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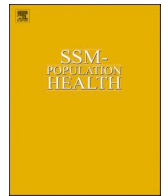
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The impact of social networks on sleep among a cohort of college students

Cheng Wang^{a,*}, Stephen Mattingly^b, Jessica Payne^b, Omar Lizardo^c, David S. Hachen^d

^a Department of Sociology, Wayne State University, Detroit, MI, USA

^b Department of Psychology, University of Notre Dame, Notre Dame, IN, USA

^c Department of Sociology, University of California Los Angeles, Los Angeles, CA, USA

^d Department of Sociology, University of Notre Dame, Notre Dame, IN, USA

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ABSTRACT

Background: Sleep duration and quality are associated with physical and mental wellbeing. This paper examines social network effects on individual level change in the sleep quantity and quality from late adolescence to emerging adulthood and its associated factors, including the influence of peers on sleep behavior and the impact of changes in network size.

Methods: We use sleep data from 619 undergraduates at the University of Notre Dame obtained via Fitbit devices as part of the NetHealth project. The data were collected between August 16, 2015 and May 13, 2017. We model trends in sleep behaviors using latent growth-curve models.

Results: Controlling for the many factors known to impact sleep quantity and quality, we find two social network effects: increasing network size is associated with less sleep and a student's sleep levels are influenced by his or her peers. While we do not find any consistent decline in sleep quantity over the 637 days, daily fluctuations in sleep quantity are associated with changes in network size and the composition of a student's network. As a student's network gets bigger, s/he sleeps less, and when a student's contacts sleep more (or less) than s/he does, the student becomes more like his or her contacts and sleeps more (or less).

Conclusions: Social networks can and do impact sleep, especially sleep quantity. In contexts where students want to have larger networks, the difficulties of increasing network size and maintaining larger networks negatively impact sleep. Because of peer influence, the effectiveness of interventions designed to improve sleep practices could be increased by leveraging student social networks to help diffuse better sleep habits.

1. Introduction

Sleep patterns change across the human lifespan (Hirshkowitz et al., 2015; Ohayon et al., 2004; Iglowstein et al., 2003). As indicated by the National Sleep Foundation, recommended sleep duration ranges from over 14 hours for newborns to 7 or 8 hours for 65 and over adults (Hirshkowitz et al., 2015). However, it is still undetermined whether decreases in sleep duration stop in late adolescence (>18 years of age) (e.g., Ferrie et al., 2011; Vitiello et al., 2004) or whether there is a gradual decrease during not only early adulthood (e.g., Walsemann et al., 2017) but also the entire human lifespan (e.g., Carrier et al., 1997; Youngstedt et al., 2016; Matricciani et al., 2017; Basner & Dinges, 2018; Kocovska et al., 2021). In addition to duration, measures of sleep quality may change over time, including sleep efficiency, sleep onset latency, and the number of awakenings experienced throughout the night

(Carrier et al., 1997; Foley et al., 2007; Vitiello et al., 2004).

Outside of aging, other factors likely play a role in changing sleep behavior over time, such as peer behavior. Peer influence on sleep has recently been able to be examined due to increases in study sizes and better sampling techniques. For example, the Add Health project (Harris et al., 2019) consists of longitudinal survey and health data from adolescence to adulthood. Mednick et al. (2010) analyze these data and find that higher network centrality (i.e., having more contacts) is detrimental to sleep – the more people a person is connected to, the worse that individual's sleep is. Another study examining the same data using simulation methods finds a good deal of social influence – “in the average group of four people, an additional hour of sleep of each of the friends translates to about 45 minutes in the individual sleeping duration” (Liu et al., 2013). Additional work has considered the impact of loneliness and lack of social support on sleep. For example, Cacioppo

* Corresponding author.

E-mail addresses: chengwang@wayne.edu (C. Wang), ndlabmanager@gmail.com (S. Mattingly), jpayne7@nd.edu (J. Payne), olizardo@soc.ucla.edu (O. Lizardo), dhachen@nd.edu (D.S. Hachen).

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et al. (2002) find that increased loneliness leads to reduced sleep quality. Another study reports that both women and men with low social support and/or high psychosocial demands have poorer sleep quality, although this effect is magnified for women (Nordin et al., 2005). Increased social media usage has also been correlated with poorer sleep, though the mechanism may be more related to internet addiction than social networks or social interactions per se (Xanidis & Brignell, 2016). While the measures and methodologies of these studies differ, they suggest that people's social interactions with others impact their sleep quantity and quality. In this study we focus on two aspects of these social interactions: the number of people with whom a person interacts (network size) and the sleep habits of those persons. We expect people with large networks to have poorer sleep, both in terms of quantity and quality. We also expect people to mirror their contacts, with those whose contacts sleep less (or more) than them to change and sleep less (or more) as well. In other words, we expect sleep habits can diffuse within a population through the social (peer) influence of a person's contacts.

We expect these two social network effects on sleep – network size and peer influence – to be evident even when we control for the many factors that prior research has shown to be associated with sleep such as personal traits, psychological states, environmental conditions, and various behaviors and activities (Billings, Cohen, et al., 2020). Because of their association with people's social network size and composition, it is important to control for these factors in the analysis. Below we briefly review past research on four sets of predictors.

Personal factors. Previous systematic review indicates that sleep varies with personal factors such as gender, race/ethnicity, age, religious affiliation, and health (Kocevska et al., 2021). Mixed findings are reported for the gender difference in sleep behavior: Mednick et al. (2010) indicate that shorter sleep duration is common among females; Jean-Louis et al. (2000) suggest that females have longer time in bed, higher sleep efficiency, but similar sleep onset latency as males; and Tsai and Li (2004) find that females have earlier bedtime and wake time, longer sleep onset latency, more frequent awakenings, and about the same level of time in bed and sleep efficiency as males. As women age, they may get less sleep than men (Ohayon et al., 2004; Kocevska et al., 2021). Turning to race and ethnicity effects, ethnoracial minorities, especially African Americans, have shorter sleep duration and more naps than whites (Jean-Louis et al., 2000; Mednick et al., 2010; Sheehan et al., 2019). Regarding religiosity, sleep quality is not found to be affected by frequency of attendance at religious services, frequency of prayer, secure attachment to God, and anxious attachment to God (Ellison et al., 2011). Among health characteristics, overweight and obese individuals sleep less than those with a normal body mass index (BMI) but show the same level of sleep disturbance (Gupta et al., 2002; Ekstedt et al., 2013; Kocevska et al., 2021).

Psychological factors. Personality is another factor that can affect sleep, but the findings are mixed. While Soehner et al. (2007) find no relationship between personality variables and sleep duration, Randler (2008) indicates that individuals with higher agreeableness and conscientiousness spend more time on sleeping. Other studies suggest that poor sleep quality is related to low conscientiousness and high neuroticism (Duggan et al., 2014), and conscientious individuals have earlier bedtime and wake time (Gray & Watson, 2002), as well as less frequent emotional napping (to improve their mood) and slightly more frequent mindful napping (to refocus) (Duggan et al., 2018). When considering mental health, there is a clear link between insomnia and depression (Rao et al., 2009; Szklo-Coxe et al., 2010). Depressed individuals also take more naps (Foley et al., 2007). For chronotype, morningness, or the tendency of being most active and alert in the morning, is a predictor of earlier bedtime and wake time (Carrier et al., 1997) and lower nap frequency (Park et al., 1997).

