13 Wearable Technologies in Lifestyle Medicine

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Abbreviations

A1C	Hemoglobin A1c
BMI	Body mass index
BP	Blood pressure
ECG	Electrocardiogram
HR	Heart rate
MARD	Mean absolute relative difference

Introduction

The traditional encounter model between patient and healthcare professional is evolving under the strong influences of chronic care models, economic constraints, and advanced technologies. Wearable technologies will be a cornerstone of early and sustainable preventive care to not only offset the consequences of chronic disease, but also as an effective tool to prevent chronic disease risk, progression, and consequences. Wearable technologies are electronic computing devices, capable of primarily functioning passively, attached and detached from the body freely, and commonly connected with the Internet. The incorporation of wearable technologies into the cloud has been recently referred to as the "Internet of Things" (IoT), and when specifically incorporating medical wearables, the "Internet of Medical Things" (IoMT). The coordination of smartphone applications, wearables, and point-of-care testing (e.g., in a Lifestyle Medicine Center) allows individual adaptations to activities of daily living [1]. Intelligent healthcare systems have been described utilizing Wireless Body Area Network concepts to link sensors with a hub in a reliable and scalable way, especially as integration becomes more complex with more and more wearables being used [2]. Sensor data can also be incorporated into electronic health records for both inpatients and outpatients [3]. Protected health information can be safeguarded using Integrated Circuit Metric technology, which provides authentication, confidentiality, secure admission, and symmetric key generation [4].

The purpose of wearable technologies in the setting of lifestyle medicine and prevention and management of chronic disease is to measure any clinical parameter, preferably a continuous parameter, that has value to the user, and in many cases, to provide context for interpreting that measurement. A major presumption is that the measurement is interpretable and actionable in a way that improves the user's health. This is particularly attractive in low-income countries, where measurements should be easy to perform and scalable, with open access and adaptability [5].

Wearable technologies are an indispensible implementation tool in lifestyle medicine. There are two broad categories of wearable technologies: those that monitor clinical parameters (e.g., activity with a step counter; certain vital signs, such as heart rate [HR], heart rhythm, and blood pressure [BP]; and laboratory values, such as interstitial fluid glucose) and those that monitor and intervene based on clinical parameters (e.g., cardioverter-defibrillator, ultrasound, and mobility assistance). Examples of wearables that measure movement, and posture; wearables related to exosuits with sensors for augmented movement and cardiac physiology; and wearables as mixed reality goggles are shown in Fig. 13.1. There are also wearables that detect environmental factors that comprise the human exposome (e.g., acoustic noise, temperature/heat, particle number counts, and geolocation) and impact health, though there are still problems with accuracy and interpretation of these variables [6].

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Fig. 13.1 Examples of wearable technologies related to movement.* (*(**a**) Fitbit Versa2™ (https://www.fitbit.com/shop/versa [accessed on December 21, 2019]); (**b**) Nike+ FuelBand SE™ (https://www.ebay.com/c/620182438 [accessed on December 21, 2019]); (**c**) Apple Watch Series 5 Nike™ (https://www.apple.com/apple-watch-series-5 [accessed December 21, 2019]); (**d**) Samsung Galaxy Watch™ (https://www.samsung.com/ [accessed on December 21, 2019]); (**e**) Seismic™ (http://www.meggrant.com/ [accessed December 21, 2019); (**f**) BodyGuardian™ Heart (https://www.preventicesolutions.com/hcp/body-guardian-heart [accessed on December 21, 2019); (**g**) Microsoft Hololens 2™ ([accessed on December 21, 2019])

