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WEARABLE HEALTH TECHNOLOGIES IN PREVENTIVE MEDICINE: SOCIAL, BEHAVIORAL, AND CLINICAL IMPLICATIONS – A LITERATURE REVIEW

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ABSTRACT

Research Objective: The purpose of this literature review is to assess the current state of knowledge regarding wearable health technologies and their role in preventive medicine, with particular emphasis on their clinical, behavioral, and social implications. This article focuses on the impact of wearable devices on the cardiovascular system, includingatrial fibrillation detection and sleep monitoring. Furthermore, the impact of these devices on changing patient health behaviors and their integration into the healthcare system was discussed.
Methods: This article is literature review hich synthesizes 33 articles on the impact of wearable devices on sleep monitoring and preventive medicine, particularly cardiovascular diseases. The review focused on themes such as measurement accuracy, clinical applications, technological advancements, and behavioral and social impacts.
Results: Wearable devices are advanced tools capable of continuously monitoring physiological parameters. The integration of sensors, wireless communication technologies, and artificial intelligence enables real-time data collection and predictive analysis. These devices aid in the early detection of cardiovascular abnormalities (e.g., atrial fibrillation), sleep disorders, and metabolic conditions. This article addresses the limitations of measurement accuracy and challenges associated with data interpretation. Furthermore, behavioral benefits are identified, including increased health awareness and motivation for physical activity.
Conclusion: Wearable technologies, thanks to their continuous monitoring capabilities, can be a key to early diagnosis and behavior modification. Their effectiveness depends on technological capabilities, user engagement, and the healthcare system's readiness to integrate patient-generated data. To increase their importance in medicine, we must focus on standardization, algorithm transparency, cybersecurity, and equal access for all users.

KEYWORDS

Wearable Devices, Digital Health, Health Monitoring, Sleep Tracking, Preventive Medicine, Disease Prevention

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1. Introduction

In recent years, significant advancements have been observed in digital technologies and their impact on human health [17,20,25]. Among them, wearable devices are treated as one of the fastest-growing segments of the digital health ecosystem [13,25,32]. They play an increasingly important role in modern healthcare, introducing new possibilities in monitoring, prevention, and supporting disease treatment. Notably, the significant impact of COVID-19 pandemic in 2020 accelerated the implementation of solutions that enabled remote patient monitoring [9,18].

The term ‘wearables’ is broad, as it does not refer to only one device, but to a group of non-invasive devices such as smartwatches, fitness bands, chest straps, or smart rings [13,19,32]. Equipped with advanced built-in sensors, they allow for the monitoring of many vital parameters, including oxygen saturation, body temperature, blood glucose levels, sleep patterns, physical activity levels, and heart rate variability [11,13]. These parameters are measured continuously and in real-time. Additionally, the development of wireless communication technologies such as 5G, Wi-Fi, Bluetooth, ZigBee, LoRa (Long Range), and NFC (Near Field Communication) enables the transmission od collected data to mobile devices or cloud platforms [10,11]. Furthermore, the integration of artificial intelligence (AI) and machine learning (ML) algorithms for the analysis of multidimensional data sets generated by wearable device sensors provides improved pattern recognition, risk stratification, and earlier detection of abnormalities. AI-driven analyses transform raw data into predictive health information, which can have a significant impact on expanding wearable capabilities and improving the early detection and prevention of diseases [20,28].

Ongoing competition between global technology companies such as Apple, Garmin, Fitbit, Huawei, Google, and Earable has led to increased availability of these devices, which improves the affordability. Thanks to these advances, wearable devices are also used in daily life. Technological progres has made these devices increasingly lighter, more flexible, and visually attractive [20]. Increased availability of devices leads to a growing user base and more comprehensive data analysis. Many people incorporate them into their daily lives with the desire to improve their quality of life. In this context, appropriate data analysis and biofeedback can play an important role in preventing and treating diseases [25,26].

Wearable devices can actively engage users in increasing physical activity, maintaining healthy sleep patterns, and supporting a healthy lifestyle. The continuous provision of information to users about their performance can increase awareness of daily health habits and physiological state. In addition, applications use various behavior change methods – goal setting, personalized reminders, progress tracking, and gamification elements, which support the long-term maintenance of positive habits [9,25].

Early detection of diseases and health promotion are the cornerstones of preventive medicine. This is supported by wearable devices through the provision of data collected continuously over long periods. This is their main advantage over sporadic medical visits. Furthermore, during in-office consultations, patients often experience stress—sometimes referred to as 'white coat syndrome'—which can lead to inaccurate data. Such devices enable the capture of dynamic biological processes and, as a result, the detection of abnormalities that might otherwise be overlooked during a single office visit. This means that these devices are important tools in the early diagnosis of chronic diseases (e.g., heart rhythm disorders), metabolic diseases, and sleep disorders [5,16,27,29].

