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ORIGINAL PAPER

Hard Work Makes It Hard to Sleep: Work Characteristics Link to Multidimensional Sleep Health Phenotypes

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Abstract

Work is closely intertwined with employees' sleep quantity and quality, with consequences for well-being and productivity. Yet despite the conceptualization of sleep health as a multidimensional pattern of various sleep characteristics, little is known about workers' experiences of the diverse range of sleep health dimensions (e.g., sleep regularity, daytime alertness, and sleep efficiency in addition to quantity and quality) proposed by contemporary frameworks. The present study integrates modern sleep frameworks with the Job Demands-Control-Support Model to describe common multidimensional sleep health phenotypes among employees and their associations with job characteristics. Across two national samples ($N_1 = 2353$; $N_2 = 1260$) of working adults from the Midlife in the United States study, latent class analysis indicated three common sleep health phenotypes: (1) *good sleepers* who exhibit good sleep across all dimensions, (2) *catch-up sleepers* who sleep longer on non-workdays and shorter on workdays but exhibit otherwise good sleep, and (3) *short, dissatisfied, inefficient, and irregular sleepers* (SDIIs) who were suboptimal across four of the five measured sleep health dimensions. Good sleepers reported low job demands, high control, and high support (similar to a low-strain job). Catch-up sleepers reported high job control and moderate demands and support (similar to an active job). SDIIs reported high demands, low control, and low support (similar to a high-strain job). We discuss implications for job characteristics theories, sleep health frameworks, and practical management of employee sleep when measured as a multidimensional pattern of sleep health experiences.

Sleep is not only a biological necessity (Eidelman, 2002) but is now recognized as a core component of both employee health and organizational functioning. The health consequences of insufficient sleep are extensive and wide-ranging, including greater risk of depression (Zhai et al., 2015), cardiovascular disease (Cappuccio et al., 2011), and all-cause mortality (Gallicchio & Kalesan, 2009). In the workplace, poor sleep is associated with worse performance (Henderson & Horan, 2021), fewer organizational citizenship behaviors (Barnes et al., 2013), and greater risk for workplace injury (Brossoit et al., 2019) as well as engagement in abusive leadership (Tariq et al., 2019) and unethical behaviors (Barber & Budnick, 2015). Despite its importance, healthy sleep evades many workers. Sleep researchers have declared a "sleep crisis" (see Barnes & Drake, 2015) based on findings that one in three American adults experiences consistently insufficient sleep (CDC, 2021). Insufficient sleep, at this scale, costs tens of billions of dollars to economies around the world each year (Hafner et al., 2017).

Organizations shape employees' schedules, moods, energy levels, and attitudes (ten Brummelhuis & Bakker, 2012) and, in turn, have a profound influence on their sleep (Barnes et al., 2016; Basner et al., 2014; Crain et al., 2017). Careful consideration of how work experiences relate to sleep health may benefit employers and employees alike (Barnes & Drake, 2015). A growing body of research has begun to clarify the work-sleep link. This literature has generally been informed by work characteristics theories (i.e., Job Demands-Resources Theory or JDR, Bakker & Demerouti, 2014; Job Demands-Control or JDC, Karasek, 1979; Job Demands-Control-Support or JDCS, Johnson & Hall, 2011). Negative, stressful work experiences (i.e., *job demands*) often incite ruminative thoughts about work (Haun & Oppenauer, 2019; Matick et al., 2021; Van Laethem et al., 2015, 2018) and physiological activation (Härmä, 2006), which undermine good sleep. Conversely, positive work experiences (i.e., *job resources*) such as *job control* (see

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Van Laethem et al., 2013) and *social support* (Matick et al., 2021) can benefit sleep. These findings align with the *strain hypothesis* which asserts that low demands, high control, and high social support at work predict better well-being (Johnson & Hall, 2011; Karasek, 1979).

These foundational results provide a framework of work characteristics associated with employees' sleep, primarily their sleep quantity (i.e., duration) or quality (i.e., subjective satisfaction with sleep) (see Crain et al., 2017; Henderson & Horan, 2021). Now, additional efforts are needed to bring the organizational sciences into alignment with current state-of-the-art conceptualizations of sleep health. Sleep experts assert that sleep health is multidimensional, characterized not only by appropriate sleep quantity and high quality but also by other features such as daytime alertness, short sleep onset latency (i.e., time to fall asleep), and sleep schedule regularity (Buysse, 2014). Furthermore, emerging evidence from the sleep literature suggests that sleep dimensions co-occur in differing patterns within people (Lee et al., 2019; Matricciani et al., 2020). For example, although some people may experience holistically optimal or holistically suboptimal sleep health across dimensions, others may experience nuanced mixes of optimal and suboptimal characteristics (e.g., low daytime alertness despite sufficient sleep duration; Wallace et al., 2019). Rigorous measurement of sleep health should consider *multiple dimensions as they co-occur within people* ("sleep health phenotypes") to provide a comprehensive and detailed picture of employee sleep. Indeed, emerging research finds that sleep health phenotypes are indicative of a person's overall well-being, predicting outcomes like quality of life (Magee et al., 2017) and body mass index (Magee et al., 2016). Currently, however, little is known about how sleep health phenotypes manifest within working adults or how their work experiences associate with these phenotypes.

The present study combines traditional work characteristics theories (JDC[S]) with an advanced model of sleep health (Buysse, 2014) to clarify the work features associated with employees' within-person patterns of multidimensional sleep health. Our research makes two key contributions to the occupational health psychology literature. First, we aim to better describe sleep health in working adults. Using a person-centered approach across two large, independent samples, we identify common healthy and unhealthy sleep phenotypes in US working adults. We also provide validity support with regard to the healthiness of the identified sleep phenotypes by examining their associations with overall health status (i.e., self-evaluated health). These results can help determine commonly co-occurring sleep issues in working adults, which could inform interventions targeting key sleep dimensions, perhaps simultaneously. Second, we test whether work characteristics predict membership in the identified sleep phenotypes. Theoretically, this test assesses the ability of traditional work characteristic theories to explain sleep experiences, a complex but key aspect of employee health. Practically, our findings may point to the work characteristics most relevant to healthy and unhealthy sleep patterns, potentially informing healthy job design and employee sleep interventions.

Identifying Multidimensional Sleep Health Phenotypes in Working Adults

Sleep is a reversible physiological and behavioral state of unconsciousness and disengagement from the immediate physical environment (Carskadon & Dement, 2011; Chokroverty, 2017). Although the exact purpose of sleep is not known, its connection to employee well-being and performance may be explained by its role in consolidating memory (Sejnowski & Destexhe, 2000) as well as physiological, cognitive, energetic, and psychological recovery (Eidelman, 2002; Schmidt, 2014; Slater, 2008). As mentioned, current models conceptualize sleep health as a multidimensional phenomenon. Specifically, Buysse (2014) outlines six critical and unique dimensions that characterize healthy sleep in his "Ru-SATED" framework, based on their empirical associations with long-term health outcomes. The Ru-SATED dimensions include: (1) **R**eg**u**larity (i.e., variability in sleep duration and/or timing), (2) **S**atisfaction (i.e., subjective sleep quality), (3) daytime **A**lertness (i.e., lack of sleepiness and/or infrequent napping during the day), (4) **T**iming (i.e., sleep and wake times), (5) **E**fficiency (i.e., time to fall asleep, also known as sleep onset latency), and (6) **D**uration (i.e., sleep quantity per night). These dimensions have been popularized and validated in the sleep literature across a variety of methods and samples (Lee et al., 2022; Ravyts et al., 2019; Wallace et al., 2021), suggesting they are consistent and powerful indicators of sleep health.

