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*Systematic Review*

# The Use of Smart Rings in Health Monitoring—A Meta-Analysis

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**Abstract:** Smart Rings (SRs) are user-friendly devices capable of measuring various health parameters, making them suitable for remote continuous monitoring in diverse clinical settings. Since the available evidence on the accuracy of SRs recording health data is highly heterogeneous, this systematic review, conducted in accordance with PRISMA guidelines, searched for articles evaluating the efficacy of SRs for sleep, respiratory, and cardiovascular monitoring across the PubMed, SCOPUS, and ProQuest databases. Meta-analyses were conducted for health outcomes evaluated in at least three studies with a comparable study population and design, and the same comparison device. Nineteen articles were included: eleven analyses focused on sleep quality, eight on cardiovascular parameters, and one on oxygen saturation. Studies analysing cardiovascular outcomes found a good accuracy of SRs in measuring heart rate (HR) with a mean bias of −0.4 bpms (limits of agreement (LoAs): −2.7; 1.8). The meta-analyses showed variability in SRs' efficacy in monitoring total sleep time (mean bias: −21.3 min, LoAs: −69.9, 27.4) and REM duration (mean bias: −18.2 min, LoAs: −33.3, −3.1). The results highlighted the promising potential of SRs for HR monitoring. Further research is needed to clarify the reliability of SRs in monitoring sleep quality and their use directed to a broader range of health parameters. With further development, SRs could become valuable tools for healthcare professionals.

**Keywords:** smart ring; IoMT; sleep; cardiovascular; digital health; health monitoring; digital twin



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## 1. Introduction

The development of wearable health technology has introduced innovative tools suitable for real-time health monitoring, potentially transforming patient care and engagement. Connected devices such as smart rings (SRs) can monitor a range of physiological parameters. This study focuses on assessing the potential of SRs in healthcare—particularly for sleep and cardiovascular monitoring—through a systematic review and meta-analysis approach. Below, we introduce IoMT and its role in advancing wearable medical technology.

### *1.1. IoMT and Wearable Devices*

Internet of Medical Things (IoMT) refers to the integration of IoT (Internet of Things) technology into the healthcare sector [1]. This term indicates the use of connected devices, such as wearable sensors and smart medical equipment, to collect and exchange data to improve clinical decision making [2,3] (Figure 1A). Access to near-real-time data may alert users of emergency alterations in biomarkers, enabling timely medical interventions [4]. Moreover, IoMT represents an opportunity for empowering patients to monitor their own health data while potentially reducing patient care costs [5]. The combination of IoMT and telemedicine has the potential to improve patient care by allowing remote

monitoring [6]. This scenario eliminates costly in-person visits, leading to more efficient and cost-effective care [7,8]. However, IoMT faces some challenges. For example, the data integration between IoMT networks and Electronic Medical Records (EMRs) can be difficult to establish [9,10]. As IoMT devices generate large volumes of data in various formats, the lack of standard protocols complicates integration into EMR systems. Furthermore, differences in technology infrastructure across healthcare organizations and varying data-sharing regulations contribute to these difficulties. Privacy concerns and strict compliance requirements impose additional constraints on data transfer and storage, creating barriers to full integration [9–12].

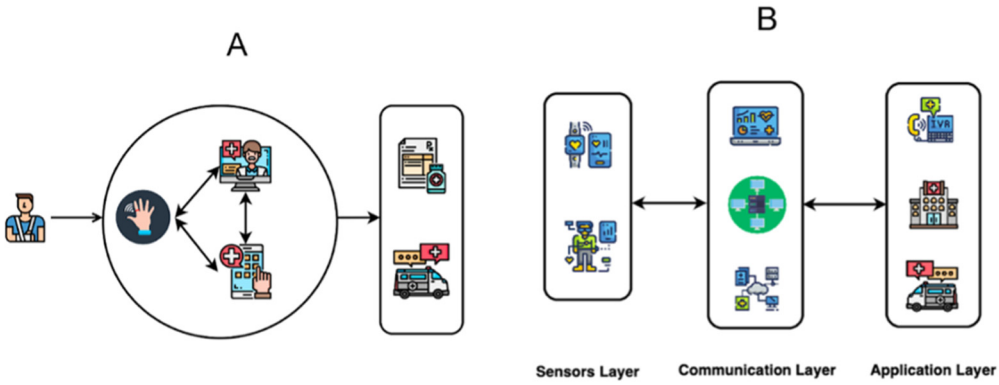


**Figure 1.** (**A**) SR's concept of function. The SR registers and collects the health data (SpO2, heart rate and others) communicating with smartphones or other devices. These data can be used to monitor patient vital signs and alert healthcare professionals to potential problems or changes in a patient's condition. (**B**) IoMT ecosystem architecture and layers. The collection layer consists of medical sensors. Devices collect the health data and transmit them to a gateway node. The communication layer stores those data and analyses them using conventional threshold values to report any abnormality. Last is the application layer: using a web-based interface, medical professionals can check and verify the diagnostics and take corresponding measures.

Moreover, healthcare institutions may struggle to collect all EMRs from different stakeholders due to data quality issues and administrative requirements, which is a major challenge in achieving interoperability [11]. Some studies have highlighted the potential privacy issues and patient data security [12,13]; thus, implementing appropriate data security strategies is essential to protect sensitive patient data [14]. Additionally, IoMT devices require high-quality evidence of their performance and accuracy before being used for clinical and diagnostic purposes.

### *1.2. Smart Rings*

SRs are compact devices worn on the finger that can monitor a variety of health metrics in real time [15], such as oxygen saturation (SpO2), heart rate (HR), sleep quality (SQ), physical activity level, and stress level [15]. SRs can be connected to smartphones or other devices [16], allowing users to view and monitor their data in real time [17] (Figure 1B). Two key benefits of SRs are their unobtrusive nature and user-friendliness, making them more comfortable to wear for extended periods of time [15], in contrast to traditional medical equipment that requires attaching sensors and wires to the body, or stationary applications that need a constant power supply [18]. The low-power design of SRs enables a prolonged usage [18] and continuous monitoring of physiological parameters in a range of clinical settings [19]. This feature allows the identification of clinical patterns that would otherwise be hard to detect [5,20]. SRs may help patients in managing their chronic disease by providing real-time feedback on their activity levels and vital signs. For example, patients with heart disease could use SRs to monitor their HR and receive alerts if it becomes abnormal [21]. Another explored application of SRs is in the mental health field, where metrics such as sleep quality, activity levels, and HR variability may provide

insight into a patient's emotional and psychological state allowing for early detection of mental health issues, such as depression and anxiety, and help patients better manage their condition [22].