Despite the numerous advantages of wearable technologies, it is important to acknowledge the challenges associated with them. Dependence on digital monitoring tools raises concerns regarding data collection, its quality, clinical integration, and cybersecurity [10,15,32]. Researchers emphasize that patient-generated health data (PGHD) suport diagnostic processes; however, its utility should depend on reliability and appropriate implementation frameworks in everyday use [1,23].

Another important issue is the integration of data collected by wearable devices into official healthcare systems. Doctors often have concerns about data reliability, information overload, and possible bureaucratic hurdles [1,23]. As a result, there is a growing demand for standardized platforms for data analysis and interpretation that will enable a safe transformation of raw data into actionable insights for both the patient and healthcare professionals [22].

The aim of this article is to evaluate current research on wearable technologies in healthcare and their role in preventive medicine. The work focuses on clinical and socio-behavioral aspects of these technologies, in particular their impact on health awareness, lifestyle change, and patient empowerment [25,32].

2. Methodology

This study is a review that focuses on current state of knowledge the use of wearable devices in healthcare, with emphasis on clinical, social and behavioral interactions. The analysis of literature was conducted with main principles of reviews. Publications were gathered by searching PubMed, Scopus, Semantic Scholar, Google Scholar. The review included articles published between 2014 and 2025. Searches were performed between Feburary and March 2026.

We used key words such as: „wearable devices”, „digital health”, „health monitoring”, „sleep tracking”, „preventive medicine” and „disease prevention”.The inclusion criteria were: articles published in English, studies analysing behavior or social implications, and research on wearable health technologies in health monitoring, prevention, and clinical practice. We excluded articles that were not available in full text or that were purely technical without health context.

After the complete analysis of titles and abstracts we performed a full text analysis regarding eligible publications. We selected 33 articles fo our review of this year.

The central thematic issues included: the accuracy and validation of the measurements, clinical application of wearable devices, technological ones such as biosensors (e.g. artificial intelligence and 5G), behavioral and social issues.

The results discussed in this review are descriptive and highlight new areas for exploration, potential clinical effects, and limitations of wearable technology in the healthcare industry.

3. Results

The reviewed articles demonstrate a significant evolution of wearable medical technologies. Initially simple physical activity monitors have transformed into tools capable of continuous monitoring of physiological parameters such as heart rate, oxygen saturation, sleep patterns, and physical activity levels. Consumer-grade devices have now achieved a high level of accuracy in monitoring parameters particularly relevant to cardiovascular health and sleep. These devices, by using photoplethysmography (PPG)-based algorithms, can detect atrial fibrillation (AF) through pulse waveform analysis [24].

Validation studies of devices such as the ŌURA Ring and Polar Vantage show a strong correlation with polysomnography in measuring total sleep time (TST) and sleep efficiency. However, these devices have difficulties distinguishing between individual sleep stages. Measurement accuracy is limited by motion artifacts, skin pigmentation, and device fit [3].

Wearable devices equipped with sensors such as accelerometers, gyroscopes, and optical sensors enable the collection of multidimensional data, which are then processed by specialized algorithms to estimate physiological and behavioral parameters [11].

Findings regarding the clinical use of patient-generated health data (PGHD) reveal a significant gap between technological capabilities and the readiness of healthcare systems. Researchers often express concerns about information overload and the lack of standardized platforms for interpreting large datasets without increasing administrative burden [1,23].

The use of artificial intelligence and machine learning enables the analysis of signals from sensors, allowing for pattern detection and health risk prediction [20, 28]. These solutions enhance the ability to process large datasets, transforming them into clinically relevant information.

4. Parameters Monitored by Wearable Devices

Wearable health technologies enable continuous monitoring of heart rate (HR) and heart rate variability (HRV). These two parameters are very important because they represent the most common functionality in portable health monitoring. Moreover, HRV can be a critical biomarker for autonomic nervous system function and stress response [7,15]. Photoplethysmography (PPG) plays a significant role in these measurements. This technique allows the detection of changes in blood volume in the peripheral circulation. PPG requires a light source, most commonly an LED, which generates light that penetrates the skin and is then absorbed by the blood and surrounding tissues. Each of these structures has its own specific optical properties. To obtain a reading, a photodetector is also required, which measures the amount of light transmitted through or reflected from the tissue. Fluctuations in light intensity, which occur during the cardiac cycle, correlate with the volume of blood present in the vessels [11]. This allows for the determination of a waveform reflecting changes in blood volume [26].

