# Association between digital biomarkers of health and anxiety: a systematic review and meta-analysis

Yolanda Lau, Natalia Chemas, Heema Ajeet Gokani, Rachel Morrell, Harisd Phannarus, Claudia Cooper, Zuzana Walker, Harriet Demnitz-King, Natalie Marchant

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## *Abstract*

**Background:** Digital biomarkers are gaining interest as proxy markers for mental health as they enable passive and continuous data collection. However, the association between digital biomarkers of health and anxiety, both generalised anxiety disorder and anxiety symptoms, remains unknown.

**Objective:** This systematic review and meta-analysis aimed to examine the association between digital biomarkers of health obtained from wrist-worn wearables and anxiety in adults.

**Methods:** Systematic literature searches were conducted across six databases, including unpublished grey literature. The final search was done on 24th September, 2024. Cross-sectional or longitudinal studies investigating the association between digital biomarkers from wrist-worn wearables and anxiety were eligible. Studies using inferential statistics or machine learning methods were both eligible. Studies were excluded if participants received diagnoses of neurodegenerative disorders or physical health conditions. Two risk of bias tools were used: the Nationale Heart, Lung and Blood Institute assessment tool for inferential statistical studies, and the modified version of the Quality Assessment of Diagnostic Accuracy Studies-2 for machine learning studies. Whenever possible, effect sizes were combined across studies, for each digital biomarker of health separately, using random-effects meta-analyses. Sensitivity analyses were performed to assess whether results differed according to anxiety type (state, trait) and age group. Otherwise, studies were synthesised narratively. This study is registered on PROSPERO, CRD42023409995.

**Results:** 32 studies from 30 articles were eligible. 25 studies used inferential statistical approaches for analysis (17 reporting sleep characteristics, four reporting physical activity, two reporting both, and two reporting heart rate variability), and seven studies used machine learning approaches. Sample size range from 17 to 60,235. Meta-analyses were conducted for four sleep metrics: sleep efficiency, wake after sleep onset, total sleep time, and sleep onset latency. Sleep efficiency (K = 8, N = 3,627, Fisher's z = -0.08, 95% confidence interval [CI] = -0.15 to -0.01, P = .026) and wake after sleep onset (K = 6, N = 3,291, Fisher's z = 0.13, 95% CI = 0.01 to 0.24, P = .029) were associated with anxiety symptoms. Total sleep time and sleep onset latency were not associated with anxiety symptoms. A qualitative synthesis of the limited number of studies examining physical activity metrics revealed that more sedentary behaviour was associated with greater anxiety symptoms.

**Conclusions:** Worse sleep efficiency, longer wake after sleep onset, and more sedentary behaviour were associated with greater anxiety symptoms. Relationships between different physical activity intensities and anxiety remain unclear due to the limited number of studies, warranting further investigation. Studies using machine learning to predict anxiety from wrist-worn wearable data had limited accuracy, potentially due to the exclusion of demographics as predictors. Future employment of metrics

measured from wrist-worn wearables and machine learning techniques could potentially be used as a screening tool for anxiety.

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# Original Manuscript

# Association between digital biomarkers of health and anxiety: a systematic review and meta-analysis

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## Introduction

Anxiety is the most prevalent mental health condition globally, impacting 301 million people in 2019[1]. Symptoms can include worry, restlessness, fatigue, difficulty concentrating, and sleep disturbances[2]. Among older adults, anxiety disorders and anxiety symptoms are common, with 1.2% to 28% experiencing anxiety disorders (generalised anxiety disorder [GAD] being the most common type) and 15% to 56% experiencing anxiety symptoms in community and clinical populations[3]. In older adults, both GAD and anxiety symptoms have been associated with increased risk of dementia[4–8]. Given the increasing global prevalence of dementia[9] and the lack of effective disease-modifying treatments, it is crucial to prioritise the identification and treatment of modifiable risk factors associated with dementia to reduce dementia cases. Therefore, early identification of anxiety in both the general population and older adults could have significant clinical implications.

Predominant methods to assess anxiety include the use of self-report questionnaires, clinical diagnoses, or a combination of both. These methods have several limitations. Self-report questionnaires measuring trait anxiety are retrospective and rely on an individual's ability, insight, and willingness to respond accurately. Clinical diagnoses require clinical expertise and are therefore time-consuming and resource-heavy. Both methods only provide a snapshot of an individual's symptomology unless assessed repeatedly, which can increase demands on both individuals and clinicians.

Leveraging digital biomarkers, defined as objective, quantifiable, physiological, and behavioural measures collected using digital devices[10], as proxy markers of anxiety has the potential to overcome the limitations outlined above. Digital biomarkers collect continuous objective data on various aspects of behaviour and physiology.

Whilst digital biomarkers can be measured using different technologies (e.g., contactless sensors, smartphones), this review focuses on wrist-worn wearable devices, which are widely used by the general public and in existing research[11,12]. Wrist-worn wearables can measure physical activity (e.g., different physical intensities), sleep (e.g., sleep efficiency) and heart rate (e.g., heart rate variability). These variables have been linked to anxiety, for example, lower physical activity levels and more sleep disturbances have been associated with more anxiety symptoms and GAD[13,14].

Two recent meta-analyses of machine learning studies examined the association between metrics collected from wearable devices and depression and anxiety, both of which are modifiable psychosocial risk factors of dementia[15,16]. They found that the models accurately classified individuals with and without depression in 89% of cases[15], and correctly identify individuals with and without anxiety in 82% of cases[16]. Similar wearable-derived metrics were used predictors in anxiety and depression models (e.g., activity, sleep, heart rate). These meta-analyses only focused on machine learning studies, however existing research also utilised inferential statistical methods.

Inferential statistical methods and machine learning models offer distinct advantages. Inferential statistical models provide interpretable results, allowing for hypothesis testing and quantifying associations between digital biomarkers of health and anxiety. In contrast, machine learning models often prioritise predictive accuracy and excels at capturing complex, non-linear relationships that may not be easily captured through inferential statistical models. Together, these two approaches offer complementary insights.

Given the growing interest in using wearable-derived metrics in mental health and dementia research, this review aims to contribute to these research fields by systematically reviewing existing studies that have investigated the association between metrics collected from wrist-worn wearables and anxiety using inferential and machine learning statistical approaches.

## Methods

This review was conducted in line with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) recommendation[17] and registered with PROSPERO in March 2023 (CRD42023409995). The PRISMA 2020 checklist[18] (Multimedia Appendix 1) and the PRISMA Abstract checklist[18] (Multimedia Appendix 2) were used.

### Search Strategy

A total of five databases (Medline, Embase, PsychINFO, Web of Science, CINAHL) were systematically searched through to April 2023. Further, unpublished grey literature searches were conducted with ProQuest Dissertations and Theses Global. Following published recommendations[19], we also checked the first 300 papers on Google Scholar. Finally, to supplement the electronic search, references of eligible papers were reviewed to identify any additional eligible studies.

The search strategy combined two search term strings with ‘AND’. Each string reflected a concept related to the research question: (i) digital biomarkers, and (ii) psychosocial risk factors of dementia (Multimedia Appendix 3). Search terms were adapted for each database. There were no restrictions imposed on date of publication. This review did not restrict the databases searches to human studies and studies published in English, and no filters were used. The initial searches were conducted on 27th April, 2023, and a subsequence search was done on 24th September, 2024.

### Study Selection

The web platform Covidence (Veritas Health Innovation (Melbourne), 2020) was used for deduplication, and to coordinate multiuser title-abstract and full-text screening. Two reviewers independently screened titles and abstracts of all the identified studies (Y.L. screened 100% of the articles, and N.C., H.A.G., R.M. and H.D.K. collectively screened 100%), followed by full-text screening. Any disagreements were resolved by a third reviewer (N.L.M. or H.D.K.), with H.D.K. only resolving conflicts for articles she had not screened at title-abstract screening stage. Inter-rater agreement was assessed using Cohen’s kappa coefficient.

In accordance with the PROSPERO registration, our search strategies encompassed a range of psychosocial risk factors for dementia was included. However, given the large number of eligible articles that made it through to the full-text screening stage, we decided to categorise these articles to different psychosocial risk factors before the data extraction stage.

The present systematic review focused on anxiety – both clinical anxiety and anxiety symptoms. Studies were selected if they: (i) were cross-sectional or longitudinal, (ii), reported data on adults with a mean age over 18 years, (iii) included research or consumer grade wrist-worn devices, (iv), assessed GAD or anxiety symptoms using standardised assessments (e.g., self-repot questionnaire, clinical diagnoses), (v) were published in an English language, peer reviewed journal or thesis/dissertation, and (vi) examined the relationship between anxiety and digital biomarkers via inferential statistics or machine learning methods. Studies were excluded if they: (i) focused on a sample that received diagnoses of neurodegenerative disorders or physical health conditions (however studies were eligible if participants without these conditions were analysed separately), and (ii) primarily focused on participants with a psychiatric comorbidity, neurological disorder or stroke

(>50% of the sample).

**Data Extraction**

A standardised form was created to extract the following data from eligible inferential statistical studies: (i) authors and year of publication; (ii) study characteristics, including type of study (i.e., cross-sectional or longitudinal); (iii) demographic information; (iv) characteristics of digital biomarker, including digital biomarker type, devices used for data collection; (v) anxiety measurement, and (vi) data required for meta-analysis (e.g., mean difference, correlation coefficients). For studies using machine learning approaches, another standardised form was created to extract the following details: (i) authors and year of publication; (ii) demographic information; (iii); ground truth assessment; (iv) characteristics of digital biomarkers; (v) machine learning task; (vi) predictor features, (vii) algorithm(s); (viii) validation method, and (ix) model performance.

**Quality Assessments**

*Cross-sectional and longitudinal studies*

The National Heart, Lung and Blood Institute (NHLBI) assessment tool was used[20]. This quality assessment tool comprises 14 criteria which are used evaluate the validity and reliability of studies. For cross-sectional studies, four criteria that are relevant to longitudinal study designs are not applicable, and were therefore omitted[21]. Scores were averaged and each study was categorised as having a “Good” (≥80), “Fair” (50–80%), or “Poor” (50%) rating, as specified in the guidelines.

*Machine learning studies*

Currently, there is no validated quality assessment tool for machine learning studies. We employed a modified version of the validated Quality Assessment of Diagnostic Accuracy Studies 2 (QUADAS-$2_{modified}$)[22], which evaluates the risk of bias of studies across four domains (participants, index text [artificial intelligence algorithms], reference standard [ground truth], and analysis), and evaluates applicability concerns across three domains (excluding analysis domain)[15].

Two independent reviewers assessed the quality of each eligible study. Any disagreements were resolved by a third reviewer.

