Smart Ring in Clinical Medicine: A Systematic Review

Eun Jeong Gong, Chang Seok Bang, Jae Jun Lee, Gwang Ho Baik

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Abstract

Background: Smart rings enable continuous physiological monitoring through finger-worn sensors. Despite growing consumer adoption exceeding 2 million users globally, their clinical utility beyond sleep tracking remains unclear.

Objective: To systematically review evidence for smart ring applications in clinical medicine, assess measurement accuracy, and evaluate clinical outcomes across medical domains.

Methods: We searched PubMed/MEDLINE, Embase, and Cochrane Library through July 31, 2025, for studies using smart rings in clinical applications. Inclusion criteria: adults ?18 years, commercially available smart rings, health-related outcomes, and English language. We excluded pure validation studies, device development papers, and pediatric populations. Two reviewers independently screened studies and extracted data. Risk of bias was assessed using ROBINS-I and RoB 2.0.

Results: From 862 citations, 107 studies met inclusion criteria (85 non-randomized studies, 14 case reports/series, 8 randomized trials) including approximately 100,000 participants. Studies were equally distributed between sleep (n=51, 47.7%) and non-sleep applications (n=56, 52.3%). The Oura Ring dominated research (77 studies, 72.0%). Smart rings demonstrated high accuracy: heart rate r=0.996 versus electrocardiography, heart rate variability (HRV) r=0.980, sleep detection 93-96% sensitivity. Non-sleep applications have demonstrated predictive capabilities across various fields: COVID-19 detected 2.75 days before symptoms (82% sensitivity, 63% specificity, n=63,153); inflammatory bowel disease flares predicted 7 weeks early (72% accuracy); bipolar episodes detected 3-7 days early (79% sensitivity); postoperative pain predicted with 70% accuracy (AUC 0.762). Gastric cancer patients showed 86% HRV reduction versus controls and HRV correlated with tumor size, tumor infiltration, lymph node metastasis and distant metastasis. However, 65% of studies had moderate-to-high risk of bias. Critical limitations included small samples (median 47-89 excluding outliers), proprietary algorithms preventing reproducibility (89% of studies), poor diversity reporting (only 35% reported race/ethnicity), and declining adherence (80% at 3 months to 43% at 12 months).

Conclusions: Smart rings have evolved beyond sleep tracking, with equal sleep/non-sleep applications confirming transformation into clinical tools capable of early disease detection through autonomic monitoring. Evidence supports use in sleep disorders, mental health monitoring, and chronic disease management. However, single-manufacturer predominance, algorithmic opacity, population homogeneity, and adherence challenges require attention before widespread clinical implementation.

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initiation of this study.

ABSTRACT

Background: Smart rings enable continuous physiological monitoring through finger-worn sensors. Despite growing consumer adoption exceeding 2 million users globally, their clinical utility beyond sleep tracking remains unclear.

Objectives: To systematically review evidence for smart ring applications in clinical medicine, assess measurement accuracy, and evaluate clinical outcomes across medical domains.

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Conclusion: Smart rings have evolved beyond sleep tracking, with equal sleep/non-sleep applications confirming transformation into clinical tools capable of early disease detection through autonomic monitoring. Evidence supports use in sleep disorders, mental health monitoring, and chronic disease management. However, single-manufacturer predominance, algorithmic opacity, population homogeneity, and adherence challenges require attention before widespread clinical implementation.

Keywords: smart ring; wearable devices; digital health; remote monitoring; clinical medicine

INTRODUCTION

Advances in digital health technologies have enabled continuous monitoring of behavioural and physiological signals through wearable devices.[1] These devices collect real-time data on individuals' daily activity, heart rate (HR), sleep and other health metrics, providing a more comprehensive view of patient health than traditional sporadic measurements [1]. The global wearable device market is now a multi-billion-dollar industry [2-4]. Wearables come in various forms—smartwatches, activity bands, patches, ear buds, clothing-embedded sensors and rings—that incorporate sensors to measure step counts, physical activity intensity, movement patterns, HR and rhythm, blood pressure, oxygen saturation, sleep, and body temperature, generating rich longitudinal datasets that may reveal subtle physiological changes preceding clinical manifestations [1,5]. Devices may be classified as consumer-grade, research-grade or medical-grade [6].

Among wearables, smart rings are emerging as discrete, finger-worn devices that leverage the finger's rich vascular anatomy to capture high-quality photoplethysmographic signals [7,8]. The thin skin, consistent pressure and absence of large muscles on the finger improve optical sensor contact and reduce motion artifacts, enabling accurate measurements of HR, respiratory rate, blood oxygen saturation and sleep cycles [7,9,10]. Finger-worn devices offer high signal clarity and are lightweight and comfortable for 24/7 monitoring [10,11]. finger-based PPG sensors can achieve a high signal-to-noise ratio when properly placed [2,7,12]. Despite these advantages, the market of finger-worn wearables is small compared with wrist- or chest-mounted devices [9].

Accuracy and reliability remain critical challenges [13]. Device algorithms must balance precision with comfort and battery life, and wearable data often require complex interpretation and clinical oversight [1]. Data privacy, regulatory and reimbursement issues, and limited capacity of healthcare staff to monitor large data streams also hinder clinical adoption [1,13].

Although smart rings have gained attention for general wellness, their clinical utility is not well characterized [9,13]. Evidence is emerging on applications in sleep monitoring, autonomic function assessment, pain prediction, infectious-disease detection and obstetric monitoring [8,9,14]. This is the first systematic review to synthesize evidence on smart rings' clinical utility across multiple medical domains. Our objectives were to summarise the domains in which smart rings have been evaluated, assess their measurement accuracy and clinical outcomes, identify methodological limitations, and discuss implications for healthcare integration.

METHODS

This systematic review followed the PRISMA 2020 reporting guidelines [15] and was registered in PROSPERO (1122044).

We searched PubMed/MEDLINE, Embase, and Cochrane Library (inception to July 31, 2025) for human studies evaluating finger-worn smart rings. Search strategies incorporated keywords and indexed terms including "smart ring," "finger-worn," "ring-shaped wearable," and device names (Table 1). Grey literature sources were searched to reduce publication bias.