By integrating reflectance pulse oximetry, these devices are capable of monitoring peripheral blood oxygen saturation (SpO_2). Long-term SpO_2 data can support the diagnosis of diseases such as respiratory or circulatory dysfunction, including obstructive sleep apnea or chronic lung disease [32]. Furthermore, built-in thermal sensors enable the tracking of circadian rhythms and early fever responses, which can also serve as biomarkers of physiological stress. Ambulatory pulse oximetry is increasingly used to assess aerobic capacity and local muscle oxygenation. This provides crucial information on physiological resilience under high load, which is particulary important in specialized sectors such as competitive sports, military operations, and aviation [11].

In addition to the above-mentioned measurements, attention should be paid to the ability to perform electrocardiographic (ECG) examinations. Special electrodes integrated into smartwatches, chest straps, or adhesive patches worn on the skin enable direct measurement of the heart's electrical activity. Changes in electrical potential associated with myocardial depolarization and repolarization are recorded by these electrodes, which then generate characteristic ECG waveforms. Subsequent analysis of changes in the intervals between successive QRS complexes, as well as changes in waveform morphology, can provide valuable information about the heart rhythm, conduction pathways, and potential abnormalities, such as atrial fibrillation, bradycardia, or tachycardia [11].

Another parameter measured by wearable devices is physical activity. This is achieved using accelerometers and gyroscopes, which, working together, detect movement in multiple axes. Special algorithms can then estimate the number of steps, distance traveled, and intensity of energy expenditure. Furthermore, they can distinguish between activities such as walking, running, sitting, or sleeping, thus supporting the assessment of lifestyle patterns and contributing to behavioral change [26].

One of the most important physiological parameters in our lives is sleep, which can also be assessed using wearable technologies. These devices combine movement data with physiological signals and then analyse patterns, ultimately enabling them to estimate metrics such as total sleep time, sleep efficiency, and individual sleep stages. Combining this with heart rate variability analysis and pulse wave characteristics increases the accuracy of sleep stage detection [15].

Another physiological indicator is dermal temperature. Built-in thermistors or infrared sensors detect subtle temperature fluctuations by measuring surface electrical resistance or infrared emission. Data from continuous skin temperature monitoring provide key information on circadian thermoregulation, metabolic fluctuations, and early markers of systemic inflammation or infection [11,32]. It should be noted that peripheral skin temperature differs from core body temperature; however, combining this information with heart rate and activity data allows for a more accurate interpretation of the physiological state. A practical example of the importance of this measurement is nocturnal temperature fluctuations, which enable the identification of changes in sleep phases and hormonal cycles. In the long term, this can serve as important reference point for preventive health monitoring [13,32].

In summary, wearable technologies, through comprehensive monitoring of key physiological parameters such as heart rate, heart rate variability, blood oxygen saturation, physical activity, sleep, and skin temperature, and their multidimensional analysis, provide a real-time picture of the user's health. This contributes to the early detection of abnormalities, lifestyle assessment, and preventive measures. However, it should be noted that data interpretation still requires consideration of technological limitations.

5. Types of Wearable Devices

Wearable devices can be classified according to the location of use on the body, the number of monitored parameters, and user comfort [11]. These technologies exist in various forms, each designed to monitor specific physiological and behavioral parameters while aligning different user preferences and use cases.

One of the types is armband-based devices. These devices have sensors which are positioned on the upper arm. That location makes that signal more stable, which results in more accurate measurement of heart rate and HRV. These devices are especially appropriate for recording detailed activity patterns and physiological responses during daily life without significant interference from wrist movement [3,28].

One of the most popular types of wearable devices are wrist-worn devices, such as smartwatches and fitness trackers. These wearables enable the measurement of heart rate, blood pressure, physical activity, stress levels, and sleep patterns. Beyond health metrics, smartwatches may monitor environmental noise levels, which can contribute to user safety. Their comforatable and ergonomic design, resembling a traditional wristwatch, allows people to wear them them throughout the day. Furthermore, wireless data transmission enables continuous health monitoring for 24 hours or longer [5,19,24]. Putting these devices on the wrist allows convenient daily wear while providing sufficient contact with the skin for optical measurements [5].

Over the last few years, devices such as the smart rings have gained great popularity. These wearable devices are small and lightweight designed, which makes them comfortable for everyday use. Just like wrist-worn devices. Devices such as the Oura Ring have been evaluated for their efficacy in measuring sleep stages, heart rate, and heart rate variability. Due to their design, smart rings continuous wear for extended periods without affecting user comfort. Morover wearing smart rings allows long-term monitoring of physological parameters with minimal disruption to daily activities. Unlike larger wearable devices, smart rings offer health monitoring in a discreet form factor. This feature makes smart rings especially useful for sleep monitoring and tracking lifestyle patterns [8,16].

