Narrative review of advances in smart wearables for noncoronary vascular disease

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ABSTRACT

Objective: Existing medical care for peripheral arterial disease, aortic aneurysms, and other forms of noncoronary vascular disease fails to integrate mobility, pain levels, and other real-time patient-generated health data, instead relying on formal hospital- or clinic-based evaluations. Wearable technology, such as smartwatches, is increasingly common and offers an opportunity to improve care by allowing the collection and use of these types of data.

Methods: We searched English language publications in MEDLINE and reviewed some of our work to perform this narrative review of wearable technology for noncoronary vascular disease.

Results: A wide range of patient-generated data may be collected using wearable technology using a spectrum of devices and platforms. There is very limited but growing work using wearable technology focused on noncoronary vascular disease. Preoperative mobility monitoring, reduction of postdischarge readmission after lower limb revascularization, and improvement of medication compliance are important examples of potential applications. We also identified several barriers to widespread use and acceptance of wearables such as patient acceptance, medical team burden, and data useability.

Conclusions: Wearable devices, such as smartwatches, offer the potential to fundamentally alter the management of noncoronary vascular disease by collecting real-time patient-generated data. There are several promising applications such as perioperative monitoring and medication compliance. Additional work on regulatory issues, cost-effectiveness, workflow integration, and acceptance by patients and clinicians will need to be completed before widespread use of wearables. (JVS-Vascular Insights 2024;2:100103.)

Keywords: Wearables; Smartwatch; Mobile health technology; Vascular disease

An important gap in patient care for noncoronary vascular disease—occlusive and aneurysmal disease including peripheral arterial disease, aortic aneurysms, and cerebrovascular disease—is understanding and integrating factors and data outside of our medical system into care. Under the social ecological model of health, an individual's health is part of a multilayer framework that includes relationships, disease, community, and society. Until recently, the tools to measure these parameters of ecological health were greatly limited because health data were collected primarily during in-person encounters with the medical system. Now, wearable devices such as smartwatches have the microprocessor capacity to handle much of these data and offer the potential for a paradigm shift to a holistic, preventative model of care, better empowering people and their physicians to manage their health.

Mobile health (mHealth) technologies—smartphones and wearables such as smartwatches—have advanced significantly and offer the potential to expand health care meaningfully with minimal disruptions. The potential for using smartwatch mHealth is amplified by its ubiquity—21% have either a fitness tracker or smartwatch based on a Pew Research Center survey of 4272 Americans, though this number is lower among patients 50 years or older, who represent most patients with noncoronary vascular disease.[1,2] These numbers are expected to increase rapidly in the next 5 years.[3] In addition to the prevalence of the technology, its ongoing rapid evolution increases the possibilities for use. The typical smartwatches today, for example, possess GPS, accelerometers, magnetometers, inertial motion sensors, microphones, and light-sensitive photodiodes alongside the ability to collect, process, and transfer data using customizable applications ("apps"). There are many manufacturers in the public and research markets, with each having an advantage (or disadvantage) for measuring multiple sensor streams and patient reports simultaneously (see Table I). New sensors continue to be miniaturized; health sensors from Qualcomm and Analog

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Table I. Data collection capabilities of wearable smart devices vs a smartphone

Device	IMU	PHYS	GEO	GSM	EMA	ATM	BATT	FIDELITY	MIC	FEASIBILITY	COST
Smartphone	++	−	+++	+++	+++	+++	+++	++	+++	+	+++
Apple Watch	+++	+++	+++	+++	++	+++	++	++	+++	+++	+++
Samsung smartwatch	+++	+++	+++	+++	++	+++	++	+	+++	+++	+++
Amazfit	+++	+	++	+	+	−	++	−	−	+++	+
Pixel watch	+++	+++	+++	+++	+	+++	++	+	+++	+++	++
Withings	+++	+++	++	+	+	−	+++	+	−	+++	+++
Fitbit	+++	+++	+	+	+	−	+++	++	−	++	+
Garmin	+++	+	+++	+	−	−	+++	+++	−	+	++
Rockley (Bioptx band)[a]	+++	+++	−	+	−	−	+++	+	−	−	+
Actigraph[a]	+++	−	−	+	−	−	+++	+++	−	+	++
Empatica[a]	+++	+++	−	−	−	−	+	+++	−	+	+++

