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Nightly sleep duration predicts grade point average in the first year of college

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Academic achievement in the first year of college is critical for setting students on a pathway toward long-term academic and life success, yet little is known about the factors that shape early college academic achievement. Given the important role sleep plays in learning and memory, here we extend this work to evaluate whether nightly sleep duration predicts change in end-of-semester grade point average (GPA). First-year college students from three independent universities provided sleep actigraphy for a month early in their winter/spring academic term across five studies. Findings showed that greater early-term total nightly sleep duration predicted higher end-of-term GPA, an effect that persisted even after controlling for previous-term GPA and daytime sleep. Specifically, every additional hour of average nightly sleep duration early in the semester was associated with an 0.07 increase in end-of-term GPA. Sensitivity analyses using sleep thresholds also indicated that sleeping less than 6 h each night was a period where sleep shifted from helpful to harmful for end-of-term GPA, relative to previous-term GPA. Notably, predictive relationships with GPA were specific to total nightly sleep duration, and not other markers of sleep, such as the midpoint of a student's nightly sleep window or bedtime timing variability. These findings across five studies establish nightly sleep duration as an important factor in academic success and highlight the potential value of testing early academic term total sleep time interventions during the formative first year of college.

sleep | grade point average | college | achievement

Significance

Total nightly sleep is a potentially important and underappreciated behavior supporting academic achievement. First-year college students from three independent universities provided sleep actigraphy for a month early in the academic term, across five separate samples. Lower average nightly sleep early in the academic term predicted lower end-of-term GPA, an effect that held even when controlling for factors known to predict end-of-term GPA, including previous-term GPA, daytime sleep, and overall academic load. Every hour of lost total average nightly sleep was associated with a 0.07 reduction in end-of-term GPA. These findings help establish nightly sleep duration as an important factor for academic success in the formative first year of college.

The first year of college is a particularly challenging transition period that has profound implications for future academic and life success (1–3). First-year grade point average (GPA) has been shown to predict whether students stay in school long-term over and above other critical factors such as gender, socioeconomic status, race, college commitment, social connectedness, and academic self-discipline (4). Moreover, meta-analyses suggest that college GPA reliably predicts future job performance success (2). Yet a fundamental question for our educational system remains: How can we better understand and promote early college achievement?

Currently, little is known about which modifiable behavioral factors improve GPA in first-year college students (5–7). Given the implications of early-college academic performance on retention and career trajectories—core interests of policymakers and educators alike—it is important to identify behavioral antecedents of academic success and optimal time windows in which targeted interventions might be most effective.

One critical factor for academic success during the first year of college is students' sleep habits. Many college students experience irregular and insufficient sleep patterns (8), and it is well established that adopting healthy sleep habits is critical for fostering learning and memory consolidation in both animal and human models (9, 10). Although prior work suggests that nightly sleep duration and daytime sleepiness may be associated with academic performance among adolescents and emerging adults, much of this previous work has been limited by self-reports of sleep (11, 12), which can be significantly biased (e.g., refs. 13 and 14). Now that activity trackers measuring objective sleep and physical activity (e.g., Fitbits) have become ubiquitous and are utilized by an ever-growing number of college students, we are in a better position to rigorously evaluate the effects of sleep patterns on academic success outside the confines of the laboratory. In the current longitudinal, multi-university analysis, we offer the first test of whether objective measures of early-term sleep (via wrist actigraphy) predict subsequent changes in GPA in a sample of first-year college students. Notably, we draw from five separate samples across three disparate US universities, which included a private science, technology, engineering, and mathematics (STEM)-focused university, a private Catholic university, and a large public state university.

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The first year of college is a major life transition period for many college students (15), marked by greater independence and autonomy, academic workload, efforts to establish new sleep habits outside the childhood home (8), and formation of new friendships (16). As such, first-year college students contend with a variety of personal, cognitive, and social demands that can impact sleep habits, which have implications for learning (17). Importantly, this time in one's life marks a critical period of development, and thus a deeper understanding of sleep behaviors has both theoretical and practical implications for developing effective interventions.

