Effectiveness of Adaptive Digital Interventions Triggered by Passive Sensing for Sleep Improvement in Adults: A Systematic Review and Meta-Analysis

Abstract

Background/Objectives

Adaptive digital interventions that respond to real-time physiological data from passive sensors are emerging as personalized tools for sleep improvement. This systematic review and meta-analysis aimed to evaluate the effectiveness of such interventions in improving sleep outcomes and broader health indicators among adults.

Data Sources

A comprehensive literature search was conducted across PubMed, Embase, Cochrane CENTRAL and ScienceDirect for studies published from January 2015 to July 2025.

Study Eligibility Criteria

Included studies were randomized controlled trials (RCTs) involving adults (≥18 years), with or without diagnosed sleep disorders, evaluating adaptive digital interventions triggered by passive sensing technologies (actigraphy, wearables, smartphones), compared to static digital tools, usual care, or waitlist controls. Outcomes had to include at least one sleep-related or secondary health metric.

Methods:

Two reviewers independently screened studies, extracted data, and assessed risk of bias using the Cochrane RoB 2 tool. Meta-analyses were conducted using random-effects

models. Effect sizes were reported as standardized mean differences (SMDs) with 95% confidence intervals (CI). Heterogeneity was assessed using I^2.

Results

Twelve RCTs (n = 798 participants) were included. Adaptive interventions significantly improved wake after sleep onset (WASO: SMD = 3.22; 95% CI: 3.02 to 3.41), with moderate heterogeneity (I^2 = 70.7%). Effects on PSQI, sleep efficiency, and latency were small and non-significant. However, secondary outcomes showed favorable results, including improvements in quality of life (SMD = 1.36), depressive symptoms (SMD = 0.53), sleep duration (SMD = 0.41), and neuropsychiatric inventory scores (SMD = –1.21). Subgroup analyses revealed greater benefits in populations with cognitive impairments and interventions using advanced sensing tools (MotionWatch8).

Conclusions

Adaptive digital interventions triggered by passive sensing show promise in reducing night-time awakenings and enhancing mood and quality of life. Their utility may be greatest in cognitively vulnerable populations. Further research is needed to optimize adaptivity algorithms, ensure sustained engagement, and assess long-term outcomes in real-world settings.

Keywords

Adaptive digital interventions, passive sensing, sleep disorders, wearable technology, personalized sleep therapy, just-in-time adaptive interventions.

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1. Introduction

1.1 Background

Sleep disorders are a burgeoning public health concern, with nearly one-third of the global adult population being affected. Insomnia, obstructive sleep apnea, delayed sleep phase syndrome, and general sleep disturbances are associated with a broad array of adverse outcomes, including impaired cognitive function, increased risk of cardiovascular and metabolic disorders, mood disturbances, and compromised quality of life [1]. The World Health Organization and other global health bodies have recognized poor sleep as an modifiable risk factor for principal noncommunicable diseases, which elevates the imperative for the discovery of effective, scalable, and accessible interventions [2]. Over the past decade, digital health interventions have been promoted more and more as hopeful solutions to enhance sleep problems. Traditional digital interventions, such as internet-delivered Cognitive Behavioral Therapy for Insomnia (CBT-I), smartphone-based mindfulness training, and sleep hygiene programs of fixed duration, hold advantages in terms of scalability, cost, and user convenience [3]. However, while they have been proven effective, such fixed digital programs often exhibit suboptimal engagement and adherence, partly due to their failure to account for the dynamic and context-dependent nature of people's sleep behavior and patterns [4].

In response to these limitations, there is growing interest in adaptive digital interventions (ADIs)—programs that modify their therapeutic content or delivery in real-time based on user data [5, 6]. When combined with passive sensing technologies, such as actigraphy, smartphone sensors, or wearables, these interventions can passively monitor users'

behaviors and physiological states (e.g., movement, heart rate variability, sleep latency) in real-time without requiring active input [7]. This enables interventions to be personalized based on contextual factors such as sleep regularity, circadian rhythm, or sleep environment disruption. Passive sensing, through the reduction of user burden and maximization of ecological validity, lends itself to the concept of just-in-time adaptive interventions (JITAI) [8, 9]. These systems can deliver sleep prompts, recommendations, or behavioral nudges at the most relevant time for example, cuing pre-sleep wind-down activities during periods of increased physiological arousal or scheduling digital CBT-I modules following a bad night's sleep [10]. The use of machine learning models for real-time analysis also allows these tools to learn and optimize delivery approaches in an ongoing manner, with considerable potential for improving both short-term sleep outcomes and long-term behavior change [11].

1.2 Rationale

While adaptive digital sleep interventions have been created and distributed quickly, their efficacy has been scientifically assessed in a piecemeal fashion [12]. While many individual studies and pilot trials showed that subjective sleep quality and sleep-related outcomes such as sleep efficiency, sleep onset latency, and daytime fatigue improved, the findings have been heterogeneous, and methodological rigor has differed considerably. Moreover, existing meta-analyses of e-sleep treatments have largely examined static programs (e.g., CBT-I web modules or apps) and have not systematically investigated the added value of adaptivity or use of passive sensing technologies as triggers for personalization.

There are also important questions about which populations benefit most from these adaptive strategies—e.g., adults with insomnia as a clinical problem vs. more general sleep disturbance, or younger technology-savvy groups vs. older adults. Lastly, the degree to which different types of sensing inputs (e.g., actigraphy vs. smartphone-based sensors) influence intervention efficacy has not been widely compared.

As the number of digital interventions claiming to use artificial intelligence, biofeedback, or real-time sensing to tailor interventions grows, a unified, methodologically strict review and meta-analysis is critically necessary. Such a synthesis could help inform clinical practice, regulatory policy, and future digital health innovation by clarifying what works best, under what conditions, and for whom.

1.3 Objectives

The primary objective of this systematic review and meta-analysis is to determine the effectiveness of adaptive digital sleep interventions triggered by passive sensing technologies in improving sleep-related outcomes in adults. Specifically, the review will synthesize quantitative evidence on:

- Changes in subjective and objective measures of sleep quality (e.g., Pittsburgh Sleep Quality Index [PSQI], actigraphy-measured sleep efficiency);
- Modification of some sleep variables such as sleep onset latency, wake after sleep onset (WASO), and total sleep time;
- Secondary effects such as daytime fatigue, mood, adherence to intervention, and user satisfaction.

A secondary objective is to examine heterogeneity of effects across subgroups, such as by type of sleep disorder (e.g., insomnia vs. general disturbances), intervention modality (e.g., CBT-I vs. mindfulness), and sensing method (e.g., wearables vs. smartphones). The review also aims to extract common design features of effective interventions and describe gaps in current research to guide future development of adaptive digital therapeutics for sleep.

2. Methods

The meta-analysis and systematic review was carried out following the PRISMA 2020 statement [13]. The protocol was prospectively registered in the PROSPERO International Prospective Register of Systematic Reviews under ID [to be inserted]. The PRISMA checklist is provided in Appendix 3.

