



Published in final edited form as:

J Occup Health Psychol. 2024 December ; 29(6): 409–430. doi:10.1037/ocp0000386.

Designing work for healthy sleep: A multidimensional, latent transition approach to employee sleep health

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Abstract

Healthy sleep is essential to employee well-being and productivity, but many modern workers do not obtain adequate sleep. Are technology-related changes to job design (i.e., computer use, sedentary work, non-traditional work schedules) related to long-term worsening of employee sleep health? The present study seeks to address this question using nationally representative data from the Midlife in the United States study (MIDUS), which includes detailed information on sleep duration, regularity, sleep onset latency, insomnia symptoms, napping, and daytime tiredness from full-time workers ($N=1,297$) at two time points separated by approximately 10 years. Using latent transition analysis to consider how these sleep health dimensions co-occur, we identify three multidimensional sleep health phenotypes at both time points: good sleepers, catch-up sleepers, and insomnia sleepers. Sedentary work is linked to the insomnia sleeper phenotype. Nontraditional work schedules are linked to the catch-up sleeper phenotype. These findings test assumptions of modern models of job design regarding the impact of technology on employee sleep health and advance measurement of sleep health in the organizational sciences to be multidimensional, within-persons, and dynamic. Further, results point to specific sleep needs in the working adult population and identify potential points of intervention via job design.

Keywords

job design; sleep; computer; sedentary work; nontraditional schedule

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Conflicts of interests/competing interests: We have no further conflicts of interest to report beyond project funding and the use of archival data.

Technological advancements have indelibly changed how jobs are designed (Cascio & Montealegre, 2014), spanning changes to task-related, physical, and temporal aspects of work (Kompier, 2006). First and most directly, technology is now more extensively integrated into daily work *tasks*. Whereas fewer than half of jobs required medium- to high-level digital skills in 2002, over two thirds did by 2016 (Muro et al., 2017). Even twenty years ago, most employees used computers as part of their daily work (Andries et al., 2002; BLS, 2003). Additionally, the shift to technology-dependent work has also contributed to different *physical* job design, namely an increase in sedentary work from 50% of jobs characterized as highly sedentary in the 1960s to over 80% more recently (Church et al., 2011). Finally, technology has changed *temporal* job design, or when work can be done, by facilitating global collaborations, self-regulated work, gig- based work, and flextime arrangements (Sparks et al., 2001). These changes contribute to a 24- hour economy wherein people can and, often, are expected to work at nonstandard times (Costa, 2001). Now around 16% of employed adults formally work nonstandard schedules (i.e., beyond a weekday, day-time schedule), and another 57% can flexibly work at nonstandard times (BLS, 2019). These elements of modern job design may have implications not only for work but for worker health (Kompier, 2006), particularly sleep health. Average sleep health seems to be worse today than in the past, and changes in the workplace, especially those related to technology, have been implicated as likely contributors (Khubchandani & Price, 2020).

The Balance Theory of Job Design suggests that (1) negative physical and psychological elements of job design threaten health and, thus, should be eliminated, and (2) balancing identified negative elements with relevant positive elements within the work system can compensate to sustain health (Carayon, 2009). Technology causes changes to the work system that may manifest as positive or negative job design elements that shape employees' attitudinal, behavioral, and health responses (Carayon, 2009; Smith & Carayon, 1989). We do not provide a complete test of Balance Theory but, instead, an application of its first tenet to identify the negative technology-related job design elements related to particular sleep issues among employees. Within Balance Theory, the most direct means of protecting employee health is by eliminating negative elements of the work system, the first step of which requires identifying those elements. Yet applied psychology research on employee sleep health tends focus on psychosocial job characteristics (e.g., job demands and resources; see Litwiller et al., 2017) as antecedents; this approach aligns with the most popular job design models that favor intrinsic elements (Hackman, 1980; Herzberg, 1974) at the costly expense of understanding the consequences of large-scale changes to extrinsic job design, such as those described by Balance Theory (Carayon, 2009). Unfortunately, job design research also tends to overlook sleep as a relevant employee health outcome despite passing recognition of its importance by theorists (Smith & Carayon, 1989). Even Balance Theory, which was purposefully developed to explain stress and health, rather than job satisfaction or performance, has not been applied to sleep research despite its explicit consideration of relevant categories of job design (e.g., technology). As a result, there is a surprising gap in understanding of how changes to potentially relevant extrinsic job design elements, including task (computer use), physical (sedentary time), and temporal (nonstandard schedule) job design, are linked to employee sleep health.

Motivated by Balance Theory and widespread assumptions about technology-related changes to work disrupting sleep, the present study therefore aims to test whether modern work is designed in ways that are harmful to employee sleep health and, conversely, whether certain job design elements could be targeted to improve employee sleep health. Good sleep is not only increasingly recognized as a key component of employee health due to its connection to physical and mental well-being (e.g., Buxton & Marcelli, 2010; Dai et al., 2020) but also as a “strategic resource” (p. 19; Barnes & Spreitzer, 2015) for organizations given its benefits to task performance (Henderson et al., 2021), workplace safety (Uehli et al., 2014), and reduced healthcare costs (Daley et al., 2009; Garbarino et al., 2016). Despite the importance of sleep health, organizational scientists often fall short of state-of-the-art measurement in three ways. First, scholars in these fields typically measure amount of sleep (quantity) or satisfaction with sleep (quality; see Crain et al., 2018), rather than the full spectrum of sleep health dimensions (e.g., quantity, quality, regularity, time to fall asleep, napping, daytime tiredness) identified in the sleep literature (Buysse, 2014). Second, even when multiple sleep health dimensions are measured, they are typically modeled as independent (i.e., as individual variables or as “composites” that sum total number of sleep problems) rather than as interdependent (Chung et al., 2021), despite indications that the dimensions are interrelated and better modeled together as a co-occurring pattern, called a profile or phenotype (Matricciani et al., 2018). One recent exception is Smith et al. (2023), who used a profile approach to identify three distinct sleep health phenotypes in a cross-sectional sample, providing an initial description of multidimensional sleep health in working adults.

Despite the promise of these initial findings, a third limitation of existing sleep research in the organizational sciences, including Smith et al. (2023), is that very little is known about how and why working adults’ sleep health changes over time, despite its inherently dynamic nature. Like many phenomena in the occupational health psychology (Langley et al., 2013; Spector & Pindek, 2016) and work-life literatures (Allen et al., 2019), sleep is indeed dynamic and its connection with work also unfolds over time. Past research using micro-longitudinal or diary-style designs (i.e., timeframes <1 month) shows that dimensions of sleep health vary from day to day but also exhibit substantial between-person variance (e.g., Eichberger et al., 2022; Hulsheger et al., 2014; ; van Erde & Venus, 2018). In contrast with these short-term fluctuations, recent evidence suggests that employees’ sleep quality (e.g., subjective insomnia symptoms) is largely stable over the meso-term (i.e., four months) and adapts back to a typical, baseline level fairly quickly (i.e., within two months) after any fluctuations (Henderson et al., 2023). Combined, the current literature suggests that although employee sleep experiences may fluctuate within a given week or month as a primary response to daily happenings at work (Ganster & Rosen, 2013), employees exhibit a stable pattern of sleep health over the course of several months, corresponding with the concept of a dynamic equilibrium or consistent baseline level of well-being over the lifetime unless a major disruption occurs (Headey & Wearing, 1989).

Yet updated perspectives on the development of well-being over time posit that the stability seen within meso-term timeframes (Headey & Wearing, 1989) may not be universal when long-term timeframes are employed. Some people (15–30%) exhibit meaningful shifts in well-being outcomes measured over one or more decades (Headey, 2006; Headey, 2010;

Headey et al., 2014; Luhmann et al., 2018). Like these other aspects of well-being, employee sleep health may also be susceptible to an occasional shift over long-term time periods despite its overall stability. Static comparisons of individual sleep health facets across different age groups suggest that, on average, people differ in their sleep health at various points in their lifespan (Jonasdottir et al., 2021; Ohayon et al., 2004), indicating that change in sleep health may be possible in the long-term. Further, a systematic review of longitudinal research on occupational well-being found that any substantial shifts in other well-being indicators (i.e., burnout, engagement, job satisfaction) over time appear to be driven by external factors, such as major job changes (Mäkikangas et al., 2016). Long-term timeframes may therefore also be required to assess changes in drivers of sleep health (i.e., job design here), as many workplace experiences appear largely stable over the course of several months and up to three years (Henderson et al., 2023; Smith et al., 2022). We examine to what extent and why employees' sleep health may shift (or not) over one decade, a prototypical long-term timeframe (Dormann & van de Ven, 2014) that goes beyond those typically used in occupational health research (Mäkikangas et al., 2016) and is theoretically long enough for meaningful shifts (see Headey, 2006; Luhmann et al., 2018).

In total, important information is missing about (1) the extent to which working adults' multidimensional sleep health phenotypes change or stabilize over time, and (2) whether and the degree to which technology-related aspects of modern job design play a role in changes to employees' multidimensional sleep health. Integrating sleep and job design research, we test change in computer use, sitting at work, and a nonstandard work schedule as potential predictors of employees' transitions in their multidimensional sleep health phenotypes across approximately one decade.

This research makes several notable contributions to theory and the research literature. Most directly, we address the three existing shortcomings in measurement and definition of sleep health in the organizational sciences (i.e., multidimensionality, co-occurrence of dimensions, and, novel to the present study, dynamicism over the long-term). Multidimensionality (Buysse, 2014) and co-occurrence (Chung et al., 2021; Matricciani et al., 2018; Wallace et al., 2022) are currently considered part of a gold standard of measurement in the sleep literature but are largely overlooked in the *employee* sleep literature (see Smith et al., 2023 for a recent exception). Yet even the sleep literature overlooks dynamicism, or how patterns of sleep health may change or stabilize over time (see Henderson et al., 2023 for a recent exception). We therefore not only advance sleep health measurement in the organizational sciences and thus provide new information about working adults' sleep health, but we also advance theoretical models in the sleep literature (i.e., the Ru-SATED model; Buysse, 2014) to consider time along with multidimensionality and co-occurrence. In other research areas, organizational scientists are having complex discussions about the important but neglected role of time in theory and research (Allen et al., 2019; Cronin & Vancouver, 2019; Smith et al., 2022), especially for occupational health topics (Spector & Pindek, 2016). By examining sleep health phenotypes across a decade-long span, we are able to contribute to this discussion by answering questions about how stable sleep health is over the long term.

