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REVIEW ARTICLE

Wearable Technology in Circadian Rhythm Research: From Monitoring to Clinical Insights

Eun Lee[1,2]
[1]Department of Psychiatry and the Institute of Behavioral Science in Medicine, Yonsei University College of Medicine, Seoul, Korea
[2]Institute for Innovation in Digital Healthcare, Yonsei University, Seoul, Korea

This review article explores the role of wearable technology in circadian rhythm research, providing an in-depth examination of its applications, benefits, limitations, and future potential. Wearable devices continuously monitor physiological parameters such as movement, heart rate, skin temperature, and light exposure, allowing researchers to analyze circadian rhythms in real-world settings. By collecting data on circadian phase shifts, amplitude, and stability, these devices offer valuable insights into the relationship between circadian rhythms and health outcomes. The article discusses the various types of wearable devices and key data collected by these devices. Additionally, it outlines analytical methods used to interpret circadian rhythms. The article also highlights the association between circadian rhythm disruptions and increased risks of cardiovascular disease, diabetes, and neurodegenerative disorders. Finally, the review addresses current challenges in wearable-based circadian research and future direction, including limited validation against gold-standard methods, restricted access to raw data, and algorithm transparency issues.

Keywords: Circadian rhythms; Wearable devices; Digital health; Sleep monitoring; Health technology

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Corresponding author: Eun Lee, MD, PhD, Department of Psychiatry, Yonsei University College of Medicine, 50-1 Yonsei-ro, Seodaemun-gu, Seoul 03722, Korea.
Tel: 82-2-2228-1620, E-mail: leeeun@yuhs.ac

INTRODUCTION

Research on circadian rhythms has been extensively conducted across various species, including humans, leading to significant discoveries. Even before the advent of digital health technologies, past findings in circadian rhythm research were groundbreaking enough to receive prestigious scientific recognition, including the Nobel Prize [1]. Nevertheless, digital health technologies, such as wearable devices, mobile applications, remote monitoring, artificial intelligence (AI), and machine learning, have created new opportunities for advancing circadian rhythm research and its clinical applications.

The gold standard for assessing circadian rhythms is dim light melatonin onset (DLMO), which involves periodically collecting saliva, blood, or urine samples in the evening under dim light conditions to measure the rise in melatonin levels, a key marker of the body's biological night. DLMO is widely used in circadian rhythm research due to its high accuracy in determining circadian phase. However, this method requires strict laboratory conditions or structured at-home saliva sampling, making it costly, labor-intensive, and impractical for large-scale or continuous monitoring. In contrast, wearable devices offer a non-invasive alternative by continuously tracking body movement, heart rate, temperature, and light exposure over extended periods [2]. This approach significantly differs from traditional laboratory-based studies, which primarily rely on single-point measurements. The introduction of wearable devices has enabled long-term data collection, allowing for the continuous tracking of 24-hour circadian variations and a more comprehensive analysis of circadian rhythms. These devices also facilitate data collection in natural environments such as homes and workplaces, providing a more accurate representation of real-life circadian rhythms. Furthermore, AI-based analysis of data collected from wearable devices is actively being explored to detect circadian rhythm abnormalities and predict diseases at an early stage [3,4].

Most wearable devices are used primarily for health promotion rather than medical purposes, with sleep and activity tracking being the most commonly utilized features. Many of these devices go beyond simple sleep-wake assessments to provide physiological indicators such as respiration, skin temperature, blood oxygen saturation, heart rate, and heart rate variability (HRV), allowing more comprehensive evaluation of circadian rhythms. Unlike traditional laboratory environments, wearable devices enable large-scale, long-term, real-world sleep data collection without bothering or discomfort.

In clinical settings, patients bring data from their wearable devices to physicians, which has become not uncommon in sleep clinics. However, the varying specifications of wearable devices and the lack of transparency in their signal-processing algorithms create challenges in assessing data reliability and validity. Moreover, no standardized guidelines exist for interpreting such data in clinical practice. Nonetheless, an increasing number of individuals track their physiological data using wearable technology and seek medical intervention based on these insights. In addition, consumer-grade wearable devices are being used for research on sleep/circadian rhythms more and more [5]. Until now, wearable devices that measure circadian rhythms, represented by sleep-wake pattern analysis, have been mainly in the form of wristwatches, but now other forms of devices such as rings are increasing rapidly [6].

