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Rethinking the sleep-health link☆

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Sleep is important for the physical, social and mental well-being of both children and adults. In this paper, we discuss the need to consider sleep as a multidimensional construct and as a component of total 24-hour activity. First, we make a case for considering sleep as a multidimensional construct, whereby all characteristics of sleep (including duration, quality, timing, and variability) and their links with health are examined. Second, we argue that sleep should also be conceptualized as part of the daily spectrum of time-use, along with other types of activity. We propose novel statistical models, in particular compositional data analysis (CoDA), as appropriate analytical methods for a new sleep paradigm.

Introduction

Sleep characteristics such as duration, quality, timing and variability have been associated with a wide range of health outcomes, including cognitive,[1] psychosocial[2] and cardiometabolic health,[3] as well as specific conditions such as Type 2 diabetes,[4] cardiovascular disease,[5] stroke[6] and obesity.[7]

Accordingly, sleep is increasingly being recognized as a central concern for population health. Heffron,[8] for example, argues that "sleep is one of the three pillars (diet, exercise and sleep) of a healthy lifestyle", while Perry and colleagues[9] emphasize the need to consider sleep as "being as critical to health as diet and physical activity". In line with these messages, the American Academy of Sleep Medicine, the Centers for Disease Control and Prevention, and the Sleep Research Society partnered on the *Healthy Sleep Project*, in an effort to improve public health by promoting healthy sleep.[8] The initiative included the *Sleep Well, Be Well* campaign, which highlighted the importance of adequate and consistent sleep, avoiding alcohol and caffeine before bed and seeking medical advice for sleep problems. Similarly, the (American) National Sleep Foundation has recently proposed the "Sleep Health Index", which attempts to capture the construct of sleep health based on multiple sleep characteristics.[10] These two approaches represent a shift in the conceptualisation of sleep in relation to population health.

Historical attempts to improve sleep largely focused on sleep duration.[11] In contrast, conceptualizing sleep as a multidimensional construct[12] and treating sleep holistically recognizes that sleep duration, as well as other sleep characteristics such as quality, timing and variability, may all be important for health.[8,12] Sleep has also traditionally been considered as divorced from the 24-hour day. However, any change in sleep duration will necessarily entail changes in the other time-use components of that day. Conceptualizing sleep as a

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component of 24-hour time use recognizes that sleep duration does not occur in isolation from other time-use domains (i.e. sedentary time and physical activity), which are also known to affect health.[13] While these two approaches may seem contradictory, they each provide a complementary and unique insight into the role of sleep.

In spite of these new perspectives, our current understanding of sleep stems from studies that examine the association between an individual sleep characteristic (often sleep duration) and a given health outcome. To date, relatively few studies have considered sleep as a multidimensional construct or as a component of daily time use. There is also no agreed framework for considering sleep in these new ways.

The purpose of this paper is, therefore, to present a rationale and a methodology for conceptualizing sleep both as a multidimensional construct and as a component of daily time use. Specifically, we discuss why sleep should be considered from these perspectives and describe statistical techniques for the analysis of sleep data within this new paradigm.

Sleep as a multidimensional construct

Over the years, there has been increasing awareness that sleep duration may not be the only characteristic contributing to optimal health and well-being. It has been recognized that other characteristics of sleep, such as sleep quality, timing and variability, may all play an important role.[12] Indeed, a Scopus database search conducted on the 25th of July 2017 reveals that the number of hits returned for publications with title or abstract key words containing a specific sleep characteristic has risen exponentially over the last twenty years, with particular growth in characteristics other than duration (Fig. 1a). Although an increase has also been observed for studies of multiple sleep characteristics, these are more recent and fewer in number (Fig. 1b). These searches were exploratory and illustrative, where sleep characteristics were entered into Scopus' key word/abstract search engine and the number of hits per year function was used to generate the graph.

Studies that examine the association between sleep and health have traditionally focused on specific sleep characteristics as individual qualities.[2,3,5,14] Recent studies have begun to examine the association of multiple sleep characteristics on a given health outcome. In a systematic review of sleep and cognition, Astill and colleagues found that sleep duration, but not sleep efficiency (a measure of sleep quality), was associated with measures of cognition and behavioral problems.[1] In contrast, Cappuccio and colleagues identified both sleep duration and quality as predictors of future risk of developing type 2 diabetes in a systematic review and meta-analysis.[4]

While considering multiple sleep characteristics as independent predictors of health acknowledges their coexistence, this approach does not account for the potential interactions between characteristics, or the inherently multidimensional nature of sleep. Indeed, the very notion of an 'independent risk factor' is complex and dependent on the statistical model.[15] Therefore, the conceptualization of the sleep-health link should shift from considering individual sleep characteristics as independent entities to understanding how multiple sleep characteristics and their interactions explain variance in health outcomes.

In the next sections, we discuss how sleep may be considered in terms of a multidimensional construct (section 2.1), which analytical techniques will help us achieve this (section 2.2), studies that have examined the multidimensionality of sleep (section 2.3), and methodological considerations for examining multiple sleep characteristics (section 2.4).

Conceptualizing sleep as a multidimensional construct

Conceptualizing sleep as a multidimensional construct is akin to the conceptualisation of other movement-based activities. Just as physical activity can be described in terms of frequency, intensity, time, and type,[16] so too can sleep be described in terms of duration, quality, timing and variability. It is possible that each characteristic of sleep has an important and unique effect on health, in the same way that different characteristics of physical activity contribute to health outcomes. For example, a 'weekend warrior' is a person who is very physically activity on the weekend but mostly sedentary on weekdays, but this pattern of activity has been shown to be protective against all-cause mortality,[17] while increasing the risk of injury.[18] Similarly, more interruptions in sedentary time have been shown to reduce metabolic risk, independent of total sedentary time and levels of physical activity, suggesting that the manner in which physical activity is accumulated is important for health.[19]

Sleep characteristics may be conceptualized as 'time-based' or 'perception-based' measures.[20] While we acknowledge that there may be a role for subjective, 'perception-based', sleep characteristics (e.g. perceived sleep quality), in this paper we consider only objectively quantified time-based sleep characteristics, and which are increasingly monitored at population[21] and individual[20] levels. We suggest four key sleep characteristics: sleep duration, timing, quality and day-to-day variability.

Objectively-quantified time-based sleep characteristics may be conceptualized, defined and operationalized in a variety of ways. Given that sleep quality may be conceptualized as both a 'time-based' or 'perception-based' measures, we will refer to sleep continuity as a proxy measures for sleep quality. This approach has been adopted by Buysse[12] as well as The National Sleep Foundation, who recently released evidence-based recommendations and guidance on indicators of good sleep quality across the lifespan.[22] This review identified objective measures of sleep continuity (sleep latency, number of awakenings, wake after sleep onset, and sleep efficiency) as appropriate indicators of sleep quality.[22] While we acknowledge that sleep characteristics may be defined in a variety of ways, how to best to define and operationalize each characteristic is beyond the scope of this paper.

Examining sleep as a multidimensional construct

We discuss three ways in which the association between sleep characteristics and health could be examined. The first method is to look at additive associations of multiple sleep characteristics. This involves examining two or more sleep characteristics within the same statistical model, considering how each accounts for others and ideally considering interaction effects between sleep characteristics. The second method is to create a composite sleep score, whereby sleep characteristics are computed to create an index of how 'good' sleep is overall. The third method provides further insight into the multidimensional nature of sleep by examining sleep profiles within individuals. A sleep profile refers to the specific combinations of different levels of different sleep characteristics experienced by individuals. For example, the sleep profile of one person may involve long, inefficient sleep times with early bed- and late rise-times that are highly variable across a week, while the sleep profile of another person may involve short, efficient sleep with late bed- and early rise-times that are fairly consistent throughout the week. Sleep profiles experienced by individuals are then associated with a given health outcome.