Each attribute (except cost) is graded as follows: unknown or not applicable (−), limited (+), moderately limited (++), and without limitations (+++) relative to their comparators. COST is graded low (+), moderate (++), and high (+++) relative to their comparators.
IMU: Inertia measurement unit. Sensors for the accelerometer and gyroscope.
PHYS: Physiological measures. Photoplethysmography for heart rate and oximetry, electrodermal activity (skin conductance), lux, electrocardiogram, temperature, respiratory rate, and hydration.
ATM: Atmosphere. Altimeter for elevation and barometer for pressure.
GEO: Geolocation. Global positioning system coordinates and magnetometer for the compass direction.
GSM: Global System for Mobile communication. Device is capable of being connected to a cellular data plan. One + is equivalent to being tethered to a smartphone for communication.
EMA: Ecological momentary assessment. Device has a screen and can be programed to display text and graphics.
BATT: Battery life. Ability of device to last >1 waking day without a charge.
FIDELITY: Established reliability and validity of sensors in peer reviewed scientific studies.
MIC: microphone.
FEASIBILITY: Ability for long duration compliance wearing the monitor. Compliance is improved with devices easily adopted by the public at large. They have functionality and style that consumers desire.
COST: low (+), moderate (++), high (+++).
[a]Monitors are not marketed to the public at large. These are research grade with some established validity and reliability.

Devices can provide inferred core body temperature from the wrist, body composition, and hydration from bioimpedance analysis, electrodermal activity for stress, and blood pressure sensing using oscillometric approaches on the wrist. Breakthroughs in new optical sensing approaches—such as multiwavelength sensing and Raman spectroscopy—are opening new opportunities to conduct noninvasive metabolic analysis, such as detecting glucose, lactate, alcohol, lipids, and others, for example, "clinic on the wrist" by Rockley Photonics.[4] In the near future, new devices will far outpace the abilities of current smartwatch models. They will house a cornucopia of health-related sensors for practitioners monitoring the risk factors for and treatment of noncoronary vascular disease.

In this narrative review, we break down the data collection capabilities of smartwatches as they pertain to clinical care for patients with noncoronary vascular disease. We gauge how sensors could be used to monitor ecological attributes important for promoting holistic patient care. However, we do not discuss the Federal Drug Administration's regulatory and governance of smart wearables for patient care; the recently released "Enforcement policy for non-invasive remote monitoring devices used to support patient monitoring" provides these details.[5] Next, we explore the role of patient-generated ecological momentary assessments (EMAs). The practical aspects are addressed by considering the technology platform to harvest remote data and seamlessly integrate them into electronic health records. We end by illustrating some example applications and identifying challenges to overcome for its acceptance to care for patients with noncoronary vascular disease.

DATA COLLECTION FROM SMART WEARABLES

Clinically relevant sensor data. A major advantage of smartwatches is the ability to capture multiple health data streams simultaneously. Coupling sensor data over time opens new opportunities to understand patient behavior and symptoms in remote settings. In a general sense, they contain an extensive array of passive sensors to measure the granular details of movement and physiological signals (eg, heart rate and oximetry). However, each manufacturer has a different sensor suite that matches their intended audience (Table I). Smartwatches often contain a plethora of sensors to build features such as fall detection, sleep quality, menstrual cycle tracking, atrial fibrillation detection, and proprietary health tracking. Some less common physiological sensors measure electrodermal activity for stress responses, skin temperature, lux (ambient light), and hydration.

Movement sensors are universal across all smart wearable devices and have important clinical applications for monitoring patients' mobility patterns. Accelerometers

measure the amount and intensity of bodily movements (eg, the wearer is walking), whereas geolocations measure gross movement (eg, the wearer moved 1 mi north of a starting position). Clinically relevant information from accelerometers includes the cumulative number of general activity levels, steps per day, and step cadence—the number of steps over a time window as a measure of movement speed. Less commonly, accelerometers may also be used to capture digital biomarkers of fine motor and autonomic nervous system function.[6] Collection of these and other data types can occur via a smartphone or smartwatch and may be augmented through wearable patches, chest bands, and rings.