We also make contributions to job design research, as well as to practice. The job design literature is founded in relatively conservative definitions focused on the core and formally

assigned aspects of work, including autonomy, feedback, and task variety, identity, and significance (Hackman & Oldham, 1980). Despite changes in both real-world job design and corresponding expansions of academic definitions of job design that better capture technology-related elements (Cascio & Montealegre, 2016; Grant et al., 2010; Parker, 2014), aligned with Balance Theory, empirical work that directly examines technology-related aspects of job design and their consequences are still surprisingly rare (Oldham & Fried, 2016). This gap is especially noticeable when it comes to technology *during work*. For instance, in the sleep literature, most research connects after-work technology use to poor sleep health (e.g., Arlinghaus & Nachreiner, 2014; Barber & Jenkins, 2014; Derks & Bakker, 2014; Lanaj et al., 2014; Park et al., 2019; Santuzzi & Barber, 2018). In general, organizational scientists call for more research delving into the impact of technological changes at work on outcomes outside of the workplace (Allen & French, 2023). We apply modern definitions of job design to empirically examine widespread but untested assumptions that technology-related changes to work itself may impair sleep health. We also test whether a primary tenet of Balance Theory can be extended to sleep as an important but neglected employee outcome in job design research and theory. Practically, our results will identify specific aspects of modern job design that can be targeted to protect employees' holistic sleep health. Further, these findings can help highlight commonly co-occurring sleep issues among working adults, which may facilitate more comprehensive and personalized intervention to specific sleep needs. Our goals align with those of the National Occupational Research Agenda (NORA), which point to employee sleep deficiency as a major area of concern and healthy job design as a promising target for improvement (NORA, 2022).

Sleep health as a multidimensional construct

Occupational health researchers recognize the importance of employees' sleep quantity and quality in protecting employee well-being and productivity at work (Crain et al., 2014; Henderson & Horan, 2021). Yet, as mentioned, sleep experts urge that sleep health consists of additional dimensions. Buysse (2014) developed the foundational SATED and, later, Ru-SATED models specifying five to six key sleep health dimensions. All Ru-SATED dimensions have been repeatedly validated as important to sleep health and overall health and well-being (Barham et al., 2021; Furihata et al., 2022; Hawkins et al., 2023; Ravyts et al., 2021).

First, **RegU**larity is defined as consistency in timing and/or duration of sleep, which we operationalize as the absolute difference in sleep duration on workdays versus non-workdays to characterize regularity of sleep duration throughout a week (Buysse, 2014). Second, **S**atisfaction describes subjective evaluations of sleep, including sleep quality or, as we operationalize it here, lack of subjective sleep issues such as insomnia symptoms (see Knutson et al., 2017). Third, **A**lertness describes low tiredness during waking hours and/or lack of napping (Buysse, 2014). We assess two subdimensions of alertness in the present study, both daytime tiredness and napping, because of the importance of daytime function for working populations (Budnick & Barber, 2015) and the need for additional research on napping as a distinctive and complicated sleep experience (Faraut et al., 2017; Milner & Cote, 2009). Forth, **T**iming is characterized by appropriate sleep onset and offset times;

it is the only dimension not captured in the present study due to lack of data availability. Fifth, **E**fficiency can either be captured by difficulty of initiating or falling back to sleep after waking up during a rest period. We operationalize it as the time to sleep onset, also called *sleep onset latency*, per Buysse (2014). Finally, **D**uration or sleep quantity is defined as total sleep time, which we operationalize as a weighted average of duration on workdays and non-workdays. Buysse (2014) and subsequent research inspired by the Ru-SATED framework has clarified what categorically healthy standing (e.g., sleep duration of 7–9 hours) versus unhealthy standing (<7 hours or >9 hours) looks like, empirically, to help define healthy sleep across these key dimensions (see Table 1).

Early adopters of this multidimensional sleep health framework developed sleep health composites (e.g., Chen et al., 2022; DeSantis et al., 2019; Dong et al., 2019; Kubala et al., 2020; Lee & Lawson, 2021), or scores that sum the number of sleep problems (or healthy sleep characteristics) across the Ru-SATED dimensions. Composites can provide a simple, holistic description of a person's sleep health (i.e., how many sleep health problems) with predictive power above and beyond individual dimensions (e.g., Lee et al., 2022). Yet, sleep experts increasingly agree that a person's sleep health can best be depicted as their specific pattern or configuration of multiple sleep health dimensions (Buysse, 2014; Matricciani et al., 2018), or also called a *sleep health phenotype*. In this way, a phenotype not only describes *how many* sleep issues co-occur but also *which* do (Smith & Lee, 2022). As Chung and colleagues (2021) elegantly summarize, sleep health dimensions are “commonly biologically or statistically dependent” (p. 1), meaning modeling them as independent rather than as interdependent and co-occurring “may lead to erroneous or partial conclusions about sleep” (p. 4). For instance, sleep duration relates to subsequent nap frequency (Owens et al., 2010), greater nap frequency is related to lower daytime alertness (McDevitt et al., 2012), more daytime alertness is likely for those without insomnia symptoms (Buysse et al., 2007). Based on the Ru-SATED framework, an optimally healthy phenotype is indicated by sleep health that meets recommended criteria for healthy sleep across all dimensions. A suboptimal sleep phenotype, however, may manifest in a variety of ways, ranging from one suboptimal sleep health dimension to entirely suboptimal sleep across all dimensions within a phenotype.

Identifying multidimensional sleep health phenotypes among working adults

Examination of sleep health phenotypes can characterize people's specific patterns of optimal and suboptimal sleep dimensions (Matricciani et al., 2018). Thus far, research using clustering analyses (e.g., latent class/profile analyses) has extracted multidimensional sleep health phenotypes among children (Lee et al., 2019; Magee & Blunden, 2020; Matricciani et al., 2020) and specific adult populations (e.g., older adults in residential communities, Wallace et al., 2019; parents of adolescents, Matricciani et al., 2021; college students, Zhou et al., 2019). A limited number of studies have begun to examine sleep health phenotypes that manifest among general (Smith & Lee, 2022) and working adults (Magee et al., 2016;; Smith et al., 2023). Yet working adults are a high-risk group in terms of sleep health. More time spent working not only directly restricts the time available for sleep (Krueger

& Friedman, 2009) but also associates with chronic sleep deprivation and sleep disorder symptoms (Swanson et al., 2011). Focused attention is required to determine the nature, causes, and consequences of multidimensional sleep health in working adults, a group that is vulnerable to and unique in their sleep issues.

Previous research has identified four common sleep health phenotypes in a general adult sample (i.e., not solely restricted to workers), using Buysse's (2014) Ru-SATED framework. One optimal phenotype was extracted, *good sleepers* who exhibited healthy sleep across five dimensions (i.e., regularity, satisfaction, alertness, efficiency, and duration). Three suboptimal phenotypes were extracted, *short, dissatisfied, and inefficient sleepers* (i.e., suboptimal sleep across three key dimensions), *nappers* (i.e., optimal nighttime sleep but frequent naps during waking periods) and *sufficient but irregular sleepers* (i.e., short weekday sleep duration but optimal weekend sleep duration and otherwise healthy sleep). We have previously validated sleep health phenotypes as indicators of poor health, such that suboptimal sleep health phenotypes were linked with poorer psychological well-being and higher number of chronic conditions relative to the optimal phenotype (Smith & Lee, 2022). In another of our studies, we examined static sleep health phenotypes in a working adult sample using the Midlife in the United States dataset (i.e., MIDUS II), finding three phenotypes similar to those previously identified: *good sleepers*, irregular *catch-up sleepers*, and the most suboptimal *short, dissatisfied, inefficient, and irregular sleepers*, who reported the lowest perceived physical health (Smith et al., 2023).

In the present study, we build upon and expand these preliminary efforts by examining whether the sleep health phenotypes identified at baseline (MIDUS II) in Smith et al. (2023) are consistently identified over time (MIDUS II and MIDUS III one decade later). Specifically, we use six sleep health indicators: (1) regularity, (2) daytime tiredness, (3) daytime nap frequency, (4) sleep onset latency or time to fall asleep, (5) duration, and (6) insomnia symptoms that are measured consistently across two timepoints over a period of ten years. Table 1 shows how these indicators map onto Buysse's (2014) Ru-SATED framework. This approach offers several advantages. First, we can assess whether common sleep health phenotypes can be extracted in U.S. working adults as they age and progress in their careers by approximately ten years. Second and in line with our goal to detail the dynamics of sleep over the long-term, we can examine extent of stability versus change in workers multidimensional sleep health phenotypes over the course of a decade. Namely, we can assess prevalence of *stayers* (i.e., those who remain in the same sleep phenotype over time) versus *movers* (i.e., those who transition to different sleep phenotypes over time). Based on the long-term dynamic nature of other well-being constructs (Headey, 2006; Headey, 2010; Headey et al., 2014; Luhmann et al., 2018) and the demonstrated stability of sleep quality in the meso-term (Henderson et al., 2023) as previously discussed, we expect most people to be stayers but a significant minority (<30%) to be movers. Third, and as will be elaborated upon in future hypotheses, we can examine how these transitions in sleep health are explained by changes in work predictors (job design) over time. Overall, we expect an optimally healthy phenotype (analogous to *good sleepers* from Smith et al., 2023) and several suboptimal sleep health phenotypes (e.g., *irregular* or *catch-up sleepers*, *nappers*, and/or *short, dissatisfied, and inefficient sleepers*) to emerge.

Research Question 1:

Do consistent and distinct sleep health phenotypes emerge among working adults over approximately ten years and, if so, what is the number and nature of those phenotypes?

Research Question 2:

What is the prevalence of “stayers” (i.e., those who remain in the same sleep phenotype over time) versus “movers” (i.e., those who transition to different sleep phenotypes over time) for each sleep health phenotype?

Modern job design elements as predictors of sleep health phenotypes over time

Balance Theory (Carayon, 2009; Smith & Carayon, 1989) suggests that aspects of job design related to technology play an important part in worker health outcomes, which we argue includes their multidimensional sleep health phenotype. Whereas, in the organizational sciences, job design is typically conceptualized as intrinsically motivating features of work – including motivator factors such as opportunity for advancement (Herzberg, 1974) and job characteristics like autonomy (Hackman & Oldham, 1980). Balance Theory more comprehensively characterizes extrinsic features, and their intrinsic consequences, as part of an interconnected work system. In this model, a work system encompasses an individual person that performs tasks using various tools and technologies, within a physical environment and under certain organizational conditions. Because of the interconnectivity between person, tasks, technologies, environment, and conditions, changes to any element in the work system are likely to change other elements. Promotion of positive worker outcomes (i.e., attitudes, behavior, health) can be achieved most directly by eliminating influential negative elements of the work system, or, when this is not possible, more indirectly by adding positive elements to balance the entire work system. Due to the dearth of research connecting extrinsic job design elements (e.g., tasks, technologies, physical environment) to employee sleep health, we aim to identify key negative elements of the work system associated with suboptimal sleep health phenotypes.