Studying additive associations and composite indices involve variable-based approaches, while studying individual profiles of sleep is necessarily a person-based approach. A person-based approach defines different subtypes of individuals that exhibit similar patterns

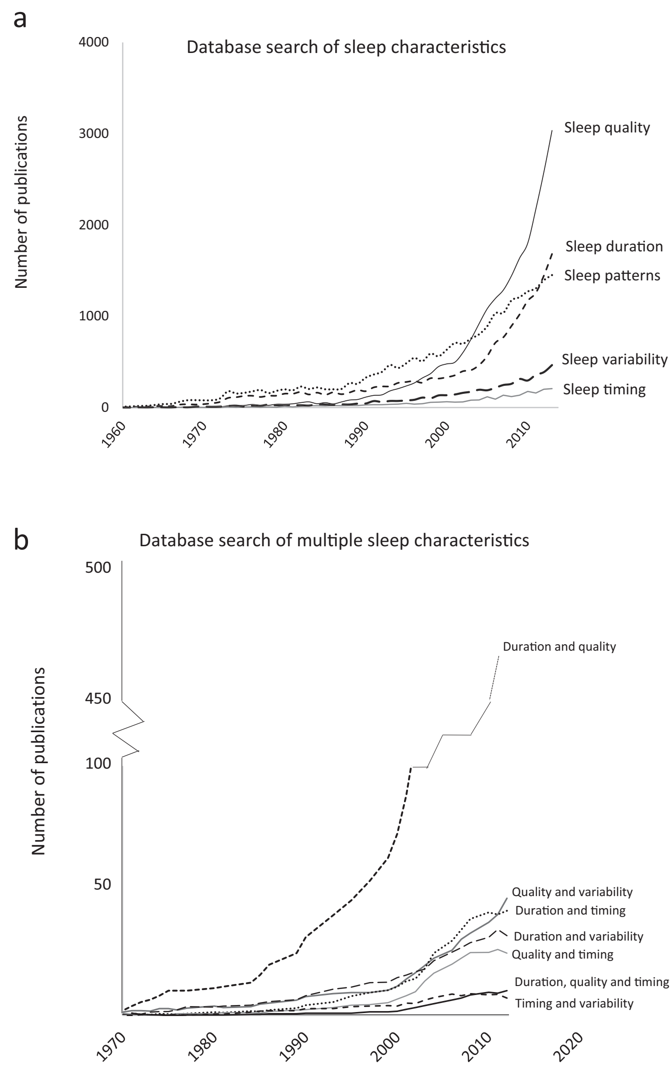

Fig. 1. a. Searches were conducted by combining the word 'sleep' and the word designating the characteristic(s). For example, 'sleep duration, quality and timing was searched used 'sleep' *and* 'duration'. b. Searches were conducted by combining the word 'sleep' and the word designating the characteristic(s). For example, 'sleep duration' was searched used 'sleep' *and* 'duration' *and* 'quality' *and* 'timing'.

of sleep characteristics. While variable-based approaches are able to compare the association between different sleep characteristics and a given health outcome, they do not necessarily account for whether or not characteristics are present in the same people.[23] Therefore, they do not reveal what kind of subgroups exist in the population and how prevalent these subgroups are. Both approaches are important for understanding sleep as a multidimensional construct.[24–26]

The statistical methods involved applying the three multidimensional approaches are described briefly below.

Examining the additive association of sleep characteristics

Regression models may be used to examine the additive association of sleep characteristics and health outcomes. However, if there is significant multicollinearity of sleep input variables, a different model, such as Partial Least Squares Regression (PLSR), may be needed. PLSR is appropriate when there are multiple predictor variables, even when those variables are correlated.[27] The method reduces the predictor variables to principal components, and regresses those components against the outcomes. Variable Importance in Projection (VIP) values can then be calculated for the predictor variables, which ranks each of the variables making up each component according to its importance for each outcome measure.[27] Results of PLSR analysis will therefore provide insight into the relative importance of each of the different sleep characteristics for a given health outcome measure. However, it is important to note that it is often difficult to interpret loadings of independent latent variables using PLSR.[28] That is, while we may be able to determine whether or not a component is associated with a given outcome, it is rather difficult to determine the relative importance of the items that make up each component.

PLSR is just one example of an alternate statistical technique that may be appropriate to handle complex, correlated sleep data. Nonparametric multi-variable modeling approaches, such as tree-structured models and random forests, are also appropriate for handling complex, correlated data with minimal assumptions and have recently been applied to sleep analysis.[29] Regularized regression techniques, such as the Least Absolute Shrinkage and Selection Operator (LASSO)[30] and Elastic Net[31] methods, are other regression approaches used to create parsimonious models when dealing with a large number of potentially correlated independent variables. These methods tend to weaken the absolute effect sizes but they are useful in situations where a large number of predictors correlate with each other and they help reduce the risk of overfitting/over-adjustment.

Examining sleep characteristics as a composite sleep score

Composite sleep scores yield a single quantitative score with a known range, and may be generated by consensus-based weighting, or by data reduction techniques such as factor analysis or principal component analysis. Composite sleep scores are helpful in the development of self-report sleep questionnaires where multiple questions relating to a particular aspect of sleep are asked and investigators are trying to determine which factors or components are most essential.[10]

Examining sleep profiles

Sleep profiles may be developed through multivariate methods such as cluster analysis or latent class analysis. Cluster analysis groups individuals within a population according to shared or similar attributes. For example, symptoms of clinical disorders may undergo cluster analysis to find subtypes of conditions and therefore to develop more accurate disease typologies and identify subgroups (who may be) particularly amenable to interventions. For population sleep, clustering would help recognize patterns of sleep that are shared by many individuals who may experience similar risks for health outcomes or respond similarly to sleep promotion efforts. A number of different clustering techniques are available that differ in the clustering algorithm used, with the most common techniques being K-means and hierarchical cluster analysis.[32] For cluster analysis, care is required to determine whether or not identified clusters are based on real patterns. This is particularly important if clusters are to be applicable for population health promotion or prevention strategies.

Latent class analysis (LCA) and latent profile analysis (LPA) are multivariate approaches that are based on structural equation modeling. In contrast to LCA, which handles categorical data, LPA handles continuous data. While both LCA and LPA are similar to cluster analysis in that it too groups individuals on shared or similar attributes, they also presume that there is an underlying latent variable that explains why those attributes are shared. LCA and LPA handle large datasets and missing data better than cluster analysis, and can also accommodate weighting and different data types.[33]

Examining sleep profiles therefore requires careful selection of appropriate statistical techniques, as well as careful decisions regarding the development of sleep profiles. Sleep profiles may be constructed with either a heuristic or model-based approach. A heuristic approach is often guided by clinical findings or expert opinion. In contrast, a model-based approach assumes different probability distributions for the observed data and is able to account for within cluster correlations, which may be preferable in some situations.[34] Given that sleep variables may include multiple data types and variables tend to be highly skewed, a recent publication by Wallace and colleagues,[35] who examined model-based approaches to clustering sleep variables, suggested assuming non-normal clusters may be preferable for both skewed and normal data. In both cases, however, there is the important challenge of selecting the appropriate number of clusters, which is present for any clustering model.