Furthermore, continuous monitoring may act as a positive feedback mechanism, nudging patients towards healthy habits [23], such as engaging in more physical activity and improving sleep hygiene. One particular SR, the Oura Ring®, has become compatible with Natural Cycles, a Food and Drug Administration (FDA)-cleared birth control app [24]. This app analyses body temperature and other fertility indicators to determine fertility status, facilitating pregnancy planning or prevention. According to the current literature, multiple SR applications have been theorized, simulated, and commercialized, ranging from monitoring hand hygiene compliance [25,26] to providing feedback systems for evaluating chest compression efficacy [27].

### *1.3. Aim of the Study*

As the use of SRs in healthcare settings continues to expand, it is important to assess the reliability and accuracy of these devices. Previous studies have highlighted the potential risk of inaccurate data collection from IoMT, leading to erroneous diagnosis, unnecessary procedures, wasted resources, and increased costs [28–30]. Since the available evidence reporting the accuracy of SRs recording health data is highly heterogeneous, and a summary of the body of literature is not yet available, this systematic review and the meta-analysis aim to evaluate the efficacy of SRs in sleep, respiratory, and cardiovascular monitoring compared to approved medical devices. Additionally, this review seeks to synthesize the findings of the included studies to provide an overview of the potential impact of these tools on patient care, emphasizing the importance of accurate and reliable data in healthcare applications.

The structure of this paper is as follows: Section 2 covers the methods used in this systematic review, including data sources, inclusion criteria, and analytical techniques. Section 3 presents the main results on the accuracy of SRs in monitoring health parameters. Section 4 discusses the implications of these findings, considering both strengths and limitations. Section 5 offers limitations. Finally, Section 6 presents the conclusions, underlining the need for further research to fully establish smart rings as reliable health monitoring tools.

## 2. Materials and Methods

As IoMT grows, research is needed to measure the effectiveness of wearable health devices. This section explains the methods used in this study, focusing on how smart rings were evaluated for accuracy in health monitoring.

### *2.1. Data Sources and Searches*

The PRISMA Statement guidelines were followed while conducting this systematic review [28]. A comprehensive literature search was conducted using three databases: MEDLINE, Scopus, and ProQuest. Search strings were composed using relevant terms to identify articles that focused on evaluating SRs' performance in health monitoring compared to approved FDA or European Conformity (CE)-marked medical devices as benchmarks. This search strategy has been shown to be an efficient approach for systematic reviews of diagnostic test accuracy studies [29]. The search strategy recommended by the Cochrane Collaboration, which combines terms for the 'target condition' and 'index test', was employed [30]. The specific search strategy for each database is available in the Supplementary Material (Table S1) (last search update: 1 July 2024). Inclusion criteria encompassed primary peer-reviewed articles, published in English, and assessing the efficacy of SRs for monitoring sleep, respiratory, and cardiovascular parameters. Exclusion criteria included non-primary studies (i.e., meta-analyses, reviews, systematic reviews, scoping reviews, opinion papers), surveys, and articles published in languages other than

English. This systematic review was registered with PROSPERO (CRD42022374308) on 28 November 2022.

### 2.2. Data Extraction

Three pairs of reviewers (MF and AC, GT and AB, FS and GS) independently screened articles, initially by title and abstract, and subsequently by full text, to determine eligibility for inclusion. Discrepancies in reviewers' decisions were resolved through discussion within each pair. Reviewers performed data extraction on the same set of articles using a standardized extraction form to ensure the reliability of the data extraction and quality assessment process. In cases where consensus on screening or data extraction could not be attained, a third independent author (DG) resolved the decision conflict. The data extraction explored multiple variables: first author, year of publication, country, number of participants, mean age, gender distribution, type of SR, control device, total time of recording, type of estimates, specific measured outcome, SR's accuracy results, and conflicts of interest. The extracted variables were summarized and reported through tabulation.

### 2.3. Quality and Risk of Bias Assessment

Risk of bias assessment of the included studies was carried out independently in pairs using the validated Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool [31]. The Grading Quality of Evidence and Strength of Recommendations methodology was applied to rate the quality of evidence [32]. Reasons used to downgrade the quality of evidence were study limitations, inconsistency, and imprecision. Indirectness was not used as a downgrading reason because studies that were not relevant were excluded before the quality assessment. Publication bias was not formally assessed so the possibility of this bias was not excluded but not considered sufficient to require downgrading the quality of evidence.

### 2.4. Data Synthesis and Analysis

To assess the consistency and accuracy of smart rings in health monitoring, we synthesised data from eligible studies and performed meta-analyses on various outcomes. Our criteria mandated that any outcome be assessed in at least three studies, and that the SR be compared with a gold-standard control device, grounding our findings in validated clinical metrics. According to the Cochrane Handbook for Systematic Reviews of Interventions [30], the use of rigorously validated control devices is essential for ensuring the accuracy and reliability of diagnostic comparisons. In the medical field, gold-standard devices like polysomnography (PSG) for sleep monitoring and pulse oximetry for oxygen saturation are widely validated [33,34].

We primarily employed the Bland–Altman method for our meta-analysis, a technique specifically tailored for comparing two methods of clinical measurement. This method evaluates the agreement between two quantitative measurements by constructing limits of agreement (LoAs). These LoAs are established around the mean difference between measurements and provide a range within which 95% of the differences between measurements lie. Using the Bland–Altman framework for meta-analysis, we utilised a limits of agreement (LoAs) approach described by Tipton [35]. This method was chosen not only because of its extensive application in primary Bland–Altman studies but also due to its capability to provide an estimate of the pooled LoAs in the larger population, transcending just the sampled individuals. It is worth noting that the 'population LoA' derived from this approach tends to be wider than those frequently reported in meta-analyses of Bland–Altman studies [35].

