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REVIEW

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A systematic review of research reporting practices in observational studies examining associations between 24-h movement behaviors and indicators of health using compositional data analysis

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Abstract

Background Compositional data analysis (CoDA) techniques are well suited for examining associations between 24-h movement behaviors (i.e., sleep, sedentary behavior, physical activity) and indicators of health given they recognize these behaviors are co-dependent, representing relative parts that make up a whole day. Accordingly, CoDA techniques have seen increased adoption in the past decade, however, heterogeneity in research reporting practices may hinder efforts to synthesize and quantify these relationships via meta-analysis. This systematic review described reporting practices in studies that used CoDA techniques to investigate associations between 24-h movement behaviors and indicators of health.

Methods A systematic search of eight databases was conducted, in addition to supplementary searches (e.g., forward/backward citations, expert consultation). Observational studies that used CoDA techniques involving log-ratio transformation of behavioral data to examine associations between time-based estimates of 24-h movement behaviors and indicators of health were included. Reporting practices were extracted and classified into seven areas: (1) methodological justification, (2) behavioral measurement and data handling strategies, (3) composition construction, (4) analytic plan, (5) composition-specific descriptive statistics, (6) model results, and (7) auxiliary information. Study quality and risk of bias were assessed by the National Institutes of Health Quality Assessment Tool for Observational Cohort and Cross-sectional Studies.

Results 102 studies met our inclusion criteria. Reporting practices varied considerably across areas, with most achieving high standards in methodological justification, but inconsistent reporting across all other domains. Some items were reported in all studies (e.g., how many parts the daily composition was partitioned into), whereas others seldom reported (e.g., definition of a day: midnight-to-midnight versus wake-to-wake). Study quality and risk of bias was fair in most studies (85%).

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Conclusions Current studies generally demonstrate inconsistent reporting practices. Consistent, clear and detailed reporting practices are evidently needed moving forward as the field of time-use epidemiology aims to accurately capture and analyze movement behavior data in relation to health outcomes, facilitate comparisons across studies, and inform public health interventions and policy decisions. Achieving consensus regarding reporting recommendations is a key next step.

Keywords Physical activity, Sedentary behavior, Screen time, Sleep

Introduction

Previous research has established independent associations between time spent engaging in physical activity [1, 2], sedentary behavior [3, 4], and sleep [5, 6] in relation to several indicators of health and health outcomes. However, studies have generally examined these behaviors in isolation, neglecting the fact that these behaviors are co-dependent and mutually exclusive over the course of a full 24-h day [7–9]. That is, time spent engaging in one behavior (e.g., physical activity) reduces time during the day available for other behaviors (e.g., sedentary behavior, sleep). Researchers have begun to acknowledge the limitation of solely focusing on individual behaviors in the past decade, sparking the shift to a novel 24-h paradigm that emphasizes the need to consider the collective influence of physical activity, sedentary behavior and sleep over the course of a whole day for health [10–12]. While consensus terminology for referring to these behaviors as a collective has yet to be established [13], they are most commonly referred to as 24-h movement behaviors, the 24-h activity cycle, physical behaviors, time-use behaviors or time-use activity behaviors.

The proliferation of research investigating how combinations of physical activity, sedentary behavior and sleep is associated with indicators of health was sparked by the release of the 24-Hour Movement Guidelines for Children and Youth in Canada in 2016 [14]. Recommendations tailored for several other segments of the population are also now available, including young children (0 to 4 years of age) [15], adults, and older adults [16], and have been adopted by several countries globally [17–21]. At present, the literature examining associations between 24-h movement behaviors and health has focused largely on guideline adherence [22–28]. Such work is important from a behavioral surveillance standpoint, but classifying individuals into groups based on whether or not they meet threshold-based behavioral recommendations [e.g., ≥60 min/day of moderate-to-vigorous physical activity (MVPA) for children and youth] may oversimplify these relationships as it fails to consider the full range of time-use estimates over the course of a whole day. This may be partly attributable to the current 24-h movement behavior data available to assess these relationships. That is, many of these studies used data from behavioral surveillance systems (e.g., U.S. National Survey of Children's Health; Korea National Health and Nutrition Examination Survey; Australian National Secondary Students' Diet and Activity Survey) that employ crude self- or proxy-reported instruments to assess physical activity, sedentary behavior and sleep in line with recommendations for each movement behavior irrespective of whether they have adopted integrated 24-h guidelines or not. However, it is becoming increasingly feasible to capture higher resolution estimates of movement behaviors within a 24-h day with recent advances and improvements in accelerometry (e.g., improved data processing, wearable device integration, cost reduction) as well as the availability of whole day recall instruments such as the Activities Completed over Time in 24-h (ACT-24) [29], Multimedia Activity Recall for Children and Adults (MARCA) [30], and 24-h Physical Activity Recall (24PAR) [31]. These advances in assessment open the door for alternative analytic approaches that can provide more nuanced insights into the integrative influence of 24-h movement behaviors on health.

Compositional data analysis (CoDA) is a statistical approach that is well suited for quantifying associations between movement behaviors and indicators of health given its ability to model the relative nature of 24-h time use data [7–9]. Specifically, CoDA considers that each movement behavior represents a mutually exclusive part of a finite period (i.e., whole day) [32]. This is done through transforming absolute values (i.e., 600 min of sleep) into relative proportions (i.e., 41.6% of a 24-h day) via sets of log-ratios (e.g., isometric, additive, centered). This relative proportion approach adjusts for the co-dependency of these behaviors, helping to address their multi-collinearity, and thus, overcoming a major challenge of traditional statistical approaches that use absolute values [7]. These properties of CoDA make this approach appropriate for analyzing time-use data with multiple components that comprise a whole day, and several techniques are available to examine different research questions related to time-use such as compositional isotemporal substitution (i.e., the influence of replacing time spent in one behavior with time spent in another behavior) [33], the Goldilocks approach (i.e., the optimal distribution of time spent in different movement

behaviors for optimal health benefit) [34], and the Many Different Roads Lead to Rome approach (i.e., different movement behavior distributions associated with equivalent health benefits) [35]. Further, CoDA can be implemented in several commonly used analytic frameworks (e.g., general linear modeling, structural equation modeling, mixture modeling). This flexibility has allowed adoption of CoDA to proliferate in the field of time-use epidemiology. An example of this growth can be seen with the literature examining 24-h movement behaviors in relation to indicators of mental health. Only two CoDA studies were included in the first systematic review of 24-h movement behaviors among children and youth published in 2020 [27], whereas eight CoDA studies examining children and youth were included in a subsequent systematic review published 4 years later [23]. This point is further underscored by a total of 61 CoDA studies (employing 24-h measurement) that were captured in an October 2022 systematic search of the literature investigating the influence of reallocating time across movement behaviors on health [36].

Despite the rapid increase in studies using CoDA, only two systematic reviews specific to this literature focused on how 24-h movement behaviors relate to indicators of health exist, with one review focused on adults [37] and the other review focused on early childhood [38]. The landscape regarding reporting practices for CoDA studies has yet to be explored, however, representing a key knowledge gap considering there is currently no formal guidance regarding research reporting practices in this area. Such issues have been recognized in other areas of research such as ecological momentary assessments (EMA) of diet and physical activity, which resulted in the creation of the Checklist for Reporting EMA Studies (CREMAS) after characterizing methodological practices in prior studies [39]. Akin to what has been established for EMA studies, investigating existing reporting practices in the CoDA literature may help to inform uniform reporting procedures in the future. Therefore, the purpose of this study was to describe research reporting practices in observational studies that have examined associations between 24-h movement behavior compositions and indicators of health using CoDA.

Methods

Protocol and registration

This review was preregistered with the International Prospective Register of Systematic Reviews (PROSPERO; submitted September 23, 2023; ID: CRD42023456880). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed [40], and items are reported using the PRISMA Checklist (see Supplemental Materials Table 1).

Inclusion criteria

We included studies that met the following nine criteria: (a) published in the English language, (b) published in peer-reviewed journals, (c) included human participants, (d) original empirical investigation, (e) observational design, (f) used CoDA techniques, (g) included time-based estimates of all three behaviors: physical activity, sedentary behavior, and sleep, (h) focused on the whole day (i.e., 24-h movement compositions), and (i) examined associations with health outcomes or indicators of health as the dependent variable. Self- or proxy-reported and device-assessed estimates of movement behaviors were included given that CoDA can be used to investigate associations between movement behaviors and indicators of health with both types of measures, including a combination of both types of measures (e.g., device-assessed sedentary behavior and physical activity, self-reported sleep). Indicators of health and health outcomes were operationalized as any indicator of physical, cognitive or mental health (e.g., working memory, bone density, physical functioning) or health outcome (e.g., mortality, overweight/obesity status, depression).

Studies were excluded for the respective nine major reasons: (a) published in a language other than English, (b) not a peer-reviewed article (i.e., Masters thesis, PhD dissertations, conference abstracts), (c) reviews, case studies, qualitative studies, protocol papers, commentaries/opinions, or book chapters, (d) used an experimental approach to assess the relationship with a health outcome, (e.g., randomized controlled trial), (e) did not use CoDA techniques (e.g., isotemporal substitution studies that did not involve log-ratio transformations), (f) examined associations with other health behaviors (e.g., diet, smoking), (g) specified the 24-h movement composition as the dependent variable, (h) did not include human participants (e.g., animal models), and (i) methods focused papers (e.g., [7, 41, 42]). Methods focused papers were excluded given that demonstrating the implementation of a CoDA technique may have had different reporting standards for the methods and results as would be expected in subsequent studies using established analytic techniques. Studies using experimental designs were excluded based on the premise that research reporting recommendations for experimental designs (Consolidated Standards of Reporting Trials guidelines [43]) differ from those that exist for observational designs [Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) [44]]. However, studies that involved cross-sectional analysis of baseline data from experimental studies were included. It is worth noting that much of the existing body of literature investigating 24-h movement behaviors in relation to health outcomes stems

from secondary data analysis of baseline experimental data and behavioral surveillance studies [22, 23, 37].

Search strategy, data extraction, and data synthesis

In consultation with a research librarian, we conducted an electronic search of eight databases. The MEDLINE EBSCO, PsycINFO, SPORTDiscus, Web of Science, CINAHL and Scopus databases were searched from inception to October 12th, 2023. The Cochrane Library, and EMBASE/Ovid databases were searched from inception to October 23rd, 2023, and October 31st, 2023, respectively. These databases were searched based on their relevance to the review topic and for consistency with previous reviews examining associations between 24-h movement behaviors and health outcomes that also searched these databases [22, 23, 27, 28]. Search terms can be found in Supplemental Materials File 1. A manual search of the *Journal of Activity, Sedentary, and Sleep Behaviors*, which at the time of conducting this review had yet to be indexed, was also performed on February 16th, 2024, given the relevance of its scope. Further, a manual search of the International Network of Time-Use Epidemiologists (INTUE) publications list was performed on March 11th, 2024, given the relevance of the Network's mission. Additional supplemental search strategies included forward (searching citationss of included papers) and backward (reviewing references within included studies) citation searches, in addition to contacting experts in the field. Forward and backward citation searches were also performed for CoDA methods papers identified by the research team [7, 33, 41, 42, 45–49].

