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10-year Stability of an Insomnia Sleeper Phenotype and Its Association with Chronic Conditions

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Abstract

Objective: To identify distinct sleep health phenotypes in adults, examine transitions in sleep health phenotypes over time and subsequently relate these to the risk of chronic conditions.

Methods: A national sample of adults from the Midlife in the United States study (*N*=3,683) provided longitudinal data with two timepoints (T1:2004-2006, T2:2013-2017). Participants self-reported on sleep health (regularity, satisfaction, alertness, efficiency, duration) and the number and type of chronic conditions. Covariates included age, sex, race, education, education, partnered status, number of children, work status, smoking, alcohol, and physical activity.

Results: Latent transition analysis identified four sleep health phenotypes across both timepoints: *good sleepers*, *insomnia sleepers*, *weekend catch-up sleepers*, and *nappers*. Between T1 to T2, the majority (77%) maintained their phenotype, with the *nappers* and *insomnia sleepers* being the most stable. In fully adjusted models with *good sleepers* at both timepoints as the reference, being an *insomnia sleeper* at either timepoint was related to having an increased number of total chronic conditions by 28-81% at T2, adjusting for T1 conditions. *Insomnia sleepers* at both timepoints were at 72-188% higher risk for cardiovascular disease, diabetes, depression, and frailty. Being a *napper* at any timepoint related to increased risks for diabetes, cancer, and frailty. Being a *weekend catch-up sleeper* was not associated with chronic conditions. Those with lower education and unemployed were more likely to be *insomnia sleepers*; older adults and retirees were more likely to be *nappers*.

Conclusion: Findings indicate heightened risk of chronic conditions involved in suboptimal sleep health phenotypes, mainly *insomnia sleepers*.

Keywords: sleep health, insomnia, nap, chronic conditions, morbidity, aging

Introduction

Aging involves neural, physiological, and functional changes that can lead to the development of chronic disease. One of the significant age-related changes is a decline in quantity of deep sleep and overall sleep quality (1,2) which poses a risk for chronic disease (3). Theoretically, sleep disturbances represent an initial reaction that, over time, can lead to disease (4,5). While studies show that poor sleep is a risk for chronic conditions (6–8), there are notable gaps in the literature. First, most prior studies used a single sleep dimension, precluding the ability to measure multiple, cooccurring dimensions and their links to chronic conditions (9,10). Second, existing evidence is primarily based on cross-sectional data that cannot assess whether changes in sleep health lead to increased or decreased risk of chronic conditions. A few studies in the cancer literature show increases in sleep problems in those with cancer (11) and a possibility of improving sleep in cancer survivors (12). Yet, there is still lack of research assessing change in sleep health and its effects on common chronic conditions over the course of aging.

Multidimensional Sleep Health Over Time

There is increasing awareness that one's sleep health needs to be measured across multiple dimensions, rather than any one individual sleep characteristic (e.g., sleep duration only). For instance, Buysse (13) suggests that six dimensions defined in his Ru-SATED framework are critical for an average adult's optimal functioning and health. Those are: **R**eg**U**larity in sleep timing and quantity, **S**atisfaction in sleep, **A**lertness during daytime, appropriate sleep **T**iming, **E**fficiency of initiating and maintaining sleep, and optimal sleep **D**uration. These sleep dimensions exist in context of each other, and may simultaneously

influence health. Co-occurring short sleep duration and poor sleep quality, for example, are risk factors for chronic conditions including hypertension (14), type 2 diabetes (15), and cardiovascular disease (16). Recently, researchers have taken a more comprehensive approach to identify several different empirically derived phenotypes of sleep health based on combinations of multiple sleep dimensions. For instance, participants with suboptimal sleep health phenotypes (e.g., "dissatisfied/inefficient sleepers" or "high sleep propensity") have higher concurrent risks of cardiovascular disease (17), and chronic physical conditions (10), and future risk of mortality (18,19). Yet, most of these studies do not capture changes in sleep health over time, despite theoretical propositions that the connection between sleep disturbances and disease endpoints may take years to develop (20).

Changes in Sleep Health and Changes in Chronic Conditions

Although there is an overall lack of longitudinal studies on sleep health and chronic conditions, the few existing studies do associate changes in sleep with health outcomes. For example, worsening sleep problems (e.g., sleep quality, refreshing sleep, sleep problems, and difficulty falling asleep) during COVID-19 were each associated with reduced mobility throughout one's community (21). Moreover, compared to people with consistently optimal nighttime sleep duration (7-8h/day), those with consistently short sleep duration and inconsistent, variable sleep duration (e.g., short to long/long to short) exhibited increased risk of multimorbidity progression (22). Based on the longitudinal associations of individual sleep dimensions with health and well-being, we now need to understand how sleep health phenotypes (within-person combinations of multiple sleep dimensions) over time relate to subsequent chronic conditions. In this study, to capture diverse chronic conditions prevalent in adulthood,

we assess the number of total chronic conditions based on a comprehensive list and six specific types of chronic conditions across physical, mental and functional domains: (a) four common chronic physical disease categories (i.e., cardiovascular diseases, cancers, respiratory diseases, and diabetes; (23)), (b) the most common mental health condition (i.e., depression; (24)), and (c) frailty, or age-related declines in physical function often associated with chronic conditions and symptoms (25,26).

Present Study

The current study examined the connection between transitions in sleep health phenotypes and chronic condition development over time. We had three aims in this study. First, we aimed to identify sleep health phenotypes that characterize one's overall sleep characteristics across five key dimensions (i.e., regularity, satisfaction, alertness, efficiency, and duration) at two timepoints approximately ten years apart. We examined how many and which sleep health phenotypes emerge among middle-aged adults and how stable the phenotypes are over the ten years. Second, we examined sociodemographic correlates of sleep health phenotypes to understand the characteristics of people who have optimal or relatively suboptimal phenotypes over time. Third, we tested whether sleep health phenotype transitions over time relate to new development of chronic conditions.