The pooled LoAs were determined using the formula $\delta \pm 2\sqrt{(\tau^2 + \sigma^2)}$, where:

- $\delta$ represents the average bias across studies (mean difference between the two methods across all studies).
- $\tau^2$ represents the between-study variation, capturing the variability in differences across studies.

- $\sigma^2$ signifies the average within-study variation in differences.

Estimates for both $\delta$ and $\sigma^2$ were derived by employing a weighted least-squares model, to account for the varying levels of precision in the studies included in our meta-analysis, providing a more balanced estimation, and minimizing the potential bias from smaller studies with high variability [36]. To calculate their standard errors (SEs), we adopted the robust variance estimation (RVE) technique. This decision was made given the presence of studies included in our review that implemented repeated-measures designs but did not accommodate for potential correlations between measurements [37]. For uniformity and ease of meta-analysis, results from individual studies were standardised (for example, HR was expressed in beats per minute (bpms); total sleep time and rapid eye movement duration were indicated in minutes). All computations were executed using the R-Studio statistical software (v.4.4.2, RStudio, PBC, Boston, MA, USA). The code relative to the data analyses is reported in the Supplementary Material (S2).

## 3. Results

This section reviews the findings on smart rings' performance in monitoring health data, including sleep, cardiovascular parameters, and oxygen levels. It highlights the strengths and limitations of smart rings for monitoring these metrics.

### *3.1. Study Selection and Description*

The initial search identified 5786 articles (PubMed n = 276, Scopus n = 351, ProQuest = 5159). A total of 753 studies were excluded after the deduplication process. A total of 5033 articles were screened, with 4977 excluded at the title/abstract screening stage. A total of 56 articles were assessed for eligibility by full-text evaluation. A final number of 19 articles [38–56] met the criteria for final inclusion (Figure 2). In order to synthetize the characteristics and the results of the included studies, all the extracted data are reported in Table 1 (as mentioned above, the information extracted were: first author, year of publication, country, number of participants, mean age, gender distribution, type of SR, control device, total time of recording, type of estimates, specific measured outcome, SR's accuracy results, and conflicts of interest). Ten studies explored sleep quality, one both sleep and cardiovascular parameters, seven only cardiovascular parameters, and one SaO2. All articles included in this systematic review were published between 2017 and 2024, with one published in 2017, four in 2020, four in 2021, four in 2022, two in 2023, and four in 2024. The studies were conducted in various countries, with five studies in the USA, two in Switzerland, three in Singapore, one in Australia, three in South Korea, three in Finland, one in Japan, and one in multiple countries. The populations were comprised of adolescents in one study, adolescents and adults in two, healthy adults in thirteen, adults with persistent atrial fibrillation (AF) in one, adults undergoing invasive blood pressure monitoring in one, and adults with sleep disorders in one. The mean number of participants enrolled was 49, with a range of 5 to 118 patients. Eleven studies analysed the efficacy of SRs in measuring sleep quality parameters, seven assessed their efficacy in measuring cardiovascular parameters, and one analysed the efficacy of SRs on measuring oxygen saturation (Table 1). Moreover, no studies analysing the cost-effectiveness of implementing SRs in sleep, cardiovascular, or respiratory monitoring were found.

**Table 1.** Characteristics of the studies using smart rings for health monitoring (sleep, cardiovascular, and SaO2 outcomes).

| Authors | Year | Country | Study Population | Sample Size | Mean Age (Years) | Gender | Ring Type | Control Device | Time Recording | Type Estimate | Specific Outcome | Measure of Assessment | Financial Statement |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sleep Quality | | | | | | | | | | | | | |
| Altini et al. [38] | 2021 | Multiple | Adolescents and healthy adults | 118 | 30.1 ± 16.4 | F:65; M:53 | OURA 2nd Gen | PSG | 440 nights | Bland–Altman Plots | TST (min) | 16.3 (12.9) | Conflicts of interest emerge |
| | | | | | | | | | | | Light sleep (min) | 58.1 (56.9) | |
| | | | | | | | | | | | Deep sleep (min) | 26.9 (29.9) | |
| | | | | | | | | | | | REM sleep (min) | 42.8 (40.5) | |
| Ghorbani et al. [44] | 2022 | Singapore | Healthy adults | 58 | 37.1 ± 13.0 | F:27; M:32 | OURA 2nd Gen | PSG | 3 nights | Bland–Altman Plots | TST (min) | −18.1 (23.4) | Yes, both from public and private |
| | | | | | | | | | | | Sleep efficiency | No Data | |
| | | | | | | | | | | | Light sleep (min) | −46.9 (42.2) | |
| | | | | | | | | | | | Deep sleep (min) | 49.9 (47.4) | |
| | | | | | | | | | | | REM sleep (min) | −21.1 (37.6) | |
| | | | | | | | | | | | WASO (min) | 16.7 (25.3) | |
| Chee et al. [42] | 2021 | Singapore | Adolescents | 52 | n/a | F:30; M:29 | OURA 2nd Gen | PSG | 15 nights | Bland–Altman Plots | TST (min) | −47.3 (24.6) | Not specified |
| | | | | | | | | | | | N1 + N2 (min) | −81.2 (32.2) | |
| | | | | | | | | | | | N3 (min) | 46.8 (36.3) | |
| | | | | | | | | | | | WASO (min) | 46.3 (22.0) (min) | |
| | | | | | | | | | | | REM (min) | −12.8 (28.9) (min) | |
| De Zambotti et al. [43] | 2017 | USA | Adolescents and healthy adults | 41 | 17.2 ± 2.4 | F:13; M:28 | OURA 1st Gen | PSG | 1 night | Bland–Altman Plots | TST (min) | −1.3 (21.7) (min) | Yes, from public |
| | | | | | | | | | | | SOL (min) | −0.2 (7.0) (min) | |
| | | | | | | | | | | | WASO (min) | 1.5 (20.7) (min) | |
| | | | | | | | | | | | N1 + N2 (min) | −3.7 (66.2) (min) | |
| | | | | | | | | | | | N3 (min) | 19.6 (41.2) (min) | |
| | | | | | | | | | | | REM (min) | −17.2 (50.2) (min) | |
| Asgari Mehrabadi et al. [39] | 2020 | Finland | Healthy adults | 45 | 33.1 ± 6.4 | F:23; M:22 | OURA 2nd Gen | Actigraphy | 6 nights | Bland–Altman Plots | TST (min) | −15.3 (39.7) (min) | Not specified |
| | | | | | | | | | | | Sleep Efficiency (%) | 1.3 (5.9) | |
| | | | | | | | | | | | WASO (min) | 17.4 (28.2) (min) | |
| Stone et al. [53] | 2020 | USA | Healthy adults | 5 | F: 22, 23, and 27; M: 41 and 26 years | F:3; M:2 | OURA 2nd Gen | EEG | 98 nights | Bland–Altman Plots | TST (min) | 0.2 (0.0, 0.4) (min) | Independent third-party evaluation |
| | | | | | | | | | | | SE | 1.7 (0.2, 3.2) | |
| | | | | | | | | | | | TWT (min) | −0.2 (−0.3, 0.0) (min) | |
| Miller et al. [50] | 2022 | Australia | Healthy adults | 53 | 25.4 ± 5.9 | F:26; M:27 | OURA 2nd Gen | PSG | 1 night | Bland–Altman Plots | TST (min) | 1.5 (40.9) (min) | Not specified |