Over the past decade, research using wearable devices to study circadian rhythms has increased significantly. A search of the PubMed database for "wearable device" shows an increase in published studies from 524 in 2014 to 4,215 in 2024, representing an 8-fold increase. A search combining "wearable device" and "circadian" reveals an increase from only one study in 2014 to 34 studies in 2024 as of the search date of February 19, 2025. However, when the search is limited to "human" and "clinical studies," the average annual publication rate remains low, at approximately one study per year. This indicates that clinical applications remain limited while research in this area is expanding.

This review aims to examine recent research on circadian rhythms using wearable devices, focusing on the following key areas: 1) the types of wearable devices utilized in circadian rhythm research, 2) the types of circadian rhythm-related data provided by wearable devices, 3) the parameters and analysis methods employed in wearable-based sleep and circadian rhythm research, 4) studies on the association between circadian rhythms measured by wearable devices and disease risk, 5) development of wearable technology for estimating DLMO using multi-sensor data, and 6) limitations and future considerations associated with using wearable devices in circadian rhythm research.

WEARABLE DEVICES FOR CIRCADIAN RHYTHM RESEARCH

Wearable devices employed in circadian rhythm research and clinical applications can be categorized into three groups: 1) devices specifically designed for research and clinical use, 2) consumer-grade devices, and 3) new research/clinical-grade wearable devices [5]. However, the distinction between consumer-grade and research/clinical-grade wearable devices is becoming increasingly blurred.

Traditional research and clinical devices are represented by actigraphy, which mainly uses a 3-axis accelerometer sensor, and sometimes also includes sensors for light exposure and skin temperature measurement. Unlike consumer-grade devices, traditional devices do not provide feedback to users and allow direct access to raw data [7]. They evaluate movement based on changes in gravitational acceleration detected by the sensor, and convert the measured movement into an estimate of sleep and wakefulness using a validated, publicly accessible algorithm. These devices are typically worn on the non-dominant wrist but can also be worn on other body parts, such as the ankle, leg, or waist, depending on the specific research application [8].

Consumer-grade wearable devices were originally developed for fitness, providing feedback to wearers. These devices typically include accelerometers and photoplethysmography (PPG) sensors to measure heart rate and HRV. More recent models incorporate a wide range of additional sensors for estimating skin conductance, temperature, global positioning system tracking, and electrocardiography, which are becoming useful for assessing sleep and circadian rhythms. Most consumer-grade devices do not allow access to raw data, and their sleep classification algorithms remain proprietary. Information on device performance for some sleep assessments is available, although it varies significantly with approach, hardware, and software [8,9]. Data are often stored in the cloud and interfaced with applications. Advancements in sensor technology, including AI-based algorithms, have driven the evolution of traditional actigraphy into modern consumer wearables, such as the Fitbit, Apple Watch, Oura Ring, and WHOOP, expanding accessibility and real-world circadian monitoring capabilities. Early consumer-grade wearables were poorly validated, and in 2018, the American Academy of Sleep Medicine stated that these devices were not yet reliable enough for direct clinical use, and they suggested that consumer-grade wearables could serve as adjunctive tools for patient communication and reference materials [10]. Since then, several validation studies have been conducted to assess the accuracy and reliability of consumer-grade wearables compared to traditional actigraphy and gold-standard methods such as polysomnography (PSG). De Zambotti et al. [11] compared two consumer-grade wearable devices against actigraphy and PSG. The results showed that the consumer-grade wearable devices overestimated total sleep time compared to actigraphy. While its sensitivity for detecting sleep was high (approximately 95%), its specificity for detecting wakefulness was low (approximately 60%). Stone et al. [12] examined eight consumer-grade wearable devices in comparison to PSG. Interday stability and intraday variability indices were consistent between the one device and actigraphy, while the other one showed slightly greater variability in circadian metrics. This suggests that some consumer wearables can reliably estimate circadian parameters, but further validation across diverse populations is needed. Recent sleep assessment capabilities offered by consumer-grade devices were initially intended to enhance wellness, but now straddle the line between wellness and medical products.