Method

Participants and procedure

Our sample is drawn from archival data from the Midlife in the United States (MIDUS) study. MIDUS is a multi-institutional, longitudinal study that used random digit dialing to obtain

a large, nationally representative sample of adults and follow their life experiences and well-being throughout adulthood (27). We used the two existing follow-ups to the core MIDUS I (1995-1996) survey, MIDUS II (2004-2006) and MIDUS III (2013-2014), as well as the corresponding Milwaukee samples, MIDUS II Milwaukee (2005-2006) and MIDUS III Milwaukee (2016-2017), which aimed at over-sampling Black participants to better understand aging and health in minority populations. Data from the self-administered questionnaire (SAQ) were used. 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 helpful documentation, and the ability to download customized datasets.

To be included in our sleep transition analysis, respondents had to answer the sleep health questions within the SAQ. Out of the complete core and Milwaukee sample (N=5,555), 529 did not provide sufficient sleep health data. Of the remaining 5,026 respondents, 73.28% responded to full demographic and health items at both MIDUS II and III, resulting in a longitudinal sample (i.e., responded at both timepoints) of N=3,683. In comparing those from the subgroup of the full sample that was excluded from analyses (i.e., baseline-only sample; N=1,872) with the final analytic sample (i.e., longitudinal sample; N=3,683),[a] the two samples did not significantly differ on sex ($F_{(1,5553)}$=3.12, p=.081) or number of children ($F_{(1,5553)}$=6.11, p=.17). However, compared to the longitudinal sample, the baseline-only sample was older (M=56.96 vs. 54.05, $F_{(1,5552)}$=68.93, p<.001) and less educated (M=6.66 vs. 7.39, $F_{(1,5552)}$=40.94, p<.001), and

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[a] Note that degrees of freedom differ slightly across comparisons due to differences in sample sizes on the comparison variables.

had a lower percentage of workers (55% vs. 68%, $F(1,5532)=93.74$, $p<.001$), a lower percentage of married/cohabitating people (66% vs. 73%, $F(1,5553)=23.89$, $p<.001$), a higher percentage of racial and ethnic minorities (23% vs. 19%, $F(1,5553)=14.15$, $p<.001$), and more chronic conditions ($M=3.01$ vs. 2.39, $F(1,4631)=51.86$, $p<.001$). Of note, though, all differences were small in size (η^2 ranging from .0001 to .016). In this manuscript, we refer to MIDUS II as Time 1 (T1) and MIDUS III as Time 2 (T2).

The final analytic sample ($N=3,683$) included slightly more women than men (66% women), was majority non-Hispanic white (80%), and had a relatively high level of formal education ($M=7.31$ out of a 12-point scale; 7 corresponds to some college-level education). At both timepoints, participants had about 2.5 children on average and about 70% were partnered (i.e., married and/or cohabitating with a romantic partner). Participants were 55 years old on average ($SD=12.45$; $Range=28$ to 85) at T1 and 63 years old on average ($SD=11.30$; $Range=39$ to 94) at T2. Most participants worked a paid job outside of the home (around 60% at both timepoints, though some were unemployed (10-15%) and some were retired (25-30%)).

Chronic conditions were fairly common at both timepoints but generally increased over time ($M_{T1}=2.54$ conditions; $M_{T2}=2.99$ conditions), including prevalence of cardiovascular conditions (15.82% at T1; 21.59% at T2), diabetes (11.16% at T1; 14.50% at T2), respiratory conditions (13.71% at T1; 15.27% at T2), cancers (12.58% at T1; 19.34% at T2), depression (8.75% at T1; 7.63% at T2) and number of frailty symptoms ($M_{T1}=0.67$ symptoms out of 5 possible; $M_{T2}=0.80$).

Measures

All items were measured consistently at both timepoints via self-report surveys (i.e., the SAQ).

Sleep Health

Due to the skewed and/or ordinal nature of self-report sleep variables[b] (28), we used categorical versions of six sleep variables that represent five sleep health dimensions (i.e., regularity, satisfaction, alertness, efficiency, and duration) collected as two timepoints as inputs for sleep health phenotypes. Sleep timing dimension was not captured through MIDUS surveys. Cut-off criteria, based on existing empirical evidence, are displayed in Table S1, Supplemental Digital Content, http://links.lww.com/PSYMED/B3.

Regularity. We operationalized sleep regularity in terms of consistency of sleep duration over the week. To do this, we took the absolute difference between workday/weekday sleep duration and non-workday/weekend sleep duration. Sleep is considered irregular if there is one hour or more of a difference between workday/weekday and non-workday/weekend sleep duration and regular if the difference is less than one hour (17).

Satisfaction (insomnia symptoms). To assess subjective sleep issues, we used three items of insomnia symptoms that align with the Diagnostic and Statistical Manual of Mental Disorders (DSM) V for clinical insomnia. Participants responded to the prompt "Please indicate how often

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[b] Sleep dimensions generally did not conform to properties of continuous variables, and a half of the sleep dimensions exhibited non-normal distributions (i.e., skewness>|2| and/or kurtosis>|7|; West et al., 1995) at both time points which could not be effectively corrected using conventional methods. Irregularity (T1: skew=2.47, kurtosis=11.74; T2: skew=2.78, kurtosis=13.34), nap frequency (T1: skew=10.30, kurtosis=54.40; T2: skew=3.90, kurtosis=32.80), and sleep onset latency (T1: skew=9.03, kurtosis=65.39; T2: skew=5.92, kurtosis=68.35).

you experience each of the following..." for "trouble falling asleep", "trouble staying asleep", and "waking up too early" on a frequency scale (1=never, 2=rarely, 3=sometimes, 4=often, 5=almost always). Because the DSM requires that insomnia symptoms be present "often or always" for diagnosis (29), participants who reported a 4+ frequency score for one or more symptoms were considered to have subjective insomnia symptoms whereas those who sometimes to never reported any symptoms were considered to have minimal symptoms.