Environmental factors. Recent systematic reviews show that sleep can be affected by natural, built, ambient, and social environmental features (Caddick et al., 2018; Billings, Hale, & Johnson, 2020; Liu et al., 2020). New sleep environments can impact sleep behavior (Edinger et al.,

1997). In addition, sleep varies from weekdays to weekends (Bin et al., 2012; Basner & Dinges, 2018), with some studies finding that sleep is longer on the weekends (e.g., Wirz-Justice et al., 1991; Wong et al., 2013; Kocevska et al., 2021) and others seeing the opposite due to later bedtime and slightly later rising time on weekends (e.g., Nixon et al., 2008). Moreover, weather, especially precipitation, snow depth, and temperature, impact sleep (Pandey et al., 2005; Obradovich et al., 2017). Previous studies also report seasonal effects with people sleeping more in the winter due to earlier bedtime and later wake time compared to summer (Wirz-Justice et al., 1991; Nixon et al., 2008; Basner & Dinges, 2018; Mattingly et al., 2021). Further, while the sleep window of inhabitants in pre-industrial societies is more correlated with sunset and sunrise time (Yetish et al., 2015), this pattern is rarely observed among populations living in the industrialized world (Peixoto et al., 2009).

Behavioral factors. Findings on the relationship between physical activity and sleep duration is inconsistent, with some studies finding no association (Nixon et al., 2008; Ortega et al., 2011; Ekstedt et al., 2013) and others suggesting that exercise increases total sleep time (Driver & Taylor, 2000). More physical activity is associated with higher sleep efficiency (Ekstedt et al., 2013) and shorter sleep onset latency (Nixon et al., 2009), but not with number of naps (Guimaraes et al., 2008). Finally, higher workload, including heavy homework for students, leads to shorter sleep duration (Charles et al., 2011; Dorrian et al., 2011; Moore & Meltzer, 2008).

While previous studies contribute to our understanding of sleep behavior, most previous work relies on survey data (which has some validity issues, see Means, Edinger, Glenn, & Fins, 2003) and models variation in sleep behavior across various socio-demographic groups instead of modelling within-person variation over time. The current study expands on prior research by using sensor data collected with Fitbit devices and employing Linear Growth Curve Models (LGCMs) to examine change in various sleep indicators. Because this sensor data is longitudinal, we are able to examine temporal trends within our population, an incoming college student cohort, over their first two years in college. The primary aim of this study is to assess the impact of each student's social network – both its size and composition in terms of sleep behaviors – on his or her own sleep behavior controlling for other well-known predictors of sleep. We do this by looking at changes in measures of sleep quantity and quality over time and modelling those changes as a function of changes in people's social networks. We conclude by discussing the implications of our findings concerning social network effects for future research and interventions designed to help college students (and others) have better sleep habits.

2. Methods

2.1. Data

This study uses data collected from the NetHealth project supported by National Institutes of Health (NIH; Wang et al., 2020; 2021). This study was approved by the Institutional Review Board of the University of Notre Dame and written informed consent was obtained from all participants. In fall 2015 the University of Notre Dame admitted 2007 full-time freshmen, among which 1069 (or 53%) were men, 938 (or 47%) were women, 1352 (or 67%) were white students, 219 (or 11%) were Hispanic students, 80 (or 4%) were African-American students, 111 (or 6%) were Asian-American students, 143 (or 7%) were students of other races (the detailed sampling frame is available from https://www3.nd.edu/~instres/CDS/2015-2016/CDS_2015-2016.pdf). The NetHealth project team used a stratified recruitment strategy designed to obtain representative proportions of each gender-race strata in the sample. The project team also estimated the maximum number of Fitbit devices that could be distributed among the participants based on the NIH budget. Recruitment occurred in three stages. 387 students were recruited in the Summer of 2015, 96 were added through recommendations from participants in Fall 2015, and 209 students were added to

the study in early Spring 2016 for a total of 692 participants. The team monitored recruitment to ascertain whether the sample's gender-race proportions were close to the makeup of the Fall 2015 incoming class, which they were.

Each participant was provided with a Fitbit Charge HR wristband and required to install the Fitbit app on their smartphones. We set up a system of office hours, online tutorials, and monitoring in order to help students sync their Fitbit data so that we could access it. Using the app, sleep data from the device was sent periodically into the Fitbit cloud from which the research team extracted features. The wristband collected minute-by-minute sleep information including bedtime, sleep states (i.e., asleep vs. awake), and rising time. Fitbit's ability to measure sleep behavior is based on a proven algorithm that utilizes movement patterns and heart rate variability (HRV) to assess sleep stages. The validity of Fitbit Charge HR in studying sleep against the gold standard of polysomnography (PSG) has been demonstrated in [Godino et al. \(2020\)](#) and [Benedetti et al. \(2021\)](#). For more detailed information on how Fitbit computes measures see <http://help.fitbit.com>. Finally, there were 619 participants having Fitbit data on the secure servers, based on which we compute both measures of sleep quantity (e.g., time asleep) and measures of sleep quality (e.g., efficiency based on time not asleep while in bed).

We also used Fitbit devices to collect physical activity data. Fitbit generates from sensor data that detect motion and heart rate 18 physical activity indicators at minute granularities: low range calories and minutes, fat burn calories and minutes, cardio calories and minutes, peak calories and minutes, steps, floors, sedentary minutes, lightly active minutes, fairly active minutes, very active minutes, marginal calories, activity calories, calories BMR, and calories out. The data used in this study were collected between August 16, 2015 (i.e., the first day of orientation week during Fall semester 2015) and May 13, 2017 (i.e., the last day of Spring semester 2017).

Communication data was also collected from participants' smartphones with specially designed applications for iOS and Android phones. We use this information to compute who is in a person's social network based on who s/he has communicated with (voice calls or text messages). Phones also provided us with geolocations in latitude and longitude allowing us to determine where a person was sleeping (parental home or at school). The contents of voice calls and text messages were not recorded. To construct social networks, we use to and from numbers contained in the smartphone logs along with the time and date of the communication event. Systems were established to help students install, setup, and maintain all the apps and their Fitbit device, and students were incentivized to upload data through the apps.

Additional data were collected through periodic surveys. When participants joined the study, they took an entry survey online on a wide range of individual traits, behaviors, psychological states, and dispositions. Surveys were administered every 3–4 months yielding longitudinal data. We use data from the Winter 2016, Summer 2016, Fall 2016, and Spring 2017 to measure behaviors, states, and tastes in the Fall semester 2015, Spring semester 2016, Fall semester 2016, and Spring semester 2017 respectively. We use the initial survey data to measure time-constant traits like a person's gender and race/ethnicity, and the longitudinal survey data to compute the number of classes a student was taking each day. Local weather details such as highest and lowest temperatures (°F), precipitation (in inches), snowfall (in inches), and snow depth (in inches) are retrieved from <http://www.usclimatedata.com/website>, and sunrise time and sunset time are retrieved from <https://www.timeanddate.com/website> for each day when a participant was sleeping. All aforementioned information is aggregated to generate a *daily* sleep, network, physical activity, and weather data set over 637 days. The timeline of each type of data is shown in [Fig. S1](#) in the supplemental material.