Retrieved references were imported into Covidence (Evidence Partners, Ottawa, ON, Canada), where duplicates were removed and titles/abstracts were reviewed by two independent reviewers (DB, SB, CG, GMB, CP, CSL, CK) for initial inclusion. After initial screening, full texts were retrieved and independently examined by two reviewers from the same group for final inclusion. A pre-piloted protocol was created for both stages prior to study selection, in which reviewers had to achieve $\geq 80\%$ accuracy prior to completing both stages. Any conflicts during each stage were resolved by a third independent reviewer. Data extraction was performed independently by two reviewers (SB, CG, GMB, CP, CP, CSL, CK) and a third reviewer examined the data for consensus (DB). Extracted data included general article characteristics (e.g., publication year, sample, study design). Data extraction for items relevant to CoDA studies were classified into seven areas, which included: (a) methodological justification; (b) behavioral measurement and data handling strategies; (c) composition construction; (d) analytic plan; (i) composition-specific descriptive statistics; (e) model results; and (f) auxiliary information (i.e., limitations of CoDA, clinical implications, funding, conflicts of interest). These categories were created based on past reporting checklists of behavioral approaches (e.g., CREMAS, STROBE), and the data extraction spreadsheet was reviewed by 11 international experts in this area to ensure all pertinent items were addressed.

Considering the focus of this review is to characterize reporting practices, data analysis focused on a numerical presentation (i.e., central tendencies and percentages) of whether items were reported (or not). Distributions of reporting practices for each item of interest are presented (yes/no/unclear) within their respective seven major reporting categories, and narratively synthesized.

Methodological quality and risk of bias assessment

All included studies used an observational design, and thus, an adaptation of the National Institutes of Health Quality Assessment Tool for Observational Cohort and Cross-sectional Studies (QATOCCS [50]) was used to assess methodological quality and validity of each study as well as their risk of bias. Study quality and risk of bias was assessed independently by two reviewers on the 14 criteria assessing clarity in reporting (e.g., research question, population details), justification of methodological choices (e.g., reliability and validity of measurement tools, sample size), and use of best practices (e.g., repeated assessments, adjusting for confounders). Each study received a "yes", "no", or "other" response to each question to then be rated as "poor", "fair", or "good" based on these considerations as concerned with the exposure (i.e., 24-h movement behaviors) and outcomes of interest (i.e., indicators of health). The responses are intended to be used as a guide for assessing the quality and risk of bias rating, however, in line with previous work that has used ranges of scores to provide quantitative evaluations [51, 52], we considered studies with a score of ≤ 4 to be "poor", between 5 to 9 to be "fair", and >9 to be "good" study quality.

Results

Included studies

The initial search identified 1995 records, which was reduced to 872 after de-duplication. Supplementary search strategies identified an additional nine articles in the *Journal of Activity, Sedentary and Sleep Behaviors*, and one article was found in the INTUE publication list. Forward (n = 1369) and backward citation (n = 3837) searches and articles from expert consultation (n = 1) identified an additional 5217 records. In total, 7212 records were identified by the search strategies, and reduced to 3818 after de-duplication. These articles were reduced to 207 for full-text review, which resulted

in 102 studies that met our inclusion criteria. Full-text articles were excluded for three main reasons: (1) wrong methods (i.e., did not use CoDA techniques; n = 66), (2) wrong behaviors (e.g., missing sleep, sedentary behavior, or physical activity within the 24-h composition; n = 16), and (3) wrong article type (n = 10). A PRISMA flow diagram is presented in Fig. 1. A list of studies excluded at full-text and reasons are presented in Supplementary Table 2. Funding and conflict of interest of included studies are included in Supplementary Table 3.

Description of studies

Study characteristics are presented in Table 1. Studies included were published between 2016 and 2024 with samples from 29 different countries: Australia: (*n* = 24), Belgium (*n* = 2), Brazil (*n* = 7), Bulgaria (*n* = 1), Canada (*n* = 11), China (*n* = 7), Colombia (*n* = 1), Czech Republic (*n* = 1), Denmark (*n* = 6), England (*n* = 6), Finland (*n* = 7), India (*n* = 1), Iran (*n* = 1), Ireland (*n* = 1), Japan (*n* = 3), Kenya (*n* = 1), Luxembourg (*n* = 2), Netherlands (*n* = 4), New Zealand (*n* = 4), Portugal (*n* = 1), Scotland (*n* = 1), Singapore (*n* = 2), Slovenia (*n* = 1), South Africa (*n* = 2), Spain (*n* = 5), Sweden (*n* = 4), United Kingdom (*n* = 10), USA (*n* = 13), and Wales (*n* = 3). Eight studies involved multi-country samples ranging from two to eight countries. A total of 79 studies used cross-sectional designs, 18 used longitudinal designs, and five included both. Analytic sample sizes ranged from 28 [53] to 130,239 [54] participants, with participants ranging in age from 1 [55] to 75.8 [56] years on average.

The majority of studies (82/102) partitioned the 24-h movement composition into four parts consisting of sleep, sedentary behavior, light physical activity (LPA) and MVPA. A three-part composition represented the fewest number of time-use categories (e.g., screen time, sleep, MVPA) [57], whereas a nine-part composition represented the greatest number of time-use categories (e.g., screen time; sleep; other: transport, work, general physical activity, chores, self-care, quiet time, social) [58]. Of the 102 studies that assessed MVPA,[1] the majority (89/102) used device-based estimates, with 12 using self- or proxy-reports, and one that used a combination of both methods [59]. Of the 99 studies that assessed LPA, the majority (89/99) used device-based estimates, with nine using self- or proxy-reports, and one study that used a combination of both methods [59]. A majority of studies (89/102) used device-based estimates to assess sedentary behavior, with only 11 studies using self- or proxy-reports. One study used a combination of both methods [59], and one study inferred daily sedentary time by subtracting sleep and physical activity estimates from 1440 min [60]. A majority of studies (60/102) used device-based estimates to assess sleep duration, with 39 studies using self- or proxy-reports, and only three studies using a combination [54, 59, 61].

Regarding analytic approaches, 64 studies examined the overall composition in relation to indicators of health, 67 studies examined associations between each behavior (relative to others) in relation to indicators of health, and 84 studies involved compositional isotemporal substitution modeling, of which 59 studies used 1-to-1 substitutions, 10 used proportional substitutions, and 15 used both approaches. A total of six studies examined optimal behavioral compositions for indicators of health, of which five of these studies used the Goldilocks approach and one study used the Many Different Roads approach.

Reporting practices

A summary of reporting practices by area and item is presented in Table 2, whereas detailed reporting practices for each study can be found in Supplementary File 2.

Methodological justification

This reporting area included two items, with the majority of studies providing sufficient information (100/102 studies; 94/102 studies, respectively). Specifically, nearly all studies mentioned CoDA in the title and/or abstract (100/102) and introduced the concept of CoDA and provided reasons for utilizing CoDA to examine associations between 24-h movement behaviors and indicators of health (94/102).

Behavioral measurement and data handling strategies

This reporting area included 14 items. The majority of studies (≥ 75%) provided sufficient information for seven items. Most studies reported the scoring/processing procedures for MVPA[2] (94/102), LPA (92/99), sedentary behavior (93/102), and sleep (90/102). Among the studies that used device-based assessments of 24-h movement behaviors, the device placement (87/90), how many minutes of wear time was considered a valid day (80/90), and how many valid days was needed to be considered a valid sample (85/90) were clearly described in most studies, but far fewer studies (44/90) clearly described which valid days were used for analysis (e.g., average across all days, four random days, proportion of weekdays and weekend). Across all studies, slightly more than half (61/100) clearly described how non-wear (if device-assessed) or time not accounted for (if self- or proxy-reported) was handled.

[1] For reporting purposes, compositions that included stepping or total physical activity were inferred as MVPA.

[2] For reporting purposes, compositions that included stepping or total physical activity were inferred as MVPA.

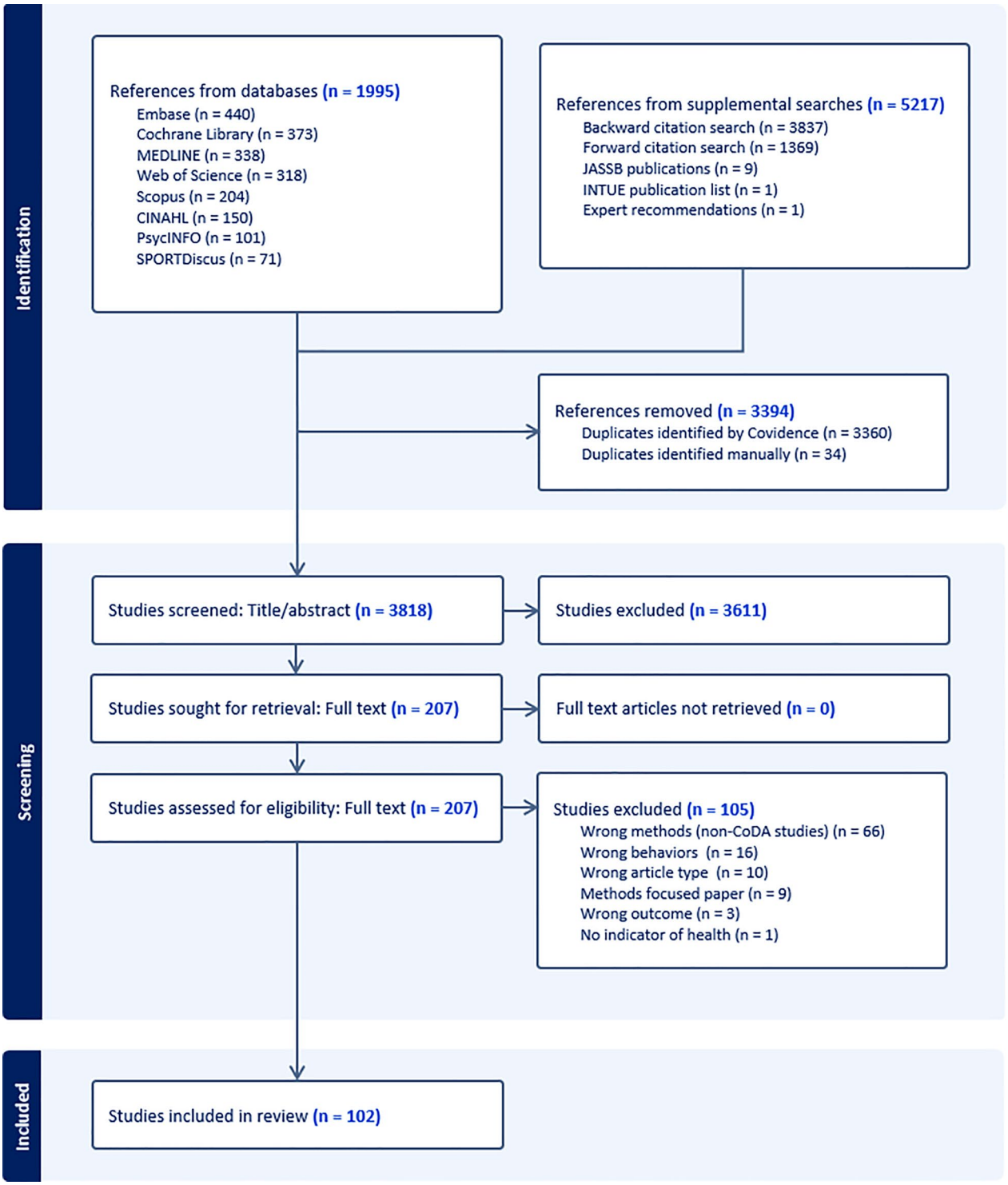

Fig. 1 PRISMA flow chart

Two of the 102 studies used a 24-h recall instrument that did not allow for time to be left unaccounted for.