Studies that have examined sleep as a multidimensional construct

To date, there have been few attempts to examine the multidimensional nature of sleep and we discuss the variable-based approaches (additive associations and composite score) and person-based approaches in turn.

Variable-based approaches to examining sleep as a multidimensional construct

Most efforts to examine the multidimensional nature of sleep involve a variable-based approach, and the majority investigate the additive association of multiple sleep characteristics by applying linear regression models[36–38] rather than a composite sleep score.

Additive associations. Several studies have examined additive associations by applying linear regression models. For example, Kjeldson and colleagues[39] found that high variability in sleep duration was associated with increased sugar-sweetened beverage intake, independent of sleep duration, in a Danish cohort of 676 children. Similarly, Kobayahi and colleagues,[40] in a retrospective cohort study of 21,148 adults, found that self-report sleep duration variability was associated with weight gain over a three-year period, independent of sleep duration. In another study of 441 adults, which examined predictors of subjective well-being, Lemola and colleagues[41] found that although total sleep time was not related to subjective well-being, variability in sleep duration was, with effects partially mediated by subjective sleep quality. Wang and colleagues[42] reported that both sleep duration and timing, but not sleep quality, were associated with higher adiposity indices, while Olds and colleagues[43] found that later bed and wake times were associated with higher body mass index, independent of sleep duration. Although such studies attempt to decipher how different sleep characteristics are associated with different health outcomes, at best they only examine the effects of two or three different sleep characteristics and more robust studies of multidimensional sleep are needed. While particular intervention strategies can target the duration, timing, continuity and day-to-day variability of sleep, these strategies are usually implemented as a package and it is unknown if interventions can target specific aspects of sleep without changing others.

Efforts to examine the multidimensional nature of sleep using more sophisticated statistical methods are relatively recent. Wallace and colleagues,[29] for example, acknowledged the clinical importance of considering sleep as a multidimensional construct and a need to move beyond traditional multivariable approaches, which are limited in modeling the complex, non-linear associations that are characteristic of sleep data. Wallace and colleagues[29] tested three different statistical methods (Cox regression, tree-structured survival analysis and random survival forest) to determine the association between multivariable sleep and mortality outcomes in a sample of 2887 men aged 65 years and older. Lower sleep continuity and rhythmicity were associated with an increased risk of all-cause mortality in all analyses. However, although traditional Cox regression analyses identified sleep duration as a significant predictor of mortality, it was not significant in full multivariable models. While random survival forest analyses revealed the Variable Importance Statistics (VIMP) of all sleep characteristics to be 8.8%, the VIMP of sleep duration, timing and quality, individually, was <1%. Methods such as random forest survival may be superior to traditional methods in identifying the relationships between sleep as a multivariable construct and health outcomes.

Composite scores. To our knowledge, there have only been a few attempts to examine sleep as a multidimensional construct using a composite sleep score. The Sleep Health Index used factor analysis to help identify three underlying constructs of sleep duration, sleep quality, and sleep disorders, which were included as sub-indices of the composite index scored from 0 to 100.[10] The Sleep Health Index was cross-sectionally correlated with self-reported stress and overall health, but has yet to be linked to longitudinal health outcome measures to confirm its usefulness.[10] We note that the Sleep Health Index is also entirely based on self-reported sleep. Furihata and colleagues[44] examined the relationship between sleep characteristics of sleep (based on self-reported sleep duration, satisfaction, onset-latency, mid-sleep time and day-time sleepiness) and depression in a sample of 6485 women with a mean age of 80 years. In this study, both individual characteristics of sleep and aggregate measures of sleep health were associated with depression. Specifically, poorer sleep health was associated with a greater prevalence of depression (OR 1.26–5.41) and increased odds of developing depression over a six year period (OR 1.32–3.15).

Person-based approaches to examining sleep as a multidimensional construct

Cluster and latent class analysis have previously been used in clinical populations[45–47] but only recently in population-based studies of sleep. Magee and colleagues,[48] for example, applied cluster analysis to characterize sleep quality subtypes in children, rather than looking across multiple sleep characteristics. Similarly, the National Sleep Foundation[49] devised five different sleep 'personalities' based on the 2005 Sleep in America poll. These sleep profiles include "Healthy, Lively Lark" (not affected by sleep problems, almost always get the sleep they need, almost never feel tired or fatigued, consider themselves morning people); "Sleep Savvy Senior" (have long sleep duration, get a good night's sleep on most nights, often take two or more naps during the week, and never/rarely feel tired/fatigued), "Dragging Duos" (are often doing job-related work within an hour of going to bed, are early risers, get short sleep, feel tired/fatigued at least three days each week), "Overworked, Overweight and Over caffeinated" (are evening people, sleep less than other groups but nap more, believe they get as much or more sleep than they need, drink more caffeine than other groups, frequently experience a symptom of insomnia) and "Sleepless and Missin' the Kissin'" (are evening people who think they have a sleep problem or a symptom of insomnia, not likely to get a good night's sleep and have short sleep). Although the profiles developed by the National Sleep Foundation are a step forward, the statistical approach to determine the five 'personalities' remains unclear and they do not exclusively describe time-based characteristics of sleep. To date, these findings do not appear to be published within the scientific literature, as far as we are aware.

Sleep duration as a modifiable component of time use

Just as sleep is complex and multidimensional in nature, with characteristics of sleep not occurring in isolation, sleep does not occur independent of other components of time, but rather is a component of the 24-hour use-of-time profile. If sleep duration shortens, time awake lengthens and must be filled with other activities, in terms of energy expenditure, these activities may be sedentary (e.g. sitting, watching television until late) or physically active (e.g. waking up early to go for a swim). Just as conceptualizing sleep as a multidimensional construct recognizes that all characteristics of sleep may be important for health, so too does conceptualizing sleep as part of the 24-hour day. Indeed, many movement-based time-use behaviors have also been individually associated with health.[2,50,51] Accordingly, it is important to consider sleep as part of the *entire* 24-hour activity profile or "activity composition" of a day when examining the impact of sleep on health.

When considering sleep as part of the entire 24-hour activity profile, components of time may be measured subjectively, using 24-hour time-use recalls, or objectively, via accelerometry. As discussed earlier, accelerometers are increasingly being applied in large, population-based studies to examine time-use. Given that accelerometers are designed to measure movement-based activities, accelerometer-derived 24-hour time-use profiles are appropriate measures of the 'activity composition'. This is an important area of research and the focus of the next sections, however, we acknowledge that there are other ways to divide 24-hour time-use.

While considering sleep as a multidimensional construct and as part of the activity composition may appear distinct ideas, both attempts provide a more holistic approach to conceptualize sleep. Further, it is important to recognize that statistical techniques that examine sleep as part of the activity composition are also able to account for sleep as a multidimensional construct (discussed further in section 3.3).

The following section discusses sleep as a component of the day and factors that influence sleep time (Section 3.1), followed by discussion on why sleep should be considered as part of the 24-hour activity composition, rather than in isolation, when examining the sleep-health link (Section 3.2). Section 3.3 introduces compositional data analysis (CoDA), a statistical technique used to examine sleep in the context of all other time-use components. While we acknowledge that statistical approaches for "multidimensional sleep" and "sleep as part of 24-hour time" are not mutually exclusive, these two approaches are conceptually different and thus consider them separately. We discuss the CoDA technique as it is increasingly being recognized for time-use data analysis.

