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OUR FUTURE PHYSICIANS: AN EXAMINATION OF MEDICAL STUDENTS' PSYCHOLOGICAL HEALTH

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# Biometrically measured sleep in medical students as a predictor of psychological health and academic experiences in the preclinical years

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**ABSTRACT**

**Background:** Student wellness is of increasing concern in medical education. Increased rates of burnout, sleep disturbances, and psychological concerns in medical students are well documented. These concerns lead to impacts on current educational goals and may set students on a path for long-term health consequences.

**Methods:** Undergraduate medical students were recruited to participate in a novel longitudinal wellness tracking project. This project utilized validated wellness surveys to assess emotional health, sleep health, and burnout at multiple timepoints. Biometric information was collected from participant Fitbit devices that tracked longitudinal sleep patterns.

**Results:** Eighty-one students from three cohorts were assessed during the first semester of their M1 preclinical curriculum. Biometric data showed that nearly 30% of the students had frequent short sleep episodes (<6 hours of sleep for at least 30% of recorded days), and nearly 68% of students had at least one episode of three or more consecutive days of short sleep. Students that had consecutive short sleep episodes had higher rates of stress (8.3%) and depression (5.4%) symptoms and decreased academic efficiency (1.72%).

**Conclusions:** Biometric data were shown to significantly predict psychological health and academic experiences in medical students. Biometrically assessed sleep is poor in medical students, and consecutive days of short sleep duration are particularly impactful as it relates to other measures of wellness. Longitudinal, biometric data tracking is feasible and can provide students the ability to self-monitor health behaviors and allow for low-intensity health interventions.

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Undergraduate medical education; medical student; sleep; biometric; wellness

## Background

An increased rate of psychological health issues in medical students as compared to their age-matched non-medical student peers is well documented. Psychological and health issues include the development of burnout, sleep disturbances, depression or anxiety symptoms, and decreases in personal care [1–4]. To date, there hasn't been a clear understanding of effective interventions to address these wellness issues in medical students, and most of what we understand surrounding sleep quality is based solely on student perceptions.

The perception of quality of sleep issues is common in medical students. Concurrently, it is well documented that sleep problems can directly impact stress and psychological health, physical health, and cognitive functioning (including learning and the formation of memories) [5,6]. Quality sleep consists of several factors including total duration, sleep latency, restlessness, and consistency of duration as well as timing of sleep from day to day [7].

The present study is an evaluation of medical student sleep behaviors during their first medical school year using both biometric data collection via personal health trackers (FitBits) and self-reported sleep and sleep problems. The present study also seeks to understand the relationship of biometric sleep data to self-reported wellness through the use of validated surveys to assess other aspects of medical student wellness. The goal of the present study was to determine the feasibility of using a personal health tracker as a non-invasive low-stress mechanism for tracking medical student sleep and determine key sleep indicators that might suggest other wellness-related issues for students (e.g., depression, anxiety, burnout, etc.).

## Materials & methods

Between August 2018 and August 2020, 81 first year (M1) pre-clinical medical student participants were recruited to participate in this study (Oakland University IRB #1285854-7). Participants consented to participating in the study throughout their first (M1) through fourth (M4) years of medical school; however, only M1 data is presented in the current

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manuscript. A neutral broker was used to maintain anonymity between students and faculty. After consenting to the study and providing demographic information, participants received FitBits to enable biometric data collection (sleep, heart rate, physical activity) through Fitabase's proprietary API tool (www.fitabase.com). While polysomnography (PSG) remains the gold standard for short duration (typically, one night) clinical sleep studies, consumer wearable devices such as FitBits are widely used by researchers in search of feasible mechanisms to track sleep parameters in a real-life environment over long periods of time [8–10]. FitBits have been shown to have comparable results to clinical sleep studies for tracking key sleep parameters in a variety of populations (ex. adults, adolescents and insomnia disorder patients) given their known limitations [8,11–14]. All participants were given a new Charge HR FitBit device (models 2–4 based on year of recruitment to the study and currently available FitBit model, www.fitbit.com). All the Charge HR models used in this study (2–4) are commercially available wrist accelerometers, which have a three-axis acceleration sensor, altimeter, vibration motor, and optical heart rate monitor and have been shown to be a valid tool for estimating sleep parameters (including total sleep duration and sleep onset times) utilizing the same algorithm [8,15–17]. Each participant wore their study provided device for the duration of the study, which normalized the tracking accuracy of the devices for an individual during the study as well as across the participants. Device charge and data syncing are tracked through the Fitabase platform.

