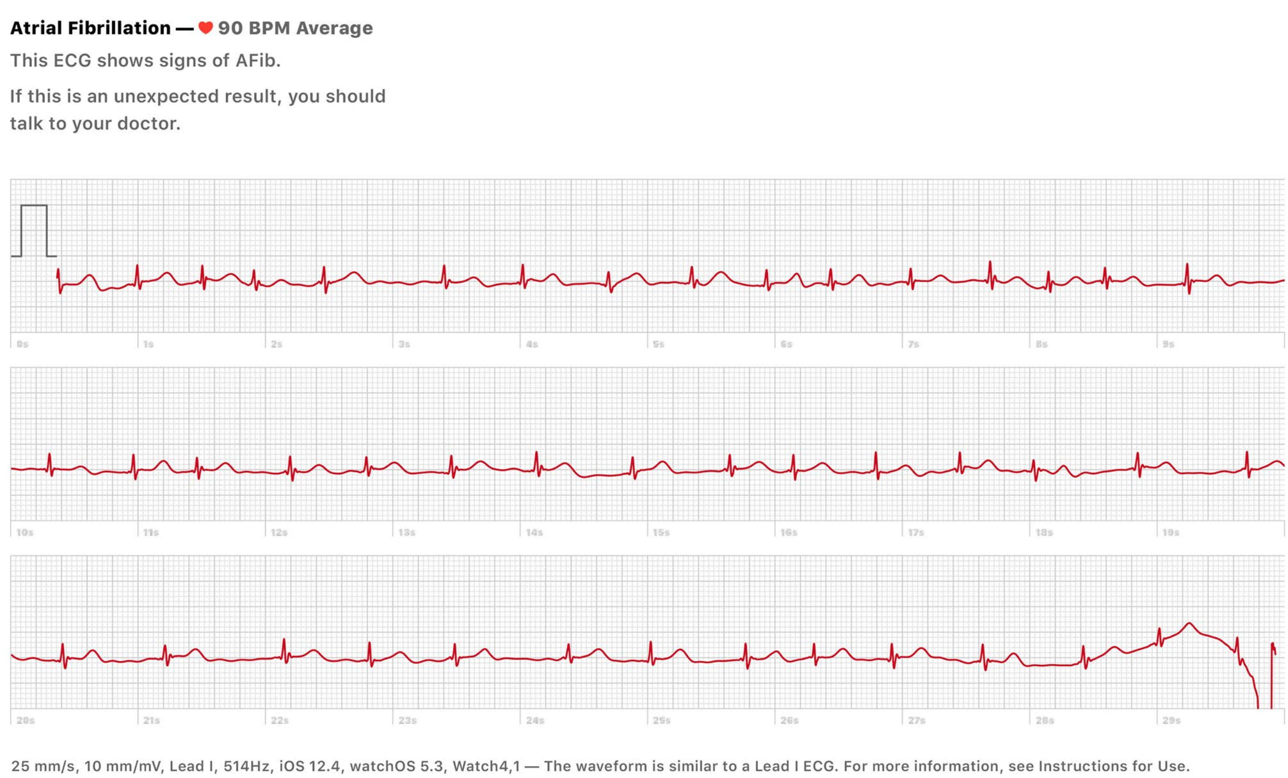


Fig. 4 ECG obtained by patient on Apple Watch showing atrial fibrillation after the patient received an irregular rhythm notification. In this instance, the Apple Watch detected atrial fibrillation that may have otherwise gone undiagnosed until potentially symptomatic or found incidentally at a clinical encounter. Such early diagnosis and subsequent treatment may possibly lead to reduction in stroke events, which is being investigated

air. Typically, the most accurate measurement of VO2 max requires completion of cardiopulmonary exercise testing, a fairly involved procedure where an individual exercises at increasing intensity wearing a face mask that directly measures oxygen levels in inhaled and exhaled air. This value can then be compared to gender-based norms to stratify individuals based on their fitness level [17]. Though measurement through this method is considered the gold standard, it is unsurprisingly more time and resource-intensive. Smartwatches instead calculate VO2 max based on a user's heart rate response to physical activity during submaximal exertion such as walking, running, or hiking, which is beneficial as it requires fewer resources and allows the feature to be applicable to a larger population of users (Fig. 5). However, limitations to the accuracy of the algorithm must be appreciated, particularly in individuals whose heart rate does not increase appropriately to compensate for demand, such as those with heart failure or those taking AV nodal blockers [18]. Ideally, an individual should log in to the Apple Watch if they are taking beta-blockers or calcium channel blockers so that the algorithm appropriately accounts for their lower predicted maximum heart rate.