Eligible studies were original reports using smart rings for clinical applications. We included observational studies, diagnostic accuracy studies, trials, case series/reports, and prediction models. Technical papers without human data were excluded and only full-text English-language publications were included. The search strategy for relevant articles is described in Table 1. Two reviewers (EJ Gong and CS Bang) independently screened and extracted data and disagreements were resolved by consensus or consultation with a third author (JJ Lee). Risk of bias was assessed using ROBINS-I [16] and RoB 2 [17] Given clinical heterogeneity, we synthesised results narratively by domain.

Table 1. Searching strategy to find the relevant articles.

Database: MEDLINE (through PubMed)
#1 "smart ring"[tiab] OR "ring-shaped wearable"[tiab] OR "finger-worn"[tiab]: 61 #2 "Oura"[tiab] OR "Circul"[tiab] OR "CART-I"[tiab]: 143 #3 #1 OR #2: 188 #4 #3 AND English[Lang]: 186
Database: Embase

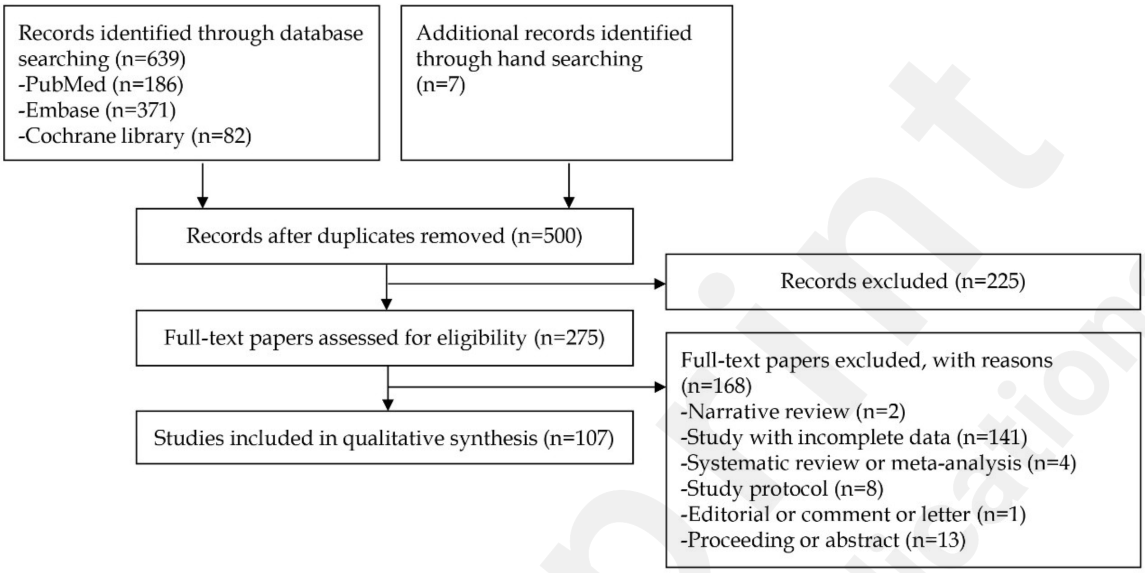
#1 'smart ring':ab,ti,kw OR 'ring-shaped wearable':ab,ti,kw OR 'finger-worn':ab,ti,kw: 549 #2 'Oura':ab,ti,kw OR 'Circul':ab,ti,kw OR 'CART-I ':ab,ti,kw: 267 #3 #1 OR #2: 790 #4 #3 AND ([article]/lim OR [article in press]/lim OR [review]/lim) AND [English]/lim: 371
Database: Cochrane Library
#1 'smart ring':ab,ti,kw OR 'ring-shaped wearable':ab,ti,kw OR 'finger-worn':ab,ti,kw: 32 #2 'Oura':ab,ti,kw OR 'Circul':ab,ti,kw OR 'CART-I ':ab,ti,kw: 54 #3 #1 OR #2: 82

RESULTS

Study selection and inclusion

Literature search yielded 639 records from databases and 7 additional records from manual screening. After removing duplicates, 500 unique records remained. Following title/abstract screening, 275 full-text articles were assessed for eligibility. Of these, 168 were excluded. Ultimately, 107 studies met inclusion criteria (Figure 1).

Figure 1. Study selection flow



Study characteristics

The 107 included studies covered 85 non-randomized studies, 14 case reports/series, 8 randomized trials. Studies were published between 2019-2025, with 69.2% published in 2024-2025. Collectively enrolling approximately 100,000 participants, though skewed by large datasets (the largest 63,153 individuals).18 Sample sizes ranged from single cases to tens of thousands. Most studies recruited healthy volunteers, though some targeted specific patient populations. Research split almost evenly between sleep-related applications (n=51, 47.7%) and non-sleep applications (n=56, 52.3%). The Oura Ring featured in 72% of studies. Other devices included the Circul ring for pulse oximetry, CART-I cuffless blood pressure ring, Movano's oxygen-sensing ring, and Moodmetric stress-tracking ring (**Multimedia Appendix 1**)

Sleep studies

Study design and populations of sleep studies

Among the 51 sleep studies, observational designs predominated (n=35, 68.6%), followed by cross-sectional studies (n=11, 21.6%), randomized studies (n=3, 5.9%), and case reports/series (n=2, 3.9%). Studies encompassed healthy adults (n=8), healthcare workers (n=3), athletes (n=6), and clinical populations with sleep-disordered breathing, chronic pain, dementia, and post-surgical patients (**Multimedia Appendix 1**).

Device performance in sleep assessment

Validation against polysomnography

Multiple validation studies established accuracy for sleep detection. Robbins et al. demonstrated 95% sensitivity with 83% specificity using the Oura Ring [19]. The latest Oura Ring Generation 3 showed sensitivity of 94.4-94.5% and specificity of 73.0-74.6% across 421,045 epochs [20]. However, sleep staging accuracy remained challenging at 53.18% [21]. Multi-device comparison studies revealed variable performance, with intraclass correlation coefficient of 0.77 for total sleep time but poor agreement for sleep stages [22].