Regarding sleep, roughly half (50/102) of the studies clearly conceptualized sleep (e.g., 24-h, nocturnal only, day only), but fewer (37/102) clearly defined sleep (e.g., sleep variable of interest and how it was calculated and/or defined). Very few studies included naps in the composition (17/102), although it was unclear in 44 studies.

Table 1 Study characteristics

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Asano et al. [96]	113	75.2 (4.6)	40.7% female	Japan	Phase angle	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM; Proportional ISM
Bezerra et al. [97]	123	55.2 (9.2) months	50.4% female	Brazil	Executive function	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Bianchim et al. [98]	Children: 86; Adults: 43	Children: 13.6 (2.8); Adults: 24.6 (4.7)	Total: 48% female; Child: 47% female; Adults: 48% female	Australia, South Wales	FEV1%	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Biddle et al. [99]	435	66.9 (7.4)	61.7% male	UK	Glucose regulation, Insulin sensitivity	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SL; Sitting; Standing; Stepping	Individual; 1-to-1 ISM
Blodgett et al. [100]	4738	46	52.3% female	England, Scotland, Wales	Depression	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Blodgett et al. [101]	15,253	53.7 (9.7)	54.7% female	Netherlands, UK, Australia, Denmark, Finland	BMI, Waist circumference, HDL cholesterol, Total: HDL cholesterol ratio, Triglycerides, HbA1c	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA; Standing	Individual; 1-to-1 ISM
Booker et al. [60]	2805	60.7 (11.7)	62% female	USA	High-sensitivity c-reactive protein	Cross-sectional	Questionnaire (self-reported)	Questionnaire (self-reported)	Other: Computed from the subtraction of time spent in PA and sleep from 1440 min	Questionnaire (self-reported)	SB; SL; Lying down; Total PA	1-to-1 ISM
Brakenridge et al. [61]	648	Low risk: 56.0 (9.8); High risk: 60.2 (9.3)	Lower Diabetes Risk: 52.7% female; Higher Diabetes Risk: 60.7% female	Australia	Glycaemic measures (HbA1c, FPG, 2hPLG)	Cross-sectional	Device-based	Device-based	Device-based	Device-based; Questionnaire (self-reported)	SL; Sitting; Standing; Stepping	Individual; 1-to-1 ISM
Brayton et al. [64]	33	15.8 (1.2)	52% female	USA	Concussion recovery	Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual
Cabanas-Sánchez et al. [102]	X: 2,489; L: 1,679	X: 71.7 (4.3) L: 71.4 (4.2)	X: 53.1% female; L: 51.7% female	Spain	Depression, Loneliness, Happiness, Global mental health	Cross-sectional; Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Carson et al. [103]	4169	11.4 (0.1)	51.3% male	Canada	BMI, Waist circumference, Systolic BP, Diastolic BP, Behavioral strengths and difficulties, Triglycerides, Cholesterol, C-reactive protein, Insulin, Aerobic fitness	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported); Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Carson et al. [104]	552	3.5 (0.0)	49.2% female	Canada	Waist circumference, BMIz	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; Individual
Chao et al. [105]	1475	20.7 (1.6)	68.0% female	China	Anxiety symptoms	Cross-sectional	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Chastin et al. [54]	130,239	ABC: 52.8 NHANES 2003–2006: 63.6 REGARDS: 63.4 UK Biobank: 62.3 Whitehall II: 69.4 Women's Health Study: 72.0	ABC: 44% female NHANES 2003–2006: 49.3% female REGARDS: 54% female UK Biobank: 56.2% female Whitehall II: 25.9% female Women's Health Study: 100% female	Sweden, USA, UK	All-cause mortality	Longitudinal	Device-based	Device-based	Device-based	Device-based; Questionnaire (self-reported)	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Chen et al. [62]	8045	2018: 3.8 (1.3) 2019: 3.8 (1.3) 2020: 3.9 (1.3) 2021: 3.8 (1.3)	2018: 51.3% female 2019: 48.6% female 2020: 50.0% female 2021: 51.1% female	Singapore	Quality of life	Cross-sectional	Questionnaire (proxy-reported)		Questionnaire (proxy-reported)	Questionnaire (proxy-reported)	SB; SL; Total PA	Overall; Individual; 1-to-1 ISM
Chen et al. [106]	389	11.9 (2.1)	50.1% female	China	BMI	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM; Proportional ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Chong et al. [107]	X: 127 L: 88	X: 11.7 (0.5) L: 11.8 (0.4)	Cross-sectional: 57.5% female Longitudinal: 59.1% female	Australia	Psychosocial health: Internalizing problems, Externalizing problems, Total difficulties, Prosocial behavior, Psychological distress	Cross-sectional; Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual
Chong et al. [108]	909	10.4 (0.5)	53.1% female	Australia	Psychosocial health: Emotional symptoms, Conduct problems, Hyperactivity, Peer relationship problems, Prosocial behavior	Longitudinal	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Screen time; SL; Other: Self-care/ Domestic activities, PA, Social, Education, Recreational screen use, Quiet time, Passive transport	Overall; Individual; Proportional ISM
Clarke et al. [109]	2838	46.4	51.8% female	USA	Mortality	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM; Proportional ISM
Collings et al. [110][a]	1046	51.2 (12.2)	53.5% female	Luxembourg	Waist circumference, Total body fat, Systolic blood pressure, Diastolic blood pressure, Fasting glucose, Triglycerides, HDL-c, Fasting insulin, APoB/A, Cardiometabolic risk score	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Collings et al. [111][a]	1001	50.6 (12.2)	53.4% female	Luxembourg	Arterial stiffness	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM
Curtis et al. [112]	430	41.3 (11.7)	74% female	Australia	BMI, HRQoL, Anxiety, Depression, Stress	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Curtis et al. [113]	322	40.4 (5.9)	58.1% female	Australia	Symptoms of depression, anxiety, and stress	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM
de Faria et al. [114]	217	16.0	49.4% female	Brazil	Symptoms of depression and anxiety	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Del Pozo Cruz et al. [115]	3233	47.4 (19.5)	52.1% female	USA	Depressive symptoms	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Domingues et al. [116]	185	16.0 (1.0)	49.2% female	Brazil	BMIz	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Dumuid et al. [117]	1728	9–11	56% female	Australia, Canada, UK, Finland	Body fat %	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM
Dumuid et al. [118]	122	65.4 (2.9)	61% female	Australia	Cardio-respiratory fitness (VO2max), BMI, Total cholesterol; Blood pressure (systolic and diastolic); Fasting blood glucose; Waist-to-hip ratio	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Dumuid et al. [119]	5855	9–11	45% female	Australia, England, Canada, Finland, Portugal, USA, Brazil, Colombia, China, India, South Africa, Kenya	HRQoL	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; Proportional ISM
Dumuid et al. [120]	971	11.9 (0.4)	50% female	Australia	Body composition	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM; Proportional ISM
Dumuid et al. [121]	804	11.9 (0.4)	49.6% female	Australia	Bone density, Bone geometry, Bone strength	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; Goldilocks
Dumuid et al. [122]	1182–1137	12 (0.4)	49% female	Australia	Fitness, Adiposity	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Goldilocks

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Dumuid et al. [123]	82	APOE E4 non-carrier: 65.1 (7.7) APOE E4 carrier: 67.1 (7.1)	APOE E4 non carrier: 58% female APOE E4 carrier: 64% female	Australia	Cognitive function	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Proportional ISM
Dumuid et al. [35]	2123	14.4 (0.5)	50% female	Australia	Physical functioning	Cross-sectional	Questionnaire (self-reported)		Questionnaire (self-reported)	Questionnaire (self-reported)	Screen time; SL; Other: Self-Care, School-Related, Quiet Time, PA, Domestic/Social Activities	Overall; Many Different Roads
Fairclough et al. [124]	169	10.3 (0.3)	50.3% female	England	BMI, Percentage of waist circumference-to-height ratio, Cardiorespiratory fitness, Peak oxygen uptake (VO2 peak)	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Fairclough et al. [125]	359	11.5 (1.4)	50.7% female	England	Self-esteem, Depression, Emotional and behavioral problems, Executive function	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Fairclough et al. [65]	301	11.1 (1.6)	60.1% female	England	Mental health	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MPA; VPA	Overall; Individual; Goldilocks
Farrahi et al. [126]	3443	46.6 (0.5)	55.5% female	Finland	Cardiometabolic health markers: Plasma glucose, Serum insulin, Total cholesterol, HDL cholesterol, LDL cholesterol, Triglycerides	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM; Proportional ISM
Feter et al. [127]	8608	58.9 (8.6)	55.9% female	Brazil	Cognitive function	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	1-to-1 ISM; Proportional ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Franssen et al. [128]	61	33.6 (10.7)	33% female	Belgium	Cardiovascular health: Systolic and diastolic BP, Mean arterial pressure, Resting heart rate, HDL cholesterol, LDL cholesterol, Triglycerides, Clustered cardiometabolic risk score; Glucose tolerance: Fasting glucose, Fasting insulin, glucose 120 min, Insulin 120 min, Matsuda index, Insulinogenic index, Homeostatic model assessment of insulin resistance, Homeostatic model assessment of insulin sensitivity, Muscle insulin sensitivity index; Waist circumference, Fat mass percentage, Cardiorespiratory fitness	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA; Standing	Individual
Gupta et al. [129]	827	45 (10)	46% female	Denmark	Blood pressure	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; Proportional ISM
Gupta et al. [130]	669	45.1 (9.9)	45% female	Denmark	Systolic and diastolic blood pressure	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Proportional ISM
Gupta et al. [131]	929	44.9 (9.7)	45% female	Denmark	Long-term sickness absence	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA; Standing	Overall; Individual; Proportional ISM
Gupta et al. [132]	807	45.1 (9.7)	54.4% male	Denmark	Obesity: Waist circumference, BMI, Fat %	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA; Standing	Other: Latent profile analysis

