Exploring the Role of Wearable Devices in Promoting Behavior Change and Monitoring Health Outcomes

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Background

Wearable devices (WDs), defined as electronics embedded within accessories or clothing that collect and share behavioral and physiological data, have become increasingly popular over the past decade. In 2024, a study found that 59% of respondents owned a WD such as an Apple Watch (44%) or Fitbit (42%).[1] This level of adoption and new products entering the market (e.g., Oura Ring) underscore the expanding role of WDs in personal health monitoring and their potential for broader application in public health initiatives.

WDs have become more affordable, more widely adopted, and more technologically advanced over time. As of 2024, the wearable technology market size was estimated at $84 billion and projections estimate the market size to reach $186 billion by 2030 (a calculated annual growth rate of around 14%).[2] Even the most basic WDs now include features such as sleep quality tracking, heart rate monitoring, and stress indicators.[3,4] While much of the early research around WDs has focused on physical activity, there is increasing evidence that they can play other meaningful roles in promoting better health.[5–7]

In the United States, public health and medical researchers use WDs as tools to explore persistent health differences across demographic groups, such as people with chronic diseases, lower socioeconomic status, and advanced age. Such health differences affect access to care, quality of treatment, and health-related differences.[8,9] By providing real-time data and enabling personalized, technology-supported interventions, WDs offer new opportunities to help mitigate persistent health differences on a wide scale.

This research brief explores the growing role of WDs in promoting behavior change and highlights emerging best practices for designing accessible, technology-supported programs that are responsive to the varied needs and experiences of the populations they aim to serve.

Wearable devices application to individual health promotion

WDs allow individuals users to monitor their health continuously and in real time. These non-invasive devices use embedded sensors to track a wide range of physiological and behavioral indicators, such as physical activity, sleep, heart rate monitoring, and stress indicators, offering insights into users' everyday health patterns and enabling self-management, personalized feedback, and early detection of potential concerns.[9] We review common WD functionalities below.

Physical Activity

Monitoring physical activity, such as step count, is one the primary functions of WDs. Even in the 1960's, researchers monitored physical activity through step counters, although they existed long before – in fact, Leonardo da Vinci is credited with inventing the first mechanical step counter during the Renaissance![10] Yet, step trackers were not widely used among the general population until after approximately 2011.[10]

Sleep

Sleep is fundamental to human productivity and health,[11] and accordingly, sleep tracking is another of the most developed and widely used features of WDs. Both basic and advanced WDs are capable of monitoring various aspects of sleep, including time to fall asleep, sleep duration, wake frequency throughout the night, and total time spent in bed.[12] These data points allow users and researchers to identify patterns of sleep disturbance and their associated health impacts, especially in populations where poor sleep is linked to chronic conditions, such as people with asthma or anxiety.[13]

Most consumer WDs accurately capture key sleep metrics, but advanced models like Fitbit Sense 2 and the Oura Ring provide more reliable estimates of sleep stages like deep and rapid eye movement (REM) sleep. In a U.S. validation study comparing WDs against polysomnography (the gold standard for sleep assessment), the Oura Ring outperformed both Fitbit Sense 2 and Apple Watch in sleep-stage classification, particularly for wake and deep sleep detection.[14] As the use of WDs expands in public health contexts, sleep data remain a key area of focus due to the accessibility of many commercially available devices and accumulating evidence of the connection between quality sleep and overall health.