Alertness (daytime tiredness and nap frequency). To measure daytime tiredness, participants were asked to "Please indicate how often you experience each of the following...feeling unrested during the day" on a frequency response scale (1=never, 2=rarely, 3=sometimes, 4=often, 5=almost always). Consistent with the insomnia symptom cut-off, participants who reported a 4+ frequency score for the item were considered to be high on daytime tiredness whereas a score of 3 or lower indicated low daytime tiredness. To measure daytime nap frequency, participants responded to the prompt "During a usual week, how many times do you nap for 5 minutes or more?". Excessive napping is regarded unhealthy for adults (30), particularly for chronic condition incidence (31). Thus, we considered three categories of nap frequency(30) including never (0/week), sometimes (1-3/week), and frequent napping (4+/week, indicating naps most days).

Efficiency (sleep onset latency). Participants answered one question about their sleep onset latency: "How long does it usually take you to fall asleep at bedtime?". More than 30 minutes to fall asleep were considered suboptimal whereas 30 minutes or less was considered optimal (30).

Duration. Sleep duration was assessed using two items, asking "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?" reported in hours and minutes. We calculated a weighted average of workday duration (x5/7) and non-workday duration (x2/7) based on a standard five-day work week to estimate overall average sleep duration. Using recommendations from the National Sleep Foundation (32), we categorized sleep duration into short (7 or fewer hours), optimal (between 7 and 9 hours), or long (9 or more hours).

Chronic Conditions

To assess chronic conditions across physical, mental, and functional domains, we measured the number of total chronic conditions and six specific types of chronic conditions, including four chronic physical diseases, depression, and frailty.

Number of total chronic conditions. Participants reported at both T1 and T2 how many chronic conditions they experienced or been treated by a medical doctor in the past 12 months by responding to a checklist of 30 items. We excluded three items (chronic sleep problems, anxiety/depression, and alcohol/drug problems) to (1) avoid conceptual overlap with our predictor that might inflate relationships (i.e., sleep health phenotypes and transitions with sleep problems), (2) minimize redundancy with one of the chronic condition outcomes we already included (i.e., depression), and (3) focus on chronic physical conditions that may relate to sleep transitions rather than behavioral health outcomes (alcohol/drug problems and sleep conditions may have different etiology) (33,34). The full list of conditions includes: asthma/bronchitis/emphysema, tuberculosis, other lung problems, joint or bone disease,

sciatica/lumbago/recurring backache, persistent skin trouble, thyroid disease, hay fever, recurring stomach trouble, urinary or bladder problems, constipated all or most of the time, gall bladder trouble, persistent foot trouble, varicose veins requiring medical treatment, AIDs or HIV infection, lupus or other autoimmune disease, persistent trouble with gums or mouth, persistent trouble with teeth, high blood pressure or hypertension, migraine headaches, diabetes or high blood sugar, multiple sclerosis/epilepsy/other neurological disorder, stroke, ulcer, hernia/rupture, piles/hemorrhoids, and swallowing problems.

Four specific chronic physical diseases. We assessed four common chronic physical disease categories based on previous research (23): cardiovascular diseases, diabetes, cancers, and respiratory diseases. Participants were asked "In the past 12 months, have you experienced or been treated for any of the following" for a variety of health conditions on a binary response scale (yes/no). *Cardiovascular diseases* were assessed using ten items: "heart attack", "angina", "high blood pressure", "valve disease (including mitral valve prolapse, aortic insufficiency, bicuspid aortic valve)", "hole in heart (including atrial septal defect, ventricular septal defect)", "blocked artery (including blocked/closed artery, coronary artery disease, coronary heart disease, and ischemia)", "irregular heartbeat", "heart murmur", "heart failure", and "other. *Diabetes* was assessed using one item "diabetes or high blood sugar". *Cancers* included "breast", "cervical", "colon", "lung", "lymphoma or leukemia", "ovarian", "prostate", "skin or melanoma", "uterine", or "other". *Respiratory diseases* were assessed using three items "asthma, bronchitis, or emphysema", "tuberculosis", and "other lung problems". We created a binary variable for each of the four categories such that presence of any condition within that category was coded as 1 whereas absence of condition was coded as 0.

Depressive symptoms. Because depression is underdiagnosed relative to depression symptom prevalence (35), we used a binary (yes/no) item assessing depressive symptoms, "During the past 12 months, was there ever a time when you felt sad, blue, or depressed for two weeks or more in a row?"

Frailty. We created a count of frailty symptoms guided by the five dimensions outlined by Fried et al. (2001) and guided by cut-offs in the empirical literature (37), weight loss, exhaustion, low physical activity, slowness, and weakness. *Weight loss* was assessed by one binary (yes/no) item "During the past 12 months, did you lose 10 pounds or more because of illness or health problems". *Exhaustion* was assessed by one binary (yes/no) item "During two weeks in the past 12 months, did you feel more tired out or low on energy than usual?". *Low physical activity* was by asking participants "How much does your health limit you in doing each of the following?" for five physical activity items (i.e., climbing one flight of stairs, climbing several flights of stairs, walking more than a mile, walking one block vigorous activities, moderate activities) on a frequency scale (1=a lot, 2=some, 3=a little, 4=not at all); participants reporting "a lot" of limitations on two or more activities were considered to have low physical activity symptoms. *Slowness* was assessed via two items focused on walking short distances (i.e., "How much does your health limit you...walking one block? Walking several blocks"; again, those reporting "a lot" of limitations on either (on a 1 to 4 frequency scale) were considered to have slowness symptoms. Finally, *weakness* was assessed via one item "How much does your health limit you lifting or carrying groceries" on the same frequency scale (1 to 4), with "a lot" again being the cut-off for weakness symptoms present. We then calculated a total frailty symptom score from zero to five based on the number of symptoms present.