Self-report data were collected using validated surveys (including emotional health, sleep health, and burnout) at three salient timepoints across the academic year. For all self-reported data, only participants who completed the entirety of the individual scale were included in the analysis of each scale as scoring for each scale depends on participants' answers to all components of the respective scale. The present analyses explored biometric data from late fall of each participant's M1 year (October through December), as well as data from the corresponding November survey. This time frame was chosen as it represents first-year medical students' experiences after they have completed the first set of preclinical courses, and prior to the winter break.

## Measures

### Biometric sleep data

Fitabase data was accessed for all enrolled participants. Fitabase data analyzed for the present study included: sleep onset time, wake time, and hours of sleep per day. The raw Fitabase data was transformed into 2 key sleep variables: frequency of short sleep days and consecutive days of short sleep. Short sleep duration days were defined as days with less than 6 hours of sleep. Although the National Sleep Foundation recommends 7–9 hours of sleep per night for our population's age range, we acknowledge that this ideal range is not typically met for practitioners in the medical field [6,18].

Frequency of short sleep duration days was calculated by the number of short sleep duration days divided by the total number of sleep records. We categorized individuals into frequent short sleep duration days or infrequent short sleep duration (see Table 1 for variable definitions). As frequent short sleep days were a calculated ratio, including total number of sleep records, we only used data from students with recorded FitBit data for 60% or more of the possible recorded days ($n = 44$). Students who did not consistently wear their device during sleep were excluded (<60% of possible days with recorded biometric data).

For consecutive days of short sleep, all students with any biometric sleep data during the M1 October to December period were included. This approach allowed us to capture any instances of consecutive days of short sleep.

### Emotional health

Self-reported emotional health was evaluated using the Depression Anxiety Stress Scales (DASS) [19]. The DASS consists of 21 items and contains subscales for depression, anxiety, and stress. Each scale has established cutoffs and moderate and severe cutoffs for each subscale were examined. Analyses were conducted with each subscale dichotomized to identify students meeting or not meeting the 'severe' cutoff.

### Sleep health

Self-reported sleep health was evaluated using the Pittsburgh Sleep Quality Index (PSQI) which is a frequently used, reliable and valid measure to examine sleep quality problems [20]. The PSQI consists of

**Table 1.** Key variables and definitions.

| Biometric Sleep Terms | Definitions |
|---|---|
| Short Sleep | <6 hours sleep duration in a given day |
| Frequent Short Sleep | More than 30% of a participant's recorded days |
| Consecutive Short Sleep | Consecutive nights with less than 6 hours of sleep |
| Consecutive Short Sleep Episode | 2+ consecutive short sleep days |

19 items which assess sleep quality concerns, such as latency, efficiency, and disturbances. The global score was used for the present analyses. Although the standard cutoff of 5 indicates a higher likelihood of sleep problems, given the high rate of endorsement of sleep quality concerns in our population, a higher evidence-informed cutoff of 8 for young adult populations was used to dichotomize (yes/no for self-reported poor sleep quality) for the purpose of the present analyses [21].