Geolocations can be summarized to capture community mobility. Metrics such as total distance traveled and the time spent away from home are characteristics of movement outside the home (Fig 1). In gerontology, this concept is referred to as "life-space mobility," or the routine movement of individuals through defined areas of the environment, which is connected with the intuitive concepts of community mobility.[7] Life-space mobility has been associated with important end points such as health care utilization, and physical and cognitive functioning.[8–10] Similar to daily activity logs, life-space mobility was first evaluated in 1985 using a burdensome movement diary that relied on patient reporting and recall.[11] Regular collection of geolocations removes this burden and provides objective data on simple yet meaningful metrics. Some examples include the number of trips taken per unit of time or the vicinity of community engagement calculated as an ellipsoid that encompasses all the trips taken during a time period (Table II).

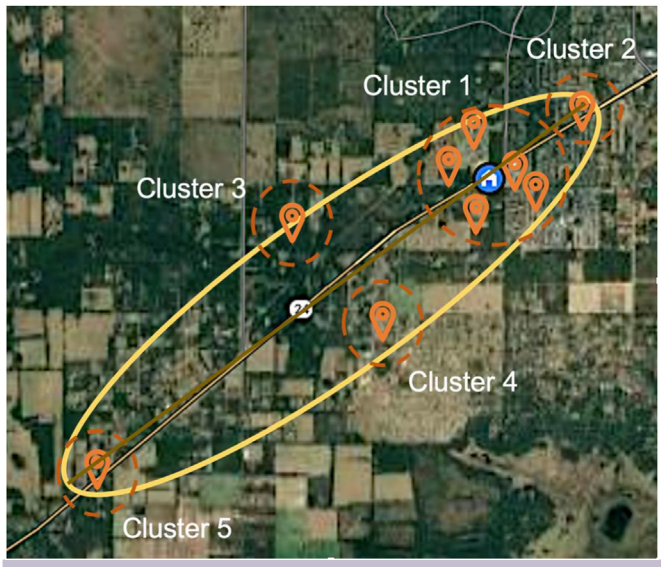

Fig 1. Measuring life-space mobility using GPS. Each *balloon point* represents a separate location recorded for the participant in a single day, and the *white and blue home symbol* indicates the participant's home. Measures of the *ellipse* (*yellow*) drawn to encompass the points may be used as one measure of life-space mobility.

Patient-reported outcomes and ecological momentary assessment. EMAs are contemporaneous patient-reported assessments that can enhance the understanding of symptoms and adverse events as well as other psychosocial and ecological barriers to treatment adherence. Clinically relevant examples include pain level, medication side effects as with cilostazol, and incision and wound status (see Table III comparing traditional vs smart wearable assessments). In many of these cases, reporting of the relevant data is delayed until the patient is seen in the clinic or is able to reach the treatment team via telephone or the electronic health record. Delays in reporting can lead to delays in diagnosis and treatment, which in turn can lead to adverse outcomes. Reporting of patient-reported outcomes traditionally has occurred through interview/paper-based or computer adaptive testing that have both relied on patient recall (eg, what was the worst pain level you had last week?). It is now well-known that patient recall is often unreliable, and reliance on such recall can bias results. For example, patients asked to recall pain levels routinely overestimated pain by 35% compared with EMA levels, which are captured in-the-moment.[12] By varying the frequency of prompting, EMA also increases the granularity of data collection (eg, pain level assessed every hour) beyond that feasible with traditional instruments and makes recall-based questions unnecessary.

EMA today is commonly collected through smart devices. Personal smartphones now dominate the EMA literature by using text messaging or a dedicated "app" to prompt patients to respond to questions at scheduled times. Only recently, smartwatches have become an innovative alternative with advantages over smartphones. Smartwatches provide microinteractions with participants that reduce burden and promote better compliance. In prior work, microinteraction EMAs—where people are prompted with fast, glanceable questions that could be answered in a few seconds—were developed on smartwatches and compared with less-frequent EMA prompts on smartphones. Researchers found that although prompts on the smartwatch were eight times more frequent than those on the smartphone, participants were 35% more compliant with the smartwatch.[13] Participants also responded to EMAs in less time and reported the EMAs to be less distracting on the smartwatch than on the smartphone.[13] Therefore, EMAs on a smartwatch might serve as an excellent approach to ease the burden on patients and promote adherence in longitudinal studies.