Heart Rate Recovery

Continuous recording of heart rate during activity and recovery allows for another powerful metric of fitness that is often overlooked, called heart rate recovery (HRR). HRR is typically defined as the measure of how quickly one's heart rate decreases after exercise, typically measured at a 1-min interval. There is strong support for HRR as an effective prognostication tool in the literature. A decrease in heart rate after exercise is believed to correlate strongly with fitness and vagal reactivation by the parasympathetic nervous system, and individuals with attenuated heart rate recovery have been consistently found to have an increased risk of cardiovascular events and all-cause mortality [19–21]. In practice, individuals with an HRR less than 12 bpm after 1 min are considered to have an abnormal value, alerting the clinician of an above-average risk individual who may benefit from additional counseling and physical conditioning, such as cardiac rehab, though no studies specifically discussing a pragmatic method to incorporate analysis of HRR into clinical practice were found. Figure 6 shows

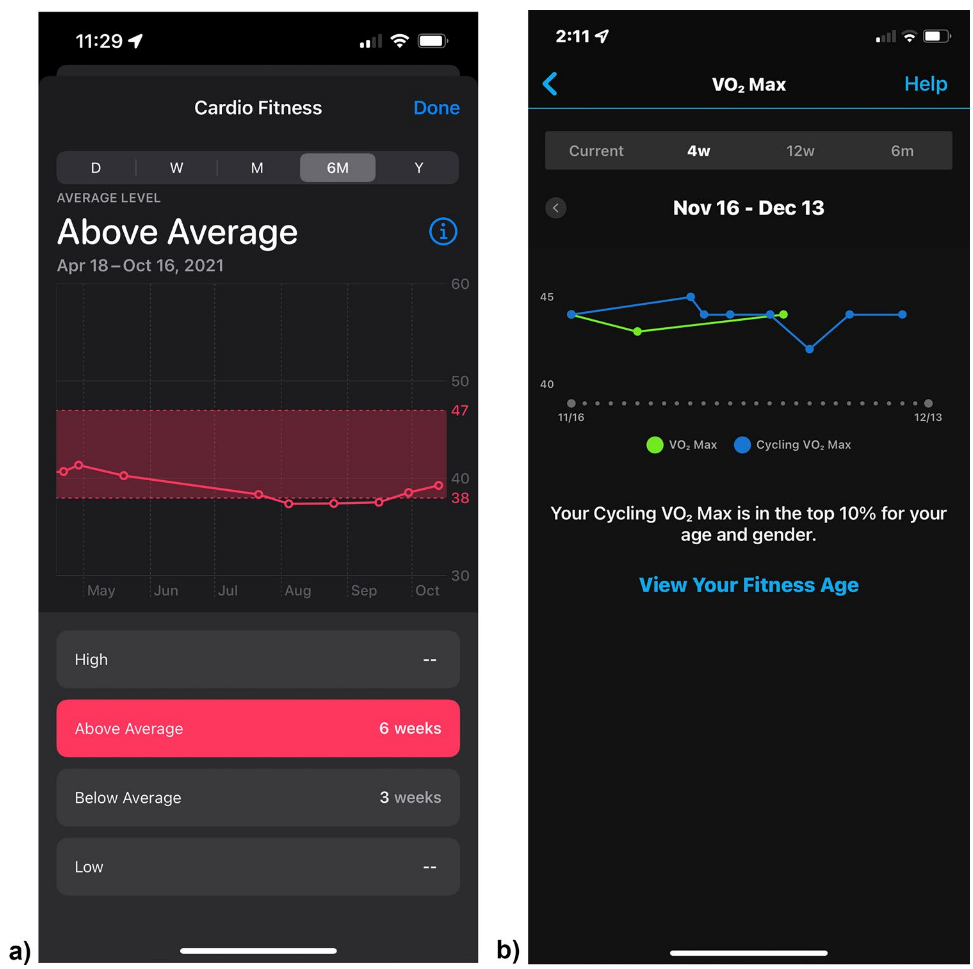


Fig. 5 VO2 max displayed in Apple Health (**a**) and Garmin Apps (**b**). This data is calculated in the background during exercise and can be trended over time to monitor fitness and functional capacity objectively

HRR automatically displayed on a recorded workout in the Apple Fitness App. Some other smartwatches have their own way to display HRR, and it can easily be measured by the wearer by simply noting HR at the end of an intense workout and again at 1 min into recovery. Likely, other smartwatch brands will better incorporate this into their software given evidence for its predictive value and consumer demand.