One strength of Balance Theory’s consideration of extrinsic job design elements is its explicit inclusion of technology. Technology has massively changed when, where, and how work is done (see Cascio & Montealegre, 2016; Grant et al., 2010; Parker, 2014), and this is reflected in Balance Theory’s proposition that technology is a main element of the work system that meaningfully influences both job design and employee outcomes. In fact, technology may have spurred changes to the work system that could affect worker well-being, including their sleep health. Kompier (2006) highlights several potential threats to worker health in the wake of technological advancement, including (1) increase in technology use to complete work tasks (i.e., changes to task-related job design), (2) the more sedentary nature of many jobs (i.e., changes to physical job design), and (3) the 24-hour economy (i.e., changes to temporal job design). Job design theorists, including those who developed Balance Theory, similarly point to time spent at computers (Carayon & Smith, 2000), sedentary time at work (Parker & Zhang, 2016; Smith et al., 1999), and non-standard timing of work (Carayon, 2009; Parker & Zhang, 2016) as elements of the

work system changed by technology and urgent targets for job design research. Based in Balance Theory, we propose that technological advances within work systems have resulted in three overarching changes to job design (i.e., computer use, sedentary behavior, nontraditional work schedules) that, theoretically, may act as negative design elements that undermine employee health. We describe each of these elements of job design and their expected connection to sleep health, a central part of employee health that fits, but has not yet been included, as an outcome of job design within Balance Theory.

To begin, jobs may differ structurally in their dependence on technology like computers, which may shape the external physical environment with which an employee interacts. For instance, a data analyst may spend most of their day on the computer whereas a food service worker may interact with computers less frequently. This job design element may also shift over time, for instance as an increase in computer use for the food service worker as their purchasing systems become more technologically reliant. These differences in technology use over time may relate to changes in sleep health. Electronics emit blue light, which alters circadian processes and, thus, sleep-wake patterns (Burkhart & Phelps, 2009; Shigeyoshi et al., 1997). Blue light disruptions are most relevant to those who, formally or informally, work late; blue light emission is most likely to impact sleep when it occurs later in the biological day (Chang et al., 2015; Ishizawa et al., 2021), namely before bed rather than during the typical workday. Additionally, computer use can incite technostress, or psychological distress specific to technology use (see Richardson, 2017), perhaps explaining its association with adults' poorer mental and sleep health (Thomée et al., 2012). Moreover, prolonged and frequent computer use can lead to a constellation of physical symptoms including eye strain, pain in the head, neck, and shoulders, and blurry vision (Blehm et al., 2005; Korpinen et al., 2012), all of which relate to poorer sleep quality (Patil et al., 2019). Indeed, in line with each of these explanations, exposure to information and communication technology does relate to insufficient sleep (Suganuma et al., 2007), sleep disturbances (Thomée et al., 2007), shorter sleep quantity, and poorer sleep quality (Lanaj et al., 2014). As such, changes in computer use represent the first job design factor expected to relate to corresponding changes to a pattern of unhealthy sleep across multiple dimensions.

Hypothesis 1:

An increase in computer use frequency at work, time 1 to time 2 (7–13 years later) is associated with maintenance of suboptimal sleep health phenotypes over time or transitions from healthier to suboptimal phenotypes over time.

A second relevant element of job design is sedentary work, or extent of stationary time expending little physical effort at one's job. Sedentary work has markedly increased in prevalence over the past several decades (Church et al., 2011), and this is often attributed to technological advancements that reduce physical labor needs (Peng et al., 2018). Scholars argue that because sedentary behavior associates with poor mental and physical health, it may interfere with healthy sleep (Yang et al., 2017). Frequent sedentary time has been associated with both too short (Lakerveld et al., 2016; Štefan et al., 2019) and too long sleep duration (Štefan et al., 2019), each of which indicate unhealthy sleep. Further,

sedentary time relates to subjective difficulty falling asleep (Vancampfort et al., 2018) and physiological measures of sleep inefficiency (Madden et al., 2014). Meta-analysis also associates sedentary behavior with increased insomnia risk and sleep disturbance symptoms (Yang et al., 2017). Thus, a sedentary job may be a negative job design factor that, as it increases over time, relates to development of more suboptimal sleep health phenotypes, given its known links to individual sleep health problems.

Hypothesis 2:

An increase in sedentary activity frequency work, time 1 to time 2 (7–13 years later) is associated with maintenance of suboptimal sleep health phenotypes over time or transitions from healthier to suboptimal phenotypes over time.

A final relevant feature of temporal job design is work schedule type. Extensive previous research demonstrates that atypical work hours and work shifts extend sleep onset latency, increase sleep disturbances (i.e., wake after sleep onset or WASO; Chang & Peng, 2021) and daytime sleepiness (Booker et al., 2018), and reduce sleep quality and quantity (Booker et al., 2018). In fact, the prevalence of sleep issues among shift workers lead to the development of a shift work sleep disorder clinical diagnosis (American Sleep Disorders Association, 1990) involving severely disrupted sleep because of one's work schedule. These detrimental effects can be explained by the misalignment of these work schedules with natural circadian rhythms and sleep/wake cycles (Costa, 1996). These negative sleep implications likely also extend to those who are not formally involved in shiftwork but engage in other overtime or flextime practices that functionally lead to nonstandard work schedules. Using information-communication technology to work after hours is meta-analytically connected to greater strain, including poorer sleep quality (Kühner et al., 2023). However, the specific consequences of these temporal job design factors for multidimensional sleep health are not known. We hypothesize that over-time changes to nonstandard work schedules will predict unfavorable transitions in multidimensional sleep health.

Hypothesis 3:

Maintenance of or transitions to nonstandard schedules from time 1 to time 2 (7–13 years later) is associated with maintenance of suboptimal sleep health phenotypes over time or transitions from healthier to suboptimal phenotypes over time.

Method

Procedure

To achieve the large sample size required for our person-centered analyses (Bray & Dziak, 2018) and access the over-time data required by our research questions, we used existing data from the Midlife in the United States study (MIDUS). MIDUS is an interdisciplinary, longitudinal data collection effort aimed at understanding health over the lifespan in a national sample. Please note that this study was not preregistered and data and study materials specific to the present study are not publicly available; however, multiple raw MIDUS datasets, including those used in the present analysis, are available

online (<https://www.midus.wisc.edu/data/index.php>). Additional information on the MIDUS datasets and previous studies using the MIDUS datasets, including in total and by the current research team, can be found in Supplemental Table 1. We followed guidelines on the use of archival data in applied psychology research (Fisher & Chaffee, 2018) and ethical principles for repeated use of a dataset across multiple projects (Kirkman & Chen, 2011). Most notably, of the existing sleep research using MIDUS data, no other publications have used job design theory or examined longitudinal transitions in workers' sleep health phenotypes, distinguishing our research (see <https://www.midus.wisc.edu/findings/pubtopics.php?topic=Sleep>).

Two waves of MIDUS data provide extensive work and sleep health information (MIDUS II and III) and were thus used in our analyses. Additionally, we used both core MIDUS data and Milwaukee MIDUS data, the latter of which aimed to add racial diversity to MIDUS datasets by targeting Black participants. MIDUS II (Core: 2004–2006; Milwaukee: 2005–2006) and III (Core: 2013–2014; Milwaukee: 2016–2017) are follow-ups to the original MIDUS I data collection (1995–1996). A national sample of adults 25–74 were recruited for MIDUS I via random digit dialing. The Milwaukee sample was selected by screening households in Milwaukee, Wisconsin in areas of the city that had higher concentrations of Black adults. Overall MIDUS data represent the U.S. adult population. We used data from the self-administered questionnaire (SAQ) portion of MIDUS, consisting of self-report surveys.

Participants

MIDUS II and III respondents who indicated that they were working 30 or more hours per week at both time points were included in our analytic sample to ensure that change in job design factors could be assessed ($N=1,297$). The analytic sample worked 45.61 hours per week on average, had an even sex distribution (53.97% male), and was primarily non-Latinx white (88.97%). Per Chou and Choi's (2011) categories, approximately half (47%) of the sample worked in executive, managerial, and professional occupations, 35% worked in technical, clerical, service, and sales occupations, and 18% worked in crafts, labor, and military occupations. The sample reported slightly higher educational attainment, on average ($M=7.11/12.00$, indicating at least some college), than the national average. The majority of the sample was partnered (74.01% were married and/or cohabitating with a romantic partner) and had 2 children on average. Participants were 46.60 years old at MIDUS II ($SD=7.47$, $Range=33$ to 75) and 55.97 at MIDUS III ($SD=7.36$, $Range=42$ to 83).

Because participants needed to report job design and sleep experiences at both time points to be included in our analyses, there was no attrition between our time 1 analytic sample and time 2 analytic sample. However, to assess how our selection criteria might have impacted the characteristics of our analytic sample, we conducted comparison analyses. Compared to the full MIDUS core and Milwaukee combined sample ($N=3,676$; $M=55.03$ at II and 63.36 at III), our working analytic sample ($N=1,297$) was significantly younger (Cohen's $d=1.02$ at II and $.90$ at III), likely due to our exclusion of retirees. There were also medium-sized significant differences in the number of children ($d=.26$) and self-rated physical health ($d=.28$), such that the analytic sample reported fewer children ($M=2.12$

compared to 2.54) and better physical health ($M=2.67/5.00$ compared to $M=2.41/5.00$). There were small significant differences in sex ($d=.15$) and race ($d=.20$), such that fewer women (46% compared to 53%) and racial minorities were in the analytic sample (11% compared to 19%). The analytic sample did not significantly differ from the full sample on marital status or education. Overall, the working subsample was younger, slightly healthier, slightly less diverse, and had fewer children than the full MIDUS core and Milwaukee sample.

Measures

MIDUS studies sometimes use adapted or abridged scales, but all measures are thoroughly vetted by subject matter experts before data collection and validated in subsequent studies after data collection. More information on MIDUS measurement can be found at their website <https://www.midus.wisc.edu/data/index.php>

Job design

Computer use at work. One item asked participants “How often does your job require you to work on a computer?” on a scale from 1 (*never*) to 5 (*all of the time*).

Sedentary work. One item asked participants “How often does your job require you to sit for long periods of time?” on a scale from 1 (*never*) to 5 (*all of the time*).

Nonstandard work schedule. Participants were asked to rate the frequency at which they worked during certain times of day, on average (1=*less than once a month or never*, 2=*1 to 3 times per month*, 3=*once a week*, 4=*2 to 3 times per week*, 5=*4 or more times per week*). Four items captured work schedules, including working days, evenings, nights, and weekends. A binary work schedule variable was created, such that working once a week or more (3+ score) at any nonstandard time (evening, night, weekend) was considered a nonstandard schedule (=1) whereas rarely or never working at non-day times was considered a standard schedule (=0).