In the case of a smartwatch, the device is programmed to prompt wearers to input current symptoms (see example prompts in Fig 2). Patients may answer by

Table II. Examples and definitions of mobility measures based on GPS

GPS features	Definition
Excursion	
Excursion size	The furthest distance traveled from home within a specific time window
Excursion span	The furthest distance between all locations away from home
Total distance	The total distance traveled between all locations away from home
Ellipsoid	
Ellipse major axis	The longest diameter passing through the center of the ellipse. The ellipse is estimated to be the minimum area encompassing all the GPS coordinates in two dimensions
Ellipse minor axis	The shortest diameter passing through the center of the ellipse
Ellipse area	The area of the ellipse
Clustering	
No. of clusters	The number of clusters where nearby locations are grouped together. It provides information on where individuals spend most of their time
Entropy	The level of uncertainty in the time spent in different clusters
Frequency of trips	
Frequency of trips	The number of trips away from home
Homestay	The ratio of the GPS coordinates within the home radius (ie, 100 m) to the total number of coordinates

tapping on the screen or rotating the crown (side button) or watch face bezel for questions that have responses across a continuous distribution (eg, 1-10 response) (Fig 3). For example, smartwatch wearers may be asked about pain four times daily, which is impractical using traditional methods. Thus, EMA via mHealth technology creates the possibility of mapping the trajectory of important patient-reported outcomes, such as pain, in a granular and longitudinal manner that has been impractical up to this point.

Questions about compliance with important medications can also be tracked. Medications, including statins, antiplatelets, cilostazol, and gabapentin, for optimization and treatment of comorbid conditions are the cornerstone of much of vascular disease treatment. Unfortunately, compliance is low, with reports of 50% to 60% for cardiovascular medications.[14] Statin and antiplatelet regimens have been highlighted as particularly important by both the Society for Vascular Surgery in the Global Vascular Guidelines and the American College

Table III. Clinical measures for noncoronary vascular disease in traditional visits vs those potentially obtained through remotely collected smart wearables

Measure	Traditional in-person visit	Smart wearable assessment
Vital signs	In-person measurement	Remote longitudinal monitoring
Postoperative wounds	Observation	Remote longitudinal monitoring
Medication compliance	Recall (eg, Have you been taking your medications?)	EMA medication compliance
Activities of daily living	Recall	EMA
Mobility	Observation and patient recall	Life-space mobility Step count Walking speed using cadence
Pain	Recall	EMA
Mood	Recall	EMA
Fatigue	Recall	EMA
Health events	Recall	EMA
Physical activity level	Recall	Step count Total activity minutes Light/moderate/vigorous activity classification via an accelerometer

EMA, Ecological momentary assessment.

Fig 2. Example of prompts after surgery for chronic limb-threatening ischemia. Each *color bar* represents a question or set of questions as listed below. Note varied distributions of questions, some of which are asked multiple times daily while others are asked only once weekly.

of Cardiology guidelines.[15,16] Noncompliance may be related to a lack of information on the medications and their importance, the regimen itself, forgetfulness, side effects, or other issues. EMA collection can facilitate mHealth interventions to promote and aid medication compliance with reminders or tailored messaging. To date, there have been limited studies using smartphone-based interventions to improve compliance with cardiovascular medications for primary and secondary prevention of coronary artery disease with mixed and modest results.[14,17] Encouragingly, there have been positive results for adherence for HIV, antirejection medication for organ transplantation, and other chronic diseases.[18,19] Unfortunately, there has been limited or no significant work on mHealth-based interventions for medication compliance for noncoronary vascular disease.