Heart Rate Variability

The autonomic nervous system is also closely related to another metric called heart rate variability (HRV), which is a measure of the small variation between successive heartbeats, measured in milliseconds. This is a measurement that is also becoming increasingly popular and available on smartwatches. It is believed that at rest, a high HRV is favorable as it implies a heart that is better able to tolerate stress. Likewise, decreases in HRV are associated with an increased risk for new cardiac events and all-cause mortality [22]. Several studies validate photoplethysmography-based HRV compared to the gold standard of ECG, in both healthy adults, as well as athletes [23, 24]. It is difficult to identify normal and abnormal values, as age and gender need to be considered and there are no current studies that establish norms. There are, however, data collected by device manufacturers that help to show the average values of those who use the devices. Such data show that among > 24,000 users, the average HRV was 59 ms with 75% of users falling between 46 and 72 ms [25]. The Whoop, a subscription-based health tracker and coaching software, also tracks HRV and their data show that the middle 50% of those aged 20–25 years old have an average HRV between 55 and 105 ms, while those aged 60–65 years old have an average HRV between 25 and 45 ms.

Similar to HRR, there is currently no consensus on the best way to interpret HR variability for clinical purposes, though this is likely to change as this is an area likely to see numerous future studies given the growing data sets

Fig. 6 Heart rate recovery displayed in the Apple Fitness App. The bottom of the left screenshot shows HR during the exercise activity and the bottom of the right screenshot shows heart rate recovery once the exercise activity is ended, after 1 min and after 2 min

obtained by various fitness trackers and smartwatches [26]. A recent study of > 270 patients showed that HRV < 8 ms was an independent predictor of ICU admission in COVID-19 patients > 70 years old [27].

At present, HRV is not a standard feature on all smartwatches and some manufacturers display it as a proprietary stress score, instead of providing the absolute value in ms. The Apple Watch leads by displaying HRV in ms in the heart section of the iOS Health App, also showing trends over time (Fig. 7). Fitbit devices can measure HRV, but as of the time of this writing, the data is only available to those who subscribe to a paid membership, as is the case with the Whoop band. As this metric is likely to be a fruitful area of research, future smartwatch software iterations are likely to further incorporate it.

6-Min Walk Distance

Another fitness metric provided by the Apple Watch is a 6-min walk distance (6MWD) (Fig. 8a). Normal values are typically 400–700 m [28]. Like VO2 max, this value allows for stratification of individuals into groups based on fitness level and also has evidence supporting its use for

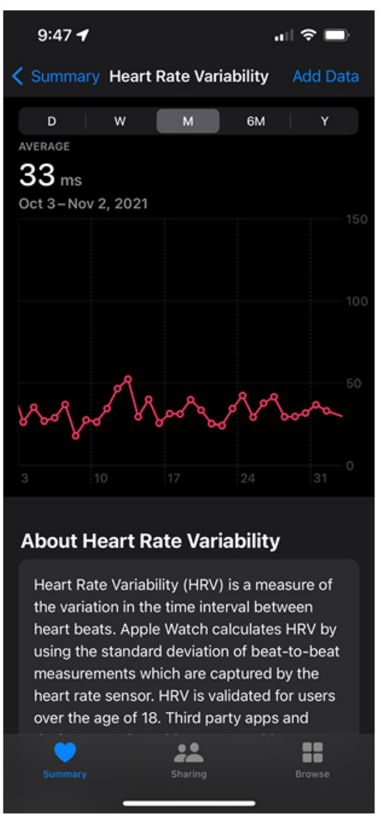


Fig. 7 Heart rate variability displayed in the Apple Health App, 1-month timescale