Clinical Scenarios

The value of wearable technologies becomes evident across levels of sophistication, clinical disorders, and endpoints (Table 13.1). These devices can provide simple chores, such as keeping a record of steps or calories, to inform conversations with the lifestyle medicine professional, to enable locomotion in a patient with paraplegia, to enable physical activity and to reduce cardiometabolic risk. There are also platforms, such as HealthSnap™ (www.healthsnap.io [accessed on December 22, 2019]), that capture, analyze, and present a broad range of lifestyle variables with many derivative services. This is a rapidly changing landscape, and each Lifestyle Medicine Center will need to identify areas of interest and then consider how relevant wearables can be successfully implemented in their programs. The decision of whether to utilize a wearable device in patient care needs to be carefully considered, depending upon the patient population. Simpson and Mazzeo [7] found that health-tracking devices/applications might actually be detrimental in patients with eating disorders, serving as a reminder that these technologies are still, for the most part, in the development and early implementation stage. There are many other wearable technologies that may influence the implementation of lifestyle medicine, such as those related to obstetrics and neonatology, mental health, ostomy function, lymphedema, hearing and vision, and artificial kidneys, but describing a complete potpourri of devices is beyond the scope of this chapter.

Table 13.1 Examples of wearable technologies in healthcare[a]

Clinical target	Device	Description
Cancer	Optune™	Emits tumor-treating fields to treat glioblastoma
	Vivofit 2™	Correlates activity with behavior
Cardiovascular	Apple Watch™	HR/rhythm and energy expenditure
	BodyGuardian Heart™	Adhesive strips, mobile telemetry, cardiac event monitoring
	Fitbit Blaze™/ Charge 2™	HR/rhythm
	Garmin Forerunner™	HR
	Microsoft Kinect™	Correlates skin color with HR
	Phillips Actiwatch™	Measures mobility and sleep
	Preventice BodyGuardian™	ECG measures HR and respiratory rate
	Samsung Galaxy Gear™	HR/rhythm
	TomTom Spark™	HR
	ZioPatch™	ECG monitoring patch to detect AF
Diabetes	Dexcom™	Glucose sensor
	Freestyle Libre™	Glucose sensor
	Serenita™	Relaxation app measuring hemodynamics
Neurology	Empatica™	Wrist-worn detection of seizure counts
	ExoAtlet™	Exoskeleton used in multiple sclerosis
	iCalm™	Wrist-worn detection of seizure counts
	Nightwatch™	Wrist-worn detection nocturnal seizures, movement, HR
Nutrition	Healbe's GoBe 2™	Bioelectrical impedance detection of food intake
	SilkLab™	Tooth-mounted monitor for glucose, salt, and alcohol
	Styr life™	Voice-activated food logging
	The Bite Counter™	Wrist-worn device correlates with oral intake
Orthopedics	Fitbit™	Integrates physical activity with coaching sessions
	LUMOback™	Wearable back device provides posture information
	Micro-Motionlogger™	Correlates activity with clinical symptoms
	Primewalk™	Robotic power-assist locomotor for paraplegia
	ZetrOZ sam™	Provides low-intensity therapeutic ultrasound
Physical activity	ActiGraph™	Rest/activity monitor (e.g., fidgeting versus deskwork)
	ActivPAL™	Activity/incline monitor for sitting, standing, and stepping
	Bio2Bit Move™	Real-time muscle activity monitor
	Coffee WALKIE™	Wrist/waist-worn monitor
	Fitbit Flex™	Monitor with personalized predictors; reminders to exercise
	Seismic™	Powered garment with sensors to assist movement
	SenseWear Armband™	Monitors sleep, posture, and activity
Platform	HealthSnap™	Presents range of lifestyle variables
	Hololens™	Patient education and telemedicine
Sleep	SnoreLab™	Monitors snoring and provides analysis
	WatchPAT™	Monitors rest/activity, hemodynamics, and oximetry

[a]Devices listed are those that monitor clinical parameters with/without intervention. Smartphone apps are not included here. With some exceptions, specific device models are not provided since they frequently change over time. See Table 13.2 for expanded list of glucose sensors. Abbreviations: *AF* atrial fibrillation, *ECG* electrocardiogram, *HR* heart rate

Cardiometabolic-Based Chronic Disease

Cardiometabolic risks include obesity, dysglycemia, unhealthy eating patterns, physical inactivity, tobacco use, hypertension, hypercholesterolemia, poor sleep hygiene, unhealthy behaviors, and inflammation [8–11]. Wearable technologies that address cardiometabolic risk factors will be presented according to the evidence and three clinical scenarios: abnormal adiposity, movement, and sleep; dysglycemia; and cardiovascular disease (CVD).