2.2. Measures

Eight dependent variables were constructed from the sleep data generated by Fitbit devices, including time in bed (in hours), total sleep time (in hours), sleep efficiency (i.e., the ratio of total sleep time over time in bed), number of sleep episodes, sleep onset latency (i.e., minutes to fall asleep), hourly awakening frequency, bedtime (in hours), and rising time (in hours). It should be noted that Fitbit specifies the day of a sleep episode by the rising time irrespective of whether the bedtime is before or after midnight. About 91% of the daily cases are monophasic sleep, nearly 9% are two sleep episodes, and fewer than 1% involve three or more sleep episodes. For cases with polyphasic sleep, i.e., daily cases with two or more sleep episodes, time in bed and total sleep time are sums of multiple episodes, efficiency is the ratio of those two sums, and all the other dependent variables are computed using the longest sleep episode that day.

Turning first to the *social network* factors, the uniqueness of the NetHealth data is that it contains social network data on who was in each participant's in-study personal network on each day based on their communicative interactions via voice calls and text messages. We use this network data to identify the set of people (alters) which the respondent (ego) has communicated with that day. We measure the size of that set each day and use that as a measure of a person's network position (degree centrality). To assess the impact of peers on a person's sleep, we average for each of the eight sleep indicators the values among an ego's alters on that day.

As noted above, we include a wide range of other factors that are known to be associated with sleep. *Personal* factors include sex (Male, Female), race and ethnicity (White, Latino, African American, Asian American, Other), religious preference (Catholic, Protestant, Other religion, No religion), and Body Mass Index (BMI; weight/height²). *Psychological* factors include the big five personality traits (standardized scores on extraversion, agreeableness, conscientiousness, neuroticism, and openness; [John et al., 1991](#)), depression levels using the standardized Center for Epidemiologic Studies Depression scale (CES-D; [Radloff, 1977](#)), chronotype assessed by the standardized Morningness Eveningness Questionnaire (MEQ) scale ([Horne & Östberg, 1976](#)), and the mean score across the sleep trouble items from the Pittsburgh Sleep Quality Index (PSQI; [Buysse et al., 1989](#)). Both the personal traits and psychological measures are time-constant variables measured during the first survey administered prior to arrival on campus. *Environmental* factors include each participant's place where they slept (home, campus, other places) detected by comparing the latitude and longitude data obtained from their smartphones and that of their home addresses and residence halls on campus. We also use daily measures of weather indicators and weekday/weekend status (Sunday, Monday to Thursday, Friday, Saturday). We further categorize days by academic calendar (Normal school day, Mid-term break, Winter break, Summer break, Thanksgiving holidays, Easter holidays, Orientation week, Final exam week). Our basic daily *behavioral* factors include physical activity generated as a standardized factor score of 18 items reported by Fitbit devices (Cronbach's $\alpha = 0.89$) and the number of classes a student had each day. The environmental and behavior factors are all time-varying features which are measured for each day.

2.3. Analytical method

A latent growth-curve model (LGCM) is estimated for each of the eight sleep indicators using maximum likelihood methods with Stata V15.1 software. The LGCM approach is appropriate because we have high resolution (daily) longitudinal data with both time-varying and time-constant predictors. As shown in [Fig. 1](#), each dependent variable y is a function of two latent variables, the within-subject intercept (or initial value) η_0 and a linear slope (or rate of change) η_1 , as well as time-varying variables x , with ε representing the random errors. When time-constant variables z are taken into account, their effects on the

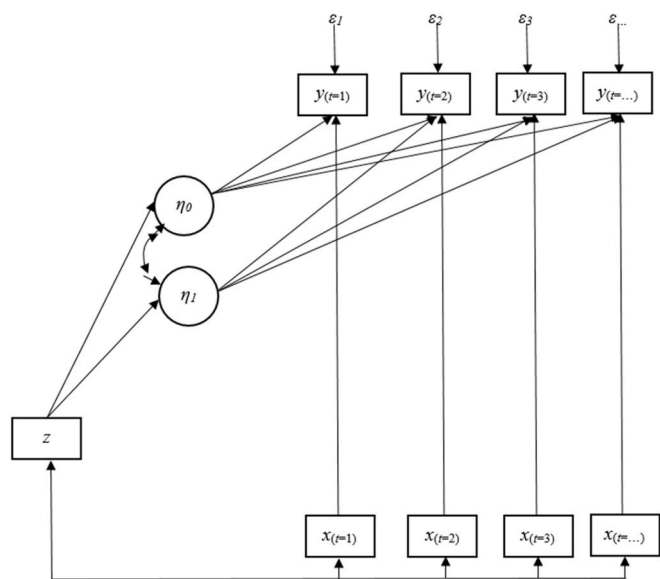


Fig. 1. Statistical framework of latent growth-curve model.

dependent variable y are going through η_0 and η_1 , reflecting between-subject variability in these two latent variables. If the effect of η_1 on y is statistically insignificant, there is no need to perform further growth curve analysis; otherwise, nonlinear growth trajectory such as quadratic and cubic slopes can be estimated as well. We use the LGCM framework to estimate the effects of both time-constant and time-varying traits, including network position and peer influence factors. It should be noted that in these models the units of analysis are people-days as we have daily data on persons over a two-year period. The LGCM allows us to look at between-person differences in sleep, but most importantly overtime variation for each person.

2.4. Sample attrition

As mentioned earlier, while we initially recruited 692 participants, we only received Fitbit data from 619 students. Among these 619 participants, we filtered out day in which we received very little Fitbit data. Because Fitbit devices record a zero for minutes in which the device detects no activity or sleep, we use the percentage of minutes in a day that a person has non-zero activity or sleep data and set the threshold as we have done in other studies to require at least 80% of the minutes to have non-zero values (Wang et al., 2020, 2021). After the threshold is applied, over the 637 days, we have data from the typical participant for 335 of those days, so about 47.4% of the daily Fitbit data is missing. While the LGCM routine can deal with these intermittent interruptions and missing data in the daily data series, if there is not enough daily data, the routine discards the case when estimating models. Table S1 in the supplemental material displays the summary statistics of gender, race and ethnicity, and religious preference of participants entering the models and those omitted. The distributions are for the most part similar. To assess the impact of bias, we estimate a logistic regression model predicting the status of participants in these two cohorts. The only statistically significant effect is that a participant identifying as belonging in the other race category is 54% less likely to enter the models ($p < 0.05$). Overall, attrition bias based on the usual demographic factors appears to not be a concern in the current study.

3. Results

3.1. Descriptive statistics

The time-varying variables are summarized in Table 1. On average,

Table 1 Summary of time-varying variables.

Variables for each individual each day	Mean (SD) or n (%)
Daily time in bed (hours)	7.53 (1.93)
Daily total sleep time (hours)	6.99 (1.84)
Daily sleeping efficiency (%)	92.81 (6.63)
Daily number of sleep episodes	1.14 (0.38)
Daily sleep onset latency (minutes)	2.67 (5.01)
Daily frequency of awakenings per hour	1.72 (0.91)
Daily bedtime	1.70 (2.51)
Daily rising time	8.93 (2.24)
In-study contacts' average daily time in bed (hours)	7.40 (1.63)
In-study contacts' average daily total sleep time (hours)	6.88 (1.60)
In-study contacts' average daily sleeping efficiency (%)	92.96 (6.93)
In-study contacts' average daily number of sleep episodes	1.13 (0.32)
In-study contacts' average daily sleep onset latency (minutes)	2.60 (4.20)
In-study contacts' average daily frequency of awakenings per hour	1.60 (0.76)
In-study contacts' average daily bedtime	1.73 (2.08)
In-study contacts' average daily rising time	8.87 (1.84)
Daily network size	10.28 (7.33)
Daily activity	0.01 (0.58)
Daily number of courses taken	2.50 (1.17)
Daily sleep at home (1 = yes)	20,505 (25.15%)
Daily sleep at residence hall (1 = yes)	53,172 (65.12%)
Number of cases	81,543 (100.00%)
Variables for each day	
Weather indicators	
Highest temperature (°F)	58.39 (19.56)
Lowest temperature (°F)	40.22 (16.69)
Precipitation in inch	0.12 (0.40)
Snowfall in inch	0.17 (0.80)
Snow piling depth in inch	0.44 (1.40)
Sunrise	7.42 (0.61)
Sunset	19.24 (1.41)
Number of days	637 (100.00%)