**Synthesis and analysis**

Effect sizes were combined across studies, separately for each type of digital biomarker of health, using random-effects meta-analyses. When effect sizes were unavailable, other available data were used for calculations (e.g., t-test statistic). Random-effects meta-analyses were used as it takes into account between-study heterogeneity[23].

To ensure only one effect size from each included study was used in the primary meta-analysis, studies were selected based on an *a priori* determined hierarchy. Specifically, we prioritised: (i) largest sample size, (ii) unadjusted over adjusted estimates, and (iii) trait (chronic/ongoing) over state (present moment) anxiety, when more than one study used the same cohort. Trait anxiety refers to the general tendency to respond with anxiety across various situations, whereas state anxiety is a temporary response reflecting the present moment[24]. Since trait anxiety reflects a chronic condition with long-term implications and offers a more stable measure of general anxiety levels, it was the focus of our analysis.

Sensitivity analyses were conducted to examine whether results differed according to anxiety type (trait and stage anxiety), and age group (young, middle, older).

For each meta-analysis, heterogeneity was assessed using $Tau^2$ (between study variance) and $I^2$ (proportion of total variation in study estimates that is due to heterogeneity[25]). Publication bias was assessed by inspecting funnel plots when there were 10 or more studies included in a meta-analysis[26].

All analyses were conducted using the '*metafor'* package in R (version 4.2.2).

Qualitative synthesis was conducted for studies using inferential statistical approaches that were not included in the meta-analysis. These studies were synthesised based on the type of digital biomarkers of health examined (i.e., sleep metrics, activity metrics). On the other hand, studies using machine learning approaches were not meta-analysed and were synthesised qualitatively, ordered by performance metrics (i.e., accuracy, sensitivity, precision, and F1 score).

## Results

### Study Selection

After the removal of duplicates, title/abstract screening and full-text review, 365 articles were eligible (Figure 1). Of these, 30 articles focused on anxiety. Inter-rater reliability was high, with Cohen's kappa's of 0.73 (substantial agreement) and 0.83 (almost perfect agreement) at the title/abstract screening and full-text review stages, respectively.

### Study and Participants Characteristics

When an article reported outcomes from different cohorts or separately analysed different populations (e.g., male and female), each result was treated as a different study derived from the same article. This resulted in 32 studies from 30 articles. Of these, 25 studies (78.1%) used inferential statistical approaches for analysis while seven studies (21.9%) used machine learning approaches.

*Studies using inferential statistical approaches*

Characteristics of studies that used inferential statistical approaches are presented in Table 1, Multimedia Appendix 4 and summarised in Multimedia Appendix 5. There was a total of 25 studies from 24 articles (cross-sectional: $k$ = 16 [64.0%], longitudinal: $k$ = 5 [20.0%]), both cross-sectional and longitudinal: $k$ = 4 [16.0%]). The study sizes ranged from 17 to 60,235 participants (median = 118). Almost half of the studies assessed trait anxiety or clinically diagnosed anxiety ($k$ = 13 [52.0%]), nine assessed state anxiety (36.0%) and three assed both state and trait anxiety (12.0%). The majority of studies were conducted in young adults ($k$ = 15 [60.0%]), five in middle-aged adults (20.0%), four in older adults (16.0%), and one did not report age data (4.0%).

Most studies assessed sleep ($k$ = 17, 68.0%), four studies (16.0%) assessed physical activity, two studies (8.0%) assessed heart rate variability, and two studies (8.0%) assessed both sleep and activity. The majority of sleep studies assessed the following four sleep metrics: total sleep time (i.e., total time spent in bed), wake after sleep onset (i.e., time spent awake after initially falling asleep), sleep efficiency (i.e., ratio of total sleep time to the total time spent in bed), and sleep onset latency (i.e., time it takes to fall asleep after going to bed). Regarding physical activity, sedentary behaviour, light physical activity and moderate-vigorous physical activity were most commonly assessed.

**Table 1**. Characteristics of samples eligible for systematic review and/or meta-analysis of studies using inferential statistical approaches

| Study | Study | N | Population | Anxiety | Wearable | Digital |
|---|---|---|---|---|---|---|

| | **design (follow-up time)** | | **type** | **measure (type)** | **device (research/ consumer-grade)** | **biomarker type (sub-type)** |
|---|---|---|---|---|---|---|
| Bullis, 2016 (USA)[27]* | Cross-sectional | 30 | Clinical samples and healthy controls | Clinical diagnosis (DSM-V) (trait) | Actiwatch (research) | Sleep (SOL, TST, SE, WASO) |
| | Longitudinal (14 days) | 30 | Clinical samples and healthy controls | Clinical diagnosis (DSM-V) (trait) & daily symptom ratings (ecological momentary assessment) (state) | Actiwatch (research) | Sleep (SOL, TST, SE, WASO) |
| Casanova et al., 2023 (UK)[28] | Cross-sectional | 95,776 | General population | GAD-7 (trait) | Axivity AX3 (research) | Activity (physical activity, SB) |
| Cox et al., 2018 (USA) [29] | Cross-sectional | 138 | Undergraduate students and community adults | Momentary anxiety (state) | ActiGraph wGT3X-BT (research) | Sleep (TST) |
| | Longitudinal (9 days) | 138 | Undergraduate students and community adults | Momentary anxiety (state) | ActiGraph wGT3X-BT (research) | Sleep (TST) |
| D'Aurizio et al., 2023 (Italy)[30]* | Cross-sectional | 60 | Prisoner and healthy control | STAI (trait and state) | Actiwatch Spectrum Plus (research) | Sleep (SOL, SE, TST, WASO) |
| Dillon et al., 2018 (Ireland) [31] | Cross-sectional | 397 | Patients (population-representative random sample, from a primary care centre) | HADS-A (state) | GENEActiv accelerometer (research) | Activity (SB, LPA, MVPA) |
| Doane et | Cross- | 82 | Adolescent | DASS-A | Actiwatch | Sleep (sleep |

| | | | | | | |
|---|---|---|---|---|---|---|
| al., 2015 (USA)[32]* | sectional | | transition to college | (state) | Score (research) | start time variability, SOL, SE, TST) |
| | Longitudinal (1 year) | Follow-up 1: 76 Follow-up 2: X71 | Adolescent transition to college | DASS-A (state) | Actiwatch Score (research) | Sleep (sleep start time variability, SOL, SE, TST) |
| El-Sheikh et al., 2013 (USA) (female) [33]* | Cross-sectional | 135 | Cohabiting couples | BAI (trait) | Octagonal Basic Motionloggers (research) | Sleep (TST, SE, SOL) |
| El-Sheikh et al., 2013 (USA) (male)[33]* | Cross-sectional | 135 | Cohabiting couples | BAI (trait) | Octagonal Basic Motionloggers (research) | Sleep (TST, SE, SOL) |
| Facer-Childs et al., 2022 (Australia) [34] | Cross-sectional | 68 | Elite Football League Atheletes | GAD-7 (trait) & DASS-A (state) | GENEActiv actigraphy devices (research) | Sleep (snooze time, SE, TST, TIB) |
| Feng et al., 2021 (USA) [35] | Cross-sectional | 14 | Ophthalmology Residents | DASS-A (state) | Fitbit Alta HR (consumer) | Sleep (lower average sleep on call) and Activity (average daily exercise) |
| Fuller-Rowell et al., 2024 (USA)[36]* | Cross-sectional | 874 | Small towns and semi-rural communites | BAI (trait) | Octagonal Basic Motionloggers (research) | Sleep (TST, night-to-night variability, SE, SOL) |
| Hofman et al., 2022 (Netherlands)[37] | Cross-sectional | 1943 | General population | HADS-A (state) | GENEActiv (research) | Sleep (TST) and Activity (SB, LA, MVPA) |
| Huang et | Cross- | 321 | College | SAS | Axivity | Activity (SB – |

| | | | | | | |
|---|---|---|---|---|---|---|
| al., 2022 (China)[38] | sectional | | students | (state) | AX3 (research) | total, weekend, weekdays) |
| Jo et al., 2024 (Korea)[39] | Longitudinal (4 weeks) | 47 | Young adults | GAD-7 (trait) | Samsung Galaxy Active 2 (consumer) | HRV (time-domain measures: RMSSD, SDNN, SDSD, PNN50; frequency-dimain measures: LF, HF, LF/HF) |
| Kandola et al., 2021 (UK)[40] | Longitudinal (2 years) | 60,235 | General population | GAD-7 (trait) | Axivity AX3 (research) | Activity (SB, LPA, MVPA) |
| Lee et al., 2021 (USA, Austrlia, South Korea)[41]* | Cross-sectional | 17 | Elite esports athletes | STAI (state) | Readiband V5 (research) | Sleep (TST, SOL, WASO, SOT, WT) |
| Nguyen et al., 2023 (Australia) [42]* | Cross-sectional | 101 | Newly recruited paramedics | GAD-7 (trait) | Actiwatch Spectrum or Spectrum PRO (research) | Sleep (TST, WASO, SOL, SE) |
| | Longitudinal (6 months) | 101 | Newly recruited paramedics | GAD-7 (trait) | Actiwatch Spectrum or Spectrum PRO (research) | Sleep (TST, WASO, SOL, SE) |
| Okawara et al., 2024 (Japan)[43] | Longitudinal (60 days) | 279 | Office workers | STAI trait subscale (trait) | Apple Watch (consumer) | HRV (HF, LF, LF-to-HF ratio, LnccL/H) |
| Spira et al., 2008 (USA) [44]* | Cross-sectional | 59 | Adults with primary insomnia | STAI (trait and state) | Actiwatch-L (research) | Sleep (WASO, SE, SOL) |
| Spira et al., 2009 (USA) [45]* | Cross-sectional | 3040 | Community-dwelling older women | Goldberg Anxiety Scale (trait) | SleepWatch-O (research) | Sleep (TST, SE, time awake after sleep onset, SOL, napping time) |

| | | | | | | |
|---|---|---|---|---|---|---|
| Straus et al.,2023 (USA)[46] | Longitudinal (8 weeks) | 2021 | Trauma survivors from emergency department | Smartphone-based questionnaires (state) (measured 6 times over the 8 weeks period) | Verily Life Sciences (research) | Sleep (number of transitions between sleep and wake) |
| Stremler et al., 2017 (Canada) [47] | Cross-sectional | 118 | Parents of critically ill hospitalised children | STAI (state) | Octagonal Basic Motionlogger actigraphs (research) | Sleep (TST, number of nocturnal awakenings, individual sleep variability) |
| Swanson et al., 2023 (USA)[48]* | Cross-sectional | 1197 | Postmenopausal women | GAD-7 (trait) | Actiwatch-2 (research) | Sleep (sleep irregularity, sleep midpoint outside 2-4am) |
| Walters et al., 2020 (Australia) [49] | Cross-sectional | 110 | Without sleep disorders | BAI (trait) | Respironics Actiwatch Spectrum Pro (research) | Sleep (SE) |
| Zheng et al., 2024 (USA)[50] | Longitudinal xs(4.5 years) | 6785 | General population | Electronic health records | Fitbit (consumer) | Sleep (TST, sleep stages, sleep regularity) |