Within Buysse's framework, healthy sleep is not defined by each of these dimensions in isolation but, rather, together as a "multidimensional pattern" (p. 12) reflecting healthy sleep across each dimension. Conversely, unhealthy sleep may vary in its manifestation, ranging from only one unhealthy dimension in the context of otherwise healthy sleep to entirely unhealthy sleep across all dimensions. This definition of sleep health as the co-occurrence of a variety of dimensions has spurred recommendations to apply person-centered analyses (e.g., cluster, latent class, latent profile analyses; Matricciani et al., 2018). Whereas traditional variable-centered strategies (e.g., regression, ANOVA) assume a given sample and population are relatively homogenous and can therefore be accurately described by "a single set of 'averaged' parameters", person-centered strategies can detect unobserved subpopulations "characterized by different sets of parameters" (p. 8, Morin et al., 2016). In this way, person-centered analyses allow sleep researchers to detect subpopulations that differ in their multidimensional sleep health and thus to identify common configurations of the various sleep dimensions as they exist within people (Matricciani et al., 2018).

Researchers have recently begun to identify multidimensional sleep phenotypes, particularly among children (Lee et al., 2019; Magee & Blunden, 2020; Magee et al., 2017; Matricciani et al., 2020). Adults, whose benchmarks of healthy sleep differ significantly from children's (Hirshkowitz et al., 2015; Ohayon et al., 2017), have also been sampled in several sleep phenotype studies. These initial studies on adults consistently reveal a prevalent *good sleeper* phenotype, for whom all or most sleep dimensions are optimal. The number of unhealthy sleep phenotypes identified, however, ranges from one (Yildirim & Boysan, 2017) to four (Lee et al., 2022; Magee et al., 2016; Yu et al., 2017). Although certain phenotypes are replicated across two studies (i.e., long sleep duration, Magee et al., 2016; Matricciani et al., 2021; poor subjective sleep, Magee et al., 2016; Selvi et al., 2018), many unique phenotypes idiosyncratic to one sample have also been identified. For instance, Wallace et al. (2019) found a phenotype exhibiting long duration and high daytime sleepiness in the context of otherwise satisfying sleep, Magee et al. (2016) found a minor sleep disturbances phenotype, and Yu et al. (2017) found a difficulty falling asleep phenotype, all of which were unique to those studies.

The lack of clarity in the existing literature's description of various forms of adults' unhealthy sleep may be a function of the varying populations sampled. By targeting specific populations—such as community-dwelling older adults (Wallace et al., 2019), patients with major depressive disorder (Selvi et al., 2018), Australian parents of adolescents (Matricciani et al., 2021), or Chinese college students (Zhou et al., 2019)—researchers may be identifying unhealthy sleep phenotypes (i.e., co-occurring sleep issues) idiosyncratic to those groups, resulting in inconsistent findings across studies. Seemingly, unhealthy sleep manifests differently across various adult populations. Working adults are a substantial population that suffer unique sleep challenges (e.g., short duration, heightened sleep disorder symptoms; Swanson et al., 2011). As such, information is needed about how healthy and unhealthy sleep manifests in this at-risk group. Yet only one study, thus far, has examined sleep phenotypes in a working adult sample (Magee et al., 2016). This study revealed a healthy *good sleeper* profile as well as four unhealthy phenotypes (*poor sleepers*, *frequent sleep disturbances*, *minor sleep disturbances*, and *long sleepers*) and validated these phenotypes as predictors of physical fitness outcomes (i.e., body mass index, waist circumference, and physical activity). Further information about multidimensional sleep health phenotypes among working adults is needed for several reasons. First, the person-centered analyses used to identify the phenotypes are empirically derived; in this nascent research area, replication across worker samples is needed to determine whether findings are generalizable. Second, strong sleep health frameworks, such as Ru-SATED (Buysse, 2014), should be but are rarely applied in these efforts. We explore sleep health phenotypes in two nationally representative and independent samples of adult workers to add rigor and potentially increase generalizability to the foundational work in this area. We also assess five of the six critical sleep health dimensions outlined by Buysse (2014), excluding only *timing* which was not measured in the present dataset.

> **Research Question 1**: What sleep health phenotypes emerge in working adults when considering five key dimensions (i.e., regularity, satisfaction, alertness, efficiency, and duration)?

As part of this aim, we examine the validity of the sleep health phenotypes in predicting employee health, namely self-evaluation of physical health which can be considered "a simple but valid proxy measure for health status" (p. 419, Froom et al., 2004). Establishing validity is an important step in rigorously substantiating results of person-centered analyses (Morin et al., 2016; Spurk et al., 2020) and, here, may provide information about the relative healthiness of different within-person patterns of sleep health dimensions among working adults. Thus, to facilitate interpretability of the identified sleep health phenotypes, we explore what they indicate about a person's perceived health status.

Exploring the Connection Between Work Characteristics and Sleep Health Phenotypes

Experiences at work are a meaningful determinant of sleep experiences (Litwiller et al., 2017). Indeed, previous research has reported the associations of job characteristics with individual sleep variables. Such research often supports the strain hypothesis within JDC(S): demands generally undermine healthy sleep (e.g., Litwiller et al., 2017) whereas control (de Lange et al., 2009; Litwiller et al., 2017) and support (Kent de Grey et al., 2018; Linton et al., 2015) generally benefit healthy sleep. Most of this research focuses on sleep quantity and quality, as mentioned, but there is some emerging support for this model with some of the remaining Ru-SATED facets (Iwasaki et al., 2018; Radstaak et al., 2015; Van Laethem et al., 2018).

Despite a considerable pattern of support for JDC(S) in these studies, other research reports unexpected results when linking work experiences to various sleep facets. For instance, JDC(S) suggests that job demands should undermine healthy daytime alertness in the form of more frequent napping. Counter to this expectation, the limited research examining job demands and napping finds the inverse relation, such that lower demands relate to more frequent napping (Barthe et al., 2016; Karhula et al., 2013). This finding is not conceptually surprising, as people with lower job demands may nap more frequently due to their greater logistical availability and lower physiological activation, but it is not accurately described by the strain hypothesis. Furthermore, it is unknown whether frequent napping in this context represents poor sleep health, because other sleep dimensions have not been assessed. In another study, lower job control unexpectedly related to longer, rather than shorter, sleep duration (Takahashi et al., 2014). Further, studies that connect job characteristics to multiple sleep facets report differential associations (Bernecker & Job, 2020; Hu et al., 2019; Litwiller et al., 2017), indicating that job characteristics do not uniformly impact sleep health. In total, previous studies linking JDC(S) and sleep are limited by lack of consideration of multiple dimensions of sleep health and, especially, their interactions within persons.

We use a person-centered strategy not only because it can detect unacknowledged subpopulations (e.g., people who differ in their multidimensional pattern of sleep health facets, per Research Question 1) but also because it can help explain unexpected findings—and uncover new information—by capturing unique experiences of such subpopulations via their differential associations with antecedents and outcomes (Gabriel et al., 2015). Based on significant but not entirely consistent support of JDC(S) when predicting individual sleep health outcomes in existing variable-centered research, we expect some general propositions of JDC(S) to carry over to our more nuanced, person-centered approach but also explore new insights into the work-sleep link when multidimensional sleep health phenotypes are considered.

We expect the strain hypothesis to generally explain the prediction of the *most* optimal sleep health phenotype (i.e., with optimal standing on all dimensions) and *relatively* suboptimal sleep phenotypes (i.e., with suboptimal standing on one or more dimensions) by job characteristics. Of note, we focus on direct associations of individual job characteristics rather than interactive associations among multiple job characteristics due to limited support for buffering effects (i.e., interaction between job demands with control and social support) relative to direct effects in previous research (Alarcon, 2011; Gonzalez-Mulé et al., 2021; Häusser et al., 2010; Litwiller et al., 2017). We predict that job characteristics associated with low strain (i.e., lower job demands, higher control, and higher support) will be more likely for those in the most optimal sleep phenotype, or *good sleepers*. Compared to this group, those in suboptimal sleep health phenotypes may be more likely to have job characteristics associated with greater strain (i.e., higher job demands, lower control, and lower support). Though these expectations are consistent with JDC(S) propositions, our findings may determine the specific positive and negative job characteristics associated with newly identified within-person patterns of sleep health dimensions in working adults.