Mobile health architecture. Mobile devices are quickly gaining the ability to capture more health-related sensor data while enabling direct interaction through the screen. This is specifically true for publicly marketed wearable devices where developers continue to pack in more sensors and algorithms in a small space. Because of their direct skin connection, wearables can detect light-sensitive photodiodes that can be coupled with other onboard sensors and microprocessors for measuring a variety of physiological measures. Besides the existing measures of heart rate, future wearables are expected to include blood pressure, hydration, and

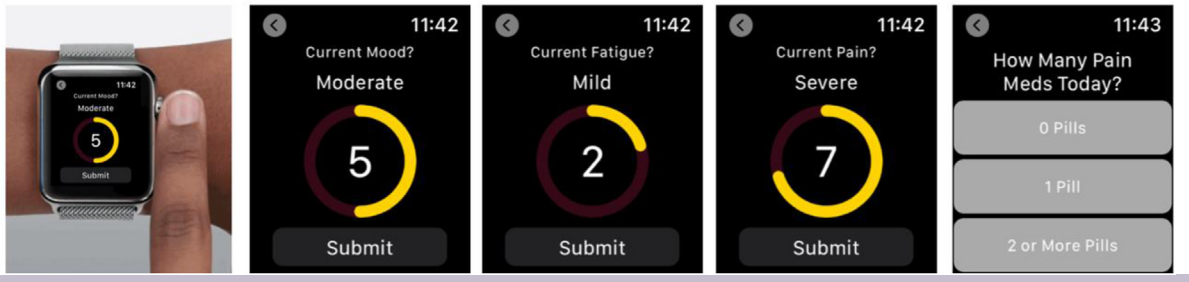

Fig 3. Smartwatch interface. Example of smartwatch interface for active data collection on the Apple Watch (Apple).

glucose that are ideal for augmenting traditional clinical care in a remote manner.[20] Merging these physiological data with EMA symptoms and patient-reported outcomes offers a completely new method for disease surveillance and treatment. Despite its potential, there is little evidence in the literature surrounding building smartwatch apps and customizing them for specific clinical and research efforts. The cause for this gap is logical—there are significant technical and other barriers including customizing the smartwatch user interface for collecting patient-reported outcomes, harnessing raw sensor data, and securely sending data to the cloud, with all components being done simultaneously.

There are several research platforms that cater to remote data collection for research (Table IV). These platforms were designed for research purposes to collect sensor data or use the interface to interact with the research participant. No matter which system is used, a collaboration between software and health care provider teams is required. Many vendors offer services for app development that can be quite costly for the build and the continued maintenance. In addition, once built, apps are static—any changes require recoding. As a result, existing apps are not designed to allow customization without the need for significant coding and software development.

New approaches are promoting fluid customization, which would lower some obstacles to remote data collection. The Real-time Online Assessment and Mobility Monitor (ROAMM) platform developed at the University of Florida is one such platform.[21] ROAMM was developed in 2019 to facilitate the movement toward a connected system of mobile computing and wearable sensing. ROAMM uses a "campaign" approach that allows users to customize the questions on the watch screen (eg, rate your pain), the sensors used (eg, GPS tracking), and the frequency of data collection (eg, GPS position every 15 minute vs 60 minute). The system is built using a cloud architecture for campaign creation, managing devices, visualizing, downloading, and

Table IV. Comparison of potential platforms to collect remote health data from smart mobile devices

Platform	ROAMM	Apple research kit	Google research kit	ohmage	Open data kit	Mydata helps	Eureka	mCerebrum
Wearable compatible	✓	✓	✓	–	–	✓	✓	–
Cross-OS	✓	–	✓	✓	✓	✓	✓	✓
Open source	✓	✓	✓	✓	✓	–	–	✓
Customizable	✓	✓	✓	✓	✓	✓	✓	✓
Raw sensor collection	✓	✓	–	✓	–	–	–	✓
Scalable	✓	–	–	✓	✓	✓	✓	✓
Ready now	✓	–	–	–	–	–	–	–
Usability	✓	✓	–	✓	✓	✓	✓	–
Peer-review	✓	–	–	✓	✓	–	✓	✓