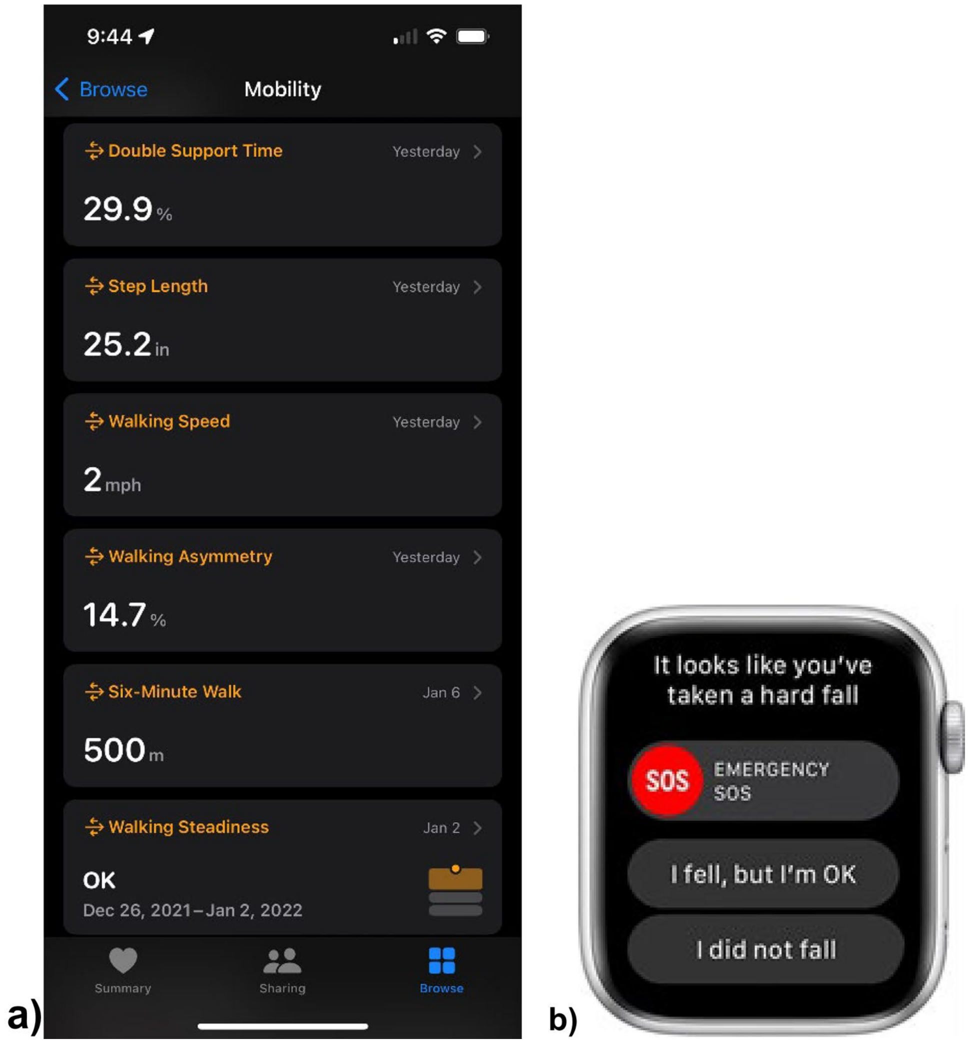
prognostication of several disease states. A meta-analysis evaluating the prognostic significance of baseline 6MWD showed that lower 6MWD was independently associated with a higher risk of all-cause mortality, readmission, and overall poor prognosis in patients with heart failure [29].

So what is the most effective way that a clinician can incorporate a review of all these metrics into practice? Since studies have shown that more than half the reduction in all-cause and cardiovascular mortality occurs when individuals move from the least fit group to the next least fit group, reviewing step count, VO2 max, and 6MWD with patients during smartwatch interrogation provides an effective tool for clinicians to identify individuals that are habitually sedentary and deconditioned and attempt to target them aggressively for lifestyle modification, including routine moderate-intensity exercise or more formal cardiac rehabilitation [20, 21, 30]. Overall, the literature reviewed supports evaluating cardiopulmonary fitness based on VO2 max and 6MWD from an Apple Watch as an excellent alternative to a traditional cardiopulmonary exercise test in select individuals, as it can easily be incorporated into a clinic visit to assist with risk stratification and physical activity counseling.

Mobility and Fall Detection

The Apple Watch offers metrics in the area of mobility such as double support time (the portion of time that both feet touch the ground when walking), walking asymmetry, stride length, and walking speed (Fig. 8a), which may be able to predict fall risk in the future. This data may be compared to population averages to identify those who can benefit from physical therapy evaluation for cane or walker usage in an effort to prevent or reduce falls and associated fractures. However, there is much still unknown about which aspects of gait contribute most to stability and how to most effectively utilize these new metrics in practice. As older individuals tend to have these gait changes, it is important to identify whether these new mobility metrics are actually associated with increased fall risk. One study suggested that increased double support time was actually a beneficial adaptive mechanism, as it decreases an individual's momentum and allows them more time to successfully recover after a loss of balance [31]. Furthermore, as it is difficult to increase double support percentage when walking at a constant speed, people will tend to walk more slowly to increase the time spent in double support [32]. Overall, these studies support the idea that these typical gait changes associated with elderly individuals are associated mainly with fear of falling, and do not actually correlate with increased risk of falling itself. However, when reviewing whether fall risk was influenced by walking speed, there was one study that did find that a decrease in gait speed by 10 cm/s in a year was associated

Fig. 8 **a** iOS Apple Watch Mobility Metrics. Each metric may be selected for further information, including normal ranges for comparison. **b** Apple Watch fall detection notification allowing a user to dismiss if okay or call EMS. If not dismissed, EMS will be called automatically



with an increased risk of falls [33]. Though these metrics provided with Apple Watches do have potential as a means of continuous gait assessment and disease prognostication, further studies are needed to help clinically apply these data.

Additionally, all Apple Watches from Series 4, SE, and onward also include the fall detection feature (Fig. 8b). Upon detecting a possible fall, the watch will wait for the user to respond to an alert, and if the user does not respond and remains immobile for more than 1 min, it will automatically call emergency services [34]. The user can also specify if a fall occurred or not, which helps Apple improve the fall detection algorithms over time. Fall detection can be beneficial in elderly patients, especially those who live alone. Many patients have Apple Watches but are unaware of its safety features, which also include the ability to directly call emergency services by pressing and holding the side button. As care providers, we can help close this gap and help patients maximize the benefit of the devices they already wear. Enabling these features takes just seconds in the general settings, SOS section on the Apple Watch.