The present studies utilized wrist actigraphy to evaluate the relationship between sleep and GPA early in the Winter/Spring academic term during the first year of college. We selected this critical window for evaluating sleep-GPA relationships because it is a more stable period of sleep patterning prior to midterm and final examination periods and is a time window that affords the opportunity for targeted sleep interventions (*SI Appendix*, Table S1). In preregistered discovery analyses (https://osf.io/5xngv; https://osf.io/x76b4), we first tested the sleep–GPA relationship in a sample of first-year college students which revealed that early-term nightly sleep assessed by wrist actigraphy was significantly and positively associated with end-of-term GPA. Subsequently, we preregistered confirmatory hypotheses in order to evaluate the observed prospective, directional association of sleep on GPA in four independent longitudinal samples of first-year students.

Results

Descriptive results of sleep actigraphy data indicated that first-year college students across all five samples slept, on average, 6 h 37 min per night (SD = 51 min). Sleep actigraphy data also showed that, on average, students slept 29 min more on weekends compared to weeknights (Mweekend-sleep = 6 h 58 min, SD = 63 min; Mweeknight-sleep = 6 h 29 min, SD = 58 min). Table 1 provides more information on early-term sleep characteristics aggregated across the five samples. In the discovery study (Study 1), early-term total nightly sleep was positively associated with end-of-term Spring GPA (N = 77, β = 0.003, p < .01), an effect that persisted even after controlling for Fall term GPA prior to the Winter/Spring academic term (N = 77, β = 0.002, p < .01). This relationship between early-term sleep and end-of-term GPA was also observed in the confirmatory studies across a diverse group of universities. Specifically, greater early academic term total nightly sleep time was associated with higher end-of-term GPA when controlling for previous-term GPA: Study 2 (N = 140, β = 0.002, p = .01), Study 3 (N = 139, β = 0.002, p < .01), and Study 4 (N = 147, β = 0.001, p = .01), and while this relationship was in the same direction, it was not statistically significant in Study 5 (N = 131, β = 0.001, p = .34). A subsequent pooled analysis aggregating all four confirmatory studies showed that greater early-term total sleep time (TST) was significantly associated with higher GPA when controlling for previous-term GPA (N = 557, β = 0.001, p < .01) which corresponds to a 0.07 improvement in GPA for every additional hour of nightly sleep (see Fig. 1 and Table 2 for all regression results).

Table 1. Early-term sleep characteristics of first-year college students across five samples

Measure	Mean	SD
Total nightly sleep	6 h, 37 min	50.9 min
Nightly sleep weekday	6 h, 29 min	58.0 min
Nightly sleep weekend	6 h, 58 min	62.8 min
Daytime sleep	41 min	27.4 min
Waketime	9:17 AM	78.7 min
Waketime weekday	8:56 AM	84.5 min
Waketime weekend	10:11 AM	100.7 min
Bedtime	2:01 AM	81.0 min
Bedtime weekday	1:48 AM	88.3 min
Bedtime weekend	2:33 AM	94.2 min
Midpoint sleep	5:39 AM	72.7 min
Midpoint sleep weekday	5:22 AM	77.5 min
Midpoint sleep weekend	6:22 AM	88.0 min
Bedtime variability	0.45 h	1.39 h

A series of sensitivity analyses evaluated whether variables commonly associated with nightly sleep and GPA (i.e., daytime sleep, demographic characteristics, and academic term load) might impact this association. Descriptive analyses showed that students across all five samples had an average daytime sleep duration of 41 min (SD = 27.4 min; see Table 1 for pooled descriptives, *SI Appendix*, Table S6 in supporting online materials for individual study descriptives). The supporting online materials (pg. 3) provide information on how daytime sleep data were acquired and analyzed from Fitbits. Results of covariate-adjusted multiple regression analyses in the pooled confirmatory samples revealed that controlling for previous-term GPA, daytime sleep, race, gender, and first-generation status did not significantly alter the strength of the association between nightly sleep duration and end-of-term GPA (N = 557, β = 0.001, p < .01). Likewise, in a subsequent pooled analysis of confirmatory Studies 2, 3, and 5, total academic term load (operationalized as the total number of enrolled term academic units; Study 4 did not collect these data) was added to the previous model. Results of multiple regression analyses indicated that statistically controlling for each of these variables did not appreciably affect the strength of association between total nightly sleep and end-of-term GPA (N = 405, β = 0.001, p < .01).