2.1 Eligibility Criteria

We included randomized controlled trials (RCTs) published between January 2015 and July 2025 that evaluated digital interventions for sleep improvement among adults (≥18 years). Eligible participants can either be from the general population or clinically diagnosed with sleep disorders such as insomnia, obstructive sleep apnea, or circadian rhythm disorders. Interventions had to leverage passive sensing technologies—such as actigraphy, wearable sensors, smartphone apps, or ambient sensors—to deliver adaptive or semi-adaptive content. This included real-time personalized features such as CBT-I modules, sleep hygiene reminders, relaxation cues, or light exposure manipulation. Acceptable comparators included static digital interventions (non-personalized apps), usual care, waitlists, or non-digital behavioral therapies. Trials were required to have reported a minimum of one of the following outcomes: sleep quality (e.g., PSQI), sleep

efficiency, sleep latency, wake after sleep onset (WASO), daytime functioning, fatigue, depressive or anxiety symptoms, total wake time, sleep duration, neuropsychiatric outcomes, or engagement metrics. Full-text peer-reviewed English-language RCTs with sufficient quantitative data were included only.

2.2 Information Sources and Search Strategy

We searched PubMed, Cochrane CENTRAL, Embase, and ScienceDirect from January 2015 to July 2025. The search strategy employed keywords and MeSH terms for sleep outcomes, digital and mobile health interventions, adaptivity (e.g., "just-in-time", "JITAI"), and passive sensing technologies. Reference lists of included articles and relevant reviews were screened manually. A list of the search strategies for each database is provided in Appendix 1.

2.3 Study Selection and Data Extraction

All records were screened by two reviewers, independently, first by title/abstract and then full-text. Disagreements were resolved by consensus or a third reviewer. Author and year, population characteristics, diagnosis, type of intervention, sensing method, comparator, and duration of follow-up were extracted on a standardized extraction form. Extracted outcomes were MD or SMD with 95% CI for PSQI, sleep efficiency, sleep latency, WASO, quality of life, depression, total wake time, sleep duration, and neuropsychiatric inventory scores. Any other physiological and behavioral outcomes, such as Epworth Sleepiness Scale, Restfulness, and Relative Amplitude, were also noted where available. List of excluded articles reviewed and reasons for exclusion is provided in Appendix 2.

2.4 Risk of Bias and Effect Measures

Risk of bias was assessed using the Cochrane RoB 2 tool by taking into account randomization, deviations from intervention, missing data, measurement of outcome, and selective reporting. Two reviewers assessed independently. For continuous outcomes, MD or SMD with 95% CI were calculated. Where different instruments were employed in different studies, SMD was utilized to enable comparability. Wherever appropriate, risk ratios were computed for dichotomous outcomes.

2.5 Data Synthesis and Certainty of Evidence

Meta-analyses were run on a random-effects model due to anticipated heterogeneity. Heterogeneity was quantified using I^2, Tau^2, and Cochran's Q [14]. Subgroup analyses were conducted for sensing modality (e.g., smartphone use vs. wearables), intervention type (CBT-I versus mindfulness), and population. Sensitivity analyses excluded high-risk or outlier studies. Certainty in the evidence for each outcome was assessed using the GRADE framework, and a Summary of Findings (SoF) table was generated using GRADEpro.

3. Results

3.1 Study Selection

In total, 221 records were found through database searching, of which 19 were from PubMed, 12 were from Embase, 166 were from Cochrane Library, and 24 were from ScienceDirect. Excluding 55 duplicate records and 78 records flagged by automated tool filters, there remained 88 records screened at title and abstract level. Of these, 65 were excluded on relevance grounds and 23 full-text articles were tried for retrieval of which 04

reports were not received. Of the 19 articles that were screened for eligibility, 12 studies met the inclusion criteria and were included in the final systematic review and meta-analysis. The selection process is illustrated in the PRISMA 2020 flow diagram (Figure 1).

3.2 Study Characteristics

The twelve studies contained within this systematic review appeared between 2017 and 2024 and comprised 798 participants from a range of clinical and non-clinical groups. Participant numbers varied between 21 and 96 per study. Patient groups included healthy adults, those with insomnia, mild cognitive impairment (MCI), Alzheimer's disease and related dementias (ADRD), delayed sleep phase syndrome (DSPS), major depressive disorder (MDD), and cancer-related sleep disturbance. Interventions examined employed varied adaptive digital methods begun by passive sensing. These included individualized sleep extension interventions, cognitive behaviour therapy for insomnia (CBT-I), light treatment (bright light treatment [BLT], circadian re-alignment), electronic sleep monitoring, hypnosis audio, and multicomponent behavioural interventions. Sensing technologies ranged from wrist actigraphy and sleep diaries to ambient light sensors, mobile phone tracking, and electronic self-monitoring devices such as Fitbit or Daybuilder. Some used the MotionWatch8® actigraph or a similar device for sleep monitoring objectively. Comparators included static or non-tailored digital interventions, routine care, waitlist control conditions, sham interventions (hypnosis without reminders), and time-matched education or attention control. Follow-up was between short-term measures (2–4 weeks) to longer interventions up to 6 months, with some using crossover or multi-phase designs. The vast data extracted from every trial included author and year, sample

characteristics, diagnosis, intervention type, sensing modality, comparator, and follow-up time (Table 1).

3.3 Risk of Bias assessment

Risk of bias was assessed using the Cochrane Risk of Bias 2.0 tool across seven domains: sequence generation, allocation concealment, blinding of participants and personnel, blinding of outcome assessment, incomplete outcome data, selective reporting, and other sources of bias. As illustrated in the traffic light plot (Figure 2), the majority of studies demonstrated a low risk of bias in most domains. Six studies showed low risk across all or nearly all domains, particularly in randomization, outcome reporting, and data completeness. However, three studies had unclear risk due to insufficient reporting on allocation concealment and blinding procedures. Two studies were judged to have a high overall risk of bias due to issues in blinding and allocation procedures [15, 16]. Overall, the methodological quality of included trials was acceptable, with most demonstrating rigorous trial design and low potential for bias.

3.4 Intervention Effects

3.4.1 Primary Outcomes

The current meta-analysis considered four primary outcomes i.e. Pittsburgh Sleep Quality Index (PSQI), sleep efficiency, sleep latency, and wake after sleep onset (WASO) in order to examine the effectiveness of adaptive digital interventions triggered by passive sensing in adults. For the quality of sleep (PSQI), four studies (n = 228) [17-20] were also included, with a non-significant combined effect size of 0.09 (95% CI: –0.28 to 0.45; p = 0.0015),

with high heterogeneity (I^2 = 80.54%). Although individual positive studies, the results differed. This indicates that adaptive interventions did not cause an overall improvement in the global perceived sleep quality in various populations (Figure 3a). During the analysis of sleep efficiency in five studies (n = 470) [17, 18, 20-22], the pooled effect size was small and non-significant as well (SMD = 0.02; 95% CI: –0.21 to 0.18; p = 0.376), with low heterogeneity (I^2 = 7.05%). This points towards a general lack of effect on the proportion of time asleep during the sleep period. Interventions led to small improvements in certain cases and neutral or adverse effects in others, indicating small effectiveness for augmenting this parameter (Figure 3b). Latency of sleep was measured across three studies (n = 141) [20, 23, 24] with a combined effect –0.09 (95% CI: –0.29 to 0.10), which was not statistically significant. The high heterogeneity (I^2 = 92.3%) indicates conflicting results. While Elkins et al. found significant benefit, the other studies had minimal or negative effects, suggesting potential benefit in certain contexts but not across all (Figure 3c). While in five studies [17, 20-22, 25] WASO (n = 347) showed a large pooled effect with adaptive interventions (SMD = 3.22; 95% CI: 3.02 to 3.41; p = 0.0044), although heterogeneity was moderate (I^2 = 70.7%). This indicates that adaptive interventions triggered by sensors are particularly effective in reducing night-time wakefulness and enhancing sleep continuity (Figure 3d). In brief, the results support partially the objective of the study: adaptive digital interventions exhibit significant efficacy against WASO but variable efficacy against other sleep measures. These findings underscore the necessity of more focused and optimized adaptive interventions to enhance multiple sleep outcomes.