Sleep-disordered breathing detection

Smart rings showed promising results for detecting sleep breathing disorders. The Circul ring demonstrated exceptional correlation (R^2=0.9012) with polysomnography [23]. Zhao et al. achieved 87% sensitivity and 83% specificity for detecting apnea-hypopnea index ≥5 events/hour with area under the curve (AUC) of 0.929 [24]. The Belun platform showed 77.6% sensitivity and 85.3% specificity for obstructive sleep apnea diagnosis [25].

Clinical applications in sleep

Perioperative and acute care settings in sleep studies

Sleep monitoring revealed critical clinical insights. Debbiche et al. found gynecologic surgery patients with high preoperative sleep efficiency had 3-fold lower postoperative complication rates [26]. Donahue et al. documented significant sleep architecture disruption within 72 hours post-concussion [27].

Sleep interventions

Controlled trials evaluated sleep improvement interventions. Hausenblas et al. demonstrated magnesium-L-threonate supplementation significantly improved multiple sleep parameters [28]. Breus et al. found a pressure-releasing grid mattress improved sleep quality metrics [29]. However, Armitage et al.'s randomized trial of a sleep app showed no significant improvement [30].

Special populations

Sleep patterns varied significantly across different populations and contexts. In dementia care, Ju et al. found significant correlations between sleep parameters of 11 patients and their 11 family caregivers, suggesting bidirectional sleep influences in caregiving dyads [31]. University freshmen showed markedly disrupted sleep patterns, with Soon et al. reporting bedtimes 71.76 minutes later than optimal and 42.6% of 638 students waking after class start times [32]. Professional athletes demonstrated context-dependent sleep variations, with Font et al. documenting moderate differences in total time in bed between home matches and travel days in elite handball players [33].

Large-scale population sleep studies

Willoughby evaluated 1.5 million nights of sleep data from 57,240 Oura Ring users, revealing that travel-related sleep timing disruption required more than 15 days for full recovery [34]. Viswanath et al. identified 13 distinct sleep phenotypes from 5 million nights of data in 33,152 individuals, with transition patterns differing by health status [35].

Non-sleep physiological studies

Study design and populations of non-sleep physiological studies

Among the 56 non-sleep physiological monitoring studies, observational designs were most common (n=35, 62.5%), followed by cross-sectional studies (n=13, 23.2%), case reports/series (n=6, 10.7%), and randomized controlled trials (n=2, 3.6%). Study populations included healthy volunteers (n=16), disease-specific cohorts including inflammatory bowel disease (IBD) (n=309), bipolar disorder (n=127), COVID-19 patients (n=73), and pregnant women. Sample sizes ranged from single case reports to population-level investigations with 63,153 participants [18], demonstrating the scalability of smart ring applications from personalized medicine to public health surveillance (**Multimedia Appendix 1**).

Cardiovascular and metabolic monitoring

Heart rate and heart rate variability validation

Extensive validation studies confirmed cardiac monitoring accuracy. Liang et al. demonstrated correlations exceeding 0.9 for HR variability (HRV) measurements [36]. Kinnunen et al. reported $r^2=0.996$ for HR and $r^2=0.980$ for HRV [37]. Age-related differences were noted, with accuracy varying between younger and older populations.

Advanced cardiac applications

The CART-I ring showed exceptional performance for arrhythmia detection in 25 patients, achieving 94% overall sensitivity with 100% sensitivity for ventricular fibrillation and 90% for ventricular tachycardia detection, with intraclass correlation coefficient of 0.998 for event duration measurements [38]. For blood pressure monitoring, Kim et al. validated a cuffless smart ring system in 89 healthy adults showing minimal bias (systolic: 0.16±5.90 mmHg, diastolic: -0.07±4.68 mmHg) with correlation coefficients of 0.94-0.95 [39].

Metabolic monitoring

Novel bioimpedance technology enabled non-invasive glucose monitoring with accuracy within ±20 mg/dL for 83.6% of measurements [40]. Temperature assessments revealed connections between body temperature and depression in 20,880 individuals [41].

Women's health and reproductive monitoring

Menstrual cycle physiology

Comprehensive menstrual cycle tracking revealed distinct physiological patterns. Alzueta et al. documented biphasic temperature and HRV across 117 women, with HR lowest during menses [42]. Maijala et al. quantified temperature differences of 0.23-0.30°C between follicular and luteal phases using nocturnal finger skin temperature in 22 women [43]. Findings were corroborated in Olympic athletes [44].

Ovulation and fertility

The Oura Ring demonstrated 96.4% ovulation detection rate across 1,155 ovulatory cycles from 964 women, with mean prediction error of 1.26 days compared to 3.44 days for calendar-based methods, representing a 3-fold improvement [45].

Pregnancy monitoring and prediction

Continuous monitoring revealed distinct physiological trajectories. Keeler Bruce et al. tracked 120 pregnancies, identifying temperature deviations distinguishing outcomes [14]. Machine learning (ML) approaches achieved <2 days error at 8 days before labor onset [46]. Erickson et al. reported 79% accuracy within a 4.6-day prediction window [47].

Disease detection and prediction

Infectious disease surveillance

Smart rings demonstrated early disease detection capabilities. For COVID-19, Mason et al. achieved 82% sensitivity with 63% specificity, detecting infections 2.75 days before testing in 63,153 participants.[18] Military applications showed similar promise with AUC 0.82 and 2.3 days lead time [48]. For influenza, Hadid et al. developed ML models achieving

AUC 0.89 for predicting systemic inflammatory response [49].

Chronic disease management

Continuous monitoring enabled prediction of disease exacerbations. In 309 IBD patients, Hirten et al. identified HRV patterns that differed between flare and remission states, with changes detectable 7 weeks before clinical flares [50]. For mental health conditions, Ortiz et al. demonstrated that activity variability detected depressive episodes in bipolar disorder 7.0 days earlier than sleep changes, with 79% sensitivity in 127 patients [51]. However, device limitations were noted in neurological conditions, with Reithe et al. finding poor cross-device compatibility for Parkinson's disease monitoring in 15 patients and 16 controls [52].