Another type includes chest straps and adhesive patches, which are primarily used for monitoring cardiovascular activity. It should be emphasized that they are much more accurate in capturing heart rate and electrocardiogram (ECG) data compared to wrist-worn technologies. Therefore, these devices are more often extensively utilized in clinical and research environments, than in everyday life [3].

The fourth group of devices we would like to present is smart textiles, which represent a significant advancement in wearable technology. These technologies integrate sensing capabilities directly into everyday apparel. These platforms facilitate the collection of physiological parameters data without compromising wearer ergonomics [11,20]. Currently, such devices are used to improve sports performance, rehabilitation and long-term monitoring of chronic diseases.

The next group consist of ear-worn devices, commonly referred to as hearing aids [3, 14]. These are placed in or around the ear, providing greater stability than wrist-worn devices. The impact of this positioning reduces motion-related noise and increases the reliability of heart rate and sleep measurements [21, 29]. Additionally, hearing aids can use audio or EEG signals to assess sleep quality or detect breathing patterns. This makes them a subtle and practical tool for long-term health prevention.

In summary, wearable devices come in many forms, differing in design, measurement techniques, body placement, number of monitored parameters, and user comfort. This allows users to choose devices based on their visual preferences and the parameters they prioritize. Smartwatches and fitness trackers are most common in everyday life, although the recent growing interest in smart rings should not be overlooked. Ear-worn devices and smart textiles offer higher measurement accuracy but are less convenient for everyday use. By selecting appropriate form factors and sensor combinations, wearables can provide accurate, continuous monitoring of cardiovascular, sleep, metabolic, and behavioral parameters, enabling personalized health management and long-term preventive care [10,13,20].

6. Cardiovascular Monitoring

Cardiovascular disease (CVD) is a leading cause of morbidity and mortality worldwide. Its significant impact on premature deaths and the burden on healthcare systems is substantial. Therefore, early detection of cardiovascular abnormalities is crucial, as it allows for the rapid and effective implementation of primary and secondary prevention. As previously mentioned, recent years have seen rapid technological development in wearable devices, enabling continuous monitoring of physiological parameters in real-world conditions. Devices equipped with advanced sensors enable the measurement of parameters such as heart rate, heart rate variability (HRV), physical activity level, and, in some cases, electrocardiographic (ECG) signals [20]. Thanks to these measurements, wearable devices can be used in cardiology, where one of their most important applications is the detection of heart rhythm disturbances, particularly atrial fibrillation (AF). Atrial fibrillation is the most common sustained cardiac arrhythmia, and its incidence increase with age. This condition is associated with a significantly increased risk of stroke, heart failure, and cardiovascular death; consequently, it places a significant burden on the healthcare system. In many cases, it is asymptomatic or nonspecific, making early diagnosis difficult, and it may only becomes apparent after causing serious, often irreversible complications. PPG, which allows for the measurement of heart rate, enables the identification of arrhythmias. Based on these data, an analytical algorithm can detect patterns characteristic of atrial fibrillation, alerting the user to potential arrhythmias [5].

Here, we would like to present a practical application of this technology: a population-based study assessing the ability of a smartwatch to detect atrial fibrillation in the general population. The study involved over 400,000 Apple Watch users and analysed their heart rate using an optical PPG sensor. An algorithm designed to detect irregular heart rhythms was then used. The data were sent to a heart rhythm monitoring app on mobile devices. The heart rate signal was continuously analysed, and when an irregular heartbeat was detected, the user received an email notification. Participants who received this information were then sent an ECG patch, which they were required to wear for 7 days. This additional testing, in the form of ambulatory ECG monitoring, allowed for the confirmation or exclusion of arrhythmia in a clinically reliable manner [24]. The study found that although irregular rhythm alerts were generated infrequently, the proportion of confirmed positive cases after additional testing was relatively high. The study provided that these algorithms can effectively identify individuals requiring specialized cardiology care. These findings highlight the potential of wearable technologies as a screening tool for arrhythmia detection in the general population. The authors of the study emphasize that wearable devices are intended to identify individuals who require further diagnostic evaluation rather than replace clinical assessment [24].

Beyond detecting arrhythmia, wearable technologies enable continuous monitoring of heart rate at rest and during physical activity. This allows us to obtain important information about the functioning of the cardiovascular system. For example, a chronically elevated resting heart rate may be associated with an increased risk of cardiovascular disease. Additionally, heart rate variability analysis allows for the assessment of autonomic nervous system. Combining this data with physical activity measurements offers a multidimensional assessment of lifestyle and cardiovascular risk profile. This can be valuable for implementing primary prevention strategies [20].