NetHealth participants spent 7.53 hours (i.e., 7 hours and 32 minutes) in bed per day with 93% sleep efficiency, or have about 7 hours of total sleep time. An average participant went to bed at 1:42 a.m. (1.7 hours after midnight) and got out of bed at 8:56 a.m. The average participant on a typical day fell asleep in 2 minutes and 40 seconds and had approximately 1.7 restless periods or awakenings per hour. Participants spent 65% of their days sleeping in residence halls on campus, 25% days sleeping at home, and 10% of the days sleeping at other places. Considering social network factors, the average participant on a typical day had 10 contacts and took 2.5 classes per day during academic terms. Regarding the sleep behavior of alters in an ego's network, the average levels among contacts (an ego's alters) are very similar to the average levels among our participants (egos), as both egos and their alters were drawn from the same population, the NetHealth study participants.

Fig. S2 to Fig. S9 in the supplemental material show the scatter plots and linear prediction plots with 95% confidence intervals for the eight dependent variables related to sleep behavior. Only the number of sleep episodes and the frequency of awakenings per hour indicate decreases over time. No quadratic or piecewise linear trend is evident in any of these figures. A similar pattern is evident for physical activity as shown in Fig. S10 in the supplemental material.

Table 2 displays descriptive statistics for the time-constant variables sex, race and ethnicity, religious preference, BMI, personality, depressive symptoms, chronotype, and self-reported sleep troubles.

3.2. LGCM estimates

For ease of reading and presentation, the LGCM results for each set of factors (trend, social network, personal, psychological, environmental, and behavioral) are presented separately in Table 3 to Table 8. Note however that in estimating each model for each sleep outcome, all features presented in Tables 3–8 are included. We separate them out here only for the purpose of presenting the results. For each of the eight

Table 2
Summary of time-constant variables.

Variables for each individual	Mean (SD) or n (%)
Female (1 = yes)	314 (50.73%)
Race and ethnicity	
White (1 = yes)	405 (65.43%)
Latino (1 = yes)	80 (12.92%)
African American (1 = yes)	37 (5.98%)
Asian American (1 = yes)	57 (9.21%)
Other (1 = yes)	40 (6.46%)
Religious preference	
Catholic (1 = yes)	455 (73.51%)
Protestant (1 = yes)	66 (10.66%)
Other religion (1 = yes)	26 (4.20%)
No religion (1 = yes)	72 (11.63%)
BMI	22.82 (3.35)
Extraversion	-0.01 (0.72)
Agreeableness	0.01 (0.60)
Conscientiousness	0.04 (0.62)
Neuroticism	-0.02 (0.64)
Openness	-0.01 (0.58)
Depression	0.06 (0.45)
Morningness inclination	0.03 (0.39)
Sleep troubles	0.57 (0.38)
Number of individuals	619 (100.00%)

models, the Root Mean Square Error of Approximation (RMSEA) is smaller than .06 and the Comparative Fit Index (CFI) is greater than 0.95, both suggesting a good fit. The intercept, number of cases, number of individuals, and four goodness-of-fit indicators are shown in Table 3 and they are not duplicated in the rest of tables. In the other tables one parameter is estimated for a time-varying variable x – its direct effect on each dependent variable y (Models 1–8) – and two parameters for each time-constant factor z , one indicating z 's effect on the within-subject intercept η_0 on the very first day, and the other indicating z 's effect on the linear slope η_1 for each dependent variable y over the 637 days (the z

\times day parameter). Our main focus is on the effects of the time-varying social network factors, especially network size and the average sleep levels for a person's contacts. These time-varying variables and the others included in the models can vary from day to day, so significant findings indicate that daily changes in sleep patterns are predicted by daily changes in these variables.

Time trend. Before turning to these social network effects, Table 3 shows estimates for a linear change trend in the outcome variables. For six out of the eight sleep outcomes, the parameter estimates indicating linear change in that outcome are not statistically significant. Sleep efficiency decreases and awakening frequency evidence increases over time, but the magnitudes of these trend effects are very small. In models not reported here, we estimate the quadratic effects for these two sleep indicators and neither parameter estimate is statistically significant. We conclude that in this population the participants maintained relatively consistent sleep levels. This stability at the population level does not mean that there is no variation across persons in their sleep durations or sleep quality temporal patterns. Individual sleep patterns can and do change over time. The issue is whether those changes can be predicted by changes in the traits of their social networks holding constant their personal traits and other changes occurring to them and in their environment.

Social network factors. Table 4 reports the estimated parameters for the average sleep trait for a person's contacts and for the size of social network. Peer influence is evident for time in bed, total sleep time, time to bed, and time getting up. The later an ego's peers' bedtime or rising time, the later the ego's bedtime or rising time. By impacting bedtime and rising time, a person's peers impact the ego's total time in bed and sleep time. An ego gains approximately 6.5 minutes of sleep for every hour his or her typical peer sleeps. So, for example, one student has contacts who sleep on average 6 hours per night and a second student has friends who sleep on average 9 hours per night, then the model results indicate that the second student is likely to sleep 19 minutes more

Table 3
Result on time trend from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Time in bed	Total sleep time	Sleep efficiency	Number of sleep episodes	Sleep onset latency	Frequency of awakenings	Bedtime	Rising time
Day	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.01* (-0.02, -0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.01)	0.00*** (0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)
Intercept	6.17*** (5.20, 7.13)	6.19*** (5.19, 7.19)	99.89*** (94.07, 105.70)	1.16*** (0.98, 1.33)	1.93 (-0.57, 4.42)	0.66* (0.06, 1.27)	1.73** (0.44, 3.02)	7.58*** (6.66, 8.50)
Number of cases	16,185	16,185	16,185	16,185	16,185	16,185	16,185	16,185
Number of individuals	308	308	308	308	308	308	308	308
Goodness-of-fit								
AIC	58843.72	57362.45	87472.19	12682.30	95218.06	32506.49	60711.34	59505.95
BIC	59328.31	57847.04	87956.77	13170.67	95702.64	32991.08	61195.93	59990.54
Wald chi-square/df	2102.06/58	2118.32/58	249.80/58	209.22/58	66.19/58	357.74/58	2071.87/58	3514.50/58
Log-likelihood	-29358.86	-28618.23	-43673.09	-6278.15	-47546.03	-16190.25	-30292.67	-29689.98