Mental health and cognitive applications

Depression and mood disorders

Multiple approaches showed promise for mental health monitoring. Borelli et al. achieved F1-score of 0.744 for depression detection using multimodal passive sensing and machine learning in 28 undergraduates [53]. Large-scale analysis by Mason et al. revealed associations between elevated body temperature and depressive symptoms in 20,880 individuals [41]. Fudolig et al. identified two fundamental HR dynamics patterns that correlated with mental health outcomes in 599 college students [54].

Stress and anxiety management

Intervention studies demonstrated measurable improvements. Balsam et al.'s mindfulness app study in 20 pregnant women showed significant reductions in stress ($p=0.005$), anxiety ($p=0.01$), and pregnancy-specific anxiety ($p<0.0001$) with physiological correlates captured via Oura Ring [55]. Healthcare workers during the pandemic showed improved resilience with structured interventions monitored through wearables [56].

Cognitive function

Smart rings enabled objective cognitive assessment. Rovini et al. successfully differentiated 8 mild cognitive impairment patients from 10 healthy controls using reach-to-grasp motion analysis [57]. In community-dwelling older adults, Qin et al. found sleep regularity strongly correlated with executive function performance in 773 participants aged 65-80 years [58].

Physical activity and performance

Validation studies

Activity tracking showed variable accuracy. Kristiansson et al. reported strong correlations for step count ($r=0.93$ laboratory, $r\geq0.76$ free-living) and energy expenditure validation in 32 healthy adults [59]. However, Niela-Vilen et al. found systematic overestimation in 42 adults, with Oura overestimating steps by 1,416 daily and sedentary time by 17 minutes compared to ActiGraph accelerometer [60].

Athletic performance and recovery

Smart rings provided insights into athlete physiology. Bigalke et al. demonstrated that ≥7 hours sleep correlated with peak power output in 24 Division I baseball players [61]. Smith et al. revealed divergent effects of energy availability on recovery in 20 endurance athletes, with 24-hour exercise-induced low energy availability extending total sleep time while diet-induced restriction reduced mean overnight heart rate [62].

Novel clinical applications

Emergency medicine

Smart rings enhanced emergency care delivery. Lee et al. developed a proof-of-concept device with compression depth estimation accuracy within 1.4-2.2mm absolute error in 4 emergency medical professionals [63]. They validated its performance in the following randomized trial. Ahn et al.'s study in 20 healthy volunteers showed ring-guided cardiopulmonary resuscitation achieved 88.7% accurate rate-depth proportion versus 22.6% in controls ($p=0.033$) [64].

Occupational health

Workplace implementations demonstrated feasibility and clinical utility. In US Navy shipboard personnel, Kubala et al. reported 71±38% individual adherence rates in 853 personnel, establishing operational feasibility in challenging environments [65]. Police officers showed HRV fluctuations that predicted stress and somatization changes, as documented by de Vries et al. in 68 officers [66].

Population health surveillance

Large-scale monitoring enabled syndromic surveillance. Kasl et al. demonstrated fever detection capabilities in 16,794 participants [67]. During pregnancy, continuous monitoring proved feasible with >80% adherence until late pregnancy in 15 Hispanic women, though postpartum adherence dropped to 31% [68].

Methodological quality

According to ROBINS-I assessment for observational studies, overall risk of bias was low in 16 studies (15.0%), moderate in 56 studies (52.3%), and high in 35 studies (32.7%). Primary sources of bias included: Small sample sizes, particularly in pilot studies and case reports (n<10 in 8 studies), Disease-specific populations limiting generalizability, Lack of polysomnography validation for sleep studies (noted in 35% of sleep studies), Missing data and variable adherence rates (ranging from 31% to 87%), and Reliance on self-reported outcome measures for subjective symptoms. For randomized trials (RoB 2.0), two studies showed moderate risk and five showed high risk of bias, primarily due to lack of blinding, missing outcome data, and COVID-19 pandemic disruptions affecting study protocols (**Multimedia Appendix 1**).

DISCUSSION

This systematic review of 107 studies encompassing approximately 100,000 participants reveals that smart rings have evolved substantially beyond their origins as sleep trackers. The near-equal distribution between sleep (47.7%) and non-sleep applications (52.3%) marks a pivotal transition in the field, demonstrating their emergence as versatile clinical tools capable of continuous physiological monitoring across diverse medical domains.

Our findings demonstrate robust measurement accuracy for core physiological parameters, with HR showing exceptional correlation and HRV compared to gold-standard electrocardiography [37]. These accuracy levels exceed those reported for many wrist-worn devices, likely due to the finger's superior vascular anatomy and reduced motion artifacts during measurement [7,10]. The clinical significance extends beyond accuracy metrics—smart rings demonstrated predictive capabilities that could transform disease management paradigms. The ability to detect COVID-19 2.75 days before symptom onset [18] and predict IBD flares 7 weeks in advance [50] represents a shift from reactive to proactive healthcare delivery.

The expansion into women's health applications deserves particular attention. The 96.4% ovulation detection accuracy[45] and ability to predict labor onset within 2 days error at 8 days before delivery [46] could revolutionize reproductive health monitoring. These capabilities, combined with continuous pregnancy monitoring that distinguished outcomes based on temperature patterns [14], suggest smart rings could address critical gaps in women's health surveillance, particularly in resource-limited settings where access to frequent clinical monitoring is challenging.

The clinical utility of HRV measurement extends beyond these applications. Traditional electrocardiography studies have shown that HRV decreases by 86% in gastric cancer patients and correlates with tumor progression markers [69], suggesting that smart rings' accurate HRV monitoring capability could potentially enable non-invasive cancer progression surveillance.

While the large aggregate sample size and diversity of applications represent strengths, several critical limitations threaten the generalizability and clinical translation of these findings. The overwhelming dominance of the Oura Ring (72%) creates a concerning single-point dependency that limits cross-platform validation and raises questions about the generalizability of findings to other devices. This concentration mirrors early smartwatch research dominated by Apple Watch studies, potentially creating vendor lock-in effects that could limit clinical adoption [13].

The proprietary nature of algorithms used in 89% of studies represents a fundamental barrier to scientific reproducibility and clinical validation. Without access to underlying computational methods, independent verification becomes impossible, potentially masking device-specific biases or limitations. This algorithmic opacity contrasts sharply with traditional medical devices where measurement principles are transparent and standardized [6].