Sleep health

Statisticians recommend using categorical indicators and latent class techniques (rather than continuous indicators and latent profile techniques) for mixture modeling when the indicator variables are skewed, as is the case with sleep variables (Wallace et al., 2018). Within the present data, most of the sleep health dimensions (i.e., sleep duration, regularity, sleep onset latency, and nap) exhibited non-normal distributions (i.e., skewness>|2| and/or kurtosis>|7|; West et al., 1995) at one or both time points. We therefore used empirical evidence to create cut-off scores differentiating optimal and suboptimal sleep for all sleep health variables to maintain consistency and interpretability across the dimensions (see Table 1 for a summary). These cut-offs align with previous values used in MIDUS research (Lee et al., 2022) but reorganize some sleep dimensions to provide a more detailed and accurate representation of sleep health (Buysse, 2014).

Regularity. Sleep regularity can refer to consistency in duration or timing (Wallace et al., 2022). MIDUS surveys only provide data relevant to duration, which we use here to

calculate sleep duration regularity (see also Smith & Lee, 2021; Lee et al., 2022). We calculated an absolute value of the difference between workday duration and non-workday duration, such that a higher score indicates less regularity in sleep duration throughout the work week. Regular sleep is characterized by a difference of one hour or less between workday and non-workday duration; irregular sleep is characterized by a difference of greater than one hour (see Lee et al., 2022).

Satisfaction (Subjective insomnia symptoms). Frequency of three subjective sleep issues (i.e., “trouble falling asleep”, “trouble staying asleep” and “waking up too early”) were assessed in response to the prompt “Please indicate how often you experience each of the following...” (1=never, 2=rarely, 3=sometimes, 4=often, 5=almost always). These three symptoms are consistent with those defined in the Diagnostic and Statistical Manual of Mental Disorders (DSM) V for clinical insomnia, which requires symptom presence “often or always” (Ohayon, 2002). Thus, participants who experienced one or more insomnia symptom often or almost always were sorted into the insomnia symptoms present group; those who never, rarely, or sometimes experienced all three insomnia symptoms were considered to have no symptoms present.

Alertness (daytime tiredness and nap frequency). One item assessing frequency of “feeling unrested during the day” was assessed in response to the prompt “Please indicate how often you experience each of the following...” (1=never, 2=rarely, 3=sometimes, 4=often, 5=almost always). To keep consistency with the insomnia symptoms cut-off, which uses the same response scale, those who reported often or almost always feeling unrested were considered to be high on daytime tiredness; those who answered never, rarely, or sometimes were considered low.

Nap frequency was assessed via one item asking participants, “During a usual week, how many times do you nap for 5 minutes or more?”. Other factors such as nap length, nap timing, nap motivation, and previous experience with napping may shape whether napping is beneficial or detrimental in adults (Milner & Cote, 2009); however, excessive napping is considered unhealthy for adults (Ohayon et al., 2017) because it can lower sleep drive and sometimes sleep efficiency or quality at night (Jefferson et al., 2005) and is associated with adverse health consequences such as heart disease and cancer (Jung et al., 2013). We used three categories of nap frequency (Ohayon et al., 2017): never (0/week), sometimes (1–3/week), and frequent (4+/week, indicating naps most days).

Efficiency (sleep onset latency). One question asking participants “How long does it usually take you to fall asleep at bedtime?” was used to assess sleep onset latency. Suboptimal sleep onset latency was characterized by greater than 30 minutes to fall asleep; optimal sleep onset latency was characterized by 30 or fewer minutes (Ohayon et al., 2017).

Duration. Two parallel items assessed sleep duration: “How much sleep do you usually get at night (or in your main sleep period) on weekdays or workdays?” and “...on weekends or your non-workdays?”. To approximate total average sleep duration, we used a weighted average of workday duration ($\times 5/7$) and non-workday duration ($\times 2/7$) based on a standard five-day work week. Three categories were created for sleep duration based on

the recommendation for an average adult by the National Sleep Foundation (Hirshkowitz et al., 2015): short (7 or fewer hours), optimal (between 7 and 9 hours), and long (9 or more hours).

Analytic Strategy

Identification of sleep health phenotypes and transitions. Latent transition analysis (LTA) was run in Mplus, wherein latent class solutions were simultaneously extracted at time 1 (MIDUS II) and time 2 (MIDUS III). Like related cross-sectional techniques (e.g., latent class and profile analyses), LTA can be used to determine the best-fitting number of classes or sleep health phenotypes. However, unlike these cross-sectional techniques, LTA also provides information about phenotypes at multiple time points and about a person's likelihood of transitioning from one phenotype to another over time (Nyulund-Gibson & Choi, 2018). Six categorical sleep health variables were used as class indicators: duration, regularity, sleep onset latency, nap frequency, daytime tiredness, and insomnia symptoms. The best fitting number of classes was selected based on a holistic evaluation of various model fit statistics, and the classes were named based on defining characteristics. Specifically, low AIC, BIC, and SSA-BIC suggest good fit, although AIC is considered relatively inferior (Nyulund et al., 2007; see Spurk et al., 2020) due to its tendency to overestimate the appropriate number of classes (McLachlan & Peel, 2000; Morgan, 2015; Nylund et al., 2007; Tofighi & Enders, 2008). Higher entropy is desirable as it indicates a higher degree of certainty in sorting participants into the identified classes (.80+ is considered "good" and .60–.80 is considered "acceptable"; Muthén & Muthén, 2007; Jung & Wickrama, 2008; Muthén, 2004). As is recommended by statisticians, entropy was used as a descriptor of the solution rather than as criteria in class selection (Lubke & Muthén, 2007; Masyn, 2013; Tein et al., 2013). Other common fit statistics, namely LMR and BLRT, are not available for mixture analyses in Mplus when more than one categorical latent variable is used.

Next, Mplus sorted participants into classes and, in turn, transition groups indicating class membership at each time point, based on posterior probabilities (i.e., likelihood of belonging to a given latent class). To name the classes, we considered the proportion of participants within the phenotype that were sorted into the unhealthy versus sleep health category for each dimension (e.g., high or low insomnia symptoms, appropriate or long time to fall asleep). Finally, the proportion of participants belonging to each transition group (i.e., group describing which phenotype a person belongs to at each time point, such as class 1 → class 2 or class 3 → class 3) was used to determine prevalence of "staying" and "moving" from one phenotype to another.

Associations between sleep health phenotype transitions and job design. To assess associations between changes in job design and sleep health phenotype transitions, the three standardized changes in job design features were simultaneously modeled as predictors of the latent transition groups, with the largest group used as the reference, in a multinomial regression models. In both sets of analyses, hours worked per week, income, education, sex, race, age, parental status, and number of young children (≤ 5 years old) were included as control variables given previously identified disparities in sleep health based

on sociodemographic characteristics and health status (Jackson et al., 2015; Laposky et al., 2016; Magee et al., 2011). We also controlled for job demands given that extrinsic job design features and psychosocial job characteristics are interconnected within the Balance Theory of Job Design, and our aim was to examine the sleep health phenotypes associated with the hypothesized extrinsic job design features above and beyond any demands they may create. Per Kam et al., (2016), we used z-scores rather than raw scores when modeling changes in job design for continuous job design variables and controls. Time 1 values were used for stable categorical controls (e.g., sex, race).

Results

Descriptive statistics and correlations are reported in Table 2. The sleep health facets are weakly to moderately correlated but do not exceed standard cut-offs (ranging from $<.70$ to $<.90$) for discriminant validity (Carlson & Herdman, 2010; Rönkkö & Cho, 2022). The MIDUS worker sample exhibits fairly healthy sleep overall except for somewhat short sleep duration ($M=6.50$ hours at MIDUS 2; $M=6.07$ at MIDUS 3) and irregular sleep duration (over 80 minutes difference between workday and non-workday sleep at MIDUS 2 and MIDUS 3).

Identification of sleep Health Phenotypes and Transitions

Based on holistic evaluation of model fit statistics, the three-class solution was chosen due to its low BIC and SSA-BIC; it also exhibited sufficient entropy (see Table 3). As shown in Table 4 and Figure 1, three similar classes were extracted at time 1 and time 2. The first class, *good sleepers* (~57% at time 1 and time 2) was characterized by relatively low proportions of unhealthy sleep across all characteristics. The second class, *catch-up sleepers* (~25% at both time points) was characterized by relatively healthy sleep except for high nap frequency and irregular sleep (i.e., long non-workday sleep compared to short workday sleep); as such, they were named catch-up because napping and non-workday sleep are considered ways to attempt to compensate or “catch up” on sleep (Leger et al., 2020). The third and final class, *insomnia sleepers* (~18% at both time points) was characterized by high insomnia symptoms, short duration, long sleep onset latency, high daytime tiredness, and somewhat irregular sleep, all of which map onto insomnia experiences. Membership to this class does not necessarily equate to clinical insomnia. In response to Research Question 1 (i.e., number and nature of sleep health phenotypes among working adults), three classes were identified: a highly optimal group, a highly suboptimal group, and a catch-up group.

In response to Research Question 2 (i.e., proportion of “stayers” vs. “movers” for each phenotype), Table 5 and Figure 2 shows the percentage of each phenotype at time 1 (*good*, *catch-up*, and *insomnia sleepers*) who transition to each phenotype at time 2. Participants were most likely to stay in the same class over time (81% for *good sleepers*, 58% for *catch-up*, and 90% for *insomnia sleepers*), though transitions also commonly occurred. *Good sleepers* and *catch-up sleepers* were more likely to transition to one another than to *insomnia sleepers*. Similarly, *insomnia sleepers* were less likely to transition to *good* (7%) or *catch-up* (3%).

Job Design Factors as Correlates of Sleep Health Phenotype Transitions

Hypotheses 1–3 expected that an increase in computer use at work, sedentary work, or nontraditional work schedule, respectively would be associated with maintenance of suboptimal sleep health phenotypes or transitions from healthier to suboptimal sleep health phenotypes over time. Unexpectedly, an increase in computer use at work was unexpectedly associated with lower (rather than higher) likelihood of *insomnia*→*insomnia* transition ($B=-1.26$, $SE=.53$, $p=.02$) relative to *good*→*good*, contrary to H1. However, as expected, an increase in sitting at work was associated with higher likelihood of *insomnia*→*insomnia* ($B=.38$, $SE=.15$, $p=.01$) relative to *good*→*good*, supporting H2. Neither computer use nor sitting at work related to maintenance of or transitions into *catch-up sleeper*. Finally, largely as expected (H3), an increase in non-traditional work schedules from time 1 to time 2 was associated with transitions to catch-up sleep (*good*→*catch-up*: $B=.66$, $SE=.29$, $p=.02$; *catch-up*→*catch-up*: $B=.481$, $SE=.23$, $p=.04$; *insomnia*→*catch-up*: $B=2.68$, $SE=1.16$, $p=.02$) relative to consistently good sleep (*good*→*good*). Hypothesis 3 was partially supported in that nontraditional schedules related to maintenance of or transition to *catch-up sleeper* but not the *insomnia sleeper*. Full results are reported in Table 6.