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

Table 4
Results on social network factors from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Time in bed	Total sleep time	Sleep efficiency	Number of sleep episodes	Sleep onset latency	Frequency of awakenings	Bedtime	Rising time
Average measure of dependent variables among ego's in-study contacts	0.11*** (0.10, 0.13)	0.11*** (0.10, 0.13)	0.01 (-0.01, 0.02)	0.02 (-0.00, 0.04)	-0.01 (-0.02, 0.01)	0.00 (-0.01, 0.02)	0.08*** (0.07, 0.09)	0.09*** (0.08, 0.11)
Daily network size	-0.01** (-0.01, -0.00)	-0.01** (-0.01, -0.00)	-0.00 (-0.02, 0.01)	-0.00 (-0.00, 0.00)	0.01 (-0.01, 0.02)	-0.00* (-0.00, -0.00)	-0.00 (-0.01, 0.00)	-0.01*** (-0.01, -0.00)

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

Table 5
Results on personal factors from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Time in bed	Total sleep time	Sleep efficiency	Number of sleep episodes	Sleep onset latency	Frequency of awakenings	Bedtime	Rising time
Female (1 = yes)	-0.04 (-0.30, 0.21)	0.01 (-0.26, 0.28)	0.01 (-1.61, 1.62)	-0.03 (-0.07, 0.02)	0.47 (-0.19, 1.13)	-0.41*** (-0.58, -0.25)	-0.59*** (-0.95, -0.24)	-0.58*** (-0.82, -0.34)
Female × Day	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)
Latino (1 = yes)	-0.14 (-0.50, 0.22)	-0.25 (-0.62, 0.13)	-0.60 (-2.85, 1.64)	0.03 (-0.04, 0.09)	0.38 (-0.55, 1.30)	-0.03 (-0.26, 0.20)	0.10 (-0.39, 0.59)	0.01 (-0.33, 0.35)
Latino × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)
African American (1 = yes)	-0.63* (-1.25, -0.01)	-0.50 (-1.14, 0.14)	-1.52 (-4.94, 1.91)	0.13* (0.01, 0.25)	0.48 (-1.18, 2.14)	-0.11 (-0.48, 0.27)	0.35 (-0.46, 1.15)	-0.52 (-1.11, 0.07)
African American × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.01, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.01, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)
Asians American (1 = yes)	-0.15 (-0.61, 0.33)	-0.07 (-0.57, 0.43)	-0.62 (-3.42, 2.19)	-0.08 (-0.17, 0.01)	0.14 (-1.10, 1.38)	0.05 (-0.25, 0.35)	-0.33 (-0.98, 0.32)	-0.36 (-0.83, 0.10)
Asians American × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00* (0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)
Other race (1 = yes)	-0.22 (-0.87, 0.44)	-0.16 (-0.84, 0.52)	0.01 (-3.93, 3.95)	-0.04 (-0.16, 0.08)	-0.92 (-2.64, 0.81)	0.08 (-0.33, 0.49)	-0.34 (-1.21, 0.53)	-0.49 (-1.11, 0.12)
Other race × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.01, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.01)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)
Protestant (1 = yes)	0.15 (-0.30, 0.59)	0.22 (-0.24, 0.69)	1.66 (-1.03, 4.35)	0.06 (-0.02, 0.15)	0.05 (-1.10, 1.20)	-0.00 (-0.29, 0.28)	0.32 (-0.28, 0.92)	0.49* (0.07, 0.91)
Protestant × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00* (-0.00, -0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)
Other religion (1 = yes)	0.51 (-0.10, 1.12)	0.47 (-0.17, 1.11)	0.97 (-2.97, 4.91)	-0.05 (-0.17, 0.07)	-0.45 (-2.07, 1.17)	0.34 (-0.04, 0.73)	-0.62 (-1.44, 0.20)	-0.07 (-0.65, 0.51)
Other religion × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.01, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.01)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)
No religion (1 = yes)	-0.11 (-0.57, 0.36)	-0.27 (-0.75, 0.22)	-0.37 (-3.12, 2.38)	-0.07 (-0.16, 0.01)	0.66 (-0.53, 1.84)	0.10 (-0.19, 0.39)	0.07 (-0.56, 0.70)	0.14 (-0.30, 0.58)
No religion × Day	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.01)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)	0.00 (-0.00, 0.00)
BMI	0.02 (-0.02, 0.06)	0.00 (-0.04, 0.04)	-0.30* (-0.54, -0.06)	0.00 (-0.01, 0.01)	0.06 (-0.04, 0.16)	0.04*** (0.02, 0.07)	0.03 (-0.02, 0.08)	0.04* (0.01, 0.08)
BMI × Day	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	0.00* (0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00*** (-0.00, -0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

than the first student.

While peer influence is evident for sleep quantity, for sleep quality there is no such effect. Having peers who have more sleep interruptions or problems falling asleep does not lead egos to also have these problems.

In regard to the size of a person’s social network, students with larger networks sleep less (Model 2) because they are in bed less (Model 1). While the finding that people with larger networks sleep less is anticipated, we expected this would be due to more social engagements that result in later bedtime compared with those with fewer contacts. However, we find that those with larger networks have similar bedtime (Model 7) but get up earlier than those with small networks (Model 8). We also find a small but significant effect of network size on one measure of sleep quality, frequency of awakenings (Model 6).

Tables 5 and 6 present parameter estimates for time-constant predictors. For each possible predictor z , two parameters are estimated, one for its main effect on each of the outcome variables (η_0 in Fig. 1) and another for its effect on the change in the outcome overtime (η_1 in Fig. 1, the $z \times$ Day effect in Tables 5 and 6). As seen in Tables 5 and 6, almost all of the effects on change in linear slope are not significant at the 0.05 level, implying that individual traits impact the overall level of various outcome variables but not the rates of change in those outcomes. In what follows we focus therefore on the main effects.

First, regarding the *personal* factors in Table 5, females have less frequent awakenings and they have earlier bedtime and rising time than males. However, there is no gender difference in sleep duration. African American participants compared to Whites have shorter time in bed and more sleep episodes, but otherwise are not significantly different from

white participants. Protestants, compared to Catholics, get out of bed later but show no significant difference on the other sleep indicators. Participants with higher BMIs get out of bed a little bit later. However, the slightly lower sleep efficiency and more frequent awakenings cancel out that effect, leading to no net effect of BMI on sleep duration.

Psychological factors. As shown in Table 6, conscientious and morning type participants are characterized by earlier bedtime and rising time as well as fewer sleep episodes (i.e., naps). Higher openness is related to earlier rising time and thus shorter total sleep time, but not shorter time in bed. Depressed individuals have more sleep episodes, but net of other factors depression is not associated with sleep. Those who report sleep problems prior to coming to the university spend more time in bed but do not sleep more because they also have more frequent awakenings.