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Healy et al. [53]	28	13.7 (3.0)	76.7% male	USA	BMI	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM; Proportional ISM
Hofman et al. [133]	1943	70.9 (9.3)	51.6% female	Netherlands	Depressive symptoms, Anxiety symptoms	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM
Hyodo et al. [56]	76	75.8	63% female	Japan	Executive function	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MPA	Individual; 1-to-1 ISM
Kandola et al. [134]	60,235	55.9 (7.7)	56% female	England, Scotland, Wales	Depressive symptoms, Anxiety symptoms	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Kastelic et al. [135]	2333	18–44; 45–64; 65+	74% female	Slovenia	Lower back pain frequency, Lower back pain intensity	Cross-sectional	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Kim et al. [59]	1247	50.1 (12.5)	57.3% female	USA	BMI	Cross-sectional	Device-based; Questionnaire (self-reported)	Device-based; Questionnaire (self-reported)	Device-based; Questionnaire (self-reported)	Device-based; Questionnaire (self-reported)	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Kitano et al. [136]	1095	50.2 (9.5)	68.6% female	Japan	Psychological distress	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Kuzik et al. [137]	95	45 (0.7)	30.5% female	Canada	Physical development: Motor skills, Adiposity, Growth; Cognitive development: Response inhibition, Visual-spatial working memory, language; Social-emotional development: Sociability, Externalizing problems, internalizing problems, Prosocial behaviour, Cognitive self-regulation, Emotional self-regulation, Behavioural self-regulation	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Larisch et al. [138]	348–370	41 (9)	68% female	Sweden	Depression, Anxiety, Wellbeing	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Lau et al. [139]	426	3.8 (0.6)	45.8% female	China	Executive function	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Le et al. [140]	361	22.6 (5.3)	72.5% female	Australia	Daily affect	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA; Other: Time awake in bed	Individual; 1-to-1 ISM
Lee et al. [141]	136	73 (2)	100% female	USA	Metabolic syndrome	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Lemos et al. [142]	270	4.0 (0.8)	51% female	Brazil	Physical fitness: Cardiorespiratory fitness, Speed-agility, Lower body muscular strength	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Lewthwaite et al. [63]	95	70.5 (6.8)	37% female	Australia	Breathlessness, Anxiety and depressive symptoms, HRQoL	Longitudinal	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM; Proportional ISM
Lin et al. [143]	2375	20	50% female	USA	Depressive symptoms	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual
Lu et al. [144]	135	4.6 (0.5)	49.63% male	China	Executive function	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Lund Rasmussen et al. [145]	659	13.9 (2.8)	48.5% female	Czech Republic	BMI, Adiposity	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Goldilocks
Madden et al. [146]	54	71.4 (0.6)	56% female	Canada	Waist circumference, Triglycerides, HDL, Systolic blood pressure, Fasting glucose, Continuous metabolic syndrome risk score	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual
Marshall et al. [147]	37	11.9 (1.6)	57% male	Wales	Anthropometrics, Arterial stiffness, Cardiac autonomic activity	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Marshall et al. [148]	101	12.4 (1.6)	45% female	Wales	Arterial stiffness	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Matricciani et al. [149]	Children:1073; Adults: 1378	Children: 12.0 (0.4) Parents: 44.0 (5.1)	Children: 50% males Parents: 13% males	Australia	BMI, Systolic blood pressure, Diastolic blood pressure, Metabolic syndrome severity score, Glycoprotein acetyls, Apolipoprotein B/A1	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM; Proportional ISM
McGee et al. [150]	119	5.7 (0.2)	47% female	Canada	Body composition	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
McGregor et al. [151]	7776	Adults: 41.3 (0.2) Older Adults: 69.3 (0.3)	Adults: 50.4% male Older Adults: 47.6% male	Canada	BMI, Waist circumference, Aerobic fitness, Resting heart rate, HDL cholesterol, Triglycerides, Blood glucose, Insulin levels	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Individual
McGregor et al. [152]	1468	63.1 (0.2)	48.3% female	USA	Mortality	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Mellow et al. [153]	384	65.5 (3.0)	68.5% female	Australia	Cognitive function	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual
Mellow et al. [154]	378	65.6 (3.0)	67.5% female	Australia	Cognitive function: Long-term memory, Executive function, Processing speed; Brain gray matter: Total, lateral ventricle, bilateral frontal lobe, bilateral temporal lobe and bilateral hippocampus volumes	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM; Proportional ISM
Migueles et al. [155]	93	10 (1)	40% female	Spain	Gray matter volume (left and right hippocampus)	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Migueles et al. [156]	X: 315; L: 201	4.5 (0.1), 9.6 (0.1)	N/R	Sweden	Body composition, BMI, Cardiorespiratory fitness, Motor skills, Muscular fitness	Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual
Mitchell et al. [157]	4481	47 (0.6)	52% female	England, Scotland, Wales	Cognition	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Mota et al. [158]	204	4.5 (0.8)	50.5% female	Brazil	Fundamental movement skills	Cross-sectional	Device-based	Device-based	Device-based	Questionnaire (proxy-reported)	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Murray et al. [159]	770	20.4 (0.7)	55% female	Canada	Depressive symptoms, Self-rated mental health	Cross-sectional	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Ng et al. [160]	1,179	12.0 (0.4)	49% female	Australia	Adiposity, HRQoL	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM; Proportional ISM
Niemelä et al. [161]	4147	53	58% female	Finland	Major adverse cardiac events	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Olds et al. [58]	105	62.3 (4.3)	51.4% female	Australia	Mental health: Depression, Anxiety, Stress, Well-being, Life satisfaction, Self-esteem	Longitudinal	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Screen time; SL; Other: Transport, Work, PA, Chores, Self-care, Quiet time, Social/Domestic Activities	Overall; 1-to-1 ISM
Oviedo-Caro et al. [162]	130	32.8 (4.5)	100% female	Spain	Adiposity, Cardiorespiratory fitness	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Pina et al. [163]	Scotland: 150; South Africa: 138	60–85	78% & 82% female	Scotland, South Africa	Musculoskeletal health: Muscle strength, Muscle mass, Physical performance, and Bone mineral density	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual
Powell et al. [164]	366	4.6 (5.3)	46% female	Ireland	Cardiometabolic health markers	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA; Standing	Individual; 1-to-1 ISM; Proportional ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Rees-Punia et al. [165]	549	30–65	58% female	USA	Weight change	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MPA; VPA	Overall; Individual; 1-to-1 ISM
Runacres et al. [166]	176	13.8 (1.8)	47.7% female	UK	Aerobic fitness (VO2 max)	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MPA; VPA	Individual; 1-to-1 ISM
Sampasa-Kanyinga et al. [57]	14,620	14.9 (1.2)	65.1% female	Canada	Depressive symptoms	Longitudinal	Questionnaire (self-reported)		Questionnaire (self-reported)	Questionnaire (self-reported)	Screen time; SL; MVPA	Individual; 1-to-1 ISM; Proportional ISM
Sandborg et al. [167]	X: 273 L: 242	31 (4)	100% female	Sweden	Cardiometabolic health, Body composition	Cross-sectional; Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM; Proportional ISM
Segura-Jiménez et al. [168]	296	12.8 (2.4)	49% female	Spain	Inflammatory markers: CRP, C3, C4, Leptin, TNF-α, IL-6, Adiponectin	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	1-to-1 ISM
Smith et al. [169]	258	9.7 (0.5)	48.4% male	Iran, England	Fundamental movement skills	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Smith et al. [170]	34	66.9 (4.5)	56% male	Australia	Neuroplasticity	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual
St Laurent et al. [171]	388	51.5 (9.5) months	44.6% female	USA	Cognition, Social-emotional health	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Goldilocks
Su et al. [172]	1475	20.7 (1.60)	68% female	China	Depression symptoms	Cross-sectional	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Suorsa et al. [173]	213	63.5 (1.1)	82% female	Finland	BMI, Waist circumference	Longitudinal	Device-based	Device-based	Device-based	Questionnaire (self-reported)	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Swindell et al. [174]	1462	52.8 (11.1)	66% female	Denmark, Finland, The Netherlands, UK, Spain, Bulgaria, Australia, New Zealand	Cardiometabolic risk factors: BMI, Waist circumference, Body fat %, Triglycerides, Glucose fasting, Glucose 2 h, Insulin, HOMA-IR, HDL-C, LDL-C, Total cholesterol, hs-CRP, HbA1c, Systolic BP, Diastolic BP	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; 1-to-1 ISM
Talarico et al. [175]	434	10–13	50.2% female	Canada	BMIz, Waist circumference, Log fat mass index	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; Proportional ISM

Table 1 (continued)

Study	Analytic sample size	Age in years: [1]Mean and/or range	Sex/gender	Country	Indicator(s) of health	Type of Study	MVPA Measure	LPA Measure	SB Measure	SL Measure	What parts was the day partitioned into?	CoDA Associations Examined
Tan et al. [176]	370	8–10	50.5% female	Singapore	HRQoL	Cross-sectional; Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; 1-to-1 ISM
Taylor et al. [55]	380	1, 2, 3.5, 5	48.5, 43.7, 46.3, and 49.2% female	New Zealand	Body composition, Bone health	Cross-sectional; Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Individual; Proportional ISM
Taylor et al. [177]	690	7.9 (1.1)	51.5% female	New Zealand	BMI	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA; Other: WASO	Proportional ISM
Taylor et al. [178]	392	3.5, 5	50% female	New Zealand	Psychosocial and mental health	Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Proportional ISM
Tyler et al. [179]	359	11.5 (1.4)	49.3% male	England	Motor competence	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Vanderlinden et al. [180]	410	71.3 (6.3)	71% female	Belgium	Mental well-being	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM
Verhoog et al. [181]	1934	70.9 (9.3)	51.5% female	Netherlands	HRQoL	Cross-sectional	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM
Walmsley et al. [182]	87498	40–79	58% female	UK	Cardiovascular disease	Longitudinal	Device-based	Device-based	Device-based	Device-based	SB; SL; LPA; MVPA	1-to-1 ISM; Proportional ISM
Wang et al. [183]	437	20.1 (1.7)	51.7% female	China	Depression, Anxiety, Stress	Longitudinal	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	Questionnaire (self-reported)	SB; Screen time; SL; LPA; MVPA	Overall; Individual; 1-to-1 ISM

[1] Age in months indicated if not reported in years

[a] Also examined 5-part composition with prolonged and non-prolonged sedentary behavior

N/R not reported, *X* cross-sectional, *L* longitudinal, *HRQoL* Health related quality of life, *LPA* light physical activity, *MVPA* moderate-to-vigorous physical activity, *SB* Sedentary behavior, *SL* sleep, *WASO* wake after sleep onset

For studies with device-based sleep estimates, less than half (25/63) used sleep diaries to aid with data processing, and few (15/63) clearly reported how wake bouts were addressed.