Table 3 provides the pooled study results for these covariate-adjusted sensitivity analyses. The supporting online materials *SI Appendix*, Table S3 provides more information on individual study results.

To further explore the total nightly sleep–GPA relationship in the pooled sample, students were binned by average nightly sleep into three groups in thresholded sensitivity analyses: students who slept on average <6, 6 to 7, and 7+ h (Table 3). Specifically, students who slept <6, 6 to 7, and 7+ h had average Spring term GPA values of 3.25, 3.48, and 3.51, respectively. Moreover, these Spring term GPA values corresponded to a change from baseline (Fall Term) GPA of −0.13, 0.02, and 0.01, indicating that it was the <6 h nightly sleepers that suffered on end-of-term GPA. Specifically, both Winter/Spring term GPA and GPA change scores show notable increases in GPA between <6 h and 6+ h suggesting that less than 6 h of nightly sleep may be detrimental to academic performance, and that dipping below 6 h of average nightly sleep may be a threshold where sleep goes from being helpful to harmful on student GPA (Table 4).

The relationship between sleep and GPA was most robust with total nightly sleep; there were no reliable relationships with other sleep variables across datasets. While there were significant relationships found in the discovery study between a student's average nightly sleep window ("midpoint sleep") and variability in their bedtime ["bedtime mean-successive squared difference (MSSD)"] with GPA (controlling for previous-term GPA), these relationships were not robust across the four confirmatory studies (see supporting online materials). Specifically, earlier average student nightly sleep

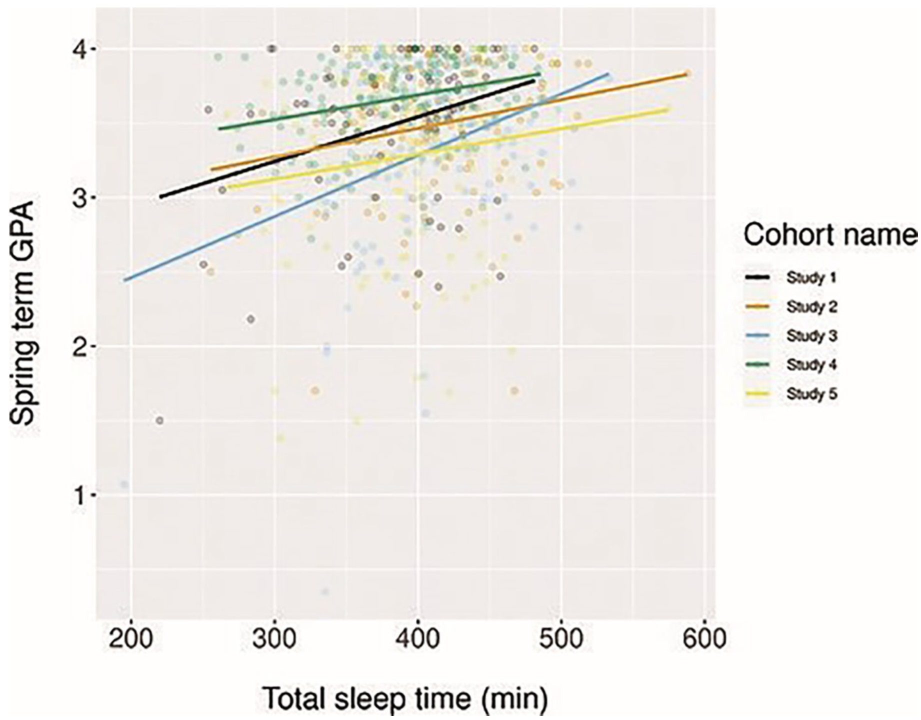

Fig. 1. Early-term total sleep time (TST) is associated with Spring term GPA. Linear regression models for early academic term TST vs. Spring academic term GPA (not controlling for previous-term GPA) are plotted by study.

windows were significantly associated with higher GPA in the discovery study and study 4, but not in studies 2, 3, and 5 (*SI Appendix*, Table S4). Likewise, lower variability in students' bedtime was significantly associated with higher end-of-term GPA in the discovery study but was not in studies 2, 3, 4, and 5 (*SI Appendix*, Table S4).