Hypothesis 1. Higher job demands will be associated with a higher likelihood of membership in a suboptimal sleep phenotype compared to the most optimal sleep health phenotype (or good sleepers).

Hypothesis 2. Lower job control will be associated with a higher likelihood of membership in a suboptimal sleep phenotype compared to the most optimal sleep health phenotype (or good sleepers).

Hypothesis 3. Lower social support will be associated with a higher likelihood of membership in a suboptimal sleep phenotype compared to the most optimal sleep health phenotype (or good sleepers).

Method

Participants and Procedure

We used data from the Midlife in the United States study (MIDUS), which collected national samples to better understand health across adulthood. The large size and nationally representative nature of MIDUS samples make this data well suited for latent class analyses, which can suffer from lack of generalizability if samples are small (e.g., < 500; Spurk et al., 2020) or idiosyncratic (Morin et al., 2018). The study team has published on sleep health using MIDUS data before, so we report data transparency information in Appendix A. We conducted parallel analyses across two independent MIDUS samples (i.e., subsets of MIDUS II and MIDUS Refresher samples) to further increase the rigor of our person-centered analyses. To be included in the present analytic samples, participants had to complete the self-administered questionnaire (SAQ) and indicate that they were working for pay, for at least 30 h per week, at the time of the survey.

Sample 1

Sample 1 drew from the MIDUS II (M2) dataset, which includes data from (a) the MIDUS II core study, conducted from 2004 to 2009 as a follow-up to the original MIDUS I survey, and (b) the MIDUS II Milwaukee study, conducted from 2004 to 2006 to add racial diversity to the core sample by targeting Black participants. Of the 5555 people ($N_{\text{Core}} = 4963$; $N_{\text{Milwaukee}} = 592$) who completed the MIDUS II survey, 2943 were working adults. After removing participants who did not complete the SAQ or, if they did, did not provide complete data for all relevant sleep items required for our sleep phenotype analysis (i.e., latent class analysis), the final analytic Sample 1 included 2353 workers.

Sample 2

Sample 2 drew from the MIDUS Refresher (MR) dataset, which includes data from (a) the MIDUS Refresher core study, conducted from 2011 to 2014 to recruit new participants for the MIDUS study, and (b) the MIDUS Refresher Milwaukee study, conducted from 2012 to 2013 to add racial diversity to the core refresher sample by targeting Black participants. Of the 4085 people ($N_{Core}=3577$; $N_{Milwaukee}=508$) who completed the MIDUS Refresher survey, 1832 were working adults. After exclusion of those who did not complete the SAQ or all relevant sleep items, the final analytic Sample 2 included 1260 workers.

The two analytic samples (i.e., workers only) were generally similar in their sociodemographic characteristics. Sample 1 was 50 years old on average ($SD=8.96$), and Sample 2 was 45 years old on average ($SD=11.83$). Both samples exhibited fairly even gender distribution (Sample 1 = 54% male, Sample 2 = 57% male). Both samples were also mostly non-Hispanic white (80% in both). Most participants were married and/or cohabitating with a romantic partner in both samples (approximately 73% in both samples). Sample 1 had more children on average ($M=2.63$, $SD=1.49$) than did Sample 2 ($M=1.88$, $SD=1.46$). Mean education levels were comparable in both samples (Sample 1 = 7.54/12.00, Sample 2 = 8.23/12.00), corresponding to some college but no degree or an Associate's degree on average. Furthermore, work hours were comparable across Sample 1 ($M=45.36$, $SD=8.45$) and Sample 2 ($M=44.15$, $SD=9.94$).

Measures

All data was collected via a self-report survey. More detailed information about the development and validation of scales used in the MIDUS studies can be found on their website (https://midus.wisc.edu/).

Sleep Health Dimensions

Five of Buysse's six RuSATED dimensions of sleep health were assessed in MIDUS and thus included as indicators of sleep health in the present analyses: **R**eg**U**larity, **S**atisfaction, daytime **A**lertness, **E**fficiency, and **D**uration. We use categorical rather than continuous sleep health variables based on evidence that (a) sleep dimensions are often highly skewed even in healthy and homogenous samples and (b) that non-elliptical clustering methods (e.g., latent class

Table 1 Ru-SA(T)ED sleep dimension measurement and categorization

Dimension	Variable	Assessment	Cut point
R(U)egularity	Consistency of sleep duration	Difference between workday sleep duration and non-workday sleep duration	Irregular: absolute value > 60 min (Lee et al., 2022); *Regular: absolute value ≤ 60 min
Satisfaction		*Please indicate how often you experience each of the following:*	Dissatisfied: *often* or *almost always* (on at least 1 of the 4 items) *Satisfied: *never*, *rarely*, or *sometimes* (on all 4 items) (see Chen et al., 2017; Ohayon et al., 2017)
	Trouble falling asleep	Have trouble falling asleep	
	Nocturnal awakenings	Wake up during the night and have difficulty going back to sleep	
	Early awakenings	Wake up too early in the morning and be unable to get back to sleep	
	Unrested upon waking	Feel unrested during the day, no matter how many hours of sleep you had	
Alertness	Nap frequency	During a usual week, how many times do you nap for 5 min or more?	*No naps: 0 Occasional naps: 1–3 Frequent naps: ≤ 4 (see Ohayon et al., 2017)
Efficiency	Sleep latency	How long does it usually take you to fall asleep at bedtime?	*Efficient: ≤ 30 min Inefficient: > 30 min (Ohayon et al., 2017)
Duration	Workday sleep duration	How much sleep do you usually get at night (or in your main sleep period) on workdays or workdays?	Short duration: < 7 *Optimal duration: ≥ 7 & ≤ 9 (Hirschkowitz et al., 2015) Long duration: > 9

Note. The sixth Ru-SATED dimension, timing, was not measured in MIDUS core survey. Optimal categories, as defined by the sleep literature, are indicated by * analysis using categorical indicators) provide more accurate results than elliptical methods (e.g., latent profile analysis using continuous indicators) when skewness is present (Wallace et al., 2018a, b). The sleep literature provides empirically supported recommendations for optimal scores for adults across these various dimensions as described in detail below, which we use to determine a priori cutoff scores to distinguish optimal and relatively suboptimal sleep across each sleep health dimension. Table 1 summarizes the items and cut-off values used.

Regularity can be operationalized as consistency in sleep and wake timing and, thus, sleep duration across the week (Kwon et al., 2019). We calculated regularity using the absolute value of the difference between sleep duration on workdays and non-workdays, such that a higher value indicates more extensive irregularity in sleep duration across the week. Regularity was dichotomized into regular/optimal sleep schedule (|difference| ≤ 60 min) or irregular sleep schedule (|difference| > 60 min; see Lee et al., 2022).

Satisfaction describes one's subjective sleep experience (e.g., how "good" or "poor" it was; Buysse, 2014). In MIDUS, sleep satisfaction was assessed via four items capturing frequency of poor subjective sleep experiences (e.g., waking up too early, waking up in the night; see Chen et al., 2017). For all four items, the five-point response scale ranged from 1 to 5 (i.e., 1 = *never*, 2 = *rarely*, 3 = *sometimes,* 4 = *often*, 5 = *almost always*). Mild sleep issues are admissible within the range of healthy sleep quality (Ohayon et al., 2017). Thus, satisfaction was dichotomized into satisfied/optimal (i.e., *never*, *rarely*, or *sometimes* on *all four* items, indicating infrequent subjective sleep issues) or dissatisfied (i.e., *often* or *almost always* on at least one of the four items, indicating one or more frequent subjective sleep issues).

Daytime Alertness is defined as attentive wakefulness (Buysse, 2014) and operationalized in a variety of ways including low daytime sleepiness ratings and/or infrequent napping. In MIDUS, lack of daytime alertness was assessed via one item asking participants to report how frequently they nap for 5 min or longer in a typical week. Napping is likely to increase as nocturnal sleep is insufficient and homeostatic sleep pressure increases (Cousins et al., 2021; Dijk et al., 1987). Although the scholarly literature on the healthiness of naps is inconsistent, a high frequency of naps is considered unhealthy for most adults according to the National Sleep Foundation (Ohayon et al., 2017). Three categories were thus created to describe nap frequency: no naps/optimal (i.e., 0), occasional naps (i.e., 1–3/week, indicating naps on some days), and frequent naps (i.e., 4 or more naps/week, indicating naps on most days).