Composition construction

This reporting area included five items. The majority of studies (≥75%) provided sufficient information for two items. That is, all 102 studies described how many parts (i.e., behaviors) the day was partitioned into and nearly all studies (101/102) reported how the behaviors were transformed via sets of log ratios. Very few studies (6/102) clearly described the definition of a day (e.g., midnight to midnight/wake to wake), although most studies (67/102) clearly described the time-bound window that the composition was closed to (e.g., exactly 24 h, mean wear time of sample). Further, few studies (27/102) clearly described how zeros in the behavioral data were handled. Among these studies, eight did not find cases with zeros during inspection, whereas 19 observed zeros and reported how they were handled.

Analytic plan

This reporting area included five items. The majority of studies (≥75%) provided sufficient information for two items. Specifically, nearly all studies (101/102) clearly reported the analytic technique (e.g., linear regression, latent profile analysis) used after compositional transformation, and whether covariates were adjusted for (99/102). We were able to infer how missing data was handled in more than half of the studies (64/102). In many instances the techniques used to handle missing data were not outright stated (e.g., listwise deletion, mean substitution, multiple imputation), but enough information was provided to determine which procedures were implemented. Less than a third of studies (29/101) compared the analytic sample to the total sample,[3] and very few (15/102) studies provided a power analysis.

Composition-specific descriptive statistics

This reporting area included three items. The majority of studies (≥75%) provided sufficient information for one item. Most studies (74/102) reported the geometric means of the parts that comprised the 24-h movement composition (i.e., relative percentages of time spent in each behavior), whereas nearly all studies (97/102) reported the arithmetic and/or compositional means for each behavior. Of these studies, roughly one third (34/97) reported both the arithmetic (i.e., absolute) and compositional (i.e., adjusted to 24 h) means, nearly two thirds (60/97) reported only the compositional means, two studies reported only the arithmetic means [62, 63], and in one study it was unclear which means were reported [64]. Roughly half of studies (51/102) reported the compositional variation matrix, which shows the correlation between compositional parts.

Model results

This reporting area included nine items. The majority of studies (≥75%) provided sufficient information for six items. Over half of studies (64/102) reported overall model statistics regarding whether the 24-h movement behavior composition was significantly associated with the health outcome, of which only 25 studies included a standardized effect size (e.g., R^2). Four studies reported a standardized effect size for the relationship between the 24-h movement behavior composition and indicator of health despite not reporting whether a significant association was observed.

Of the 67 studies that examined associations between each behavior (relative to others) in relation to indicators of health, less than half (25/67) reported associations for each behavior only if the overall model was significant, but four of these studies did not report statistical information that could be used to determine effect sizes for all behaviors (e.g., beta coefficient without standard error). 36 studies reported associations for each behavior regardless of whether the overall model was significant. Six out of 67 studies reported associations for only some behaviors (relative to others), regardless of whether the overall model was significant.

For studies that computed compositional isotemporal substitution models, roughly half (43/84) only examined time reallocations for indicators of health significantly associated with the overall 24-h movement behavior composition. In contrast, very few studies (9/84) computed isotemporal substitution models regardless of whether the overall 24-h movement behavior composition was significantly associated with the health outcome. In the remaining 32 studies, it was not reported whether the overall 24-h movement behavior composition was significantly associated with indicators of health. In all but one study (83/84) [54], it was clearly reported whether 1-to-1 (e.g., 10 min in MVPA replaced with 10 min in sleep) or proportional replacement (e.g., 10 min in MVPA proportionally reallocated across all other behaviors) was used. Most studies (69/84) reported substitutions across all behaviors, whereas some studies (15/84) only reported substitutions for select behaviors. Most studies (72/84) reported model statistics for reallocating time across behaviors, including effect sizes (e.g., beta coefficients with standard error or 95% confidence intervals).

[3] Reporting in one study did not allow for comparison as we were unable to determine whether the analytic sample or total sample was reported, resulting in this item being reported out of 101 instead of 102 studies.

Among the six studies that examined optimal behavioral compositions for indicators of health, all studies (6/6) clearly described the optimal % of the health outcome (e.g., best 5%, 85th percentile), and nearly all studies (5/6) reported estimates for the optimal amount of time spent in each behavior, including a range (Goldilocks approach) or different options (Many Different Roads approach) associated with the optimal % of the outcome. One study using the Goldilocks Approach only reported the exact optimal time-use estimates, but not the associated ranges of optimal time spent in each behavior [65].

Auxiliary reporting

This reporting area included four items and focused on placing CoDA findings within context, and general article reporting practices. The majority of studies (≥75%) provided sufficient information for two items, in that nearly all studies reported funding sources (100/102) and conflicts of interest (95/102). Very few (16/102) studies acknowledged potential limitations of using CoDA, or the clinical meaningfulness of the effect sizes observed (22/102).

Methodological quality and risk of bias assessment

The study quality and risk of bias results are presented in Table 3. The majority of studies (81/102) were considered to be fair quality, with only 19 considered to be good quality and two considered poor quality.

Discussion

The purpose of this systematic review was to describe research reporting practices in observational studies that have examined associations between 24-h movement behaviors and indicators of health using CoDA techniques. There has been considerable growth in this body of literature since Chastin and colleagues' [41] first applied these technique to examine associations between 24-h movement behaviors and indicators of health in 2015, as evidenced by the inclusion of 102 observational studies with compositional exposures. While there was consistency across studies in reporting items specific to methodological justification, other areas had considerably more variation. Nevertheless, our results for study quality and risk of bias suggest that, to date, most published CoDA studies rely on rigorously collected data from quality samples, giving support for the utility of this approach as an impactful technique for public health researchers and policy makers. This rapidly growing body of literature has clear opportunities to improve reporting practices to provide further rigorous evidence surrounding the associations between 24-h movement behaviors and indicators of health. Doing so may help future systematic reviews and meta-analyses, and thus should be a top priority. The following sections provide detailed descriptions of our results by reporting areas.

Methodological justification

Given the recent shift from studying physical activity, sedentary behavior and sleep independently to the novel 24-h movement paradigm, it is encouraging to see that most studies (92%) introduced the statistical concept of CoDA and explained why CoDA is particularly well-suited for examining associations between 24-h movement behaviors and indicators of health. Despite receiving increased attention and adoption in recent years, the 24-h movement paradigm may still be novel to the audience of many journals depending on where authors submit manuscripts, thus requiring methodological justification to help readers understand the rationale behind adopting a compositional approach. It is also promising that nearly every study (98%) mentioned CoDA (or "compositions") in the title and/or abstract, which will help with discovering CoDA studies in systematic searches of the literature.

Behavioral measurement and data handling strategies

It was encouraging that the majority of studies provided sufficient detail for half of the 14 items, but considerable improvements can be made in this area. While most studies (88–93%) described their data scoring/processing procedures for each behavior, reporting could be more clearly articulated to ensure the procedures are reproducible. For instance, authors who use the open-source 24-h accelerometry processing package GGIR [66] in R could include their data processing parameters in the supplemental materials as these are typically customized to each study and variations will influence the output. It is also worth noting that commercial wearables may pose challenges for transparency and reproducibility as many manufacturers use propriety algorithms to process data, although the availability of device-agnostic metrics derived from consumer wearable data may help to overcome this issue [67]. Other aspects of data handling were also consistently reported such as device placement and inclusion criteria that inform whether an accelerometry sample is considered valid (i.e., minimum daily wear time, number of valid days). This may be attributable to existing recommendations for reporting accelerometry methods in physical activity studies [68, 69]. However, greater consistency in reporting which valid days were selected for analysis (e.g., average across all days, four random days) is needed. This is particularly relevant in light of recent work demonstrating how different data handling strategies influence associations between 24-h movement guideline adherence and overweight/obesity

Table 2 Summary statistics for reporting practices by item

Area	Item	n/N (%)
Methodological justification	Was CoDA mentioned in Title/Abstract?	100/102 (98%)
	Was the concept of CoDA introduced and reasons provided for utilizing CoDA to examine associations between 24 h movement behaviors and indicators of health?	94/102 (92%)
Behavioral measurement and data handling strategies	Were the scoring/processing procedures for sleep described?	90/102 (88%)
	If device-based sleep assessment, was a sleep log used to aid in data processing?	25/63 (40%)
	If device-based sleep assessment, was it clear how wake bouts were addressed?	15/63 (24%)
	Was sleep clearly conceptualized (i.e., 24-h, nocturnal only, day only)?	50/102 (49%)
	Was sleep clearly defined (i.e., sleep duration, time in bed)?	37/102 (36%)
	Were naps included in the composition?	Yes: 17/102 (17%) Unclear: 44/102 (43%)
	Were the scoring/processing decisions for sedentary behavior clearly described?	93/102 (91%)
	Were the scoring/processing decisions for LPA clearly described?	92/99 (93%)
	Were the scoring/processing decisions for MVPA clearly described?	94/102 (92%)
	If device-based measurement, was device placement described?	87/90 (97%)
	If device-based measurement, was how many minutes of wear time was considered a valid day described?	80/90 (89%)
	If device-based measurement, was how many valid days was needed to be considered a valid sample described?	85/90 (94%)
	If device-based measurement, was which valid days were used for analysis described?	44/90 (49%)
	Was how non-wear (if device-assessed) or time not accounted for (if questionnaire) described?	61/100 (61%)
Composition construction	Was how many parts (i.e., behaviors) the day was partitioned into clearly described?	102/102 (100%)
	Was how the behaviors were transformed (e.g., isometric log-ratio) described?	101/102 (99%)
	Was the definition of a day (e.g., Midnight to Midnight/Wake to Wake) described?	6/102 (6%)
	Was the time-bound window that the composition was closed to (e.g., exactly 24 h, mean wear time of sample) described?	67/102 (66%)
	Was how zeros in the behavioral data were handled clearly described?	27/102 (26%)
Analytic plan	Was the analytic technique after compositional transformation reported clearly?	101/102 (99%)
	Were covariates adjusted for within CoDA models clearly outlined?	99/102 (97%)
	Was how missing data was handled in the full dataset described?	64/102 (63%)
	Was a comparison between those included in the analytic sample vs the full sample performed?	29/101 (29%)
	Was a power analysis reported?	15/102 (15%)
Composition-specific descriptive statistics	Were the geometric means (% of time) for each behavior reported?	74/102 (73%)
	Were the arithmetic and/or geometric compositional means reported?	97/102 (95%)
	Was the compositional variation matrix reported?	51/102 (50%)