*Abbreviations*: BAI, Beck Anxiety Inventory; DASS-A, Depression, Anxiety and Stress Scale-Anxiety Subscale; GAD-7, Generalized Anxiety Disorder-7; HADS-A, Hospital Anxiety and Depression Scale - Anxiety section; HF, absolute power of the high-frequency band; HRV, heart rate variability; LF, absolute power of the low-frequency band; LF/HF, ratio of LF-to-HF power; LnccL/H, log-transformed coefficient of component variance of the low-frequency component to high-frequency component power ratio; LPA, light-intensity physical activity; MPA, moderate-intensity physical activity; MPA, vigorous-intensity physical activity; MVPA, moderate-to-vigorous physical activity; PNN50, percentage of successive RR intervals that differ by more than 50ms; RMSSD, root mean square of successive RR interval differences; SAS, Self-Rating Anxiety scale; SB, sedentary behaviour; SD, standard deviation; SDNN, standard deviation of NN intervals; SDSD, standard deviation of RR interval intervals; SE, sleep efficiency; SOL, sleep onset latency; SOT, sleep onset time; ST, sedentary time; STAI, State-Trait Anxiety Inventory; TIB, Time in bed; TST, total sleep time; WASO, Wake after sleep onset; WT, wake time

Notes: *studies included in meta-analyses

*Studies using machine learning approaches*

Characteristics of studies using machine learning approaches are presented in Table 2 and Multimedia Appendix 6. A total of seven studies from six articles were included. The study sizes ranged from 60 to 727 participants (median = 352). All studies used algorithms trained with a labelled dataset to select predictors for predict anxiety (i.e., supervised learning). Included studies used a variety of digital biomarker of health as predictors in their models, e.g., heart rate variability, sleep, activity.

**Table 2**. Characteristics of samples for studies using machine learning approaches

| Study | Population Type | N | Anxiety measure (type) | Wearable device (Consumer or research-grade) | Machine Learning Task | Predictor(s) | Algorithm(s) |
|---|---|---|---|---|---|---|---|
| Coutts et al., 2020 (UK) Trial 1[51] | University students | 68 | DASS-A (state) and STAI (trait & state) | Biobeam band (research) | Binary classification (supervised) | Heart rate variability | Deep Neural Networks (LSTM) |
| Coutts et al., 2020 (UK) Trial 2[51] | University students | 584 | DASS-A (state) and STAI (trait & state) | Biobeam band (research) | Binary classification (supervised) | Heart rate variability | Deep Neural Networks (LSTM) |
| Fukuda et al., 2020 (Japan) [52] | Office workers | 60 | DAMS (state) | Fitbit Charge 3 (Consumer) | Binary classification (supervised) | Sleep actigraphy data (13 features, e.g., total sleep time, number of wake) | RF |
| Lee et al., 2022 (Korea) [53] | Older adults with mild cognitive impairment | 352 | Clinical diagnosis (Trait) | Fitbit Alta HR2 (Consumer) | Binary classification (supervised) | Model 1: 24-hour activity rhythms and sleep patterns[1]<br><br>Model 2: Model 1+ Minimal K-GAI (5 items) | Logistic regression, SVM, RF, GBM |
| Lee et al., 2024 (Korea) [54] | Older adults with mild cognitive impairment | 352 | Clinical diagnosis (Trait) | Fitbit Alta HR2 (Consumer) | Binary classification (supervised) | Model 1: Activity, sleep<br><br>Model 2: Activity + Minimal K-GAI | Convolutional neural network, LSTM, Residual Network |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Saylam et al., 2023 (USA)[55] | Office workers | 727 | Single item[2] (state) | Garmin smartwatch (consumer) | Regression | Activity, stress, sleep, heart rate | RF, XGB, LSTM |
| Saylam et al., 2024 (USA)[56] | College students | Baseline: ~700<br><br>Follow-up: 300 | BAI | Fitbit (consumer) | Regression | Activity and sleep | RF, XGB, LSTM |

*Abbreviations*: BAI, Beck Anxiety Inventory; DAMS, Depression and Anxiety Mood Scale; DASS-A, Depression, Anxiety and Stress Scale - Anxiety Subscale; Gradient Boosting Machine; K-GAI, Korean version of Geriatric Anxiety Inventory; LSTM, Long Short-Term Memory networks; RF, Random Forest; STAI, State-Trait Anxiety Inventory; SVM, Support Vector Machine; GBM, Gradient Boosting Machine, Extreme Gradient Boosting

Notes:
[1]Model 1: 24-hour activity rhythms (inter-daily stability [the stability of an activity rhythm of a daily pattern], intra-daily variability [the variability of the activity rhythms throughout the day], dominant rest phase onset) [the start time of the 5 hour period with the least activity within 24 hour] and sleep patterns (total sleep time, sleep onset latency, wake after sleep onset, sleep quality)
[2]Single item question "Please select the response that shows how anxious you feel at the moment. Response scale: 1 (Not at all anxious), 2 (A little anxious), 3 (Moderately anxious), 4 (Very anxious), 5 (Extremely anxious)."

**Quality Assessment**

*Studies using inferential statistical approaches*

For studies that conducted both cross-sectional and longitudinal analyses, quality assessment was based on the longitudinal studies. Of the 25 studies, ten (40.0%) received a 'Good' quality rating, the remainder received a 'Fair' rating ($k$ = 15, 60.0%) (Multimedia Appendix 7).

*Studies using machine learning approaches*

The quality assessment tool for studies using machine learning approaches assesses the risk of bias across four domains: participants, index test, reference standard, and analysis. Four studies were rated as having a high risk of bias in the participants domain. For index test, ground truth, and analysis, all studies were rated as either low risk or unclear. There were either unclear or low concerns regarding applicability of the studies to our review question across the participants, index test, and reference standard domains (Multimedia Appendix 7).

**Quantitative Synthesis of Cross-sectional Studies**

Random-effects meta-analyses were performed for nine studies that provided combinable effect sizes[27,30,32,33,36,41,42,44,45]. All studies were cross-sectional and assessed associations between sleep metrics and anxiety symptoms.

No association between sleep onset latency (SOL) and anxiety symptoms was observed ($k$ = 9, N = 3643; Fisher's $z$ = 0.04, 95% confidence interval [CI] = -0.05 to 0.13, $P$ =.36; Figure 2 and Multimedia Appendix 8), with evidence of moderate to substantial heterogeneity between studies ($I^2$ = 49.77%). The results remained unchanged in sensitivity analyses based on anxiety type and age group (Multimedia Appendix 8 and Multimedia Appendix 9). One study was not eligible for meta-analysis but found that higher SOL was associated with more anxiety symptoms[36].

No association between total sleep time (TST) and anxiety symptoms was observed ($k$ = 9, $N$ = 4459;

Fisher's $z$ = -0.004, 95% CI = -0.03 to 0.03, $P$ = .90; Figure 3 and Multimedia Appendix 8), with very low heterogeneity between studies ($I^2$ = 0%). The results remained unchanged in sensitivity analyses (Multimedia Appendix 8 and Multimedia Appendix 9). Although four studies were not eligible for quantitative synthesis, their findings aligned with those from the meta-analysis[29,37,47], except for one study that found a positive association between poor sleep – as measured by a composite including TST and other sleep metrics – and anxiety symptoms[34].

Worse sleep efficiency (SE) was associated with greater anxiety symptoms ($k$ = 8, $N$ = 3627; Fisher's $z$ = -0.08, 95% CI = -0.15 to -0.01, $P$ = .03; Figure 4 and Multimedia Appendix 8), with low heterogeneity between studies ($I^2$ = 28.70%). This result was not significant in sensitivity analyses (Multimedia Appendix 8 and Multimedia Appendix 9). Of the three studies ineligible for quantitative synthesis, two found no association between SE and anxiety symptoms[25,31], while the other found results consistent with the primary meta-analysis[34].

Longer wake after sleep onset (WASO) was associated with greater anxiety symptoms ($k$ = 6, $N$ = 3291; Fisher's $z$ = 0.13, 95% CI = 0.01 to 0.24, $P$ = .03; Multimedia Appendix 8 and Figure S1), with low to moderate heterogeneity between studies ($I^2$ = 40.62%). These results persisted in trait anxiety but not other groups in sensitivity analyses (Multimedia Appendix 8 and Multimedia Appendix 9).

**Qualitative Synthesis of Inferential Statistical Studies**

*Sleep*

Six studies investigated the association between sleep metrics not included in the meta-analyses and anxiety. Sleep start variability[32], sleep onset time[41], wake time[41], number of nocturnal awakenings[47], sleep variability[47] and sleep timing[48] were not associated with anxiety symptoms. Lower average sleep among doctors who were on call was negatively associated with anxiety symptoms[35]. Other studies found that higher sleep irregularity[48] and sleep duration variability[36] were associated with more anxiety symptoms.

Six studies reported the longitudinal association between sleep and anxiety[27,29,32,42,46,50]. While one study found no association between baseline sleep metrics (i.e., SE, WASO, SOL, and TST) and anxiety at 6 months follow-up in paramedics[42], the majority of studies did observe an association over varying periods of time. Lower TST compared to an individual's personal TST average was associated with higher anxiety levels on the next day[29]. Anxious mood also predicted next day's poorer sleep (i.e., lower SE, longer WASO and less TST) in individuals with clinical anxiety, but not in healthy controls[27]. Worsening sleep continuity (measured by the number of transitions between sleep and wake) was associated with worsening anxiety over an 8-week period[46], lower SE and longer SOL were associated with more anxiety symptoms at 1 year follow-up[32], and sleep patterns (increased sleep irregularity, decreased deep and REM sleep percentage, and increased light sleep percentage) captured through continuous monitoring over a median period of 4.5 years were associated with increased odds of GAD[50]. Additionally, they identified a non-linear, J-shaped relationship between average daily sleep duration and GAD – compared with the median average daily sleep of 6.8 hours, individuals with an average daily sleep duration of 5 hours or 10 hours had increased odds of GAD.

*Activity*

Five studies investigated the association between sedentary behaviour and anxiety[28,31,37,38,40]. While one study found no association between sedentary behaviour with anxiety symptoms[38] the remainder did observe associations. Individuals with moderate to severe anxiety symptoms in primary care settings spent more time in sedentary activity per day than participants with no

significant anxiety[31]. This finding was supported by another study that used isotemporal substation models (which assess the effect of hypothetically replacing one activity with another while keeping the total time constant), which found that replacing moderate-vigorous physical activity with sedentary behaviour was associated with higher odds of having clinically relevant anxiety symptoms[37]. Another study found that while sedentary time was not associated with current GAD and anxiety symptoms[28], it was associated with lower odds of lifetime GAD, and in males when stratified by sex[28]. The association between sedentary behaviour and anxiety symptoms was also supported in a longitudinal study, with more baseline sedentary behaviour with more anxiety symptoms at follow-up[40].