### Burnout

The Oldenberg Burnout Inventory (OBI) was used to assess burnout and has been determined to be a reliable and valid measure of burnout [22]. Subscales assess exhaustion and disengagement, and standard cutoffs were used. For the present analyses, meeting the cutoff for either exhaustion or disengagement was coded as endorsement 'risk of burnout' (yes/no). It is important to note that this scale has been used extensively in medical school students and is used to assess burnout nationally on the American Association of Medical Colleges Year 2 Questionnaire (AAMC Y2Q) provided to second-year medical students [23].

### Educational related perceptions

The Student Subjective Wellbeing Questionnaire (SSWQ) was used for the purpose of evaluating educational related perceptions [24]. Subscales assess the constructs of joy of learning, school connectedness, educational purpose, and academic self-efficacy. Each subscale was analyzed as a continuous variable.

### Analyses

Analyses were conducted in SPSS 28. Chi-square analyses were conducted for dichotomous variables (i.e., emotional health outcomes, burnout, self-reported sleep quality) and ANOVAs were conducted for continuous outcomes (i.e., learning related perceptions).

## Results

A total of 81 first-year medical students were enrolled into the study in their first semester of medical school. The sample was 45.7% ($n = 37$) female, and the average age was 24 years old ($SD = 3.5$).

### Overall sleep and wellness

Evaluation of the first-year students' November aggregated perception-based self-reported surveys brings high rates of perceived poor sleep quality, psychological symptoms (depression, anxiety, and stress), and risk of developing burnout to the forefront of self-reported student wellness concerns (Table 2). The study participants' self-reported burnout scores were consistent with the school-wide and national aggregate AAMC Y2Q self-reports. Based on the biometric data collected, most participants averaged less than 7 hours of sleep per night with an average bedtime after 12 am throughout the first semester time period (October – December) (see Table 2). For FitBit biometric data presented in Tables 2 & 3, only students who had data for 60% or more of the possible days during the time frame were included in analyses ($n = 44$). Students who did not consistently wear their device during sleep were excluded from these analyses (<60% of possible days with recorded biometric data). It was observed that 56.82% ($n = 25$) averaged less than 6 hours of sleep per night, while only 15.91% ($n = 7$) averaged 7+ hours of sleep per night. This is in contrast to self-reported average sleep on the PSQI, where only 13.6% of students reported less than 6 hours of sleep, though most students reported less than 8 hours of sleep.

**Table 2.** M1 Student participant biometric sleep data, self-reported wellness and self-reported educational ratings.

| Measure | | Mean(SD)/%(N)[a] | Number of Participants with Data |
|---|---|---|---|
| **Biometric Sleep Characteristics** | | | |
| Bedtime (FitBit)[b] | *M (SD)* | 12:26 AM (SD = 1 hr 35 mins) | 44 |
| Time Sleeping (FitBit)[b] | *M (SD)* | 6hrs 29 mins (SD = 1 hr 25 mins) | 44 |
| **Self-Reported Sleep and Psychological Health Ratings** | | | |
| Poor Sleep Quality (standard) | Yes *% (n)* | 98.2% ($n = 54$) | 55 |
| Poor Sleep Quality (cutoff of 8) | Yes *% (n)* | 74.5% ($n = 41$) | 55 |
| Depression Moderate | Yes *% (n)* | 20.4% ($n = 10$) | 49 |
| Depression Severe | Yes *% (n)* | 4.1% ($n = 2$) | 49 |
| Stress Moderate | Yes *% (n)* | 66.0% ($n = 33$) | 50 |
| Stress Severe | Yes *% (n)* | 6.0% ($n = 3$) | 50 |
| Anxiety Moderate | Yes *% (n)* | 8.0% ($n = 4$) | 50 |
| Anxiety Severe | Yes *% (n)* | 0.0% ($n = 0$) | 50 |
| Burnout Risk | Yes *% (n)* | 24.5% ($n = 12$) | 49 |
| **Self-Reported Educational Specific Ratings** | | | |
| Joy of Learning | *M (SD)* | 13.90 (SD = 1.74) | 48 |
| School Connectedness | *M (SD)* | 14.25 (SD = 1.67) | 48 |
| Educational Purpose | *M (SD)* | 14.06 (SD = 1.66) | 48 |
| Academic Self-Efficacy | *M (SD)* | 14.23 (SD = 1.53) | 48 |

[a]Data were collapsed for the present analyses (data collected across 3 M1 cohorts).). [b] For FitBit biometric data, only students who had data for 60% or more of the possible days during the time frame were included in analyses ($n = 44$).