Population homogeneity poses another significant challenge. Only 35% of studies reported race/ethnicity data, and most participants were young, healthy, educated individuals from high-income countries. Given known variations in photoplethysmographic signal quality across skin tones and the documented disparities in wearable device accuracy among different ethnic groups [7], this homogeneity severely limits the applicability of findings to diverse clinical populations who might benefit most from remote monitoring.

The documented decline in adherence from 80% at 3 months to 43% at 12 months reveals a critical implementation challenge that transcends technical accuracy. This adherence trajectory, while better than some digital health interventions, remains insufficient for chronic disease management requiring continuous monitoring [68]. The reasons for discontinuation—including comfort issues, battery life constraints, and data interpretation burden—highlight the need for user-centered design improvements and clinical workflow integration strategies [2,12].

Our findings align with and extend previous systematic reviews of wearable devices in clinical settings [1,2,9]. While prior reviews focused primarily on measurement validation [9], our analysis reveals the transition toward clinical outcome prediction and intervention guidance. The balanced distribution between sleep and non-sleep applications contrasts with earlier reviews that emphasized sleep as the primary use case, confirming the technology's maturation beyond its initial consumer wellness focus [4,5].

Several priority areas emerge for advancing smart ring clinical applications. First, multi-vendor validation studies using standardized protocols are essential to establish device-agnostic clinical guidelines. Second, algorithm transparency through open-source initiatives or regulatory requirements could enhance scientific rigor and clinical trust [6]. Third, purposeful recruitment of diverse populations, particularly those with chronic conditions and from underrepresented groups, is critical for ensuring equitable healthcare applications [3].

The integration of smart rings into clinical workflows requires careful consideration of data management, interpretation, and liability issues. The volume of continuous data generated presents both opportunities and challenges for healthcare systems already struggling with information overload [1].

Limitations

This review has several limitations. The heterogeneity of populations, devices, and outcomes precluded meta-analysis, limiting quantitative synthesis. Publication bias toward positive findings may overestimate device performance, particularly given the prevalence of industry-sponsored studies. The rapid evolution of smart ring technology means newer devices and algorithms may have addressed some identified limitations.

Conclusions

Smart rings demonstrate accuracy and predictive capabilities across clinical domains, with equal sleep/non-sleep distribution confirming evolution from wellness devices to clinical tools. However, device diversity limitations, algorithmic transparency, population representativeness, and long-term adherence challenges require attention through rigorous research and user-centered design to realize potential for enhanced clinical care.

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Conflicts of Interest:

None declared.

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Each author’s contribution:

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Multimedia Appendix 1

Supplementary Table 1-6

[DOC File, 117 KB-Multimedia Appendix 1]

Multimedia Appendix 2

PRISMA checklist

[DOC File, 32 KB-Multimedia Appendix 1]

References

1. Hughes A, Shandhi MMH, Master H. Wearable Devices in Cardiovascular Medicine. Circ Res. 2023;132(5):652-670. doi: 10.1161/CIRCRESAHA.122.322389.

2. Lodewyk K, Wiebe M, Dennett L, et al. Wearables research for continuous monitoring of patient outcomes: A scoping review. PLOS Digit Health. 2025;4(5):e0000860. doi: 10.1371/journal.pdig.0000860.

3. Nagappan A, Krasniansky A. Knowles M. Patterns of Ownership and Usage of Wearable Devices in the United States, 2020-2022: Survey Study. J Med Internet Res. 2024:26:e56504. doi: 10.2196/56504.

4. Dhingra LS, Aminorroaya A, Oikonomou EK, et al. Use of Wearable Devices in Individuals With or at Risk for Cardiovascular Disease in the US, 2019 to 2020. JAMA Netw Open. 2023;6:e2316634. doi: 10.1001/jamanetworkopen.2023.16634.

5. Adepoju VA, Jamil S. Biswas MS, Chowdhury AA. Wearable Technology in the Management of Chronic Diseases: A Growing Concern. Chronic Dis Transl Med. 2024;11(2):117-121. doi: 10.1002/cdt3.156. eCollection 2025 Jun.

6. Seneviratne MG, Connolly SB, Martin SS, Parakh K. Grains of Sand to Clinical Pearls: Realizing the Potential of Wearable Data. Am J Med. 2023;136(2):136-142. doi: 10.1016/j.amjmed.2022.10.006.

7. Kim KB, Baek HJ. Photoplethysmography in wearable devices: a comprehensive review of technological advances, current challenges, and future directions. Electronics. 2023;12(13):2923. doi: 10.3390/electronics12132923

8. Morimoto M, Nawari A, Savic R, Marmor M. Exploring the Potential of a Smart Ring to Predict Postoperative Pain Outcomes in Orthopedic Surgery Patients. Sensors (Basel). 2024;24(15):5024. doi: 10.3390/s24155024.

9. Fiore M, Bianconi A, Sicari G, et al. The use of smart rings in health monitoring—a meta-analysis. Applied Sciences. 2024;14(23):10778. doi: 10.3390/app142310778

10. Volpes G, Valenti S, Genova G, et al. Wearable Ring-Shaped Biomedical Device for Physiological Monitoring through Finger-Based Acquisition of Electrocardiographic, Photoplethysmographic,

and Galvanic Skin Response Signals: Design and Preliminary Measurements. Biosensors (Basel). 2024 Apr 20;14(4):205. doi: 10.3390/bios14040205.

11. Sel K, Osman D, Huerta N, et al. Continuous cuffless blood pressure monitoring with a wearable ring bioimpedance device. NPJ Digit Med. 2023;6(1):59. doi: 10.1038/s41746-023-00796-w.

12. Hannan AL, Harders MP, Hing W, et al. Impact of wearable physical activity monitoring devices with exercise prescription or advice in the maintenance phase of cardiac rehabilitation: systematic review and meta-analysis. BMC Sports Sci Med Rehabil. 2019;11:14. doi: 10.1186/s13102-019-0126-8. eCollection 2019.

13. Bayoumy K, Gaber M, Elshafeey A., et al. Smart wearable devices in cardiovascular care: where we are and how to move forward. Nat Rev Cardiol. 2021;18(8):581-599. doi: 10.1038/s41569-021-00522-7.