Table 2. Results of linear regression of early-term total sleep time (TST) by spring term GPA by cohort with and without controlling for previous-term GPA

Previous-term GPA covariate	Cohort	*n*	R^2	β	*p*
No	All Cohorts	634	.04	0.002	<.01**
	Study 1	77	.10	0.003	<.01**
	Study 2	140	.05	0.002	<.01**
	Study 3	139	.12	0.004	<.01**
	Study 4	147	.10	0.002	<.01**
	Study 5	131	.02	0.002	.12
	All Confirmatory (Studies 2 to 5)	557	.04	0.002	<.01**
Yes	All Cohorts	634	.42	0.001	<.01**
	Study 1	77	.41	0.002	<.01**
	Study 2	140	.39	0.002	<.01*
	Study 3	139	.48	0.002	<.01**
	Study 4	147	.48	0.001	<.01*
	Study 5	131	.34	0.001	.34
	All Confirmatory (Studies 2 to 5)	557	.43	0.001	<.01**

Notes: The number of students in each sample is reported by *n*, the R^2 value is the multiple R^2 of the entire linear regression model, the β is the beta coefficient of the sleep feature term, and the *p*-value is the significance of the sleep feature term at the .05 alpha level; *$p < .05$; **$p < .01$.

Discussion

It is well known that rates of total nightly sleep have been decreasing among adolescents and young adults over several decades (e.g., refs. 18 and 19), and there is much discussion about how this growing sleep debt is contributing to increases in young adult depression, obesity risk, and driving-related accidents (20). Here we show in five studies across three universities that total nightly sleep time also may have significant consequences for academic achievement in the formative first year of college. Less early-term nightly sleep was associated with worse end-of-term GPA (and conversely more average nightly sleep was associated with higher end-of-term GPA). In particular, less than 6 h of nightly sleep was especially harmful for end-of-term GPA, relative to students' previous-term GPA. The prospective relationship between total nightly sleep and end-of-term GPA persisted even after controlling for previous-term GPA, and when controlling for additional factors known to be related to sleep and academic achievement (e.g., daytime sleep, academic load, gender, race, or first-generation college student status).

While researchers have long suspected that sleep may play a key role in academic success, prior work has relied on cross-sectional, retrospective self-report assessments of TST to assess the relationship between TST and GPA in college student samples (11, 12, 21). A cross-sectional, retrospective study design using self-report sleep measures is limited in that subjective sleep duration is not a reliable measure of objective sleep duration (22, 23). Also, single-time point assessment is vulnerable to reporting bias and numerous validity concerns relative to longitudinal sleep diary measures (24, 25). In the current work, we address these limitations with multiple prospective longitudinal studies and provide novel evidence across diverse first-year student populations at three American universities that TST early in the term prospectively predicts end-of-term GPA. Findings from objective wrist actigraphy sleep data suggest that higher early-term TST predicts greater end-of-term GPA, measured at time intervals prospectively ranging from 5 to 9 wk.

Table 3. Results of covariate adjusted multiple regression analyses of early-term total sleep time (TST) by spring term GPA, daytime sleep, demographic characteristics, and academic term load

Feature	Covariates	Cohort	*n*	R^2adj	*β*	*p*
Total	Cumulative GPA,	Study 1	77	.39	0.002	.02*
Nightly sleep time	Total daytime sleep, Gender, Race, First-Gen status	All confirmatory (Studies 2 to 5)	557	.43	0.001	<.001**
	Cumulative GPA	Study 1	77	.38	0.002	.02*
	Total daytime sleep, Gender, Race, First-Gen status	Confirmatory (Studies 2, 3, 5)	405	.40	0.002	<.001**
	Academic term load					

Notes: Academic term load was not captured in Study 4; The number of students in each sample is reported by *n*, the adjusted R^2 value is the adjusted multiple R^2 of the entire multiple regression model, the *β* is the beta coefficient of the sleep feature term, and the *p*-value is the significance of the sleep feature term at the .05 alpha level; *$p < .05$; **$p < .01$.