Efficiency is defined as ease of falling and returning to sleep (Buysse, 2014) and can therefore be operationalized as sleep onset latency. Sleep onset latency was assessed via one item asking participants how long in hours and minutes it takes them to fall asleep at bedtime. Efficiency was dichotomized into efficient/optimal sleep (sleep onset latency ≤ 30 min) and inefficient sleep (i.e., sleep onset latency > 30 min; see Ohayon et al., 2017).

Duration was assessed via one item asking participants to report the number of hours and minutes of sleep they get during their main sleep period on a typical workday. Three categories were used to describe sleep duration: short (i.e., < 7 h), optimal (i.e., between 7 and 9 h), and long duration (i.e., > 9 h; see Hirshkowitz et al., 2015).

Self-Rated Health Status

Participants responded to one item, "In general, would you say your physical health is…?" Responses were coded from 1 (*poor*) to 5 (*excellent*). As this is a one-item measure that may be prone to self-report bias when assessing its

Table 2 Descriptive statistics and correlations

	M (M2/MR)	*SD* (M2/MR)	1	2	3	4	5	6	7	8
1. Job demands	13.71/15.50	5.21/3.15		**. 45**	**−.20**	.01	**.06**	**.15**	**.06**	**−.10**
2. Job control	14.80/16.40	5.61/13.09	**.20**		**. 27**	**−.08**	**−.05**	**.17**	**−.12**	**.16**
3. Workplace social support	8.93/8.39	3.90/1.96	**−.19**	**.22**		−.01	.01	−.01	**.09**	−.01
4. Sleep irregularity (hr.)	1.01/1.01	2.85/1.07	.05	**−.10**	−.02		.04	**.06**	**.12**	**−.28**
5. Sleep dissatisfaction	2.46/2.48	0.84/0.83	**.14**	**−.10**	**−.12**	.01		**.08**	**.44**	**−.28**
6. Nap frequency/week	3.32/1.42	5.26/2.29	−.05	**−.13**	−.02	.04	.05		.01	**−.09**
7. Sleep inefficiency (min.)	0.72/0.42	5.35/0.44	.01	**−.07**	**−.07**	**.06**	**.47**	.01		**−.22**
8. Sleep duration (hr.)	6.69/6.83	3.40/1.06	**−.08**	**.06**	**.07**	**−.31**	**−.24**	**−.17**	**-.18**	

Note. Bold values are significant at $p < .05$. Values below the diagonal represent correlations for the M2 sample. Values above the diagonal represent correlations for the MR sample

Table 3 Model fit statistics for the latent class solutions

Sample	# of classes	Free parameters	AIC	BIC	SSA-BIC	Entropy	BLRT (p)
Sample 1 (M2)	1	7	14290.89	14331.23	14308.99		
	2	15	13899.64	13986.09	13938.43	.56	−7138.45 (< .001)
	3	23	13851.96	**13984.52**	**13911.44**	.56	**−6934.82 (< .001)**
	4	31	**13849.23**	14027.90	13929.31	**.62**	−6902.98 (.10)
Sample 2 (MR)	1	7	8846.60	8882.57	8860.34		
	2	15	8655.17	8732.25	8684.61	.55	−4416.30 (< .001)
	3	23	**8605.13**	**8722.33**	**8649.27**	**.83**	**−4312.59 (< .001)**
	4	31	8603.65	8762.96	8664.49	**.75**	−4279.07 (.33)

Note. Bold text indicates best fitting solution according to each model fit statistic. The holistically best-fitting solution across the various statistics highlighted in gray

relation to the sleep phenotypes, we controlled for **negative affect** as recommended by previous research (Reio, 2010). Five items (e.g., "irritable", "upset") from the Positive and Negative Affect Schedule (PANAS; Watson et al., 1988) were included in MIDUS. Participants indicated how frequently (1 = *none of the time* to 5 = *all of the time*) they experienced each negative emotion, on average, over the past 30 days. We used the mean of the five items ($\alpha_{M2} = 0.80$; $\alpha_{MR} = 0.78$).

Job Characteristics

Job Demands ($\alpha_{M2} = 77$; $\alpha_{MR} = 0.73$) Job demands was assessed by the sum of five items that concerned cognitive demands, work overload, role conflict, time inadequacy, interruptions, and work intensity on a five-point frequency scale (1 = *never* to 5 = *all of the time).*

Job Control ($\alpha_{M2} = 0.74$; $\alpha_{MR} = 0.76$) Nine items were used to measure job control by taking the sum of items across two dimensions, *skill discretion,* which was assessed via three items (e.g., "How often does your work demand a high level of skill or expertise) and *decision authority*, which was assessed via six items (e.g., "How often do you have a choice in deciding how you do your tasks at work?). A five-point frequency scale was used for all items (1 = *never* to 5 = *all of the time*).

Social Support ($\alpha_{M2} = 72$; $\alpha_{MR} = 0.72$) A total social support score was calculated by taking the sum of five items across two sources of support, coworker and supervisor. Two items focused on coworker support (e.g., "How often do you get support from your coworkers?") and three focused on supervisor support (e.g., "How often do you get the information you need from your supervisor or superiors?"). A five-point frequency scale was used for all items (1 = *never* to 5 = *all of the time*).

Results

Analytic Approach

First, both datasets were screened for unlikely or nonsensical responses, which were found in two skewed variables, sleep efficiency and duration. Specifically, participants who reported efficiency (i.e., sleep onset latency or time to fall asleep) greater than 15 h (top 1% of responses), or greater than or equal to their time spent sleeping were excluded (3 participants in M2; 5 participants in MR). Furthermore, participants reporting 1 h or less (bottom 1% of responses) of sleep on average were excluded (2 participants in M2; 2 participants in MR). Descriptive statistics and correlations for both samples are reported in Table 2.

Next, we conducted latent class analysis (LCA) in MPlus to extract the appropriate number of sleep phenotypes in each sample based on a holistic evaluation of the potential solutions' model fit statistics and their interpretability within sleep theory. The five categorical sleep dimensions were used as latent class indicators. The identified classes were named based on their defining sleep health characteristics (i.e., the sleep health categories to which most participants within a certain class belong). We also considered the similarities versus differences between the latent classes identified across the two samples across three key criteria (see Eid et al., 2003; Morin et al., 2016): (1) *configural* (i.e., number of classes), (2) *structural* (i.e., response probabilities for each class indicator), and (3) *distributional* (i.e., relative size of classes) similarity. It is important to note, as Morin et al. (2016) explain "differences [in latent classes across samples] do not represent an inherent limitation in the data" but, instead, that "both similarity and differences provide important, albeit different, directions for subsequent investigation" (p. 235). Similarities provide evidence of generalizability across groups whereas differences provide equally important evidence of limitations to generalizability, or factors that may differ across groups or samples.

General Linear Modeling (GLM) in SPSS was then used to examine the associations between membership to the sleep health classes and health status (i.e., self-evaluated physical health), adjusting for negative affect. Finally, we used the R3STEP function in MPlus to determine the association between job characteristics and the identified sleep phenotypes. The R3STEP function runs multinomial logistic regressions between potential antecedents and relative probability of belonging to a certain latent class.