Three studies examined the association between light activity, moderate-vigorous physical activity and anxiety[31,37,40], and reported mixed findings. Individuals with moderate to severe anxiety symptoms spent less time in light physical activity than those without significant levels of anxiety, however no difference was observed with moderate-vigorous physical activity[31]. When using isotemporal substitution models to examine light physical activity, one study found that replacing sedentary behaviour with light physical activity was associated with a decrease in anxiety symptoms[31], while another study found no association[37], and a longitudinal study found that replacing sedentary behaviour with light physical activity was associated with more anxiety symptoms at follow-up[40]. Regarding moderate-vigorous physical activity, one study found that replacing sedentary behaviour with moderate-vigorous physical activity was associated with lower odds of clinically relevant anxiety symptoms[37], whereas a longitudinal study found that replacing baseline sedentary behaviour with moderate-vigorous physical activity was associated with lower anxiety symptoms at follow-up[40], and yet another study found no association[31].

Three studies investigating other activity metrics (average daily exercise duration, total sedentary time on weekdays and weekends, overall physical activity) [28,35,38], two did not find associations with anxiety symptoms[35,38]. One study found that more physical activity was associated with lower odds of current and lifetime GAD and lower anxiety symptoms, similar findings were observed when stratified by sex for both men and women[28].

*Heart rate variability*

Two studies investigated the association between heart rate variability (HRV) metrics and anxiety[39,43]. HRV metrics can be examined in either the time-domain (measuring the amount of variability in intervals between heartbeats over time), or the frequency domain (measuring how HRV is distributed across different frequency bands). Within the frequency domain, the high frequency component has been linked with parasympathetic nervous system (PNS) activation and the low frequency component has been linked with sympathetic nervous system activation (SNS). Both central tendency and variability of metrics can be assessed in the HRV time and frequency domains.

One study focusing on the frequency domain found that compared to a low trait anxiety group, the high trait anxiety group showed greater variability in HRV frequency metrics associated with PNS activation and the consistency of this activation, SNS activation, and the balance of PNS and SNS activation (e.g. low frequency/high frequency HRV) in addition to daily changes of this balance. Additionally, a higher mean and greater variance in daily changes in the balance of PNS and SNS activation were associated with increased odds of having trait anxiety[43]. In contrast, a separate study observed that higher mean low frequency (SNS activation) was associated with lower anxiety scores, and that mean high frequency HRV (PNS activation) and the low frequency/high frequency ratio were not associated with anxiety symptoms[39]. This study also examined the association between HRV time domain metrics and anxiety at two different time points, and found that higher

mean deviation from the average HRV and short-term variations in heart rate were associated with lower anxiety scores[39].

**Qualitative Synthesis of Machine Learning Studies**

Of the seven studies included in this review, some studies utilised multiple algorithms within the same study, each with multiple performance metrics. Accuracy measures correct classifications (i.e., presence/absence of anxiety). Sensitivity is the ability to detect true positives (i.e., correct identification of individuals with anxiety), while precision is correct classification among predicted positives (i.e., how many individuals classified as having anxiety actually have anxiety). F1 score balances precision and sensitivity, and mean absolute error (MAE) measures the average prediction error, with lower MAE signifying better performance.

Three studies reported 13 accuracy estimates, ranging from 56.3% to 94.6%[51–53]. Two studies reported nine sensitivity estimates (range: 56.3% to 94.6%), nine reported precision estimates (56.3% to 94.8%), and nine reported F1 score estimates (range: 55.9% to 94.6%)[52,53]. Fifty-six MAE estimates were reported from two studies[55,56].

One article using two cohorts found better accuracy in predicting anxiety using frequency-domain HRV and nighttime HRV (63.9%-69.4%) data than time-domain HRV and daytime (63.2%-63.4%%) data[51]. They also found that nighttime HRV data (maximum accuracy: 69.4%) performed better than day time data (maximum accuracy: 63.2%)[51].

One study with older adults who had mild cognitive impairment found that combining activity (24-hour activity rhythm), sleep, and anxiety questionnaire items improved model performance across accuracy (91.0%-94.6% vs. 56.3%-59.9%), precision (91.4%-94.8% vs. 56.4%-61.0%), recall (91.0%-94.6% vs. 56.3%-59.9%), and F1 scores (90.9%-94.6% vs.55.9%- 59.0%) compared to models that excluded anxiety questionnaire data[53]. Similarly, another study using the same sample found that combining activity (step count) and sleep stages achieved a predictive success rate for participants without anxiety (98%) but had a low predictive success rate identifying those with anxiety (18%)[54]. Models including anxiety questionnaire items improved the predictive success rate for identifying participants with anxiety (82%) and maintained a good predictive success rate at identifying those without anxiety (95%). These studies did not report feature importance in their models.

Two studies predicted anxiety in office workers[52,55]. One study, using 13 sleep metrics, achieved a F1 score of 75.6% and identified that the top five important predictors were REM sleep time ratio, REM sleep minutes, light sleep time ratio, deep sleep time ratio, and total wake time ratio[52]. Another study, using data wearable (activity, stress, sleep and heart rate data) and smartphone, found that the best non-time-based model (i.e., without incorporating temporal data) predicted anxiety with a MAE of 0.6316. Time-based models showed improved performance, with an MAE of 0.3729 when using data from the previous three days to predict next day's anxiety[55]. They found that the top 20 predictors included measures of sleep (bedtime, wake time, sleep duration), stress (low stress duration), and activity (highly active duration).

One study comparing four modelling approaches – conventional, multitask learning approach (model trained to solve multiple tasks simultaneously), time-based approach, and time-based multitask approach – found that time-based models using data from the previous 15 days to predict next day's anxiety achieved the lowest MAE (0.0047), followed by the time-based multitask model (MAE: 0.0083), the conventional model (MAE: 0.1277), and the multitask model (MAE: 0.1347)[56].

While activity, sleep and heart rate were considered, the top 20 predictors did not include any of these metrics.

## Discussion

This review aimed to advance scientific understanding of the association between digital biomarkers of health collected from wrist-worn devices and anxiety. Specific interest centered on determining which digital biomarkers of health have been the focus of existing research, and which demonstrate the strongest evidence of an association with anxiety. 32 studies were included in this systematic review, of which nine were included in meta-analyses. Meta-analyses were conducted for four sleep metrics (SE, WASO, TST, SOL) and revealed that SE and WASO were associated with anxiety, while TST and SOL were not. It was not possible to conduct meta-analyses for physical activity metrics, however, qualitative synthesis suggests that sedentary behaviour was associated with higher levels of anxiety.

### Sleep

Our meta-analytic findings found that lower SE and more WASO are associated with anxiety, rather than overall sleep duration and time to fall asleep. The Pittsburgh Sleep Quality Index (PSQI), commonly used to assess subjective sleep, is comprised of seven components (sleep quality, sleep latency, sleep duration, sleep efficiency, sleep disturbance, use of sleep medication, and daytime dysfunction). Existing research using the PSQI generally report that shorter sleep duration, poor sleep quality, lower sleep efficiency, and longer sleep onset latency are associated with anxiety disorders in both young and older adults[57–60]. In addition, worse subjective sleep quality has also been associated with more non-clinical levels of anxiety symptoms[61,62]. Our meta-analytic findings align with existing studies on subjective SE, but do not resemble existing evidence on subjective TST and SOL. The association between SE, WASO and anxiety symptoms were attenuated in the younger adults sensitivity analyses, suggesting a potential age effect. However, we were unable to conduct well-powered sensitivity analyses for older adults due to the limited number of eligible studies ($k$ = 2) in the meta-analysis.

Research examining associations between anxiety and sleep metric derived from Polysomnography (PSG), the gold standard measurement of objective sleep, has been limited. One review identified six studies investigating polysomnographic sleep, and found decreased SE and TST, and increased WASO in individuals with GAD compared with healthy controls[63]. Another review examined sleep metrics derived from electroencephalography (EEG) and found that individuals with GAD had decreased TST, and increased WASO and SOL compared with healthy controls; however no differences in SE were observed[14] .

Our meta-analytic findings align with PSG/EEG studies regarding WASO and partially with SE, but not with TST and SOL. Only two studies included in our meta-analysis asked participants to press an event marker to indicate when they began to fall asleep[27,64]. Without these event markers, estimating SOL may be less accurate, as different sleep behaviours can influence wrist movements. Differences in TST could also be attributed to differences in sample characteristics; the majority of studies (88.9%) in our review assessed anxiety symptoms, whereases the studies using questionnaires and PSG/EGG focused on individuals with clinical anxiety. This suggests that a relationship between TST and anxiety may emerge in clinical anxiety, but not in subthreshold anxiety symptoms.

### Physical activity

Our review found that sedentary behavior was associated with greater anxiety symptoms, but the associations with light physical activity and moderate-vigorous physical activity were inconsistent. The observed positive association between sedentary behaviour and anxiety symptoms aligns with

existing findings[65,66]. A meta-analysis, where the majority of studies used self-report questionnaires to measure sedentary behaviour (85.7%), found a small positive association between sedentary behaviour and anxiety[66]. Similar to our review, their study populations were largely composed of healthy individuals rather than those with anxiety disorders. It may be that stronger associations emerge with more severe anxiety. For example, one study included in our review observed a significant association only when assessing clinical vs. non-clinical anxiety symptoms, rather than analysing anxiety as a continuous variable (with mean anxiety score below the clinical threshold)[37]. This potential threshold effect is also further supported in another study included in our review, which found that individuals with more severe anxiety symptoms engaged in more sedentary behaviour than those with no significant anxiety symptoms[31].

The two cross-sectional studies examining the association between light physical activity and anxiety in the current review reported divergent findings. This inconclusive finding is supported by a systematic review that found inconsistent results regarding the relationship between light physical activity and anxiety in two studies of adults that which used objective measures[67].

We found inconsistent evidence regarding the association between moderate-vigorous physical activity and anxiety, aligning with existing studies which measured moderate-vigorous physical activity via self-report questionnaire. One study found that meeting the moderate-vigorous physical activity guideline (e.g., ≥150 minutes weekly of moderate-vigorous physical activity) based on self-reports was associated with more anxiety symptoms cross-sectionally but not longitudinally in middle-aged adults and older adults over a 2 year follow-up[68]. Another study found that higher self-reported moderate-vigorous physical activity was associated with a lower incidence of GAD in older adults[69]. However, these findings should be interpreted with caution, considering the limitations associated with self-reported activity levels, such as social desirability and recall bias, and over- or under-reporting[70].