Sleep as a component of time: Influencing factors

Social, environmental and economic factors, as well as individual behaviors and biology, are known determinants of health, including sleep. Since sleep is a time-based activity, it is sensitive to time constraints that are at least partly mediated by socioeconomic factors. For instance, economists Biddle and Hamermesh[52] found that people traded sleep time for wages, demonstrating the importance of economic factors in determining opportunities for sleep. Sleep duration differs by level of education, occupation, and income.[53–55] Short sleep duration is associated with spending more time doing paid work and working multiple jobs.[56,57] Parenting style (e.g. level of parental control around children's bedtime),[58] the number of children in a household and caring responsibilities have also been associated with sleep duration.[59,60] These structural constraints have raised the question of whether "we [can] truly trade off our daily activities for more sleep".[61]

These studies have shown that there are time-based trade-offs with sleep but, given the relationship between socioeconomics and sleep, people do not have total control over use-of-time decisions.[61] Efforts to improve sleep duration, however, have assumed that more sleep may automatically be achieved through modifying the time-structure of other activities. For example, delaying school start times and allowing flexible work schedules are regularly recommended interventions for increasing habitual sleep duration.[62] Similarly, education and awareness programs to increase public understanding of the importance of sleep have been suggested for reducing discretionary behaviors that impact on sleep time, such as television viewing and small screen use. However, altering the time available for sleep may not be as easily achieved as often suggested. It is also unclear how people would choose to use an extra hour of discretionary time delivered by an intervention: for example, it could be any of more sleep, more activity, or more (unhealthy and therefore undesirable) television time.[61] Hence we need to understand how sleep fits within the 24-hour use of time and how the composition of daily activity influences health.

Sleep as part of the 24-hour time use composition

A person's 24-hour day can be divided into time spent in a number of activity domains. For example, a day could be divided into time spent in sleep, in sedentary behaviour, or in physical activity. At any point in time, a person would generally only engage in one of these activities (they are mutually exclusive) and the entire day can be explained by all of the activities collectively, i.e., there is never a time when a person is not engaging in one of these activities (they are exhaustive). Importantly, each day only ever has a total of 24 hours. This means that if time spent in one activity is increased, there is less time available in the day for the remaining activity

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domains. It follows that the durations of activity domains within a day are completely co-dependent with each other. In fact, when all daily activity domains are considered, statistically they must be perfectly multicollinear. For example, one hour of sleep may be lost to compensate for an extra hour of sedentary behaviour. Alternatively, one hour of sleep may be lost to compensate for an extra hour of physical activity. While in both examples sleep has varied by exactly the same duration, the health implications of the two scenarios are likely to be quite different. It is therefore important to include all time-use domains in the analysis.

Time spent sleeping,[2] being physically active[51,63] and sedentary[50,64] have all been linked to health and well-being. Since the duration of these activities are co-dependent, it does not make sense to consider time in individual activities without reference to all the remaining activities that together constitute the complete 24-hour day. Almost all studies investigating the relationship between sleep duration and health, but have focused only on the sleep component, ignoring the impact of the remaining hours of the day.[63] Conversely, previous work investigating the relationship between physical activity and health has predominantly focused on time within the waking day without considering the impact of sleep. For individuals, this would provide answers on the healthiest way to spend their time whilst, for public health, knowing the trade-offs between the activity components would be invaluable in designing interventions that aid people in achieving a healthy routine and lifestyle.

Until recently, the public health focus has been on the so-called "activity behaviors" individually, with governments and medical bodies producing separate guidelines for recommended amounts of physical activity, screen time, and sleep. However, there is increasing consensus that activity behaviors are codependent, and that optimal health may be associated with *patterns* of behaviors rather than individual behaviors.[65] Recently, Canadian researchers produced 24-hour movement guidelines[66] integrating sleep, sedentary and physical activity guidelines for children. The Australian and New Zealand governments are soon to follow suit.[67]

Compositional data analysis (CoDA)

Reframing the sleep-health link in terms of the 24-hour time-use paradigm ensures every minute of the day is attributed to an activity domain, without omission or overlap. Reframing the sleep-health link in this manner also integrates sleep with physical activity and sedentary behaviour, thus contributing to a greater understanding of the lifestyle-health relationship. The overall health effect of the daily activities will be a function of the overall time allocation across all domains, rather than allocation in one domain only.

Methodologically, the 24-hour time-use paradigm requires that all activity domains be included in the model, without omission. This is problematic because, as previously described, the activity domains are exhaustive and mutually exclusive, and hence perfectly multicollinear, in that the variance in any one of the domains is completely explained by the variance in the remaining domains. Standard statistical models such as multiple linear regressions are impossible when the complete set of activities and their durations are used. To overcome the issue of multicollinearity, one or more activity domains have traditionally been omitted from statistical analysis.[65,68] However, this "leave-some-out" approach is also problematic because the influences of the omitted activity on health remains unknown and results may be misleading.[69] Until recently, this statistical pitfall has undermined study findings.[69]

Time-use data are a special type of data, called compositional data. Compositional data are by nature multivariate because compositions are made up of parts. These parts are mutually exclusive and exhaustive and their sum is constant (in this case, the invariant 24-hour day). As a result, compositional data convey relative information.

Compositional data have been widely studied in other scientific fields (e.g., geochemistry, geology), and a branch of statistics now exists dedicated to their analysis (compositional data analysis, or CoDA). While it was previously not possible to include all parts of a composition in statistical models due to perfect multicollinearity among component parts, CoDA has emerged as a feasible method for the statistical analysis of complete compositions.

To overcome the problem of multicollinearity, CoDA expresses the composition as a set of log ratios. The set of log ratios contains all relative information about every part of the composition (sleep, sedentary time and physical activity). The type of log ratio transformation most commonly used in time use epidemiology is the isometric log ratio transformation. This is because isometric log ratios can be used to represent the composition in any multivariate statistical model. Furthermore, unlike the other types of log ratio transformations (i.e. centered log ratio and additive log ratio transformations), isometric log ratios can be constructed to provide information regarding one compositional part, relative to the remaining parts. This gives an indication of the *relative dominance* of that compositional part in relation to a health outcome. A detailed description the types of log ratio transformations can be found elsewhere.[13,68,70]

Once the composition has been expressed as a set of isometric log ratios, these ratios can be used as variables in traditional statistical models, alongside other covariates of interest, such as sex, age, and sleep characteristics other than duration (i.e. sleep continuity, timing, and variability). For example, the isometric log ratios can be used to represent the compositional parts of the 24-h day as explanatory variables in a multiple linear regression model, and a health outcome measure can be used as the dependent variable. The significance of the composition as an explanatory variable can be determined by an ANOVA test of the linear model by considering the F-statistic and p-value for the set of isometric log ratios.