**Table 1.** *Cont.*

| Authors | Year | Country | Study Population | Sample Size | Mean Age (Years) | Gender | Ring Type | Control Device | Time Recording | Type Estimate | Specific Outcome | Measure of Assessment | Financial Statement |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Lee et al. [48] | 2023 | South Korea | Adults with sleep disorders | 53 | 43.6 ± 14.1 | 36 F; 39 M | OURA 3rd Gen | PSG | 350 h | Bland–Altman Plots; sensitivity, specificity | N1 (min)<br>N2 (min)<br>Light sleep (min)<br>Deep sleep (min)<br>REM sleep (min)<br>Deep/REM (min)<br>Wake (min)<br>HR (bpms)<br>HRV (RMSSD, ms)<br>Light sleep (sensitivity)<br>Light sleep (specificity)<br>Deep sleep (sensitivity)<br>Deep sleep (specificity)<br>REM (sensitivity)<br>REM (specificity)<br>REM (Bland–Altman Bias) | No data<br>No data<br>19.8 (57.4) (min)<br>2.4 (56.4) (min)<br>−20.7 (35.3) (min)<br>No data<br>−3.1 (36.1) (min)<br>0.1 (4.5)<br>−10.2 (39.4)<br>0.51<br>0.76<br>0.78<br>0.80<br>0.71<br>0.87<br>−9.5 | Yes, from public |
| Ong et al. [51] | 2023 | Singapore | Healthy adults | 60 | 38.5 ± 15.1 | 34 F; 26 M | OURA 3rd Gen | PSG | 1 night | Bland–Altman Plots | TST<br>WASO<br>Light Sleep<br>Deep sleep<br>REM<br>SE (%) | 0.9 (34.6)<br>−11.2 (30.6)<br>−14.7 (38.4)<br>7.6 (30.5)<br>8.1 (24.2)<br>0.2 (8.2) | Yes, both from public and private |
| Kainec et al. [45] | 2024 | USA | Healthy adults | 53 | 22.5 ± 3.5 | 31 F; 22 M | OURA 2nd Gen | PSG | 1 night | Bland–Altman Plots | TST<br>WASO<br>Light Sleep<br>Deep sleep<br>REM<br>SE (%) [Dominant Hand] | −13.9 (41.1)<br>39.6 (0.4 x ref)<br>−49.5 (59.0)<br>94.9 (0.6 x ref)<br>5.8 (37.7)<br>1.5 (4.2) | Yes, from public |
| Svensson et al. [55] | 2024 | Japan | Healthy adults | 96 | 41.9 ± 13.8 | n/a | OURA 3rd Gen | PSG | ≤3 nights | Bland–Altman Plots | | | Yes, from private |

**Table 1.** *Cont.*

| Authors | Year | Country | Study Population | Sample Size | Mean Age (Years) | Gender | Ring Type | Control Device | Time Recording | Type Estimate | Specific Outcome | Measure of Assessment | Financial Statement |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | TST [Dominant Hand] | 3.6 (25.0) | |
| | | | | | | | | | | | Light Sleep [Dominant Hand] | −4.2 (23.2) | |
| | | | | | | | | | | | Deep sleep [Dominant Hand] | 2.2 (33.4) | |
| | | | | | | | | | | | REM [Dominant Hand] | 5.6 (17.6) | |
| | | | | | | | | | | | SE (%) [Non-Dominant Hand] | 1.1 (4.8) | |
| | | | | | | | | | | | TST [Non-Dominant Hand] | 2.1 (26.2) | |
| | | | | | | | | | | | Light Sleep [Non-Dominant Hand] | −5.0 (40.5) | |
| | | | | | | | | | | | Deep sleep [Non-Dominant Hand] | 3.1 (33.8) | |
| | | | | | | | | | | | REM [Non-Dominant Hand] | 4.1 (17.8) | |
| Cardiovascular outcomes | | | | | | | | | | | | | |
| Miller et al. [50] | 2022 | Australia | Healthy adults | 53 | 25.4 ± 5.9 | F:26; M:27 | OURA 2nd Gen | PSG | 1 night | Bland–Altman Plots [mmHg] | HR (bpms); HRV (RMSSD, ms) | 0.1 (4.5) −10.2 (39.4) | Not specified |
| Cao et al. [41] | 2022 | Finland | Healthy adults | 35 | 32.3 ± 6.4 | F:19; M:16 | OURA 3rd Gen | ECG | 1 night | Bland–Altman Plots | HR (bpms) | −0.4 (−0.9, 0.0) | Yes, from public |
| Schukraft et al. [52] | 2022 | Switzerland | Adults requiring invasive BP monitoring | 25 | 68.9 ± 6.4 | F:10; M:15 | Senbiosys device (SBF2003) | Invasive BP measure-ments | 9 min | Bland–Altman Plots [mmHg] | SBP | 2.3 ± 11.3 | Yes, from public |
| | | | | | | | | | | RMSE [mmHg] | | 7.3 | |
| | | | | | | | | | | Bland–Altman Plots [mmHg] | DBP | BAP: 0.5 ± 6.9 | |
| | | | | | | | | | | RMSE [mmHg] | | RMSE: 3.6 | |
| | | | | | | | | | | RMSE [mmHg] | MBP | RMSE: 3.6 | |
| Kinnunen et al. [46] | 2020 | Finland | Adults | 60 | 31.6 ± 11.8 | F:40; M:20 | OURA 1st Gen | ECG | 5 min segment; 1 night | Bland–Altman Plots | HR (bpms) | −0.6 [−1.4, 0.1] | Yes, from private |
| Stone et al. [54] | 2021 | USA | Healthy adults | 5 | 20.33 ± 2.08 F: 19.50 ± 0.71 | F:2; M:3 | OURA 2nd Gen | ECG (5 lead) | 3 or 5 min | Bland–Altman Plots | HR (bpms) | −2.3 (−5.6, 0.9) | Yes, from private |