Table 2 (continued)

Area	Item	n/N (%)
Model results	Were the overall composition model statistics in relation to the outcome reported?	64/102 (63%)
	If associations between each behavior (relative to the other behaviors) in relation to the outcome were examined, were model statistics including standardized effect sizes (e.g., standardized beta) for each individual behavior reported?	25/67 (37%)
	If isotemporal substitution was used, was the overall composition significantly associated with the outcome?	43/84 (51%)
	If isotemporal substitution was used, was it clearly reported whether 1 to 1 or proportional replacement was computed?	83/84 (99%)
	If isotemporal substitution was used, were substitutions across all behaviors reported?	69/84 (82%)
	If isotemporal substitution was used, were the model statistics for replacing each behavior with time spent in the other behaviors reported, including effect sizes?	72/84 (86%)
	If an optimal behavioral composition model was reported, was the overall composition significantly associated with the outcome?	6/6 (100%)
	If an optimal behavior model was reported, were the estimates for optimal time spent in each behavior reported (in text, Table or a Figure), including a range (Goldilocks) or different options (Many Different Roads) associated with an optimal % of the outcome?	5/6 (83%)
	If an optimal behavior model was reported, was the range associated with an optimal % of the outcome clearly described (e.g., 5%)?	6/6 (100%)
Auxiliary reporting	Were limitations of compositional data analysis discussed?	16/102 (16%)
	Was clinical meaningfulness of the effects discussed?	22/102 (22%)
	Were study funding sources reported?	100/102 (98%)
	Were conflicts of interest reported (including no COI)?	95/102 (93%)

status [70]. With consistent reporting of accelerometry data handling strategies, readers would be better able to evaluate the generalizability of the data to all days of the week. Despite the advantages of accelerometry, thorough and transparent reporting practices regarding the data handling are warranted regardless of the instrument used to assess 24-h movement behaviors.

Special attention should also be given to reporting practices surrounding sleep as a behavioral component in CoDA studies. Although sleep is a more recent addition to CoDA time-use analyses, researchers have been using accelerometers to measure sleep (i.e., actigraphy) since the early 1970s [71]. Similar to wake-time movement behaviors, there are recommendations and various approaches to processing and reporting sleep metrics measured via actigraphy [72–74] and questionnaires [75, 76]. However, there are notable gaps among included studies with adequately reporting sleep measures. Measurement periods of sleep (e.g., 24-h, nocturnal, daytime sleep, or naps) were often undefined or only overnight sleep was addressed or measured even though daytime sleep could be present in the sample. For example, daytime sleep was often not mentioned or studies using accelerometry did not use a sleep log to help with scoring additional sleep periods. Thus, in such cases, daytime sleep could be misclassified as sedentary behavior or, when processed with GGIR (without a sleep log), only the single longest sustained inactivity bout (i.e., sleep period) could be estimated. Further, like physical activity, sleep 'time' can be categorized into various metrics (e.g., time in bed, sleep duration), but most studies did not clearly identify the variable that was used or how it was defined. Additionally, whether wake after sleep onset (WASO) at night were included in their sleep measure was commonly unreported. Altogether, there is room to improve reporting practices of sleep in time-use studies and the adoption of common terms and recommendations that have been promoted among sleep science research is recommended [73, 74, 77, 78].

Composition construction

Studies had variable reporting in this area, with consistent reporting for two areas, and low reporting in the remaining three. First, the most consistent reporting

across studies (100%) related to describing how many parts the day was partitioned into and how the behaviors were transformed via log ratios (99%). Although we were able to infer how many parts the day was partitioned into in all studies, researchers are encouraged to more clearly articulate such information in their data analysis section. Constructing the 24-h movement behavior composition is a crucial step before any CoDA approach can be undertaken. Beyond these two items, information pertaining to the time-bound window and composition closure was less consistently reported. One potential explanation for the former is that researchers may assume the reader interprets the composition having been closed to exactly 24 h despite alternative options (e.g., mean wear time of the sample). Nevertheless, this should be made clear. The latter finding was somewhat surprising given how many studies used GGIR to process their accelerometry data and its requirement to specify what constitutes a day as part of the code. Such reporting may be particularly valuable for studies investigating within-person effects regarding how daily movement compositions relate to health outcomes also measured daily (e.g., HDL and LDL cholesterol, stress). Finally, it was concerning that only a quarter of studies acknowledged zeroes given the challenges that zeros present in the behavioral data can pose for CoDA. Of the 19 studies that observed zeros, the most common procedures to address this issue were imputation using the log-ratio expectation maximization algorithm or multiplicative replacement using a fixed value in the dataset (e.g., 65% of the smallest possible non-zero value). This is promising as recent work has shown that these methods are preferred over simple replacement for preserving the data structure [79]. Researchers are advised to clearly indicate that behavioral data was inspected for zeros and report the procedures used to address this issue if such values are present in the dataset.

Analytic plan

Existing studies have consistently reported the analytic technique(s) used after compositional transformation (101/102) as well as whether covariates were adjusted for (99/102). In fact, acknowledging that key confounding variables were adjusted for was one of the items that contributed to the positive study quality and risk of bias scores observed. However, far fewer reported how missing data was handled, compared the analytic sample to the total sample or provided a power calculation. Understanding how missing data was handled has implications for generalizability and can influence the magnitude of the effects observed [80]. Similarly, contrasting the analytic and total sample can help identify any systematic differences that may introduce bias into the results. The low number of studies that computed a power analysis is likely attributable to most CoDA studies involving secondary data analysis, but as the 24-h movement paradigm sees greater adoption, it is reasonable to expect reporting of sample size estimates to become more common as studies are designed with the primary goal of examining how 24-h movement behaviors relate to indicators of health. Further, power calculations for 24-h movement behavior studies may not be as straightforward as more traditional analytic approaches and formal guidance has yet to be published. The lack of sample size justifications was one of the primary items that was a detriment to study quality and risk of bias scores.

Composition-specific descriptive statistics

Compositional descriptive statistics describing centrality were presented more than those for dispersion as evidenced by most studies reporting the compositional (92%) or geometric means (73%) and roughly half reporting the compositional variation matrix. The arithmetic means for each behavior (35%) were reported much less often than the compositional means. While reporting all these metrics within a manuscript may introduce some redundancy, researchers should consider allocating those not reported to the electronic supplemental materials.

Model results

Model results reporting was perhaps the most inconsistent among the various sections of the manuscripts that we examined, which may largely be attributed to selective reporting due to the lack of general standards in the field. Only 64 studies indicated whether the overall 24-h movement behavior composition was significantly associated with the outcome of interest, with even fewer reporting standardized effect sizes (e.g., R^2). To our knowledge, there is currently no formal guidance regarding whether researchers should proceed to conduct subsequent analyses only if the overall composition is significant, but this topic deserves clarification. We raise this point because we found inconsistency in procedures adopted to date in that some studies moved on to subsequent modeling techniques (e.g., individual behaviors, isotemporal substitution) only if the overall model was significant, whereas others computed subsequent models regardless. Other studies even proceeded to subsequent modeling techniques without acknowledging whether the overall composition was related to the outcome. In these cases, it is possible that such analyses were only conducted if the overall model was significant, but insufficient reporting precludes such conclusions.

Another issue pertains to selective reporting of certain behaviors that comprise the composition. That is, several studies examining associations for individual

Table 3 Study quality and risk of bias assessment by study

	Asano et al. [96],	Bezerra et al. [97],	Biddle et al. [99],	Blodgett et al. [100],	Blodgett et al. [101],	Booker et al. [60],	Brakenridge et al. [61],	Brayton et al. [64]	Cabanas-Sánchez et al. [102]	Carson et al. [103]	Carson et al. [104]	Chao et al. [105]	Chastin et al. [54]
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
3. Was the participation rate of eligible persons at least 50%?	No	No	Other	Yes	Other	Yes	Yes	Yes	Yes	Yes	Yes	Other	Other
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	Yes	Other	No
5. Was a sample size justification, power description, or variance and effect estimates provided?	No	No	No	No	No	No	No	Yes	No	No	No	No	No
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	No	No	No	No	No	No	Yes	Yes	No	No	No	Yes
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	No	No	No	No	No	No	Yes	Yes	No	No	No	Yes

Table 3 (continued)

	Asano et al. [96],	Bezerra et al. [97],	Biddle et al. [99],	Blodgett et al. [100],	Blodgett et al. [101],	Booker et al. [60],	Brakenridge et al. [61],	Brayton et al. [64]	Cabanas-Sánchez et al. [102]	Carson et al. [103]	Carson et al. [104]	Chao et al. [105]	Chastin et al. [54]
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	No	Yes	Yes	No	No	Yes	No	Yes	No	No	Yes	No	No
10. Was the exposure(s) assessed more than once over time?	No	Other	No	No	No	No	Other	No	Yes	No	No	No	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	Other	Other	Other	No	Other	Other	Other	Other	Other	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	Other	Other	Other	Other	Other	Other	Yes	No	Other	Other	Other	No
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
Totals	6	7	7	7	5	7	7	11	10	6	8	4	6

Table 3 (continued)

	Chen et al. [62]	Chen et al. [106]	Chong et al. [107]	Chong et al. [108]	Clarke et al. [109]	Collings et al. [110]. D&MS	Collings et al. [111] Atherosclerosis	Curtis et al. [112]	Curtis et al. [113]	de Faria et al. [114]	del Pozo-Cruz et al. [115]	Domingues et al. [116]	Dumuid et al. [117] Qual Life Res
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3. Was the participation rate of eligible persons at least 50%?	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Other	No	Other
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	No	Other	Yes	Yes	Yes	Yes	Yes	Other	Yes	Yes	Yes	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	No	No	No	No	No	No	No	No	No	Yes	No	Yes	No
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	No	Yes	Yes	Yes	No	No	No	No	No	No	No	No
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	No	Yes	Yes	Yes	No	No	No	No	No	No	No	No

Table 3 (continued)