O2 Monitoring

Most flagship smartwatch models today including, but are not limited to, Apple Watch (Series 6 or newer), Fitbit Sense, Samsung Galaxy Watch 3, and many Garmin models are capable of measuring blood oxygen levels (Fig. 9). There is one small study that directly compared SpO2 measurements between the Apple Watch and commercial oximeters in COPD, ILD, and healthy patients and found strong correlations between the devices [35]. As such, these devices may be useful for monitoring patients on home oxygen to determine the ongoing need or to titrate therapy. There is currently little data available regarding the accuracy and reliability of nocturnal oxygen monitoring using wearable technology. Overall, there is certainly potential to use these features for ambulatory oxygen monitoring, and further research combining microphones, HR, accelerometer, and O2 levels may lead to an effective screen for obstructive sleep apnea. Also, in the future, such aggregate data may help to identify COPD or heart failure exacerbations earlier when interventions may be

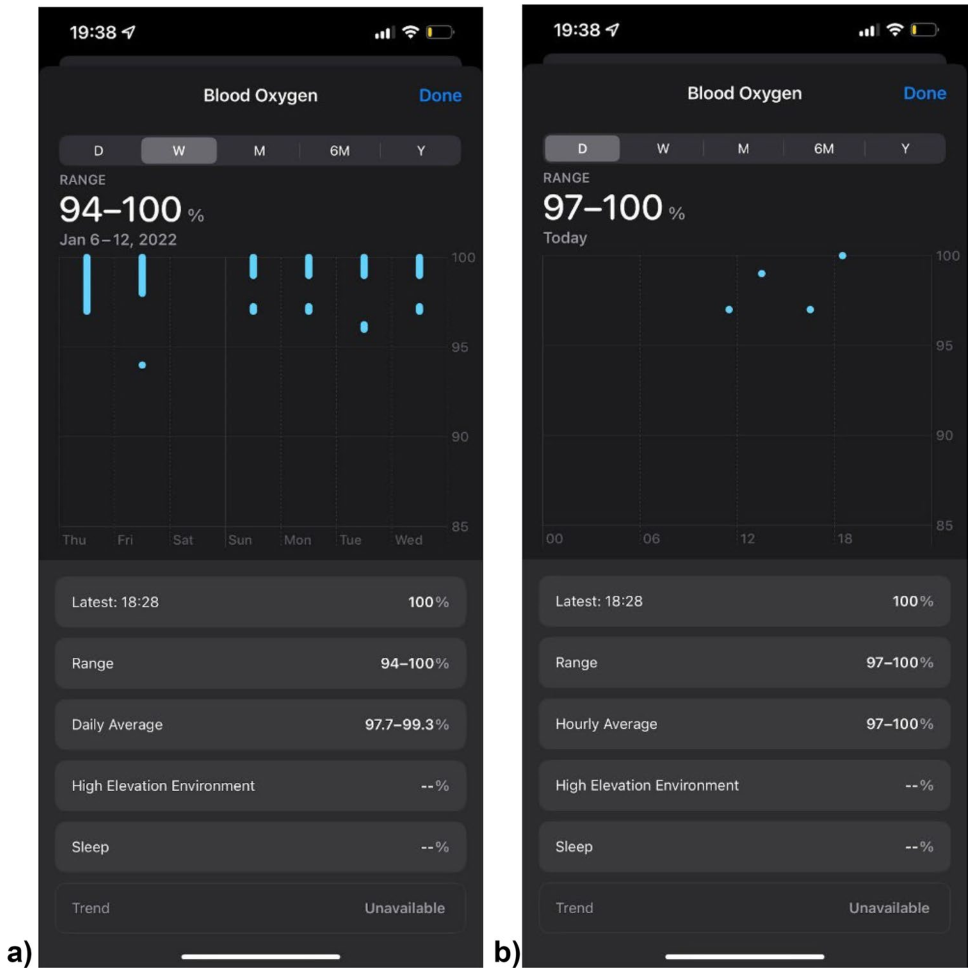


Fig. 9 Oxygen saturation displayed in iOS over 1 week (**a**) and 1 day (**b**)