14. Keeler Bruce L, González D, Dasgupta S, Smarr BL. Biometrics of complete human pregnancy recorded by wearable devices NPJ Digit Med. 2024;7(1):207. doi: 10.1038/s41746-024-01183-9.

15. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021:372:n71. doi: 10.1136/bmj.n71.

16. Sterne JA, Hernán MA, Reeves BC, et al. ROBINS-I: a tool for assessing risk of bias in non-randomised studies of interventions. BMJ. 2016:355:i4919. doi: 10.1136/bmj.i4919.

17. Sterne JAC, Savović J, Page MJ, et al. RoB 2: a revised tool for assessing risk of bias in randomised trials. BMJ. 2019:366:l4898. doi: 10.1136/bmj.l4898.

18. Mason AE, Hecht FM, Davis SK, et al. Detection of COVID-19 using multimodal data from a wearable device: results from the first TemPredict Study. Scientific reports. 2022;12(1):3463. doi: 10.1038/s41598-022-07314-0.

19. Robbins R, Weaver MD, Sullivan JP, et al. Accuracy of Three Commercial Wearable Devices for Sleep Tracking in Healthy Adults. Sensors (Basel). 2024;24(20):6532. doi: 10.3390/s24206532.

20. Svensson T, Madhawa K, Nt H, et al. Validity and reliability of the Oura Ring Generation 3 (Gen3) with Oura sleep staging algorithm 2.0 (OSSA 2.0) when compared to multi-night ambulatory polysomnography: A validation study of 96 participants and 421,045 epochs. Sleep Medicine. 2024;115:251-263. doi: 10.1016/j.sleep.2024.01.020. Epub 2024 Jan 26.

21. Herberger S, Aurnhammer C, Bauerfeind S, et al. Performance of wearable finger ring trackers for diagnostic sleep measurement in the clinical context. Sci Rep. 2025;15(1):9461. doi: 10.1038/s41598-025-93774-z.

22. Kainec KA, Caccavaro J, Barnes M, et al. Evaluating Accuracy in Five Commercial Sleep-Tracking Devices Compared to Research-Grade Actigraphy and Polysomnography. Sensors (Basel). 2024;24(2):635. doi: 10.3390/s24020635.

23. Meira e Cruz M, Chen E, Zhou Y, et al. A wearable ring oximeter for detection of sleep disordered breathing. Respir Med. 2025:242:108092. doi: 10.1016/j.rmed.2025.108092.

24. Zhao R XJ, Zhang X, Peng M, et al. Comparison of Ring Pulse Oximetry Using Reflective Photoplethysmography and PSG in the Detection of OSA in Chinese Adults: A Pilot Study. Nat Sci Sleep. 2022;14:1427-1436. doi: 10.2147/NSS.S367400. eCollection 2022.

25. Ou YH, Ong J, Thant AT, et al. The Belun sleep platform to diagnose obstructive sleep apnea in patients with hypertension and high cardiovascular risk. J Hypertens. 2023;41(6):1011-1017. doi: 10.1097/HJH.0000000000003426.

26. Debbiche I, Wang CC, Gomez-Roas M, et al. Rest assured: High sleep efficiency reduces postoperative complications and opioid prescriptions in patients undergoing surgeries with gynecologic oncologists. Gynecol Oncol. 2025:194:119-124. doi: 10.1016/j.ygyno.2025.01.007.

27. Donahue CC, Barnes LE, Hertel JN, Resch JE. Acute Changes in Sleep Stages Following Concussion in Collegiate Athletes: A Pilot Study. J Athl Train. 2025. doi: 10.4085/1062-6050-0629.24. Online ahead of print.

28. Hausenblas HA, Lynch T, Hooper S, et al. Magnesium-L-threonate improves sleep quality and daytime functioning in adults with self-reported sleep problems: a randomized controlled trial. Sleep Med X. 2024:8:100121. doi: 10.1016/j.sleepx.2024.100121

29. Breus M, Hooper SL, Lynch T, et al. Effectiveness of a grid mattress on adults' sleep quality and health: A quasi-experimental intervention study. Health Sci Rep. 2024;7(4):e2046. doi: 10.1002/hsr2.2046.

30. Armitage BT, Potts HWW, Irwin MR, Fisher A. Exploring the Impact of a Sleep App on Sleep Quality in a General Population Sample: pilot Randomized Controlled Trial. JMIR Form Res.

2024:8:e39554. doi: 10.2196/39554.

31. Ju E, Guo Y, Park JI, et al. Sleep Quality of Persons with Dementia and Family Caregivers in Korean Americans: Wearable Technology to Study the Dyadic Association. West J Nurs Res. 2025;47(5):404-412. doi: 10.1177/01939459251323675. Epub 2025 Mar 17.

32. Soon CS, Chua XY, Leong RLF, et al. A Longitudinal Study of Sleep in University Freshmen: Facilitating and Impeding Factors. Sleep. 2025:zsaf156. doi: 10.1093/sleep/zsaf156

33. Font R, Ortega-Becerra M, Tremps V, et al. Analysis of sleep quality and quantity during a half-season in world-class handball players. Biol Sport. 2025;42(3):247-255. doi: 10.5114/biolsport.2025.148578.

34. Willoughby AR, Vallat R, Ong JL, Chee MWL. Insights about travel-related sleep disruption from 1.5 million nights of data. Sleep. 2025;48(7):zsaf077. doi: 10.1093/sleep/zsaf077.

35. Viswanath VK, Hartogenesis W, Dilchert S, et al. Five million nights: temporal dynamics in human sleep phenotypes. NPJ Digit Med. 2024;7(1):150. doi: 10.1038/s41746-024-01125-5.

36. Liang T, Yilmaz G, Soon CS. Deriving Accurate Nocturnal Heart Rate, rMSSD and Frequency HRV from the Oura Ring. Sensors (Basel). 2024;24(23):7475. doi: 10.3390/s24237475.

37. Kinnunen H, Rantanen A, Kenttä T, Koskimäki H. Feasible assessment of recovery and cardiovascular health: accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG. Physiol Meas. 2020;41(4):04NT01. doi: 10.1088/1361-6579/ab840a.