Abnormal Adiposity, Movement, and Sleep

The mainstay of obesity management is to achieve an optimal body composition (adiposity amount and distribution) and decreased risk for obesity-related complications for a specific patient [8]. This is primarily, but not exclusively, accomplished through healthy eating and physical activity. Wearable technologies interrogate various nutritional and movement variables and can provide a cost-effective and durable adjunct to strategies and tactics delivered in the Lifestyle Medicine Center.

Manual reporting of food intake is generally unreliable [12]. Mobile, dietary self-monitoring, such as image analysis systems that identify foods and estimate portion sizes, can be a valuable tool [13, 14]. Turner-McGrievy et al. [15] found that the total number of days tracking at least two eating occasions per day correlated with improved adherence, highlighting the need for techniques to improve performance of these technologies. Recently, a voice-based mobile nutrition monitoring system has been developed that is based on speech and natural language processing, text-mining techniques, and a tiered matching algorithm that searches nutritional databases to provide a dietary composition monitoring function [16]. Weathers et al. [17] found that the use of The Bite Counter (a wrist-worn device that detects a rolling of the wrist that correlates with bites; http://icountbites.com/ [accessed on December 24, 2019]) is as effective as mental tracking for achieving eating goals. In another study by Shen et al. [18], bite-counting protocols have a sensitivity of 75% with positive predictive value of 89% for actual bites determined by video monitoring. Wearable technologies also support behavioral weight loss in patients with serious mental illnesses [19]. Nevertheless, in the Innovative Approaches to Diet, Exercise and Activity (IDEA) randomized, controlled trial ($N = 470$) of young adults (age 18–35 years) with a body mass index (BMI) between 25 and <40 kg/m^2, the use of wearable technologies compared with standard behavioral interventions resulted in less weight loss over 24 months [20]. The results are not fully explained by the authors and point out that more formal research studies into behavioral mechanisms in patients with abnormal adiposity, especially over longer periods of time, are needed to better understand the role for and mechanism of action of wearables [21].

In a study of patients with metabolic syndrome (central obesity 83.0%; hyperglycemia 54.7%; hypertension 90.6%; hypertriglyceridemia 83.7%; and low high-density lipoprotein cholesterol 54.7%), a 12-week intervention using a wrist- or waist-worn physical activity monitor (Coffee WALKIE +Dv.3™) improved engagement with regular walking and cardiometabolic risk factors, especially hypertension [22]. Using behavioral analytics, the system was able to provide personalized exercise predictors derived from Fitbit Flex™ output and smartphone assessment of daily stress experience and was associated with a 6.5% ($p = 0.04$) greater likelihood of exercising [23]. There are also wearable devices (e.g., Bio2Bit Move™) that perform real-time monitoring of muscle activity [24].

In a study by Kingsley et al. [25], there were large differences in activity intensity estimates among wrist-worn accelerometers, especially below moderate intensity levels (<3 metabolic equivalents or METs). In overweight/obesity, inclinometers (e.g., ActivPAL™ and ActiGraph™) are more error-prone for sedentary to upright transitions and stepping time, compared with sedentary behavior and standing time [26]. Moreover, in children, total activity counts are generally affected by moderate- and vigorous-intensity physical activity but can also be confounded by total wear time [27].