**Heart rate variability**

Our review found inconclusive evidence on the association between HRV and anxiety, as only two articles were included in this review. An existing meta-analysis on HRV found that individuals with GAD had reduced high frequency and time-domain HRV[71], which means they may have less flexibility in adapting to stress. This partially aligns with the findings from one of the studies included in the current review, where higher mean time-domain HRV was associated with lower anxiety symptoms[39]. However, this study also found that greater high frequency HRV variability was associated with more anxiety symptoms. The discrepancy in findings may be due to the focus of the existing meta-analysis on clinical anxiety, whereas the two studies in our review examined anxiety symptoms.

**Studies using machine learning approaches**

Machine learning approaches emphasise building models that generalise to new data. These approaches offer advantages over inferential statistical methods by handling large datasets and capturing both linear and non-linear relationships between variables without strong assumptions about variable relationships. However, machine learning models can be challenging to interpret due to their “black box” nature, where decision-making processes are not transparent[72].

In this review, machine learning models predicting anxiety had accuracies ranging from 56.3% to 69.4% (excluding models that used anxiety questionnaires as inputs). The accuracies reported here are lower than machine learning models using any wearable devices to predict depression (70-89%) [15] and anxiety (82%)[16], which utillised a range of predictors (e.g., heart rate, activity, sleep,

audio, and skin temperature). This may be explained by the lack of demographic predictors, which might enhance model accuracy. Indeed, some studies in the depression and anxiety machine learning reviews used demographic data as predictors, further supporting the potential utility of these predictors to improve prediction of anxiety. Another potential reason for the lower accuracy in this review may be that we focused solely metrics measured from wrist-worn wearables, whereas their review included other types of digital biomarkers collected from other types of wearable devices (e.g., audio data). Finally, the models with the highest accuracy in our review included anxiety questionnaires as a predictor to predict clinically diagnosed anxiety, likely inflating model performance due to circularity.

Linking findings from studies using inferential statistical approaches and machine learning, SE and WASO were associated with anxiety in studies using inferential statistical approaches. They were also included as predictors in two machine learning studies[52,56]. However, only one reported feature importance, and neither reported the direction of the relationship between these metric(s) and anxiety. To improve transparency and interpretability of machine learning models, future research should report both feature importance and the directionality.

**Wrist-worn wearable devices**

Digital biomarkers from wrist-worn wearables offer several benefits over traditional assessments of anxiety as they allow for continuous data collection over long periods without the need for repeated administration. In addition, these largely affordable and minimally intrusive devices can be used in natural settings, providing valuable insights into sleep and activity habits. While both research-grade and consumer-grade devices are less precise than PSG in measuring sleep[73–75], this may be due to their indirect measurement (e.g., based on movement). Despite this limitation, they are generally considered valid tools for sleep assessment[73,76]. Moreover, PSG is neither cost-effective nor practical for large-scale real-world studies. Given that the majority of the studies in our review used research grade devices, a key remaining question is whether these findings generalise to consumer-grade wrist-worn devices, which are more widely accessible to the general population.

There are also benefits to using self-report data. Self-report questionnaires can capture subjective experiences, such as perceived levels of exercise or sleep quality, which wearables cannot measure. Further, they have potential to record underlying reasons for poor sleep, for example, such as bad dreams or pain. Therefore, while wrist-worn wearables offer advantages, incorporating self-report measures can provide a more comprehensive understanding of both objective and subjective experience.

**Strengths, limitations and future directions**

To the best of our knowledge, this is the first review to examine the association between digital biomarkers of health from wrist-worn wearables and anxiety. We employed double screening for all studies to ensure a rigorous selection process and to minimise bias. We also included grey literature to reduce potential publication bias and provide a more comprehensive review of existing studies.

This review has several limitations. First, the majority of included studies focused on young adults. Part of the impetus for this review was to explore whether metrics measured from wrist-worn wearables could eventually be used as a screening tool for dementia risk, as indicated by changes in anxiety symptoms. However, the number of studies conducted in older adults is scarce. Future studies involving older adult participants would enrich our understanding of the association between digital biomarkers of health and anxiety in the context of dementia, given that anxiety is a potentially modifiable factor associated with dementia risk. Second, despite previous literature showing associations between physical activity and anxiety[77,78], few studies in our review focused on

activity-related metrics, which precluded a meta-analytic synthesis of these findings. Wrist-worn devices generally provide more objective measurements of activity compared to self-report, which can be influenced by different biases[79], highlighting the need for further research. Third, although our search strategy and eligibility criteria allowed for the inclusion of any metrics measured by wrist-wearables, the majority of the studies focused on sleep metrics. This highlights an opportunity for future research to explore a wider range of metrics that could be associated with anxiety (e.g., other activity metrics such as step count). Finally, while machine learning has potential in predicting anxiety, the quality of these studies need improvement. For example, future studies need to carefully consider the predictors used. None of the included machine learning studies considered demographics as potential predictors, despite existing research indicating sex differences in anxiety[80]. In addition, to increase the interpretability of machine learning models, future studies should increase interpretability by reporting SHAP values or feature importance scores (machine learning studies included in this review do not always report these). Additionally, most of the studies focused on a single metric (e.g., sleep), despite the potential for the models to include multiple predictors. More research utilising machine learning approach is needed, especially to compare whether this approach is superior to traditional approaches that use inferential statistics in predicting anxiety.

Wrist-worn wearable devices offer a scalable and non-invasive method to passively and continuously monitoring anxiety symptoms. Metrics collected from these devices have the potential to serve as a screening or detection tool for anxiety, allowing individuals at risk of developing clinical anxiety to be identified before consulting a clinician. If these metrics and models have high predictive accuracy, they could support clinicians in identifying at risk individuals and provide timely assessments and interventions. Before such an approach can be implemented in real-world clinical practice, more research is essential. In order to develop a clinically meaningful prediction model using s, interdisciplinary collaboration is crucial (e.g., clinicians, machine learning experts). This will ensure the models are accurate, interpretable, clinically meaningful, and integrated into the healthcare system rather than remaining a research-focused tool.

**Conclusion**

Our meta-analyses found significant cross-sectional associations between sleep efficiency, wake after sleep onset and anxiety. Although the number of studies was limited, there was evidence that sedentary behaviour is associated with anxiety. However, existing studies on light, moderate-vigorous physical activity and heart rate variability present inconsistent or inconclusive findings, highlighting the need for more research. Further, following a comprehensive review of the literature, it became apparent that there are few machine learning studies in this area, and their quality is variable. While machine learning is increasingly used to analyse wearable data, its application for predicting anxiety remains in the early stages. As the field of wearable data and mental health advances, leveraging machine learning techniques will be advantageous, as they can integrate multiple predictors and analyse complex relationships. Machine learning and digital biomarkers could become a powerful tool for early detection of anxiety, symptom monitoring and management, and prevention. They may allow for identification of early signs related to anxiety, facilitating timely intervention. Additionally, continuous monitoring could potentially help manage anxiety symptoms, assess the effectiveness of ongoing treatments, and provide real-time data to inform personalized healthcare, thus enhancing clinical outcomes through proactive and tailored interventions. Finally, given that anxiety is a modifiable psychological factor associated with dementia, metrics form wrist-worn wearables could also be used for early detection of dementia risk. Further research including

older adults will help advance our understanding of how digital biomarkers for anxiety could help identify dementia risk.

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**Data availability**
The dataset generated and analysed during the current study are available from the corresponding author on reasonable request.

**Competing interests**
All authors declare no financial or non-financial competing interests.

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Protocol development: Y.L., H.D-K., N.L.M.
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Screening, data extraction, and risk of bias assessment: Y.L., N.C., H.A.G., R.M.
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**Figure 1**. PRISMA flow diagram illustrating the systematic process

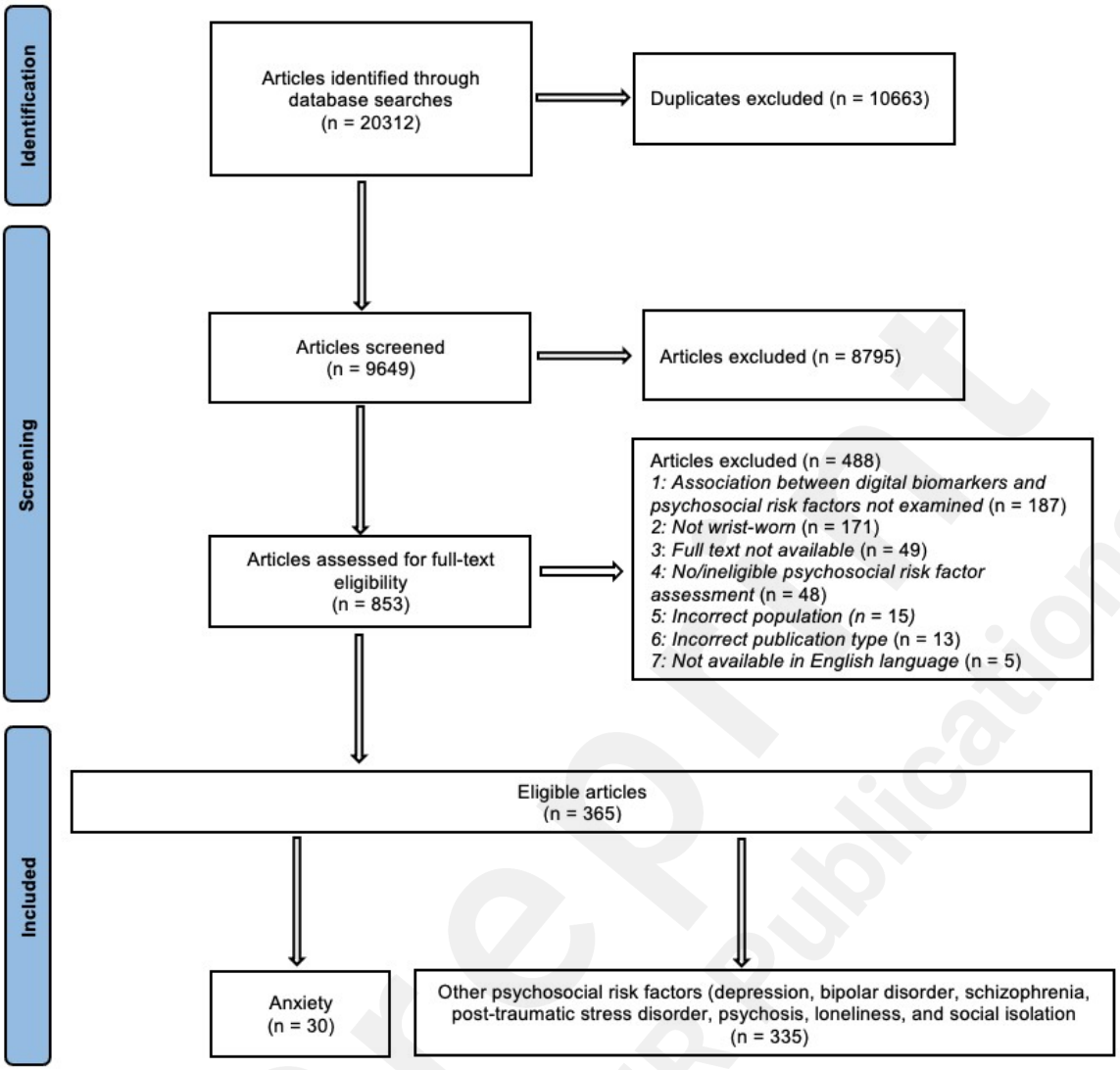


**Figure 2**. Forest plot of the associations between sleep onset latency and anxiety symptoms. Effect sizes are Fisher's z with corresponding 95% confidence intervals (CI)