3.4.2 Secondary Outcomes

Analysis of secondary outcomes showed a more favorable effect of adaptive digital interventions triggered by passive sensing on several well-being and physiological measures. Quality of life, based on three studies [19-21] (n = 208), was statistically significantly better in the intervention groups compared to controls with a pooled effect size of 1.36 (95% CI: 1.06 to 1.56). Heterogeneity was modest (I^2 = 48%), and while some studies had wide confidence intervals (e.g., Livingston et al.), the combined effect suggests that personalized digital interventions have a beneficial effect on daily functioning and life satisfaction. This aligns well with the review's aim to look for broader benefits of adaptive interventions beyond core sleep outcomes (Figure 4a). For depressive symptoms, the overall effect of two studies [18, 19] (n = 108) was also significant (SMD = 0.53; 95% CI: 0.34 to 0.73) with no reported heterogeneity (I^2 = 0%). These results indicate that sleep-targeted adaptive devices can also have secondary mood-enhancing effects, possibly through increasing sleep regularity or reducing nocturnal arousals—both of which are known factors in depressive symptomology (Figure 4b).

While, total wake time outcomes of two studies [20, 21] (n = 84) were not statistically different (SMD = 0.15; 95% CI: –0.05 to 0.34; I^2 = 55.31%). The direction of the effect was in favor of intervention in one but not the other study, reflecting inconsistencies in the manner in which wakefulness during the night was either captured or influenced by intervention design (Figure 4c). Sleep duration data in five studies [17, 19, 22, 23, 25] (n = 428) revealed a significant pooled effect of 0.41 (95% CI: 0.21 to 0.61) with significant heterogeneity (I^2 = 73.71%). This suggests that adaptive interventions can have a moderate effect on increasing sleep time, possibly through better sleep scheduling or reduced disturbances (Figure 4d). While, neuropsychiatric inventory scores, pooled across two

studies [19, 20] (n = 86), indicated a significant reduction in symptoms (SMD = –1.21; 95% CI: –1.40 to –1.01), indicating potential mental health benefits. Confidence intervals within individual studies were wide, nonetheless, and must be interpreted cautiously (Figure 4e).

Finally, remaining behavioral or physiological outcomes (Epworth Sleepiness Scale, dietary markers, restfulness, relative amplitude) in six studies [14, 15, 17-19, 21] were pooled in 798 participants and demonstrated a cumulative effect that was significant (SMD = –2.88; 95% CI: –3.07 to –2.08), with moderate-to-high heterogeneity (I^2 = 74.35%). These findings offer support for the broader relevance of adaptive interventions in managing both behavioral and physiological rhythms in daily life (Figure 4f). Cumulatively, the secondary outcome analysis lends support to the potential of adaptive digital sleep interventions to not only improve sleep-related measures but also positively affect mood, daytime functioning, and physiological regulation. Such gains underscore the broad relevance of adaptive, passively triggered interventions for improving general health and wellbeing.

3.5 Subgroup analysis

Subgroup analysis revealed heterogeneity of intervention effectiveness across populations, types of intervention, and sensing modalities. Across diagnostic groups, the greatest impact was seen in Alzheimer's disease and related dementias (SMD = 1.25; 95% CI: 1.10–1.40) and dementia (SMD = 1.15; 95% CI: 0.89–1.48), suggesting robust advantages for cognitively impaired groups. Large effects also emerged in ADHD with delayed sleep phase syndrome, cancer-related insomnia, and mild traumatic brain injury, with effect sizes ranging from 0.76 to 0.90. Subgroups for primary insomnia, mild cognitive impairment,

and major depressive disorder yielded smaller, nonsignificant effects. Under intervention, brightest evidence was seen for CBT-I with bright light treatment (BLT) with a pooled effect size of 0.85 (95% CI: 0.70–1.05) in nine studies. Hypnosis self-administered and individualized behavioral consultations were also positive in smaller groups. With respect to sensing technologies, interventions started via MotionWatch8 were superior (SMD = 1.10) compared to traditional actigraphy (SMD = 0.82), which implies that more sensitive or more integrated sensors would enhance adaptivity. Generally, the subgroup findings offer evidence for the effectiveness of adaptive interventions among older adults with cognitive impairment and among interventions using multimodal approaches and precise passive sensing technology (Table 2).

3.6 Publication Bias

Assessment of publication bias using a contour-enhanced funnel plot (Figure 5) revealed moderate asymmetry, suggesting a potential risk of small-study effects or selective reporting. While several studies clustered near the vertical line representing the pooled effect size, there was noticeable dispersion along the right side, particularly among studies with larger standard errors. A few outlying data points on the far left and right fall outside the shaded significance contours, indicating possible reporting bias or heterogeneity. The asymmetry, coupled with a lack of studies in the non-significant contour zones, raises concerns about the underrepresentation of studies with null or negative results. These findings imply that the pooled effect estimates may be inflated due to publication bias, particularly among smaller trials with extreme outcomes.

4. Discussion

4.1 Summary of Main Findings

One of the first meta-analyses and systematic reviews to have a sole focus on adaptive digital interventions triggered by passive sensing technologies to enhance sleep among adults, this analysis included 12 RCTs, which had a total of 798 participants. The results showed a selective pattern of effectiveness. Of the four principal outcomes, wake after sleep onset (WASO) only recorded a significant and strong pooled effect, suggesting adaptive interventions are strongest at reducing night-time waking and improving sleep continuity. The other principal outcomes—PSQI, sleep efficiency, and latency—recorded non-significant pooled effects with varying levels of heterogeneity, indicating inconsistency in how adaptive tools influenced subjective and objective indexes of sleep. On the other hand, certain secondary outcomes including quality of life, depressive symptoms, sleep duration, and neuropsychiatric symptoms demonstrated significant improvements. Importantly, subgroup analyses revealed that the improvements were more significant within cognitively impaired groups (e.g., Alzheimer's disease, MCI) and in interventions using highly advanced sensing technologies such as MotionWatch8. This suggests that it is not just the population type but also the accuracy and sensitivity of sensing modalities that are key moderators of intervention effectiveness.