Analytic approach

We used latent transition analysis (LTA) to extract common sleep health phenotypes over time. LTA extends cross-sectional clustering techniques like latent class analysis (LCA) to a longitudinal context (38). LCA explores how multiple dimensions of sleep health co-occur within a person and, as a result, potential subgroups within an overall population (i.e., sleep health phenotypes indicated by common within-person patterns of sleep health dimensions), whereas LTA additionally describes how a person's membership to a subgroup may be stable or change over time.

We used the three-step approach to LTA (39). Step one estimates latent class or transition models using only the latent class indicators, or variables considered part of the focal within-person pattern (i.e., sleep health dimensions here). Guided by previous studies (40–42), a good-fitting solution was determined by, in order of importance, lowest BIC and SSA-BIC statistics, theoretical interpretability of the classes, sufficient class sizes (i.e., >1% and/or >25 cases), lowest AIC statistic, and sufficient entropy (>.60 is acceptable)[c]. The LTA was run in Mplus, which extracted latent classes from the two timepoints simultaneously. Step two creates a latent transition variable, indicating whether a person remains in the same group or transition to a new one over time, based on the latent class posterior distribution output from step one.

In step three, the latent transition groups are linked to expected covariates and outcomes. Here, we first used multinomial logistic regression to test how background characteristics including sociodemographics (age, sex, race/ethnicity, education, partnered status, and number

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[c] Model fit statistics with significance testing (e.g., LMR, BLRT) are not available when class indicators are all categorical.

of children), work status (working, retired and not employed), and health behaviors (smoking status, alcohol consumption frequency, and physical activity) concurrently relate to sleep health phenotypes. Considering the potential non-linear relationship between age and sleep, we also used life stage categories (i.e., young adult: 18-29, established adult: 30-44, mid-life adult: 44-64, and older adult: 65+), instead of continuous age, to our analysis of background characteristics. We next used Poisson regression (for the number of total chronic conditions) or log-binomial regression (for each specific chronic condition type) to test the latent transition variable (i.e., sleep health phenotype transitions) as a predictor of each chronic condition outcome at T2, controlling for T1. In this model, we also adjusted for sample identifier (core vs. Milwaukee sample) and aforementioned sociodemographics, work status, and health covariates. The largest transition group identified in steps one and two was used as the reference group, outputting a risk ratio for the focal group compared to the reference.

Results

Identifying Sleep Health Phenotypes and Transitions

Four common sleep health phenotypes were identified at both timepoints, based on lowest BIC and SSA-BIC model fit statistics and sufficient entropy (see Table S2, Supplemental Digital Content, http://links.lww.com/PSYMED/B3). The characteristics of the phenotypes can be found in Table S3A, http://links.lww.com/PSYMED/B3, and Figure 1. The first phenotype, *good sleepers* (44% at T1; 33% at T2), were characterized by optimal sleep health across all dimensions. The second phenotype, *insomnia sleepers* (25% at T1; 27% at T2), were characterized by four co-occurring sleep problems that map onto clinical insomnia symptoms: short sleep duration, high daytime tiredness, frequent insomnia symptoms, and long time to fall

asleep. The third phenotype, *weekend catch-up sleepers* (18% at T1; 5% at T2), were characterized by irregular sleep (specifically, short average sleep duration but longer sleep on non-workdays/weekends). The final phenotype, *nappers* (13% at T1; 35% at T2), were characterized by mostly good sleep but frequent daytime naps.

Notably, although the same phenotypes were identified at both timepoints, their prevalence at each timepoint differed. Namely, *nappers* became much more common at T2 (perhaps because napping is common as adults age) and *weekend catch-up sleepers* became much less common at T2 (perhaps because this phenotype has been associated with varying work schedules in the past, which may become less common as adults age). As shown in Supplemental Table S3B, Supplemental Digital Content, http://links.lww.com/PSYMED/B3, *insomnia sleepers* and *nappers* were largely stable; respectively, 92% and 97% remained in the same phenotype approximately ten years later. In fact, *nappers* never transitioned to *good* or *weekend catch-up sleepers*. Approximately two-thirds of *good sleepers* remained in the same phenotype (68%) but the rest transitioned to *nappers* (28%) or to other phenotypes. *Weekend catch-up sleepers* were highly unstable (only 27% remained in the same phenotype) and most likely to transition to *nappers* (52%).

Background Characteristics of the Sleep Health Phenotypes Over Time

Full results are reported in Table S4, http://links.lww.com/PSYMED/B3, but we also summarize notable findings significant at both timepoints. Age, education, and work status were consistently associated with the sleep health phenotypes across both T1 and T2. Older people were less likely to be *weekend catch-up sleepers* (T1: B=-.022, SE=.010, p=.048; T2 B=-0.041,

SE=.010, *p*<.001) and more likely to be *nappers* (T1: *B*=.051, *SE*=.010, *p*<.001; T2: *B*=.042, *SE*=.002, *p*<.001) at both timepoints. These age-related results remained consistent when we used life stage categories instead of continuous age (Table S5, http://links.lww.com/PSYMED/B3). Higher education was associated with lesser likelihood of being an *insomnia sleeper* than a *good sleeper* at both timepoints (T1: *B*=-.070, *SE*=.030, *p*=.020; T2: *B*=-.11, *SE*=.020, *p*<.001). Retirees were more likely to be *nappers* at both timepoints (T1: *B*=.71, *SE*=.24, *p*<.001; T2: *B*=.53, *SE*=.19, *p*=.010). Workers were less likely to be *insomnia sleepers* than they were *good sleepers* at both timepoints (T1: *B*=-.44, *SE*=.17, *p*=.010; T2: *B*=-.49, *SE*=.12, *p*<.001) whereas people who were not employed were more likely to be *insomnia sleepers* at both timepoints (T1: *B*=.61, *SE*=.22, *p*=.010; T2: *B*=.85, *SE*=.18, *p*<.001).