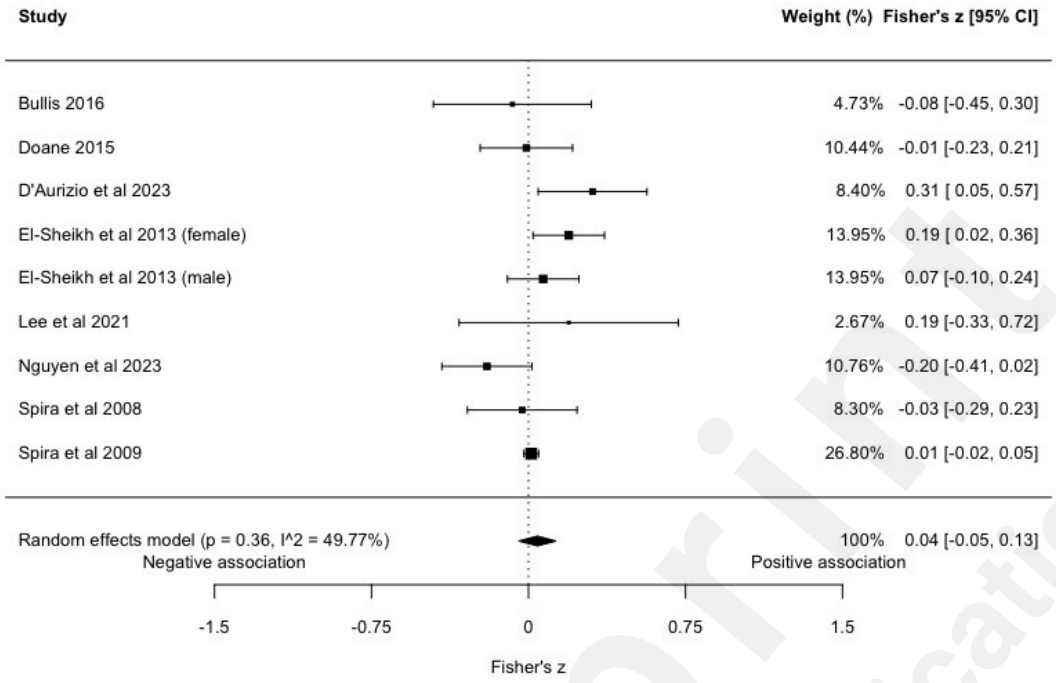


**Figure 3.** Forest plot of the association between total sleep time and anxiety symptoms. Effect sizes are Fisher's z with corresponding 95% confidence intervals (CI)

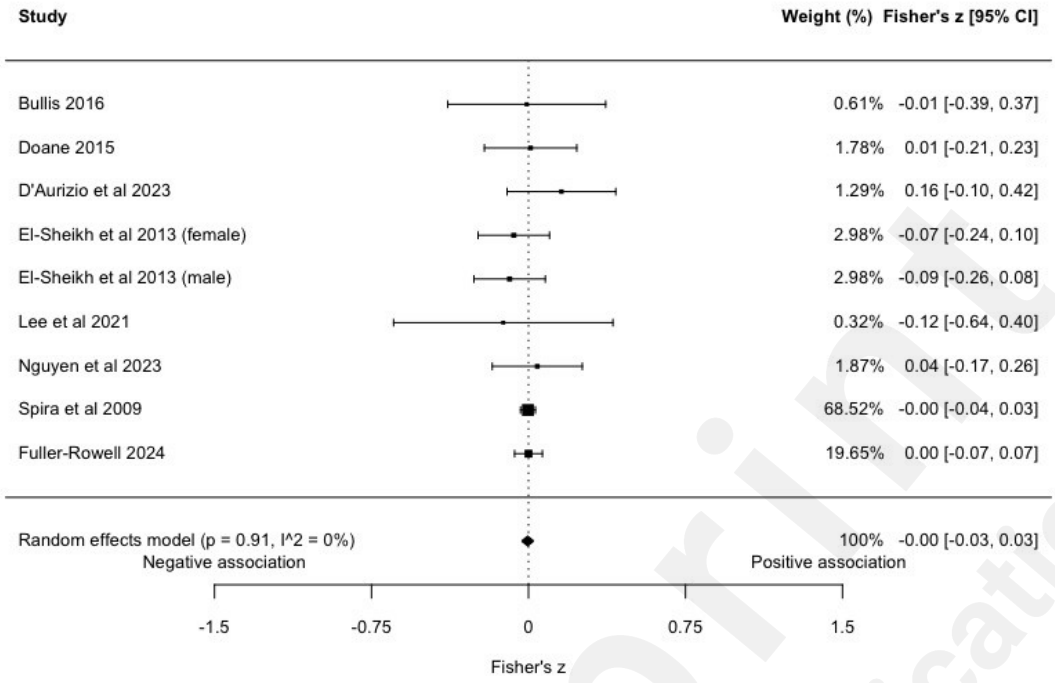


**Figure 4.** Forest plot of the association between sleep efficiency and anxiety symptoms. Effect sizes are Fisher's z with corresponding 95% confidence intervals (CI)

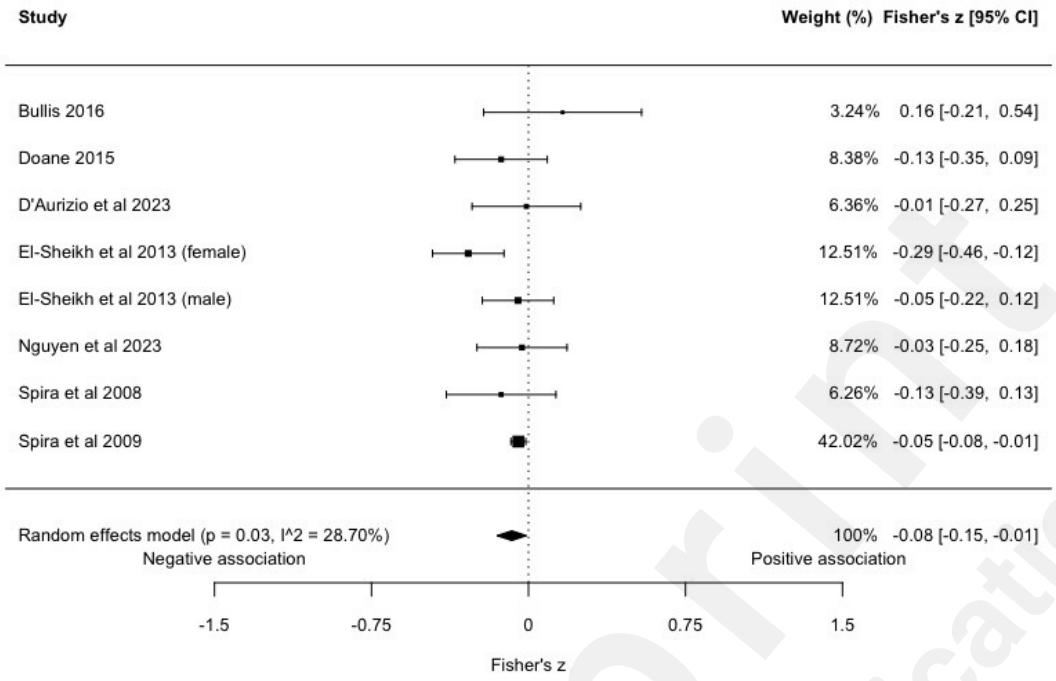
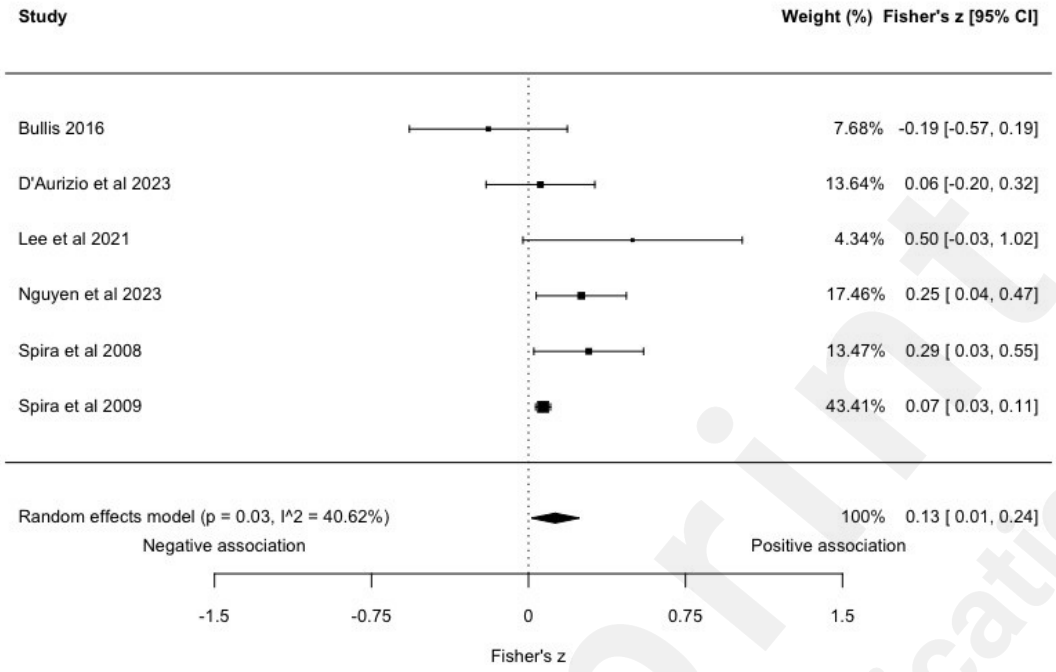