A significant advantage of these devices is the continuous monitoring of parameters over extended periods – spanning days, weeks, or even months. This allows for the identification of subtle changes in cardiovascular function that might otherwise go undetected during occasional doctor visits. Furthermore, such analyses can be particularly useful in monitoring chronic diseases, assessing treatmednt effectivness, and identifying early warning signs of deteriorating health [20]. A breakthrough in wearable technology and its impact on healthcare came with the integration of these devices with digital medical platforms and big data analytics systems. Using machine learning (ML) algorithms, data can be processed to identify cardiovascular risk patterns and create predictive models supporting personalized medicine. In the long term, wearable technology may enable, or at least facilitate, the detection of cardiovascular abnormalities even in the asymptomatic phase, potentially allowing for clinical intervention before the onset of symptoms [20].

7. Sleep Monitoring

Sleep is a natural physiological state essential for physical and mental regeneration. It allows the body to maintain proper functioning of the cardiovascular system, metabolism, and immune response. It's important to emphasize the impact of sleep disorders, including poor quality or short duration, on the increased risk of chronic diseases such as hypertension, diabetes, heart disease, and mood disorders. Therefore, sleep monitoring is an important tool in preventive healthcare and the development of healthy behaviors. [7,15]

Thanks to technological advances in recent years, non-invasive and continuous sleep monitoring has become possible in natural, everyday conditions. Wearable technologies, in addition to being equipped with sensors measuring movement, heart rate, and heart rate variability (HRV), can also incorporate EEG sensors. Analysis of the collected data allows for the classification of sleep stages - sight sleep, deep sleep, and REM (rapid eye movement) sleep. Additionally, these devices allow for the simultaneous assessment of total sleep time (TST), the number of awakenings, sleep efficiency, and circadian rhythm regularity [8, 29]. All these data allows for monitoring both the quality and structure of sleep, which is crucial in preventive medicine.

Validation studies have shown that some devices, such as the ŌURA Ring and Polar Vantage, demonstrate high agreement with polysomnography (PSG) - the clinical gold standard - especially in terms of total sleep time, while their accuracy in detecting wakefulness is more limited [8,16]. *Henriksen et al.* emphasize the inaccuracy of classifying specific sleep stages, especially phases of NREM sleep. Adequate analysis depends on the quality of the sensors and the sophistication of the algorithm. These discrepancies result from inherent limitations of optical technology, motion artifacts, and individual user characteristics, such as skin type and nocturnal activity patterns [2, 29]. Moreover, validation studies conducted by de Gans et al. indicate that distinguishing between NREM sleep stages is associated with a high risk of error, and the results vary depending on the device and the manufacturer [7].Therefore, sleep monitoring using consumer-grade wearable devices must be interpreted with caution, especially when applied clinically. Incorrect classification of sleep stages can lead to inaccurate assessment of sleep quality and potentially misleading conclusions about health status [7]. Asgari Mehrabadi et al. conducted a sleep study comparing a smartwatch, a smart ring, and actigraphy, which is considered the gold standard for sleep analysis in ambulatory settings. The study lasted 7 days and included 53 adults. In their conclusions, the authors stated that smart rings demonstrated better accuracy than smartwatches; however, both devices are suitable tools for assessing total sleep time. Among their limitations, they also noted an underestimation of wakefulness, which leads to an artificially inflated estimation of sleep efficiency [2].

As previously mentioned, the ability to collect long-term data is crucial not only for assessing cardiovascular function but also for sleep monitoring. Collecting data over multiple nights, followed by trend analysis, allows for the early detection of subtle changes in circadian rhythm or sleep quality. This approach is particularly beneficial in preventing and treating chronic sleep problems, as well as assessing the impact of lifestyle, physical activity, and environmental factors on rest [15, 21]. Integrating sleep data with other physiological parameters allows for a comprehensive assessment of the relationship between sleep patterns and cardiovascular, metabolic, or psychological risk [2, 16]. Equally important are behavioral aspects. In response to the question of whether regular use of devices and active interpretation of the results can increase awareness of sleep hygiene, support positive lifestyle changes, and improve sleep health, Berryhill et al. reported in their study on healthy adults that there was no significant improvement in sleep. However, they noted that these devices do not worsen sleep. Moreover, they highlighted the risk of "orthosomnia," defined as an excessive focus on achieving perfect sleep, which ultimately led to poorer sleep quality due to increased stress [4].

It should be noted that measurement accuracy can be subject to significant error, as it depends on proper device fit, consistent use, and the reliability of the underlying algorithms. Many factors, both user-dependent, such as nocturnal movements, activity intensity before sleep, irregular circadian rhythms, and individual physiological differences, can influence data reliability [2, 8]. Consumer devices can be useful in screening for conditions such as obstructive sleep apnea, chronic insomnia, or parasomnias, but they can never replace clinical diagnosis [15, 29].

