ANNUAL REVIEWS

Annual Review of Medicine

Wearable Devices: Implications for Precision Medicine and the Future of Health Care

Mohan Babu,[1] Ziv Lautman,[1,2] Xiangping Lin,[1] Milan H.B. Sobota,[1] and Michael P. Snyder[1]

[1]Department of Genetics, Stanford University School of Medicine, Stanford, California, USA; email: mpsnyder@stanford.edu

[2]Department of Bioengineering, Stanford University School of Medicine, Stanford, California, USA

Annu. Rev. Med. 2024. 75:401–15

First published as a Review in Advance on November 20, 2023

The *Annual Review of Medicine* is online at med.annualreviews.org

https://doi.org/10.1146/annurev-med-052422-020437

Keywords

wearables, longitudinal, early detection, COVID-19, precision medicine

Abstract

Wearable devices are integrated analytical units equipped with sensitive physical, chemical, and biological sensors capable of noninvasive and continuous monitoring of vital physiological parameters. Recent advances in disciplines including electronics, computation, and material science have resulted in affordable and highly sensitive wearable devices that are routinely used for tracking and managing health and well-being. Combined with longitudinal monitoring of physiological parameters, wearables are poised to transform the early detection, diagnosis, and treatment/management of a range of clinical conditions. Smartwatches are the most commonly used wearable devices and have already demonstrated valuable biomedical potential in detecting clinical conditions such as arrhythmias, Lyme disease, inflammation, and, more recently, COVID-19 infection. Despite significant clinical promise shown in research settings, there remain major hurdles in translating the medical uses of wearables to the clinic. There is a clear need for more effective collaboration among stakeholders, including users, data scientists, clinicians, payers, and governments, to improve device security, user privacy, data standardization, regulatory approval, and clinical validity. This review examines the potential of wearables to offer affordable and reliable measures of physiological status that are on par with FDA-approved specialized medical devices. We briefly examine studies where wearables proved critical

for the early detection of acute and chronic clinical conditions with a particular focus on cardiovascular disease, viral infections, and mental health. Finally, we discuss current obstacles to the clinical implementation of wearables and provide perspectives on their potential to deliver increasingly personalized proactive health care across a wide variety of conditions.

INTRODUCTION

Vital physiological parameters including heart rate (HR), sleep, blood oxygen saturation, blood pressure (BP), physical activity, and skin temperature can provide critical insights into the physical health status of individuals (1–3). Typically, clinical consultations only happen after manifestation of symptoms, and they may require physical visits, invasive blood draws, or tissue biopsy; may increase risk of infection; and can be difficult to access. While measurements taken during clinical visits provide discrete and high-quality physiological data for diagnosing and treating health conditions, they are also infrequent and limited to comparative measurements against the average of a population. This primarily reactive approach misses presymptomatic physiological changes associated with onset of disease and does not account for interindividual differences, making it easy for significant health changes in a particular person to go unnoticed while they are within the normal measurement ranges of the reference population. Wearable health devices and digital diagnostics offer an alternative proactive health approach to longitudinally track each individual's normal baseline, identify significant health changes at the earliest stages, and monitor the impact of personalized health interventions.

WEARABLE R-EVOLUTION

A wearable health device (wearable) is any miniaturized electronic device with sensors that can be worn on the body or integrated into clothing or other body-worn accessories that are capable of noninvasive, longitudinal monitoring of vital physiological and biochemical parameters. Wearable form factors include smartwatches, smart rings, smart wrist bands, and smart patches, among many others; all allow for data transfer across devices through wireless technologies (**Figure 1**) (4, 5). Recent advances in hardware and software technologies have enabled the integration of microelectronic, micromechanical, and optical sensors, such as photoplethysmography, gyroscopes, and accelerometers, leading to miniaturized, highly sensitive, and cheaper wearables for physiological monitoring (6). Wearable technologies are already revolutionizing health care through remote, noninvasive, and longitudinal real-time monitoring of health signals during daily activities (5). Recent studies have demonstrated the potential of wearable smartwatches in reliably tracking changes associated with macrophenotypes such as fatigue, Lyme disease, inflammatory responses, and insulin-sensitive and -resistant states; predicting cardiometabolic health; and passively predicting atrial fibrillation (7–11). Machine learning algorithms such as DeepHeart applied to wearable data have been successful in detecting type 2 diabetes (85% accuracy), atrial fibrillation (97% accuracy), sleep apnea (90% accuracy), hypertension (82% accuracy), and cardiovascular disease (CVD) risk (11). More recently, smartwatch-based physiological monitoring was shown to successfully detect both symptomatic and presymptomatic COVID-19 infections (12–14).

HR: heart rate

BP: blood pressure

CVD: cardiovascular disease

Besides early detection of infectious diseases, wearables can also play an important role in disease prevention. Recent studies have shown an inverse and linear relationship between daily step counts and various diseases, alongside reductions in cancer and CVD mortality risk (approximately 40% and 49%, respectively) with vigorous intermittent physical activity (15, 16). With data showing that use of wearables results in individuals increasing their physical activity (17),