Sedentary behavior is generally any waking behavior in a sitting or reclining posture with <1.5 METs [28]. A preliminary study using the SenseWear Armband™ (for sleep and activity) and activPAL™ (for posture) devices can simultaneously measure sleep, posture, and activity [28]. Sedentary behavior varies according to occupation using device-measured movements, with office workers having the greatest, and laborers the lowest sedentary time; of note, higher BMI and BP correlate with sedentary time [29]. In a prospective cohort study using wrist-worn accelerometers ($N = 91{,}648$), Kim et al. [30] found that subjects with high levels of physical activity, lower sedentary or screen [TV viewing and computer use] time, and sleep times of 7 hours/day were more physically active at 5.7 year follow-up. On the other hand, subjects with increased, compared with decreased, dynamic sitting (fidgeting and deskwork; assessed with a hip-worn accelerometer [ActiGraph GT3X™]) was associated with a lower BMI, smaller waist circumference, and lower risk for metabolic syndrome [31]. In addition, novel designs for smart shirts, integrating individual factors and machine learning algorithms, provide highly accurate information about sedentary behavior that is useful for designing active lifestyles, especially for frail, elderly people [32]. Future studies will need to discern how each component of sedentary behavior, and components of physically active lifestyles, contributes to sustainable health outcomes.

Obstructive sleep apnea is an obesity-related complication related to pulmonary function that compromises quality of life by reducing energy and wakefulness during the day-time, while also exacerbating problems with glycemic and weight control. Sleep quality (e.g., ratio of deep sleep to total sleep) estimated using an accelerometer, and correlated with data from pulse activity trackers, body weighing scales, and BP monitors, found that poor sleep quality was associated with being a male, young, having a fast heart rate, and having high BP, whereas increased total sleep was associated with increased weight [33]. Research is currently underway using wearable sensor data from electrodermal activity to more accurately measure sleep efficiency and quality [34].

The wrist-worn WatchPAT 200™ is a four-channel unattended home device that measures peripheral arterial tone, pulse oximetry, HR, and actigraphy (rest/activity cycles). Surges of sympathetic activity detected with this device correlate with apnea/hypopnea events [35]. This information can be useful in high-risk patients where polysomnography is not available [35]. In another study, Lin et al. [36] found that wearable piezoelectric thoracic and abdominal bands detect obstructive versus central sleep apnea with 81.8 ± 9.4% accuracy. The CBT-i Coach™ is a mobile app that has been shown to improve subjective sleep based on cognitive-behavioral therapy in patients with insomnia [37]. Obesity-related lung disease also includes an increased risk for asthma. A wireless wearable ultrasound sensor has been developed for early detection of asthma progression by measuring the FEV1/FVC ratio [38]. In patients with chronic obstructive pulmonary disease and mean BMI of 28.6 kg/M^2, activity levels measured by a ActiGraph wGT3X-BT™ accelerometer for 7 consecutive days identified 3 behavioral constructs: [1] low-intensity movement associated with mobility, daily activities, health status, and BMI; [2] high-intensity movement associated with younger age and minimal self-care limitations; and [3] sleep associated with body adiposity and poor lung function [39].

Dysglycemia

The management of type 1 and type 2 diabetes includes lifestyle medicine, particularly medical nutrition therapy and healthy eating, as well as mitigation of other CVD risk factors that often includes pharmacotherapy. In patients with or suspected as having dysglycemia, especially as efforts are underway to mitigate cardiometabolic risk factors, capturing and visualizing glucose patterns and correlating them with eating patterns and physical activity provides a unique and valuable opportunity for motivation and lifestyle change. In fact, wearable glucose sensors are an integral part of single- and dual-hormone, closed-loop hormone (insulin ± glucagon) delivery systems that facilitate safe exercise and physical activity by reducing hypoglycemic episodes [40]. Various glucose-sensing technologies are available to increase patient engagement and motivation to improve glycemic control. Currently, there are some significant concerns about wearable glucose-monitoring devices: accuracy, battery life, burden to patients, comfort, confidentiality, cost, market stability, and standardization [41].

Many sensors are available. There is a curvilinear relationship between the mean absolute relative difference (MARD) and frequency of large (>20%) deviations in glucose determinations [42, 43]. This relationship is consistent across the full range of devices and manufacturers (Table 13.2) [42, 43]. Wrist-borne non-invasive glucose monitors use photoplethysmographic optical sensors and have a MARD in the 7.40–7.54%, which is at the lower part of the range for available glucometer models (5.6–20.8%) [44].