Post hoc analyses

Supplemental analyses without control variables and with additional occupational variables. We ran several supplemental analyses including those without controls for transparency and those that considered additional variables to provide more specifics beyond the main results. The adjusted results presented above were largely consistent with the unadjusted model excluding control variables (see Supplemental Table 2 for unadjusted results; see Supplemental Table 3 for control variable coefficients). Further, in addition to significant associations above and beyond job demands, results did not appear to be driven by occupation type, though those in craft, labor, and military occupations were more likely to be consistent *catch-up sleepers* than professional or clerical occupation groups (see Supplemental Table 4). Post hoc analyses parsing out frequency of working different types of nontraditional schedules (i.e., evenings, nights, and weekends) indicated that working at night may be driving the *catch-up sleeper* results in Hypothesis 3. As shown in Supplemental Table 5, increased frequency of working at night associated with consistent *catch-up sleep* (*catch-up*→*catch-up*: $B=0.31$, $SE=.08$, $p<.001$) whereas an increase in working weekends was not significantly associated with any *catch-up sleeper* transition groups and an increase in working evenings was associated with lower likelihood of consistent *catch-up sleep* relative to consistent *good sleep* (*catch-up*→*catch-up*: $B=-.21$, $SE=.08$, $p=.01$).

Phenotype validation against actigraphy and other independent sleep scales. To validate the three sleep health phenotypes identified in our main analyses, we used objective actigraphy data and independent self-report sleep scales collected from the same participants as part of a separate data collection effort, the MIDUS II Biomarker Study (2004–2009). A subset of MIDUS II respondents ($N=1,255$) participated in the self-report biomarker survey, another subset of whom ($N=441$) provided objective sleep data using Actiwatch (Mini Mitter Actiwatch-65; Philips Corporation, Andover, MA) wrist actigraphy devices over seven consecutive days. A total of 413 working adults completed the self-report

sleep questions within the Biomarker Study, and of the smaller actigraphy sample, 143 were working adults and, thus, included in our post hoc analyses. Although these samples were smaller than the main analytic sample, representation of the phenotypes was similar for both the self-report biomarker survey (54% *good*, 29% *catch-up*, and 17% *insomnia sleepers*) and actigraphy (57% *good*, 26% *catch-up*, and 17% *insomnia sleepers*) compared to the main sample (57% *good*, 26% *catch-up*, 17% *insomnia sleepers*). We used multinomial regression models to test how, at the first time point, the three phenotypes significant differed on self-report and actigraphy sleep health dimensions¹.

Actigraphy validation. The actigraphy device contains a motion sensor that collects body movements (per 30 second intervals). The MIDUS research team used Actiware 5 software to process the actigraphy data²; we used average scores across all data collection days to assess overall sleep health. Actigraphy collected sleep variables included *wake after sleep onset (WASO)* or total minutes of wakefulness between start and end of main sleep period not including sleep onset latency, *sleep efficiency* or percentage of time spent asleep relative to total time spend in bed, and *sleep duration* or time elapsed between sleep start and end times. Neither *catch-up sleepers* nor *insomnia sleepers* significantly differed from *good sleepers* on objective sleep onset latency (*Catch-up*: $B=-3.66$, $SE=4.47$, $p=.41$; *Insomnia*: $B=10.48$, $SE=5.45$, $p=.054$) or WASO (*Catch-up*: $B=-6.49$, $SE=25.62$, $p=.80$; *Insomnia*: $B=-3.73$, $SE=31.22$, $p=.90$). However, *insomnia sleepers* did report less efficient sleep than *good sleepers* ($B=-17.04$, $SE=7.83$, $p=.03$); no differences were significant for *catch-up sleepers*. *Insomnia sleepers* also reported shorter actigraphy sleep duration than *good sleepers* ($B=14.60$, $SE=7.36$, $p=.047$); no differences were significant for *catch-up sleepers*. In total, *insomnia sleepers* reported shorter and less efficient sleep (i.e., greater % of the rest period spent awake) than *good sleepers*.

Self-report validation. Self-report sleep was captured using the Pittsburgh Sleep Quality Index (PSQI; Buysse, 1989), which captures sleep health across 19 items (e.g., “during the past month, how would you rate your sleep quality overall?”); scores range from 0 to 21, with higher global scores indicating poorer sleep quality (>5 indicates categorically poor sleep quality). As expected, *good sleepers* reported better sleep quality (a lower PSQI score; $M=0.40/21.00$) than both *catch-up sleepers* ($M=2.51$, $B=0.92$, $SE=.42$, $p=.03$) and *insomnia sleepers* ($M=13.86$, $B=2.63$, $SE=.51$, $p<.001$), and *catch-up sleepers* reported better sleep quality than *insomnia sleepers* ($B=1.71$, $SE=.56$, $p=.002$). This rank-order of subjective sleep quality (*good sleepers* > *catch-up sleepers* > *insomnia sleepers*) matches the theoretical expectation, derived from the RuSATED model, that *good sleepers* are the most optimal phenotype, *catch-up sleepers* are relatively suboptimal but still sufficient (i.e., $PSQI<5$), and *insomnia sleepers* are the most suboptimal phenotype (i.e., $PSQI>5$).

¹Actigraphy data was not used as input for the sleep health phenotypes because (1) the portion of the already smaller actigraphy sample that was working adults resulted in a sample size smaller than that needed for latent class analyses (500+; Tein et al., 2013) and (2) actigraphy data was not yet available for MIDUS III at the time of original analyses, meaning latent transition analyses could not be conducted.

²Additional information about actigraphy data collection, cleaning, and processing can be found in the Actigraphy Rest-Activity Rhythm Protocol section of the MIDUS 2: Biomarker Project summary available at the ICPSR website: <https://www.icpsr.umich.edu/web/NACDA/studies/29282?classification=NACDA.IV>.

Finally, we also compared key subscale scores of the PSQI. All subscale scores range from 0 to 3, wherein higher scores indicate poorer sleep. Whereas *catch-up sleepers* reported comparable sleep disturbances ($M=1.12$, $B=.12$, $SE=.07$, $p=.09$) relative to *good sleepers*, *insomnia sleepers* reported more disturbances ($M=1.28$, $B=.25$, $SE=.11$, $p=.003$). Yet both *catch-up sleepers* ($M=1.32$, $B=.27$, $SE=.09$, $p=.002$) and *insomnia sleepers* ($M=1.43$, $B=.35$, $SE=.11$, $p<.001$) reported more daytime dysfunction compared to *good sleepers*. These component results align with the phenotype characteristics found in the main study results, providing validity evidence. Compared to *good sleepers*, *catch-up sleepers* may suffer in terms of daytime alertness (e.g., napping in the main results and daytime dysfunction here) but exhibit otherwise sufficient sleep, whereas *insomnia sleepers* struggle with a variety of subjective sleep health dimensions.

Discussion

Technology-related changes to job design (e.g., greater computer use, more sedentary time, higher prevalence of nonstandard work schedules) in recent decades have been blamed (Khubchandani & Price, 2020) for mass sleep deficiencies among modern adults, sometimes called the sleep deprivation epidemic (Roennenberg, 2013; Stranges et al., 2012). The Balance Theory of Job Design suggests that these aspects of a work system are likely influential over worker health outcomes (Carayon, 2009; Smith & Carayon, 1989), but connections to sleep health are currently missing. In fact, to our knowledge, there have been no formal empirical efforts to test if, how, and to what extent changes in these elements of modern job design truly relate to employees' sleep health. Building on cross-sectional evidence that workers may exhibit one of three distinct sleep health phenotypes (Smith et al., 2023), or within-person configurations of key sleep health dimensions, we find that three distinct phenotypes are common among working adults and can be replicated approximately one decade later. Namely, workers may exhibit an optimal sleep health phenotype (i.e., *good sleepers*) or one of two suboptimal phenotypes (i.e., *weekend catch-up sleepers* or *insomnia sleepers*) that are largely consistent with those identified cross-sectionally. We also validate these sleep health phenotypes using independent sleep data (actigraphy and self-report) for the first time.

Additionally and as a more novel and notable contribution, we find that workers are largely stable (about 60–90%) in their sleep health phenotypes over the course of a decade, in line with the stability suggested by dynamic equilibrium theory (Headey & Wearing, 1989) and extending recent evidence of overarching stability of one sleep dimension (i.e., quality) over several months (Henderson et al., 2023). Yet we present new evidence that the stability of sleep health varies based on specific sleep health phenotype. Finally, despite this stability, transitions to a different phenotype are possible and co-occur with changes in job design elements (e.g., sedentary time, work schedule). Overall, we find that working adults tend to exhibit one of three sleep health phenotypes with relative consistency over ten years but that any shifts in sleep health may be explained by corresponding shifts in key elements of job design.

Scholarly implications

Sleep is becoming a widely researched topic in the organizational sciences (see Crain et al., 2019), and, as a result, it is acknowledged as an essential ingredient to employee well-being and productivity (Barnes & Watson, 2019; Brossoit et al., 2019; Mullins et al., 2014; Schultz & Burton, 2018). Despite this growth, sleep is a relatively nascent topic in the organizational sciences, and our measurement has not kept pace with the sleep scholarship that recognizes the multidimensional (Buysse, 2014; Matricciani et al., 2018) and dynamic (Ohayon et al., 2017) nature of sleep health. We answer calls to assess sleep health as a phenotype (Chung et al., 2021; Matricciani et al., 2018) – or configuration of multiple dimensions of sleep health as they exist within a person – and the dynamic nature of these phenotypes over time. By examining these issues in working adults, we clarify how sleep health tends to manifest for this group that may be especially vulnerable to sleep difficulties (Swanson et al., 2011), describing common patterns of co-occurring sleep issues and, for the first time, how likely employees are to improve, maintain, or worsen in their holistic sleep health over a decade.

Findings from this study show that workers in the United States fit within three common sleep health phenotypes and that prevalence rates remain relatively consistent over time. At both time points, over half of working adults in our representative sample were *good sleepers*, exhibiting optimal sleep across all measured dimensions. One quarter were *catch-up sleepers* at each time point, exhibiting mostly optimal sleep (i.e., appropriate duration, low daytime tiredness, low insomnia symptoms, short sleep onset latency) but long weekend sleep and frequent daytime naps. At both time points, about 18% of our sample were *insomnia sleepers*, exhibiting suboptimal sleep consistent with insomnia symptoms (i.e., short duration, long sleep onset latency, high daytime tiredness, high insomnia symptoms). Working adults' multidimensional sleep health seems to manifest in one of three ways over the course of a decade: *good sleepers*, *catch-up sleepers*, and *insomnia sleepers*. These sleep health phenotypes and proportions are largely consistent with those we previously identified in the same dataset cross-sectionally, across two independent subsamples of working adults (i.e., MIDUS II core and refresher samples; Smith et al., 2023). Although the MIDUS worker sample aged between the baseline (MIDUS II) and follow-up (MIDUS III) data collections, sleep health phenotypes can be consistently identified both cross-sectionally (Smith et al., 2023) and longitudinally. Other phenotypes identified in non-worker samples (e.g., *nappers*) were not found here, suggesting that work status may be an important determinant of sleep health phenotypes. Together with our new post hoc validation of these phenotypes using actigraphy and self-report sleep data (i.e., *insomnia sleepers* < *catch-up sleepers* < *good sleepers* in terms of sleep health), growing evidence supports these three sleep health phenotypes as common in working adults over time.