Sleep medicine guidelines indicate that adolescents should be getting 8 to 10 h of nightly sleep (26), but first-year college students in the present samples slept on average 6 h and 37 min each night (*SD* = 51 min). Furthermore, a high proportion of our first-year college students in the five samples slept less than 6 h per night on average (21%), and only 5% of students met the minimum guideline of at least 8 h of night sleep in these samples. While these patterns of insufficient sleep may be troubling, they have also been found across other collegiate student samples (8, 27). While it is striking to observe a large number of first-year college students getting well below the minimum 8 h of total nightly sleep in these samples, it may help explain why there was a robust linear relationship between sleep and GPA, and why less than 6 h of average nightly sleep was negatively associated with end-of-term GPA. Previous studies in community-dwelling adults show a curvilinear relationship, such that too little sleep, as well as too much sleep, have been associated with poor cognition, mental health problems, and increased mortality risk (28, 29). But the current findings diverge and indicate no such reduction (yet a slight increase) in academic performance even at the very top end of the total nightly sleep range in these first-year college students (Fig. 1), likely due to there being so few >8-h nightly sleepers in these samples.

The effects of sleep on GPA were most robust for total nightly sleep. While average nightly sleep window (midpoint sleep) and variability in students' bedtime (bedtime MSSD) emerged as potentially important sleep variables for predicting GPA (controlling for previous-term GPA) in the discovery study, they were not robust or reliable predictors across the four confirmatory datasets. The emergence of total nightly sleep as the most robust predictor is consistent with a growing literature showing that TST may be an important predictor for a broad range of health and cognition outcomes (30, 31). The present work focused on sleep variables that could be extracted from wrist actigraphy, and it will be important in future studies to evaluate whether additional sleep variables, such as daytime sleepiness (32), might also predict GPA. One intriguing avenue worth pursuing is to examine whether insufficient total nightly sleep produces patterns of daytime sleepiness that may compromise executive functioning capacities (e.g., attention, working memory) during academic learning periods.

Table 4. Average Spring term GPA binned by early-term total sleep time (TST)

TST	*n*	Spring term GPA	GPA change
<6 h	107	3.25	−0.13
6 to 7 h	262	3.48	0.02
7+ h	188	3.51	0.01

Notes: GPA change is the Spring term GPA minus the student's baseline GPA.

The first year of college is a particularly important period for understanding sleep patterns and academic achievement. For many students, the first year of college is a major life transition between childhood and adulthood. First-year college students are making some of their first efforts to establish independent sleep habits, and often doing so amidst new competing pressures of work and dorm life activities, and a challenging academic course load. The present work highlights the importance of getting adequate early-term nightly sleep for academic achievement, suggesting that sleep behavior interventions early in the academic term could be helpful for first-year college students. Conducting prospective randomized controlled trials of behavioral interventions targeting TST could serve the dual purpose of evaluating the causal role of early-term TST on increasing end-of-term GPA, and identifying translational interventions for boosting first-year academic success. To our knowledge, there are no randomized controlled trials of interventions targeting TST improvement in college students, despite there being substantial levels of insufficient sleep in this population. Cognitive Behavioral Therapy for Insomnia (CBT-I) and mindfulness intervention approaches hold some promise (33–35).

The present findings encourage future work on the behavioral and neurobiological mechanisms linking sleep with academic performance among young adults. Future research could evaluate whether reduced total nightly sleep impairs academic motivation or productive study habits over the course of the academic term (17). It is also possible that reduction in rapid eye movement (REM) sleep due to sleep restriction may be an important mechanism, as REM sleep duration is linked with verbal learning potential (36). Sleep spindle disruptions may also play an important role. It has been shown that chronic sleep restriction may drive a reduction in stage 2 and REM sleep, while stage 1 and slow wave sleep duration are conserved (37). Stage 2 sleep is characterized by the presence of sleep spindles, and sleep restriction among adolescents leads to a reduction of fast spindl7e amplitude (38). Fast spindle amplitude is associated with fluid intelligence in adolescence (39), and thus sleep spindles provide a possible candidate for a mechanism by which reduced TST may impact academic performance.