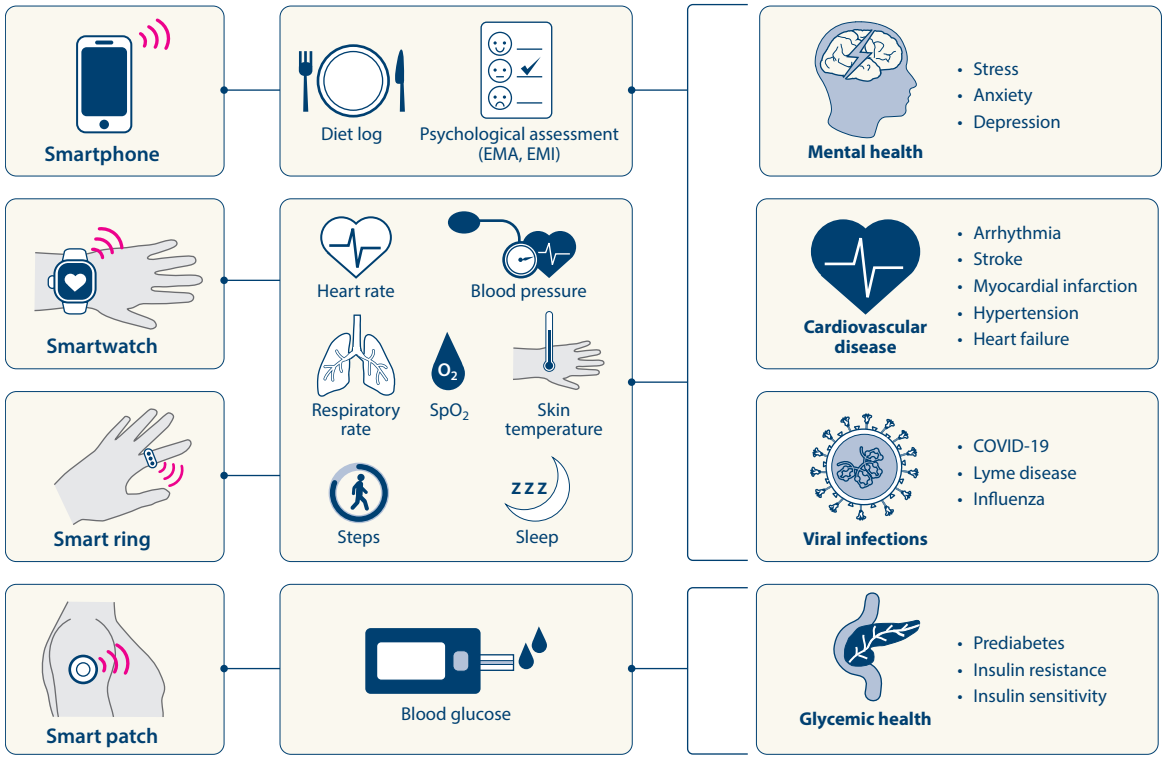

Figure 1

Wearable devices enable physiological monitoring for early detection, diagnosis, and management of mental disorders, cardiovascular diseases, viral infections, and clinical conditions. Abbreviations: EMA, Ecological Momentary Assessment; EMI, Ecological Momentary Intervention; SpO_2, blood oxygen saturation.

wearables can serve as both a fitness tracker and a health monitor for disease prevention by identifying healthy and unhealthy patterns of signals based on each individual's baseline profile (16). Wearable-based continuous glucose monitoring (CGM), while more invasive, is also revealing new aspects of glucose dynamics and uncovering highly personal glucotypes, which are patterns associated with specific individuals' food responses, that could provide personalized nutritional guidance (18). Furthermore, in recent years wearables have even shown potential in detecting changes in different psychological states, such as stress, anxiety, and depression (19), hinting at a future in which wearables can also be used for precision mental health efforts in the early diagnosis and care of psychological conditions (20). Taken together, emerging progress in wearables and data analysis is a promising new avenue for bringing personalized health out of the clinic and onto individuals' bodies to monitor their normal baselines; identify significant changes associated with infection, disease, or mental health; and help providers design tailored interventions while monitoring their efficacy over time (7).

WEARABLES FOR PRECISION MEDICINE

CGM: continuous glucose monitoring

Already established as fitness and wellness trackers, wearables are also proving to be reliable and affordable clinical tools to better understand health and disease transitions via objective and continuous monitoring of vital physiological parameters. With the proportion of US adults already

HRV: heart rate variability

RHR: resting heart rate

HF: heart failure

AF: atrial fibrillation

using wearables at ~30% and rising, increased consumer adoption is creating new opportunities for health care (21). Wearables can be tremendously useful outside of the clinic in many areas, particularly cardiometabolic health, infectious disease, and mental health. Below, we examine implications of wearables translation for the healthcare landscape in prevention, diagnosis, management, and rehabilitation.

WEARABLES IN EARLY DETECTION OF CARDIOVASCULAR DISEASE

CVDs, especially ischemic heart disease and stroke, are the leading causes of mortality, disability, and debilitating health costs (22, 23). Globally, CVD cases doubled from 271 million in 1990 to 523 million in 2019 and the number of deaths increased from 12.2 million in 1990 to 18.6 million in 2019 (22). Productivity losses and treatment costs for CVD are projected to rise to US$1,044 billion by 2030 (24, 25). Consequently, there is an urgent need for improved and cost-effective early detection and management options to reduce CVD-related mortality and treatment costs, which wearables are well-positioned to meet.

Analysis of physiological measures such as HR and heart rate variability (HRV), or variations in the time interval between two consecutive heartbeats, can predict the risk of CVD. High resting heart rate (RHR) was associated with an increased risk of coronary artery disease and all-cause death in healthy individuals and a strong predictor of adverse outcomes in heart failure (HF) patients (26–28). Electrocardiogram (ECG) has been the gold standard for HR measurements in clinical settings, but HR can now be measured accurately and longitudinally using commercially available wearables such as smartwatches. For example, in an analysis from a 24 h study of HR by Apple Watch 3, the smartwatch was found to achieve 95% accuracy compared to standard ECG (29). A recent study on data collected from more than 8 million participants found diverse metrics of cardiac autonomic function through a similar 24 h study of HRV by Fitbit consumer wrist-worn tracking devices, showed that wearables can be used for remote monitoring of cardiovascular health (30–32). HR and especially RHR showed significant intra- and inter-individual variability depending on age, sex, body mass index, and sleep duration. Additionally, longitudinal discrete HR changes, rather than single measurement, were found to be associated with cardiovascular outcomes (33). Wearable-based longitudinal HR/HRV data not only can reveal individual specific baselines but also can reliably detect deviations from those baselines well before the development of CVD (33).

Atrial fibrillation (AF), an irregular and rapid heart rhythm, is associated with increased risks for stroke, HF, and other adverse cardiovascular outcomes (34). Due to its paroxysmal and asymptomatic nature, up to a million cases of AF per year remain undiagnosed in the United States alone (35). Traditional AF screening methods using standard 12-lead ECG devices are hampered by a limited period of rhythm recording and, due to their clinical footprint, may not be usable for screening asymptomatic patients and the detection of paroxysmal arrhythmias. Consequently, wearables have emerged as convenient tools to diagnose symptomatic and asymptomatic cases of AF. For example, the Apple Heart Study with >400,000 Apple Watch users found that, among those receiving an "irregular rhythm" notification, 34% were confirmed to have AF lasting >30 s via subsequent ECG patch monitoring, with an 84% positive predictive value of the algorithm for concurrent AF on the ECG patch (30). In a multinational cardiovascular remote cohort study, the Apple smartwatch was demonstrated to detect AF with high accuracy (98.0% sensitivity and 90.2% specificity) compared to a gold standard 12-lead ECG (9, 29). In a similar vein, a recent Fitbit heart study with 455,699 participants used a photoplethysmography-based irregular heart rhythm detection algorithm and found a high positive predictive value (98.2%) for concurrent AF on subsequent ECG patch monitoring to identify participants likely to have AF (30, 31).

Hypertension (high BP) is a well-known CVD risk factor and affects more than 1 billion people globally (36). The diagnosis of hypertension is hampered by infrequent cuff-based oscillometric measurements, which are not useful for capturing circadian and activity-based variations in BP (37, 38). Smartwatches are emerging as alternative tools for accurate, sensitive, and continuous BP monitoring that is on par with regulated medical devices (39, 40). Additionally, smartwatch measures of BP are more convenient to collect, especially during sleep, exercise, and daily activities when the measurements with standard upper arm BP devices are not practical.