Heart Health

Most WDs also monitor heart health using photoplethysmography sensors to provide continuous heart rate measurements during rest and physical activity.[15] These readings are useful for understanding cardiovascular fitness and stress response, and researchers often implement these readings in fitness and behavioral health interventions.[16,17] WDs collect heart data, including heart rate, oxygen saturation, physical activity, burned calories, and electric signals to the heart data.[18] In the United States, cardiovascular disease is the leading cause of death for most populations and costs the health care industry more than $250 billion.[19] More people monitoring their heart health through WDs could lower both the individual risk of cardiovascular disease and future costs for healthcare treatment, and research in this vein is unfolding.[20,21]

Stress

In addition to sleep and heart rate, many WDs now offer features designed to capture indicators of mental health and emotional well-being.[13] These features include advancements with electroencephalogram abilities that can track brain activity and possible depressive states.[13] In some studies, researchers have used reduced activity variance from wearable data as a behavioral signal related to anxiety, pain, and disrupted sleep.[22] Such applications expand the role of WDs from fitness-focused tools to more holistic wellness monitors.

Summary

As wearable technologies continue to evolve, so does their ability to offer dynamic health insights across physical and behavioral domains. Increasingly, devices integrate artificial intelligence to provide personalized nudges, goal setting, and feedback loops—serving as virtual health coaches that can promote long-term behavior change.[4] Taken together, sleep tracking, heart rate monitoring, and stress-related data collection form a powerful triad of WD-provided data for understanding and supporting health behaviors across populations.

Implementation

WDs have been integrated into a growing number of public health studies and intervention programs aimed at measuring behavior, improving health outcomes, and increasing user engagement.[6,15,17] Researchers have used WDs to collect real-time biometric data on sleep, physical activity, and physiological stress, which are then used to tailor interventions, monitor adherence, and assess program efficacy over time.[13,17,23,24]

A 2022 scoping review found that most WD-based health research has focused on tracking step count, heart rate variability, and sleep duration—three markers associated with cardiovascular health, behavioral patterns, and overall well-being.[25] These indicators are commonly incorporated into public health studies that target lifestyle-related conditions like obesity, metabolic syndrome, and anxiety.[13,22,26] For example, multiple interventions have paired WDs with self-management strategies or coaching tools to increase physical activity levels, promote weight loss, or manage chronic conditions.[16,27]

In addition to monitoring outcomes, WDs are also used to encourage and reinforce healthy behaviors such as moving more and getting more sleep.[5,16,17,26,27] Some studies have embedded WDs within gamified health apps, goal-setting programs, or nudging platforms that provide feedback, rewards, or prompts based on the data captured by the device.[28] This combination of real-time feedback and behavioral reinforcement has been shown to support lifestyle modification and increase engagement across different groups such as pediatric, urban, and aging populations.[28,29]

The integration of WDs into intervention research has expanded to include mental health and sleep-related studies. For example, researchers studying trauma recovery have used activity variance data from WDs to assess indicators of pain, anxiety, and sleep disturbances.[22] Others have deployed devices in observational trials tracking the effects of environmental stressors, medication, or behavioral therapies on biometric indicators.[25]

Overall, the increasing use of WDs in public health interventions reflects a shift toward more personalized, technology-driven methods of health monitoring and behavior change. WDs allow researchers to collect high-frequency, naturalistic data while also offering participants accessible and engaging tools to support their own health goals. This dual function—as both a data collection tool and an intervention mechanism—makes WDs uniquely positioned to bridge the gap between research and real-world applications.

Concerns and challenges

Despite the promise of WDs in health monitoring and intervention, researchers must address several concerns to ensure their effectiveness across populations. A critical challenge is the technological limitations of device accuracy. Typically, consumer WDs use green light sensors in photoplethysmography to measure heart rate, but these sensors often produce less reliable readings for individuals with darker skin tones due to higher melanin absorption.[30,31] While red or infrared light sensors offer improved accuracy, they are more common in clinical settings and less common in commercial devices due to higher costs and increased motion sensitivity.[30,31]

In addition to accuracy concerns, barriers to access and adoption significantly affect the reach of WD-based interventions. People from lower-income backgrounds, those with limited health insurance coverage, and communities with lower digital literacy are less likely to own or engage with WDs.[32] Cost remains a primary limitation, as many insurance plans do not cover WDs, and out-of-pocket expenses can be prohibitive.[33] Additionally, older people have been found to be less likely to use or engage with newer WDs due to uncertainty about the technology's benefits, how devices work, and higher rates of cognitive impairments that make device use more difficult.[34] These limitations result in less representation of at-risk demographic groups in WD-focused health research, limiting the generalizability of findings and perpetuating existing gaps.