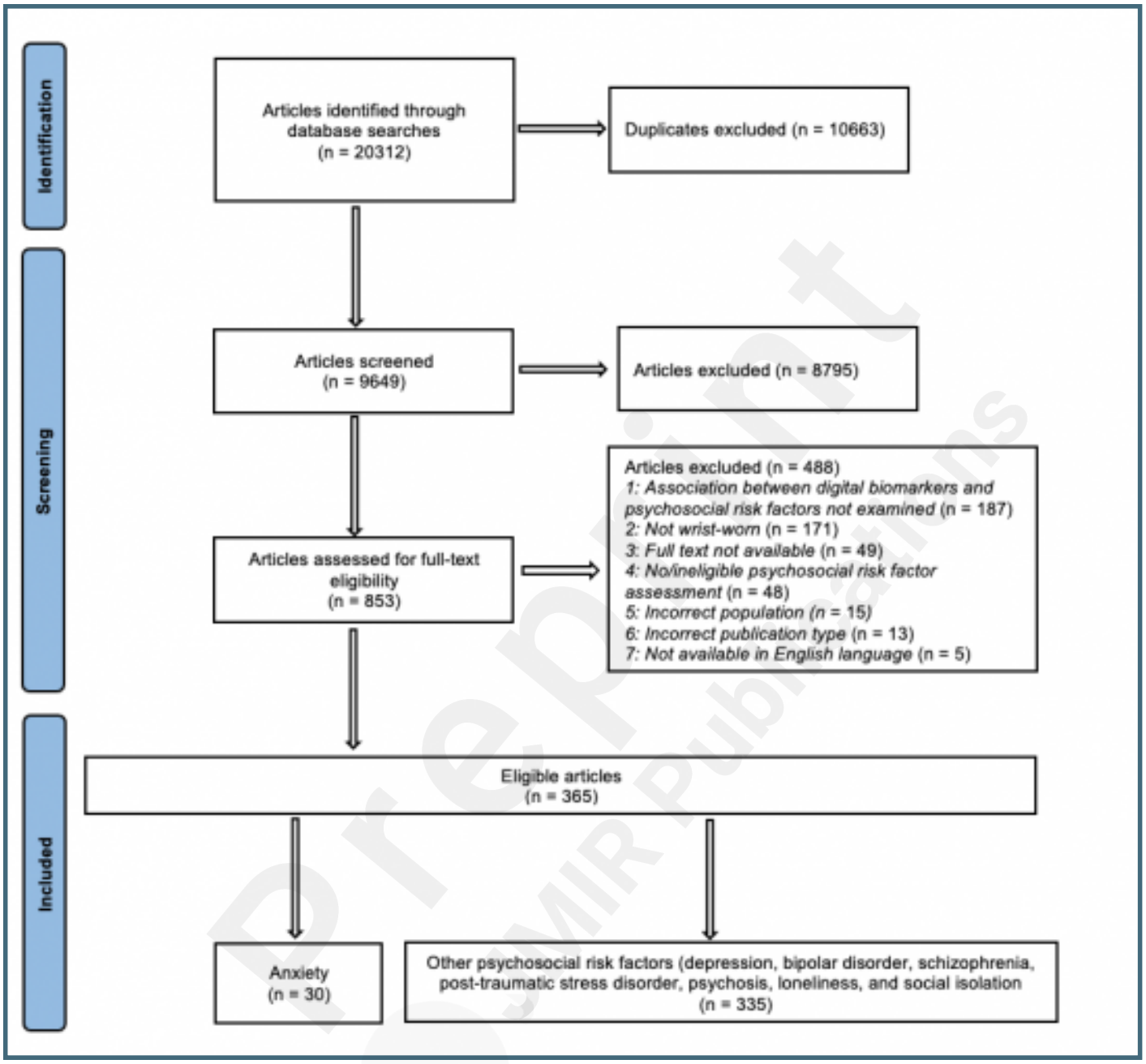
**Figure 5.** Forest plot of the association between wake after sleep onset and anxiety symptoms. Effect sizes are Fisher's z with corresponding 95% confidence intervals (CI)



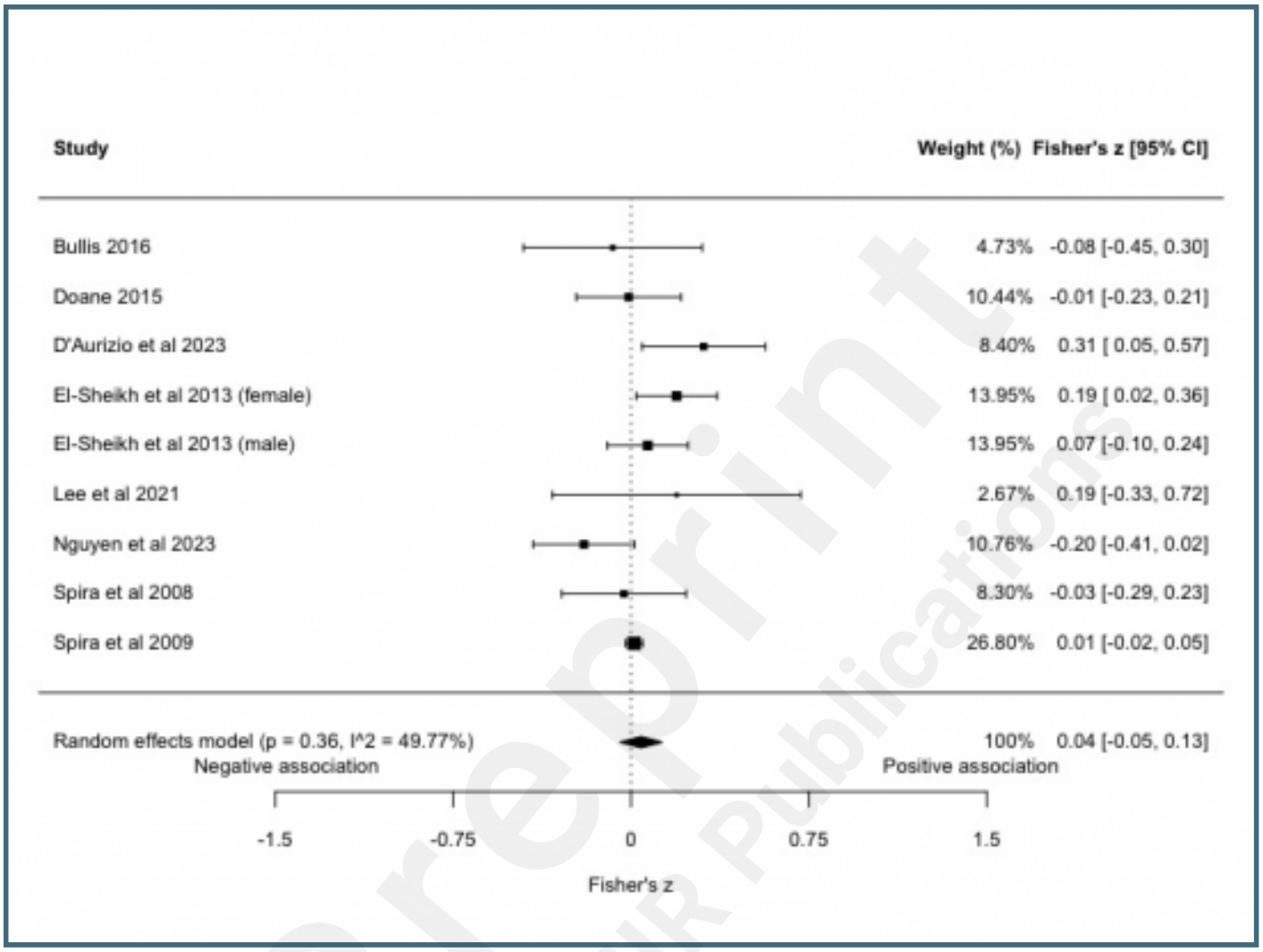
# Supplementary Files

# Figures

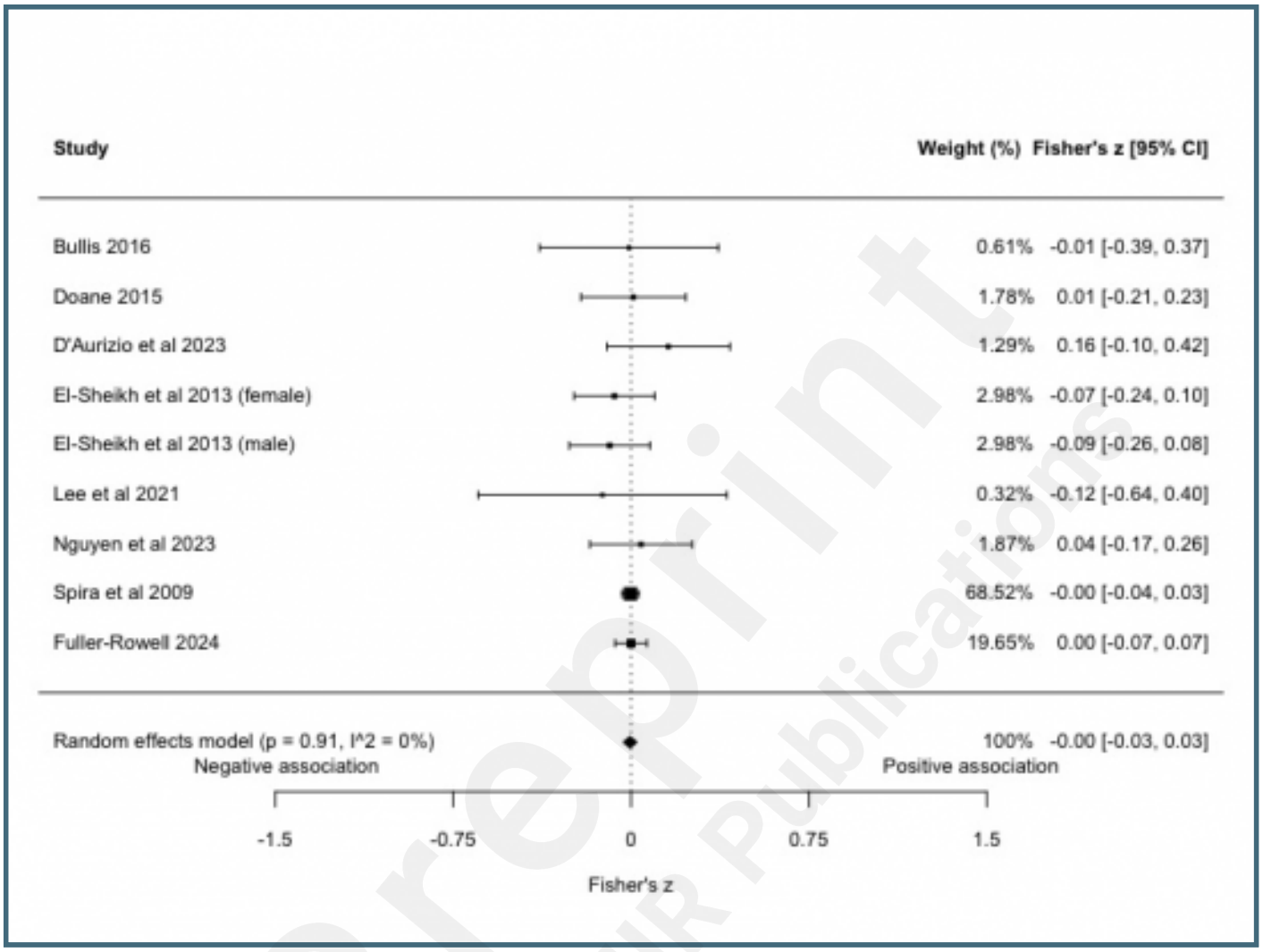
PRISMA flow diagram illustrating the systematic process.