Related to our goal to understand the dynamics of multidimensional sleep health, organizational scientists have called for long-term study designs examining of the stability of various aspects of employee well-being to improve measurement and temporally sensitive theory (Mäkikangas et al., 2016). So far, research suggests that sleep health – albeit measured as independent dimensions rather than a multidimensional phenotype – may exist as a dynamic equilibrium wherein short-term fluctuation occurs (e.g. van Erde & Venus, 2018) but in the context of meso-term stability (Henderson et al., 2023). We add needed

information about long- term stability and change. People are most likely to remain in the same sleep health phenotype over the long-term (i.e., approximately one decade), rather than transition to a new one. The prevalence of stability (60–90% of the sample) aligned with our expectations based on previous findings that 70–85% of people experience stable health and well-being in the long-term (Headey, 2006; Headey, 2010; Headey et al., 2014; Luhmann et al., 2018). Although dynamic equilibrium theory was developed to describe psychological well-being, our findings add to growing support for its application to other constructs related to worker health such as work- family conflict (Smith et al., 2022) and, here and in Henderson et al. (2023), sleep. Integrating this research with previous findings, sleep health can fluctuate from day to day and may even shift over months or years, but *most* people exhibit a stable constellation of co-occurring sleep dimensions that persist over a decade.

Beyond the tenets of dynamic equilibrium theory and Henderson et al.'s (2023) recent findings, however, the present study newly shows that the stability of sleep health differed based on a person's baseline sleep health phenotype. *Insomnia sleepers* were the least likely to transition to a new phenotype over time; unfortunately, 90% of *insomnia sleepers* remained in the same highly suboptimal phenotype. Other research relatedly finds that people diagnosed with chronic insomnia do tend to experience persistent sleep problems one year later (Pillai et al., 2016), but our results indicate that co-occurring insomnia symptoms may be likely to persist over ten years. Indicating similar stability as *insomnia sleepers*, only 20% of *good sleepers* transitioned to a new phenotype, most of whom transitioned to *catch-up sleeper* (17%). *Catch-up sleepers* were the most likely to transition. Although *catch-up sleepers* often remained in the same phenotype (58%), they also commonly transitioned to *good* (36%) or to *insomnia sleepers* (6%). It is possible that *catch-up sleep* is primarily an adaptation to external circumstances (rather than a stable internal preference), making this phenotype likely to change when those circumstances change. The connection between nontraditional work schedules and *catch-up sleep* in the present study supports this potential explanation, as do previous findings that being younger or unpartnered relate to irregular sleep schedules (Lee et al., 2022). Applied more broadly, dynamic equilibrium perspectives should consider that the stability of health outcomes like sleep may not solely differ based on significant life events, as previously theorized, but also based on severity and nature of earlier health experiences (i.e., baseline sleep phenotypes here).

The present results also show that although sleep phenotypes are often stable, technology-related job design features seem to have implications for employees' sleep health phenotype transitions when they do occur (i.e., for 10–40% of people depending on baseline phenotype). The connection between job design and sleep health phenotypes was robust even after accounting for sociodemographic factors and job demands. Lack of physical activity at work differentiated between *good* and *insomnia sleepers*. As expected, an increase in **sedentary time** at work related to remaining in or transitioning to the *insomnia sleeper* phenotype. This finding is consistent with past research showing the association between general (rather than job- specific) sedentary time and insomnia (Chen et al., 2014; Yang et al., 2017). In this study, we add rigorous evidence that sedentary time at work is associated with a maintenance of increase in a constellation of various, co-occurring insomnia

symptoms over the course of a decade. Given the substantial increase in sedentary work (Church et al., 2011), its association with the maintenance or increase in a constellation of co-occurring insomnia symptoms over one decade is highly concerning. Counter to our hypotheses, an increase in **computer use** at work related to remaining in or transitioning to the *good sleeper* phenotype over *insomnia sleeper*. This finding could be attributed to the fact that MIDUS measurement of computer use does not specify timing of the use. Past work connecting screen time with poor sleep examines nighttime technology use (e.g., Vallance et al., 2015), rather than technology use during work hours. If computer use is limited to the daytime, use would not violate sleep hygiene recommendations to avoid active technology before bed (Gradisar et al., 2013). In fact, in some cases, workplace technology can help employees complete tasks in more efficient ways, to the benefit of their health (Bala & Venkatesh, 2016; Piszczek, 2017). Although definitive explanations could not be identified in the present data, perhaps the benefits of workplace computer use often outweigh the expected technostress associated, explaining the unexpected link to better sleep health found here.

People who remained in or who transitioned to **nontraditional work schedules**, specifically more frequent work during nighttime, were more likely to be consistent *catch-up sleepers* or transition to *catch-up sleepers* over time. While shift work has been linked to poor sleep quality in general (Chang & Peng, 2021), our findings add that any people working at night may attempt to deal with their misaligned sleep/wake cycle via a combination of daytime napping and weekend catch-up sleep. The *catch-up sleep* phenotype was also prominent among military, labor, and craft occupations in our post-hoc analyses. Based in past findings that many manual labor or skilled professionals (sometimes called “blue-collar”) have more physically demanding jobs (Azevedo et al., 2021) as well as erratic and/or on-demand work schedules, we speculate that the physical exhaustion and irregular schedules of people in these occupations may drive them to engage in “catch-up” strategies of napping and sleeping in on non-workdays despite seemingly getting healthy sleep during their normal sleep periods. Previous evidence in a general, national adult sample suggests that napping and long weekend sleep are insufficient in promoting healthy sleep (Leger et al., 2020), yet naps are empirically related to lower sleepiness during work for employees on non-standard schedules (Ruggiero & Redeker, 2014) and are clinically recommended for people diagnosed with shift work disorder (Wickwire et al., 2017). As such, not only is nontraditional work schedule a significant risk factor for the *catch-up sleeper* phenotype, but it is also possible that type of formally assigned work shift may moderate the health effects of being a *catch-up sleeper*. Of note, the *catch-up sleeper* phenotype exhibits sufficient sleep quantity and quality and, thus, would not have been identified by traditional one- or two-dimensional approaches typically applied in the organizational sciences. Examining multidimensional sleep health phenotype trajectories allowed the discovery of *catch-up sleepers’* specific constellation of sleep experiences and identified the potential role of nontraditional work schedules in maintaining or inciting these experiences.

The above findings have important implications for the Balance Theory of Job Design. Balance Theory is under-utilized in occupational health psychology research, despite its unique ability to describe an essential question to the modern workplace: how technology-

related changes to job design impact employee health (Carayon, 2009; Carayon & Smith, 2000; Kompier, 2006; Parker & Zhang, 2016; Smith et al., 1999). Our results show that Balance Theory can be extended to describe sleep health. Namely, we identify negative elements of job design (i.e., sedentary work, nontraditional schedules) that relate to suboptimal sleep health phenotypes. The counterintuitive association between work-related computer use and the *good sleeper* phenotype suggests that elements of a job's design may be difficult to universally define as negative or positive within Balance Theory; the specific outcome measured (e.g., sleep health vs. other attitudes, behaviors, and health outcomes) may be necessary context when determining how to balance positive and negative job design factors. Moreover, Balance Theory should be integrated with theory and research specific to the relevant outcome to provide more detailed explanations. For instance, in our results, sedentary work and nontraditional schedules relate to different suboptimal sleep health phenotypes (i.e., *insomnia sleeper* and *catch-up sleeper*, respectively). Whereas Balance Theory would simply call both of these job design elements negative factors, integration with Buysse's (2014) RuSATED sleep health framework and previous empirical work on job design better explain their differential links with specific sleep health phenotypes.

Practical implications

These results suggest that task-related, physical, and temporal job design are meaningfully linked to multidimensional employee sleep health over time and, as such, may be useful targets of intervention. Importantly, we urge organizations to consider the *specific* co-occurring sleep issues that are of high risk for their employees based on job design – and urge sleep intervention developers to consider the need to target particular job design challenges and sleep phenotypes. For instance, general sleep interventions attempting to improve either sleep quantity or quality may not be optimal for employees on nontraditional schedules, who instead may require help with their frequent napping and irregular sleep schedules. We wonder if the underwhelming effectiveness of many workplace sleep programs (Robbins et al., 2019) could partially be due to lack of specificity and targeting of workforce vulnerabilities and needs.

Organizations employing workers who operate on nontraditional schedules, specifically working during the night, should be aware that their workforces may be vulnerable to *catch-up sleep*. Some employees may work during non-traditional times by choice, such as in flexible work arrangements (Bolino et al., 2021), so self-imposed work at nighttime should also be considered a potential risk in addition to formal shiftwork arrangements. Both should be reduced when possible to decrease odds of *catch-up sleep*. When direct changes to work schedules are not possible, existing interventions developed to improve sleep for workers on nontraditional schedules could be applied, though their effectiveness for co-occurring suboptimal sleep dimensions (i.e., frequent napping, long weekend sleep) is not yet known. For example, light exposure (Olson et al., 2020) and improved scheduling adjusted for chronotype (Declercq et al., 2022) could serve as more immediately adjustable targets and should be tested in relation to the *catch-up sleeper* phenotype.

Similarly, existing interventions that aim to increase physical activity among sedentary workers (e.g., Carr et al., 2016) could be tested in the context of sleep to see if they are

effective when targeting an interdependent pattern of sleep issues. Given that *insomnia sleeper* is the most suboptimal but also the most stable phenotype (i.e., least likely to change), future efforts should examine whether reducing sitting time at work may lead to transitioning from the insomnia sleeper to some other phenotype. Conversely, based on our findings, work-related computer use may not be a primary area for concern in terms of employee sleep health. Moreover, sleep health interventions can also supplement changes to job design, but our findings suggest that they require more detailed measurement of sleep health (i.e., beyond quantity and quality). *Catch-up sleepers* report sufficient sleep quantity and quality and, thus, may go undetected as suboptimal sleepers using traditional measurement, despite their irregular sleep and frequent napping. Further, *insomnia sleepers* report a constellation of sleep issues that may be interdependent and best tackled together. We extend calls to develop workplace interventions targeting multiple dimensions of employee sleep health (Chung et al., 2021) to also consider specific needs of common sleep health phenotypes.