**Table 1.** *Cont.*

| Authors | Year | Country | Study Population | Sample Size | Mean Age (Years) | Gender | Ring Type | Control Device | Time Recording | Type Estimate | Specific Outcome | Measure of Assessment | Financial Statement |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Kwon et al. [47] | 2020 | Korea | Adults with persistent AF who underwent cardioversion recruited prospectively | 100 | 63.8 ± 8.5 | F:19; M:81 | CART (Sky Labs Inc) + Deep Learning Algorithm | ECG (1 lead) | 15 min | Accuracy, Sensitivity, Specificity, Positive predictive value, Negative predictive value, AUCa (95% CI) | AF | Accuracy: 96.9<br>Sensitivity: 98.9<br>Specificity: 94.3<br>Positive predictive value: 95.6<br>Negative predictive value: 98.7<br>AUCa (95% CI): 0.99 (0.99–0.99) | Yes, from private |
| Boukhayma et al. [40] | 2021 | Switzerland | Healthy adults | 7 | 34.3 ± 5.3 | M:7 | Prototype | ECG (4 leads) | 37.10 h of sleep and 35.11 h of wake recording | MAE; ME; RMSE; MAPE | beat-to-beat detection accuracy; | (MAE) of 8.10 ms; (ME) of 0.24 ms; (RMSE) of 13.97 ms; (MAPE) of 0.80% | Not specified |
| Kim et al. [56] | 2024 | Korea | Healthy adults | 89 | 40.1 ± 12.0 | M: 42; F: 47 | CART (Sky Labs Inc) | BP measurement by auscultation | 526 SBP samples; 513 DBP samples | Bland–Altman | SBP<br>DBP | 0.2 (5.9)<br>−0.1 (4.7) | Yes, from private |
| SaO2 outcomes | | | | | | | | | | | | | |
| Mastrototaro et al. [49] | 2024 | USA | Healthy adults | 11 | 26.9 ± 4.1 | F: 5; M: 6 | Prototype | Masimo Radical-7 pulse oximeter | n/a; 258 samples | RMSE | SaO2 | 2.1% | Yes, from private |

M: Male; F: Female; OURA: Oura Ring®; Gen: generation; PSG: polysomnography; TST: total sleep time; REM: rapid eye movement; WASO: Wake After Sleep Onset; N1, N2, N3: Stages of NREM Sleep (N1: light sleep, N2: intermediate-depth sleep, N3: deep sleep or slow-wave sleep); SE: Sleep Efficiency; SOL: Sleep Onset Latency; EEG: Electroencephalography; HR: heart rate; HRV: heart rate variability; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure; MBP: Mean Blood Pressure; ECG: Electrocardiogram; AF: atrial fibrillation; BPMs: Beats Per Minute; RMSSD: Root Mean Square of the Successive Differences; AUCa (95% CI): Area Under the Curve with 95% confidence interval; BAPs: Bland–Altman Plots; MAE: Mean Absolute Error; ME: Mean Error; RMSE: Root Mean Square Error; MAPE: Mean Absolute Percentage Error.