It is also possible to create an interpretable set of isometric log ratios, where one of the ratios represents all the information regarding one part (such as sleep duration), but it must be considered relative to the compensatory change in all remaining parts.[71] For example, a positive beta and significant p-value for the ratio may represent an increase in the outcome variable when sleep is increased, while all remaining parts are decreased by equal proportions to maintain an overall constant sum of 24 hours. This linear model can be used as a formula to estimate the difference in an outcome associated with isotemporal substitutions between compositional parts, relative to a baseline composition (for example, to estimate the difference in body mass index associated with shifting one hour from sleep to sedentary behaviour [keeping physical activity constant], or for shifting one hour from sleep to physical activity [keeping sedentary behaviour constant]).[72]

Using the log-ratio approach, compositional variables capturing the durations of sleep and 24-h time-use domains are expressed as real variables in Euclidean space and can be used as independent variables in statistical models, together with other multi-dimensional descriptors of sleep. For example, a multiple linear regression model may have as its dependent variable BMI, and as its independent variables: the 24-h time-use composition (time in sleep, sedentary behaviour and physical activity) expressed as log-ratios, with sleep timing, sleep efficiency and sleep variability as covariates. As discussed earlier, there are a number of techniques that could be employed to handle the independent variables, which are likely to be correlated**.** However, these alternate techniques are not designed for data of a relative nature. This means that they are not designed to deal with compositional data, such as time spent in various domains throughout the day. These data are not just multi-collinear,

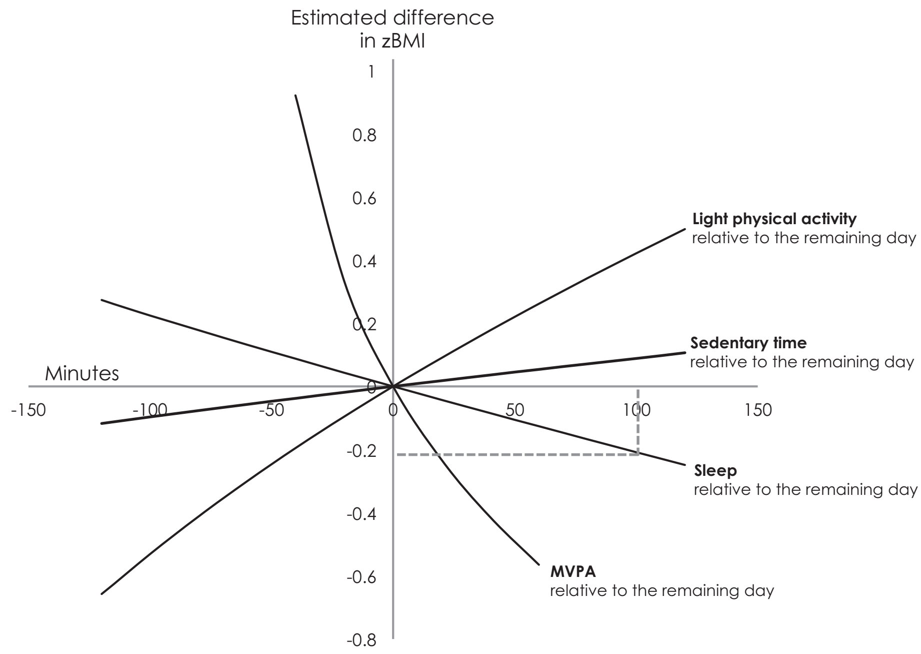


Fig. 2. Expected change in zBMI for reallocation of fixed durations of time from one time-use component to another (adapted from Dumuid[74]).

they exist in a specific geometry. Therefore, even if one or more components are excluded from the statistical model, the remaining included components are nonetheless relative data, and should be treated accordingly. This is not a new concept. In 2001, Shanahan & Flaherty wrote, "time devoted to one domain of activity takes on full meaning only when viewed in terms of its functional relation to time spent in other domains".

The CoDA approach was initially proposed in relation to time use by Aitchison[68] and Zhu and colleagues[73] and later explicated by Pedisic,[69] before being formalized by Chastin and colleagues in 2015.[70] A few studies have applied compositional data analysis to time-use data.[13,72] Such analyses require 24-hour activity measures, either through time use surveys, accelerometry, or even direct observation. Chastin et al[46] found that among 1937 adults of the NHANES 2005–6 cycle, sleep duration, derived from actigraphy non-wear time, was favorably associated with BMI and diastolic blood pressure (relative to all remaining time components). Subsequently, a 2016 compositional data analysis by Carson and colleagues[63] reported a favorable association between sleep duration (relative to remaining components) and obesity risk, systolic blood pressure and behavioral attributes among 4169 children and youth aged 6–17 years.

There are systematic differences in analyses performed using compositional and traditional approaches because CoDA requires compositions to be expressed and analyzed as log-ratios. Findings from CoDA will always be in relation to a reference or a starting composition and the estimated association of reallocating a fixed duration of time from one activity to another will differ depending on the starting composition. In practical terms, when a person who only achieves 4 hours of sleep displaces 1 hour of sleep for sedentary time, the associated change in health will differ to that of a person who starts with 12 hours of sleep and displaces 1 hour for sedentary time. Secondly, the relationship between the amount of time reallocated between compositional parts and the estimated change in the outcome will not be linear, that is, the change in health associated with the reallocation of two hours of sleep to another activity will not be twice that of a one hour reallocation of sleep. Thirdly, CoDA may find that the amount of change in health associated with the reallocation of time is asymmetrical depending on whether time is increased or decreased. For example, the health benefit of allocating an extra hour to sleep may be less than the deficit of losing 1 hour of sleep to another activity.

Treating sleep duration as a relative construct (i.e., % or proportion of the 24-h day) means that an increase in sleep of 60 minutes (e.g., from 6 to 7 hours) is not identical to a decrease of 60 minutes (e.g., from 7 hours to 6 hours), although the absolute difference (60 minutes) is the same in both scenarios. This is because 6 is increased to 7 by applying a factor of 7/6 (i.e., 1.167, in other words it is increased by 16.7%), whereas 7 is decreased to 6 by applying a factor of 6/7 (i.e., 0.86, or 7 is decreased by 14%). This means that associations between health and increase/decrease of sleep may be asymmetrical. Treating sleep duration as a relative construct rather than an absolute construct may impact results. For example, if an individual's sleep duration is only 3 hours/night, a decrease of 1 hour is equivalent to a 33% relative decrease. However, if their sleep duration is 10 hours/night, the same absolute decrease of 1 hour is equivalent to only a 10% relative decrease. The health associations between the two scenarios may be quite different. We draw attention to these asymmetrical associations. For example, Fig. 2 (adapted from Dumuid[74] $n = 440$ Australian children) shows that the reallocation of time from sleep to moderate-to-vigorous physical activity was associated with lower decreases in body mass index compared to the magnitude of increase in body mass index when the same amount of time was reallocated in the opposite direction (from moderate-to-vigorous physical activity to sleep). Specifically, a reallocation of 15 min from sleep to moderate-to-vigorous physical activity was associated with only -0.06 units of body mass index, while the opposite reallocation (15 min from moderate-to-vigorous physical activity to sleep) was associated with $+0.14$ units of body mass index. This asymmetry is not unexpected, and reflects a common pattern in dose–response curves, which are often logarithmic, displaying declining benefits with marginal increases in exposures.