WEARABLES IN MANAGEMENT OF CARDIOVASCULAR DISEASE

Physiological measures from wearables have been used for risk stratification in HF patients. For example, a 6-min walk test administered via pedometer was used to predict HF severity and death in HF patients (41). Similarly, HRV measures were shown to predict the response to cardiac synchronization therapy in mildly symptomatic HF patients (42). Wearable-based heart rhythm data have the potential to empower AF patients in their care via targeted approaches to anticoagulation treatments timed around episodic AF events (43). Wearables are also poised to revolutionize the care of patients with myocardial infarction. For example, the MiCORE study involving 200 patients with myocardial infarction found a 43% lower likelihood of readmission at 30 days for patients receiving a guideline-driven, self-management program comprising a mobile application integrated with an Apple Watch and a Bluetooth BP cuff. Furthermore, implementation of the intervention was found to save up to $6,000 per patient (44). Wearables are further poised for improved early detection, diagnosis, and management of CVD in a cost-efficient and resource-efficient manner, ultimately improving the quality of life of patients.

WEARABLES, INFECTIOUS DISEASE, AND PREPARING FOR THE NEXT PANDEMIC

Vaccines and antiviral drugs are important measures in the control of infectious diseases but require significant time and resources to develop as mitigation measures for emerging threats (45). Traditional public health measures, such as isolating infected people and quarantining potentially exposed people to protect people at high risk of mortality, can be effective and efficient ways to delay the spread of infectious diseases, especially before a vaccine or antiviral drug is available. Wearables such as smartwatches or smartphones can be used to track and notify users about COVID-19 exposure by utilizing advanced digital contact tracing technologies (46), such as Bluetooth, WiFi (47–49), Global Positioning System, QR codes (46), and Zigbee (50). For example, if a wearable user is infected by COVID-19 and reported through the system, other users who were in close contact with the infected user can be informed of potential exposure and take appropriate precautions, such as self-quarantining and testing.

Accumulating evidence shows that viral infections can lead to detectable changes in an individual's physiological parameters (7, 51). COVID-19 infection involves multiple organs and impacts the respiratory, cardiovascular, and neurological systems. These impacts drive physiological abnormalities including dyspnea, cardiac abnormalities, fatigue, sleep disturbances, and headache (52). Wearables such as smartwatches, which allow these multidimensional physiological signals to be continuously monitored (53), can be used for real-time alerts, early symptom detection (12, 14, 54), and monitoring of reactions to COVID-19 vaccination (55–57). For example, using retrospective physiological and activity data collected via smartwatches from 32 individuals with known COVID-19 infection, a previous study showed that 63% of the COVID-19 cases could have been detected before symptom onset (12). Another study using a real-time smartwatch-based alerting

system from 84 participants infected with COVID-19 showed that up to 80% of the COVID-19 cases could have been detected up to 3 days before symptom onset (14). In the Warrior Watch Study ($n = 297$), subtle changes in HRV measured by smartwatches were able to predict the onset of COVID-19 up to 7 days before diagnosis (54). These results suggest that activity tracking and health monitoring via wearables can be used for self-monitoring, by family members, or by paramedics to help manage COVID-19 cases. These data provide additional information to help physicians to plan treatments, such as to decide whether a ventilator is needed, and help physicians to monitor reactions to vaccines, new treatments, and reinfections. Furthermore, wearables can also be applied to manage PASC (postacute sequelae of SARS-CoV-2) and the early detection and the management of other infectious diseases (51), such as seasonal influenza (58, 59) or Lyme disease (7).

During the acute phase of the COVID-19 pandemic, healthcare systems around the world were overwhelmed by intensive care patients (60). Future pandemics are inevitable. Given recent experience with COVID-19, now is the time to prepare for the next pandemic to ensure that it is less disruptive and deadly. Inclusion of new technologies and decentralized measures, such as broad deployment of infectious disease–detecting wearables (**Figure 1**), can help lay the groundwork for improved pandemic responses across the world (60).

WEARABLES AND THE FUTURE OF MENTAL HEALTH

In 2019, the World Health Organization estimated that approximately 970 million people worldwide, approximately 1 in 8, were living with a mental health disorder (61). Anxiety and depression were the most prevalent conditions, affecting an estimated 301 million (3.95%) and 280 million (3.59%) people, respectively (61, 62). In the United States alone, 1 in every 5 adults experience a mental health disorder (63), and the lifetime prevalence of mental health disorders has been estimated at 46.4% of the population (64).

Currently, most mental health clinical assessments rely on interviews and on self-report-based questionnaires to capture a patient's experiences over some period of time. For example, the Patient Health Questionnaire–9 is a standardized form that assesses degrees of depression and the Generalized Anxiety Disorder–7 questionnaire measures severity of anxiety. Unfortunately, these methods require involvement of professionals, are expensive, and are time-consuming (65). Furthermore, these methods can be affected by patients' recall bias and often lack the ability to capture the dynamics of different disorders that require real-time and frequent sampling of patients (66). Finally, despite the increasing need for mental health services, there was a 10.2% decrease in the median number of psychiatrists per 100,000 US population from 2003 to 2013 (67), creating further barriers to care.

Wearables, via their passive, real-time, and continuous monitoring of physiological and behavioral measures, have the potential to provide more objective assessments of mental health disorders while creating new avenues for diagnosis and care at a fraction of the cost of traditional methods (20). Continual monitoring of various physiological parameters (HR, respiratory rate, etc.) and behavioral parameters (sleep, physical activity, etc.) has already shown promising results in detection of stress, anxiety, and depression (**Figure 1**) (19, 68, 69).

Previous studies have investigated various models of commercially available wearables, equipped with different arrays of sensors, to assess mental health disorders. Most studies have used machine learning models, especially support vector machines, random forest (RF), and k-nearest neighbor, to make predictions about an individual's mental health (19, 68, 69). Can et al. (70) used Samsung Gear S/S2 and Empatica E4 devices and obtained 84.67% and 90.40% accuracy (using RF and multilayer perceptron), respectively, to detect acute stress in 9 individuals across 9 days by

using HR, electrodermal activity, and accelerometer data (ground truth stress level of individuals was measured using NASA task load survey). Tsai et al. (71) used Garmin Vivosmart 4 devices with detection accuracy of 67.4–81.3% for different machine learning algorithms (support vector machines, RF, and k-nearest neighbor) in the detection of panic disorders in 59 individuals across 1 year by using average HR and RHR data with deep sleep duration (ground truth panic level of individuals was measured using Panic Disorder Severity Scale). Narziev et al. (65) used Samsung Galaxy S3 devices and obtained overall accuracy of 96.0% (using RF) in depression classification in 21 individuals across 4 weeks by using physical activity and sleep stages (ground truth depression level of individuals was measured using the Patient Health Questionnaire-9). Multiple other studies have shown promising results in detecting anxiety, depression, and stress by using HRV, temperature, respiration rate, and other measures (19, 68, 69).