Environmental factors. In Tables 7 and 8 we present parameter estimates for the other time-varying predictors besides a person’s network size and the sleep patterns of their contacts. Table 7 contains estimates for environmental conditions having to do with daily changes in weather, days of the week, break periods, and other calendar changes. Students have unchanged bedtime but later rising time when sleeping at their parental homes compared to sleeping at other places, and later bedtime and even later rising time in residence halls when sleeping on campus compared to sleeping at other places, indicating that students tend to have longer sleep duration in familiar settings. Turning to day of the week effects, using Sundays as the baseline, on Mondays through Thursdays participants have earlier bedtime and rising time, leading to similar sleep duration as they have on Sundays. Students also appear to have more sleep interruptions during the week. On Fridays (which pertain to sleep periods for Thursday night into Friday morning)

Table 6
Results on psychological factors from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Time in bed	Total sleep time	Sleep efficiency	Number of sleep episodes	Sleep onset latency	Frequency of awakenings	Bedtime	Rising time
Extraversion	0.01 (−0.16, 0.18)	0.04 (−0.14, 0.22)	0.15 (−0.93, 1.23)	−0.00 (−0.03, 0.03)	0.25 (−0.19, 0.69)	−0.04 (−0.16, 0.07)	0.05 (−0.18, 0.28)	0.08 (−0.08, 0.24)
Extraversion × Day	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00* (−0.00, −0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00* (0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)
Agreeableness	−0.11 (−0.34, 0.11)	−0.15 (−0.38, 0.09)	0.10 (−1.31, 1.51)	−0.00 (−0.05, 0.04)	0.07 (−0.51, 0.64)	−0.08 (−0.22, 0.07)	0.28 (−0.03, 0.58)	0.17 (−0.04, 0.38)
Agreeableness × Day	−0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)
Conscientiousness	0.07 (−0.16, 0.29)	0.15 (−0.08, 0.38)	0.50 (−0.86, 1.87)	−0.06** (−0.10, −0.01)	−0.28 (−0.86, 0.30)	−0.04 (−0.18, 0.10)	−0.65*** (−0.95, −0.35)	−0.43*** (−0.64, −0.22)
Conscientiousness × Day	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	0.00* (0.00, 0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	0.00* (0.00, 0.00)	0.00 (−0.00, 0.00)
Neuroticism	−0.04 (−0.27, 0.19)	−0.04 (−0.28, 0.20)	−0.06 (−1.50, 1.39)	0.03 (−0.01, 0.07)	0.16 (−0.43, 0.74)	−0.07 (−0.22, 0.08)	0.01 (−0.31, 0.32)	−0.14 (−0.35, 0.08)
Neuroticism × Day	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)
Openness	−0.17 (−0.38, 0.04)	−0.26* (−0.48, −0.04)	−1.14 (−2.49, 0.22)	0.03 (−0.01, 0.07)	0.08 (−0.47, 0.62)	0.04 (−0.10, 0.18)	−0.04 (−0.33, 0.25)	−0.24* (−0.44, −0.04)
Openness × Day	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)
Depression	0.24 (−0.18, 0.66)	0.26 (−0.17, 0.69)	0.68 (−1.61, 2.97)	0.14*** (0.06, 0.22)	0.10 (−0.99, 1.20)	0.10 (−0.16, 0.35)	0.03 (−0.52, 0.58)	0.05 (−0.36, 0.45)
Depression × Day	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.01, 0.00)	−0.00** (−0.00, −0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)
Morningness inclination	−0.06 (−0.45, −0.34)	−0.17 (−0.58, 0.25)	−1.48 (−3.95, 0.99)	−0.07* (−0.15, −0.00)	0.31 (−0.71, 1.33)	0.24 (−0.01, 0.50)	−0.67* (−1.21, −0.13)	−0.59** (−0.96, −0.21)
Morningness inclination × Day	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	0.00* (0.00, 0.01)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00** (−0.00, −0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)
Sleep troubles	0.43* (0.08, 0.77)	0.32 (−0.04, 0.67)	−1.04 (−3.18, 1.11)	0.03 (−0.03, 0.09)	−0.62 (−1.51, 0.27)	0.27* (0.05, 0.49)	−0.24 (−0.70, 0.23)	0.17 (−0.15, 0.50)
Sleep troubles × Day	0.00 (−0.00, 0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	0.00* (0.00, 0.00)	0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)	−0.00 (−0.00, 0.00)

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

students have slightly more sleep episodes (i.e., naps), slightly earlier bedtime, earlier rising time, and overall shorter sleep duration than on Sundays. On Saturdays, participants have slightly lower sleep efficiency, slightly less frequent awakenings, and slightly later rising time, but the other indicators show no significant difference compared to Sundays.

Because orientation week and final exam week are more stressful periods compared to normal school days, we expect sleep patterns to be different and they are. During orientation week, participants have lower sleep efficiency, more frequent awakenings, earlier bedtime, and even earlier rising time, which lead to shorter sleep duration. During final exam week, students go to bed later, rise earlier, have fewer sleep episodes, and have poor sleep quantity and quality. Breaks from school are different. Participants go to bed earlier during mid-term breaks, rise later during winter breaks and Easter holidays, and thus have longer sleep duration than when school is in session. However, summer breaks show a different pattern from short breaks, more similar to academic term. Participants have both earlier bedtime and rising time, resulting in similar sleep duration during summer breaks and the school year. Weather also impacts sleep. Participants rise earlier on warmer days and later on cold days. Participants are in bed less and sleep less when it is hotter. On rainy days, participants have fewer awakenings, rise later, and thus have longer sleep duration. Consistent with prior work (Peixoto et al., 2009), sunset time and sunrise time have no effect on sleep patterns.

Behavioral factors. In Table 8 we report estimates for two other time-

varying covariates pertaining to two things that can change daily – a person’s physical activity level and the number of classes he or she has. Students who are more physically active on a given day spend less time in bed and sleep less. They also go to bed earlier and get up earlier. It could be that the shorter sleep duration is due to the much earlier rising time that is somewhat but not fully counteracted by earlier bedtime. A similar pattern is evident on days that students have lots of classes. When students have more classes, they go to bed earlier and get up much earlier. As in the case of physical activity, this leads to less time in bed and less sleep.

4. Discussion

While prior research indicates that sleep quantity declines during late adolescence and emerging adulthood (Walsemann et al., 2017), in this population of college students no downward trend is evident. This is not to say that students’ sleep levels are constant over time. They go up and down, depending on changes in a person’s social network, environment, and other behaviors. Consistent with prior research (Carrier et al., 1997; Vitiello et al., 2004), we do find a small negative trend in sleep quality (declining efficiency and increasing awakenings). There are a few time-constant factors that predict change in sleep quality, the magnitudes of which are small.

While there is no “average” up or down trend in sleep quantity, we do find that changes in a person’s social network are associated with