The application of CoDA methodology to time-use data is described in recent statistical contributions.[13,70,74] Dumuid et al.[13] provides an example of the use of CoDA for regression modeling, using data from 5828 children aged 9–11 years. This study explored relationship between body mass index (BMI) z-scores and accelerometer-measured 24-hour time-use composition. The time-use composition consisted of four parts: sleep, sedentary time, light physical

Box 1

Box 1: Example of CoDA

Dumuid et al. (13) considered the time-use composition as four parts: sleep, sedentary time, light physical activity and moderate-to-vigorous physical activity (MVPA). This composition was expressed as a set of three isometric log ratios, where the first ratio contained sleep duration in its numerator, and the remaining parts in its denominator. Thus, the set of isometric log ratios representing the composition was:

$$ilr1 = \sqrt{\frac{3}{4}}\ln\frac{Sleep}{\sqrt[3]{Sedentary \cdot Light\ physical\ activity \cdot MVPA}}$$

$$ilr2 = \sqrt{\frac{2}{3}}\ln\frac{Sedentary}{\sqrt{Light\ physical\ activity \cdot MVPA}}$$

$$ilr3 = \frac{1}{\sqrt{2}}\ln\frac{Light\ physical\ activity}{MVPA}$$

The above ratios were used as explanatory variables in a multiple linear regression model, with zBMI as the dependent variable. The model was also adjusted for a range of sociodemographic covariates. The beta coefficient for the first ratio (*ilr*1) was reported to be -0.82 (Table 1). This means that as sleep increased relative to the remaining parts, *z*BMI was estimated to decrease. The beta coefficient was further interpreted in terms of an absolute effect size, using equations presented in Dumuid et al. (13). However, the above model provided information only about the dominance of sleep, relative to the remaining parts. The model did not provide information about the dominance of any other compositional part. If other parts are also of interest, new regression models have to be executed, using differently constructed isometric log ratios. For example, a set of isometric log ratios capturing the dominance of sedentary time, relative to the remaining parts, can be constructed as:

$$ilr1 = \sqrt{\frac{3}{4}}\ln\frac{Sedentary}{\sqrt[3]{Light\ physical\ activity \cdot MVPA \cdot Sleep}}$$

$$ilr2 = \sqrt{\frac{2}{3}}\ln\frac{Light\ physical\ activity}{\sqrt{MVPA \cdot Sleep}}$$

$$ilr3 = \frac{1}{\sqrt{2}}\ln\frac{MVPA}{Sleep}$$

In Dumuid et al. (13), a second model (Model 2) was run, using the above set of ratios as explanatory variables. The beta coefficient for the first ratio (*ilr*1) from Model 2 was reported to be 0.35 (Table 1), meaning that as sedentary time increased relative to the remaining parts, *z*BMI was estimated to increase.

The process was repeated two more times to obtain beta coefficients for light physical activity (relative to remaining, Model 3), and MVPA (relative to remaining, Model 4). The beta coefficients in Table 1 correspond to ratios, thus they convey relative information. Yet, because the 24-hour day has a meaningful absolute total (24 hours, or 1440 minutes), the ratios can be re-expressed in absolute terms (e.g., minutes). Figure 3, adapted from Dumuid et al. (13), shows that longer sleep duration of 100 minutes (from the population mean of 539 min/day) was associated with –0.2 zBMI. The 100 minutes of extra sleep were drawn pro-rata from the remaining time-use parts.

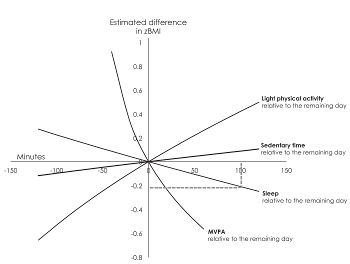
The CoDA regression model can also be used to estimate the difference in an outcome associated with isotemporal substitutions between compositional parts, relative to a baseline composition (for example, to estimate the difference in BMI associated with shifting one hour from sleep to sedentary time [keeping light physical activity and MVPA constant], or for shifting one hour from sleep to MVPA [keeping light physical activity and sedentary time constant])(72).

Table 1: Multiple linear regression analyses of the relationship between the first isometric log ratio and zBMI

	beta (β)	SE	*t*-value	*p-value*
Model 1:*ilr*1: Sleep relative to remaining parts.	-0.82	0.13	-6.22	<0.001
Model 2:*ilr*1: Sedentary time relative to remaining parts.	0.35	0.10	3.30	<0.001
Model 3:*ilr*1: Light physical activity relative to remaining parts.	1.34	0.10	13.19	<0.001
Model 4:*ilr*1: MVPA relative to remaining parts.	-0.87	0.05	-16.11	<0.001

ilr: isometric log ratio, MVPA: moderate-to-vigorous physical activity, SE: standard error. All models adjusted for sex, highest parental education, number of siblings, number of parents and country of residence.

Figure 3 The relationship between time-use parts and zBMI.



BMI: Body mass index, MVPA: moderate-to-vigorous physical activity. Difference in minutes modeled around the population mean composition of: Sleep = 539; sedentary = 525; light physical activity = 320; MVPA = 57 min/day

activity and moderate-to-vigorous physical activity (MVPA). This composition was expressed as a set of three isometric log ratios, where the first ratio expressed sleep duration in relation to the other parts. Using these ratios as explanatory variables in a multiple linear regression model, with zBMI as the dependent variable, it was then possible to determine from the regression coefficient for the first ratio that zBMI decreased as sleep increased *relative* to the remaining parts. The CoDA regression model also allowed estimating the expected difference in BMI associated with relative change in one of the parts. Box 1 draws on the study by Dumuid et al.[13] to provide a more detailed summary of CoDA, as a practical example.

It remains largely unknown how sleep duration, as one component of the 24-hour day, affects aspects of health.[75–77] To date, time-use epidemiological studies using CoDA have to our knowledge mostly been cross-sectional, precluding any indication of causality. However, where longitudinal data are available, the change in composition (expressed as isometric log-ratio coordinates) can be used as the explanatory variable in the multiple linear regression model, with the change in outcome variable as the dependent variable. There is much scope for future development of CoDA within the field of time-use epidemiology. Reframing the sleep-health link in terms of the 24-hour time-use paradigm requires every activity domain to be considered in the analysis, including sleep. CoDA capitalizes on the increasing availability of 24-hour data (especially via accelerometry) and promises to offer new, statistically sound insights into the health impact of sleep. One limitation is that while scoring algorithms exist for accelerometers to distinguish inactivity attributed to sleep from inactivity of other sorts, accelerometers are as yet, unable to distinguish between different types of sedentary behaviors (e.g. reading vs. watching television etc.), which may be of importance. Concurrent use-of-time recalls, as well as the development of accelerometer pattern recognition, may therefore be helpful. Further, it is important to note that CoDA considers all activity types (i.e. sleep, physical activity, and sedentary time) in terms of duration. Just as we acknowledge the importance of considering sleep as a multidimensional construct, it may be just as important to consider the timing and day-to-day variability of physical activity and sedentary time in this way. This may be an important area for future research.

Conclusion

Interventions and public policies to improve population sleep are still in their infancy. There is a clear need to move from a focus on individual sleep characteristics and health outcomes towards an integrated approach to sleep as part of a healthy lifestyle. Sleep should be reconceptualised both as a multidimensional construct and as a modifiable component of a 24-hour day. Such an understanding is important for increasing the effectiveness of public health efforts that aim to modify sleep to improve health outcomes. Applying multivariable statistical techniques, such as compositional data analysis, may provide novel insights into the role of sleep, its interactions with other lifestyle risk factors, and ultimately, its contributions to public health and wellbeing.

Conflict of interest

There are no conflict of interests to declare.