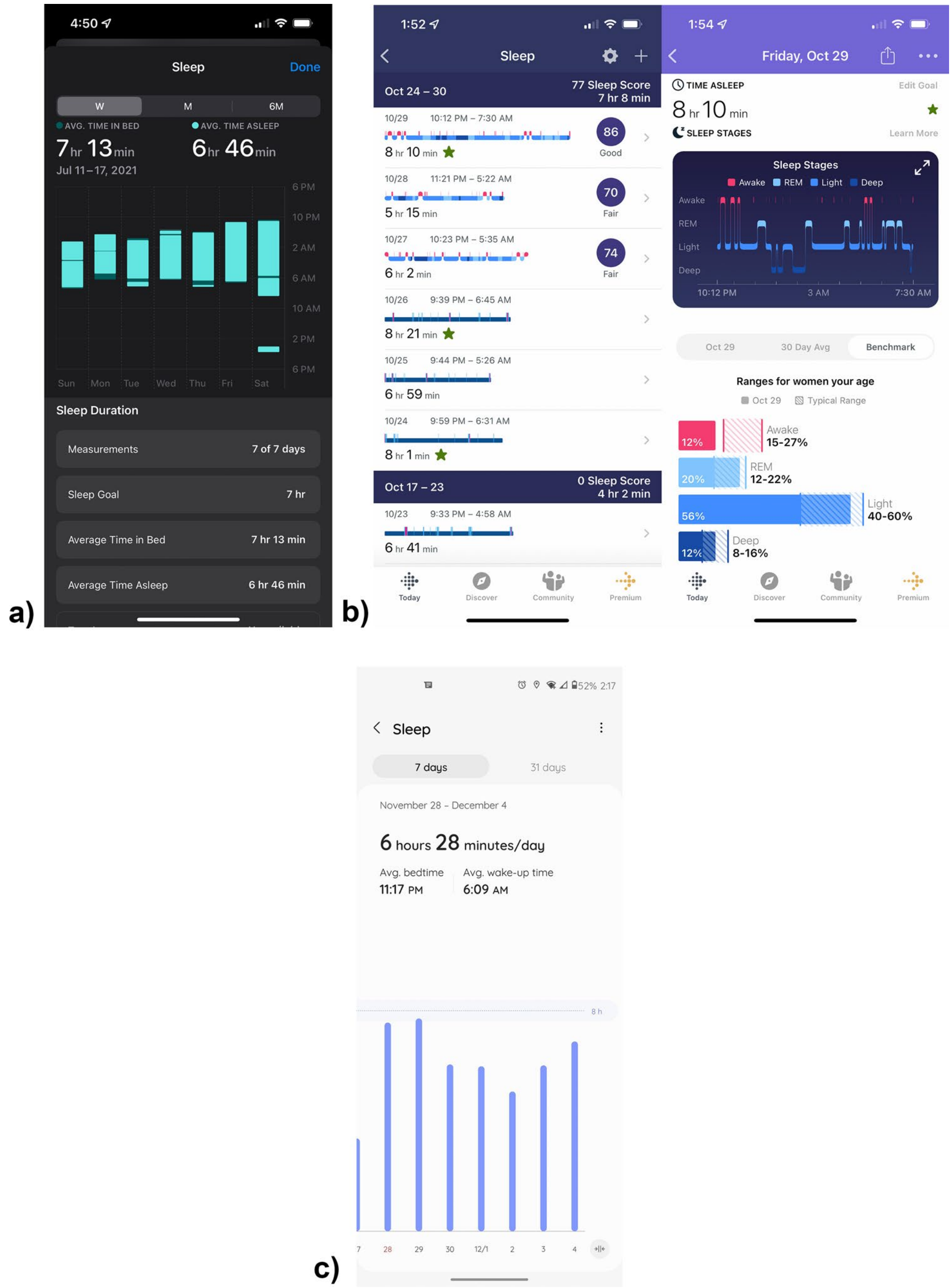
able to prevent hospitalization. Until such studies are done to guide use, clinicians may use smartwatch oxygen data in combination with history and physical exam to guide further workup, such as referral for PFT or sleep study based on the pattern of desaturation/hypoxia. Also, the data may be used for reassurance when appropriate and when found to correlate with data obtained by traditional medical equipment. Given the potential for false readings, outlying data points may be difficult to interpret as true hypoxia vs. artifact and recurring trends with clinical correlation are more likely to be meaningful or prompt further workup.

Sleep Tracking

Another common feature available in most current smartwatches is sleep tracking (Fig. 10). Sleep–wake detection with actigraphy devices (sensors that detect rest and activity) has been repeatedly validated for measuring sleep duration against the gold standard of polysomnography. This technology utilizes accelerometry, and in more advanced devices, the addition of ambient light and plethysmography, to predict whether the wearer is awake or sleeping [36]. This information has utility for clinicians, as it is well established in the literature that inadequate sleep is associated with increased mortality and contributes to the development of cardiovascular disease, as well as other conditions [37]. Evaluation of sleep trends by the clinician also has the potential to screen high-risk individuals and provide appropriate counseling and intervention to promote improved sleep hygiene, especially in individuals who already have standard underlying risk factors for cardiovascular disease. As a contemporary example, an Apple Watch may deliver an irregular rhythm notification to a patient who then obtains an ECG on the watch confirming the presence of newly diagnosed atrial fibrillation. Further interrogation of the watch may reveal poor sleep and episodes of nocturnal hypoxia, which would prompt the clinician to screen for obstructive sleep apnea, in addition to the standard management of atrial fibrillation. The patient may also be obese and activity goals can be set and monitored as well, all of which will help improve overall health and reduce cardiovascular risk.