Relative Risk for Chronic Conditions Based on Sleep Health Phenotype Transitions

Number of total chronic conditions. Table 1 shows results testing whether count of total chronic conditions at T2 differed across the sleep health phenotype transition groups, controlling for T1 count and all other covariates. Average number of total chronic conditions per transition group are reported in Supplemental Table S6, http://links.lww.com/PSYMED/B3. Relative to the largest and most optimal group (i.e., *good sleeper □ good sleeper*), five transition groups were at a higher risk for more chronic physical conditions, ranging from 28% to 81% greater risk. Four of the five at-risk groups involved belonging to the *insomnia sleeper* phenotype at one or both timepoints (i.e., *good sleeper □□insomnia sleeper*, *insomnia sleeper □□good sleeper*, *insomnia sleeper□ insomnia sleeper*, and *weekend catch-up sleeper □ insomnia sleeper*). *Good sleeper □□napper* transition group also exhibited slightly heightened risk, though the lowest risk of the five groups (28%). These associations were found after controlling for sociodemographic, health,

and work covariates. Table S7, http://links.lww.com/PSYMED/B3, shows that the associations of the covariates with the number of total chronic conditions at each timepoint, which were all in the expected directions.

Specific types of chronic conditions. Results are reported in Table 2 as well as Figure S1, http://links.lww.com/PSYMED/B3. At least one sleep health phenotype transition group was at heightened risk for three of the four chronic physical condition categories, relative to consistently good sleepers (i.e., *good* □ *good*). For cardiovascular conditions, consistent *insomnia sleepers* (i.e., *insomnia sleeper* □ *insomnia sleeper*) were at 72% higher risk (*95% CI*=[1.04, 2.82]) than consistently *good sleepers*. For diabetes, consistent *insomnia sleepers* again were at higher risk (188%; 95% CI=[*95% CI*=1.72,4.79]) as were consistent *nappers* (128%; *95% CI*=[1.26,4.09]) and *weekend catch-up sleepers* □ *nappers* (137%; *95% CI*=[1.21,4.60]). For chronic respiratory diseases, no sleep health phenotype transition group exhibited significantly higher risk for these conditions compared to consistently *good sleepers*. For cancers, only *nappers* □ *insomnia sleepers* exhibited higher risk (45%; *95% CI*=[1.16,1.83]).

For depressive symptoms, consistent *insomnia sleepers* were at 95% higher risk (*95% CI*=[1.47,2.59]) and *good sleepers* □ *insomnia sleepers* were at 89% higher risk (*95% CI*=[1.15,3.11]) than consistently *good sleepers*. For frailty, four groups exhibited higher risk relative to consistently *good sleepers*: consistent *insomnia sleepers* (68% higher; *95% CI*=[1.22,2.29]), *good sleepers* □ *insomnia sleepers* (108% higher; *95% CI*=[1.31,3.28]), *good sleepers* □ *nappers* (62% higher; *95% CI*=[1.12,2.33]), and especially *nappers* □ *insomnia sleepers* (456% higher; *CI*=[1.29,23.79]).

Discussion

This is the first study to use multidimensional, longitudinal approach examining sleep health as a modifiable risk factor for key chronic conditions, across physical, mental, and functional domains. Building on emerging research that identified several sleep health phenotypes (10,17,19,43), we identified four sleep health phenotypes in a national sample of midlife adults that emerged consistently over one decade. Common sleep health phenotypes were replicated over time; most participants remained in the same phenotype, but some participants moved in and out of the phenotypes over time. Novel findings from this study include specific constellations of sleep characteristics that indicate increased risks for the development of chronic conditions and sociodemographic groups who may be more vulnerable to both poor sleep health and chronic conditions. Below, we discuss main findings from this study.

The most important findings from this study are that specific constellations of sleep characteristics may increase the risk of subsequent chronic conditions. Being an *insomnia sleeper* at one or both timepoints was a consistent risk for more chronic conditions and all types of those examined, except respiratory conditions. The literature reports that insomnia-related characteristics such as short sleep duration combined with poor sleep quality are risk factors for hypertension, type 2 diabetes, cardiovascular disease, and chronic physical conditions (10,15–17). Findings from the current study add to this line of literature by showing how having co-occurring sleep problems across multiple dimensions (i.e., short sleep duration, high daytime tiredness, frequent insomnia symptoms, and long time to fall asleep) that map onto clinical insomnia symptoms at either of the two timepoints over a decade increases the risk of chronic conditions. Note that many of the chronic condition types that were associated with the *insomnia*

sleeper phenotype are modifiable conditions (cf., chronic respiratory conditions that were not associated with any other sleep health phenotypes may be less modifiable through changes in health behaviors like sleep). The *napper* phenotype also emerged as a relatively common risk. Appropriate use of napping may be beneficial to compensate for nighttime sleep loss (44). However, our results show that transitioning to the *napper* phenotype may increase risks for more chronic conditions, especially for diabetes and frailty. This may relate to age-related changes in both sleep and physical conditions, as frequent napping, incident diabetes, weight loss, exhaustion, low physical activity, slowness, and weakness are generally prevalent in later life (45).