OS, Operating system; *ROAMM*, Real-time Online Assessment and Mobility Monitor.
Wearable compatible: Has a stand-alone wearable-specific app or has summary data from a smartwatch.
Cross-OS: Collects data from Android Wear OS, Apple i-OS, or others (Tizen).
Open source: Code (app and cloud) is available and usable to the community. Not checked if unknown.
Customization: Can be customized quickly from the start and during data collection without significant developmental time.
Raw sensor data: Collects raw data without interference from postprocessing features.
Scalable: Can be scaled quickly to meet I-RISE2AI data collection goals that require existing cloud services.
Ready now: The platform is ready today with minimal development time to meet the Bridge2AI accelerated timeline.
Usability: Established usability in people's hands (other than developers).
Peer-review: Platform has established peer-reviewed publications.

summarizing data collected from the campaign. The goal is to accelerate the adoption of smartwatches and mobile wearable data in both clinical care and research settings.

PRACTICAL APPLICATIONS FOR NONCORONARY VASCULAR DISEASE

Example applications. Existing clinical applications for smartwatches and other wearables for noncoronary vascular disease are limited and contrast with the immense potential of these technologies. Most efforts related to condition management in the noncoronary vascular space have focused on claudication with mixed results. The home-based monitored exercise for peripheral artery disease trial randomized 200 patients to usual care or telephone-based coaching with a remote activity monitor. At 9-month follow-up, there were no differences in changes in 6-minute walk distance, walking impairment questionnaire scores, short form-36 physical function score, and a variety of other patient-reported outcomes.[22] Gardner et al[23] randomized 180 patients to a control group receiving light resistance training, supervised exercise therapy, or a home-based exercise program based on an activity monitor. They found an improvement in claudication onset time, peak walking time, 6-minute walk distance, short form-36 physical function, and walking impairment questionnaire scores in the intervention arms compared with the control arm. Moreover, the home-based arm had a 6-minute walk distance, and markers of inflammation and vascular function that were superior to the supervised exercise therapy arm. Most recently, McDermott et al[24] found that a high-intensity home-based exercise program evaluated by a wearable accelerometer and supported by coaching was superior to low-intensity home-based exercise at improving 6-minute walk distance. Although there are many additional efforts at application design and implementation ongoing, the field as a whole is in early development.[25] As further evidence, consider that there are no significant mHealth efforts related to aortic aneurysms and the most advanced form of peripheral arterial disease, chronic limb-threatening ischemia.

Pre- and postoperative monitoring. Preoperative monitoring may be informative in a variety of clinical conditions. Monitoring a patient's response to walking therapy or cilostazol offers the most straightforward example of mobility (gait speed, total distance walked, life-space mobility, etc) data that could directly inform decisions regarding surgical intervention. Similar data could, however, impact the management of other conditions. For instance, identical data could aid in the holistic assessment of patient fitness before open aneurysm repair and offer a basis for interventions, such as prehabilitation. Similarly, longitudinal collection of pain, mobility, fatigue, falls, and other data spanning the pre- and postoperative periods could identify patients with the worst recovery trajectories, who could benefit from earlier intervention.

Readmission and postdischarge complication rates are substantial after many types of vascular surgery. Open revascularization after chronic limb-threatening ischemia, for example, is associated with a 30% major postoperative complication rate and a 7% to 18% readmission rate.[26] Increased office visits may not be practical for patients with limited mobility, social support, or financial resources. Smart wearables with graphical interfaces may be especially helpful for these patients and may improve the care of the postoperative patient by improving patient/clinician communication, reducing the frequency of in-person visits, and reducing complications and readmissions via early detection and management.

There have been efforts to create apps to address many facets of postoperative care—compliance with postoperative exercises,[27] a platform for patient-clinician communication,[28] monitor pain,[29] and so forth—in a variety of surgical specialties. For instance, Gunter et al[30] reported on the sole postoperative app for vascular patients focused on wound monitoring. Patients were able to submit images of their wounds via a dedicated smartphone app and answer basic questions relevant to surgical site infections. In a cohort of 40 patients, 45% of patients submitted images of the wound daily for 2 weeks with an overall submission rate of 90%.[30] Seven surgical site infections were detected with no false positives and one false negative. Clinician and patient satisfaction were high. Unfortunately, there are no definitive trials that directly compare the use of smart wearables with the current standard of care.