New research and clinical wearable devices distinguish themselves from consumer-grade devices by allowing access to raw data and disclosing sleep-wake classification algorithms [5]. Many of these devices feature advanced PPG sensors, mobile app integration, and cloud-based data storage. Although primarily focused on sleep and circadian rhythm research, they often have other health-promoting functions as well.

CIRCADIAN DATA FROM WEARABLE DEVICES

Wearable devices provide a range of physiological and behavioral data that can be used to analyze circadian rhythms. The primary categories of data include movement from accelerometer, HRV, skin temperature, light exposure, and respiratory patterns. These metrics allow researchers to assess circadian phase shifts, amplitude, and stability.

As mentioned earlier, wearable devices used in sleep/circadian rhythm research, whether research-purpose or consumer-grade, contain an accelerometer. Raw accelerometer data is typically provided at a relatively high sampling frequency. The data collected while worn, before being converted in any form, is referred to as "raw data." The term "raw data" refers to the actual signal values recorded by the device's sensors at a specific sampling frequency. Researchers can edit and transform this raw data to create parameters of a type that is relevant to their intended use.

PPG sensors capture changes in blood volume during the cardiac cycle using light reflection or transmission [7]. PPG measures pulse rate and pulse rate variability, which can be used to estimate sleep stages. Pulse rate variability from PPG corresponds to HRV. HRV is influenced by parasympathetic regulation of cardiac rhythm, baroreflex, mechanical stimulation, and hormones. Therefore, HRV measured at rest is used as an indicator of parasympathetic regulation of cardiac rhythm in the context of stress response. The current limitation is that PPG sensor values measured while stationary are reliable, but values measured while moving are difficult to trust [13]. Although PPG values are only an indirect estimate of cardiac activity, they can indicate physiological activities and processes that cannot be captured by other signals [14].

Wearable devices equipped with wearable thermistors and infrared sensors can also measure body temperature fluctuations over a 24-hour period to assess circadian rhythms. Wearable devices equipped with ambient light sensors can assess light exposure patterns that are important for circadian phase changes. Some wearable devices can monitor respiration rate and blood oxygen levels, which vary with the sleep-wake cycle [15].

WEARABLE-BASED CIRCADIAN RHYTHM ANALYSIS METHODS

Wearable devices use algorithms to provide sleep-related parameters by distinguishing between sleep and wake states [16]. Bedtime and wake time are behavioral indicators that are typically self-reported. Bedtime refers to the time a person attempts to fall asleep, while wake time is when they end their sleep attempt. Most devices automatically detect the start and end of each sleep period. The time between bedtime and wake time is used to calculate key sleep metrics such as sleep onset latency, time awake after sleep onset, total sleep time, and sleep efficiency [8]. Additionally, devices estimate sleep stages using either publicly available algorithms or proprietary methods based on heart rate and HRV patterns, which characterize different sleep stages [16].

Circadian rhythms are analyzed by collecting physiological and behavioral markers over extended periods using wearable devices. These devices track activity patterns, physiological signals, and environmental factors to infer the body's internal biological clock. The most common approach involves wearable devices equipped with accelerometers that measure body movements. This data is then processed to estimate sleep-wake cycles, daily activity levels, and 24-hour activity rhythms, providing insights into circadian patterns. Key circadian rhythm indices include interday stability, intraday variability, and relative amplitude [17]. Interday stability measures the consistency of daily activity patterns, with higher values indicating more stable rhythms. Intraday variability reflects how fragmented activity is throughout the day, with higher values indicating greater irregularity. Relative amplitude quantifies the difference between the most active 10 hours and the least active 5 hours. Additionally, circadian parameters such as amplitude and acrophase can be estimated by fitting a cosine curve to activity data [18].

Circadian changes in heart rate and HRV, measured using PPG, are key indicators of circadian rhythm. Heart rate is typically lower at night and higher in the morning, while HRV is generally higher during sleep and lower during wakefulness [13]. Circadian rhythms can also be assessed using continuous glucose monitoring sensors, skin temperature sensors, and light exposure sensors. Data from these parameters can be integrated and analyzed to provide comprehensive insights into circadian patterns. The sleep regularity index is a parameter used to evaluate the consistency of an individual's sleep patterns and assess circadian rhythms. It is calculated by measuring the probability that a person's sleep state remains the same at two different points within a 24-hour period. A value closer to 100% indicates a more consistent sleep pattern [18].