We also identify sociodemographic groups who may be more vulnerable to poor sleep health and thus may have higher risk for developing chronic conditions. Younger adults were more likely to be *weekend catch-up sleepers*, whereas older adults were more likely to be *nappers*. These results are in line with the literature reporting higher sleep debt in younger individuals and increased napping in older adults, especially after retirement (46,47). Our results also support that one's sleep health may relate to socioeconomic status (48), such that those with higher socioeconomic status are less likely to have a suboptimal sleep health phenotype. For example, those with higher education were less likely to be *insomnia sleepers* at either timepoint. Moreover, work status was an important variable that was associated with sleep health phenotype membership, such that being a retiree was associated with increased risk of being a *napper* and not being employed was associated with increased risk of being an *insomnia sleeper*. Paid work provides not only income and life purpose, but also temporal structure that may help maintaining a regular sleep/wake cycle, which may be important for optimal sleep health.

Moreover, our findings show that sleep health phenotypes are largely stable across adulthood. Although some participants (23%) changed membership across the sleep health phenotypes over time, most (77%) remained in the same phenotype. The stability of the sleep health phenotypes was more apparent in those with the two suboptimal phenotypes. Specifically, over 90% of *insomnia sleepers* stayed in the same phenotype. Moreover, *nappers* were the least likely to transition to a different phenotype (97% were stayers). *Weekend catch-up sleepers* that seem to emerge among younger adults mostly due to work, were the most likely to transition (only 27% were stayers). The good news is that this phenotype did not significantly increase the risk of chronic conditions in our study. However, risk may go up later because those who belonged to *weekend catch-up sleepers* were more likely to move to *napper* or *insomnia sleeper* phenotypes (60%) rather than to *good sleeper* phenotype (13%). Overall, this study shows stability of sleep health in general, although the degree of stability may depend on specific phenotypes.

There may be divergent mechanisms that lead to different sleep health phenotypes. Although certain sleep health phenotypes, like *weekend catch-up sleepers* and *good sleepers*, appear to be flexible, whereby individuals can shift between them over time, other phenotypes, such as *nappers*, seem more rigid. Considering the background characteristics of this phenotype (i.e., older age, retirees), the extent of rigidity found in the *napper* phenotype may relate to irreversible age-related changes in circadian rhythm, physiological decline, or disease pathology such as depression and nocturia (45). Another rigid and suboptimal phenotype is the *insomnia sleeper*. In the case of this phenotype, stress may be a contributing factor (49), as individuals in

this phenotype were more likely to report low resources (e.g., unemployed, lower education). These factors may exhibit greater stability in late adulthood. While potential mechanisms may differ, membership and transition into these two suboptimal phenotypes (i.e., *napper*, *insomnia sleeper*) were associated with heightened risk for multiple chronic conditions. Moreover, the associations were independent of age and other background characteristics, suggesting the unique risk that these sleep health phenotypes may have on chronic conditions. Further research is warranted to investigate specific mechanisms underlying suboptimal sleep health phenotypes and their associations with chronic conditions.

Chronic conditions and sleep phenotypes likely have bidirectional relationships. In this study, we attempted to minimize the possibility of reverse directionality, such as a chronic condition leading to a specific sleep health phenotype (e.g., diabetes contributing to individuals belonging to the napper phenotype) by controlling for baseline chronic conditions (e.g., adjusting for T1 diabetes when predicting T2 diabetes). Consequently, our results suggest that the transition to the *napper* phenotype from T1 to T2 is associated with a higher risk of newly developing diabetes at T2 with the likelihood of diabetes at T1 being held constant for the entire analytical sample. Nonetheless, our analysis, based on only two timepoints fairly far apart (approximately 10 years) cannot completely eliminate the possibility of reverse directionality. Some individuals may have developed chronic conditions during the 10-year interval between T1 and T2, potentially influencing transitions in sleep health phenotypes. More research is needed to see whether the findings are replicated across studies using different samples and employing varied (shorter and more frequent) timescales.

Based on our results, future sleep prevention programs should not be one-size-fits-all. Our findings point to two distinct suboptimal sleep health phenotypes (i.e., *insomnia sleeper, napper*) that should be targeted due to their increased risks for chronic conditions – but likely targeted differently (i.e., depending on sociodemographic vulnerability and specific phenotype). First and foremost, targeting co-occurring sleep problems found in the *insomnia sleeper* phenotype may potentially protect against developing a host of chronic conditions. Moreover, future research uncovering nuances in napping – under what circumstances napping is particularly harmful – may also be important, because being a *napper* at any timepoint was associated with increased risks for diabetes, cancer, and frailty. Our results further help to identify at-risk sociodemographic groups for each of the suboptimal phenotypes and consider them urgent sleep intervention targets, namely unemployed or those with lower education (*insomnia sleepers*) and retirees and older adults (*nappers*).

Limitations and Future Directions

This study is not without limitations. First, the sleep timing dimension of the Ru-SATED model was not captured through the MIDUS survey and was therefore not accounted for in our sleep health phenotyping. Future research may want to include sleep timing as an indicator of sleep health phenotypes to get an even more comprehensive picture of overall sleep health. Also, insomnia symptoms and sleep onset latency used to capture sleep satisfaction and efficiency, respectively, may not sufficiently capture each dimension. Moreover, only self-reported sleep measures were used due to sleep actigraphy data only being available for a limited number of participants. We also converted the continuous sleep variables to categorical using empirical cut-offs; although artificial categorization loses potentially meaningful variance and should be

avoided when possible, psychometric properties of the variables representing sleep dimensions deemed this approach most appropriate—categorization is the recommended strategy to extract accurate and interpretable phenotypes when using non-normally distributed data. Future research could use combined actigraphy and self-report to best capture each sleep dimension. Additionally, we used only one of the approaches to measure sleep health in this study; there are other approaches, such as creating composite scores of sleep health based on theoretically-driven or empirically-derived cutoff values (50,51). Second, the MIDUS sample was, on average, relatively privileged in terms of race, education, and health status. Attrition in MIDUS also favored healthier people, workers, and white individuals. Thus, racial/ethnic minorities, marginalized, and people struggling with health conditions may be under-sampled, masking or reducing overall effects. Replication of this study in a sample of adults with greater sociodemographic diversity to better represent the general population may account for possible differences in the relationship between sleep health and chronic conditions for these individuals. Lastly, this study was observational, thus causality cannot be determined. Further, only two timepoints limit our ability to examine potential mechanisms of change. Future work may need to include more timepoints to examine *how and why* changing membership in sleep health phenotypes leads to the development of chronic conditions. In this study, we assessed long-term changes, but sleep health and chronic condition symptoms may fluctuate in conjunction with one another from day to day and stress and behavioral mechanisms may play roles.