Identifying Latent Classes of Sleep Health

In answer to RQ1 regarding the number and nature of sleep health phenotypes detected among working adults, three latent classes of sleep health were identified consistently across the M2 and MR samples based on holistic evaluation of model fit (see Table 3 for summary of model fit statistics). Most importantly, the bootstrap likelihood ratio test (BLRT) reached a point of non-significance at the four-class solution in both samples, favoring the three-class solution (Nylund et al., 2007; Tein et al., 2013). Similarly, the SSA-BIC and BIC (in both samples) and AIC (in MR) both reach minimum values at the three-class solution, also indicating its good fit. Entropy was good (Clark & Muthén, 2009) for the three-profile solution in MR. Notably, though, despite its otherwise good fit, the three-class solution exhibited an entropy just below the "acceptable" range in M2 (i.e., 0.60 to 0.80 is considered acceptable and 0.80 + is considered good; Muthén & Muthén, 2007; Jung & Wickrama, 2008; Muthén, 2004), suggesting some degree of uncertainty in sorting participants into the three classes (Thompson et al., 2011). That said, entropy is not recommended for class selection (Lubke & Muthén, 2007; Masyn, 2013; Tein et al., 2013) and the average posterior probabilities of the three classes (i.e., probability of the model accurately predicting class memberships) were acceptable at 0.76 and 0.98 in M2 and MR, respectively, supporting the three-class solution.

Characterizing the Three Sleep Health Classes Across the Two Samples

The proportion of participants in each sleep class belonging to each sleep health category (e.g., satisfied versus dissatisfied; short versus appropriate versus long sleep duration) is reported in Table 4. Three similar classes were indeed identified across the two samples, (1) *good sleepers*, (2) *short, dissatisfied, inefficient, and irregular sleepers*, and (3) *catch-up sleepers* (see Fig. 1). Class 1 was the most prevalent in both samples (40% in M2; 53% in MR), but an independent-samples proportions test revealed that the relative prevalence of class 1 in the samples significantly differed ($z = -7.08$, $SE = 0.02$, $p < 0.001$) The class was characterized by low probability of belonging to any suboptimal sleep health category across the five dimensions. Thus, class 1 was named *good sleepers*. Across both samples, class 2 made up less than one-third of the total sample (27% in M2; 27% in MR), with no significant difference in relative prevalence across the samples ($z = 0.14$, $SE = 0.02$, $p = 0.45$). Class 2 was characterized by a high proportion of people belonging to four suboptimal sleep categories: dissatisfied sleep, short sleep duration, inefficient sleep (i.e., long sleep onset latency), and high irregularity; however, frequent napping was not particularly common (i.e., < 50% of the class belonging to this category) in either sample. This class was therefore named *short, dissatisfied, inefficient, and irregular sleepers*, representing the most suboptimal sleep phenotype. Finally, class 3 (32% in M2; 20% in MR) was significantly more prevalent in M2 than in MR ($z = 7.68$, $SE = 0.02$, $p < 0.001$).

Table 4 Characteristics of the three latent sleep health classes

Sample	Class	%	Irregularity		Dissatisfaction		Lack of Alertness			Inefficiency		Suboptimal Duration		
			Regular	Irregular	Satisfied	Dissatisfied	Never naps	Occasional naps	Frequent naps	Approp. SOL	Long SOL	Short	Appropriate	Long
1 (M2)	Good	40.42%	0.72	0.28	0.83	0.17	0.09	0.62	0.29	0.97	0.04	0.23	0.73	0.05
	SDII	27.20%	0.45	0.55	0.11	0.89	0.16	0.42	0.41	0.54	0.46	0.67	0.3	0.02
	CU	32.38%	0	1	0.86	0.15	0.05	0.62	0.33	0.92	0.09	0.50	0.50	0
		Sig. diff.	CU>SDII>Good		SDII>Good + CU		SDII>CU>Good			SDII>CU>Good		SDII>CU>Good		
2 (MR)	Good	53.70%	0.54	0.46	0.84	0.16	0.60	0.30	0.10	0.94	0.06	0	0.96	0.04
	SDII	26.98%	0.43	0.57	0	1	0.51	0.32	0.17	0.59	0.41	0.66	0.32	0.02
	CU	20.32%	0.26	0.74	0.88	0.12	0.55	0.26	0.19	0.92	0.09	1	0	0
		Sig. diff.:	CU>SDII>Good		SDII>CU>Good		SDII + CU>Good			SDII>CU+Good		CU>SDII>Good		

Note. Values indicate proportion of participants in each class that belong to each sleep health category. *SDII*, short, dissatisfied, inefficient, irregular sleeper; *CU*, catch-up sleeper; *SOL*, sleep onset latency; *Approp*., appropriate; *Sig. diff.*, significant differences ($p < .05$), determined by mean comparisons tests examining differences in suboptimal sleep health categories across the samples

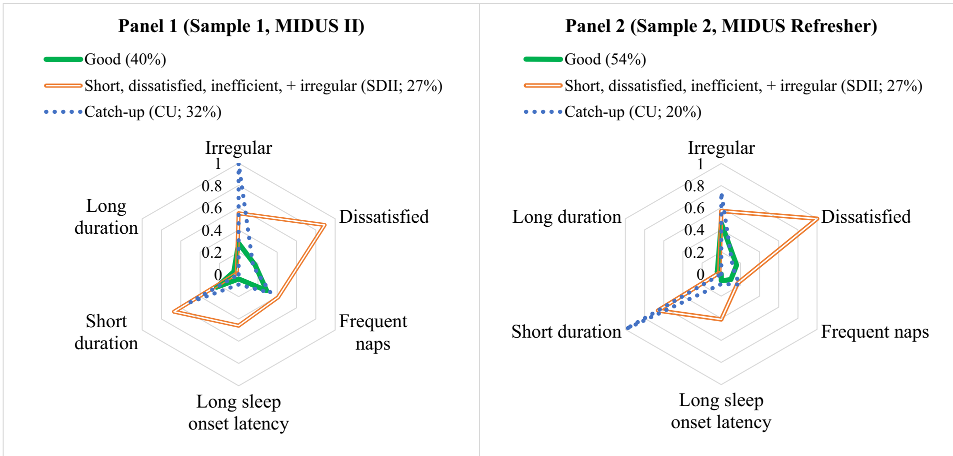

Fig. 1 Three sleep health classes across the two samples. *Note*. Graphs depict the proportion of latent class members with suboptimal sleep health on a given dimension (e.g., irregular sleep as opposed to regular sleep; short duration as opposed to optimal duration). Values near the center of the graph (0) indicate a low proportion of that latent class exhibits suboptimal sleep on that dimension; values near the outer edge of the graph (1) indicate most of that latent class exhibits suboptimal sleep on that dimension. Classes can be characterized by which sleep health dimensions they exhibit relatively extreme values (i.e., higher or lower than other classes) given that these are nationally representative samples

Class 3 characterized by a high proportion of irregular sleep and short workday sleep duration in both samples. Further inspection of participants belonging to class 3 indicated that all class members' irregularity was a function of short workday sleep duration coupled with comparatively longer non-workday sleep duration. Thus, this class was labeled *catch-up sleepers*.

In terms of generalizability, we found strong configural generalizability evidence, as three classes were consistently identified across both samples. Furthermore, independent-samples mean difference tests between the three sleep health phenotypes (see Table 4) revealed strong structural generalizability (i.e., characteristics of the classes) across the samples. For both samples, *good sleepers* were characterized by the lowest levels of suboptimal sleep health across all dimensions; *short, dissatisfied, inefficient, and irregular sleepers* were characterized by significantly worse sleep health than *good sleepers* across all dimensions in both samples; *catch-up sleepers* were characterized by the highest irregularity (i.e., short workday and long non-workday sleep) in both samples. However, we only found partial evidence for distributional generalizability (i.e., relative proportion of participants belonging to each class)—only for *short, dissatisfied, inefficient, and irregular sleepers* (about one quarter of each sample) but not for *good sleepers* (more prevalent in MIDUS Refresher) or *catch-up sleepers* (more prevalent in MIDUS II). In total, three largely generalizable sleep health classes were identified in two independent samples, though the proportion of participants belonging to each class differed depending on the sample.