Wearable interfaces also provide measurements of glucose and alcohol in sweat that correlate with blood levels [45, 46]. In addition, a paper microfluidic device for integration into a silicone mouthguard has been developed to measure salivary glucose [47]. Many other paper-based electrochemiluminescence analytic devices, including 3-D origami devices, are suitable for wearing and available for detecting not only glucose but also metal ions, virulent DNA, pathogenic bacteria, and tumor cells [48]. Still other lab-on-skin devices can measure temperature, blood pressure, electromyography, electroencephalography, electrocardiography, hydration, blood oxygenation, wound care, lactate, and pH [49]. Cholesterol

Table 13.2 Current continuous glucose-monitoring sensors[a]

Device	MARD %	Calibrations	Lifetime days	Comments
Medtronic Enlite Sensor™	13.6	q 12h	6	Adjunctive only Acetaminophen Interference
Medtronic Guardian Sensor 3™	10.6 (abdomen)	q 12h	7	Adjunctive only
	9.1 (arm)			Acetaminophen interference
Freestyle Libre™	11.4	None	14	Scanning required
Freestyle Libre II™	n/a	None	14	Scanning required Improved sensors
Dexcom G4 Platinum™	9	q 12h	7	Adjunctive only
Dexcom G5 Mobile™	9	q 12h	7	Acetaminophen Interference
Dexcom G6™	10	None	10	Has "urgent low soon" alert
Senseonics Eversense™	11.4	None	90	Adjunctive only Inserted/removed in doctor's office

[a]Adapted from Cappon et al. [43]. A full disposable Dexcom G7™ is anticipated in 2020–2021 with real-time monitoring, factory calibration, extended sensor life, with simple application, and significant cost reduction. Other models will be updated as well, especially with improved connectivity with insulin pumps, and Lifestyle Medicine Centers will need to keep pace with these advances. Abbreviation: MARD – mean absolute relative difference

monitoring is also important for cardiometabolic risk reduction and can be performed using organic electrochemical transistor-based sensors [50]. Electrochemical nose-bridge sensors on eyeglasses have been developed to detect glucose, lactate, and other analytes [51]. Even contact-lens biosensors are being developed for analysis of tear glucose levels in patients with diabetes [52]. Another area of active research is the development of wearables that measure foot temperature to provide a means of early detection of peripheral neuropathy and foot ulceration in patients with diabetes [53].

There are also various apps available to patients to store and analyze data from wearable glucose sensors, providing further incentives and motivation for patients: mySugr App™, Glooko™, and Livongo™. The use of these apps is associated with improved glycemic control (by hemoglobin A1c; A1C) according to a meta-analysis by Bonoto et al. [54]. Another type of app that has benefit in patients with diabetes is Serenita™. This is an interactive relaxation app based on acquiring a photoplethysmography signal from a mobile phone camera lens, measuring blood flow, HR, and HR variability, and providing feedback to the user, which in a clinical trial was found to reduce BP, A1C, and fasting plasma glucose [55].

Cardiovascular Disease

Mobile health technology involving apps and wearable devices guide patients to lead healthy lifestyles and reduce CVD risks [56]. Several devices have been developed and are currently available to enrich cardiovascular monitoring and guide lifestyle medicine interventions, particularly physical activity. These wearable devices can be sorted into heart rhythm and electrocardiography systems, HR monitors, daily activity monitors, hemodynamic technologies, remote dielectric sensing, and bioimpedance monitoring [57]. The Preventice BodyGuardian™ monitors heart and respiratory rates via single lead electrocardiogram (ECG) and Phillips Actiwatch Spectrum Pro™ monitors mobility and sleep and can be used to record physiological changes and pharmacological responses, though fit-for-purpose validation studies are needed for wide scale use [58].