Novel use of smartwatches which highlights the potential of combining sensors for therapeutic use is demonstrated by

Fig. 10 Sleep metrics displayed in **a** iOS Health, **b** Fitbit, and **c** Samsung Health



the NightWare App [38]. This creative treatment for nightmares uses information from the HR sensor and accelerometer on the Apple Watch to detect when a user is having a nightmare. Then, using the haptic engine on the Apple Watch, short vibrations are delivered to the user which can interrupt a nightmare without waking the patient. This App is available by prescription and aims to treat nightmares, which are associated with psychiatric disorders, insomnia, suicide attempts, and reduced daytime function [39–41]. Such innovative apps are simply the beginning and represent the leading edge of a wave of diagnostic and therapeutic apps to come.

Smartwatch Interrogation: Documentation and Reimbursement

As highlighted in this review, wearable technology provides several continuous health metrics that can be tracked, such as step count, HR, mobile ECG, oxygen saturation, and sleep

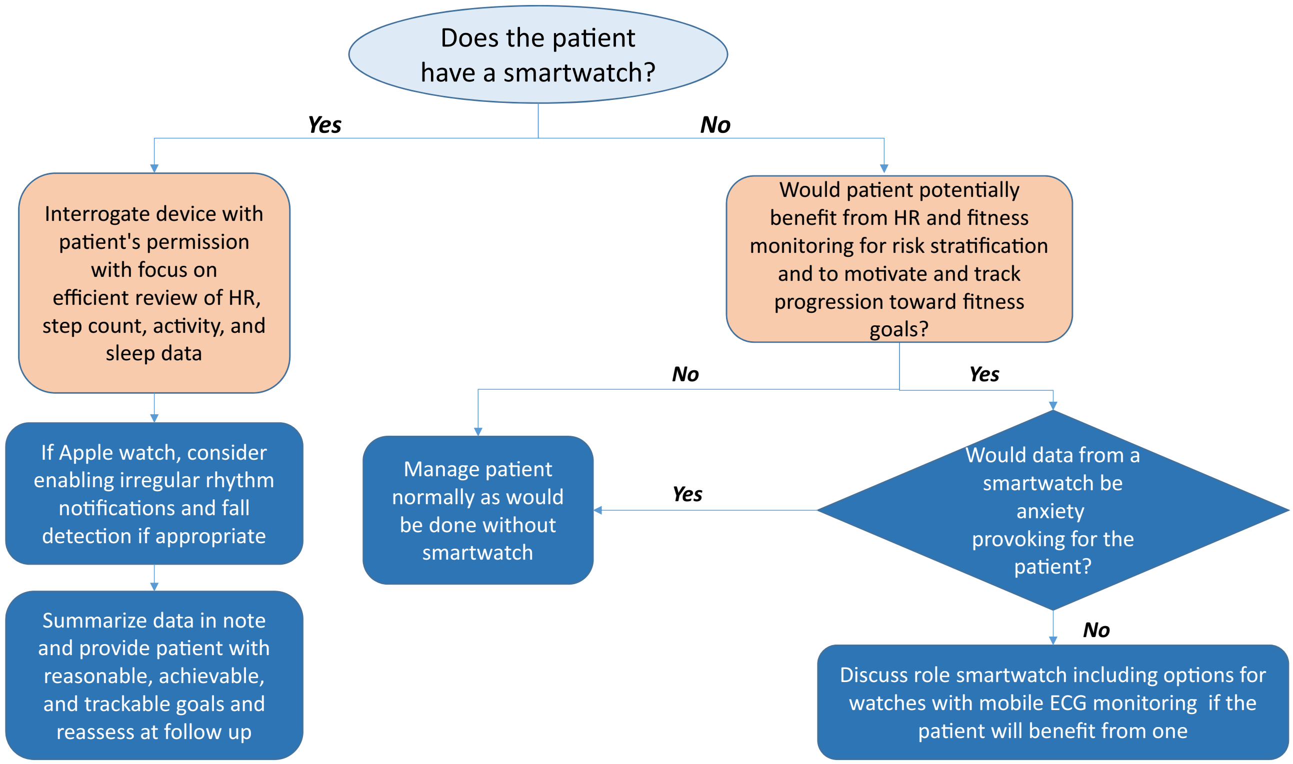


Fig. 11 Proposed flowchart to approach patients in clinic who have or could benefit from smart devices in their clinical management

duration/quality, and this data may be used for meaningful patient counseling. As there is no billable code for "smartwatch interrogation," there is no standard for documentation, either. Advocating for the creation of billable codes for interrogation and documentation of wearable technology is important to help incentivize clinicians to incorporate such practices in routine visits.