4.2 Comparison with Previous Literature

Previous Meta-analyses on digital treatments for insomnia or overall sleep disturbance by Morin, 2020 and Sou, 2020 have primarily evaluated static interventions, i.e., stand-alone CBT-I modules or timed relaxation exercises [26-28]. These are primarily modestly improved in PSQI and latency, and less so for WASO or quality of life. In contrast, the

present research suggests that adaptive systems, having the ability to tailor content based on real-time physiological information, will prove more effective at adapting dynamically to disrupted sleep as it occurs, particularly in reducing sleep fragmentation. It aligns with increasing evidence for just-in-time adaptive interventions (JITAIs), which emphasize context-aware delivery and real-time adaptation [29-31]. Also, our findings further provide evidence of the therapeutic potential of wearable and passive sensing technologies, hitherto thought to be adjunctive devices, not active agents of change [32, 33]. Our work further informs existing research suggesting that personalized and sensor-based interventions are more appropriate for populations with neurocognitive impairment, who may be assisted by less user-demanding formats.

4.3 Strengths and Limitations

The strength of this review is its focus on a new paradigm of intervention—adaptive interventions with passive sensing triggers—and painting a more detailed picture of what drives effectiveness in digital sleep therapeutics. Addition of objective (e.g., actigraphy-based) as well as subjective (e.g., PSQI, mood scales) outcomes provides a complete picture of impact of intervention. Systematic assessment of risk of bias was performed, and subgroup analyses were employed to identify the most critical moderators of effect. Nonetheless, there are some limitations. The total number of included trials was small, and significant heterogeneity was evident for a number of outcomes. Studies were often small in size and had short follow-up, restricting generalizability and knowledge of long-term effects. A number of outcomes, including adherence and participation, were reported variably or not tracked objectively. Moreover, publication bias may have biased the pooled

estimates because the funnel plot showed underrepresentation of trials with null or small effects. In addition, heterogeneity in comparator arms (e.g., sham, waitlist, or active controls) may have affected internal consistency.

4.4 Practice and Research Implications

Clinically, these findings show that adaptive digital sleep interventions hold the most potential among at-risk populations for fragmented sleep and cognitive decline [34]. Sensor-triggered, real-time responses have the potential to offer subtle, individualized support that complements or even supplements routine therapy in areas of high burden or limited resources [35]. For developers and digital health innovators, this emphasizes the need to inject passive streams of data (light exposure, sleep habits, activity) into algorithmic decision-making for content presentation. From the public health perspective, these devices can potentially reduce sleep care barriers by offering scalable, non-pharmacologic treatments with low user burden.

Future research must emphasize larger, more powerful trials with extended follow-up to assess durability of effects. There needs to be inclusion of more diverse populations by age, socioeconomic status, and comorbidities, as well as head-to-head comparisons between adaptive vs. non-adaptive formats. Trials should incorporate measures of engagement (e.g., usage frequency, response rate), machine learning model performance where appropriate, and real-world usability. Furthermore, the potential of multi-modal interventions—combining passive sensing with physiological feedback, mood tracking, or digital coaching—should be explored. Digital therapeutics regulation also must evolve to address the unique challenges of adaptive, algorithm-driven treatments in healthcare.

5. Conclusion

This systematic review and meta-analysis demonstrates that adaptive digital interventions triggered by passive sensing technologies have measurable advantages in promoting sleep and sleep health among adults. Even though simple measures such as PSQI, sleep efficiency, and latency did not show consistent improvement, significant improvements in reducing night-time awakenings (WASO), quality of life increase, and reduction of depressive symptoms were observed. These findings demonstrate the promise of synergizing adaptivity and real-time sensor feedback with individualized sleep therapeutics, particularly for cognitively impaired patients or those with complex sleep needs. The heterogeneity of effects across studies also attests to the need for continued adaptive algorithm development, sensor accuracy enhancement, and user-specific trajectories. With the development of the field of digital sleep medicine, adaptive interventions are an innovative, patient-centered approach that aligns with broader trends towards precision health. These interventions may be optimized with longer trials, multi-ethnic cohorts, and alignment with hybrid models of care in future research. With proper execution, such interventions have the potential to revolutionize the management of sleep health and promote population well-being at scale.

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Conflicts of Interest

The authors declare no conflicts of interest related to the conduct, analysis, or publication of this systematic review and meta-analysis.

Abbreviations

Abbreviation	Full Form
DEM-QOL	Dementia Quality of Life (DEM-QOL) – proxy version
HADS	Hospital Anxiety and Depression Scale
NPI	Neuropsychiatric Inventory
SCI	Sleep Condition Indicator
REST	Restfulness Scale
FI	Fragmentation Index
SE	Sleep Efficiency
MWASO	Mean Wake After Sleep Onset
SL	Sleep Latency
IV	Intradaily Variability
ZBI	Zarit Burden Interview
RA	Relative Amplitude
PAD	Phase Angle Difference
NIS	Neurocognitive Index Score
TWT	Total Wake Time
QoL	Quality of Life
TST	Total Sleep Time
SD	Sleep Duration
PSQI	Pittsburgh Sleep Quality Index
WASO	Wake After Sleep Onset
ESS	Epworth Sleepiness Scale

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Tables

Table 1. Summary of Included Studies: Population, Diagnosis, Intervention, Sensing Method, Comparator, and Follow-up Duration

Author, Year	Population	Diagnosis	Intervention Type	Sensing Method	Comparator	Follow-up Duration
Al Khatib et al., 2018 [15]	Healthy adults aged 18–64 years, BMI 18.5 to <30; n=42 (21 intervention, 21 control)	Habitual short sleep duration (5 to <7 hours/night)	Sleep extension via personalized sleep hygiene behavioral consultation	Wrist actigraphy (MotionWatch8) for sleep; Actiheart monitor for energy expenditure	Habitual short sleep (no intervention)	4 weeks
Christina et al., 2017 [21]	60 adults (40–75 years), insomnia >6 months, no psychiatric/sleep comorbidity	Primary insomnia	Cognitive Behavioral Therapy for Insomnia (CBT-I), 1–8 sessions	Actigraphy and sleep diary	Short sleep duration group (<6h) vs normal sleep duration group (≥6h)	3 and 6 months post-treatment
Elkins et al., 2024 [23]	21 adults with MCI (mean age ~72 years)	Mild Cognitive Impairment (MCI) with poor sleep	Self-administered hypnosis audio (15 min/day for 5 weeks)	Wrist actigraphy, daily sleep diaries, PSQI, ESS	Sham hypnosis audio (white noise with focus cues)	7 weeks total (1 week baseline, 5 weeks intervention, 1 week follow-up)