References

1. Astill RG, Van der Heijden KB, Van Ijzendoorn MH, Van Someren EJW. Sleep, cognition, and behavioral problems in school-age children: a century of research meta-analyzed. *Psychol Bull*. 2012;138(6):1109–1138.
2. Chaput JP, Gray CE, Poitras VJ, Carson V, Gruber R, Olds T, et al. Systematic review of the relationships between sleep duration and health indicators in school-aged children and youth. *Appl Physiol Nutr Metab*. 2016;41(6):S266–S282.
3. Matthews K, Pantesco E. Sleep characteristics and cardiovascular risk in children and adolescents: an enumerative review. *Sleep Med*. 2016;18(1):36–49.
4. Cappuccio FP, D'Elia L, Strazzullo P, Miller MA. Quantity and quality of sleep and incidence of type 2 diabetes: a systematic review and meta-analysis. *Diabetes Care*. 2010;33(2):414–420.
5. Cappuccio FP, Cooper D, D'Elia L, Strazzullo P, Miller MA. Sleep duration predicts cardiovascular outcomes: a systematic review and meta-analysis of prospective studies. *Eur Heart J*. 2011;32(12):1484–1492.
6. Li W, Wang D, Cao S, Yin X, Gong Y, Gan Y, et al. Sleep duration and risk of stroke events and stroke mortality: a systematic review and meta-analysis of prospective cohort studies. *Int J Cardiol*. 2016;223:870–876.
7. Cappuccio F, Taggart F, Kandala N, Currie A, Piele E, Stranges S, et al. Meta-analysis of short sleep duration and obesity in children and adults. *Sleep*. 2008;31(5):619–926.
8. Heffron T. Sleep Well, Be Well: A national health priority. Available from: http://sleepeducation.org/news/2014/05/16/sleep-well-be-well-a-national-health-priority; 2014.
9. Perry G, Patil S, Presley-Cantrell L. Raising awareness of sleep as a healthy behavior. *Prev Chronic Dis*. 2013;10.
10. Knutson K, Phelan J, Paskow M, Roach A, Whiton K, Langer G, et al. The National Sleep Foundation's sleep health index. *Sleep Health*. 2014;3:234–240.
11. Matricciani L, Olds T, Blunden S, Rigney G, Williams M. Never enough sleep: a brief history of sleep recommendations for children. *Pediatrics*. 2012;129(3):548–556.
12. Buysse D. Sleep health: can we define it? Does it matter? *Sleep*. 2014;37(1):9–17.
13. Dumuid D, Stanford T, Martin-Fernández J, Pedišić Ž, Maher C, Lewis L, et al. Compositional data analysis for physical activity, sedentary time and sleep research. *Stat Methods Med Res*. 2017:1–13.
14. Hart C, Cairns A, Jelalian E. Sleep and obesity in children and adolescents. *Pediatr Clin North Am*. 2011;58(3):715–733.
15. Brotman D, Walker E, Lauer M, O'Brien R. In search of fewer independent risk factors. *Arch Intern Med*. 2005;165(2):138–145.
16. Chaput J, Saunders T, Carson V. Interactions between sleep, movement and other non-movement behaviours in the pathogenesis of childhood obesity. *Obes Rev*. 2017;18(1):7–14.
17. Lee I, Sesso H, Oguma Y, Paffenbarger R. The "weekend warrior" and risk of mortality. *Am J Epidemiol*. 2004;160(7):636–641.
18. Roberts D, Ouellet J, McBeth P, Kirkpatrick A, Dixon E, Ball C. The "weekend warrior": fact or fiction for major trauma? *Can J Surg*. 2014;57(3):E62.
19. Healy G, Dunstan D, Salmon J, Cerin E, Shaw J, Zimmet P, et al. Breaks in sedentary time. *Diabetes Care*. 2008;31(4):661–666.
20. Pelayo R. Commentary on National Sleep Foundation sleep quality recommendations. *Sleep Health*. 2017;3(1):20–21.
21. Lauderdale D, Philip Schumm L, Kurina L, McClintock M, Thisted R, Chen J, et al. Assessment of sleep in the national social life, health, and aging project. *J Gerontol B*. 2014;69(S2):S125–S133.
22. Ohayon M, Wickwire E, Hirshkowitz M, Albert S, Avidan A, Daly F, et al. National Sleep Foundation's sleep quality recommendations: first report. *Sleep Health*. 2017;3(1):6–19.
23. von Eye A, Bogat G, Rhodes J. Variable-oriented and person-oriented perspectives of analysis: the example of alcohol consumption in adolescence. *J Adolesc*. 2006;29:981–1004.
24. Pyburn E. Persons can Speak Louder than Variables: Person-Centered Analyses and the Prediction of Student Success: James Madison University; 2015.
25. Laursen B, Hoff E. Person-centered and variable-centered approaches to longitudinal data. *Merrill Palmer Q*. 2006;52(3):377–389.
26. Bauer D, Shanahan M. Modeling complex interactions: person-centered and variable-centered approaches. In: Little T, Bovaird J, Card N, editors. Modeling ecological and contextual effects in longitudinal studies of human development; 2007.
27. Haenlein M, Kaplan A. A beginner's guide to partial least squares analysis. *Underst Stat*. 2004;3(4):283–297.
28. Pirouz D. An overview of partial least squares. *SSRN Electron J*. 2006 (https://poseidon01.ssrn.com/delivery.php?ID=810001098099073023004090118083126014105075065059020026109103101004092029110092013123022050008059054001039118004127006081001114110027068000046090121006064007086093037022075024092001023087070083031065095117075001031092002112084126067098104079118089068&EXT=pdf).
29. Wallace M, Stone K, Smagula S, Hall M, Simsek B, Kado D, et al. Which sleep health characteristics predict all-cause mortality in older men? An application of flexible multivariable approaches. *Sleep*. 2017;41:1–12.
30. Tibshirani R. Regression shrinkage and selection via the lasso. *J R Stat Soc*. 1996;58(1):267–288.
31. Zou H, Hastie T. Regularization and variable selection via the elastic net. *J R Stat Soc*. 2005;67(2):301–320.
32. Tan P, Steinbach M, Kumar V. Introduction to Data Mining. Essex: Pearson; 2014.
33. Collins L, Lanza S, editors. Latent class and latent transition analysis. With applications in the social, behavioral, and Health Sciences; 2010.
34. Aggarwal C, Reddy C. Data Clustering : Algorithms and Applications. Boca Raton: CRC Press; 2013.
35. Wallace M, Buysse D, Germain A, Hall M, Lyengar S. Variable selection for skewed model-based clustering: application to the identification of novel sleep phenotypes. *J Am Stat Assoc*. 2017;113:95–110.
36. Paavonen E, Räikkönen K, Pesonen A, Lahti J, Komsi N, Heinonen K, et al. Sleep quality and cognitive performance in 8-year-old children. *Sleep Med*. 2010;11(4):386–392.
37. Lemola S, Räikkönen K, Scheier M, Matthews K, Pesonen A, Heinonen K, et al. Sleep quantity, quality and optimism in children. *J Sleep Res*. 2011;20(1):12–20.
38. Tonetti L, Fabbri M, Filardi M, Martoni M, Natale V. Effects of sleep timing, sleep quality and sleep duration on school achievement in adolescents. *Sleep Med*. 2015;16(1):936–940.
39. Kjeldsen J, Hjorth M, Andersen R, Michaelsen K, Tetens I, Astrup A, et al. Short sleep duration and large variability in sleep duration are independently associated with dietary risk factors for obesity in Danish school children. *Int J Obes (Lond)*. 2014;38(1):32.
40. Kobayashi D, Takahashi O, Shimbo T, Okubo T, Arioka H, Fukui T. High sleep duration variability is an independent risk factor for weight gain. *Sleep Breath*. 2013;17(1):167–172.