Cardiac rehabilitation is a form of secondary prevention to avert a subsequent cardiac event. The Apple Watch™, Fitbit Blaze™, TomTom Spark™, and Garmin Forerunner™ measure HR with acceptable accuracy and can therefore be incorporated in cardiac rehabilitation sessions [59], though there may be overestimations in energy expenditure with the Apple Watch™, when compared against indirect calorimetry [59, 60]. In addition, three wrist-worn devices (Apple Watch series 2™, Samsung Galaxy Gear S3™, and Fitbit Charge 2™) accurately measure baseline and induced supraventricular tachyarrhythmia HRs [61]. There are many other wrist-worn devices measuring a wide range of biological signals. Interestingly, there is also an earlobe photoplethysmographic sensor that represents a less expensive alternative for detecting subclinical atrial fibrillation [62]. Overall, the selection of any device should be based on validation by clinical studies and a thorough understanding of shortcomings, such as decreased specificity for atrial fibrillation, inaccuracy for tachycardia, and decreased sensitivity for chronotropic incompetence in evaluation for bradycardia [63].

In patients who have had a transient ischemic attack or ischemic stroke, early and prolonged monitoring for paroxysmal atrial fibrillation using the ZioPatch™ (an ECG monitoring patch) is more cost-effective and superior in terms of detection rates, compared with shorter-duration Holter monitoring (16.3% vs. 2.1% [OR 8.9; 95% CI 1.1–76.0; $p = 0.026$]) [64]. In German patients, a wearable cardioverter-defibrillator provided an alternative to implantable devices for those with poor left ventricular function at risk for sudden cardiac death [65]. In the foreseeable future, devices of this type may allow for more patients to engage in structured secondary prevention programs.

Potential future wearable technologies are exciting, providing perspective and a realistic glimpse of what lifestyle medicine looks like on a population-based scale. These devices provide more detailed information about cardiovascular physiology, which can be correlated in real time with physical activity to optimize preventive strategies. Photoplethysmography is currently used for pulse oximetry, but by leveraging knowledge in waveform morphology and propagation theory, this technology can provide cuffless estimations of BP [66]. In fact, a wireless, wearable chest device has been developed that measures and analyzes HR and BP by detecting ECG, photoplethymography and ballistocardiogram signals, sending them via Bluetooth to a mobile phone and then to a server where offline MATLAB based operations are run [67]. Using another technology, chest vibrations that correlate with heartbeats are measured by seismocardiography, typically through the use of rigid accelerometers or non-stretchable piezoelectrical membranes, but moving forward, with ultrathin and stretchable e-tattoos [68]. However, even these innovations are challenged by difficulties with analysis, confounders, low sensitivity, and cost, paving the way for computing and analyzing second derivatives of pulse waveforms with the use of flexible, self-powered, ultrasensitive pulse sensors to detect a wider range of CVDs, including arrhythmia, coronary heart disease, and atrial septal defect [68].

By using a soft electro-mechanical-acoustic cardiovascular sensing tattoo, continuous BP readings can be derived based on the associations of systolic time intervals and systolic/diastolic BPs [69]. In patients with or at-risk for heart failure, a non-invasive, point-of-care skin patch sensor can monitor left ventricular fluid dynamics and stroke volume [70]. Clinical compensated versus decompensated heart failure status can be better predicted with wearable seismocardiography after exercise with the assistance of machine-learning algorithms [71]. Along these lines, lung fluid volume detection by remote dielectric sensing using a wearable vest can reduce rehospitalizations in patients with acute decompensated heart failure [72]. In a study by Lim et al. [73] of 233 normal volunteers that integrated data from wearable sensors, lifestyle questionnaires, cardiac imaging, and sphingolipid profiling, various risk categories could be determined, such as the extent that heart size is affected by exercise, or what chronic diseases may be more likely based on associations with specific sphingolipids.

One of the more interesting innovations lately is a wireless intraoral retainer that fits against the palate and contains hybrid electronics that quantify sodium intake in the management of hypertension [74]. There are even contactless innovations. The Microsoft Kinect™ device is a validated technology that reads small variations in skin color that correlate with HR measurements [75]. This device employs Eulerian Video Magnification, photoplethysmography, and videoplethysmography [75].

Orthopedics

There are various wearable technologies that can treat orthopedic and rheumatologic disorders, which ultimately serve to improve physical activity and lower risks for chronic disease. Many of these techniques can be incorporated in the physical therapy program in the Lifestyle Medicine Center or Clinical Service Line.