Despite compelling preliminary evidence from research studies, the practical deployment of wearables for mental health applications is hindered by the small sample sizes, short study durations, and lack of consistent validation common in research studies. Moreover, there is currently no universally accepted and highly accurate prediction model available for mental health applications like the deep convolutional neural networks used in medical image classification to facilitate disease diagnosis (72). In order to comprehensively assess the precision and practicality of wearables in mental health applications, it is imperative to conduct extensive clinical validation studies with larger cohorts over prolonged durations leveraging novel computational analysis designs, including machine learning, anomaly detection, and human-in-the-loop reinforcement learning from questionnaires and alerts.

The implications of achieving clinical validation for wearables in the objective assessment of mental health disorders could reshape the future of mental healthcare systems, especially precision psychiatry. A real-time assessment of an individual's mental health, specifically of anxiety, depression, and stress levels, could be an early alert and detection system before the onset of severe symptoms. Once an alert is triggered by abnormal readings departing from a previous baseline, an individual could use the Ecological Momentary Assessment, a short mental health e-survey, to log and confirm symptoms. Subsequently, a personalized treatment plan in the form of the Ecological Momentary Intervention could be delivered to the individual smart device without the need for a face-to-face consultation with a clinician. This allows for immediate and personalized interventions that can also be shared with a clinician for further enhancement, enabling more patients to access mental healthcare services. Guidelines around safety, privacy, and liability will have to be developed for large-scale deployments to ensure that patient well-being is centered in the user experience and intended outcomes.

CHALLENGES IN CLINICAL IMPLEMENTATION OF WEARABLES

Although research studies have provided compelling evidence for the potential of wearables in precision health, clinical implementation is constrained by several factors (**Figure 2**). This section highlights some common hurdles and potential solutions.

Cost and Performance

Wearable device costs may hinder their accessibility to individuals of low socioeconomic status and may cause new health disparities if deployed indiscriminately. Public and private insurance systems need to implement value-based reimbursement plans to include outcomes such as physical activity and lifestyle modifications. Beyond sensor accuracy, continuity of monitoring is also a crucial performance characteristic, reduced by repeated interruptions due to finite battery life or even by abandonment due to itching, discomfort, or other dissatisfaction (73). Addressing battery

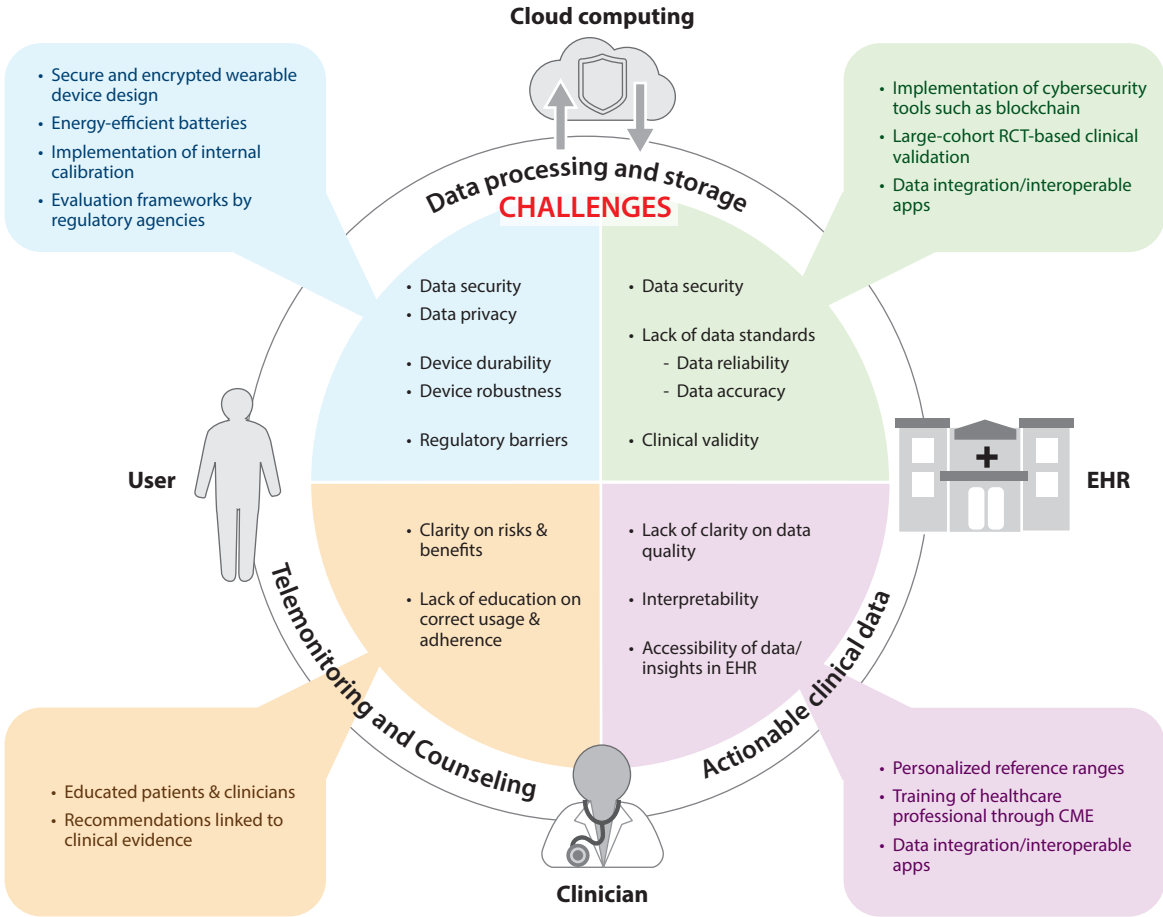

Figure 2

Major challenges and possible solutions in clinical implementation of wearable devices for precision health. Abbreviations: CME, continuing medical education; EHR, electronic health record; RCT, randomized controlled trial.

life, tolerance, sensor accuracy, and ease of correct use will enable increased utility, higher sampling rates, and increased participation across the broader population in resource-limited settings.

Data Security and Privacy

Challenges for the use of wearables in clinics include data reliability and accuracy, data security, and privacy, among others (68). Proper encryption, authentication mechanisms, and privacy controls are needed to ensure data security and privacy of protected health and personal information. There is also a need for a standardized evaluation framework for wearables to ensure comparable data reliability and accuracy across different device models. Wearables-based longitudinal data also require computing infrastructure and resources for data acquisition and storage, data analysis, and utilization in a secured environment. For example, 1,000 participants over a 1-year period of continuous wearable data measurement can easily generate >1 TB of data per year. While there are open-source software frameworks, such as the Personal Health Dashboard platform, for the deployment of big data health projects to store, organize, and process such data sets (74),

significant investments in both computational and human resources are still needed to support large wearable studies and their clinical translation.