CHALLENGES TO OVERCOME

Patient compliance. Patient compliance with mobile devices and apps may be diminished by lack of comfort or familiarity with mHealth technology and by the burdens of use. The impact of these will likely vary by use and subpopulation. There are, however, reassuring data to suggest that mHealth technology use is still feasible in a population of older patients. For example, a pilot study of patients with osteoarthritis with a mean age of 73 years found that 89% were willing to participate in a year-long study wearing a smartwatch.[31] Another study that prompted wearers to report pain levels three times a day for a mean of 13 days found that the response rate was 82%.[32] Burden of use is impacted both by the specific data collection protocol and by the requirement of the technology. For example, smartwatches typically require charging at least daily. Careful patient screening, education, and thoughtful design of data collection protocols can improve adherence.

Clinical workflow integration and compliance. Adoption of smartwatch data has been hindered by providers' perceptions on information overload, concerns about liability from lack of timely review,[33,34] and fears around patient privacy.[35] A few recent initiatives (such as Apple Health and CommonHealth) provide mHealth programming interfaces or limited remote data integration with a single vendor such as Cerner (Caren RPM[36]). Despite these efforts, integrating remote data within the already overly complex clinical workflow still poses many usability and workflow challenges.[2] Most notably, there is a lack of usability and workflow guidelines to facilitate patient sign-up and providers' processing of incoming remote data. Lastly, sensors generate a vast quantity of data; they require meaningful summarization and visualization that is intuitive and informative for clinicians.[36,37] A qualitative study using semistructured interviews with 12 providers from internal medicine, family medicine, geriatric medicine, nursing, surgery, rehabilitation, and anesthesiology confirmed that while smartwatch data are perceived as a relative advantage and that these data are compatible with current practices, dense smartwatch data may burden physicians.[38,39]

Integration of mHealth data into care may impose a significant burden on the medical team. mHealth allows for the collection of large amounts of data, but sifting through it to identify salient information may be challenging in the context of already busy workflows. The complexity of integrating mHealth into outpatient care is high but may be even higher for inpatient care involving multidisciplinary teams of physicians, physical and occupational therapists, nurses, and others. Minor changes—for example, the efficient visual presentation of selected data—may overcome some of these challenges, but broad acceptance and integration of mHealth into the workflow requires a systematic approach. Principles from the Technology Acceptance Model may be used with modifications geared toward health informatics,[36] emphasizing perceived ease of use and identifying usage barriers. The model and its iterations also suggest that perceptions regarding usefulness and ease of use along with organizational characteristics and culture are able to account for much of the behavior regarding acceptance of new technology.[40,41] As such, interventions tailored to these factors—education and outreach, tailored workshops, etc—are required for facilitating acceptance.

CONCLUSIONS AND FUTURE DIRECTIONS

Smart wearable technology offers the extraordinary possibility of improving patient engagement, medication adherence, treatment, postoperative surveillance, physician-patient communication, and allowing remote education on disease risk factors and lifestyle modification, among others. However, there are several overlapping challenges that must be overcome before smart wearable technology becomes an accepted tool for medicine. First, there is sparse evidence establishing effectiveness to improve health outcomes. Research into using smart wearables to measure outcomes or inform providers is still in its infancy, and much work remains on effectiveness and cost-effectiveness. Given increased scrutiny on value and the substantial resources required to implement and use mHealth-based surveillance or intervention, significant additional work will be required to establish effectiveness before widespread acceptance. Second, the limits and nature of patient compliance with mHealth-based surveillance are unknown. Although substantial amounts and types of information can be collected passively, compliance remains crucial because some data such as pain scores require active participation. A corollary to patient compliance is acceptance by the health care team. Any application of mHealth technologies that adds to documentation burden and data overload is unlikely to be widely accepted. Last, the generation, storage, and use of vast amounts of patient data will require solutions to novel regulatory and privacy-related issues. In the coming years, we are likely to see many commercial and academic efforts focused on the use of wearables that will help outline possible solutions to these challenges and delineate the role of wearables in modern health care.

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None.

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