Limitations and future directions

All data for the main analyses were collected via self-report surveys, which may contribute to common method bias (CMB; Podsakoff et al., 2003). Objective job design data (e.g., from O*NET based on job title) could be incorporated in the future to deal with CMB. For sleep, although we include “objective” actigraphy data to validate our self-report profiles, actigraphy data was not used for profile identification. Subjective and objective measurement are considered related but not redundant and, therefore, complimentary when measuring sleep (Girschik et al., 2012; Zinkhan et al., 2014). For instance, in another study using MIDUS data, researchers found significant but small correlations ($r=.10$ to $.28$) between a composite of self-report sleep quality and actigraphy duration, midpoint, sleep onset latency, and wake after sleep onset (WASO) (Teas & Friedman, 2021). Moreover, a mismatch between subjectively and objectively measured sleep characteristics can indicate additional sleep issues (Bianchi et al., 2013). While incorporating objective measurement of sleep involves high cost, participant burden, and small sample size, joint assessment of subjective, objective, and match between subjective/objective sleep characteristics in determining sleep health phenotypes could potentially uncover new phenotypes or provide unknown information about existing phenotypes.

Several limitations should also be noted related to the archival sample and study design. First, although the data was collected at two time points rather than cross-sectionally, the design still does not test temporal precedence needed for strong causal inference (Shadish et al., 2002). We hope that our findings can ground future repeated-measures longitudinal studies that tease out directionality and timeline of change (Taris & Kompier, 2014). Additionally, in the MIDUS datasets, we could not definitively determine whether participants' job design elements changed within the same job over the two time points or changed due to a job change. While we focused on the three technology-related job design elements (i.e., computer use, sedentary work, and nonstandard schedules), we were unable to determine whether changes in these elements were indeed driven by technology. The current design still allows for examination of general increases or decreases in each design element, but future studies could gather more information behind changes in job

design elements. The MIDUS samples themselves also aim to be representative of U.S. adults – and are more representative than smaller-scale, more sparsely resourced research projects. Yet, as it applies to our study goals, the present analytic sample (i.e., a working adult subsample of MIUDS 2 and 3) is slightly less diverse than the general working adult population in the U.S in terms of race and ethnicity (BLS, 2021). We applaud MIDUS researchers for using targeted recruiting in their Milwaukee samples to increase diversity, and we encourage continued and expanded efforts in the future, among MIDUS and other ongoing data collections, to better describe more of the working population. For this reason, we also urge future researchers to replicate our findings in different and, especially, more diverse samples to test the generalizability of the sleep health phenotypes across working populations. These efforts should be grounded in strong sleep theory, such as the RuSATED framework (Buysse, 2014), when making decisions about sleep measurement and by best practice analytic guidelines for testing similarity of solutions across samples (Morin et al., 2016). Whereas consistent application of the same sleep dimensions and cut-off scores used here across different measurement techniques (i.e., self-report vs. actigraphy) and samples could enable tests of generalizability, inclusion of additional dimensions (e.g., timing, which was not included in the MIDUS dataset) or alternative measurement (e.g., evaluative measures of sleep quality, rather than sleep complaints, to measure satisfaction) could help expand understanding of the identified phenotypes and potentially identify new ones.

It is also notable that, at the time of this study, MIDUS only provided two waves of data assessing sleep health (MIDUS 2 and 3). Two waves of data are not sufficient to meet most standards of longitudinal design (Ployhart & MacKenzie, 2014). Thus, although the currently available data facilitates detailed understanding of how job design and sleep health associate over one decade, true causal attributions cannot be made. In particular, the two-wave design limited our ability to propose and test mediation, which requires at least three waves of data (Cole & Maxwell, 2003; O’Laughlin et al., 2018). Thus, we would also encourage future research in this area to rigorously test theoretically supported mediators to provide more explanatory detail about the mechanisms and causal chain of events connecting job design to employee sleep health (MacKinnon et al., 2007). The collection of additional MIDUS data would also allow extension of the timeline of sleep phenotype trajectories and provide more recent data, beyond 2017, when considering questions about current technology and sleep. Further, an extension could answer questions about how sleep phenotypes change across life stage, age, or, for example, when people transition from employment to retirement. Additionally, the first wave in our study (MIDUS 2) began data collection in 2004, and the second wave (MIDUS 3) ended data collection in 2017. Since then, not only has technology continued to advance but the COVID-19 pandemic has drastically changed where, when, and how work is done (e.g., Collins et al., 2020; McDowell et al., 2020). Purposeful additions to future MIDUS data collections could include variables that support the most up-to-date understanding of sleep health (i.e., also including timing) and, especially, of technology-related job design elements.

Finally, our model is limited in its ability to fully test Balance Theory. We test its first tenet by identifying two negative elements of job design as they relate to specific patterns of suboptimal sleep health. Now, additional efforts theoretically and practically needed

to identify positive elements of job design that would counterbalance effects for each suboptimal sleep health phenotype (i.e., second tenet of the theory) and test mediators such as cognitive, psychological, or physical loads (i.e., mechanisms proposed by the theory; Carayon, 2009).

Conclusion

Employers have a financial interest and, some argue, moral obligation to design work that protects employee health (Pfeffer, 2010, 2018). Yet protection of employee sleep health is challenging not only because of the overwhelming prevalence of sleep issues (Roennenberg, 2013; Stranges et al., 2012) but because technology has comprehensively and continually changed how jobs are designed. The present study connects technology-related job design to specific phenotypes of suboptimal sleep health over one decade, which extends the Balance Theory of Job Design to the context of employee sleep health. Sedentary work is linked to an *insomnia sleeper* phenotype, exhibiting four co-occurring insomnia symptoms. Nontraditional work schedules, specifically night shifts, are linked to a *catch-up sleeper* phenotype, who nap during the day and sleep longer on weekends. Although about half of workers in a national representative sample were *good sleepers*, all sleep health phenotypes – whether optimal or suboptimal – were typically stable, in line with expectations from dynamic equilibrium theory but expanding the previous timeline of stability from months (Henderson et al., 2023) to a decade. This elevates the challenge but also importance of sleep health interventions, like those targeting job design. Informed job design could potentially protect employees from becoming trapped in a pattern of suboptimal sleep that could persist at least as long as a decade. Occupational health researchers should consider measuring employee sleep health as a dynamic and multidimensional phenomenon to more accurately and deeply understand this key ingredient in worker health and productivity.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgements:

Since 1995 the Midlife in the United States Study has also been funded by the following: John D. and Catherine T. MacArthur Foundation Research Network, National Institute on Aging (P01-AG020166), and National Institute on Aging (U19-AG051426). Data and documentation for all MIDUS projects are available to other researchers at the Inter-university Consortium for Political and Social Research (ICPSR). In addition to the publicly-available data at ICPSR, a MIDUS-Colectica Portal (midus.colectica.org) contains rich searchable metadata, links to documentation, and the ability to download datasets. The current study was not preregistered with an analysis plan in an independent, institutional registry.

Funding:

This study was supported by grants from the National Institute on Aging (PI: Lee, Grant No. 1R56AG065251 – 01A1).

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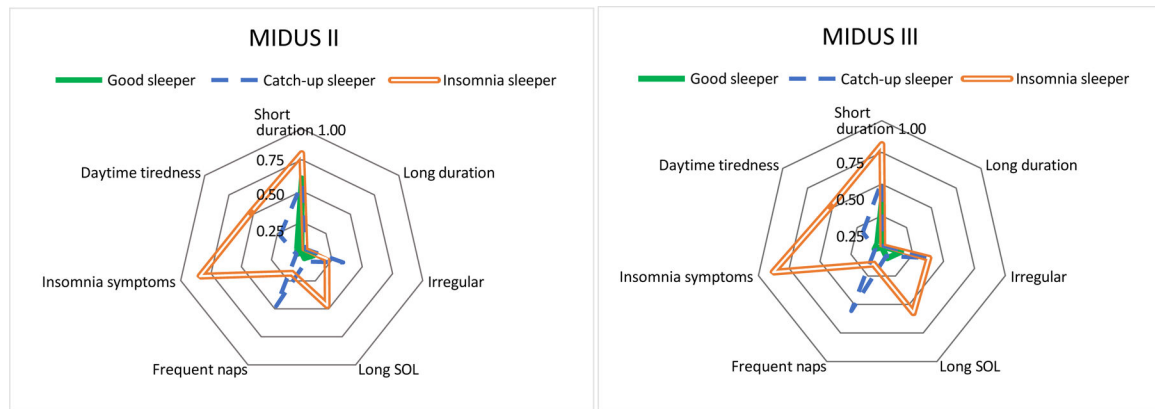


Figure 1.

Proportion of each of the three identified latent classes exhibiting suboptimal sleep health across six dimensions at each time point.

Note. SOL=sleep onset latency. Values indicate proportion of each class exhibiting suboptimal levels of each sleep health characteristic based on cut-offs from the sleep literature (i.e., short duration is <7 hours; long is >9 hours; irregular is > 1 hour difference between weekend and workday sleep duration; long sleep onset latency is >30 minutes; frequent naps are 4+/week (or naps on most days); insomnia symptoms and daytime tiredness cut-offs are “often” or “almost always” on these subjective experience. Values closer to the center indicate more optimal sleep (i.e., closer to 0% of the phenotype exhibiting suboptimal sleep on that dimension) whereas values closer to the perimeter indicate more suboptimal sleep (i.e., closer to 100% of the phenotype exhibiting suboptimal sleep on that dimension).

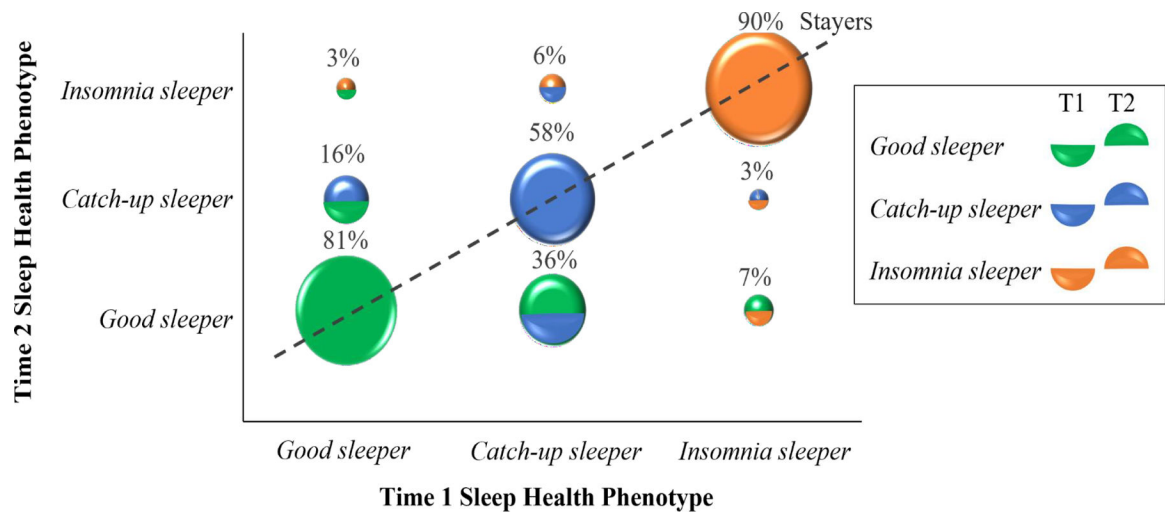


Figure 2.