Data Standards for Clinical Utility

Most research studies demonstrating wearable-based early detection, diagnosis, and management of diseases have been performed with small sample sizes, short duration, and lack of external validation. Interindividual variations and baseline heterogeneity, the lack of uniformity in the characteristics of each measured individual, pose additional challenges in obtaining consistent and accurate sensor readings over time. Further complicating matters is sensor drift, a gradual deviation in a sensor's readings, which can also be influenced by these factors. To tackle these complexities and enhance the quality of the collected data, it is crucial to design and implement longitudinal heterogeneity studies (56, 75, 76). Clinical validation with large cohorts monitored for longer periods of time, on the scale of a year and more, will be needed to establish safety parameters, quality control metrics, and comparisons to the current standard of care.

Algorithm Design

Like other analysis-based diagnostics, wearables-based diagnosis algorithms can be susceptible to false positive signals leading to user anxiety, increased use of healthcare resources, and treatment side effects. Thus, just as pharmaceuticals have data quality or manufacturing controls, algorithms should meet quality control standards before they can be applied in clinical practice, ideally taking into account uncertainty of the underlying measurements.

Integration with the Current Healthcare System

Long-standing challenges in integrating wearable technology with the existing healthcare system include uncertainty around data quality driven by a lack of standardization, the low accessibility of data to clinicians, and the regulatory barriers for using consumer devices in clinical practice (77). There is an ongoing need for data collection, transfer standards, and more generalizable analytics platforms that can relay information useful to the patient and clinician directly to the electronic health record while preserving patient privacy and data security—enabling broader use of wearable data in the clinic and the development of closed-loop intervention systems (78). Wearables as diagnostics are already quite common, but these take the form of consumer devices alerting their users that they should consult a doctor for follow-up, thereby confronting more healthcare professionals with the consequences of wearable data without systemic support or infrastructure for the use of such systems.

IMPACT OF WEARABLES ON THE FUTURE OF HEALTH CARE

Technological innovations in wearable design combined with increasing global adoption (in 2022 alone, 492.1 million devices were shipped) are making wearables more accurate, useful, and ubiquitous (68, 79). With the rising prominence of deep learning models and advances in time-series data forecasting (80), wearables are poised to play a major role in the future of health care.

Prevention

Currently, most people enter the healthcare system when a disease state has manifested and is diagnosed by a physician. However, $730 billion of healthcare costs in a single year in the United States alone are attributable to modifiable risk factors such as diet, exercise, and timely access to care (81). As mentioned above, wearables as fitness trackers are already affecting users by helping to

increase their physical activity, which is impactful in prevention of cardiometabolic disorders (16). Although motivating people to change to healthier behaviors is difficult, personalized recommendations for individual lifestyle modifications have been shown to be more effective than general recommendations, and wearables could provide the data for such tailored recommendations (82). Not only should the preventive measures be personalized, but so should the motivational approach, as people may respond differently to motivators such as health benefits, gamification, or competition. The role of healthcare practitioners could be to guide patients in the use of wearables to incrementally implement lifestyle changes to lower disease risk. Taking wearable data into account when advising patients could provide a better picture than patient reports on lifestyle alone (83) and provide an entirely new way for clinicians to monitor progress. However, the lack of incentives, on top of aforementioned challenges around data like quality and access, will slow changes (**Figure 2**).

Diagnosis

In diagnostics, the promise of wearables is to monitor each individual's health status and to detect potential conditions early, requiring minimal active effort from the user. Wearables have already demonstrated this in CVD detection, for which both purpose-built and consumer devices have received clearance by the US Food and Drug Administration (FDA) (84). In AF in particular, wearables have closed a diagnostic gap around conditions that are hard to observe during infrequent ambulatory visits. Beyond that, we previously demonstrated the potential of wearables in predicting and detecting infectious diseases such as COVID-19 on a broad scale (14). However, the promise of using wearables for a more nuanced, individualized understanding of disease as a spectrum between sick and healthy is far from being realized. Furthermore, the move of consumer-grade devices toward clinical use blurs the line between medical devices and consumer gadgets. This mandates careful consideration of who has access to what data as competing interests need to be balanced. For example, while data leading to diagnoses are of high interest to providers and payers, patients also have rights to privacy and secure data handling. These questions will only become more pressing; with diagnostic features becoming a selling point for consumers, the implication for healthcare professionals is that they will be confronted more and more with wearables and the data they produce.

Treatment and Management

Great strides have been made toward the adoption of wearable technologies in the treatment and management of chronic cardiometabolic diseases, such as in diabetes using CGM. Insulin treatment has long been personalized to some degree. Wearables are now enabling a new level of precision by giving direct and continuous feedback, providing insight and improving care quality in situations that are harder to manage, such as after exercise. The integration of wearable approaches with clinical care is accelerating, especially for conditions similar to diabetes, where specialists with deep patient relationships use purpose-built devices for better personalization of treatment. CGM devices can provide a higher-resolution picture of how glucose levels change in response to diet, activity, and medication, potentially leading to better personalized treatment (14). As these devices have overcome regulatory barriers and become available through prescriptions, healthcare providers have been incentivized to enhance their knowledge and educate their patients. This synergy of healthcare professionals specializing in specific conditions and the exciting semipersonalized treatment approach could act as a catalyst for broader adoption. Further promising areas for clinical applications lie in treatment stratification for cardiovascular conditions, patient adherence monitoring, or using measures from wearables as clinical endpoints.

Aftercare and Rehabilitation

Wearables could also help prevent adverse events and improve patient rehabilitation, which is of increasing interest in the context of an aging population (85). Foundational work has uncovered the potential of wearables in detection of specific events such as falls (86) and sepsis (87). Due to the ubiquity of accelerometers, HR sensors, and an already personalized approach (88), physical therapy and rehabilitation could be an area where wearables may have great impact. There is a growing body of evidence around the usefulness of wearables in aftercare and rehabilitation, although not nearly as expansive as that for diagnostic applications. Similar to positive effects in physical activity of healthy populations, wearables have been found to be useful for rehabilitation after orthopedic surgery and in cardiovascular conditions, where HR data can predict adverse events in HF patients (26, 89, 90). However, integration with existing structures is not as straightforward as in diagnostic alerting systems, where adoption can be driven by consumers. Broad application, extending the reach of the care team in both in- and outpatient settings, seems unlikely to become reality soon (91, 92).