### Frequent short sleep

Sleep duration is an important aspect of sleep health. We have defined short sleep as 6 or less hours of total sleep within a 24-hour period. On average, students had 30.0% (SD = 17.7%) of their recorded days defined as Short Sleep, and 48.9% ($n = 22$) were categorized as having Frequent Short Sleep.

Using the biometrically generated Frequent Short Sleep/Infrequent Short Sleep as an indicator, we compared perception-based sleep/psychological symptoms and educational-related subjective outcomes (Table 3) assessed in the November wellness surveys. Surprisingly, the Frequent Short Sleep and Infrequent Short Sleep groups self-reported similar rates of poor sleep quality. Frequent Short Sleep students reported significantly less psychological symptoms of severe stress and burnout risk as compared to Infrequent Short Sleep students.

When learning related subjective outcomes were analyzed via the subscales of the Student Subjective Wellbeing Questionnaire, Frequent Short Sleep students reported a statistically significantly higher rate of both subjective school connectedness and educational purpose as compared to Infrequent Short Sleep students. In contrast, Frequent Short Sleep students reported a statistically significantly lower rate of subjective academic efficacy.

### Consecutive short sleep days

Consecutive Short Sleep days (as compared to frequency of short sleep) can be especially problematic, in part because of increased sleep debt. Unsurprisingly, between October – December of their first medical school semester, many students (67.1%) had at least one episode of 2 consecutive days of short sleep; and 37.8% of students had at least one episode of 3 or more consecutive days of short sleep.

We further categorized students as either high Consecutive Short Sleep days (having at least one occurrence of 2 or more consecutive days of short sleep) or low occurrence of Consecutive Short Sleep days (no episodes of 2 or more consecutive days of short sleep). Students with 2+ days of Consecutive Short Sleep reported worse psychological health and poorer school-related outcomes (Table 4). Specifically, we found higher rates of severe depression symptoms, severe stress symptoms, and risk of burnout. We also find that students with 2+ days of Consecutive Short Sleep rated all school experience scales lower than the students with low occurrence of Consecutive Short Sleep days, with the academic efficacy subscale reaching statistical significance.

## Discussion

Overall, we found that medical students in their first year of medical school have impaired sleep across multiple indicators, biometric and self-report. We found impaired sleep through both biometric (percentage of short sleep duration days and consecutive short sleep days) and self-reported sleep problems (assessed through the Pittsburgh Sleep Quality Index). Biometric data of our participants showed that only 15.91% ($n = 7$) averaged 7 hours or more of sleep per night, with over half of students averaging less than 6 hours of sleep per night.

Our biometric data is also in contrast to the perception-based self-report. Self-reported average sleep on the PSQI in our sample showed that less than 14% of our students believed they were sleeping less than 6 hours per day; however, most students did report less than 8 hours of sleep per day. Additionally, the biometrically assessed sleep of our sample was in contrast to the self-reported item in the AAMC Y2Q assessing average daily sleep, for which 80.9% of Class of 2022 students ($n = 11{,}534$) nationally reported sleeping 7 or more hours per night (41.6%

Table 3. Biometric frequent short sleep and self-reported well-being.