There are limitations to the present research. First, there have been debates about the accuracy of measuring sleep using wrist actigraphy and commercially available sleep trackers, relative to polysomnography (40, 41). The present study used wrist actigraphy Fitbits to track sleep patterns, which may underestimate total nightly sleep by 7 to 67 min (41), suggesting that students in the present samples may have been sleeping more than the estimates by wrist actigraphy suggest. On a subset of days in four of our samples, we evaluated Fitbit nightly TST against concurrent daily self-reported sleep diaries TST (see online supporting materials and *SI Appendix*, Tables S6–S9). There was a strong correspondence between the two TST measures

($r = 0.70$, $p < .001$), with wrist actigraphy estimating a shorter nightly TST time relative to sleep diaries by 3 min. Nonetheless, even if one conservatively assumes that the average increase in actual nightly sleep was 67 min relative to what we observed in our student samples using wrist actigraphy, it still means that 62% of students in these samples were still getting less than 8 h of total nightly sleep, the minimum recommendation for young adult nightly sleep (26). Future studies evaluating academic achievement outcomes would benefit from assessing total nightly sleep with additional gold standard measures (e.g., polysomnography).

Second, the present research focused on an early Winter/Spring term month of sleep in first-year college students. Sleep was not tracked during Spring Break periods, and our studies indicate that the prospective TST–GPA effect was present in studies that tracked early-term sleep before (Studies 1, 4, and 5) and after (Studies 2 and 3) Spring Break. But a worthwhile endeavor for future studies will be to also evaluate whether sleep-GPA links are also present in the Fall academic term in first-year college students (or in the second year of college or beyond), and whether adjusting the early-term sleep time window may qualify or extend these TST–GPA associations. The purpose of our present work was to identify an optimal time window when sleep patterning is being established and when early intervention could be offered to improve academic success. The early months of the first year Winter/Spring term may provide an ideal window of opportunity for translational intervention efforts. Third, while the relationship between early-term TST and end-of-term GPA was robust in our pooled sample across four confirmatory studies at three different universities—there was one individual study (Study 5) that was not statistically significant when previous-term GPA was included as a control variable. Follow-up analyses evaluated whether there were moderating variables that could explain this, but none were identified. Thus, it will be important for future studies to not only evaluate moderators but also evaluate the strength of the TST–GPA relationship in new samples of first-year college students. Fourth, one strength of the present work is that the sleep–GPA relationship persists even when controlling for factors like daytime sleep, overall academic load, gender, race, and first-generation student status. But it is possible that other variables could play a role in the sleep and academic performance relationship (e.g., depression, substance use).

Conclusions

First-year college students are getting insufficient sleep, and the present work indicates that it may carry significant costs for their academic achievement. Over 600 students in five studies drawn across three different American universities slept on average 6 h and 37 min per night early in their academic terms, a rate highlighting significant accumulating sleep debt. Moreover, every hour of nightly sleep lost was associated with a 0.07 decrease in end-of-term GPA. The present findings call for more research on sleep–achievement outcomes in young adults, and encourage new public health efforts to help young adults get more sleep.

Materials and Methods

Overview. Study 1 was used as a discovery dataset to determine which early-term sleep features were predictive of end-of-term GPA. From these analyses (described in the preregistration here: https://osf.io/5xngv), the following features were preregistered for confirmation in Studies 2, 3, and 5: bedtime variability, midpoint sleep time, and TST. The description of how sleep features were extracted is available in the online supporting materials.

Initially, bedtime variability (measured using MSSD) and the midpoint of one's nightly sleep window were significant predictors of GPA in our discovery analysis (Study 1). However, these effects were not robust and did not predict GPA across the confirmatory datasets (*SI Appendix*, Table S4).

To ensure the TST effect was robust, we submitted a second preregistration to test the TST effect on held-out Study 4 (https://osf.io/x76b4). This preregistration included a second hypothesis to test bedtime variability without outliers as this feature was significant in exploratory analyses across Studies 1 to 3 (*SI Appendix*, Table S5).