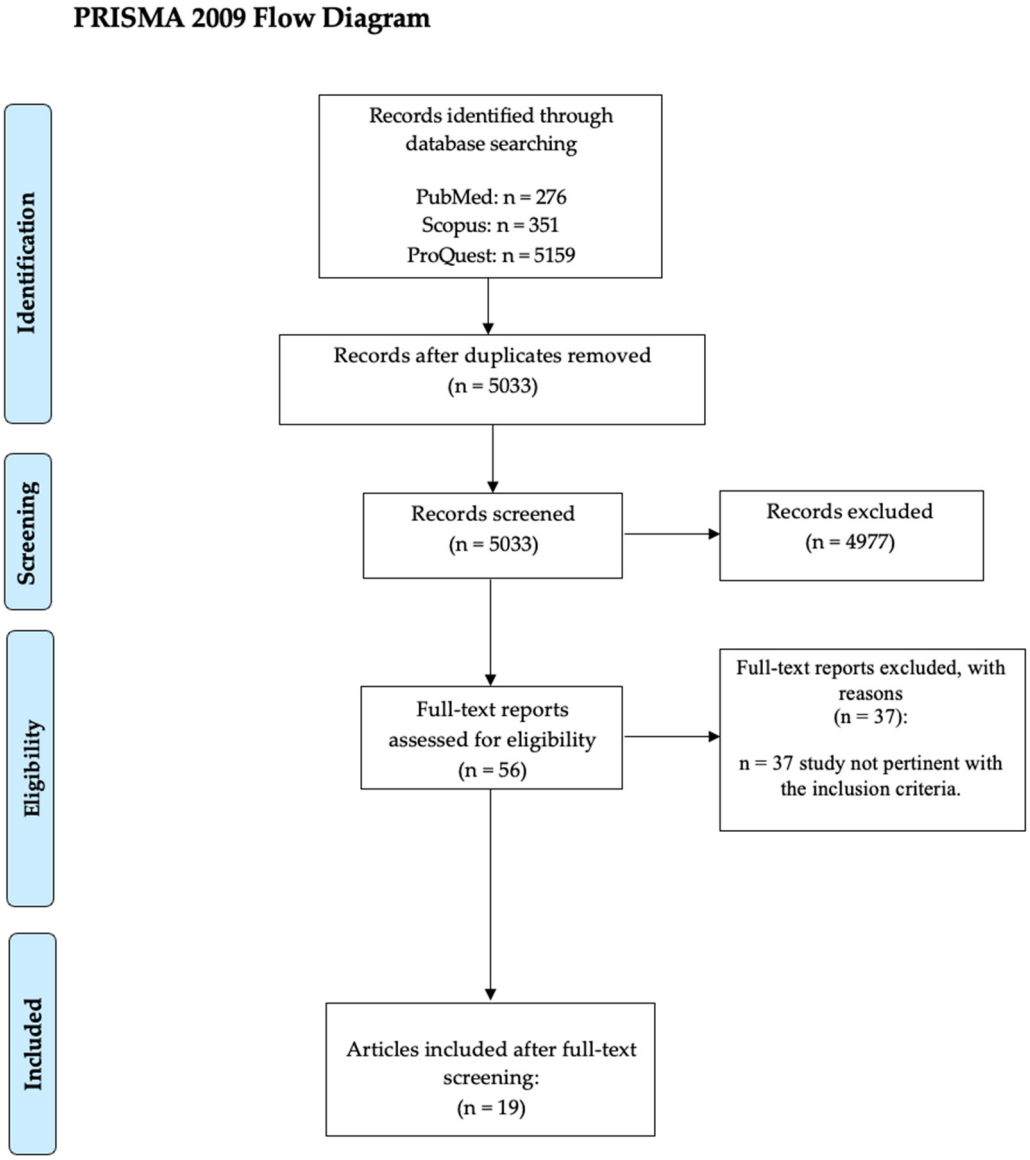


**Figure 2.** PRISMA flowchart describing the selection process of the included studies.

### *3.2. Sleep Quality*

A total of eleven studies assessed the accuracy of SRs in measuring sleep quality outcomes (Table 1). The mean nights of recording were 57 ± 138, with a range from of one to 440 nights. The second generation of Oura Ring® was the most studied type of SR, in seven studies, and the first generation of Oura Ring® was analysed in one, while three focused on the third generation of Oura Ring®. The control devices were the standard PSG in nine studies, actigraphy in one, and electroencephalography (EEG) in one (Figure 3). In three studies, funding was not specified, three studies were funded by public resources, two from both public and private fundings, one was an independent third-party evaluation, and in one, conflicts of interest emerged. The outcomes explored were: total sleep time (TST) in ten studies, rapid eye movement (REM) time in nine, light sleep time in seven, deep sleep time in seven, N1 and N2 sleep (equivalent to light sleep) in two, N3 sleep (equivalent to deep sleep) in two, Wake After Sleep Onset (WASO) in six, and Sleep Efficiency (SE) in four. All outcomes were analysed through Bland–Altman Plots. The studies' results demonstrate heterogeneity in the data, indicating that the estimates may not always be statistically accurate. A meta-analysis was conducted on three studies that analysed the accuracy of the second generation of Oura Ring® compared to PSG (Table 2). These meta-

analyses showed a pooled mean bias for TST equal to −21.30 min (SD = 5.4, LOA_L = −69.9, LOA_U = 27.4, CI_Lm = −45,916.4, CI_Um = 45,873.8), and a pooled mean bias for REM sleep equal to −18.2 min (SD = 5.8, LOA_L = −33.3, LOA_U = −3.1; CI_Lm = −281.5, CI_Um = 245.1). The sensitivity analyses also showed the presence of strong uncertainty around the results for the TST outcome due to the width of the LoAs confidence intervals, without substantially altering the interpretation of the main analysis results. However, the sensitivity analysis for REM obtained by removing the results from Chee et al. [42] showed a substantial decrease in the uncertainty of the results with a pooled mean bias of −20.8 min (SD = 6.1; LoA_L = −32.9; LoA_U = −8.8; CI_Lm = −36.3; CI_Um = −5.4), denoting a very low heterogeneity between the results of the two remaining studies for this outcome [44,50] (Table S3).

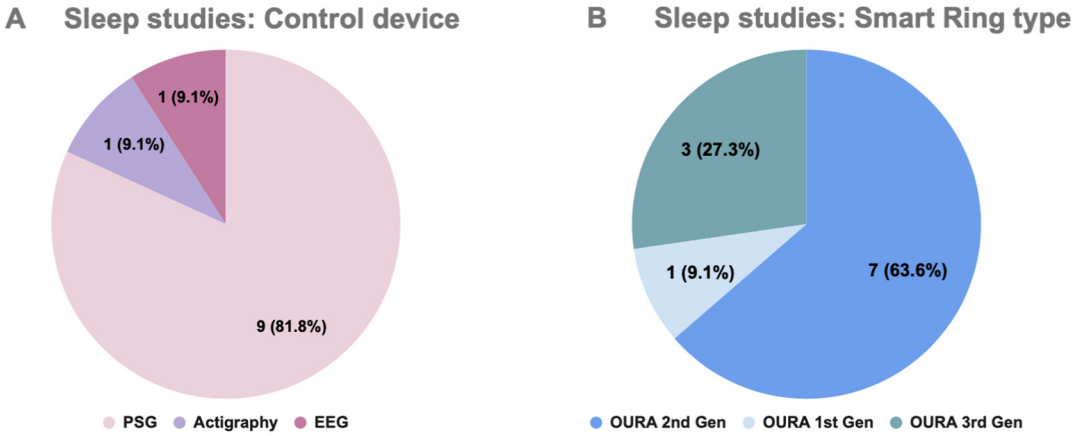


**Figure 3.** (**A**) Sleep studies: control device characteristics. PSG: polysomnography. EEG: electroencephalography. (**B**) Sleep studies: smart ring characteristics. Gen: generation.

**Table 2.** Results of the meta-analyses of the accuracy of Oura Ring® in monitoring sleep quality compared to PSG.

| | Mean Bias (min) | SD | LoAs | CI_Lm | CI_Um |
|---|---|---|---|---|---|
| TST | −21.3 | 5.4 | −69.9, 27.4 | −45,916.4 | 45,873.8 |
| REM | −18.2 | 5.8 | −33.3, −3.1 | −281.5 | 245.1 |

Abbreviations: SD = Standard Deviation, LoAs = limits of agreement, CI_Lm = 95% confidence interval lower bound of the lower LoA, CI_Um = 95% confidence interval upper bound of the upper LoA.