| | Frequent Short Sleep (50.0%, $n = 22$) | Infrequent Short Sleep (50.0%; $n = 23$)[a] |
|---|---|---|
| **Self-Reported Sleep** | | |
| Poor Sleep Quality (PSQI >8) | 76.5% ($n = 13$) | 70.6% ($n = 12$) |
| Total PSQI Score | 9.00 (1.94) | 9.06 (2.68) |
| Sleep Quality Rating (PSQI Quality Item rated 'Fairly Bad' or 'Very Bad' | 70.6% ($n = 12$) | 70.6% ($n = 12$) |
| Average Hours of Sleep Per Night | 6.04 (0.57) | 6.62 (0.63) |
| **Psychological Symptoms *%(n)*** | | |
| Depression Severe | 5.9% ($n = 1$) | 0.0% ($n = 0$) |
| Anxiety Severe | 0.0% ($n = 0$) | 0.0% ($n = 0$) |
| Stress Severe | 0.0% ($n = 0$) | 10.5% ($n = 2$) |
| Burnout Risk | 12.5% ($n = 2$) | 38.1% ($n = 8$) |
| **Educational Subjective Outcomes *M(SD)*** | | |
| Joy of Learning | 14.53 (1.55) | 13.48 (1.66) |
| School Connectedness* | **14.82 (1.24)** | **14.00 (1.52)** |
| Educational Purpose* | **14.65 (1.22)** | **13.90 (1.30)** |
| Academic Efficacy* | **14.76 (1.30)** | **14.10 (1.18)** |

[a]Frequent Short Sleep is defined as 30% (or more) of sleep records with less than 6 hours of sleep. Infrequent Short Sleep is defined as less than 30% of sleep records with less than 6 hours of sleep.* Indicates a statistically significant difference with a $p < 0.10$.

**Table 4.** Episodes of 2+ consecutive short sleep days and self-reported well-being.

| | Episodes of 2+ Consecutive Days of Short Sleep (*n* = 55) | No Episodes of 2+ Consecutive Days of Short Sleep (*n* = 27)[a] |
|---|---|---|
| **Self-Reported Sleep** | | |
| Poor Sleep Quality (PSQI >8) | 66.7% (*n* = 24) | 78.6% (*n* = 11) |
| Total PSQI Score | 8.61 (2.49) | 9.36 (2.17) |
| Sleep Quality Rating (PSQI Quality Item rated 'Fairly Bad' or 'Very Bad' | 66.7% (*n* = 24) | 78.6 (*n* = 11) |
| Average Hours of Sleep Per Night | 6.07 (1.21) | 6.71 (0.75) |
| **Psychological Symptoms *%(n)*** | | |
| Depression Severe | 5.4% (*n* = 2) | 0.0% (*n* = 0) |
| Anxiety Severe | 0.0% (*n* = 0) | 0.0% (*n* = 0) |
| Stress Severe* | **8.3% (*n* = 3)** | **0.0% (*n* = 0)** |
| Burnout Risk* | **27.8% (*n* = 10)** | **16.7% (*n* = 2)** |
| **Educational Subjective Outcomes *M(SD)*** | | |
| Joy of Learning | 13.84 (1.84) | 13.92 (1.56) |
| School Connectedness | 14.13 (1.83) | 14.33 (0.99) |
| Educational Purpose | 13.95 (1.86) | 14.25 (0.97) |
| Academic Efficacy* | **14.03 (1.72)** | **14.75 (0.62)** |

[a]Episodes of 2+ Consecutive Days of Short Sleep is defined as 2 or more days in a row that 6 or less hours of sleep were biometrically recorded. * Indicates a statistically significant difference with a $p < .05$.

reporting more than 8 hours) [23]. These findings suggest that students' self-perceptions of sleep duration do not align well with biometrically assessed sleep, with self-reported sleep duration being greater than actual sleep duration. In our sample, nearly half of our students had at least 30% of their recorded sleep episodes at 6 or less hours. Further, in considering the sleep deficit, commonly known as 'sleep debt,' that can occur through consecutive days of short sleep, we found that nearly 38% of medical students had at least one episode of 3 or more days in a row of short sleep, and 67% had at least one episode of 2 or more days in a row of short sleep during the 3-month period of biometric tracking.