Data Collection and Setting. All participating students from all included studies provided written informed consent. Each study was approved by the host institution's Institutional Review Board, including Carnegie Mellon University (CMU), the University of Washington (UW), and Notre Dame University (ND).

University 1. Study 1 and Study 5 were drawn from a private, STEM-focused university in the Spring term of 2018 and 2017, respectively, as part of a larger study on student well-being.

Students were recruited via student mailing lists and online student Facebook groups. First-year students were recruited in Study 5 and first and second-year students were recruited in Study 1. In our analyses, we only consider first-year students. Otherwise, both Study 1 and Study 5 had similar designs. After expressing interest in the study, students were invited to the laboratory for a study information session and completed basic demographic questionnaires that were used to screen for study eligibility. Students were deemed eligible if they met the year of study criteria, were a full-time student, and owned a data-enabled smartphone. Eligible students were invited to participate in the semester-long study and attend the baseline session in the lab.

At the baseline session, those who agreed to participate provided informed consent to have their data collected and were enrolled in the study. Students then downloaded the AWARE data collection app (42) to capture data from iOS or Android smartphones, were provided a Fitbit Flex 2 to track sleep and physical activity, and were instructed to wear the Fitbit on their nondominant hand throughout the term. The Fitbit Flex 2 was chosen as it provided an objective measure of sleep with acceptable accuracy at a reasonable cost (43).

Students also completed a series of self-report questionnaires to assess their baseline health and well-being. These same questionnaires were filled out again at the end of the term. Additionally, students were sent Ecological Momentary Assessments via a link to a Qualtrics survey during weeks 1, 7, and 14 of the term to capture various measures of well-being in real-time. The university registrar provided GPA data (both previous-term GPA and GPA at the end of the Spring term), in addition to other institutional variables.

University 2. The samples in Study 2 and Study 3 were drawn from a large, public university in the Spring term of 2018 and 2019, respectively, as part of a larger study on student well-being. Since the university operates on the quarter system, we use "term" to refer to the corresponding Spring time period (i.e., Spring semester or Spring quarter) to maintain consistency across datasets. In both Study 2 and Study 3, sleep was tracked via the Fitbit Flex 2 across the academic term and GPA was provided by the university registrar. Although Study 2 gathered data from both Winter and Spring terms in 2018, here we only consider the student data from the Spring term. Details on participant recruitment and study design for Study 2 can be found in the methods of Sefidgar et al. (44). Study 3 methods and design mirrored Study 2, yet differed slightly in that it was conducted in Spring 2019 and included both first and second-year students (and all second-year students had participated in Study 2). For Study 3, we only analyzed the data from the first-year students.

University 3. The sample in Study 4 was drawn from a private Catholic university in the Spring term of 2016 as part of a larger study on tracking student health and social networks. In Study 4, sleep was tracked via the Fitbit Charge Heart Rate (HR) across the academic term, and individual class grades were provided by the university registrar. Since course credits were not provided, both baseline and cumulative GPAs were calculated by an unweighted average of the individual course grades (only considering the courses with an assigned letter grade). The Fitbit Charge HR was chosen as a lower-cost alternative to actigraphy with comparable performance on sleep/wake classification measures (43). Details on participant recruitment and study design for Study 4 can be found in the methods of Purta et al. (45), with additional information available on the NetHealth portal (http://sites.nd.edu/nethealth/).

Sleep Feature Extraction. The raw Fitbit sleep data, as provided by the Fitbit Application Programming Interface (API), consists of excised, minute-by-minute sleep data. Specifically, this means that if a participant slept, the Fitbit would report the sleep episode as a series of "sleep" minutes, and label it as "awake" or "restless" any of the minutes within that sleep episode for which it would sense non-trivial movement. During periods when the participant is awake (i.e., those times outside sleep episodes), the Fitbit API does not provide any labeling of those minutes as either or awake. Similarly, if the participant chooses to not wear their Fitbit, or if their Fitbit runs out of charge, there is no labeling of those minutes as either sleep or awake.