CONCLUDING REMARKS

The biomedical potential of wearables for early detection, diagnosis, and management of acute and chronic clinical conditions has been demonstrated by several research findings through longitudinal monitoring. Furthermore, wearables have shown promise in reducing the healthcare burden via prevention of serious and costly medical events, lowering hospital readmission rates, decreasing emergency room visits, and improving post-treatment and rehabilitation outcomes. Although more evidence is needed in many conditions such as CVD, and the lack of data standards, accessibility, and regulatory clarity must be addressed, wearables will increasingly impact clinical care. With more device makers obtaining FDA clearance or Conformite Européenne (CE) marking (73) for their devices, this regulatory route could emerge as a new standard for wearable clinical translation. Increased use of consumer-grade wearables with diagnostic features will send more and more patients to clinics, confronting practitioners with the technology itself and the data it generates, including both its value and caveats. With continued technological innovations in wearable designs and computational advances including artificial intelligence, wearables are poised to become more powerful and sensitive, enabling their application to new areas including infectious disease and mental well-being. Together with rising global smartwatch usage, remote physiological monitoring using consumer-grade wearables will play a key role in ushering in an era of precision health care. Cardiac rehabilitation and the treatment of metabolic diseases like diabetes may be the next areas where wearables can deliver better patient monitoring and personalized treatment due to the combination of highly specialized care and an already quasi-personalized blood glucose management approach.

DISCLOSURE STATEMENT

M.P.S. is a cofounder and scientific advisor of Personalis, SensOmics, Qbio, January AI, Fodsel, Filtricine, Protos, RTHM, Iollo, Marble Therapeutics and Mirvie. He is a scientific advisor of Genapsys, Jupiter, Neuvivo, Swaza, and Mitrix. No other authors have competing interests.

ACKNOWLEDGMENTS

M.B. is supported by the Finnish Cultural Foundation Postdoctoral Fellowship. Z.L. is supported by the William K. Bowes Jr. Stanford Graduate Fellowship. M.P.S. is supported by grants from the National Institutes of Health. The authors thank Alexander Honkala for thoughtful comments on the article.

LITERATURE CITED

1. Bouchard C, Rankinen T. 2001. Individual differences in response to regular physical activity. *Med. Sci. Sports Exerc.* 33(6 Suppl.):S446–51
2. Lewis DA, Kamon E, Hodgson JL. 1986. Physiological differences between genders. Implications for sports conditioning. *Sports Med.* 3(5):357–69
3. Witt D, Kellogg R, Snyder M, et al. 2019. Windows into human health through wearables data analytics. *Curr. Opin. Biomed. Eng.* 9:28–46
4. Gambhir SS, Ge TJ, Vermesh O, et al. 2021. Continuous health monitoring: an opportunity for precision health. *Sci. Transl. Med.* 13(597):eabe5383
5. Dunn J, Runge R, Snyder M. 2018. Wearables and the medical revolution. *Per. Med.* 15(5):429–48
6. Ates HC, Nguyen PQ, Gonzalez-Macia L, et al. 2022. End-to-end design of wearable sensors. *Nat. Rev. Mater.* 7(11):887–907
7. Li X, Dunn J, Salins D, et al. 2017. Digital health: tracking physiomes and activity using wearable biosensors reveals useful health-related information. *PLOS Biol.* 15(1):e2001402
8. Lim WK, Davila S, Teo JX, et al. 2018. Beyond fitness tracking: the use of consumer-grade wearable data from normal volunteers in cardiovascular and lipidomics research. *PLOS Biol.* 16(2):e2004285
9. Tison GH, Sanchez JM, Ballinger B, et al. 2018. Passive detection of atrial fibrillation using a commercially available smartwatch. *JAMA Cardiol.* 3(5):409–16
10. Price ND, Magis AT, Earls JC, et al. 2017. A wellness study of 108 individuals using personal, dense, dynamic data clouds. *Nat. Biotechnol.* 35(8):747–56
11. Ballinger B, Hsieh J, Singh A, et al. 2018. DeepHeart: semi-supervised sequence learning for cardiovascular risk prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, 32(1). **https://doi.org/10.1609/aaai.v32i1.11891**
12. Mishra T, Wang M, Metwally AA, et al. 2020. Pre-symptomatic detection of COVID-19 from smartwatch data. *Nat. Biomed. Eng.* 4(12):1208–20
13. Quer G, Radin JM, Gadaleta M, et al. 2021. Wearable sensor data and self-reported symptoms for COVID-19 detection. *Nat. Med.* 27(1):73–77
14. Alavi A, Bogu GK, Wang M, et al. 2022. Real-time alerting system for COVID-19 and other stress events using wearable data. *Nat. Med.* 28(1):175–84
15. Stamatakis E, Ahmadi MN, Gill JMR, et al. 2022. Association of wearable device-measured vigorous intermittent lifestyle physical activity with mortality. *Nat. Med.* 28(12):2521–29
16. Master H, Annis J, Huang S, et al. 2022. Association of step counts over time with the risk of chronic disease in the All of Us research program. *Nat. Med.* 28(11):2301–8
17. Brickwood K-J, Watson G, O'Brien J, et al. 2019. Consumer-based wearable activity trackers increase physical activity participation: systematic review and meta-analysis. *JMIR mHealth uHealth* 7(4):e11819
18. Hall H, Perelman D, Breschi A, et al. 2018. Glucotypes reveal new patterns of glucose dysregulation. *PLOS Biol.* 16(7):e2005143
19. Hickey BA, Chalmers T, Newton P, et al. 2021. Smart devices and wearable technologies to detect and monitor mental health conditions and stress: a systematic review. *Sensors* 21(10):3461
20. Lautman Z, Lev-Ari S. 2022. The use of smart devices for mental health diagnosis and care. *J. Clin. Med. Res.* 11(18):5359
21. Chandrasekaran R, Katthula V, Moustakas E. 2020. Patterns of use and key predictors for the use of wearable health care devices by US adults: insights from a national survey. *J. Med. Internet Res.* 22(10):e22443
22. Mensah GA, Roth GA, Fuster V. 2019. The global burden of cardiovascular diseases and risk factors: 2020 and beyond. *J. Am. Coll. Cardiol.* 74(20):2529–32
23. Roth GA, Mensah GA, Fuster V. 2020. The global burden of cardiovascular diseases and risks: a compass for global action. *J. Am. Coll. Cardiol.* 76(25):2980–81
24. Tsao CW, Aday AW, Almarzooq ZI, et al. 2023. Heart disease and stroke statistics—2023 update: a report from the American Heart Association. *Circulation* 147(8):e93–621
25. Roth GA, Mensah GA, Johnson CO, et al. 2020. Global burden of cardiovascular diseases and risk factors, 1990–2019: update from the GBD 2019 study. *J. Am. Coll. Cardiol.* 76(25):2982–3021