8. Accuracy and Validation of Wearable Devices

Wearable medical technologies can be helpful in clinical prevention and physiological monitoring, but data accuracy and reliability are crucial for effective integration. These devices collect a wide range of biological signals and then use advanced algorithms to process and classify these data. It should be emphasized that their clinical significance and role in preventive medicine depend largely on the accuracy of the sensors, as well as the rigorous validation of the analytical models used [3, 21].

As previously mentioned, the most commonly used cardiovascular monitoring technology is optical photoplethysmography (PPG), which assesses changes in blood volume to estimate heart rate and rhythm. Manufacturers use PPG sensors because they are relatively inexpensive and convenient for continuous use; however, evidence highlights their significant sensitivity to multiple sources of error. A study by Bent B. et al. (2020) showed that factors such as motion artifacts, variations in skin pigmentation, ambient light interference, subcutaneous tissue thickness, perpheral perfusion and device location can significantly impact measurement accuracy. Furthermore, it is noted that errors are not random but systematic, which in practice means that certain populations—especially those with darker skin or a higher body mass index—may be more susceptible to lower accuracy. Furthermore, studies have shown that many commonly used smartwatches expose users to errors in heart rate measurements during intense physical activity, often exceeding clinically acceptable error margins. Therefore, it is important to remember to note that while data collected under resting conditions may be reliable, their reliability under dynamic conditions decreases significantly. Unfortunately, this limitation significantly limits its use in real-world clinical decision-making. Therefore, although PPG technology remains suitable for everyday monitoring, its use in more demanding conditions requires improved algorithms and more accurate sensor calibration [3].

Wearable devices have achieved significant success in detecting cardiac arrhythmias, particularly atrial fibrillation (AF). The Apple Heart Study demonstrated that smartwatches, using PPG-based algorithms, can recognize irregular heart rhythms and prompt users to seek further medical evaluation. Furthermore, confirmation of these findings using ambulatory ECG patches supports the role of wearable devices as effective screening tools at the population level [8]. However, the authors emphasize that the accuracy of AF detection depends largely on the ability of predictive models to distinguish actual arrhythmic events from motion-related noise. Current research suggests that diagnostic specificity has been improved by combining PPG data with contextual information—such as physical activity level or body position; however, further validation in diverse populations is still needed [5, 20, 24].

Sleep monitoring also has similar limitations. In wearable devices, actigraphy data, heart rate measurements, and heart rate variability (HRV) are key parameters for accurate sleep monitoring. Validation remains a much greater challenge than in diagnosing arrhythmias, as the gold standard for diagnosis, polysomnography (PSG), encompasses EEG, EOG, and EMG signals. Current consumer devices on the market do not record such data [7,15]. Comparative studies indicate that devices such as the ŌURA ring and Polar Vantage demonstrate good agreement with PSG in estimating total sleep time and detecting wakefulness; however, they are less accurate in differentiating between sleep stages. Data inconsistency is often a direct consequence of the use of proprietary algorithms, indicating a lack of transparent and standardized clinical validation frameworks [16, 29].

Furthermore, attention is drawn to the opaque nature of proprietary ML algorithms, which directly impacts the clinical validity of wearable devices. As South B. R. et al. (2014) noted, systematic errors can occur even in the early stages of data processing and annotation, automatically leading to erroneous subsequent analysis. This problem is further exacerbated by the proprietary nature of the software [30]. Canali et al. (2022) also hghlight that this undermines note trust in clinical practice and complicates regulatory oversight [5].

Although modern ML models and Big Data approaches are increasingly used to improve accuracy, this is often achieved through personalization of physiological baselines [12,31]. Analysis and software limitations introduce another challenge: the so-called "black box" effect. Limited visibility into how health outcomes are generated prevents independent verification by clinicians and complicates regulatory oversight. This drives the need for more transparent and open validation frameworks. Taken together, these challenges underscore the need to develop interpretable artificial intelligence (AI) systems and standardized validation protocols before data from wearable devices can be fully integrated into evidence-based medicine. Although current devices are suitable for general health monitoring, their transformation into reliable clinical tools will require further refinement to avoid risks such as "digital hypochondria" and false reassurances, and to truly contribute to reducing the global burden of chronic disease [25, 32].

