Title: Detecting stress in college freshman from wearable sleep data

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Abstract

Sleep plays an important role in health and functioning, yet little is known about how it is linked to stress in young adults. Consumer wearables have been particularly successful at quantifying sleep and may be useful in identifying changes in mental health. The transition to college has a notable impact on both stress and sleep behaviors. Students from a public university provided continuous biometric data and answered weekly surveys for their first semester of college (*N*=507). Longitudinal models showed that increased average respiratory rate during sleep was associated with higher weekly perceived stress scores, effects that persisted after controlling for gender, race, first-generation status, mental health history, trauma history. Specifically, for every increased breath per minute, the odds of experiencing moderate-to-high stress were 1.25 times higher (a 25% increase), holding demographic and psychological history variables constant. Notably, relationships with stress were specific to respiratory rate, but were not found with other sleep measures previously linked to stress, such as heart rate variability, total sleep hours, sleep efficiency, sleep onset latency, and wake up count. Consistent with previous work, female gender, a previous mental health diagnosis, and previous exposure to multiple traumas were significantly associated with self-reported stress. These findings point to respiratory rate as a potentially important factor to measure due to its robust association with stress among college students. Wearable data may help us identify, understand, and to better predict stress, a strong signal of the ongoing mental health epidemic among college students.

Main Text

Introduction

Chronic stress has been linked to behavioral changes and adverse health outcomes [1]–[3]. In particular, elevated stress impacts sleep quality and quantity [4], [5]. The relationship between stress and sleep has been shown to be bi-directional [6], [7]; sleep disruptions can also impact mood [4]. Coincident with the onset of common mental health disorders, such as anxiety and depression, college is a period of time marked by insufficient sleep and irregular sleep patterns [8], [9]. A recent multi-university study found that more than 60% of college students met the criteria for poor sleep [10]. Stress, often associated with the transition to college [11], has been identified as the greatest predictor of decreased sleep quality in young adults [12]. There is a growing literature showing that sleep is an important predictor for success in college [8], [13] and health outcomes later in life [14], [15].

However, the relationship between stress and sleep responses does not follow a uniform dose-response due to between and within individual differences over time [16]. The chronicity of stressors and individual coping behaviors [17] also influence the impact of stress on sleep [18], [19]. Additionally, demographic, and psychological differences, including mental health diagnosis [20], social support [21], and exposure to adverse life events in childhood [22] significantly influence the magnitude of the impact of stress on sleep measures. Previous evidence for the relationship between stress and sleep often lacks information on previous psychological history, are carried out in laboratory settings [23], are based on self-reported sleep data or are small sample sizes [24]. Absent experimental protocols, repeated measures of sleep and stress across a large population are needed to observe sufficient variation within and between individuals to assess whether sleep measures can be used to infer changes in mental health measures.

The widespread use of consumer-grade wearables makes it possible to rigorously measure and evaluate biometric contributors to sleep disturbances and mental health measures in large-scale studies [25], [26]. These studies have provided insight into the mechanistic and temporal relationships between sleep and stress. Previous work using machine learning on wearable sleep data and mental health has shown that sleep abnormalities, especially changes in sleep rhythms, are associated with the probability of mental illness onset [27]. Specifically, stress has been linked to reduced total sleep time (TST), increased sleep onset latency (SOL), prolonged sleep latency, and lower sleep efficiency [18], [19], [28]–[30]. Physiological indices during sleep, such as lower heart rate variability (HRV) [31]–[33] increased heart rate (HR) [24], and variation in average respiratory rate (ARR) [34], [35] have also been linked to stressful exposures. Recent work using skin conductance and temperature from wearable sensor data, has shown accuracy in classifying college students as high or low stress [36].

The stability of nightly ARR within healthy individuals, particularly the low internight variability in median nighttime respiratory rate [37], makes it a potentially useful metric for tracking changes in wellness and has been used to assess stress reactivity [38]–[41]. ARR has gained attention due to its relationship to COVID-19 infection [37] and increases in 3-5 breaths/min can signal health deterioration [42]. Changes in these cardiorespiratory measures have been detected in college students following stressful exposures [34]. While wearable devices vary in the metric and the quality of these measures, the Oura ring has been validated for accurate sleep measurement [43]–[45]. The Oura ring uses photoplethysmography (PPG) [46] to derive respiration rate, a validated measure for capturing variation [47].

The present study utilizes nightly sleep data from a consumer wearable and weekly surveys to evaluate the relationship between sleep and stress in the first semester of college. We selected this critical window for evaluating the relationship because it is a period associated with heightened stress and during which sleep behaviors change for many students. In the current longitudinal study, we investigate whether sleep measures from biometric data taken continuously with an Oura ring could be used to predict subjective measures of stress in first-year college students. Given the health implications of stress and sleep disruptions, utilizing continuous biometric data to detect heightened stress in young adults offers the potential for rapid assessment and targeted, preventative interventions.

Results

Our data includes weekly surveys and biometrics from a first-year college cohort (*N*=507) (Table 1). Participants completed at least three weekly surveys and with Oura ring data for at least three nights in the week preceding the survey (*N*=2,603) (*SI Appendix,* Figure S1). Biometric data revealed that first-year college students slept, on average, 7.31 hours per night (*SD* = 0.85 hours). Participants had a mean individual variance of 1.36 hours of total sleep time (TST) during the study (*SD* = 0.67 hours). Over the course of the study, participants' ARR varied by an average of 0.89 breaths (*SD* = 0.51). Weekly surveys revealed that the average Perceived Stress Score (PSS) for participants was 16.43 (*SD* = 6.26). 66.12% (1,721/2603) of weekly survey responses indicated moderate-to-high stress (PSS>=14).