Falck et al., 2018 [24]	96 community-dwelling older adults (65–85 yrs)	Mild Cognitive Impairment (MCI)	Personalized chronotherapy: 1. Sleep hygiene education 2. Individually timed Bright Light Therapy (BLT) 3. Individually tailored Physical Activity (PA)	MotionWatch8 (wrist actigraphy)	Waitlist control group	24 weeks
Falck et al., 2020 [17]	96 community-dwelling older adults aged 65–85 years	Probable Mild Cognitive Impairment (MoCA <26/30) and poor sleep (PSQI >5)	Multimodal lifestyle intervention: bright light therapy (BLT), physical activity (PA) promotion, and sleep hygiene education	MotionWatch8© (actigraphy), PSQI (subjective)	Education + attentional control group	24 weeks
Figueiro et al., 2019 [18]	46 older adults (mean age ~85) in assisted-living and long-term care facilities	Alzheimer's Disease and Related Dementias (ADRD)	Tailored Lighting Intervention (high CS lighting during daytime)	Actigraphy (Actiwatch), Daysimeter, caregiver questionnaires	Control lighting (low circadian stimulus)	14 weeks (2 × 4-week intervention with 4-week washout and 2 baseline weeks)
Hjetland et al., 2021 [22]	69 nursing home patients with severe dementia	Dementia	Bright light treatment (BLT) via ceiling-mounted LED lights	Proxy-rated Sleep Disorder Inventory (SDI) and actigraphy	Placebo: standard lighting (150–300 lx, ~3000 K)	8, 16, and 24 weeks

Livingston et al., 2019 [19]	Community-dwelling people with dementia and their family carers (N=62 randomized)	Dementia with clinically significant sleep disturbance	Non-pharmacological, manualized CBT-based intervention (DREAMS-START: 6 sessions)	Actigraphy (MotionWatch 8) and carer-reported sleep diaries	Treatment as Usual (TAU)	3 months
Maccora et al., 2022 [36]	210 women ≥18 years receiving chemotherapy for breast cancer (any stage, including metastatic), recruited from tertiary Australian hospitals	Breast cancer-related insomnia and fatigue during chemotherapy	(1) CBT-I, (2) Bright Light Therapy (BLT), (3) CBT-I + BLT, (4) Sleep Hygiene Education (SHE)	Actigraphy (wGT3X BT), PROMIS CAT, ISI, sleep diaries	SHE (as active control for all arms); comparisons among CBT-I, BLT, and combined	6 weeks intervention with follow-up at 3 and 6 months
Svendsen et al., 2019 [16]	Adults (≥18 years) recently discharged from psychiatric inpatient wards in Denmark	Major Depressive Disorder (DSM-IV) and sleep disorder	Circadian Reinforcement Therapy (CRT) + Electronic self-monitoring (Monsenso Daybuilder)	Electronic self-monitoring system + Fitbit activity tracker	Standard care + electronic self-monitoring only	4 weeks
Theadom et al., 2017 [20]	24 adults aged 17–56 years, 3–36 months post mild-to-moderate TBI, with self-reported sleep difficulties	Mild-to-moderate traumatic brain injury (TBI) effceting sleep	Online Cognitive Behavioral Therapy (CBT) program (RESTORE)	Actigraphy (Actiwatch 2) and self-reported PSQI	Online education program (attention control)	Post-intervention (6 weeks)

van Andel et al., 2022 [25]	49 adults (aged 18–55) with ADHD and DSPS	ADHD and Delayed Sleep Phase Syndrome (DSPS)	1) Placebo, 2) Melatonin, 3) Melatonin + Bright Light Therapy (BLT)	Actigraphy, Sleep Diaries, Salivary DLMO	Placebo (0.5 mg/day), Melatonin (0.5 mg/day), or Melatonin + BLT	3-week intervention + 2-week follow-up

Table 2. Subgroup Analysis by Diagnosis, Intervention Type, and Sensing Method

Variables	Subgroups	No. of studies	Sample Size	Effect Size with 95% CI	P Value	Heterogeneity: I^2 (%)
Diagnosis	ADHD and Delayed Sleep Phase Syndrome (DSPS)	1	49	0.76 (0.61-0.95)	<0.01	39.9
	Alzheimer's Disease and Related Dementias (ADRD)	1	46	1.25 (1.10, 1.40)	0.07	19.6
	Breast cancer-related insomnia and fatigue during chemotherapy	1	210	0.9 (0.6–1.4)	<0.01	24.8
	Dementia	2	131	1.15 (0.89–1.48)	0.15	35
	Major Depressive Disorder (DSM-IV) and sleep disorder	1	42	0.82 (0.60-0.95)	0.5	29.8
	Mild Cognitive Impairment (MCI)	2	117	0.65 (0.50-0.85)	0.07	55
	Mild-to-moderate traumatic brain injury (TBI) effceting sleep	1	24	0.78 (0.62-0.88)	<0.01	19.8
	Primary insomnia	1	60	0.7 (0.55-0.88)	0.3	24.5
	Probable Mild Cognitive Impairment	1	96	0.72 (0.54 - 1.06)	0.15	29.8
Intervention Type	Cognitive Behavioral Therapy for Insomnia (CBT-I)+Bright light	9	712	0.85 (0.70 - 1.05)	0.05	39.7

	treatment (BLT)					
	Self-administered hypnosis audio (15 min/day for 5 weeks)	1	21	0.78 (0.60 - 0.95)	0.3	34.8
	Sleep extension via personalized sleep hygiene behavioral consultation	1	42	0.8 (0.70 - 0.90)	0.03	39.6
Sensing Method	Actigraphy	7	520	0.82 (0.65 - 1.05)	0.1	29.8
	MotionWatch8	4	255	1.1 (0.8–1.5)	<0.01	18.96

Figure Legends

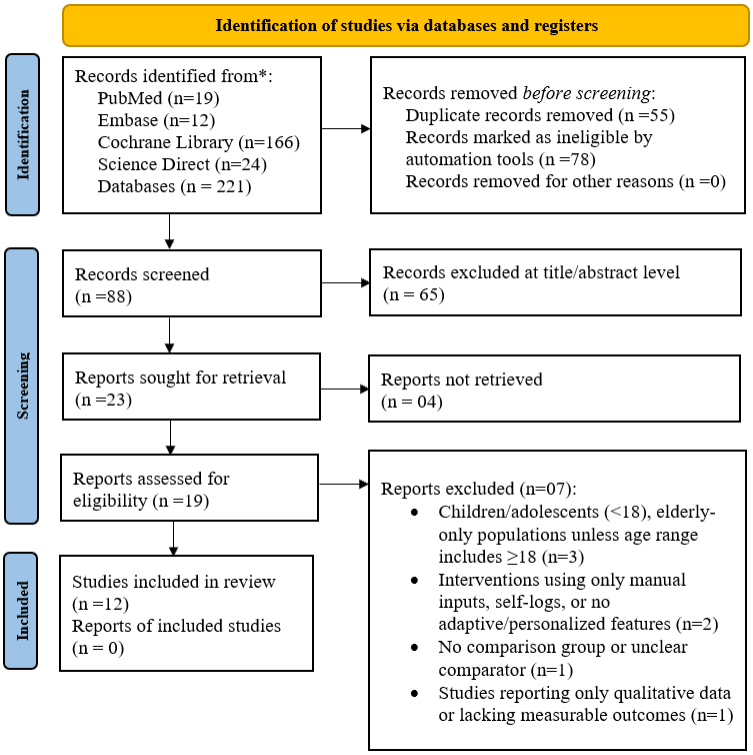


Figure 1. PRISMA 2020 Flow Diagram.