38. van Steijn NJ, Pepplinkhuizen S, Postema PG, et al. Ventricular arrhythmia detection with a wearable ring-type photoplethysmography sensor: A feasibility study. Heart Rhythm. 2025:S1547-5271(25)02554-8. doi: 10.1016/j.hrthm.2025.06.008.

39. Kim J, Chang SA, Park SW. First-in-Human Study for Evaluating the Accuracy of Smart Ring Based Cuffless Blood Pressure Measurement. J Korean Med Sci. 2024;39(2):e18. doi: 10.3346/jkms.2024.39.e18.

40. Sanai F, Sahid AS, Huvanandana J, et al. Evaluation of a Continuous Blood Glucose Monitor: A Novel and Non-Invasive Wearable Using Bioimpedance Technology. J Diabetes Sci Technol. 2023;17(2):336-344. doi: 10.1177/19322968211054110.

41. Mason AE, Kasl P, Soltani S, et al. Elevated body temperature is associated with depressive

symptoms: results from the TemPredict Study. Sci Rep. 2024;14(1):1884. doi: 10.1038/s41598-024-51567-w.

42. Alzueta E, Gombert-Labedens M, Javitz H, et al. Menstrual Cycle Variations in Wearable-Detected Finger Temperature and Heart Rate, But Not in Sleep Metrics, in Young and Midlife Individuals. J Biol Rhythms. 2024;39(5):395-412. doi: 10.1177/07487304241265018.

43. Maijala A, Kinnunen H, Koskimäki H, et al. Nocturnal finger skin temperature in menstrual cycle tracking: ambulatory pilot study using a wearable Oura ring. BMC Womens Health. 2019;19(1):150. doi: 10.1186/s12905-019-0844-9.

44. Dupuit M, Barlier K, Tranchard B, et al. Heart Rate Variability Measurements Across the Menstrual Cycle and Oral Contraceptive Phases in Two Olympian Female Swimmers: A Case Report. Sports (Basel). 2025;13(6):185. doi: 10.3390/sports13060185.

45. Thigpen N, Patel S, Zhang X. Oura Ring as a Tool for Ovulation Detection: Validation Analysis. J Med Internet Res. 2025:27:e60667. doi: 10.2196/60667.

46. Basavaraj C, Grant AD, Aras SG, Erickson EN. Deep learning model using continuous skin temperature data predicts labor onset. BMC Pregnancy Childbirth. 2024;24(1):777. doi: 10.1186/s12884-024-06862-9.

47. Erickson EN, Gotlieb N, Pereira LM, et al. Predicting labor onset relative to the estimated date of delivery using smart ring physiological data. NPJ Digit Med. 2023;6(1):153. doi: 10.1038/s41746-023-00902-y.

48. Conroy B, Silva I, Mehraei G, et al. Real-time infection prediction with wearable physiological monitoring and AI to aid military workforce readiness during COVID-19. Sci Rep. 2022;12(1):3797. doi: 10.1038/s41598-022-07764-6.

49. Hadid A, McDonald EG, Ding Q, et al. Development of machine learning prediction models for systemic inflammatory response following controlled exposure to a live attenuated influenza vaccine in healthy adults using multimodal wearable biosensors in Canada: a single-centre, prospective controlled trial. Lancet Digit Health. 2025;7(7):100886. doi: 10.1016/j.landig.2025.100886.

50. Hirten RP, Danieletto M, Sanchez-Mayor M, et al. Physiological Data Collected From Wearable

Devices Identify and Predict Inflammatory Bowel Disease Flares. Gastroenterology. 2025;168(5):939-951.e5. doi: 10.1053/j.gastro.2024.12.024.

51. Ortiz A, Halabi R, Alda M, et al. Day-to-day variability in activity levels detects transitions to depressive symptoms in bipolar disorder earlier than changes in sleep and mood. Int J Bipolar Disord. 2025;13(1):13. doi: 10.1186/s40345-025-00379-6.

52. Reithe H, Marty B, Torrado JC, et al. Cross-evaluation of wearable data for use in Parkinson's disease research: a free-living observational study on Empatica E4, Fitbit Sense, and Oura. Biomed Eng Online. 2025;24(1):22. doi: 10.1186/s12938-025-01353-0.

53. Borelli JL, Wang Y, Li FH, et al. Detection of Depressive Symptoms in College Students Using Multimodal Passive Sensing Data and Light Gradient Boosting Machine: Longitudinal Pilot Study. JMIR Form Res. 2025:9:e67964. doi: 10.2196/67964.

54. Fudolig MI, Bloomfield LSP, Price M, et al. The Two Fundamental Shapes of Sleep Heart Rate Dynamics and Their Connection to Mental Health in College Students. Digit Biomark. 2024;8(1):120-131. doi: 10.1159/000539487.

55. Balsam D, Bounds DT, Rahmai AM, Nyamathi A. Evaluating the Impact of an App-Delivered Mindfulness Meditation Program to Reduce Stress and Anxiety During Pregnancy: Pilot Longitudinal Study. JMIR Pediatr Parent. 2023 Dec 25:6:e53933. doi: 10.2196/53933.

56. Croghan IT, Hurt RT, Fokken SC, et al. Stress Resilience Program for Health Care Professionals During a Pandemic: A Pilot Program. Workplace Health Saf. 2023;71(4):173-180. doi: 10.1177/21650799221093775

57. Rovini E, Galperti G, Manera V, et al. A wearable ring-shaped inertial system to identify action planning impairments during reach-to-grasp sequences: a pilot study. J Neuroeng Rehabil. 2021;18(1):118. doi: 10.1186/s12984-021-00913-4.

58. Qin S, Ng EKK, Soon CS, et al. Association between objectively measured, multidimensional sleep health and cognitive function in older adults: cross-sectional wearable tracker study. Sleep Med. 2025;132:106569. doi: 10.1016/j.sleep.2025.106569.

59. Kristiansson E, Fridolfsson J, Arvidsson D, et al. Validation of Oura ring energy expenditure and steps in laboratory and free-living. BMC Med Res Methodol. 2023;23(1):50. doi: 10.1186/s12874-

023-01868-x.