	Chen et al. [62]	Chen et al. [106]	Chong et al. [107]	Chong et al. [108]	Clarke et al. [109]	Collings et al. [110]. D&MS	Collings et al. [111] Atherosclerosis	Curtis et al. [112]	Curtis et al. [113]	de Faria et al. [114]	del Pozo-Cruz et al. [115]	Domingues et al. [116]	Dumuid et al. [117] Qual Life Res
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	No	No	Yes	No	No	Yes	Yes	No	No	Yes	No	No	Yes
10. Was the exposure(s) assessed more than once over time?	No	No	Yes	Yes	No	No	No	No	No	No	No	No	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	No	Other	Yes	No	Other	Other	Other	Other	Other	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	Other	No	Yes	Yes	Other	Other	Other	Other	Other	Other	Other	Other
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Totals	6	6	10	10	11	8	8	6	7	9	6	6	7

Table 3 (continued)

	Dumuid et al. [118] Maturitas	Dumuid et al. [119] BMC Pub Health	Dumuid et al. [120]	Dumuid et al. [121]	Dumuid et al. [122]	Dumuid et al. [123]	Dumuid et al. [35] JAD	Faircloug h et al. [124]	Fairclough et al. [125]	Fairclough et al. [65]	Farrahi et al. [126]	Feter et al. [127]	Franssen et al. [128]
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3. Was the participation rate of eligible persons at least 50%?	Yes	Yes	No	No	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	Yes	Yes	No	No	No	No	No	No	No	No	No	No	Yes
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	No	No	No	No	No	No	No	No	No	No	No	No
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	No	No	No	No	No	No	No	No	No	No	No	No
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes

Table 3 (continued)

	Dumuid et al. [118] Maturitas	Dumuid et al. [119] BMC Pub Health	Dumuid et al. [120]	Dumuid et al. [121]	Dumuid et al. [122]	Dumuid et al. [123]	Dumuid et al. [35] JAD	Faircloug h et al. [124]	Fairclough et al. [125]	Fairclough et al. [65]	Farrahi et al. [126]	Feter et al. [127]	Franssen et al. [128]
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	No	Yes	No	Yes	Yes	No	No	Yes	Yes	No	Yes	No	No
10. Was the exposure(s) assessed more than once over time?	No	No	Other	No	No	No	Other	No	No	No	No	Other	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12. Were the outcome assessors blinded to the exposure status of participants?	No	Other	Other	Other	Other	No	Other	Yes	Other	No	No	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	No	Other	Other
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Totals	8	9	6	7	8	7	7	8	8	5	8	7	8

	Gupta et al. [129]	Gupta et al. [130]	Gupta et al. [131]. IJoO	Gupta et al. [132] IJBNPA	Healy et al. [53]	Hofman et al. [133]	Hyodo et al. [56]	Kastelic et al. [135],	Kandola et al. [134]	Kim et al. [59]	Kitano et al. [136]	Kuzik et al. [137]	Larisch et al. [138]
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No

Table 3 (continued)

	Gupta et al. [129]	Gupta et al. [130]	Gupta et al. [131]. IJoO	Gupta et al. [132] IJBNPA	Healy et al. [53]	Hofman et al. [133]	Hyodo et al. [56]	Kastelic et al. [135],	Kandola et al. [134]	Kim et al. [59]	Kitano et al. [136]	Kuzik et al. [137]	Larisch et al. [138]
3. Was the participation rate of eligible persons at least 50%?	No	Yes	Yes	No	Other	Other	Other	Other	No	Yes	Other	No	No
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	No	No	No	No	No	No	No	No	Yes	No	No	No	No
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	No	No	Yes	No	No	No	No	Yes	No	No	No	No

Table 3 (continued)

	Gupta et al. [129]	Gupta et al. [130]	Gupta et al. [131]. IJoO	Gupta et al. [132] IJBNPA	Healy et al. [53]	Hofman et al. [133]	Hyodo et al. [56]	Kastelic et al. [135],	Kandola et al. [134]	Kim et al. [59]	Kitano et al. [136]	Kuzik et al. [137]	Larisch et al. [138]
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	No	No	Yes	No	Yes	No	Yes	Yes	No	No	No
10. Was the exposure(s) assessed more than once over time?	No	No	No	No	No	Other	No	No	No	No	No	No	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	Other	Other	No	Other	Other	Other	Other	No	Other	Other	Other	Other

Table 3 (continued)

	Gupta et al. [129]	Gupta et al. [130]	Gupta et al. [131]. IJoO	Gupta et al. [132] IJBNPA	Healy et al. [53]	Hofman et al. [133]	Hyodo et al. [56]	Kastelic et al. [135],	Kandola et al. [134]	Kim et al. [59]	Kitano et al. [136]	Kuzik et al. [137]	Larisch et al. [138]
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Totals	7	8	7	8	7	6	7	6	10	8	6	6	5
	Lau et al. [139]	**Le et al. [140]**	**Lee et al. [141]**	**Lemons et al. [142]**	**Lewthwaite et al. [63]**	**Lin et al. [143]**	**Lu et al. [144]**	**Lund Rasmussen et al. [145]**	**Madden et al. [146]**	**Marshall et al. [147]**	**Marshall et al. [148]**	**Matricciani et al. [149]**	**McGee et al. [150]**
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3. Was the participation rate of eligible persons at least 50%?	No	No	Yes	Yes	No	Other	Yes	Yes	Yes	Other	Other	Yes	No
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	No	No	No	No	Yes	No	Yes	No	No	No	No	No	Yes

Table 3 (continued)

	Lau et al. [139]	Le et al. [140]	Lee et al. [141]	Lemons et al. [142]	Lewthwaite et al. [63]	Lin et al. [143]	Lu et al. [144]	Lund Rasmussen et al. [145]	Madden et al. [146]	Marshall et al. [147]	Marshall et al. [148]	Matricciani et al. [149]	McGee et al. [150]
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	No	No	No	Yes	No	No	No	No	No	No	No	No
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	No	No	No	Yes	No	No	No	No	No	No	No	No
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	No	No	No	No	Yes	Yes	Yes	No	No	No	No	No
10. Was the exposure(s) assessed more than once over time?	Other	No	No	Other	Yes	No	Other	No	No	Other	Other	No	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other

Table 3 (continued)

	Lau et al. [139]	Le et al. [140]	Lee et al. [141]	Lemons et al. [142]	Lewthwaite et al. [63]	Lin et al. [143]	Lu et al. [144]	Lund Rasmussen et al. [145]	Madden et al. [146]	Marshall et al. [147]	Marshall et al. [148]	Matricciani et al. [149]	McGee et al. [150]
13. Was loss to follow-up after baseline 20% or less?	Other	Other	Other	Other	No	Other	Other	Other	Other	Other	Other	Other	Other
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Totals	7	5	7	7	10	7	9	8	6	6	6	7	7

	McGregor et al. [151]	McGregor et al. [152]	Mellow et al. [153]	Mellow et al. [154]	Migueles et al. [155]	Migueles et al. [156]	Mitchell et al. [157]	Mota et al. [158]	Murray et al. [159]	Ng et al. [160]	Niemelä et al. [161]	Olds et al. [58]	Oviedo-Caro et al. [162]
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
3. Was the participation rate of eligible persons at least 50%?	Yes	Yes	Other	Yes	Yes	Other	Yes	No	Yes	No	No	Other	Other
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study pre-specified and applied uniformly to all participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	No	No	Yes	Yes	No	No	No	Yes	No	No	No	Yes	No

Table 3 (continued)

	McGregor et al. [151]	McGregor et al. [152]	Mellow et al. [153]	Mellow et al. [154]	Migueles et al. [155]	Migueles et al. [156]	Mitchell et al. [157]	Mota et al. [158]	Murray et al. [159]	Ng et al. [160]	Niemelä et al. [161]	Olds et al. [58]	Oviedo-Caro et al. [162]
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	Yes	No	No	No	Yes	No	Other	No	No	Yes	Yes	No
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	Yes	No	No	No	Yes	No	No	No	No	Yes	No	No
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	No	Yes	No	No	No	No	No	No	Yes	No	No	No	Yes
10. Was the exposure(s) assessed more than once over time?	No	No	Other	No	Other	Yes	No	Other	Other	No	No	Yes	Other
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 (continued)

	McGregor et al. [151]	McGregor et al. [152]	Mellow et al. [153]	Mellow et al. [154]	Migueles et al. [155]	Migueles et al. [156]	Mitchell et al. [157]	Mota et al. [158]	Murray et al. [159]	Ng et al. [160]	Niemelä et al. [161]	Olds et al. [58]	Oviedo-Caro et al. [162]
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	Yes	Other	Other	Other	No	Other	Other	Other	Other	No	Yes	Other
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Totals	7	11	7	8	7	9	7	7	8	6	8	10	7

	Pina et al. [163],	Powell et al. [164]	Rees-Punia et al. [165]	Runacres et al. [166]	Sampasa-Kanyinga et al. [57]	Sandborg et al. [167]	Segura-Jiménez et al. [168]	Smith et al. [169] SJMSS	Smith et al. [170], Clin Neurophysiol	St. Laurent et al. [171]	Su et al. [172],	Suorsa et al. [173]	Swindell et al. [174]
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Yes
3. Was the participation rate of eligible persons at least 50%?	Yes	No	No	Yes	Other	Yes	No	Other	Yes	No	Yes	No	Yes

Table 3 (continued)

	Pina et al. [163],	Powell et al. [164]	Rees-Punia et al. [165]	Runacres et al. [166]	Sampasa-Kanyinga et al. [57]	Sandborg et al. [167]	Segura-Jiménez et al. [168]	Smith et al. [169] SJMSS	Smith et al. [170], Clin Neurophysiol	St. Laurent et al. [171]	Su et al. [172],	Suorsa et al. [173]	Swindell et al. [174]
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Other	Yes	Yes	Other	Yes	Yes	Yes	Other	No	Yes	No	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	Yes	No	No	No	No	Yes	No	No	No	No	No	No	No
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	No	Yes	No	Yes	Yes	Yes	No	No	No	No	Yes	No
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	No	Yes	No	Yes	Yes	Yes	No	No	No	No	Yes	No

Table 3 (continued)

	Pina et al. [163],	Powell et al. [164]	Rees-Punia et al. [165]	Runacres et al. [166]	Sampasa-Kanyinga et al. [57]	Sandborg et al. [167]	Segura-Jiménez et al. [168]	Smith et al. [169] SJMSS	Smith et al. [170], Clin Neurophysiol	St. Laurent et al. [171]	Su et al. [172],	Suorsa et al. [173]	Swindell et al. [174]
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	No	No	Yes	No	No	No	Yes	No	No	Yes	No	No	No
10. Was the exposure(s) assessed more than once over time?	Other	Other	No	No	Yes	Yes	Yes	No	No	No	No	Yes	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	Other	No	Other	No	No	No	Other	Other	Other	Other	Yes	Other