26. Zhang D, Wang W, Li F. 2016. Association between resting heart rate and coronary artery disease, stroke, sudden death and noncardiovascular diseases: a meta-analysis. *Can. Med. Assoc. J.* 188(15):e384–92
27. Fox K, Ford I, Steg PG, et al. 2008. Heart rate as a prognostic risk factor in patients with coronary artery disease and left-ventricular systolic dysfunction (BEAUTIFUL): a subgroup analysis of a randomised controlled trial. *Lancet* 372(9641):817–21
28. Singh N, Moneghetti KJ, Christle JW, et al. 2018. Heart rate variability: an old metric with new meaning in the era of using mHealth technologies for health and exercise training guidance. Part two: prognosis and training. *Arrhythm. Electrophysiol. Rev.* 7(4):247–55
29. Nelson BW, Allen NB. 2019. Accuracy of consumer wearable heart rate measurement during an ecologically valid 24-hour period: intraindividual validation study. *JMIR mHealth uHealth* 7(3):e10828
30. Perez MV, Mahaffey KW, Hedlin H, et al. 2019. Large-scale assessment of a smartwatch to identify atrial fibrillation. *N. Engl. J. Med.* 381(20):1909–17
31. Lubitz SA, Faranesh AZ, Selvaggi C, et al. 2022. Detection of atrial fibrillation in a large population using wearable devices: the Fitbit Heart Study. *Circulation* 146(19):1415–24
32. Natarajan A, Pantelopoulos A, Emir-Farinas H, et al. 2020. Heart rate variability with photoplethysmography in 8 million individuals: a cross-sectional study. *Lancet Digit. Health* 2(12):e650–57
33. Quer G, Gouda P, Galarnyk M, et al. 2020. Inter- and intraindividual variability in daily resting heart rate and its associations with age, sex, sleep, BMI, and time of year: retrospective, longitudinal cohort study of 92,457 adults. *PLOS ONE* 15(2):e0227709
34. Virani SS, Alonso A, Aparicio HJ, et al. 2021. Heart disease and stroke statistics—2021 update: a report from the American Heart Association. *Circulation* 143(8):e254–743
35. Turakhia MP, Shafrin J, Bognar K, et al. 2018. Estimated prevalence of undiagnosed atrial fibrillation in the United States. *PLOS ONE* 13(4):e0195088
36. Zhou B, Carrillo-Larco RM, Danaei G, Riley LM, Paciorek CJ, et al. (NCD Risk Factor Collab.). 2021. Worldwide trends in hypertension prevalence and progress in treatment and control from 1990 to 2019: a pooled analysis of 1201 population-representative studies with 104 million participants. *Lancet* 398(10304):957–80
37. Burkard T, Mayr M, Winterhalder C, et al. 2018. Reliability of single office blood pressure measurements. *Heart* 104(14):1173–79
38. Pickering TG. 1990. The clinical significance of diurnal blood pressure variations. Dippers and nondippers. *Circulation* 81(2):700–2
39. Kario K, Shimbo D, Tomitani N, et al. 2020. The first study comparing a wearable watch-type blood pressure monitor with a conventional ambulatory blood pressure monitor on in-office and out-of-office settings. *J. Clin. Hypertens.* 22(2):135–41
40. Islam SMS, Cartledge S, Karmakar C, et al. 2019. Validation and acceptability of a cuffless wrist-worn wearable blood pressure monitoring device among users and health care professionals: mixed methods study. *JMIR mHealth uHealth* 7(10):e14706
41. Werhahn SM, Dathe H, Rottmann T, et al. 2019. Designing meaningful outcome parameters using mobile technology: a new mobile application for telemonitoring of patients with heart failure. *ESC Heart Fail.* 6(3):516–25
42. Sherazi S, Kutyifa V, McNitt S, et al. 2015. Prognostic significance of heart rate variability among patients treated with cardiac resynchronization therapy: MADIT-CRT (Multicenter Automatic Defibrillator Implantation Trial—Cardiac Resynchronization Therapy). *JACC Clin. Electrophysiol.* 1(1–2):74–80
43. Stavrakis S, Stoner JA, Kardokus J, et al. 2017. Intermittent versus Continuous Anticoagulation theRapy in patiEnts with Atrial Fibrillation (iCARE-AF): a randomized pilot study. *J. Interv. Cardiac Electrophysiol.* 48(1):51–60
44. Marvel FA, Spaulding EM, Lee MA, et al. 2021. Digital health intervention in acute myocardial infarction. *Circ. Cardiovasc. Qual. Outcomes* 14(7):e007741
45. Cockrell C, Larie D, An G. 2022. Preparing for the next pandemic: simulation-based deep reinforcement learning to discover and test multimodal control of systemic inflammation using repurposed immunomodulatory agents. *Front. Immunol.* 13:995395
46. Shahroz M, Ahmad F, Younis MS, et al. 2021. COVID-19 digital contact tracing applications and techniques: a review post initial deployments. *Transp. Eng.* 5:100072

47. Yang C, Shao H-R. 2015. WiFi-based indoor positioning. *IEEE Commun. Mag.* 53(3):150–57
48. Lim J-S, Jang W-H, Yoon G-W, et al. 2013. Radio map update automation for WiFi positioning systems. *IEEE Commun. Lett.* 17(4):693–96
49. Mazuelas S, Bahillo A, Lorenzo RM, et al. 2009. Robust indoor positioning provided by real-time RSSI values in unmodified WLAN networks. *IEEE J. Sel. Top. Signal Process.* 3(5):821–31
50. Luoh L. 2013. ZigBee-based intelligent indoor positioning system soft computing. *Soft Computing* 18(3):443–56
51. Goergen CJ, Tweardy MJ, Steinhubl SR, et al. 2022. Detection and monitoring of viral infections via wearable devices and biometric data. *Annu. Rev. Biomed. Eng.* 24:1–27
52. Crook H, Raza S, Nowell J, et al. 2021. Long covid—mechanisms, risk factors, and management. *BMJ* 374:n1648
53. Ates HC, Yetisen AK, Güder F, et al. 2021. Wearable devices for the detection of COVID-19. *Nat. Electron.* 4(1):13–14
54. Hirten RP, Danieletto M, Tomalin L, et al. 2021. Use of physiological data from a wearable device to identify SARS-CoV-2 infection and symptoms and predict COVID-19 diagnosis: observational study. *J. Med. Internet Res.* 23(2):e26107
55. Guan G, Mofaz M, Qian G, et al. 2022. Higher sensitivity monitoring of reactions to COVID-19 vaccination using smartwatches. *NPJ Digit. Med.* 5:140
56. Quer G, Gadaleta M, Radin JM, et al. 2022. Inter-individual variation in objective measure of reactogenicity following COVID-19 vaccination via smartwatches and fitness bands. *NPJ Digit. Med.* 5(1):49
57. Gepner Y, Mofaz M, Oved S, et al. 2022. Utilizing wearable sensors for continuous and highly-sensitive monitoring of reactions to the BNT162b2 mRNA COVID-19 vaccine. *Commun. Med.* 2:27
58. Keating BJ, Mukhtar EH, Elftmann ED, et al. 2021. Early detection of SARS-CoV-2 and other infections in solid organ transplant recipients and household members using wearable devices. *Transpl. Int.* 34(6):1019–31
59. Grzesiak E, Bent B, McClain MT, et al. 2021. Assessment of the feasibility of using noninvasive wearable biometric monitoring sensors to detect influenza and the common cold before symptom onset. *JAMA Netw. Open* 4(9):e2128534
60. Hedayatipour A, Mcfarlane N. 2020. Wearables for the next pandemic. *IEEE Access*. 8:184457–74
61. WHO. 2022. *Mental disorders*. Fact sheet, World Health Organ., Geneva, Switz. **https://www.who.int/news-room/fact-sheets/detail/mental-disorders**. Updated Mar. 2023, accessed Mar. 29, 2023
62. NIMH. 2023. Mental illness. *National Institute of Mental Health*. **https://www.nimh.nih.gov/health/statistics/mental-illness**. Accessed Mar. 29, 2023
63. Mental Health America. 2023. *The state of mental health in America*. Rep., Mental Health America, Alexandria, VA. **https://mhanational.org/issues/state-mental-health-america**. Accessed Feb. 20, 2023
64. Kessler RC, Berglund P, Demler O, et al. 2005. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Arch. Gen. Psychiatry* 62(6):593–602
65. Narziev N, Goh H, Toshnazarov K, et al. 2020. STDD: short-term depression detection with passive sensing. *Sensors* 20(5):1396
66. Colombo D, Fernández-Álvarez J, Patané A, et al. 2019. Current state and future directions of technology-based ecological momentary assessment and intervention for major depressive disorder: a systematic review. *J. Clin. Med. Res.* 8(4):465
67. Bishop TF, Seirup JK, Pincus HA, et al. 2016. Population of US practicing psychiatrists declined, 2003–13, which may help explain poor access to mental health care. *Health Aff.* 35(7):1271–77
68. Gomes N, Pato M, Lourenço AR, et al. 2023. A survey on wearable sensors for mental health monitoring. *Sensors* 23(3):1330
69. Long N, Lei Y, Peng L, et al. 2022. A scoping review on monitoring mental health using smart wearable devices. *Math. Biosci. Eng.* 19(8):7899–919
70. Can YS, Chalabianloo N, Ekiz D, et al. 2019. Continuous stress detection using wearable sensors in real life: algorithmic programming contest case study. *Sensors* 19(8):1849
71. Tsai C-H, Chen P-C, Liu D-S, et al. 2022. Panic attack prediction using wearable devices and machine learning: development and cohort study. *JMIR Med. Inform.* 10(2):e33063