Latent transition probabilities conditional on baseline sleep health phenotype.

Note. Bubbles represent percentage of participants in a given phenotype at time 1 (*good*, *catch-up*, or *insomnia sleeper*) who stayed in the same phenotype (i.e., “stayers”, place on the dotted diagonal line) or transitioned to a different phenotype (i.e., “movers” or darker spheres not on the diagonal) at time 2. Colors on the bottom half of the bubble represent sleep health phenotype at T1; colors on the top half of the bubble represent sleep health phenotype at T2. Values within each column sum to 100%.

Table 1.

Sleep health facet measurement and cut points.

RuSATED Dimension	Sleep Health Facet	MIDUS Items	Cut Point
Regularity	1. Regularity of sleep duration	Difference Between Workday Sleep Duration and Non-Workday Sleep Duration	Irregular: Absolute Value > 60 Minutes (Lee et al., 2022) Regular: Absolute Value ≤ 60 Minutes
Satisfaction	2. Insomnia symptoms	Please indicate how often you experience each of the following:	
		Have trouble falling asleep.	Symptoms present: Often or Almost Always (on at least 1 of the 3 items) Symptoms not present: Never, Rarely, or Sometimes (on all 3 items) (see Chen et al., 2017; Ohayon et al., 2017)
		Wake up during the night and have difficulty going back to sleep.	
		Wake up too early in the morning and be unable to get back to sleep.	
Alertness	3. Daytime tiredness	Feel unrested during the day, no matter how many hours of sleep you had.	High daytime tiredness: Often or Almost Always Low daytime tiredness: Never, Rarely, or Sometimes (to align with cut-offs for insomnia symptoms)
	4. Nap frequency	During a usual week, how many times do you nap for 5 minutes or more?	No naps: 0 Occasional naps: 1–3 Frequent naps: ≤ 4 (see Ohayon et al., 2017)
Timing	Not measured		
Efficiency	5. Sleep onset latency	How long does it usually take you to fall asleep at bedtime?	Efficient: ≤ 30 Minutes Inefficient: >30 Minutes (Ohayon et al., 2017)
Duration	6. Average sleep duration	How much sleep do you usually get at night (or in your main sleep period)? ³	Short duration: < 7 Optimal duration: ≥ 7 & ≤ 9 (Hirschkowitz et al., 2015) Long duration: > 9

Note. For duration, the question posed both for weekday/workday and weekend/non-workday. Average duration calculated using a weighted average wherein weekday duration was weighted x5 and non- workday duration was weighted x2.

Table 2.

Correlations and descriptive statistics.

	M	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. Duration T1	6.50	0.97																	
2. Irregular T1	0.81	1.39	.22**																
3. SOL T1	0.34	0.47	-.13**	.17**															
4. Insomnia	2.35	0.89	-.23**	-.01	.41**														
Symptoms T1																			
5. Tiredness T1	2.61	1.07	-.14**	.19**	.20**	.43**													
6. Nap Freq. T1	1.52	2.19	-.06	.08	.07*	.05	.12**												
7. Duration T2	6.07	2.58	.16**	-.10*	.06*	-.12**	-.07*	-.02											
8. Irregular T2	0.84	0.97	.02	.21**	.00	-.01	.07*	.06*	-.10**										
9. SOL T2	0.43	0.53	-.05	.30**	.32**	.22**	.14**	.07*	-.18**	.08**									
10. Insomnia	2.49	0.97	-.16**	-.04	.24**	.55**	.24**	.02	-.32**	.04	.35**								
Symptoms T2																			
11. Tiredness T2	2.29	1.35	-.12*	.00	.16**	.21**	.34**	.06	.48**	.14**	.14**	.50**							
12. Nap Freq. T2	1.54	2.59	-.12**	-.02	.01	-.04	.07*	.44**	.17**	.16**	-.03	-.05	.22**						
13. Sitting T1	2.86	1.23	.12**	.07	-.07*	-.07*	-.06	.10**	.01	-.02	-.02	-.06	-.03	.09**					
14. Computer T1	2.49	1.35	.19**	.08	-.03	-.03	-.01	.17**	-.01	-.02	.04	-.04	-.02	.13**	.56**				
15. Nontrad T1	0.46	0.50	.02	-.06	-.01	-.05	.02	.08*	-.07*	-.01	.06	-.05	-.01	.08*	.15**	.16**			
16. Sitting T2	2.22	1.57	.05	.02	.06*	-.03	-.06	.05	.44**	-.01	-.05	.01	.33**	.16**	.48**	.32**	.00		
17. Computer T2	1.90	1.47	.13**	.01	.02	-.06*	-.04	.11**	.40**	-.01	-.03	.01	.29**	.21**	.40**	.54**	.06*	.72**	
18. Nontrad T2	0.45	0.50	.08	.14**	.01	-.03	.07*	.14**	-.06	.01	.11**	-.03	-.04	.12**	.15**	.14**	.38**	.08**	.10**

Note. *N* ranges from 1042 to 1297.**
p<.01.

* p<.05. Continuous sleep health variables are used. SOL=sleep onset latency. Irregular = irregularity. Freq.=frequency. Computer= Computer use. Nontrad.= Nontraditional work schedule.

Table 3.

Model fit statistics for the latent transition solutions.

# of classes	Free parameters	AIC	BIC	SSA-BIC	Entropy
2	43	15000.36	15222.58	15085.99	0.8
3	80	14798.14	15211.57	14957.45	0.72
4	127	14744.88	15401.88	14997.77	0.70
5	184	14746.31	15697.19	15112.71	0.71

Note. Gray shading indicates good model fit across both time points. The bold outline indicates that the three-class solution provides the best fit across indices (i.e., lowest BIC and SSA-BIC, and acceptable entropy).

Table 4. Sleep health characteristics probabilities of the three identified latent classes at each time point.

	Class #	N	%	Short duration	Long duration	Irregular	Long SOL	Frequent naps	Insomnia symptoms	Daytime tiredness	Class name
Time 1	1	741	57.13%	0.60	0.00	0.10	0.05	0.00	0.04	0.05	Good sleeper
	2	339	26.14%	0.56	0.05	0.34	0.08	0.47	0.05	0.23	Catch-up sleeper
	3	217	16.63%	0.80	0.03	0.21	0.47	0.18	0.84	0.52	Insomnia sleeper
	Class #	N	%	Short duration	Long duration	Irregular	Long SOL	Frequent naps	Insomnia symptoms	Daytime tiredness	Class name
Time 2	1	735	56.70%	0.37	0.01	0.16	0.10	0.00	0.06	0.05	Good sleeper
	2	324	24.98%	0.52	0.02	0.38	0.08	0.56	0.05	0.19	Catch-up sleeper
	3	238	18.35%	0.81	0.01	0.38	0.57	0.15	0.88	0.52	Insomnia sleeper

Note. SOL=sleep onset latency. Values indicate proportion of each class exhibiting unhealthy or undesirable levels of each sleep health characteristic based on cut-offs from the sleep literature (i.e., short duration is <7 hours; long is >9 hours; irregular is > 1 hour difference between weekend and weekday sleep duration; long sleep onset latency is >30 minutes; frequent naps are 4+ /week (or naps on most days); insomnia symptoms and daytime tiredness cut-offs are “often” or “almost always” on these subjective experiences).

Table 5.
Latent transition probabilities conditional on baseline sleep health class.

		Class T2		
		Good	Catch-up	Insomnia
Class T1	Good	80.84%	16.46%	2.70%
	Catch-up	35.69%	57.82%	6.49%
	Insomnia	6.91%	2.76%	90.32%

Note. Percentages in each row add up to 100%. Values represent percentage of people belonging to each sleep health class at T2 given membership in a certain class at T1. Bold values indicate the sleep health class most participants belong to at T2 per each class at T1.

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Table 6.

Standardized change in job design factors associated with sleep health phenotype transitions.

Δ Job design	Focal group	B	SE	p	Exp(B)	CI
Computer use	Good→Catch-up	-0.29	0.17	0.08	0.75	[0.543,1.039]
	Good→Insomnia	0.45	0.37	0.23	1.56	[0.758,3.226]
	Catch-up→Good	0.08	0.17	0.63	1.09	[0.78,1.509]
	Catch-up→Catch-up	0.10	0.14	0.45	1.11	[0.849,1.449]
	Catch-up→Insomnia	0.07	0.32	0.82	1.07	[0.573,2.012]
	Insomnia→Good	0.31	0.48	0.52	1.36	[0.536,3.458]
	Insomnia→Catch-up	-0.15	0.15	0.29	0.86	[0.646,1.142]
	Insomnia→Insomnia	-1.26	0.53	0.02	0.28	[0.101,0.793]
Sitting at work	Good→Catch-up	0.02	0.17	0.89	1.02	[0.737,1.421]
	Good→Insomnia	-0.42	0.35	0.23	0.66	[0.327,1.312]
	Catch-up→Good	0.04	0.17	0.82	1.04	[0.745,1.452]
	Catch-up→Catch-up	-0.08	0.14	0.54	0.92	[0.703,1.203]
	Catch-up→Insomnia	-0.56	0.33	0.09	0.57	[0.298,1.086]
	Insomnia→Good	-0.85	0.45	0.06	0.43	[0.177,1.038]
	Insomnia→Catch-up	0.29	0.70	0.68	1.34	[0.336,5.309]
	Insomnia→Insomnia	0.38	0.15	0.01	1.46	[1.091,1.956]
Nontraditional schedule ^a	Good→Catch-up	0.66	0.29	0.02	1.94	[1.103,3.401]
	Good→Insomnia	-0.32	0.66	0.63	0.73	[0.201,2.64]
	Catch-up→Good	-0.25	0.29	0.40	0.78	[0.44,1.391]
	Catch-up→Catch-up	0.48	0.23	0.04	1.62	[1.026,2.552]
	Catch-up→Insomnia	0.34	0.59	0.57	1.40	[0.438,4.478]
	Insomnia→Good	1.27	0.82	0.12	3.56	[0.719,17.599]
	Insomnia→Catch-up	2.68	1.16	0.02	14.66	[1.505,142.727]
	Insomnia→Insomnia	0.33	0.25	0.18	1.39	[0.859,2.247]

Note. Bold values are significant at $p < .05$. Good→good is the reference group.

^a raw score (not z- scores) used for this binary variable (0=traditional schedule, 1=nontraditional). Positive B values indicate that a (greater than average) increase in the job design over time relates to higher probability of belonging to the focal transition group than consistently *good sleeper*; negative indicates a (greater than average) decrease in job design over time relates to higher probability of belonging to the focal group than consistently *good sleeper*. Exp(B) is odds ratio; confidence interval not including 1.00 indicates significance.