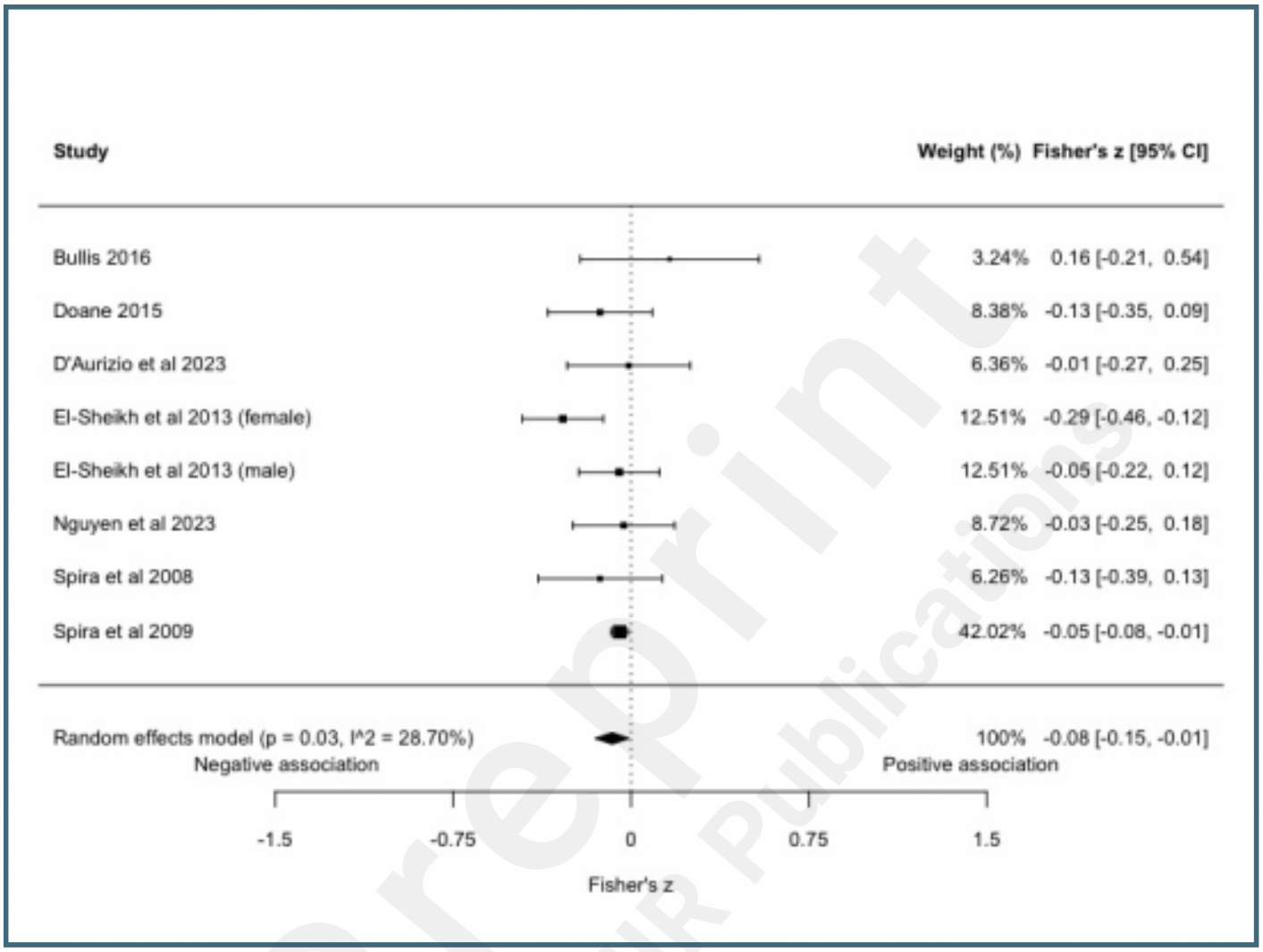
Forest plot of the associations between sleep onset latency and anxiety symptoms. Effect sizes are Fisher's z with corresponding 95% confidence intervals (CI).



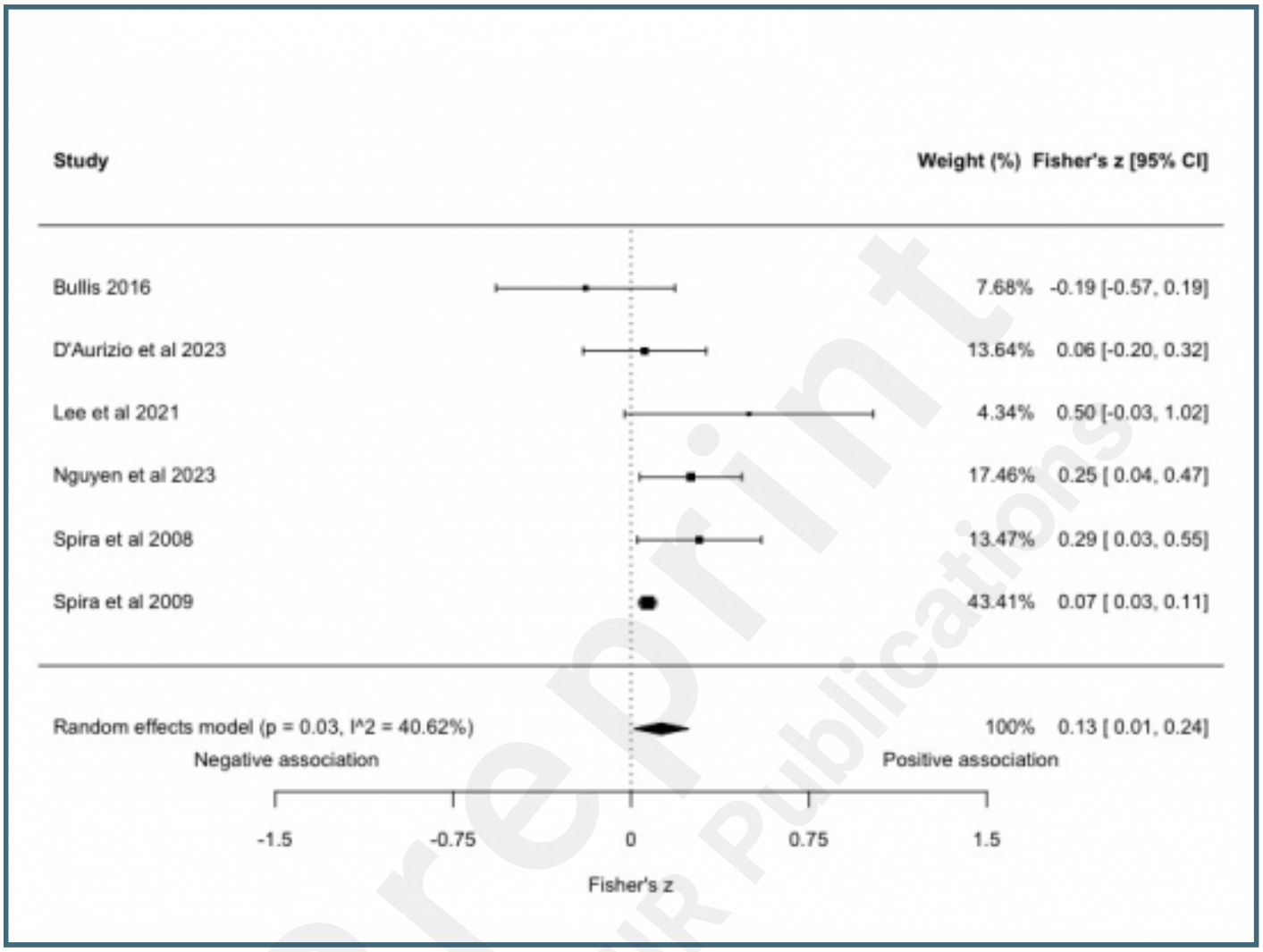
Forest plot of the association between total sleep time and anxiety symptoms. Effect sizes are Fisher’s z with corresponding 95% confidence intervals (CI.



Forest plot of the association between sleep efficiency and anxiety symptoms. Effect sizes are Fisher’s z with corresponding 95% confidence intervals (CI).



Forest plot of the association between wake after sleep onset and anxiety symptoms. Effect sizes are Fisher's z with corresponding 95% confidence intervals (CI).



# Multimedia Appendixes

PRISMA 2020 Checklist.
URL: http://asset.jmir.pub/assets/b9352ceb1e2850f28a35ff158b7efd1a.docx

PRISMA 2020 for Abstracts Checklist.
URL: http://asset.jmir.pub/assets/49bfd221d9a02a25d59e7421167e37fe.docx

Search terms.
URL: http://asset.jmir.pub/assets/65fd29d3647c2ea27f863857a77fde48.docx

Demographic characteristics of samples eligible for systematic review and/or meta-analysis of studies using inferential statistical approaches.
URL: http://asset.jmir.pub/assets/b44bbc11b5375f9321e20a4ab090fb04.docx

Summary of sample demographics from studies using inferential statistical approaches.
URL: http://asset.jmir.pub/assets/d80063d1288e126edf25a6a4d01538e5.docx

Characteristics of samples for studies using machine learning approaches.
URL: http://asset.jmir.pub/assets/a7c0153ef01f23a8fd49a28ab661075a.docx

Risk of bias.
URL: http://asset.jmir.pub/assets/63e7b3c27494634f4bdcac13cfd3ecc2.docx

Meta-analytic results for sleep metrics.
URL: http://asset.jmir.pub/assets/4484db0f36be8d9d9d8693491d70904c.docx

Forest plots for sensitivity analyses.
URL: http://asset.jmir.pub/assets/3890a9675f48aca61366c9cf8575bb5f.docx