Sociodemographic Characteristics

To further characterize the identified sleep health phenotypes, we compared the sociodemographic characteristics of their members using one-way ANOVAs (see Table 5). In both samples, *good sleepers* ($M_{M2} = 51$, $M_{MR} = 47$) were slightly older than *SDII*s ($M_{M2} = 49$, $M_{MR} = 45$). Of the three phenotypes, women were most prevalent in the *SDII* phenotype across both samples (M2:57%, MR:50%) whereas all other phenotypes were made up of ≤ 45% women. Across both samples, racial and/or ethnic minorities made up a greater proportion of *SDIIs* (M2:27%, MR:22%) than *good sleepers* (M2:16%, MR:16%). *Good sleepers* exhibited the highest proportion of partnered (i.e., married and/or cohabitating) people across both samples (M2: 75%, MR:78%). No significant differences in number of children were found in the MIDUS II sample, but *catch-up sleepers* had the most children on average ($M = 2.07$) compared to both *good* ($M = 1.79$) and *SDII sleepers* ($M = 1.86$) in MIDUS Refresher. *Good sleepers* were also more educated, on average ($M_{M2} = 7.81$, $M_{MR} = 8.64$) than *SDIIs* ($M_{M2} = 7.32$, $M_{MR} = 8.08$) in both samples. Overall, *good sleepers* may be older, partnered, and more educated; *SDIIs* may be more likely to be women or racial/ethnic minorities; *catch-up sleepers* may have more children.

Table 5 Comparison of sociodemographic characteristics of the sleep health phenotypes across the two samples

Sociodemographic variable	M2				MR			
	F	*p*	Effect size	Comparisons	*F*	*p*	Effect size	Comparisons
Age	16.34	**<.001**	0.01	G>S,C	2.06	0.13	0.003	G>S
Gender (0=W, 1=M)	12.91	**<.001**	0.01	G>C>S	10.97	**<.001**	0.017	C>G,S
Race (0=White, 1=Non-White and/or LatinX)	12.94	**<.001**	0.01	S>C>G	3.31	**0.04**	0.005	S>G
Partnered status (0=unpartnered, 1=married and/or cohabitating)	4.12	**0.02**	0.003	G,C>S	8.83	**<.001**	0.014	G>C,S
Number of children	0.18	0.84	<.001	N/A	3.39	**0.03**	0.005	C>G
Education	6.27	0.002	0.006	G,C>S	6.32	**0.002**	0.01	G>S

Note. G, good sleepers; *S*, SDIIs; *C*, catch-up sleepers. Effects indicate whether there are generally significant differences ($p<.05$) between the sleep health phenotypes on the sociodemographic variable of interest based on one-way ANOVA tests; comparisons indicate which phenotypes significantly differ from one another on that variable based on post hoc tests

Validity Support for the Sleep Health Classes Across the Two Samples

Sleep health class membership was significantly associated with self-evaluated physical health in M2, $F(2, 2059)=17.82$, $p<0.001$, and in MR, $F(2, 1253)=7.14$, $p<0.001$. Across both samples, post hoc comparisons indicated that *good sleepers* ($M_{M2}=2.83$, $M_{MR}=2.89$) reported significantly higher perceptions of their physical health than did *short, dissatisfied, inefficient, and irregular sleepers* (SDIIs; $M_{M2}=2.57$, $M_{MR}=2.53$). *Catch-up sleepers'* mean self-evaluated physical health ($M_{M2}=2.84$, $M_{MR}=2.80$) did not significantly differ from that of *good sleepers* in either sample; *catch-up sleepers* did, however, report significantly higher self-evaluated physical health than did *SDIIs* in M2 but only marginally so in MR ($p=0.10$). In total, as would be expected, *good sleepers* and *catch-up sleepers* perceived their physical health to be better than did *SDIIs*. This finding suggested that the identified sleep phenotypes were distinguished in their relative (perceived) healthiness.

Job Characteristics as Predictors of Sleep Health Classes

The association of job demands, control, and support with sleep health class membership is reported in detail below (also see Table 6) and summarized in Fig. 2.

H1 expected higher job demands would be associated with a higher likelihood of membership in a suboptimal sleep phenotype compared to good sleepers. Across the two samples, the greatest job demands were reported by the most suboptimal phenotype (i.e., *SDII*), relative to the most optimal phenotype (i.e., *good sleepers*) as expected (M2: $B=0.11$, $SE=0.02$, $p<0.001$; MR: $B=0.08$, $SE=0.02$, $p<0.001$). In the MIDUS II sample only, there was also a significant difference between *catch-up sleepers* and *good* sleepers such that *catch-up sleepers* reported higher job demands ($B=-0.07$, $SE=0.02$, $p<0.001$). Altogether, H1 was largely supported in that job demands were higher among suboptimal phenotypes (i.e., *SDII*s in both samples and *catch-up sleepers* in M2) than the most optimal phenotype (i.e., *good sleepers*).

Table 6 R3STEP results for job characteristics predicting sleep health phenotypes

Sample	Job characteristic	SDII (Good)			Catch-up (Good)			Catch-up (SDII)			Summary
		B	*SE*	*p*	*B*	*SE*	*p*	*B*	*SE*	*p*	
M2	Demands	0.11	0.02	**<.001**	0.04	0.02	**0.04**	−0.07	0.02	**<.001**	S>C>G
	Control	−0.03	0.01	**0.02**	0.01	0.01	0.25	0.03	0.01	**0.02**	G,C>S
	Social support	−0.09	0.03	**0.005**	−0.07	0.03	**0.03**	0.09	0.03	**0.005**	G>C>S
MR	Demands	0.08	0.02	**<.001**	0.05	0.02	**0.04**	−0.03	0.03	0.24	S,C>G
	Control	−0.06	0.03	**0.01**	−0.05	0.02	0.06	0.01	0.03	**0.04**	G,C>S
	Social support	−0.15	0.04	**<.001**	0.002	0.04	0.96	0.15	0.05	**0.0007**	G,C>S

Note. Columns indicate focal sleep health phenotype, followed by reference phenotype group in parentheses. Separate R3STEP analyses run for the relation between each job characteristic type. Positive B coefficients indicate that higher values of the job characteristic relate to greater probability of belonging to the focal class than the reference; negative coefficients indicate lower values of the job characteristic relate to greater probability of belonging to the focal class than the reference. *G*, good sleepers; *S*, SDIIs; *C*, catch-up sleepers. Summary column indicates significant ($p<.05$) differences

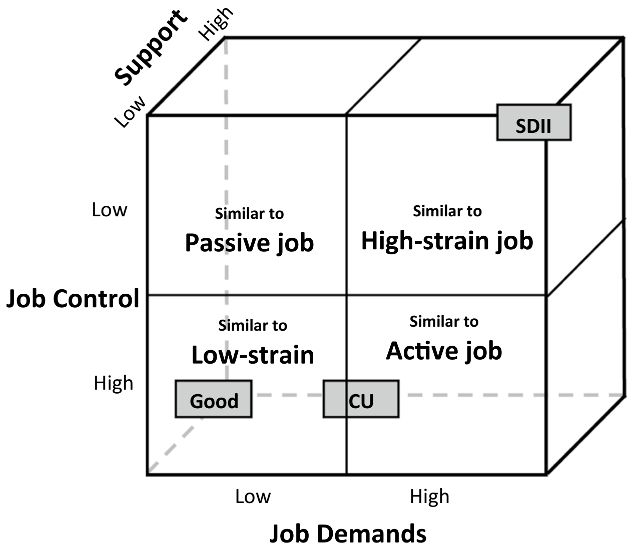

Fig. 2 Summary of job characteristics associated with each multi-dimensional sleep health phenotype. *Note.* SDII, short, dissatisfied, inefficient, and irregular sleeper; CU, catch-up sleeper. Job characteristics were modeled as independent predictors (i.e., demands, control, and support of sleep health phenotypes

H2 expected lower job control would be associated with a higher likelihood of membership in suboptimal sleep phenotypes compared to good sleepers. Across both samples, job control was lower among *SDIIs* than both *good sleepers* (M2: $B = -0.03$, $SE = 0.01$, $p = 0.02$; MR: $B = -0.06$, $SE = 0.03$, $p = 0.01$) and *catch-up sleepers* (M2: $B = -0.03$, $SE = 0.01$, $p = 0.02$; MR $B = -0.01$, $SE = 0.03$, $p = 0.04$). Job control did not significantly differ across *good sleepers* and *catch-up sleepers* in either sample. In total, H2 was supported such that *good sleepers* and *catch-up sleepers* reported higher job control than did *SDII*s across both samples.