Basic documentation of this information can be done with minimal additional time in a clinical visit. Furthermore, modern EMRs allow for the creation of quick and easy templates that can help simplify the documentation process. An example of a smartwatch interrogation template is presented below. It is our experience that the template below can be completed along with the data review in less than 5 min in most cases. Some fields may need to be modified or removed based on the specific device being interrogated.

Sample Smartwatch Interrogation Template

Device Type: ***
Heart Rate Data: resting HR ***, HR range **-***, walking HR average ***
Irregular rhythm notifications: ***
Mobile ECG review: ***
Fall detection is/is not enabled.
Oxygen saturation range: **-**%
Step count average: **** steps/day
Sleep average: * hrs/night
Counseling: ***

Though no billable code exists specifically for this purpose, time spent on smartwatch interrogation, documentation, and patient counseling can still be used for billing purposes. If approximately 15 min is spent on "preventive medicine counseling and/or risk factor interventions," then the provider can add the CPT code 99,401 to the bill, so long as this time is not double counted in the time used to generate the level of service for the overall visit. This results in an additional 0.48 wRVU and additional reimbursement of roughly $35–40 varying by region and Medicare Administrative Contractor. Alternatively, the time spent on smartwatch interrogation, documentation, and patient counseling may be added to the total time spent on the outpatient visit, including other chart review, documentation, and face to face time to calculate total time spent on a visit. As an example, if a clinician spends 35 min on chart review, documentation, and direct patient care then spends an additional 7 min on smartwatch interrogation and counseling, then the total visit time would be 42 min, which would increase the level of service from a level 4 to 5 (CPT 99,214 to 99,215), for an outpatient follow-up visit.

Additionally, smartwatch interrogation by an experienced clinician can help patients maximize the benefits from their devices, as some smartwatch features need to be enabled, such as irregular rhythm notifications and fall detection on the Apple Watch. It is our experience that many patients are unaware of many of the capabilities of their devices and reviewing data and enabling such features has been quite well received.

The outpatient visit is the optimal environment for risk factors such as physical inactivity to be addressed and intervened upon, though clinicians often face time constraints due to busy schedules. One review that analyzed documentation of exercise in the electronic medical record of family medicine physicians showed that less than half of patients had any information pertaining to their physical activity or exercise [42]. A review of the literature analyzing physical activity interventions delivered in the primary care setting found that physician-administered exercise advice and recommendations for exercise and walking programs were more cost-effective compared to gym-based and instructor-led interventions [43••]. This provides evidence of the important role that we have as clinicians, especially since we might be the only health care provider that some patients see regularly. As smartwatch interrogation provides an objective way to track improvements in patient fitness resulting from physician intervention, future studies quantifying the improvement from regular interrogation and counseling would be beneficial. Providing proof of the cost-effectiveness of smartwatch-guided interventions could provide an avenue for the development of specific smartwatch interrogation billing codes and allow providers to be more appropriately reimbursed for this much-needed prevention strategy.

Conclusion

Smartwatch use is rapidly increasing, and most patients obtain devices without consulting a clinician. As such, clinicians should embrace the data available from the variety of smartwatches that are commonly encountered. This review is certainly not an exhaustive list of data available for review, but rather a starting point of high-yield metrics in the rapidly advancing arena of mHealth. For patients who do not use smartwatches, patient selection is key. Patients who may find the technology difficult to navigate or who may find the data anxiety-provoking are not optimal candidates and may be best monitored without the use of a smartwatch (Fig. 11). Basic metrics, such as plethysmograph-based HR, overall activity, energy expenditure, step count, and sleep tracking, are available on most smartwatches, while the Apple Watch offers some additional proprietary features, such as fall detection and screening for atrial fibrillation. Review of these data can be simple and requires minimal time from the provider once comfortable with the respective phone apps. These data can provide insight into a patient's overall health and cardiovascular risk while identifying areas that can be improved upon to reduce risk. Furthermore, these devices allow for the monitoring of such metrics over time so that progress can be assessed. Given the large and rapidly growing number of devices in use today, it is becoming more relevant that providers be able to obtain and interpret these data in an efficient and meaningful way. Clinical trials taking advantage of Apple ResearchKit and the like with "site-less" study designs can help enroll a large number of patients to further elucidate the effect of smartwatch-based interventions on patient outcomes.

Declarations

Conflict of Interest Michael R. Massoomi reports payment from the ACC for speaking on lipid education; being on the Editorial Board of *Current Cardiology Reports*; and he owns index funds and has broad investments in tech companies, including Apple stock. The other authors declare that they have no conflict of interest.

Human and Animal Rights and Informed Consent This article does not contain any studies with human or animal subjects performed by any of the authors.

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