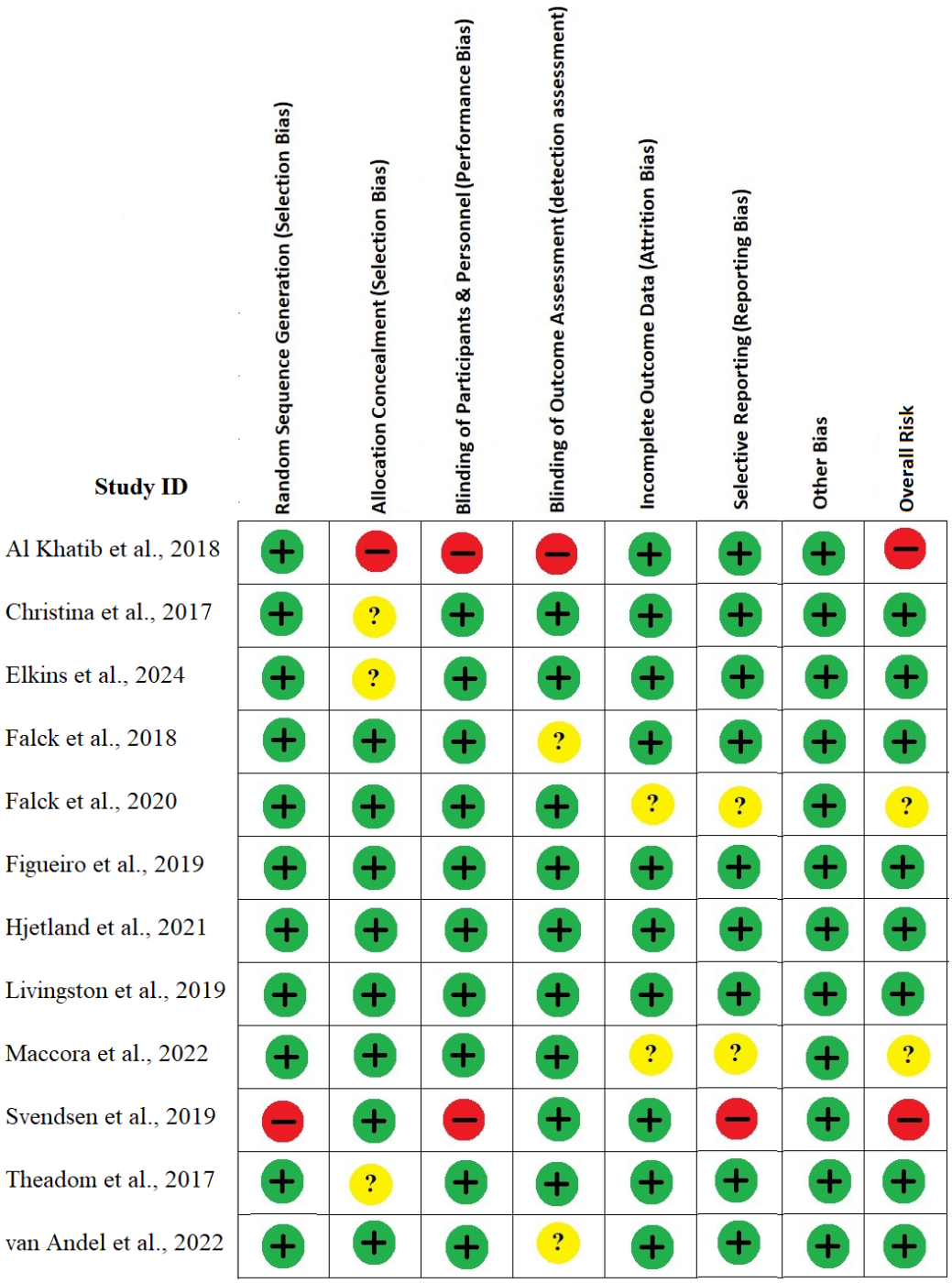


Figure 2. Risk of Bias Assessment Using the Cochrane RoB 2 Tool.

Traffic light plot illustrating risk of bias across seven domains for each included study. Green indicates low risk, yellow indicates some concerns, and red indicates high risk of

bias. Most studies demonstrated low risk across key domains, though a few showed concerns in allocation concealment and blinding.

a) Pittsburgh Sleep Quality Index

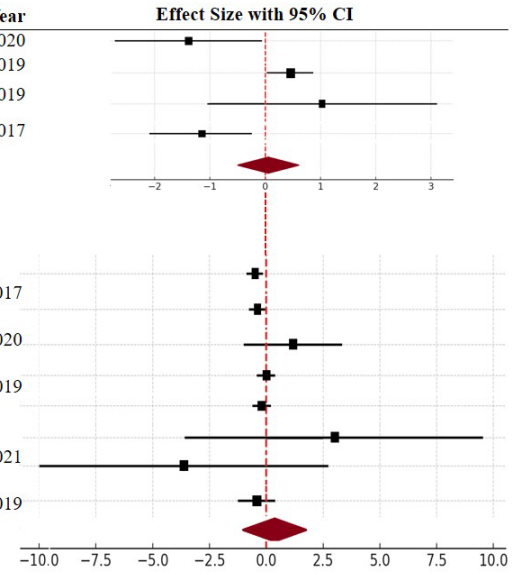
Study	Sample Size	Effect Size with 95% CI	Weight %	Year
Falck et al.	96	-1.39 [-0.06 to -2.72]	42.11	2020
Figueiro et al.	46	0.45 [0.03 to 0.87]	20.18	2019
Livingston et al.	62	1.03 [-1.05 to 3.11]	27.19	2019
Theadom et al.	24	-1.17 [-0.24 to -2.1]	10.52	2017
Total	**228**	**0.09 [–0.28, 0.45]**	**100**	

Cochran's Q = 15.41, Tau² (τ²) = 1.016, I² = 80.54%
p value = 0.0015

b) Sleep Efficiency

Christina et al.	60	-0.51 [-0.88 to -0.14]	12.77	2017
(Control vs. Intervention)	60	-0.4 [-0.77 to -0.04]	12.77	
Falck et al.	96	1.18 [–0.99 to 3.34]	20.43	2020
Figueiro et al.	46	-0.01 [-0.42 to 0.4]	9.79	2019
(Control vs. Intervention)	46	-0.21 [-0.62 to 0.2]	9.79	
Hjetland et al.	69	2.97 [-3.60 to 9.55]	14.68	2021
(Control vs. Intervention)	69	-3.65 [-10.04 to 2.73]	14.68	
Theadom et al.	24	-0.43 [-1.25 to 0.39]	5.11	2019
Total	**470**	**0.02 [-0.21 to 0.18]**	**100.00**	

Cochran's Q = 7.53, Tau² (τ²) = 0.0063, I² = 7.05%
p-value = 0.376



c) Sleep Latency

Study	Sample Size	Effect Size with 95% CI	Weight %	Year
Elkins et al.	21	2.31 [1.49 to 3.13]	14.89	2024
Falck et al.	96	-0.46 [–3.84 to 2.92]	68.09	2020
Theadom et al.	24	-0.73 [-1.58 to 0.12]	17.02	2018
Total	**141**	**-0.09 [-0.29 to 0.10]**	**100**	