9. Social and Behavioral Implications

The development of wearable technologies, in addition to changes in health monitoring practices, is contributing to changes in users' health behaviors. It is crucial to understand how these devices influence motivation to change lifestyles, maintain healthy habits, and engage in health-related social interactions, as this allow for a better understanding of their impact on preventive medicine. Constant access to health data increases users' health awareness and can lead to more active health management [9, 31]. This is achieved through self-monitoring, which forms the basis of many behavioral interventions. Regular monitoring of parameters such as step count, heart rate, and sleep quality allows users to continuously analyse their own behaviors. Sun et al. indicate that this increases user motivation to engage in physical activity, improves sleep quality, and reduces risky behaviors [31]. Researchers emphasize the important role of biofeedback and self-efficacy, which influence the ability to maintain positive behavioral changes over time. Wearable technologies, through the use of gamification elements, as well as notification and reminder systems, support behavior change processes. Users receive badges, rankings, and reminders to exercise, increasing their engagement and consistency in achieving health goals. Furthermore, user-defined daily goals can act as a stimuli for maintaining these activities over time. Del-Valle-Soto et al. emphasize that the effectiveness of these mechanisms is significantly influenced by individual user characteristics, such as intrinsic motivation, preferences, and level of digital competence [9]. It is commonly assumed that wearable technologies promote lasting behavior change; however, Piwek et al. emphasized that this assumption holds true only in the short term; empirical evidence suggests that their long-term effectiveness may be limited. This is due to the „novelty effect", where many users experience a decline in engagement after the initial period of use. Data fatigue, a lack of valuable feedback, and decreasing motivation over time predispose to this decline. Therefore, access to health data alone is not sufficient to ensure lasting lifestyle changes [25].

Furthermore, social interactions also play an important role. Wearable devices provide users with the ability to share results, compare achievements with others, and participate in health-related challenges. Webb et al. demonstrate that social support and competition can significantly increase levels of physical activity and engagement with technology [33]. These interactions can take various forms, such as emotional, motivational, or informational support, which are crucial for maintaining healthy habits. At the same time, some users prefer a more personalized approach, highlighting the need for personalized social features in wearable devices.

In the context of the healthcare system, the role of patient-generated health data (PGHD) is growing. These data can enable a better understanding of patients' daily behaviors and real-time monitoring of their health status and therefore serve as a valuable source of information for physicians. However, research indicates that healthcare professionals often have concerns about such data, particularly regarding its variable quality, lack of standardization, and the risk of information overload [1,23]. Therefore, effective integration of mobile device data into healthcare systems requires the development of appropriate analytical tools and clear guidelines for its interpretation. Alpert et al. emphasize that the way data is presented significantly influences patient behavior, with the most effective approaches involving simple visualizations, reference values, and concise summaries [1].

While wearable devices can undoubtedly offer numerous benefits, they also pose certain social and behavioral challenges, including issues related to long-term user engagement. Many people discontinue their use after an initial period of enthusiasm, limiting their effectiveness in promoting lasting behavior change. This phenomenon may result from a decline in motivation, a lack of visible results, or so-called "information fatigue" [23, 31].

It is important to emphasize that user reactions to wearable-based interventions can vary widely. While some individuals may perceive positive impacts on health behaviors resulting from social comparison and gamification, others may perceive these elements as stressful or demotivating. This highlights the need for personalized and context-specific behavioral strategies rather than a one-size-fits-all approach.

Another challenge is the risk of overreliance on device-generated data and its potential misinterpretation. As a result, users' health-related decisions may be based on incomplete or inaccurate data. This highlights the need for enhanced health education and more effective communication between patients and healthcare professionals. Furthermore, many consumers express concerns about data privacy, information security, and inequalities in access to technology, which can exacerbate existing health disparities [6].

It is also important to consider demographic differences in the use of wearable technologies. The manner and frequency of wearable device use are determined by age, education level, economic status, and digital literacy. Rieder et al. indicate that older adults may experience greater difficulties using technology, despite the significant benefits they can derive from its use in health monitoring and preventive care [26]. Younger groups of users, on the other hand, are more likely to utilize social and motivational features, which increases their level of engagement.

In summary, wearable technologies have a significant impact on health behaviors and users' social interactions, offering tools that support self-regulation, motivation, and social integration. However, their effectiveness in preventive medicine depends not only on technological advances but also on behavioral, social, and systemic factors. Understanding these aspects is essential for maximizing the impact of these devices on health interventions and their integration into healthcare systems.