Diagnostic devices provide useful information to the lifestyle medicine team. Patients with lower back pain frequently report decreased ability to adhere with medical fitness recommendations. Integrating physical activity information booklets, coaching sessions (face-to-face and telephone-based), and an activity tracker (Fitbit™) with an Internet app can decrease care seeking in patients with lower back pain after inpatient and outpatient physiotherapy program completion [76]. Results from the Micro-Motionlogger™ actigraph correlate with four validated questionnaires related to clinical symptoms, as well as clinical measurements [77]. Lumbar spine and social life dysfunction correlate with actigraphy results, but there are also individual factors that correlate with sex, BMI, low back pain, and muscle mass [77]. Using the LUMOback™ wearable back device (N = 15), a more slouched lumbopelvic posture was associated with prolonged lower back pain [78], potentially providing personalized information that can improve well-being and greater participation with physical activities.

Wearable technologies can provide interventions that enable greater mobility. In a 6-week clinical trial (N = 25), Best et al. [79] found that daily multi-hour low-intensity therapeutic ultrasound (ZetrOZ sam™; with power controller, 2 ultrasound transducers, and specialized bandages) improved pain and strength in patients with chronic tendon injuries. Also, wearable pulsed electromagnetic fields provide pain relief and greater mobility in patients with knee osteoarthritis (N = 66) [80]. More sophisticated robotic devices can facilitate increased physical activity. For example, in patients with paraplegia, the Wearable Power-Assist Locomotor with conventional knee-ankle-foot orthoses (e.g., Hip and Ankle Linked Orthosis or Primewalk™) can improve energy efficiency and lower gait demand with locomotion [81]. The wearable exoskeletal device has also been shown to be safe, feasible, and associated with improvements in spatiotemporal and kinematic factors to enable locomotion and mobility in patients with spinal cord injury [82]. Fabric-based soft robotic gloves have also been used to assist hand function in patients with upper limb paralysis after spinal cord injury [83].

Many medical fitness programs in Lifestyle Medicine Centers need to address the challenges related to increasing physical activity in the geriatric and disabled populations, particularly when there are significant orthopedic concerns. The detection of disturbances in gait speed, positional transitions, and posture correlate with mortality, disability, and cognitive impairments [84]. Using accelerometry-measured physical activity using a hip-worn ActiGraph GT3X™, numbers of steps and duration of activity were correlated with lower CVD event rates in the elderly [85]. Unfortunately, estimating energy expenditure in the elderly based on accelerometer output is not as accurate as hoped for, across physical activity intensities and even with different equations [86]. In the elderly, robot-assisted gait devices (e.g., wearable hip assist) can stabilize the trunk [87] and spring-assist actuators can increase the required motor torque [88] for walking and other physical activities. There are even devices that can attach to walkers for positional feedback to improve adherence with guidelines, though posture was not improved [89].

Neurological

The literature on wearable systems, including sensors embedded in garments, to monitor and provide feedback on posture and movement in patients with a variety of neurological disorders is emerging and not yet conclusive [90]. For instance, fall prediction and prevention in the elderly and/or frail generally involves education, footwear advice, toileting, balance training, and exercise but can be enhanced using wearable motion and environment sensors [91]. Also, in a meta-analysis, Gordt et al. [92] found that wearable sensor training exerts a positive effect on static steady-state balance and gait parameters in patients with Parkinson's disease, stroke, peripheral neuropathy, and frailty. Specifically, in patients with Parkinson's disease, soft wearable sensors can detect signs, such as bradykinesia, and inform clinicians about disease progression to optimize therapy [93]. On-shoe wearable sensors can also provide important information with turning related to gain in patients with Parkinson's disease [94]. In patients with multiple sclerosis ($N = 18$), the exoskeleton ExoAtlet™ enabled or improved walking and maintenance of vertical posture [95]. In patients with seizure disorder ($N = 69$), certain multimodal wrist-worn devices (Empatica E3™ and E4™; MIT Media Lab iCalm™) detect seizure counts more accurately than other automated systems and self-reporting [96]; this can allow for correlation with various lifestyle factors to optimize overall care. In another study ($N = 28$), the Nightwatch™ combined HR and movement data to detect a broad range of nocturnal seizures [97].