Finally, H3 expected lower social support to be associated with higher likelihood of membership in suboptimal sleep health phenotypes compared to the optimal sleep health phenotype. As expected, social support was lower among *SDII*s compared to both *good sleepers* (M2: $B = -0.09$, $SE = 0.03$, $p = 0.005$; MR: $B = -0.15$, $SE = 0.04$, $p < 0.001$) and *catch-up sleepers* (M2: $B = -0.09$, $SE = 0.03$, $p = 0.005$; MR: $B = 0.15$, $SE = 0.05$, $p = 0.0007$). In the MIDUS II sample only, social support was lower among *catch-up sleepers* than *good sleepers* ($B = -0.07$, $SE = 0.03$, $p = 0.03$). H3 was largely supported in that social support was lowest among *SDII*s and highest among *good sleepers* (and sometimes *catch-up sleepers*).

Discussion

Sleep health promotion is pivotal for employee well-being and productivity, and it requires both thorough understanding of employees' sleep health and of organizational drivers. The present study (1) provides a description of working adults' sleep health across five key dimensions (i.e., regularity, satisfaction, daytime alertness, efficiency, and duration) and (2) identifies work characteristics (i.e., job demands, resources, and support) that relate to common sleep health phenotypes. Three sleep health phenotypes were consistently identified across two national samples of working adults: (a) *good sleepers*, (b) *short, dissatisfied, inefficient, and irregular sleepers* (SDIIs), and (c) *catch-up sleepers* (CUs). *SDII*s exhibited an especially unhealthy pattern of sleep characteristics and reported lower perceived physical health. Women and racial/ethnic minority members seem to be at increased risk of belonging to this suboptimal sleep health phenotype. Furthermore, the sleep health phenotypes were distinguished by their unique experiences at work. Namely, *good sleepers* reported relatively low job demands and high control (in line with a low-strain job), *SDII*s report relatively high job demands and low control (in line with a high-strain job), and *CU*s report relatively high job control.

Theoretical Contributions

Describing Sleep Health Experiences of Working Adults

First, our findings offer detailed information about working adults' sleep experiences, newly applying a state-of-the-art sleep health framework (Buysse, 2014) to the occupational health psychology literature. Encouragingly, *good sleepers* were the most prevalent phenotype identified across both national samples (40% of MIDUS 2 and 54% of MIDUS Refresher). This group was characterized by optimal standing on all five of the sleep health dimensions (i.e., regularity, satisfaction, alertness/nap frequency, efficiency/sleep onset latency, and duration/quantity). Although *good sleepers* were relatively common in the present samples, their prevalence also indicates that existing sleep health statistics that focus on only one dimension may exaggerate the prevalence of holistically healthy sleep that better aligns with multidimensional expert conceptualizations (Buysse, 2014). Our results across two national samples specify that *good sleep*—indicated by *co-occurring* sufficient quantity and quality, as well as other key dimensions—may occur in half or less of working adults, compared to higher unidimensional estimates that 62% of US adults achieve appropriate sleep duration (i.e., 7-9 hours; Liu et al., 2014) and 70% report absence of subjective sleep quality issues (i.e., insomnia symptoms; Roth, 2007).

The remaining half of each sample belonged to one of two suboptimal sleep health phenotypes. Whereas a *good sleeper* phenotype has been consistently identified in past research (e.g., Magee et al., 2016; Wallace et al., 2019), the two suboptimal sleep health phenotypes extracted here were novel to the present study. The replication of these phenotypes across two large, nationally representative samples bolsters confidence in their description of two common manifestations of suboptimal sleep health among working adults. *SDII*s made up approximately one-fourth (27%) of both samples and exhibited short sleep duration, high subjective dissatisfaction, inefficient sleep (i.e., long time to fall asleep), and irregular sleep duration across workdays and non-workdays; however, they did not report particularly high nap frequency. As such, although various nighttime sleep issues co-occur in this group, this pattern of otherwise unhealthy sleep does not co-occur with daytime sleep health issues (i.e., napping). Past research examining the connection between nighttime sleep and daytime napping provides ambiguous results, with some studies suggesting no relation (Pilcher et al., 2001) and others suggesting napping is associated with some poor nighttime sleep characteristics (e.g., short duration; Owens et al., 2010). The present study does not conclusively resolve this debate but does align with findings that daytime and nighttime sleep issues may not be consistently linked within people. That said, frequent daytime napping may be limited by most work schedules and work environments (see National Sleep Foundation, 2008; see also the relatively low average weekly nap frequency in the present samples: $M_{M2} = 3$, $M_{MR} = 1$), perhaps explaining why it does not tend to "hang" with co-occurring nighttime sleep issues in our worker samples.

The second suboptimal sleep health phenotype, *CUs* (32% in MIDUS 2; 20% in MIDUS Refresher), experienced a suboptimal, high level of sleep schedule irregularity (i.e., short workday sleep coupled with longer non-workday sleep) but otherwise good sleep in terms of satisfaction, daytime naps, and efficiency. Interestingly, *CU*s' self-reported physical health was comparable to that of *good sleepers* (who reported no sleep issues) and significantly better than *SDII*s' (who similarly report irregular sleep but also three other co-occurring sleep issues). Previous research reports that only a subset of people who engage in non-workday catch-up sleep effectively balance their sleep debt in doing so (Leger et al., 2020). Our examination of co-occurring sleep issues provides a plausible explanation: non-workday catch-up sleep on its own (i.e., in the *CU* phenotype) may compensate for short workday sleep without a significant, immediately noticeable hit to physical health, at least that is noticeable to this group themselves; however, this kind of irregular sleep combined with other sleep issues (i.e., dissatisfaction and inefficiency as is the case with *SDII*s) seems more definitively unhealthy.

Testing Job Characteristics Theories when Predicting Multidimensional Sleep Health Phenotypes

The present findings also newly link work characteristics to employees' holistic sleep health and, in doing so, test the propositions of JDC(S) in explaining a more advanced, multidimensional characterization of sleep. In fact, our results do largely support a key tenet of JDC(S), which posits that psychological and physical strain is worse in jobs with high-strain characteristics (i.e., low demands, high control, and high support, independently) and better in jobs with low-strain characteristics (i.e., high demands, low control, and low support, independently; Karasek, 1979). *Good sleepers*, the most theoretically optimal sleep health phenotype, indeed reported relatively low job demands, high job control, and high social support in line with a low-strain job (see Fig. 1). Offering further support, *SDIIs*, the most theoretically suboptimal phenotype, reported relatively high job demands, low job control, and low social support, in line with a high-strain job (see Fig. 1). Of note, though, job characteristics consistent with a high-strain job were reported by those with holistically unhealthy nighttime sleep (i.e., the co-occurrence of short, dissatisfying, irregular, and inefficiency sleep in *SDII*s) but *not* co-occurring daytime sleep health issues (i.e., frequent napping).

The final sleep health phenotype, *catch-up sleepers* (*CU*s), reported moderate to high levels of job demands, control, *and* support (see Fig. 2). This is a novel finding that is not entirely explained by JDC(S) or other job characteristics theories. *CU*s' job characteristics fit best with those of an active job (i.e., high demands, high control) within JDC(S). Counter to the theoretically expected health-promoting effect of job control (see also Hackman & Oldham, 1976; Spector, 1986), some previous variable-centered research has shown that higher job control relates to *shorter* sleep duration overall (Park & Kim, 2019; Parkes, 2016; Takahashi et al., 2014). Here, by examining within-person configurations of multiple sleep health dimensions, we specify the link between job control and sleep duration: this short duration tends to occur on workdays, coupled with relatively longer duration on non-workdays and otherwise healthy sleep (i.e., the *CU* phenotype). This result goes beyond the scope of JDC(S)-based explanations. One potential justification for this finding is that job control is generally a resource that promotes health (hence *CU*s' mostly good sleep health), but it also depletes personal self-control resources needed to maintain rigid boundaries between work and home life (e.g., Clinton et al., 2020) and protect sleep. Relatedly, depleted self-control may also result in bedtime procrastination, later bedtimes (see Bernecker & Job, 2020), and thus shorter sleep on workdays.