### *3.3. Cardiovascular and SaO2 Parameters*

A total of eight studies analysed the accuracy of SRs in measuring cardiovascular outcomes (Table 1). The recording duration ranges between a minimum of 9 min to a maximum of 37.1 h of sleep. The accuracy of Oura Ring® devices was analysed in four studies: two studies analysed the second generation, and one the first generation, and one study the third one. Other types of SR analysed in the studies included CART Ring® in two studies, Senbiosys® in one study, and a prototype in one study. The control devices were ECG in five studies, an invasive Blood Pressure device in one study, a PSG in one study and the measurement of BP by auscultation in one (Figure 4). The outcomes explored were heart rate (HR) in five studies, atrial fibrillation (AF) in one study, and Systolic, Diastolic and Mean Blood Pressure (SBP, DBP, MBP) in two studies. Financial statements and possible conflict of interest were explored: in two studies funding was not specified, two were funded by public resources, four received private funding. A meta-analysis was conducted including three studies that analysed the accuracy of Oura Ring® devices in measuring nocturnal HR compared to ECG (Table 3). The meta-analysis found a pooled mean bias for nocturnal HR of −0.41 (SD = 1.09; LOA_L = −2.65, LOA_U = 1.81; CI_Lm = −5.95, CI_Um = 5.11).

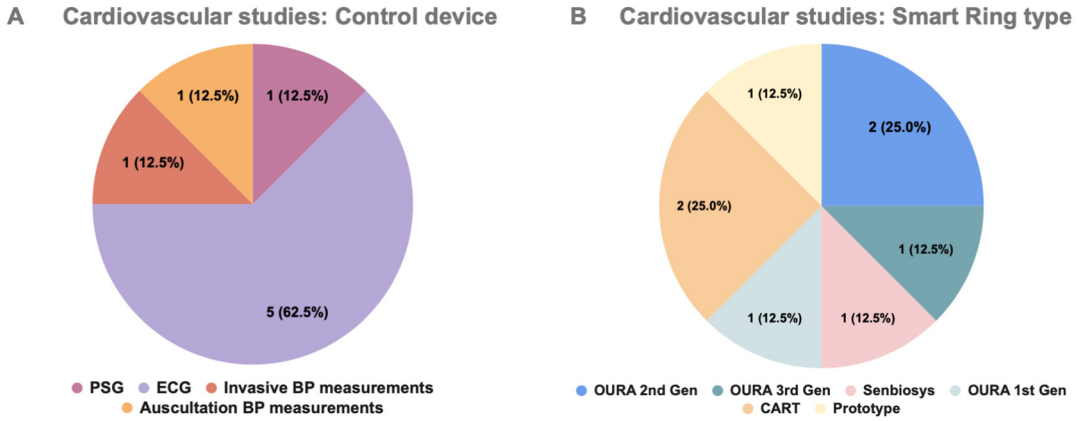


**Figure 4.** (**A**) Cardiovascular studies: control device. PSG: polysomnography. ECG: Electrocardiogram. BP: Blood Pressure. (**B**) Cardiovascular studies: smart ring type. Gen: generation.

**Table 3.** Results of the meta-analyses of the accuracy of Oura Ring® in monitoring cardiovascular parameters compared to PSG.

| | Mean Bias (min) | SD | LoAs | CI_Lm | CI_Um |
|---|---|---|---|---|---|
| Nocturnal HR | −0.4 | 1.1 | −2.7, 1.8 | −6.0 | 5.1 |

Abbreviations: SD = Standard Deviation, LoAs = limits of agreement, CI_Lm = 95% confidence interval lower bound of the lower LoA, CI_Um = 95% confidence interval upper bound of the upper LoA.

Only one study assessed the precision of SRs in measuring oxygen saturation (SaO2) with respect to a pulse oximeter (Table 1). The study was carried out in the USA, using a prototype as SR, and Masimo Radical-7 pulse oximeter as a control device, with eleven healthy adults, and it received private funding. The overall Root Mean Square Error for the SR was approximately 2.1% for both the finger and the fingertip placement.

## 4. Discussion

The main findings of this meta-analysis are the following: (a) smart rings show promising accuracy in heart rate monitoring; (b) their reliability in measuring sleep phases is highly variable; (c) this variability underscores the need for standardized research methodologies.

### *4.1. Meta-Analysis on Sleep Outcomes*

The meta-analyses on sleep outcomes revealed a considerable variability in the accuracy of SRs in analysing different sleep phases, due to the between-studies heterogeneity in the point estimates for mean biases and the considerable width of the LoAs confidence intervals. The considerable variability across studies may result from the lack of standardization in recording duration. This diversity in study protocols may impact the accuracy and reliability of sleep quality assessments using SRs, leading to the observed heterogeneity in outcomes. Future research should standardize protocols for SR validation in sleep monitoring to ensure more consistent and clinically meaningful results. Additionally, given the potential impact of smart ring technology on public health and quality of life, further exploration of its role in sleep quality monitoring is crucial [57]. In a study by Altendahl et al. [58], results indicate that duration of REM sleep may be a greater contributor to brain white matter integrity than overall sleep quality. Sleep deprivation, both in quality and duration, is associated with increased mortality risk [59,60]. This underlines the potential importance and benefits of monitoring REM and sleep time. As SRs may be suitable for this purpose, further studies analysing their accuracy are needed. Furthermore, SRs only cost USD 100–USD 300, a fraction of the costs associated with the equipment and expertise needed for PSG. Thus, these devices are potentially cost-effective sleep measurement

tools [48]. However, no study has assessed both the direct and indirect cost and considered all the health and economic benefits.

The included studies varied by study population, potentially affecting the generalizability of the results. This could also partly explain the wide uncertainty that emerged from the meta-analytical findings, since sensitivity analyses on Oura® accuracy in measuring REM, obtained by excluding the results from the one study on adolescents [42], showed an important reduction in LOAs' and CIs' width, denoting that different age groups may respond differently to sleep quality measurements.