10. Conclusions

This literature review indicates that wearable health technologies offer many new opportunities for early disease detection, health monitoring, and behavioral change, thus playing an increasingly important role in preventive medicine. Their effectiveness is determined by measurement accuracy, user engagement, and the ability of healthcare systems to integrate the generated data, rather than being solely the result of technological advances. These devices have achieved high levels of accuracy in monitoring key parameters such as heart rate and total sleep time. Photoplethysmography-based algorithms deserve particular attention, as they can effectively identify atrial fibrillation, thereby serving as population-level screening tools [5,24]. However, the limitations of sensors in dynamic conditions mean that these technologies should be viewed as a complement to, rather than a replacement for, standard diagnostics. The reviewed studies emphasize the impact of self-monitoring and gamification mechanisms on increasing users' self-efficacy, which translates into increased physical activity and improved sleep hygiene [14]. Although this effect is evident, the main challenge is the lack of long-term effectiveness and a rapid decline in user engagement [23].

Furthermore, the widespread adoption of wearable devices carries the risk of "digital hypochondria". Constant access to biometric data can lead to the overinterpretation of subtle physiological fluctuations, generating unnecessary anxiety among users and burdening healthcare systems with unnecessary consultations [16,25].

Another issue that needs to be addressed is the ethical and social implications. The collection of sensitive health data through consumer devices raises questions about privacy, information security, and the risk of data commodification by third parties [10,32]. Existing inequalities in access to technology are highlighted. If wearable-based preventive care is primarily available to individuals with high socioeconomic status and digital literacy, this could paradoxically exacerbate existing health disparities. The personalization of behavioral interventions and the development of artificial intelligence systems that can safely and ethically assist physicians in interpreting patient-generated data should be key priorities for future research. Furthermore, future efforts should prioritize the development of standardized validation frameworks, improvement of algorithm transparency, and ensuring equitable performance across diverse populations. Failure to address these limitations carries the risk that wearable technologies—rather than fulfilling their preventive potential—may exacerbate inequalities in access to healthcare, lead to misinterpretation of physiological parameters, and generate an excessive burden on healthcare systems due to an increase in false-positive results [6,20].

A critical analysis of the literature suggests that the limitations of wearable technologies are often not independent but structurally interconnected. For example, deficits in measurement precision directly influence the level of clinical trust, which consequently affects the willingness of healthcare professionals to incorporate wearable data into routine practice. Furthermore, poor standardization exacerbates the problem of information overload, leading to physicians avoiding the use of such technologies because they are required to interpret heterogeneous and often incomparable datasets. Therefore, future research should focus on addressing these issues systemically, taking into account technological, clinical, and behavioral dimensions.

Canali et al. suggest that future research should focus on developing guidelines that take into account different types of sensors and the contexts in which they are intended to be used. Additionally, they emphasize the need to further promote data analysis tools, which would enable individuals with lower technological proficiency to effectively use these devices. The authors also highlight the importance of collecting data in a way that ensures broad and diverse representation, which would help reduce the number of systematic errors [6].

11. Discussion

This review indicates that wearable devices may play a significant role in preventive medicine due to their ability to continuously monitor physiological parameters in real time. This enables the collection of data that may reveal early signs of disease.

Wearable devices can lead to measurable changes in user behavior. Continuous biofeedback and self-monitoring mechanisms significantly increase users' perceived control over their own health, often resulting in higher levels of physical activity and improved sleep hygiene [31]. Moreover, these technologies promote physical activity, better sleep-related habits, and increased health awareness. However, long-term use of such devices may decline over time due to novelty effects wearing off and user fatigue. This highlights the need for engagement-retention strategies, such as personalized feedback and adaptive interventions, to sustain their effectiveness [31]. Demographic factors also influence behavioral responses. Younger users tend to be more responsive to social media–related features, whereas older populations are more likely to rely on passive monitoring and safety-oriented functions, despite facing greater initial barriers related to digital literacy [31].

Patient-generated health data (PGHD) reveal a gap between rapid technological advancement and the readiness of healthcare systems. Researchers highlight concerns regarding information overload and the lack of standardized platforms for interpreting large datasets without increasing administrative burden [1,23]. Differences in validation protocols, outcome definitions, and reference standards hinder direct comparisons and limit the development of evidence-based guidelines for the use of medical wearable devices in clinical practice.

Advances in artificial intelligence and machine learning enable the identification of predictive patterns, forming the foundation of modern personalized preventive medicine [25,20]. However, the application of these techniques raises challenges related to transparency, interpretability, and model validation [20,28]. This suggests that the current enthusiasm surrounding wearable technologies may partly reflect general technological optimism rather than fully validated clinical evidence [6].

Despite significant technological progress, several barriers remain, including concerns about data privacy, cybersecurity risks, and unequal access to wearable technologies. These issues may limit widespread adoption, particularly among older populations or individuals with lower digital literacy [6].

Overall, wearable devices should be regarded as complementary tools that support, rather than replace, traditional healthcare practices. Their full potential can only be achieved through integration into clinical workflows, supported by standardized frameworks and validated analytical methods.

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