To calculate sleep features (e.g., midpoint sleep) we first extracted sleep episodes. To do this, we set two parameters. The first is the minimum consecutive non-awake minutes (i.e., sleep or restless) that have to exist for a sleep episode to be recorded. The second is the maximum number of consecutive awake minutes that define the beginning and end of the sleep episode. We set the first parameter as 20 and the latter as 5, so that a sleep episode is defined as at least 20 min of labeled non-awake minutes and is separated by at least 5 awake minutes on either end. In other words, a sleep episode may contain awake minutes, but there are never 5 or more consecutive awake minutes within an episode. After this episode extraction is complete, we then computed the main sleep episode. We defined the main sleep episode of Day n as the longest sleep episode that begins after Day n at noon and starts before Day (n + 1) at noon. All other sleep episodes outside the bounds of these parameters were categorized as "daytime sleep" (i.e., the sum of all the non-main episode sleep time; see *SI Appendix*, Table S6 for descriptive statistics for total daytime sleep). We calculated bedtime for Day n as the start of the main episode and wake time as the end of the main episode. Midpoint sleep is computed as the midpoint of bedtime and wake time. Time in bed was computed as the difference between wake time and bedtime and TST was time in bed minus the length of total awake/restlessness in the main sleep episode. To capture sleep window variability, we applied the MSSD measure to bedtime. The MSSD measure has been used for other sleep studies and has the advantage over other traditional measures of variability (i.e., SD) since MSSD is temporally dependent (46–48). To compute this for bedtime, we calculated the average of the squared difference of bedtime on consecutive nights within our time period. For example, if we had four successive nights of sleep, we calculated bedtime MSSD by computing the average of (night 2 bedtime−night 1 bedtime)^2, (night 3 bedtime−night 2 bedtime)^2, and (night 4 bedtime−night 3 bedtime)^2. Compared to calculating SD, this measure of variability is more precise in that it takes into account temporal aspects of the data.

Our discovery dataset (Study 1) was used to identify an early term period for which our sleep features of interest were significant in our controlled linear regression models (i.e., sleep feature and baseline GPA as independent features, and Spring term GPA as the dependent feature).

Following this, the early term period for the other cohorts was determined by identifying an early term period that most closely matched the early term period from Study 1. Early-term periods for each cohort are reported in *SI Appendix*, Table S1. For Study 4 and Study 5, identifying the early term period was straightforward as these cohorts were also on the semester system, and therefore, we used roughly 3 wk following the start of the semester for the beginning of the early term window. For Study 2 and Study 3, we had to adjust to the smaller quarter term and chose roughly 1 wk following the start of the quarter for the beginning of the early term period. These choices were then validated by checking the sleep feature graphs across time.

Specifically, TST is often initially high early in the term, and then decreases as the term period progresses. We validated our early term period choices by checking that these early term periods coincided with or followed a drop in TST, which we took to indicate a period of the term with higher academic stress.

Importantly, we intentionally identified early term periods for our confirmatory datasets without any knowledge of the GPA or academic performance data. By selecting early term periods, students who are at risk for low academic performance can be identified early in the semester during a window of time when the opportunity to introduce intra-term interventions to improve academic performance is still possible.

We included all students who have at least 20% of all possible main sleep episodes (i.e., at least five main sleep episodes) for these periods and who have available GPA data for both their prior cumulative GPA and Spring term GPA. Additionally, any student who did not have a bedtime MSSD value were removed (e.g., has five main sleep episodes but none are consecutive).

For the sensitivity analyses that included demographic characteristics as covariates, first-generation college student status was assessed by asking participants for each parent's level of schooling, and students were considered first-generation if neither parent completed any college (i.e., high school diploma or less). For the race sensitivity analyses, we created a binary label for underrepresented and non-underrepresented students. Students were considered underrepresented if either parent was Black, Hispanic or Latino, Native American, or Pacific Islander. Students were non-underrepresented if neither parent was from an underrepresented category (i.e., both parents had White and/or Asian ancestry). The results from these sensitivity analyses are presented in *SI Appendix*, Table S3.

Data, Materials, and Software Availability. The de-identified dataset for the reported results is available in the supporting online materials for replicating the main analyses reported in this paper. If there are additional analyses that readers are interested in carrying out, they can contact the corresponding author: creswell@cmu.edu.

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