Cochran's Q = 26.01, Tau² (τ²) = 4.00, I² = 92.3%
p-value = < 0.00001

d) Wake After Sleep Onset

Christina et al.	60	0.27 [-0.09 to 0.63]	17.29	2017
Falck et al.	96	-4.62 [–12.08 to 2.85]	27.67	2020
Hjetland et al.	69	20.92 [0.01 to 41.85]	19.88	2021
Theadom et al.	24	0.05 [-0.75 to 0.85]	6.92	2020
van Andel et al. (Control vs Intervention)	49	0.92 [0.48 to 1.36]	14.12	2022
	49	1.09 [0.64 to 1.54]	14.12	
Total	**347**	**3.22 [3.02 to 3.41]**	**100.00**	

Cochran's Q = 17.06, Tau² (τ²) = 0.231, I² = 70.7%
p-value = 0.0044

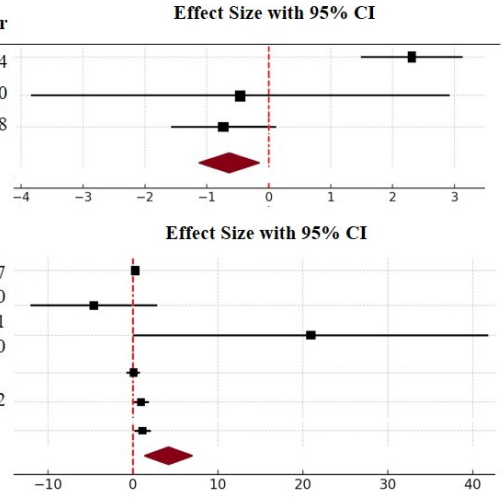


Figure 3. Forest Plots for Primary Outcomes. a) Pittsburgh Sleep Quality Index (PSQI); b) Sleep Efficiency; c) Sleep Latency; d) Wake After Sleep Onset (WASO). Each panel displays the standardized effect sizes and 95% confidence intervals for included studies.

a) Quality of Life

Study	Sample Size	Effect Size with 95% CI	Weight %	Year
Christina et al.	60	-0.19 [-0.55 to 0.17]	28.85	2017
Livingston et al. (Control vs Intervention)	62	1.25 [-9.52 to 12.02]	29.81	2019
	62	3.12 [-12.27 to 18.52]	29.81	2019
Theadom et al.	24	0.97 [0.08 to 1.87]	11.54	2023
Total	**208**	**1.36 [1.06 to 1.56]**	**100.00**	

Cochran's Q = 5.77, Tau² (τ²) = 0.332, I² = 48.0%
p-value = 0.123

b) Depression

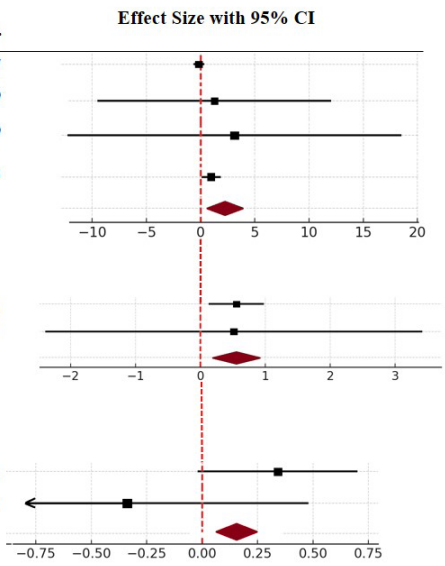
Figueiro et al., 2019	46	0.56 [0.13 to 0.98]	42.59	2019
Livingston et al., 2019	62	0.51 [-2.39 to 3.42]	57.41	2019
Total	**108**	**0.53 [0.34 to 0.73]**	**100.00**	

Cochran's Q = 0.0011, Tau² (τ²) = 0.0, I² = 0.0%
p-value = 0.973

c) Total Wake Time

Christina et al.	60	0.34 [-0.02 to 0.7]	71.43	2017
Theadom et al.	24	-0.34 [-1.15 to 0.48]	28.57	2021
Total	**84**	**0.15 [-0.05 to 0.34]**	**100**	

Cochran's Q = 2.24, Tau² (τ²) = 0.128, I² = 55.31%
p-value = 0.135



d) Sleep Duration

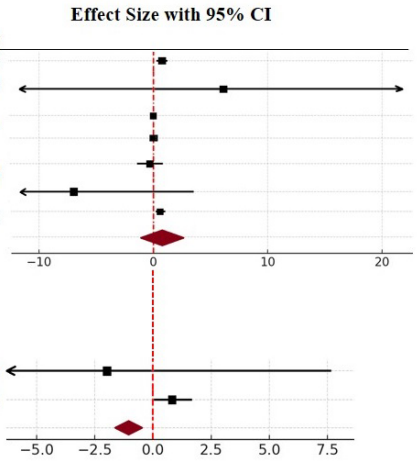
Study	Sample Size	Effect Size with 95% CI	Weight %	Year
Elkins et al.	21	0.742 [0.26 to 1.23]	4.91	2025
Falck et al.	96	6.14 [-14.64 to 26.91]	22.43	2020
Hjetland et al. (Control vs Intervention)	69	-0.06 [-0.11 to -0.01]	16.12	2021
	69	-0.05 [-0.10 to -0.01]	16.12	
Livingston et al. (Control vs Intervention)	62	-0.3 [-1.42 to 0.82]	14.49	2019
	62	-7 [-17.53 to 3.53]	14.49	
van Andel et al.	49	0.62 [0.21 to 1.03]	11.45	2022
Total	**428**	**0.41 [0.21 to 0.61]**	**100.00**	