Table 3 (continued)

	Pina et al. [163],	Powell et al. [164]	Rees-Punia et al. [165]	Runacres et al. [166]	Sampasa-Kanyinga et al. [57]	Sandborg et al. [167]	Segura-Jiménez et al. [168]	Smith et al. [169] SJMSS	Smith et al. [170], Clin Neurophysiol	St. Laurent et al. [171]	Su et al. [172],	Suorsa et al. [173]	Swindell et al. [174]
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Totals	7	6	9	6	9	11	10	4	5	7	5	10	7

	Talarico et al. [175]	Tan et al. [176]	Taylor et al. [55]	Taylor et al. [177],	Taylor et al. [178],	Tyler et al. [179],	Vanderlinden et al. [180]	Verhoog et al. [181]	Walmsley et al. [182]	Wang et al. [183]
1. Was the research question or objective in this paper clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2. Was the study population clearly specified and defined?	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
3. Was the participation rate of eligible persons at least 50%?	Yes	No	Yes	Other	Yes	Yes	Other	Yes	Yes	Yes
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Yes	Yes	Yes	Yes	Yes	Other	Yes	Yes	Yes	Yes
5. Was a sample size justification, power description, or variance and effect estimates provided?	No	No	No	No	No	No	No	No	No	Yes

Table 3 (continued)

	Talarico et al. [175]	Tan et al. [176]	Taylor et al. [55]	Taylor et al. [177],	Taylor et al. [178],	Tyler et al. [179],	Vanderlinden et al. [180]	Verhoog et al. [181]	Walmsley et al. [182]	Wang et al. [183]
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	No	Yes	Yes	No	Yes	No	No	No	Yes	Yes
7. Was the time-frame sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	No	Yes	Yes	No	Yes	No	No	No	Yes	Yes
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	No	Yes	No	Yes	Yes	No	No	No	No	Yes
10. Was the exposure(s) assessed more than once over time?	No	Yes	Yes	No	Yes	Other	No	No	No	No
11. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 (continued)

	Talarico et al. [175]	Tan et al. [176]	Taylor et al. [55]	Taylor et al. [177],	Taylor et al. [178],	Tyler et al. [179],	Vanderlinden et al. [180]	Verhoog et al. [181]	Walmsley et al. [182]	Wang et al. [183]
12. Were the outcome assessors blinded to the exposure status of participants?	Other	Other	Yes	Other	Yes	Other	Other	Other	Other	Other
13. Was loss to follow-up after baseline 20% or less?	Other	No	No	Other	No	Other	Other	Other	Yes	Yes
14. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s)?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Totals	7	10	11	7	12	5	6	7	10	12

behaviors or reallocation across behaviors did not report the results for every component of the composition. Such missing data poses an issue for quantifying effects across behaviors via meta-analysis. One reason for this may be the specificity of the research questions that have been investigated (e.g., What is the effect of reallocating time away from sedentary behavior on depression). In such instances, authors may view reporting certain estimates as irrelevant (e.g., replacing sleep with MVPA), but this information could be provided in supplementary materials. Doing so may also limit the practice of dividing a single substantial piece of research into several smaller, separate publications, otherwise known as salami slicing [81]. Finally, the field could also benefit from more consistently reporting statistical information that can be used to compute effect sizes. For instance, only reporting an unstandardized beta coefficient and indicating significance via a *p* value is insufficient. Researchers are strongly encouraged to report adequate statistical information (e.g., standardized estimates, 95% confidence intervals, standard errors) that can be used to perform meta-analysis as post-publication data requests often go unanswered [82].

While isotemporal substitution has received the most attention, other CoDA approaches are quickly emerging. Models that identify optimal behavioral compositions (i.e., Goldilocks approach; [34]) or similar behavioral compositions that result in equivalent outcomes (i.e., Many Different Roads approach; [35]) have been introduced in recent years. Perhaps due to their recency, but balanced against the limited number of studies, consistent reporting was observed across these six studies in that each study clearly reported the optimal value of the indicator of health used as a referent (e.g., best 5%) and nearly all studies provided estimates for the optimal range or different behavioral combinations associated with the optimal outcome.

Auxiliary reporting

Despite most studies introducing the concept of CoDA, few acknowledged its limitations and utility amongst clinical evidence. Inherently, one difficulty when using a compositional approach is the ability to translate the relative values (compositional components) back to values that may be more relevant in the public health sector (minutes of activity). As for utility, one potential explanation may be the availability of such metrics for the indicators of health examined. In future, authors are encouraged to describe if a meaningful difference has been established for their outcome of interest as a starting point. This also ties back to the importance of reporting of effect sizes and/or confidence intervals [83] in that if these statistics are not presented, it is challenging to determine how close to a meaningful effect there may be. Another reason relates to the scope of the journals that authors direct their manuscripts to in that clinical meaningfulness may be more commonly reported in clinically oriented journals than those focused more broadly on public health. In future, authors are encouraged to describe if a meaningful difference has been established for their outcome of interest as a starting point. In contrast, conflicts of interest (95/102) and funding sources (100/102) were consistently reported across studies, which may be driven by the requirements of journals (i.e., using the STROBE checklist).

Future directions

We found that a significant amount of information was not reported in the studies included in this review, which underscores the need for a harmonized approach and subsequent reporting checklist for observational studies utilizing CoDA to examine associations between 24-h movement behaviors and indicators of health. Unifying reporting in this rapidly growing body of literature is a key next step to be able to precisely quantify associations between 24-h movement behaviors and indicators of health. While it may be unreasonable to expect that every item is applicable when reporting individual studies given the growing variety of analytic approaches available, we believe that this review provides some initial guidance and recommendations to inform the creation of an observational CoDA checklist. The development of the CREMAS [39], another common methodology in 24-h movement behaviors research, followed similar procedures as those adopted in the present study, however, additional procedures can be adopted to achieve consensus regarding best practices for reporting moving forward. Specifically, Delphi methodology represents a useful tool to systematically reach consensus through an iterative and interactive process involving experts in the field and end-users [84]. Delphi methodology has been used often in the field of physical activity research [85–88], including checklist development (e.g., [89–91]). The present review represents a key first step in developing a reporting checklist for movement behavior studies that use CoDA, to be followed by adopting a Delphi process to achieve consensus on best practices in the field. While there are inherent limitations of such checklists, establishing reporting practices in this area stands to be an informative and succinct way of improving transparency and reproducibility. To circumvent journal-imposed word count and table limits, the checklist could be included in manuscript submissions as an electronic supplemental material, which are encouraged and available in most journals. Finally, this review only examined observational studies in which 24-h movement behaviors

were specified as the exposure, failing to consider reporting practices in studies that employ experimental designs or those specifying 24-h movement behaviors as the outcome. Examining reporting practices in other study designs may be worthwhile as the body of literature evolves and may ultimately help to inform a more comprehensive reporting checklist for all studies employing CoDA.

Strengths and limitations

Strengths of the current review include assessment of a novel and timely topic (CoDA) in the 24-h movement realm, following systematic review best practice recommendations, including multiple supplementary strategies, and a comprehensive approach to examine reporting practices using this suite of analytic techniques, which was informed by existing evidence and expert guidance. A final strength relates to the inclusion of studies that used self-reported instruments and/or device-based measures, which allowed for more studies to be included to better understand reporting practices in the field to date—an important consideration given most of the current literature involved secondary analysis of existing data sources. This inclusive approach is an important consideration given the resources available to researchers differ vastly across institutions and countries. While there are inherent differences in what is reported when using self-reported versus device-based instruments, the development and implementation of a single reporting standards checklist may be beneficial for promoting consistency in the field regardless of the instruments used to assess 24-h movement behaviors.

While the findings of this review provide valuable insights, five major limitations must be acknowledged. First, we focused on studies that used CoDA to examine associations between 24-h movement behaviors and indicators of health, but studies that only examine wake-time movement compositions are also common (i.e., no sleep) [92–94]. It is reasonable to posit that reporting practices may be similar in CoDA studies that do not include sleep, but this review also revealed a clear need to further our understanding of sleep assessment in CoDA. Second, we appreciate the overall quality of included studies was fair, which may have also translated to their mediocre reporting practices. This review also highlighted multiple areas that could be improved in future studies to enhance to rigor of reporting and general study conduct. Third, CoDA techniques applied in the field of time-use epidemiology are still emerging, and therefore, we were only able to examine reporting practices based on what exists in the literature today. As novel techniques are developed and implemented, such as a "Movement Index" score [95], reporting practices will need to be revisited. At the same time, some items we examined may not remain relevant in the future and could be removed from reporting standards. For instance, the concept of CoDA has received considerable attention as evidenced by over 100 studies included in the present review, which brings into question whether introduction and justification of using CoDA is required as audiences of this literature become more familiar with the concept. Given that reporting checklists are often updated, there exists an opportunity to update guidance as CoDA sees more widespread adoption. Fourth, we took a conservative approach when classifying items as not reported if they were not explicitly acknowledged, which may have led to underestimating of reporting in some areas. For example, only 27 studies mentioned whether the behavioral data was examined for zero values, and if present, how they were handled, but it is possible that authors felt it was implied that no zeros were present and therefore did not report this item. Such issues would be resolved with standardized reporting guidance. Finally, despite the comprehensiveness of our literature search, some studies may have been overlooked, such as those that have been published in languages other than English.

Conclusion

This review described research reporting practices in 102 observational studies that have used CoDA to investigate associations between 24-h movement behaviors and indicators of health. Study quality and risk of bias was average for this relatively new area of inquiry, which was also demonstrated in the considerable variability in CoDA research reporting practices. Consistent, clear, and detailed reporting practices are needed as the field of time-use epidemiology aims to accurately capture and analyze movement behavior data, facilitate comparisons across studies, and inform public health interventions and policy decisions. Achieving consensus regarding reporting recommendations is a key next step.

Supplementary Information

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Supplementary Material 1.
Supplementary Material 2.
Supplementary Material 3.
Supplementary Material 4.
Supplementary Material 5.

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Author contributions
CRediT author statement: DB: conceptualization, methodology, investigation, data curation, formal analysis, writing—original draft; project administration; SB: methodology, investigation, writing—original draft; CG: methodology, investigation, writing—review & editing; GB: methodology, investigation, writing—review & editing; CP: methodology, investigation, writing—original draft; CP: investigation, writing—review & editing; CSL: methodology, investigation, writing—original draft; EJ: methodology; CK: methodology, investigation, writing—original draft; project administration.

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Data availability
No datasets were generated or analysed during the current study.

Declarations

Competing interests
DB is an Editorial Board Member of the Journal of Activity, Sedentary and Sleep Behaviors. All other authors have no conflicts of interest to disclose.

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