The most commonly used method to assess the robustness of circadian rhythms is multicomponent cosinor analysis, which models periodic data and estimates key variables such as amplitude and acrophase [18]. Non-parametric actigraphy indices capture features like circadian irregularity and light exposure, while moving linear regression models are used to evaluate sleep-wake patterns at short intervals, often for characterizing basic sleep variables. Additionally, limit-cycle oscillator modeling and approximation-based least squares methods are also used to assess circadian rhythm robustness [18].

How should deviations in circadian rhythm robustness identified through analysis be interpreted? Such deviations—manifesting as decreased amplitude, deviations from sinusoidal patterns, phase delays, impaired phase alignment, increased day-to-day instability, and fragmented circadian activity—are associated with elevated risks to both physical and mental health. The interpretation of key indicators that deviate from normal circadian rhythms involves considering multiple factors collectively. However, it can be summarized as follows: For circadian rhythm-related indicators, a decrease in amplitude typically indicates a weakening of the circadian rhythm, meaning the difference between daytime and nighttime activity is reduced. However, it may also represent the normalization of a temporary amplitude increase caused by factors such as jet lag or shift work. A phase delay generally refers to a delayed sleep-activity pattern, where an individual goes to bed and wakes up later than usual. This interpretation should consider individual genetic factors and environmental influences, such as light exposure. An abnormal circadian waveform indicates a deviation from the expected pattern. While it often suggests a loss of regularity, it may also reflect an adaptation to specific environmental conditions. Variability in circadian rhythms can occur within a single cycle or between consecutive cycles. Increased fragmentation or irregularity corresponds to higher intraday variability or interday variability and typically signifies a loss of rhythm regularity. However, it can also represent a flexible response to a dynamic environment or indicate that the circadian rhythm does not follow a strict 24-hour cycle. Misalignment occurs when the correlation between different indicators is disrupted, with factors such as genes, age, seasonal changes, and meal timing influencing rhythm alignment [18].

WEARABLE-MEASURED CIRCADIAN RHYTHMS AND DISEASE RISK

Recent studies have explored the association between circadian rhythm disruptions and disease risks using wearable devices. Numerous studies have utilized the UK Biobank and US National Health and Nutrition Examination Survey (NHANES) databases. While most research focuses on disruptions in the circadian rhythm of physical activity, some studies also examine deviations in temperature and light exposure rhythms.

A prospective study has shown that increased circadian rhythm amplitude is associated with higher all-cause mortality and a greater incidence of infectious diseases, cancer, cardiovascular disease, and respiratory disease, based on activity data [19]. Another study using UK Biobank data found that decreased circadian rhythm amplitude is linked to a higher prevalence of mental disorders and negatively correlates with subjective mental health [20]. Studies have shown that circadian phase shifts are associated with cognitive decline in older adults and an increased risk of death and cardiovascular disease, with both findings based on activity data collected from wearable devices [21-23]. Recently, Shim et al. [3] developed a model called CoSinorAge that estimates physical age as a digital biomarker by analyzing circadian rhythms, demographic variables, lifestyle factors, and health conditions. This study was conducted on more than 80,000 middle-aged and elderly individuals in the UK and the US, using accelerometer data collected through wearable devices to analyze circadian rhythms. According to the study results, a 1-year increase in CoSinorAge was associated with an 8%−12% increase in overall mortality and cause-specific mortality, a 3%−14% increase in the likelihood of developing age-related diseases such as cardiovascular disease, diabetes, and neurodegenerative disorders, and an accelerated decline in physical function and overall health status. A decrease in circadian rhythm amplitude, measured through body temperature or light exposure using wearable devices, has also been linked to an increased risk of non-alcoholic fatty liver disease, diabetes, kidney disease, hypertension, and pneumonia [24-26].

DEVELOPMENT OF WEARABLE TECHNOLOGY FOR ESTIMATING DLMO USING MULTI-SENSOR DATA

DLMO is the gold standard for assessing circadian rhythms, but it is invasive, time-consuming, and impractical for large-scale or real-world monitoring because it is measured via repeated saliva, blood, or urine sampling in a laboratory or controlled environment. To address these limitations, researchers have developed models for estimating DLMO using wearable technology and multi-sensor data fusion. Estimation of DLMO leverages non-invasive physiological markers, such as HRV, body temperature, movement patterns, and light exposure, to infer melatonin phase without requiring direct hormonal sampling [27].