41. Lemola S, Ledermann T, Friedman E. Variability of sleep duration is related to subjective sleep quality and subjective well-being: an actigraphy study. *PLoS One*. 2013;8(8):e71292.
42. Wang J, Adab P, Liu W, Chen Y, Li B, Lin R, et al. Prevalence of adiposity and its association with sleep duration, quality, and timing among 9-12-year-old children in Guangzhou, China. *J Epidemiol*. 2017;27:531–537.
43. Olds T, Maher C, Matricciani L. Sleep duration or bedtime? Exploring the relationship between sleep habits and weight status and activity patterns. *Sleep*. 2011;34(10):1299–1307.
44. Furihata R, Hall M, Stone K, Ancoli-Israel S, Smagula S, Cauley J, et al. An aggregate measure of sleep health is associated with prevalent and incident clinically significant depression symptoms among community-dwelling older women. *Sleep*. 2016;40(3).
45. Tsuchiya M, Lowe A, Pae E, Fleetham J. Obstructive sleep apnea subtypes by cluster analysis. *Am J Orthod Dentofacial Orthop*. 1992;101(6):533–542.
46. Ye L, Pien G, Ratcliffe S, Björnsdottir E, Arnardottir E, Pack A, et al. The different clinical faces of obstructive sleep apnoea: a cluster analysis. *Eur Respir J*. 2014;44(6):1600–1607.
47. Miller C, Bartlett D, Mullins A, Dodds K, Gordon C, Kyle S, et al. Clusters of insomnia disorder: an exploratory cluster analysis of objective sleep parameters reveals differences in neurocognitive functioning, quantitative EEG, and heart rate variability. *Sleep*. 2016;39(11):1993–2004.
48. Magee C, Robinson L, Keane C. Sleep quality subtypes predict health-related quality of life in children. *Sleep Med*. 2017;35(1):67–73.
49. The National Sleep Foundation. Five Clusters of Sleep Patterns. Available from: https://sleepfoundation.org/sleep-news/five-clusters-sleep-patterns; 2017.
50. Tremblay M, LeBlanc A, Kho M, Saunders T, Larouche R, Colley R, et al. Systematic review of sedentary behaviour and health indicators in school-aged children and youth. *Int J Behav Nutr Phys Act*. 2011;8(1):98–120.
51. Janssen I, LeBlanc A. Systematic review of the health benefits of physical activity and fitness in school-aged children and youth. *Int J Behav Nutr Phys Act*. 2010;7(40):1–16.
52. Biddle J, Hamermesh D. Sleep and the allocation of time. *J Pol Econ*. 1990;98(5):922–943.
53. Grandner M, Patel N, Gehrman P, Xie D, Sha D, Weaver T, et al. Who gets the best sleep? Ethnic and socioeconomic factors related to sleep complaints. *Sleep Med*. 2010;11(5):470–478.
54. Patel N, Grandner M, Xie D, Branas C, Gooneratne N. "Sleep disparity" in the population: poor sleep quality is strongly associated with poverty and ethnicity. *BMC Public Health*. 2010;10(1):475.
55. Hysing M, Petrie KJ, Bøe T, Lallukka T, Sivertsen B. The social gradient of sleep in adolescence: results from the youth@ Hordaland survey. *Eur J Public Health*. 2016;27:65–71.
56. Bin Y, Marshall N, Glozier N. Secular changes in sleep duration among Australian adults, 1992-2006. *Med J Aust*. 2011;195(11–12):670–672.
57. Lallukka T, Rahkonen O, Lahelma E, Arber S. Sleep complaints in middle-aged women and men: the contribution of working conditions and work-family conflicts. *J Sleep Res*. 2010;19(3):466–477.
58. Brand S, Hatzinger M, Beck J, Holsboer-Trachsler E. Perceived parenting styles, personality traits and sleep patterns in adolescents. *J Adolesc*. 2009;35(5):1189–1207.
59. Burgard S, Ailshire J. Gender and time for sleep among U.S. adults. *Am Sociol Rev*. 2013;78(1):51–69.
60. van Tienoven T, Glorieux I, Minnen J. The impact of work and family responsibilities on healthy sleep habits. *Time Soc*. 2014;23(2):235–257.
61. Hale L. Inadequate sleep duration as a public health and social justice problem: can we truly trade off our daily activities for more sleep? *Sleep*. 2014;37(12):1879.
62. Morgenthaler T, Croft J, Dort L, Loeding L, Mullington J, Thomas S. Development of the National Healthy Sleep Awareness Project Sleep Health Surveillance Questions. *J Clin Sleep Med*. 2015;11(9):1057–1062.
63. Poitras VJ, Gray CE, Borghese MM, Carson V, Chaput J-P, Janssen I, et al. Systematic review of the relationships between objectively measured physical activity and health indicators in school-aged children and youth 1. *Appl Physiol Nutr Metab*. 2016;41(6):S197–S239.
64. Carson V, Hunter S, Kuzik N, Gray CE, Poitras VJ, Chaput J-P, et al. Systematic review of sedentary behaviour and health indicators in school-aged children and youth: an update 1. Applied physiology. *Nutr Metab*. 2016;41(6):S240–S265.
65. Saunders T, Gray C, Poitras V, Chaput J, Janssen I, Katzmarzyk P, et al. Combinations of physical activity, sedentary behaviour and sleep: relationships with health indicators in school-aged children and youth. *Appl Physiol Nutr Metab*. 2015;41:283–293.
66. Physiology CSfE. Build Your Best Day. Available from: http://buildyourbestday.participaction.com/en-ca/tutorial; 2017.
67. Ministry of Health. Physical activity. Available from: http://www.health.govt.nz/our-work/preventative-health-wellness/physical-activity; 2017.
68. Aitchison J. The statistical analysis of compositional data. *J R Stat Soc B Methodol*. 1982:139–177.
69. Pedišić Ž. Measurement issues and poor adjustments for physical activity and sleep undermine sedentary behaviour research—the focus should shift to the balance between sleep, sedentary behaviour, standing and activity. *Kinesiology*. 2014;46:135–146.
70. Chastin S, Palarea-Albaladejo J, Dontje M, Skelton D. Combined effects of time spent in physical activity, sedentary behaviors and sleep on obesity and cardio-metabolic health markers: a novel compositional data analysis approach. *PLoS One*. 2015;10(10):e0139984.
71. Hron K, Filzmoser P, Thompson K. Linear regression with compositional explanatory variables. *J Appl Stat*. 2012;39(5):1115–1128.
72. Fairclough S, Dumuid D, Taylor S, Curry W, McGrane B, Stratton G, et al. Fitness, fatness and the reallocation of time between children's daily movement behaviours: an analysis of compositional data. *Int J Behav Nutr Phys Act*. 2017;14(1):64.
73. Zhu W, Ainsworth B, Liu Y. A Comparison of Urban Black and White Women's Physical Activity Patterns. San Diego, California, USA: Annual Convention of the American Alliance for Health, Physical Education, Recreation and Dance; 2002.
74. Dumuid D, Pedišić Z, Stanford T, Martín-Fernández J, Hron K, Maher C, et al. The compositional isotemporal substitution model: a method for estimating changes in a health outcome for reallocation of time between sleep, sedentary behaviour and physical activity. *Stat Methods Med Res*. 2017:1–12.
75. Dumuid D, Olds T, Lewis L, Martin-Fernández J, Barreira T, Broyles S, et al. The adiposity of children is associated with their lifestyle behaviours: a cluster analysis of school-aged children from 12 nations. *Pediatr Obes*. 2016;13:111–119.
76. Dumuid D, Olds T, Lewis L, Martin-Fernández J, Katzmarzyk P, Barreira T, et al. Health-related quality of life and lifestyle behavior clusters in school-aged children from 12 countries. *J Pediatr*. 2017;183:178–183.
77. Dumuid D, Olds T, Martín-Fernández J, Lewis L, Cassidy L, Maher C. Academic performance and lifestyle behaviors in australian school children: a cluster analysis. *Health Educ Behav*. 2017;44:918–927.

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