Cancer

The role of lifestyle medicine in patients with or at-risk for neoplastic diseases is oriented toward prevention of risk at a population level (primordial prevention), prevention of disease in those at risk (primary prevention), prevention of disease progression in those with early, asymptomatic disease (secondary prevention), and prevention of suffering, further morbidity, and mortality in those with advanced disease (tertiary prevention). However, in patients with neoplastic disease, regardless of their staging or response to therapy, there still remains an imperative to prevent other chronic disease risks, progression, and complications. For instance, in patients fighting breast cancer, where the overwhelming focus of care is on tertiary prevention related to this primary diagnosis, the additional attention paid to preventing other chronic diseases, especially through lifestyle change, is often inadequate or completely neglected. With improved survivorships with cancer observed nowadays, this healthcare paradigm needs to be re-examined. The role of wearable technologies to concurrently improve lifestyle for prevention of cancer risk, development, and progression, as well as for other chronic diseases (e.g., cardiometabolic and neurodegenerative), is worthy of discussion and pragmatic implementation.

Healthy eating and physical activity are the core lifestyle medicine modalities, with wearable technologies playing an important role in the earlier primordial/primary/secondary prevention types. As an example, in postmenopausal women with stage I-III breast cancer who have completed primary therapy, the use of a Garmin Vivofit 2™ activity monitor with behavioral sessions was associated with more active lifestyles [98]. Among 42 colorectal cancer survivors, the use of a Fitbit Flex™ and reminder text messages was associated with increased motivation to exercise [99]. Activity monitors have also demonstrated efficacy for motivation and increased physical function in patients with advanced cancer ($N = 37$) [100]. Specifically, there were lower rates of patient-reported outcomes, as well as adverse events, hospitalizations, and mortality [100].

Implementation of Wearable Technologies

When building a Lifestyle Medicine Center or Clinical Service Line within a sponsoring healthcare system, a formal program should be developed that provides relevant wearable technologies to patients. The primary clinical endpoint of a Lifestyle Medicine Center is to decrease the risk for chronic diseases. This means that interventions will span a relatively long period of time and therefore benefits would need to be sustainable. One way to do this is through traditional educational [101] or more contemporary "robotic nudges" [102]. Wearable technology event nudges provide reminders, feedback, and planning prompts that direct human behaviors using intuition and reasoning in a certain direction over a long time, such as chronic disease self-management [103, 104].

From the outset, an expansive line of wearables should be explored that cover the full range of services offered in the Lifestyle Medicine Center. This would range from smartphone apps that monitor dietary patterns, to accelerometers, to more specialized devices for cardiopulmonary measurements or movement disorders with orthopedic or neurological conditions. As lifestyle medicine protocols are formulated within the Center, wearable technologies should be included to support these protocols. The clinical director and other assigned personnel in the facility should be familiar with the use of the devices and related operations, such as access to cloud-based data and troubleshooting protocols. Representatives from manufacturers should be invited to review the proper use of devices and apps with the healthcare professionals and staff in the Center. Personnel should be assigned to monitoring patient data and coordinating with Information Technology resources to incorporate, as easily as possible, data in the electronic health record. One could conceive a dedicated wearable technologies program within the Lifestyle Medicine Clinical Service Line, with trained personnel and a business model.

Not surprisingly, the economics of wearable technologies pose a significant obstacle to implementation by a Lifestyle Medicine Center, translating into decreased general use by patients. Many of these devices are expensive and not covered by insurance. However, many others are affordable and easy to obtain over the web, especially apps for smartphones already owned by the patient. Creative solutions should be considered by the Center's leaders, such as bundling resources and including one or more wearables for all users of the Center. Expenses for wearables that are distributed to all patients in the Center could be a line item in the total expenses as part of the business plan. Another option is to build a unique, dedicated app for the Center with startup funds or charitable donations.

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