Recent advancements in wearable technology and machine learning have enabled the development of non-invasive DLMO proxies. This approach integrates multiple physiological signals to estimate melatonin onset in real time. Data collected from wearable devices, including heart rate, HRV, body temperature, and light exposure, can help predict melatonin secretion. Melatonin release is linked to parasympathetic activation, which lowers heart rate and increases HRV at sleep onset. It is also associated with thermoregulation, leading to increased skin temperature and decreased temperature at night. Since melatonin suppression is highly sensitive to blue light exposure, tracking the timing and intensity of light exposure can help estimate circadian phase delays or advances. Ongoing research explores the use of AI-driven analysis of multi-sensor data to predict melatonin secretion. One AI-based model, incorporating HRV, body temperature, and activity data from wearable devices, estimated DLMO with an area under the curve of 77% compared to standard melatonin testing [28].

CHALLENGES AND FUTURE DIRECTIONS IN CIRCADIAN RHYTHM RESEARCH USING WEARABLE DEVICES

Research on circadian rhythms using wearable devices faces several challenges. Current commercial devices often lack validation against gold-standard methods like PSG, limiting their reliability. Restricted access to raw data and proprietary algorithms reduces transparency and hinders independent verification. Additionally, variations in device accuracy across different environments, such as among shift workers or individuals with sleep disorders, further complicate their application.

The Sleep Research Society convened an expert panel to promote the informed and appropriate use of sleep tracking technology, particularly wearable devices for sleep and circadian research [5]. The panel has published guidelines and recommendations to support the effective and reliable application of wearable technology in these fields. The summary of the recommendations is as follows: 1) When selecting a wearable device for research, it is essential to choose one that aligns with the study's objectives. Device selection will depend on whether the goal is to measure sleep duration or analyze sleep stages. 2) Additionally, consider whether collecting physiological data such as heart rate, skin temperature, and oxygen saturation is necessary. 3) Data accessibility is also crucial; verify whether the device allows access to raw data and if it provides application programming interface or software development kit support for researchers to process and analyze data. 4) Lastly, since device performance may vary depending on participants' age, health status, and lifestyle, ensure that the device has been validated for use in the study's target population.

When interpreting data from wearable devices, it is important to note that their sleep stage detection may be less accurate than PSG. Wearable devices may miscalculate sleep duration or inaccurately detect rapid eye movement and deep sleep stages. For studies requiring precise sleep stage detection, it is essential to use a device that has been validated against PSG to ensure accuracy and reliability. Finally, it is recommended to evaluate the measurement accuracy of wearable devices not only in controlled laboratory settings but also in real-world environments to ensure their reliability and applicability in everyday life.

Future research should prioritize validating wearable devices across diverse populations and settings, ensuring their accuracy and reliability. Standardizing data collection methods and promoting open-access algorithms will enhance transparency and comparability between studies. Moreover, integrating wearable devices with digital therapeutics could open new avenues for diagnosing and managing circadian rhythm disorders, paving the way for personalized healthcare solutions [29,30]. Ultimately, interdisciplinary collaboration and advancements in machine learning will be essential for unlocking the full potential of wearable devices in both research and clinical practice.

CONCLUSION

Wearable technology has significantly advanced research on human circadian rhythms, yet standardization of data collection and analysis methods remains a critical challenge. Future studies should focus on large-scale population-based research, advanced mathematical modeling, and interdisciplinary collaboration to enhance our understanding of circadian rhythms. By addressing current limitations and improving the accuracy and reliability of wearable-derived circadian rhythm data, these technologies have the potential to revolutionize both scientific research and clinical applications in circadian medicine. Further efforts should be directed toward integrating wearable data into healthcare systems, ensuring data interoperability, and establishing validated clinical guidelines to optimize their application in medical practice.

Conflicts of Interest

The author has no potential conflicts of interest to disclose.

Availability of Data and Material

Data sharing not applicable to this article as no datasets were generated or analyzed during the study.

ORCID iD

Eun Lee
https://orcid.org/0000-0002-7462-0144

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