As introduced in the methods section, although using FitBit devices for research does have some limitations (e.g., device charging & consistent wearing, over estimates of some sleep measurements, lower levels of validity when examining sleep-stage data as compared to PSG, and data collection variability due to multiple device models), reducing these effects on research data are possible [8,9,11–14,25]. While there are known limitations to FitBit devices, including overestimating total sleep time by minutes to approximately one hour (consistently per individual), and lower accuracy in identifying specific sleep stages as compared to PSG, they have been consistently shown to be useful tools for specific sleep parameter metrics such as an individual's total sleep duration monitored over long periods of time [16]. As these known sleep estimation accuracy issues typically tend to overrepresent duration times, any data collected from the FitBit devices is likely to be an underrepresentation of actual sleep in our cohorts. Furthermore, the individual longitudinal tracking of our students' FitBit sleep parameters allows for meaningful analysis. Due to the sleep stage estimation limitations, the present study has focused on sleep onset and total sleep duration sleep parameters.

In examining the relationships between sleep quality indicators and wellness surveys, we found that consecutive days of short sleep days (6 or less hours of total sleep in a 24-hour period) was especially problematic. Importantly, the persistence of consecutive short sleep days is likely contributing to cumulative sleep debt. Sleep debt and the subsequent development of more serious sleep problems are detrimental to general cognitive processes, such as attention, learning, and memory. Interestingly, research has also demonstrated that despite poor performance, perceptions of performance, concentration, attention, productivity, and effort are more positive among sleep debt/deprived participants compared to their non-deprived peers [26]. This is an indication that sleep deprivation may alter perceptions of performance and subsequently hinder motivation for changes in sleep health since no problems are perceived. This research could also partially explain some of the educational-related perceptions. Further, our data demonstrated trends toward issues with psychological symptoms, which is in line with previous research demonstrating sleep problems and poor emotional health [27]. Lastly, consecutive days of short sleep may be a better indicator of poor sleep health compared to a greater frequency of short sleep nights because of the greater demands needed to recover, at least cognitively, from chronic and consistent sleep loss. Specifically, recovery from one hour of sleep loss can take up to four days of good sleep to achieve and a week or longer to recover from sleep debt [28,29].

Our analyses find that biometrically tracked sleep provides more differentiation of students with problematic sleep patterns. We found that biometric sleep patterns predict better than sleep perception for multiple aspects of wellness. It may be that the medical student population is operating en masse within a normalization of the importance of short sleep as a rite of passage into the medical field, which could easily alter perceptions of 'good' sleep and lead to issues using perception of sleep as a factor in reporting.

## Conclusions

Our data show the importance of gaining a better understanding of medical students' objective sleep patterns/duration (biometrically collected), as opposed to their perceptions of what a medical student's sleep quality *should* look like, is key to developing mechanisms to address wellness within health care training. We believe it is increasingly important for faculty and administration to address wellness concerns and their connection to sleep quality/sleep conditions early in medical training, ideally leading to improvements in learning and wellness behaviors, especially related to burnout. Our research has found that longitudinal tracking of biometric data in medical students is feasible, and yields rich data. These data can be analyzed at both the individual level across time, as well as categorically using various aspects of the data such as demographics, curricular events, and linked wellness scale outcomes as predictors.