Conclusion

This study provides new evidence for the existence of four common sleep health phenotypes (*insomnia sleepers*, *nappers*, *weekend-catchup sleepers*, and *good sleepers*) in a

national sample of adults over one decade. Among the four phenotypes, adults who belong to the two suboptimal phenotypes (*insomnia sleepers* and *nappers*) are less likely to transition to a different phenotype. This raises a concern, because those in the two suboptimal sleep health phenotypes at one or both timepoints separated by ten years have heightened risks for chronic conditions ten years later. Future efforts should be focused more on providing targeted sleep prevention or intervention programs to delay the onset of chronic conditions in later life.

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Figure 1. Latent sleep health classes at Time 1 (MIDUS II) and Time 2 (MIDUS III).

Notes. N=3,683. Tired=subjective feelings of tiredness. SOL=sleep onset latency.

Color image is available only in the online edition at the journal's website.

Figure 1

MIDUS II

Good sleepers (44%)
Insomnia sleepers (25%)
Weekend catch-up sleepers (18%)
Nappers (13%)

MIDUS III

Good sleepers (33%)
Insomnia sleepers (27%)
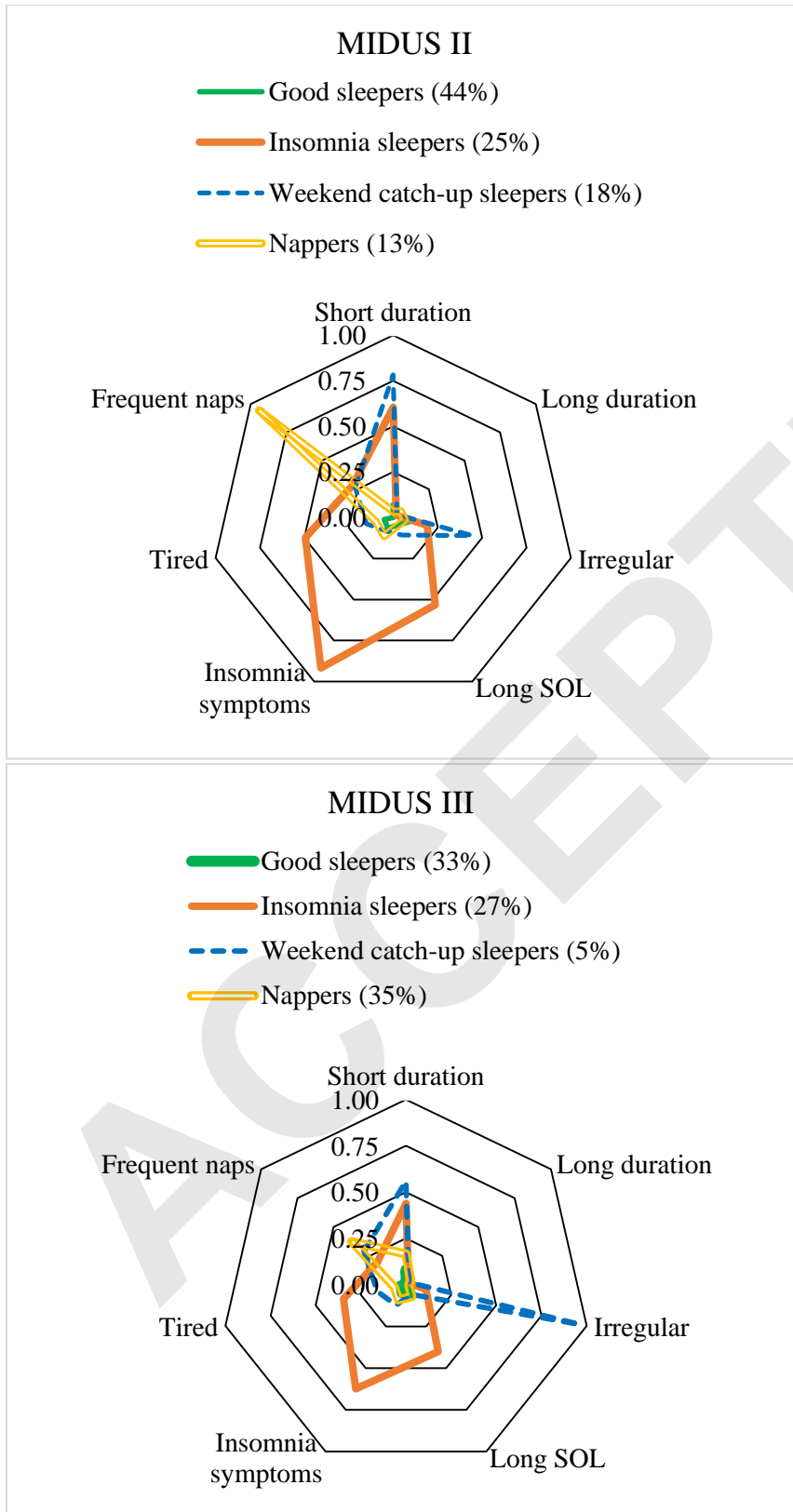Weekend catch-up sleepers (5%)
Nappers (35%)

Table 1. Results from Poisson Regression models examining the number of total chronic conditions by each sleep health phenotype transition group.