Consumer-grade WDs vary in both capability and cost. Basic models (around $100) like the Fitbit Inspire reliably track steps and total sleep time, while advanced models (typically $200–$400) such as the Fitbit Sense 2, Apple Watch, and Oura Ring offer additional metrics—like sleep stages, heart rate variability, SpO_2, and stress detection—that are more useful for detailed health intervention analysis.[35] Choosing higher-end devices can improve data precision, but they also raise questions around access and budget within public health research, especially as research-grade options can cost up to $3,000.[36]

PATH-S study: A wearable device case study

The KDHRC-developed program Personalized Approach to Habits – Sleep (PATH-S) integrates Fitbit devices with a mobile app to help teens with asthma build consistent, healthy sleep routines. Grounded in behavior change theory, the program encourages participants to choose and adopt three personalized micro-habits—such as reducing screen time before bed or preparing for sleep earlier—and the adoption and persistence of these habits are supported by gamified feedback, peer-informed messaging, and real-time data tracking.[37,38] In addition to improving sleep quality, these strategies are designed to promote asthma self-management and overall well-being.

Teens with asthma, compared to teens without asthma, are more likely to experience sleep disturbances like trouble falling asleep, wheezing during sleep, frequent nighttime wakening, and daytime sleepiness. Studies have linked poor sleep quality to a range of adverse outcomes, including decreased academic performance and heightened emotional distress.[24] Asthma symptoms impact sleep, and poor sleep, in turn, worsens asthma symptoms. Among teens with chronic diseases like asthma, tracking sleep quality is predicted to relate to better health outcomes, and improving sleep quality in this population may represent a powerful intervention point—one that wearable technologies are uniquely positioned to support.

KDHRC designed the PATH-S program to fill critical gaps in wearable health research and intervention. Unlike most WD studies, which rely on participants already owning a device, PATH-S provides all participants with a Fitbit to eliminate cost-related barriers and standardize data collection. The program also incorporates tailored, evidence-based sleep interventions via an interactive app that helps teens build and sustain healthy micro habits. PATH-S provides structured prompts, feedback, and gamified engagement tools to increase motivation and adherence across the teen population.

Importantly, by including teens regardless of background and focusing on access, usability, and consistent engagement, PATH-S aims to improve not only health outcomes among teens with chronic illnesses but also the validity of future wearable device research. It addresses both technological and social limitations that often limit the success of wearable interventions in broader public health efforts.

Conclusion

WDs continue to evolve as accessible, data-rich tools for health monitoring and personal behavior change. Their ability to track sleep, heart rate, and stress indicators has made them particularly valuable in public health research, offering insight into behaviors that impact both short- and long-term health outcomes. As these technologies become more sophisticated and widely used, they hold significant promise for supporting interventions aimed at improving wellness and disease management, especially among youth and those managing chronic conditions like asthma.

The growing body of research demonstrates that WDs can serve as both measurement tools and mechanisms for behavior change when integrated thoughtfully into intervention design. However, concerns remain around accuracy, long-term engagement, and gaps in representation across populations. Addressing these concerns is critical to ensuring that the benefits of wearable technology extend across different demographic groups and social contexts.

Programs like PATH-S illustrate how evidence-based interventions can address these gaps through proactive design. By supplying standardized devices, targeting a broad adolescent population, and focusing on a key health behavior—sleep—PATH-S offers a model for how future studies can use WDs to not only support health improvement but to strengthen the foundation for more broadly-applicable research. As public health continues to intersect with digital innovation, programs like PATH-S will help define how wearable technology can be used effectively and responsibly in real-world applications.

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