### *Limitations and future directions*

In addition to the previously described and managed limitations of the FitBit devices, the present findings are limited by the smaller number of students that have completed both the surveys and persisted with biometric monitoring, and preclude some correlations and in-depth analysis of demographically distinct subgroups. Future directions of this longitudinal project include continuing to analyze how wellness and sleep patterns change over the course of medical school and what connections to curricular events within the preclinical vs clinical years may exist. Additionally, the longitudinal nature of our project will enable unexpected analysis of how students switching into and out of remote learning due to the COVID-19 requirements affect wellness and sleep patterns in the short and long-term. Longitudinal goals include creating a predictive model of student burnout and well-being /stress as it correlates to these biometric data. Ideally, future students will be able to identify early warning signs of poor sleep health through personalized biometric data and make individual adjustments immediately prior to the development of wellness issues. The early warning of poor sleep health signs may help to prevent the rates of stress, depression and risk of burnout exhibited in participants who have extended low sleep periods. This possibility, in conjunction with early educational interventions, may lead to increased ability for students to both manage their own sleep quality and subsequent wellness behaviors, as well as be better able to educate future patients about the importance of quality sleep to overall wellness. Our goal is to generate a longitudinal database that will allow a better understanding of not only our medical students' emotional and personal well-being but also how these factors relate to curricula and wellness initiatives to inform the development of appropriate interventions.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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## Authors' contributions

LO, DB, SP and KS all contributed equally to the design, implementation, analysis and writing of this manuscript.

## Availability of data and materials

Due to the sensitive nature of the data set, data may only be available upon request.

## Ethics approval and consent to participate

Project MedWell received IRB approval in 2018 (Oakland University IRB #1285854-7).

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## References

[1] Dyrbye LN, Thomas MR, Shanafelt TD. Systematic review of depression, anxiety, and other indicators of

psychological distress among U.S. and Canadian medical students. Acad Med. 2006;81(4):354–373. doi: 10.1097/00001888-200604000-00009

[2] Wolf MR, Rosenstock JB. Inadequate sleep and exercise associated with burnout and depression among medical students. Acad Psychiatry. 2016;41(2):174–179. doi: 10.1007/s40596-016-0526-y

[3] Goebert D, Thompson D, Takeshita J, et al. Depressive symptoms in medical students and residents: a multischool study. Acad Med. 2009;84(2):236–241. doi: 10.1097/ACM.0b013e31819391bb

[4] Chang E, Eddins-Folensbee F, Coverdale J. Survey of the prevalence of burnout, stress, depression, and the use of supports by medical students at one school. Acad Psychiatry. 2012;36(3):177–182. doi: 10.1176/appi.ap.11040079

[5] Azad MC, Fraser K, Rumana N, et al. Sleep disturbances among medical students: a global perspective. J Clin Sleep Med. 2015;11(1):69–74. doi: 10.5664/jcsm.4370

[6] Rao W-W, Li W, Qi H, et al. Sleep quality in medical students: a comprehensive meta-analysis of observational studies. Sleep Breathing. 2020;24(3):1151–1165. doi: 10.1007/s11325-020-02020-5

[7] Ohayon M, Wickwire EM, Hirshkowitz M, et al. National sleep foundation's sleep quality recommendations: first report. Sleep Health; 2017. doi: 10.1016/j.sleh.2016.11.006

[8] Haghayegh S, Khoshnevis S, Smolensky MH, et al. Accuracy of wristband fitbit models in assessing sleep: systematic review and meta-analysis. J Med Internet Res. 2019;21(11):e16273. doi: 10.2196/16273

[9] Tobin SY, Williams PG, Baron KG, et al. Challenges and opportunities for applying wearable technology to sleep. Sleep Med Clin. 2021;16(4):607–618. doi: 10.1016/j.jsmc.2021.07.002

[10] Depner CM, Cheng PC, Devine JK, et al. Wearable technologies for developing sleep and circadian biomarkers: a summary of workshop discussions. Sleep. 2020;43(2). doi: 10.1093/sleep/zsz254

[11] de Zambotti M, Baker FC, Willoughby AR, et al. Measures of sleep and cardiac functioning during sleep using a multi-sensory commercially-available wristband in adolescents. Physiol Behav. 2016;158:143–149. doi: 10.1016/j.physbeh.2016.03.006

[12] Wang C, Lizardo O, Hachen DS, et al. Using fitbit data to examine factors that affect daily activity levels of college students. PLOS ONE. 2021;16(1):e0244747. doi: 10.1371/journal.pone.0244747

[13] Chinoy ED, Cuellar JA, Huwa KE, et al. Performance of seven consumer sleep-tracking devices compared with polysomnography. Sleep. 2021;44(5). doi: 10.1093/sleep/zsaa291

[14] Hamill K, Jumabhoy R, Kahawage P, et al. Validity, potential clinical utility and comparison of a consumer activity tracker and a research-grade activity tracker in insomnia disorder II: outside the laboratory. J Sleep Res. 2020;29(1). doi: 10.1111/jsr.12944

[15] Schmidt T. (FitBit Health Solutions). Personal communication. 2023.