### 4.2. Meta-Analysis on Cardiovascular Outcomes

The second meta-analysis suggests a clinically acceptable accuracy of SRs in measuring HR, considering a cut-off error of 5% between the SR measurement and the gold-standard device measurement, as suggested by Shcherbina et al. [61]. These findings suggest that SRs may represent a useful tool for monitoring HR. However, further research is needed to evaluate their capabilities in monitoring HR variability and detecting arrhythmias. These investigations would be essential for FDA and CE approval and the use of SRs in clinical practice. Unlike traditional HR monitors, which often require straps or electrodes, SRs are discrete and can be worn continuously, making them an attractive and non-invasive option for individuals who require continuous HR monitoring [62], such as atrial fibrillation patients [63].

### 4.3. Expanding the Role of Smart Rings in Digital Health

This systematic review underscores the growing interest in SR technology as a health monitoring tool. The expansion of the IoMT industry [64–67] suggests that healthcare professionals and patients will have access to a broader array of health data [68]. The integration of AI, big data, and machine learning algorithms could enable real-time data analysis and insights for clinicians and patients [69,70]. The results are in line with the current performance of other smart wearables. For example, a recent meta-analysis assessing the accuracy of smartwatches in detecting AF showed a specificity of 94% and a sensitivity of 93%. Moreover, wearable devices show promising results in monitoring the athlete's internal and external workloads, though their technology readiness level needs substantial developments, particularly in acquiring more effective biomarkers [71,72].

As part of the digital health ecosystem, SRs offer unique opportunities for building Digital Twins and developing personalized treatment plans [73,74]. Data acquired through SRs can be used to develop treatment plans tailored to the patient's specific needs, improving the efficacy of the treatment and reducing the risk of adverse events [75]. This could lead to advances in patient care and clinical decision making and potentially enhance patient–doctor relationships by streamlining communication, providing access to health information, and enabling remote monitoring and care [76,77]. However, digital health technologies must complement and empower the patient–doctor relationship, which is essential for fostering trust and empathy, both correlated with better health outcomes [78]. SRs have the potential to promote patient engagement by providing feedback and monitoring progress, which can motivate patients to make healthy lifestyle choices [79]. However, more studies are needed to understand the power of this technology in promoting a healthy lifestyle [80] and to improve adherence to treatment plans [81].

### 4.4. Challenges and Future Directions

Despite the potential of SRs to promote patient engagement and healthy lifestyle choices, more research is needed to understand their influence on behaviour and treatment adherence. Further studies may focus on standardizing the methodology of the SR accuracy assessment and measuring different sleep and cardiovascular parameters across diverse patient populations. In particular, by aligning study designs, we can better evaluate SR reliability and accuracy. Further research with diverse and larger populations is critical to validate SRs as a consistent and reliable tool in clinical practice.

Ensuring the security and reliability of SR technology is another challenge [82]. Continuous connectivity requires fault-tolerant networks with backup systems. Cybersecurity is crucial to protect patient data and maintain the digital health ethical standards [82]. Additionally, evaluating the cost–benefit and financial sustainability of SRs in healthcare systems is crucial for understanding their potential scalability and accessibility. As the technology matures and gains approval from regulatory bodies, continued investment in research and development will be necessary to maximize the potential of SRs.

## 5. Limitations

Our systematic review and meta-analysis present several limitations that should be considered when interpreting the results. The included studies exhibit considerable heterogeneity in methodology, such as the choice of the study population and the recording time, which contributes to the observed variability in the accuracy of SRs for measuring sleep. For this reason, the results of this study should not be interpreted as conclusive. Additionally, many studies had relatively small sample sizes [53] or a limited number of recording nights [43,44,50], potentially restricting the generalizability of our findings. Future research with larger and more diverse patient populations is needed to validate SRs' accuracy and reliability in health monitoring. Publication bias may have influenced the studies included in our analysis, with null or unfavourable results possibly remaining unpublished [83], leading to an overestimation of SRs' efficacy in health monitoring. Our review primarily focused on sleep and cardiovascular outcomes, but SRs can potentially monitor a broader range of health parameters. Further research is needed to evaluate their accuracy and reliability in monitoring other health parameters, such as mental health outcomes. Moreover, we did not assess the economic implications and financial sustainability of SRs in healthcare systems. Future studies should investigate cost-effectiveness and scalability to better understand their potential impact on healthcare systems and accessibility for specific patient populations. The review's limitation to English language studies may have excluded relevant research published in other languages. Furthermore, the literature shows that different ages are correlated with different sleep patterns, quality, and quantity [84]. These differences should be accounted for in the design of future studies analysing SR performance. Furthermore, general agreement on the standard acceptable cut-off error between the SR measurement and the gold-standard device measurement regarding the time of different sleep phases was not found in the current literature. Taking these limitations into account, our findings offer a preliminary understanding of the potential role of SRs in health monitoring. More comprehensive research is needed to overcome these limitations and provide a clearer picture of SRs' true capabilities in healthcare.

## 6. Conclusions

This systematic review and meta-analysis evaluated the accuracy and reliability of SRs in monitoring sleep and cardiovascular parameters compared to gold-standard medical devices. Our findings indicate that SRs show promising results in heart rate monitoring but exhibit wide variability in their ability to accurately measure different sleep phases. Despite these mixed results, the growing interest in SRs and other IoMT devices suggests that they have the potential to play a significant role in future digital health applications. The convenience and ease of use associated with SRs make these devices an attractive option for individuals requiring continuous health monitoring. However, the limitations identified in our review highlight the need for further research and development to improve the accuracy and reliability of SRs in monitoring a broader range of health parameters. Standardization of study methodologies, larger sample sizes, and cost–benefit analyses are essential to better understand the true potential of SRs in healthcare. In conclusion, while SRs show potential as health monitoring tools, further research is needed to address their limitations and fully understand their capabilities in healthcare settings. As technology advances and research continues, SRs may emerge as valuable tools for both patients and healthcare professionals, contributing to the growing field of digital health.

**Supplementary Materials:** The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/app142310778/s1, Table S1: Detailed search strategy for each database; Table S2: R script for total sleep time, rapid eye movements and heart rate meta-analysis. Table S3. Sensitivity analyses for TST and REM time.

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