60. Niela-Vilen H, Azimi I, Suorsa K, et al. Comparison of Oura Smart Ring Against ActiGraph Accelerometer for Measurement of Physical Activity and Sedentary Time in a Free-Living Context. Comput Inform Nurs. 2022;40(12):856-862. doi: 10.1097/CIN.0000000000000885.

61. Bigalke JA, Lee KM, Bigalke JR, et al. Longitudinal assessment of objective sleep and power output in Division I collegiate baseball athletes. Sleep Health 2025;11(2):241-247. doi: 10.1016/j.sleh.2024.12.009.

62. Smith ES, Kuikman M, Rusell S, et al. 24-Hour Low Energy Availability Induced by Diet or Exercise Exhibits Divergent Influences on Sleep and Recovery Indices among Female and Male Cyclists. Med Sci Sports Exerc. 2025. Online ahead of print. doi: 10.1249/MSS.0000000000003783.

63. Lee S, Song Y, Lee J, et al. Development of Smart-Ring-Based Chest Compression Depth Feedback Device for High Quality Chest Compressions: A Proof-of-Concept Study. Biosensors (Basel). 2021;11(2):35. doi: 10.3390/bios11020035.

64. Ahn C, Lee S, Lee J, et al. Impact of a Smart-Ring-Based Feedback System on the Quality of Chest Compressions in Adult Cardiac Arrest: a Randomized Preliminary Study. Int J Environ Res Public Health. 2021;18(10):5408. doi: 10.3390/ijerph18105408.

65. Kubala AG, Roma PG, Jameson JT, et al. Advancing a U.S. navy shipboard infrastructure for sleep monitoring with wearable technology. Appl Ergon. 2024:117:104225. doi: 10.1016/j.apergo.2024.104225.

66. de Vries H, Kamphuis W, van der Schans C, Sanderman R, Oldenhuis H. Trends in Daily Heart Rate Variability Fluctuations Are Associated with Longitudinal Changes in Stress and Somatisation in Police Officers. Healthcare (Basel). 2022;10(1):144. doi: 10.3390/healthcare10010144.

67. Kasl P, Keeler Bruce L, Hartogensis W, et al. Utilizing Wearable Device Data for Syndromic Surveillance: A Fever Detection Approach. Sensors (Basel). 2024;24(6):1818. doi: 10.3390/s24061818.

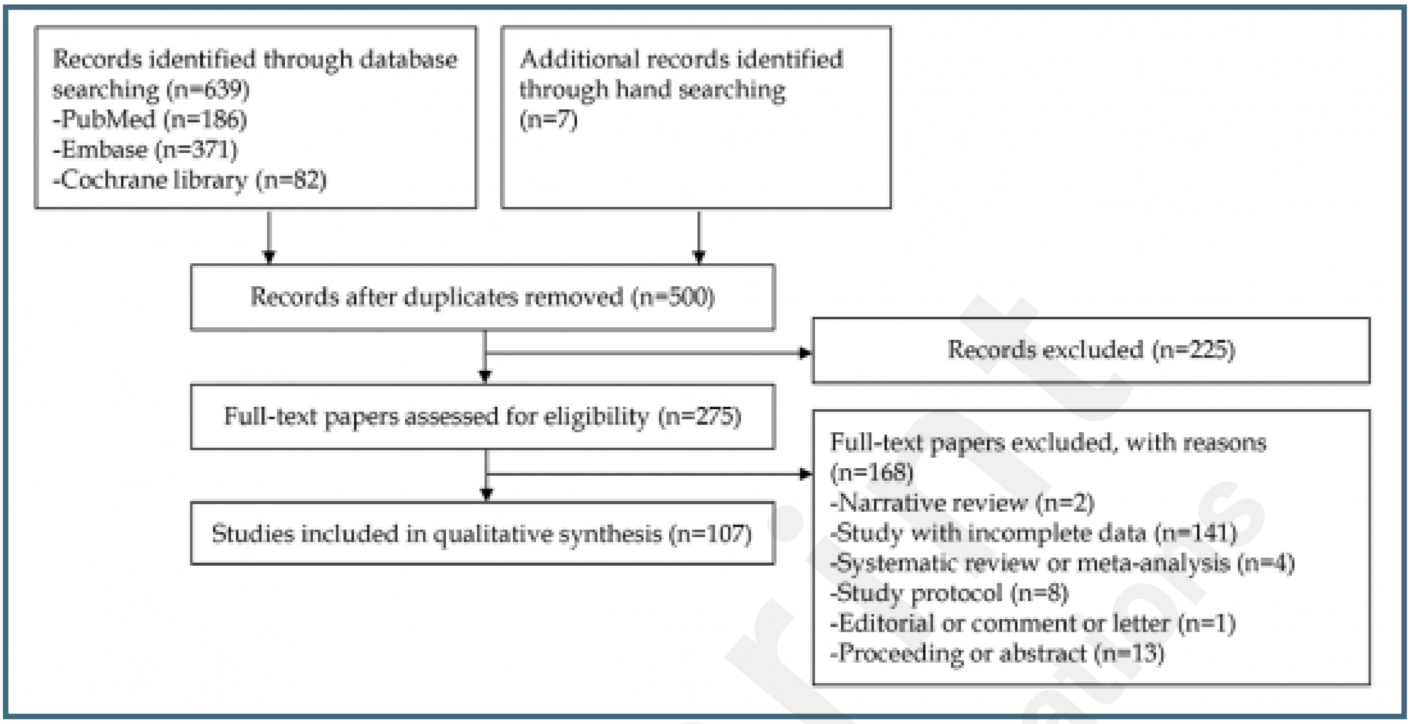
68. Sharifi-Heris Z, Fortier MA, Rahmani AM, Sharifiheris H, Bender M. Feasibility of continuous

smart health monitoring in pregnant population: A mixed-method approach. PLOS Digit Health. 2024;3(6):e0000517. doi: 10.1371/journal.pdig.0000517. eCollection 2024 Jun.

Supplementary Files

Figures

Study selection flow.



Multimedia Appendixes

Supplementary table 1-6.
URL: http://asset.jmir.pub/assets/92a979d1fcfe45319db83eea2c9d9c94.docx

PRISMA checklist.
URL: http://asset.jmir.pub/assets/92f02816efa2f112297a7d047c557811.docx