[16] Lee HA, Lee HJ, Moon JH, et al. Comparison of wearable activity tracker with actigraphy for sleep evaluation and circadian rest-activity rhythm measurement in healthy young adults. Psychiatry Investig. 2017;14(2):179–185. doi: 10.4306/pi.2017.14.2.179

[17] Creswell JD, Tumminia MJ, Price S, et al. Nightly sleep duration predicts grade point average in the first year of college. Proc Natl Acad Sci USA. 2023;120(8). doi: 10.1073/pnas.2209123120

[18] Mendelsohn D, Despot I, Gooderham PA, et al. Impact of work hours and sleep on well-being and burnout for physicians-in-training: the resident activity tracker evaluation study. Med Educ. 2019;53(3):306–315. doi: 10.1111/medu.13757

[19] Lovibond PF, Lovibond SH. The structure of negative emotional states: comparison of the depression anxiety stress scales (DASS) with the beck depression and anxiety inventories. Behav Res Ther. 1995;33(3):335–343. doi: 10.1016/0005-7967(94)00075-U

[20] Buysse DJ, Reynolds CF, Monk TH, et al. The Pittsburgh sleep quality index: a new instrument for psychiatric practice and research. Psychiatry Res. 1989;28(2):193–213. doi: 10.1016/0165-1781(89)90047-4

[21] Lund HG, Reider BD, Whiting AB, et al. Sleep patterns and predictors of disturbed sleep in a large population of college students. J Adolesc Health. 2010;46(2):124–132. doi: 10.1016/j.jadohealth.2009.06.016

[22] Demerouti E, Bakker AB, Vardakou I, et al. The convergent validity of two burnout instruments: a multitrait-multimethod analysis. Eur J Psychol Assess. 2003;19(1):12–23. doi: 10.1027//1015-5759.19.1.12

[23] AAMC Year Two Questionnaire (Y2Q). [cited 2021 Sep 30]. Available from: https://www.aamc.org/data-reports/students-residents/report/year-two-questionnaire-y2q

[24] Renshaw TL, Long ACJ, Cook CR. Assessing adolescents' positive psychological functioning at school: development and validation of the student subjective wellbeing questionnaire. Sch Psychol Q. 2015;30(4):534–552. doi: 10.1037/spq0000088

[25] Grandner MA, Lujan MR, Ghani SB. Sleep-tracking technology in scientific research: looking to the future. Sleep. 2021;44(5). doi: 10.1093/sleep/zsab071

[26] Pilcher JJ, Walters AS. How sleep deprivation affects psychological variables related to college students' cognitive performance. J Am Coll Health. 1997;46(3):121–126. doi: 10.1080/07448489709595597

[27] Baglioni C, Spiegelhalder K, Lombardo C, et al. Sleep and emotions: a focus on insomnia. Sleep Med Rev. 2010;14(4):227–238. doi: 10.1016/j.smrv.2009.10.007

[28] Kitamura S, Katayose Y, Nakazaki K, et al. Estimating individual optimal sleep duration and potential sleep debt. Sci Rep. 2016;6(1). doi: 10.1038/SREP35812

[29] Ochab JK, Szwed J, Oleś K, et al. Observing changes in human functioning during induced sleep deficiency and recovery periods. PLOS ONE. 2021;16(9):e0255771. doi: 10.1371/JOURNAL.PONE.0255771