Transition group	*B*	*SE*	*p*	*Exp(B]*	*95% CI*
Good → Insomnia	**0.37**	**0.12**	**0.002**	**1.45**	**[0.13,0.61]**
Good → WCU	0.38	0.41	0.36	1.47	[-0.43,1.19]
Good → Napper	**0.25**	**0.09**	**0.005**	**1.28**	**[0.07,0.42]**
Insomnia → Good	**0.52**	**0.19**	**0.01**	**1.67**	**[0.13,0.90]**
Insomnia → Insomnia	**0.33**	**0.07**	**<.001**	**1.39**	**[0.18,0.47]**
Insomnia → WCU	-0.40	0.37	0.27	0.67	[-1.12,0.32]
Insomnia → Napper	-0.016	0.17	0.95	0.99	[-0.34,0.32]
WCU → Good	0.17	0.14	0.21	1.19	[-0.10,0.45]
WCU → Insomnia	**0.59**	**0.12**	**<.001**	**1.81**	**[0.36,0.83]**
WCU → WCU	0.13	0.10	0.20	1.14	[-0.07,0.33]
WCU → Napper	0.17	0.10	0.08	1.19	[-0.02,0.37]
Napper → Good					
Napper → Insomnia	0.29	0.46	0.52	1.05	[-0.61,1.20]
Napper → WCU					
Napper → Napper	0.05	0.10	0.60	1.34	[-0.14,0.24]

Notes. N=2706. Good = Good sleeper. WCU=Weekend catch-up sleeper. Reference group: Good → Good. Bold values indicate statistically significant results (*p*<.05). Gray cells indicate a transition group with no members (*N*=0) or too few to make comparisons. Covariates included age, sex, race (i.e., white and non-Hispanic vs. non-white and/or Hispanic), education, core vs. Milwaukee MIDUS sample, work hours, relationship status (i.e., married and/or cohabitating vs. not), smoking status, alcohol consumption frequency, and physical activity.

Table 2. Results from log-binomial models examining the risk of specific chronic condition types by sleep health phenotype transition group.

Transition group	Cardiovascular conditions		Diabetes		Cancer		Respiratory diseases		Depressive symptoms		Frailty	
	Exp(B)	95% CI	Exp(B)	95% CI	Exp(B)	95% CI	Exp(B)	95% CI	Exp(B)	95% CI	Exp(B)	95% CI
Good → Insom	1.98	[0.91,4.31]	1.96	[0.77,4.97]	1.01	[0.91,1.13]	0.97	[0.86,1.09]	**1.89**	**[1.15,3.11]**	**2.08**	**[1.31,3.28]**
Good → WCU					0.89	[0.58,1.39]	0.88	[0.54,1.41]	0.71	[0.09,5.25]	1.48	[0.20,10.80]
Good → Nap	1.36	[0.73,2.51]	1.73	[0.90,3.29]	1.03	[0.96,1.11]	1.03	[0.94,1.11]	1.23	[0.88,1.72]	**1.62**	**[1.12,2.33]**
Insom → Good	0.8	[0.11,5.95]	0.27	[0.025,2.89]	1.06	[0.86,1.32]	0.9	[0.71,1.13]	0.91	[0.34,2.38]	1.76	[0.80,3.86]
Insom → Insom	**1.72**	**[1.04,2.82]**	**2.88**	**[1.72,4.79]**	1	[0.94,1.06]	1.05	[0.98,1.12]	**1.95**	**[1.47,2.59]**	**1.68**	**[1.22,2.29]**
Insom → WCU			0.37	[0.02,5.15]	1.04	[0.73,1.50]	1.37	[0.92,2.02]	0.7	[0.13,3.65]		
Insom → Nap	2.03	[0.77,5.37]	1.57	[0.41,5.91]	0.88	[0.75,1.04]	1.03	[0.86,1.23]	1.42	[0.65,3.08]	1.41	[0.73,2.69]
WCU → Good	1.11	[0.43,2.85]	2.11	[0.85,5.18]	1	[0.89,1.12]	0.91	[0.79,1.02]	0.82	[0.47,1.42]	0.83	[0.39,1.71]
WCU → Insom	1.17	[0.35,3.88]	1.24	[0.38,4.06]	0.91	[0.80,1.04]	0.94	[0.80,1.09]	1.32	[0.67,2.54]	1.52	[0.87,2.64]
WCU → WCU	0.92	[0.38,2.20]	1.11	[0.44,2.78]	1	[0.91,1.09]	0.91	[0.81,1.00]	1.02	[0.66,1.55]	1.39	[0.87,2.21]
WCU → Nap	1.38	[0.72,2.63]	**2.37**	**[1.21,4.60]**	1.07	[0.99,1.16]	0.99	[0.90,1.08]	0.92	[0.63,1.34]	0.97	[0.61,1.54]
Nap → Insom	6.77	[0.81,56.15]	3.97	[.092,6.95]	**1.45**	**[1.16,1.83]**	1.16	[0.91,1.48]	1.33	[0.45,3.97]	**5.56**	**[1.29,23.79]**
Nap → Nap	1.53	[0.84,2.75]	**2.28**	**[1.26,4.09]**	1	[0.93,1.07]	1.06	[0.97,1.14]	1.22	[0.87,1.69]	1.3	[0.87,1.92]

Notes. Good = Good sleeper. WCU=Weekend catch-up sleeper. Nap = Napper. Insom=Insomnia sleeper. Reference group: Good → Good. Cells in gray indicate that the focal transition group had an overall N=0 or that no participants belonging to that group reported the specific health outcome; tests for three groups (napper to good sleeper, napper to insomnia sleeper, and napper to WCU sleeper) did not output results for this reason and are excluded from this table.