Table 7
Results on environmental factors from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Time in bed	Total sleep time	Sleep efficiency	Number of sleep episodes	Sleep onset latency	Frequency of awakenings	Bedtime	Rising time
Sleep at home (1 = yes)	0.50*** (0.38, 0.62)	0.49*** (0.38, 0.60)	0.28 (-0.00, 0.56)	0.01 (-0.02, 0.04)	0.23 (-0.13, 0.59)	0.02 (-0.03, 0.07)	0.09 (-0.03, 0.22)	0.55*** (0.43, 0.67)
Sleep in residence hall (1 = yes)	0.29*** (0.15, 0.43)	0.30*** (0.16, 0.43)	0.32 (-0.02, 0.66)	0.02 (-0.02, 0.05)	-0.03 (-0.47, 0.40)	-0.00 (-0.07, 0.06)	0.78*** (0.63, 0.93)	1.05*** (0.90, 1.19)
Monday to Thursday (1 = yes)	-0.00 (-0.09, 0.08)	-0.01 (-0.09, 0.07)	-0.07 (-0.26, 0.13)	-0.01 (-0.01, 0.03)	-0.01 (-0.27, 0.25)	0.04* (0.01, 0.08)	-0.59*** (-0.68, -0.51)	-0.60*** (-0.69, -0.52)
Friday(1 = yes)	-0.21*** (-0.31, -0.12)	-0.22*** (-0.31, -0.12)	-0.15 (-0.38, 0.08)	0.03* (0.01, 0.05)	-0.08 (-0.38, 0.22)	-0.01 (-0.06, 0.03)	-0.18*** (-0.28, -0.08)	-0.44*** (-0.54, -0.35)
Saturday(1 = yes)	0.05 (-0.04, 0.14)	0.03 (-0.05, 0.12)	-0.23* (-0.44, -0.01)	0.02 (-0.00, 0.04)	-0.18 (-0.46, 0.10)	-0.05** (-0.09, -0.01)	0.08 (-0.01, 0.18)	0.09* (0.00, 0.18)
Mid-term break (1 = yes)	0.17* (0.02, 0.32)	0.14* (0.00, 0.29)	-0.28 (-0.63, 0.08)	0.01 (-0.02, 0.05)	0.06 (-0.39, 0.52)	0.03 (-0.03, 0.10)	-0.23** (-0.38, -0.07)	-0.07 (-0.22, 0.08)
Winter break(1 = yes)	0.38*** (0.22, 0.55)	0.32*** (0.16, 0.48)	-0.57** (-0.97, -0.18)	0.02 (-0.02, 0.06)	-0.05 (-0.55, 0.46)	0.14*** (0.07, 0.22)	0.00 (-0.17, 0.18)	0.37*** (0.20, 0.54)
Summer break(1 = yes)	0.09 (-0.06, 0.24)	0.08 (-0.06, 0.22)	-0.15 (-0.51, 0.20)	-0.03 (-0.07, 0.00)	-0.10 (-0.55, 0.35)	0.02 (-0.05, 0.08)	-0.49*** (-0.65, -0.33)	-0.28*** (-0.43, -0.13)
Thanksgiving holidays (1 = yes)	0.00 (-0.21, 0.21)	-0.01 (-0.21, 0.19)	-0.12 (-0.61, 0.37)	0.01 (-0.04, 0.06)	0.05 (-0.58, 0.69)	0.04 (-0.05, 0.13)	0.03 (-0.18, 0.25)	0.05 (-0.16, 0.26)
Easter holidays (1 = yes)	0.30* (0.06, 0.55)	0.29* (0.06, 0.52)	-0.08 (-0.66, 0.51)	0.01 (-0.05, 0.07)	-0.19 (-0.94, 0.56)	0.02 (-0.09, 0.13)	0.06 (-0.20, 0.32)	0.34** (0.09, 0.59)
Orientation week (1 = yes)	-0.39** (-0.64, -0.14)	-0.44** (-0.67, -0.20)	-1.29*** (-1.89, -0.69)	-0.04 (-0.10, 0.02)	0.06 (-0.71, 0.83)	0.16** (0.05, 0.27)	-0.39** (-0.65, -0.12)	-0.64*** (-0.90, -0.39)
Final exam week (1 = yes)	-0.38*** (-0.51, -0.25)	-0.45*** (-0.57, -0.32)	-1.24*** (-1.55, -0.93)	-0.04* (-0.07, -0.01)	0.06 (-0.34, 0.45)	0.14*** (0.08, 0.20)	0.16* (0.02, 0.29)	-0.16* (-0.29, -0.03)
Highest temperature (°F)	-0.00** (-0.01, -0.00)	-0.00** (-0.01, -0.00)	-0.00 (-0.01, 0.00)	0.00 (-0.00, 0.00)	-0.00 (-0.01, 0.01)	-0.00 (-0.00, 0.00)	-0.00 (-0.00, 0.00)	-0.00*** (-0.01, -0.00)
Lowest temperature (°F)	0.00* (0.00, 0.01)	0.00 (-0.00, 0.01)	-0.01 (-0.02, 0.00)	-0.00 (-0.00, 0.00)	0.00 (-0.01, 0.01)	0.00*** (0.00, 0.01)	-0.00 (-0.01, 0.00)	0.00 (-0.00, 0.01)
Precipitation in inches	0.12*** (0.06, 0.18)	0.12*** (0.06, 0.18)	0.07 (-0.07, 0.22)	0.01 (-0.01, 0.02)	-0.16 (-0.36, 0.03)	-0.03* (-0.06, -0.00)	0.01 (-0.05, 0.08)	0.13*** (0.06, 0.19)
Snowfall in inches	0.02 (-0.01, 0.05)	0.02 (-0.01, 0.04)	-0.00 (-0.07, 0.06)	0.00 (-0.00, 0.01)	0.06 (-0.03, 0.15)	-0.01 (-0.02, 0.01)	-0.02 (-0.05, 0.01)	-0.01 (-0.04, 0.02)
Snow piling depth in inches	-0.01 (-0.03, 0.01)	-0.01 (-0.03, 0.01)	-0.03 (-0.07, 0.01)	-0.00 (-0.01, 0.00)	-0.05 (-0.11, 0.01)	-0.00 (-0.01, 0.01)	0.00 (-0.02, 0.02)	-0.01 (-0.02, 0.01)
Sunrise time	0.04 (-0.05, 0.12)	0.02 (-0.07, 0.10)	0.12 (-0.08, 0.32)	-0.01 (-0.03, 0.01)	-0.08 (-0.34, 0.17)	-0.02 (-0.06, 0.02)	-0.06 (-0.15, 0.03)	-0.04 (-0.13, 0.04)
Sunset time	-0.00 (-0.04, 0.03)	-0.01 (-0.04, 0.02)	0.05 (-0.03, 0.13)	0.00 (-0.00, 0.01)	-0.05 (-0.15, 0.05)	-0.00 (-0.02, 0.01)	-0.01 (-0.04, 0.03)	-0.02 (-0.05, 0.01)

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

Table 8
Results on behavioral factors from linear growth curve models.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Time in bed	Total sleep time	Sleep efficiency	Number of sleep episodes	Sleep onset latency	Frequency of awakenings	Bedtime	Rising time
Physical activity	-0.49*** (-0.55, -0.43)	-0.45*** (-0.51, -0.40)	0.06 (-0.07, 0.20)	-0.02*** (-0.04, -0.01)	-0.09 (-0.26, 0.08)	-0.02 (-0.05, 0.00)	-0.12*** (-0.18, -0.06)	-0.54*** (-0.60, -0.48)
Number of classes	-0.20*** (-0.22, -0.17)	-0.18*** (-0.20, -0.16)	0.03 (-0.02, 0.09)	-0.01** (-0.01, -0.00)	-0.05 (-0.12, 0.02)	-0.00 (-0.01, 0.01)	-0.08*** (-0.10, -0.05)	-0.26*** (-0.28, -0.23)

Note: *p < 0.05, **p < 0.01, ***p < 0.001.

changes in how much a person sleeps. Students whose networks become more composed of people with better (or worse) sleep levels increase (or decrease) their sleep. We also find, consistent with prior research (Mednick et al., 2010), that this peer influence on sleep duration occurs

in part because peers impact a person's bedtime and rising time, but not because they affect awakenings or sleep onset latency.

Besides the peer influence effects, the size of social networks also matters. Increases in network size are associated with decreased sleep

quantity. When a student's network gets bigger, they get less sleep and spend less time in bed. There are many possible mechanisms that could lead to changes in network size being associated with sleep durations. People with large networks are more sociable, interacting with more people, and this could lead to later bedtime. However, in this population there is no association between changes in network size and bedtime, though increasing network sizes are associated with earlier rising time. It could also be that students are overwhelmed as their networks grow, as they find that maintaining a larger network is more time consuming and stressful, resulting in less sleep. Given that the pressure to have more friends and larger networks is especially pronounced among first-year college students (Arnett, 2015; Friedlander et al., 2007; Hays & Oxley, 1986), poor sleep could be the result of people having difficulty managing networks that are too big.