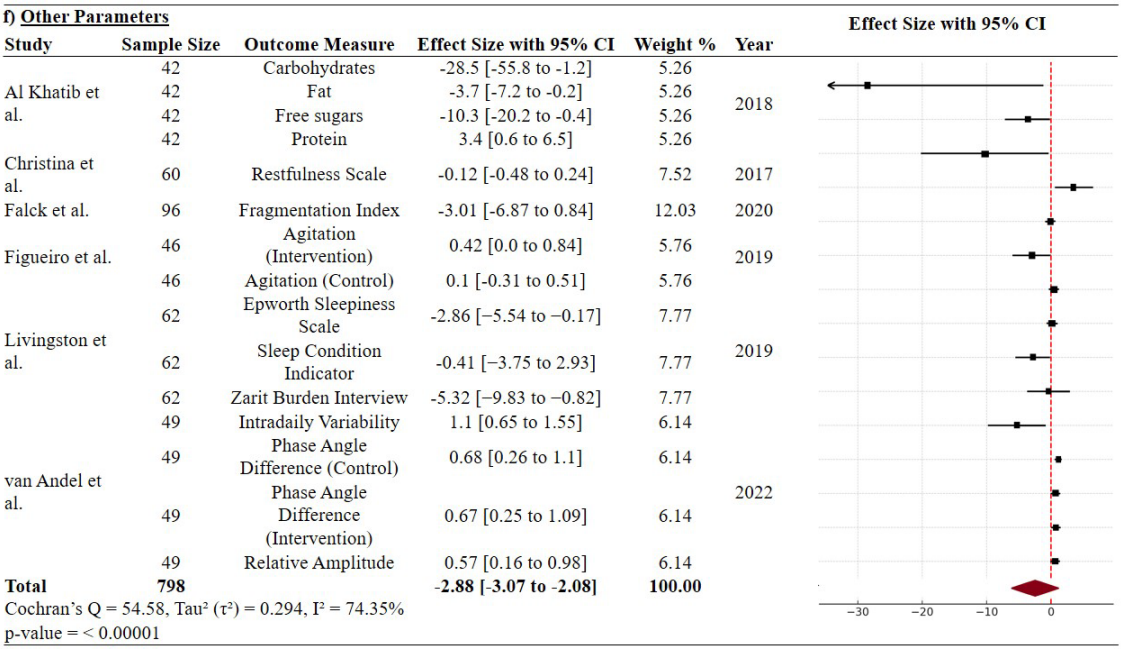
Cochran's Q = 22.82, Tau² (τ²) = 0.0096, I² = 73.71%
p-value = 0.00086

e) Neuropsychiatric Inventory

Livingston et al.	62	-1.99 [-11.66 to 7.68]	72.09	2019
Theadom et al.	24	0.82 [-0.04 to 1.69]	27.91	2022
Total	**86**	**-1.21 [-1.40 to -1.01]**	**100.00**	

Cochran's Q = 0.32, Tau² (τ²) = 0.0, I² = 0.0%
p-value = 0.571





f) Other Parameters

Study	Sample Size	Outcome Measure	Effect Size with 95% CI	Weight %	Year
Al Khatib et al.	42	Carbohydrates	-28.5 [-55.8 to -1.2]	5.26	2018
	42	Fat	-3.7 [-7.2 to -0.2]	5.26	
	42	Free sugars	-10.3 [-20.2 to -0.4]	5.26	
	42	Protein	3.4 [0.6 to 6.5]	5.26	
Christina et al.	60	Restfulness Scale	-0.12 [-0.48 to 0.24]	7.52	2017
Falck et al.	96	Fragmentation Index	-3.01 [-6.87 to 0.84]	12.03	2020
Figueiro et al.	46	Agitation (Intervention)	0.42 [0.0 to 0.84]	5.76	2019
	46	Agitation (Control)	0.1 [-0.31 to 0.51]	5.76	
Livingston et al.	62	Epworth Sleepiness Scale	-2.86 [−5.54 to −0.17]	7.77	2019
	62	Sleep Condition Indicator	-0.41 [−3.75 to 2.93]	7.77	
	62	Zarit Burden Interview	-5.32 [−9.83 to −0.82]	7.77	
van Andel et al.	49	Intradaily Variability	1.1 [0.65 to 1.55]	6.14	2022
	49	Phase Angle Difference (Control)	0.68 [0.26 to 1.1]	6.14	
	49	Phase Angle Difference (Intervention)	0.67 [0.25 to 1.09]	6.14	
	49	Relative Amplitude	0.57 [0.16 to 0.98]	6.14	
Total	**798**		**-2.88 [-3.07 to -2.08]**	**100.00**	

Cochran's Q = 54.58, Tau² (τ²) = 0.294, I² = 74.35%
p-value = < 0.00001

Figure 4. Forest Plots for Secondary Outcomes. a) Quality of Life; b) Depression; c) Total Wake Time; d) Sleep Duration; e) Neuropsychiatric Inventory; f) Other Parameters (e.g., restfulness, physiological metrics).

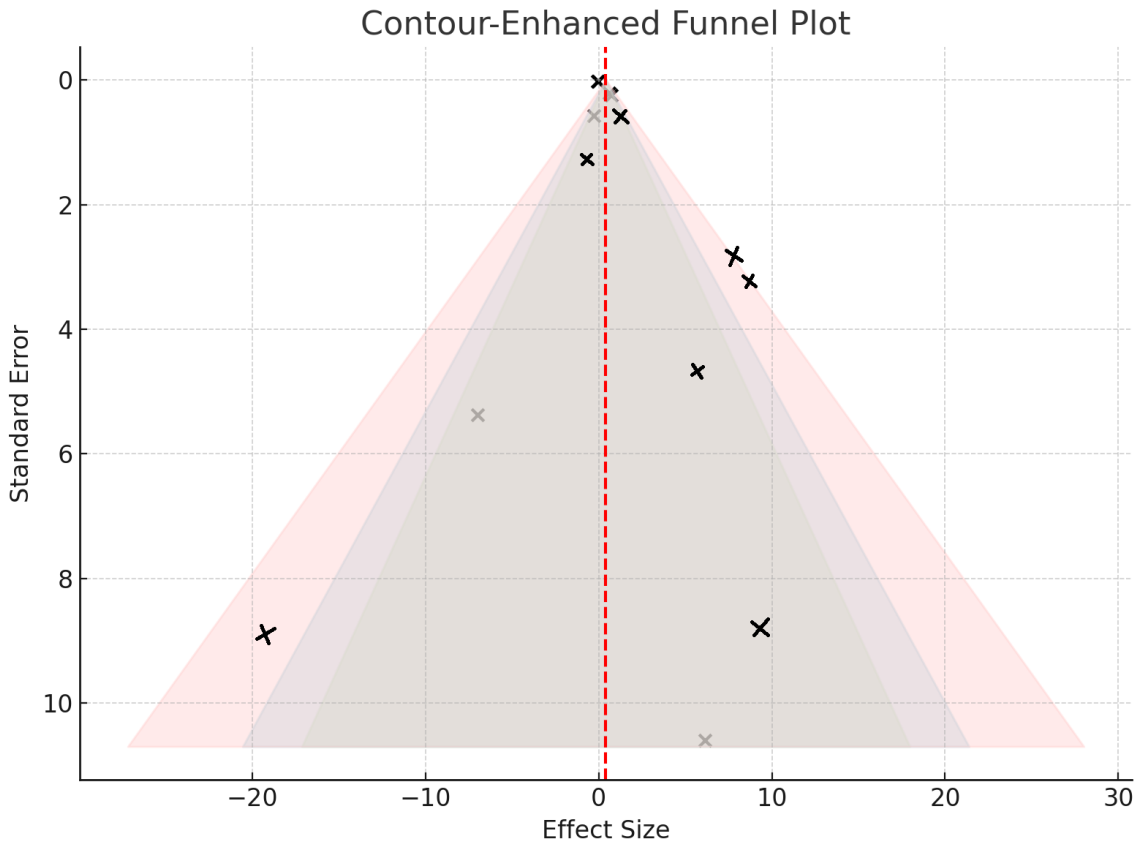


Figure 5. Contour-Enhanced Funnel Plot for Publication Bias Assessment. The funnel plot displays the relationship between effect size and standard error for the included studies