72. Barragán-Montero A, Javaid U, Valdés G, et al. 2021. Artificial intelligence and machine learning for medical imaging: a technology review. *Phys. Med.* 83:242–56
73. Xu S, Kim J, Walter JR, et al. 2022. Translational gaps and opportunities for medical wearables in digital health. *Sci. Transl. Med.* 14(666):eabn6036
74. Bahmani A, Alavi A, Buergel T, et al. 2021. A scalable, secure, and interoperable platform for deep data-driven health management. *Nat. Commun.* 12(1):5757
75. Satija U, Ramkumar B, Manikandan MS. 2018. A review of signal processing techniques for electrocardiogram signal quality assessment. *IEEE Rev. Biomed. Eng.* 11:36–52
76. Karimipour A, Homaeinezhad MR. 2014. Real-time electrocardiogram P-QRS-T detection-delineation algorithm based on quality-supported analysis of characteristic templates. *Comput. Biol. Med.* 52:153–65
77. Smuck M, Odonkor CA, Wilt JK, et al. 2021. The emerging clinical role of wearables: factors for successful implementation in healthcare. *NPJ Digit. Med.* 4:45
78. Lebak JW, Yao J, Warren S. 2004. HL7-compliant healthcare information system for home monitoring. *Conf. Proc. IEEE Eng. Med. Biol. Soc.* 2004:3338–41
79. Intl. Data Corp. (IDC). 2023. *Holiday quarter woes contribute to a full-year decline in shipments of wearable devices, according to IDC tracker*. News Release, Mar. 7. **https://www.idc.com/getdoc.jsp?containerId=prUS50462723**
80. Lim B, Zohren S. 2021. Time-series forecasting with deep learning: a survey. *Philos. Trans. A Math. Phys. Eng. Sci.* 379(2194):20200209
81. Bolnick HJ, Bui AL, Bulchis A, et al. 2020. Health-care spending attributable to modifiable risk factors in the USA: an economic attribution analysis. *Lancet Public Health* 5(10):e525–35
82. Chiang P-H, Wong M, Dey S. 2021. Using wearables and machine learning to enable personalized lifestyle recommendations to improve blood pressure. *IEEE J. Transl. Eng. Health Med.* 9:2700513
83. Beagle AJ, Tison GH, Aschbacher K, et al. 2020. Comparison of the physical activity measured by a consumer wearable activity tracker and that measured by self-report: cross-sectional analysis of the Health eHeart Study. *JMIR mHealth uHealth* 8(12):e22090
84. Prieto-Avalos G, Cruz-Ramos NA, Alor-Hernández G, et al. 2022. Wearable devices for physical monitoring of heart: a review. *Biosensors* 12(5):292
85. Bravo VP, Muñoz JA. 2022. Wearables and their applications for the rehabilitation of elderly people. *Med. Biol. Eng. Comput.* 60(5):1239–52
86. Vilarinho T, Farshchian B, Bajer DG, et al. 2015. A combined smartphone and smartwatch fall detection system. In *2015 IEEE International Conference on Computer and Information Technology; Ubiquitous Computing and Communications; Dependable, Autonomic and Secure Computing; Pervasive Intelligence and Computing*, pp. 1443–48. New York: IEEE. **https://doi.org/10.1109/CIT/IUCC/DASC/PICOM.2015.216**
87. Choi A, Chung K, Chung SP, et al. 2022. Advantage of vital sign monitoring using a wireless wearable device for predicting septic shock in febrile patients in the emergency department: a machine learning-based analysis. *Sensors* 22(18):7054
88. Adans-Dester C, Hankov N, O'Brien A, et al. 2020. Enabling precision rehabilitation interventions using wearable sensors and machine learning to track motor recovery. *NPJ Digit. Med.* 3:121
89. van Dijk-Huisman HC, Weemaes ATR, Boymans TAEJ, et al. 2020. Smartphone app with an accelerometer enhances patients' physical activity following elective orthopedic surgery: a pilot study. *Sensors* 20(15):4317
90. Bayoumy K, Gaber M, Elshafeey A, et al. 2021. Smart wearable devices in cardiovascular care: where we are and how to move forward. *Nat. Rev. Cardiol.* 18(8):581–99
91. Patel V, Orchanian-Cheff A, Wu R. 2021. Evaluating the validity and utility of wearable technology for continuously monitoring patients in a hospital setting: systematic review. *JMIR mHealth uHealth* 9(8):e17411
92. Soon S, Svavarsdottir H, Downey C, et al. 2020. Wearable devices for remote vital signs monitoring in the outpatient setting: an overview of the field. *BMJ Innov.* 6(2):55–71