Turning finally to social support, JDC(S) accurately predicted the support reported by the phenotypes in one of the two samples. Although social support was added to the original JDC (Karasek, 1979) as a buffer of the negative impact of job demands (i.e., JDCS; Karasek & Theorell, 1990), it is also frequently positioned as a direct predictor of better health and well-being (e.g., Viswesvaran et al., 1999), including sleep outcomes (Kent de Grey et al., 2018). Aligned with this expectation, the most suboptimal phenotype, *SDII*s, reported significantly lower social support than did *good sleepers* or *CU*s. Based on these findings, we encourage the development of more nuanced models of employee sleep health, to supplement and specify predictions of JDC(S) when explaining multiple aspects of sleep health and their co-occurrence. For instance, the recent Work, Nonwork, and Sleep (WNS; Crain et al., 2017) framework currently focuses on sleep quantity and quality alone but could be expanded to include multiple sleep dimensions or common sleep phenotypes and their relations with workplace experiences.

Practical Implications

Our findings call for more thorough and targeted employee sleep interventions. The co-occurrence of multiple nighttime sleep issues in *SDII*s suggests multiple such issues may need to be tackled together as part of an overall pattern of poor nighttime sleep health in working adults. Unfortunately, typical sleep interventions are often unsuccessful in improving sleep health dimensions beyond quantity and quality (Murawski et al., 2018) and, certainly, there is a severe lack of interventions that target multiple sleep health dimensions simultaneously (Chung et al., 2021; for a notable exception see Hammer et al., 2021). We hope that the identification of the *SDII* group will guide future sleep health intervention development that targets these particular nighttime sleep issues in tandem. Job design interventions could also be paired with sleep-related interventions and policies. Namely, our results indicate that high job demands and low job control are associated with the *SDII* group that could be promising targets of organizational interventions aimed at boosting employees' holistic sleep health. Such efforts could draw from new research which outlines a promising job demands-resources intervention that effectively boosts other aspects of occupational health (i.e., work engagement; Van Wingerden et al., 2016). An effective sleep health intervention adapted from this framework might be marked by significant shifts by participants from the *SDII* group to the *good sleepers* group, for example. Our sociodemographic results also indicate that work settings employing more women and/or racial/ethnic minority members may have an increased need for sleep health interventions based on the heightened *SDII* risk for these groups.

Practical interventions regarding *catch-up sleepers*, however, may be premature. Additional research is needed to determine whether any long-term health consequences emerge for *CU*s that would warrant intervention and to more clearly identify their work characteristics to guide such interventions. That said, *CU*s are distinguished from *good sleepers* by their irregular sleep schedules. *CU*s may be able to improve their sleep health to be more consistent with the *good sleeper* group by adhering to sleep hygiene recommendations to set consistent sleep and wake times throughout the week (Dijk & Lockley, 2002; Stepanski & Wyatt, 2003). Furthermore, sleep regularity may also be supported by organizational efforts to create consistent and predictable work schedules and work demands. *CU*s are likely to have more children, meaning workers with greater family demands may need specific support around sleep regularity rather than general sleep health interventions.

Limitations and Future Directions

Several limitations should be considered when interpreting the present findings. First, work, sleep, and health variables were all collected at one time point. This methodology allows for description of the co-occurrence of work experience and sleep health at a given time. However, given that bidirectional relations between these variables are commonly found (Cho & Chen, 2020; Hanson et al., 2011; Van Laethem et al., 2015), future longitudinal research may help clarify the likely reciprocal relations between sleep health phenotypes, work characteristics, and additional health variables. Second, our data which came from the Midlife in the United States studies was slightly older than the larger American working population on average which may have colored our results. Workers may react differently to job demands and resources depending on their life and career stages (Salmela-Aro & Upadyaya, 2018). Moreover, sleep characteristics change with age (Ohayon et al., 2017) and thus recommendations on healthy sleep also differ by age groups (Hirshkowitz et al., 2015). Aligned with pushes to support successful aging in the workplace (Zacher, 2015), we encourage researchers to use subgroup analyses or moderation in the future to explicitly consider age as a relevant contributor, rather than confound, to employees' sleep health.

Additionally, our description of employees' sleep health as a configuration of five key dimensions is both theoretically grounded and more detailed than past efforts but it is certainly not comprehensive. Future efforts to describe sleep health could not only expand to Buysse's (2014) sixth dimension (i.e., timing of sleep and wake), which was not available in our datasets, but also to other sleep dimensions external to Buysse's Ru-SATED framework such as chronotype (Hittle & Gillespie, 2018), sleep continuity, and rhythmicity (Wallace et al., 2018a, b). Relatedly, objective measurement (e.g., actigraphy, polysomnography) or combined use of objective and survey methodology are increasingly used to characterize sleep health (Brindle et al., 2019; Wallace et al., 2018a, b, 2021) and could be incorporated when identifying workers' sleep health phenotypes in the future. We did not capitalize on actigraphy-measured sleep as captured in MIDUS datasets because doing so would severely limit the sample sizes needed to conduct rigorous replication analyses across two independent samples. However, future research could use this data to further examine replicability using different measurement techniques now that sleep phenotypes have been established among working adults. Relatedly, although we were able to largely replicate findings across two independent samples, the replicability of the three sleep health phenotypes found here should be tested in non-MIDUS samples, including expansion of the nomological network of work, nonwork, and health constructs associated with each phenotype.

Finally, results surrounding the *CU* profile were somewhat inconsistent across the two samples examined. Because *CU sleepers* are an entirely new sleep health phenotype identified by our targeted sampling of working adults, further efforts are needed to clearly characterize the factors driving membership to this group. Individual differences are overlooked in the JDC(S) model but often interact with job characteristics to predict stress and health (Györkös et al., 2012), which may contribute to unclear results when they are not considered. Here, it is possible that some *CU* may sleep less on workdays (and compensate non-workdays) due to positive investment in work (e.g., trait engagement) whereas others may experience this same sleep health pattern due to negative, overinvestment in work (e.g., workaholism). Other work characteristics beyond the scope of JDCS (e.g., work schedule regularity) may also play a role and should be considered as well. Overall, future research considering individual differences as potential drivers of sleep health profiles, in addition to or in conjunction with work characteristics, may thus help supplement and clarify the present results.

Conclusion

Across two large, national samples, we extracted three consistent multidimensional sleep health phenotypes based in Buysse's (2014) sleep framework. Employees' optimal sleep health can be characterized by good sleep across all dimensions (i.e., *good sleepers*), which was relatively common in the present samples (40% and 54%). Employees' suboptimal sleep health may manifest one of two main ways: (1) as the unhealthiest *short, dissatisfied, inefficient, and irregular* (*SDII*) phenotype or (2) as the *catch-up* (CU) phenotype. Our results simultaneously support key tenets of the Job Demands/Control (Support) Model (e.g., the strain hypothesis) when predicting these phenotypes while also pointing to its shortcomings when sleep health is measured as multiple, co-occurring dimensions. Furthermore, these findings emphasize that employees' healthy and unhealthy sleep is more than sufficient quantity and quality—it is a complex pattern of co-occurring sleep experiences and should be conceptualized and measured as such. Traditional organizational theories may need to be supplemented with sleep-specific models that are amenable to sleep health phenotypes to better understand the complex relationships between work and sleep.

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Data Availability The data that support this study are openly available on the Inter-university Consortium for Political and Social Research (ICPSR) website (https://www.icpsr.umich.edu/web/ICPSR/series/203).

Declarations

Competing Interests As described above, this project was funded by the National Institute on Aging, and our data came from the Midlife in the United States Study. We have no further conflicts of interest to report.

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