Our models controlled for time-constant and time-varying covariates that previous research has found to be associated with sleep and which could be associated with network size and composition. Consistent with prior work (Tsai & Li, 2004), we find that women have earlier bedtime but also earlier rising time resulting in no gender differences in sleep duration. When considering sleep quality, we find that African American participants have slightly more naps relative to white participants, replicating the findings from Jean-Louis et al. (2000) and Mednick et al. (2010), though these studies also report African Americans had slightly shorter sleep duration than whites, a difference not evident in this population. For health characteristics, while Gupta et al. (2002) and Ekstedt et al. (2013) indicate that sleep duration (but not sleep quality) is worse for those with higher BMI, we find that higher BMI is associated with lower sleep quality but not shorter sleep duration.

Like other research, we find that some personality traits are associated with different levels of sleep quantity and quality. More conscientious participants have earlier bedtime and rising time as well as lower nap frequency, a finding noted by Gray and Watson (2002) and Duggan et al. (2014). However, contrary to some of these studies, we do not find personality effects on sleep duration. We also find that depressed students have more sleep episodes as in Foley et al. (2007).

The findings pertaining to time-varying covariates related to a person's environmental context are not unexpected. The sleep changes corresponding to calendar and weather fluctuations increase our confidence in the validity of our measures as they vary in ways that we would expect them to vary. Consistent with prior research (Edinger et al., 1997), students sleep better in familiar environments. The well-known processes of recovery sleep on weekends and earlier bedtimes during the week (Wong et al., 2013) are evident. Our findings replicate previous research on the effects of temperature (e.g., Nixon et al., 2008; Wirz-Justice et al., 1991) with people sleeping less when daytime temperatures are hotter. Consistent with Peixoto et al. (2009), sunset time and sunrise time have no effect on sleep behavior.

We also track and control for two daily changes that could be associated with changes in network size and composition and are also very likely to impact sleep – physical activity and the number of classes. As expected and noted in prior work (Moore & Meltzer, 2008; Charles et al., 2011; Dorrian et al., 2011), on days when students have more classes, they sleep less in part because they have to get up earlier and do not go to bed that much earlier. However, contrary to prior research (Guimaraes et al., 2008; Nixon et al., 2009; Ekstedt et al., 2013; Driver & Taylor, 2000) we do not find that those who are more physically active on a given day sleep more or better. It appears that in this highly active population, students may be forgoing some sleep by getting up earlier and not napping in order to exercise.

With these numerous controls, our findings of social network effects on sleep stand out. Controlling for multiple sets of covariates, our analysis shows that students are influenced by their peers and students sleep less when their networks get bigger. Together these findings point to the need to incorporate into sleep research social network properties and processes. They also hold out the possibility of leveraging social networks to help improve the amount and quality of sleep among college

students.

The peer influence effect implies that sleep habits and patterns can diffuse within a social network. Students who find themselves surrounded by friends who sleep more (or less) than they do are influenced to change their sleep habits in order to be more similar to those in their networks. In this way sleep behaviors can spread through a network. This diffusion can work both ways, spreading healthy behaviors or unhealthy behaviors. In a college student population where there are well-known sleep deficits and problems (Lund et al., 2010; American College Health Association ACHA, 2016), this social influence and diffusion process is likely to lead to the spread of unhealthy sleeping habits. However, it may be possible to also diffuse positive sleep practices through social networks once a critical mass within the population develops them. Through ties to those with worse habits, an emerging cluster of persons with better sleep practices can, through interpersonal contact, influence others to adopt those practices.

The potential for diffusion through a network implies that networks can be used to make interventions designed to improve sleep even more effective. In the last few years, several college initiatives have focused on raising awareness and improving college students' sleep. For example, students attending a public Midwestern university were invited to visit the sleepstayawake.org website in the spring of 2015 to watch videos and read information on healthy sleep behavior and their sleep quality was found to be improved (Hershner & O'Brien, 2018). The Sleep 101 online course was administered at four universities in fall of 2016 to improve student's knowledge about sleep (Quan & Ziporyn, 2017) and it was made mandatory for all incoming freshmen joining Harvard University in 2018. A four-week Dreaming Domers Sleep program was provided to students at the University of Notre Dame in the spring of 2020 and improved sleep habits have been reported (<https://mcwell.nd.edu/services/sleep-program/>). By focusing on delivering sleep hygiene knowledge to college students, these intervention programs create better sleep habits among some members exposed to the intervention, but not everyone. Social networks can diffuse sleep improvement to those who are not exposed to the intervention or who are more resistant to change. Networks can also help to maintain newly acquired sleep habits through peer influence. Leveraging networks to spread the impact of interventions could increase the efficacy of programs to help students sleep better and to maintain their new habits.

But it is not just peer influence that impacts sleep, but also network size, and here there are strong pressures among college students, especially incoming students, to have friends and larger networks (Arnett, 2015; Friedlander et al., 2007; Hays & Oxley, 1986) resulting in, according to our results, less sleep. How and why this occurs is something that needs to be better understood. Having more friends requires more time maintaining the network. Increases in size can be especially stressful as students are overwhelmed by additional commitments and are trying to figure out how to manage the larger network, possibly by ending some friendships. Future research needs to take into account that it may be more the changes in network size that impact sleep rather than the overall level, and that people may need to adjust their network size in order to have better sleep.

Several limitations of this study must be acknowledged. First, the NetHealth project only collected data from one campus, and further research is needed to corroborate these findings in the general population. Second, NetHealth participants had missing data, either from periodically not wearing the device, or from the devices' method of overwriting data before it could be collected. Although missing data is a common issue in longitudinal studies, future studies are needed to understand how to achieve higher compliant levels in data collected by wearing devices.

Despite these limitations, our findings have important implications. Our ability to research and theorize about how social networks impact sleep is now feasible because of the availability of high resolution temporal data on sleep made possible by wearables whose sensors generate streams of data on sleep as well as physical activity events.

With LGCM models that use time series data, researchers can model within-person overtime changes in sleep as well as between-person variation in order to see how changes in people's lives, including in their social networks, impact sleep.

Our findings pertain to a specific population, college students on a residential campus. Close proximity, many activities and contexts for forming ties and making friends, normative pressures to have friends, and many other features make this an ideal population to study whether and to what extent people's social networks impact sleep. As emerging young adults, college students are developing habits, including sleep habits, that could last for a long time. Our findings point to how the social networks of college students create both challenges to improve sleep, because of the pressure to have larger networks, and opportunities to spread better sleep habits through social networks. Addressing whether and to what extent these network processes and effects are evident in other settings is an important avenue for future work. If in other settings a person's network can change in size and who is in their network, then networks in those settings could have impacts on changes in sleep. In college where these network changes are more pronounced, their impacts on sleep and other outcomes are more detectable. As researchers continue to study how sleep habits are formed and change across multiple settings and at various life course stages, incorporating network processes and effects into models is likely to lead to new insights into sleep.

Data availability

The NetHealth data are publicly accessible via the following URL: <http://sites.nd.edu/nethealth/data-2/>.

Institutional Review Board statement

This study was approved by the Institutional Review Board of the University of Notre Dame.

Informed consent statement

Written informed consent was obtained from all participants.

Author contributions

OL and DSH acquired the fund and supervised the project. CW analyzed the data. All authors were involved in the preparation of the manuscript.

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Declaration of competing interest

The authors declare no conflicts of interest.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.ssmph.2021.100937>.

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