When pooled across all weeks, there was a significant correlation between PSS and multiple sleep measures as well as significant differences in PSS by gender, previous mental health diagnosis, and traumatic exposure history (Table 1 and Figure 1). In univariate regression models, lowest heart rate, skin temperature changes, and respiratory rate were significant explanatory variables (*SI Appendix* Table S3). The relationship between average nightly respiratory rate (ARR) and stress was the most robust; there were no reliable relationships with other sleep measures in covariate-adjusted regression analyses.

A positive relationship between night-time ARR and PSS was observed across three covariate-adjusted mixed effects regression models (*N* = 2,603) for PSS as a continuous and binary outcome: (1) a demographic covariate-adjusted model, (2) a psychological history covariate-adjusted model, (3) a combined demographic and psychological covariate-adjusted model (Table 2 and *SI Appendix* Table S5). Here, we present the results from models with PSS is a binary outcome due to its relevance to mental health assessment.

For the three models, ARR was significantly associated with the PSS (Table 2). In Model 1, the odds of being moderate-to-highly stressed were 4.77 times higher for female participants than for male participants and 5.42 times higher for non-binary participants than for male participants (*p*<0.01). For every

1-unit (1 breath per minute) increase in ARR, the odds of being moderate-to-highly stressed were 1.28 higher ($p<0.01$), controlling for demographic variables. In Model 2, having a mental health diagnosis increased the odds of being moderate-to-highly stressed by 7.83 times ($p<0.01$) compared to those who did not have a previous diagnosis ($p<0.01$). A history of traumatic exposure increased the odds of being moderate-to-highly stressed by 1.96 times ($p<0.01$). When controlling for mental health diagnosis and traumatic exposure, a 1-unit (1 breath per minute) increase in ARR, increased the odds of being moderate-to-highly stressed by 1.31 times. For Model 3, for every 1-unit (1 breath per minute) increase in ARR, the odds of being moderate-to-highly stressed increased by 1.25 times, controlling for gender, race, first-generation status, mental health diagnosis, and trauma exposure history (Figure 2).

In addition to being significantly associated with moderate-to-high stress (PSS>=14), the addition of ARR improved the model fit of all three models (Table 2). The likelihood ratio (LR) test for Model 1 comparing the null model to the full model resulted in a LR statistic of 6.96 ($p<0.01$), indicating that there is strong evidence for inclusion of ARR in Model 1. The likelihood ratio test for Model 2 comparing the null model to the full model resulted in a LR statistic of 9.05 ($p<0.01$), indicating that there is strong evidence for inclusion of ARR in Model 2. The likelihood ratio test for Model 3 comparing the null model to the full model resulted in a LR statistic of 5.85 ($p<0.05$), indicating that there is strong evidence for inclusion of ARR in Model 3. We conclude that all three models provide a significantly better fit to the data and contribute meaningfully to explaining the outcome of moderate-to-high stress.

To check the robustness of our results from mixed-effects models, we completed sensitivity analyses with multiple covariance structures and the results were consistent (*SI Appendix* Table S4). We also explored mixed effects models that use gradient-boosted trees to assess dominant predictors of stress in our sample. Results were consistent with the results of our mixed effects multi-linear regression models (*SI Appendix* Additional Methods, Table S5).

Discussion

The mental health status of young adults has been declining [48], [49], especially for those undergoing major life transitions like college [50]. Mounting evidence has shown that the mental health of college students has been severely affected by the COVID-19 pandemic [51]–[53], and that this rise is here to stay [54]. There has also been much discussion about how to address this growing need for mental health support, particularly on college campuses [55]. Wearable devices tracking sleep have been suggested as a potential mechanism for identifying changes in mental health status in college students and prompting interventions [36] because they provide a more consistent picture of vital sign measures that are linked to an health [56]. Though recent work has shown that sleep abnormalities may be useful for predicting changes in mental health [27], many epidemiologic studies using biometric wearables have been limited by small sample sizes [8] or short durations (e.g., 2 weeks or less) [57]. In this study, we enrolled a large cohort of college students to assess their stress and sleep measures over their first semester of college.

In this study, we show that average respiratory rate (ARR) is significantly associated with stress and may be useful in identifying elevated stress levels in young adults. Higher ARR was associated with higher PSS (Table 1), and those with higher ARR had an increased likelihood of reporting moderate-to-high stress for that week during the first semester of college (Table 2). The inclusion of ARR as a predictor to mixed-effects models significantly improved model fit and the explanatory value of our models (Table 2). As expected, female gender [58], [59], a previous mental health diagnosis, and traumatic exposure history [24] were significantly associated with higher stress and explain much of the variance in stress measures (Table 2); that ARR accounts for variance above and beyond these well-accepted measures is a unique contribution of this study.

This finding adds to the growing literature utilizing respiratory rate to identify changes in health [34], [41], [60]. Mechanistically there is a relationship between stress and decreased parasympathetic regulation [61] which modulates the neural pathways affecting respiratory rate [62]. Stress has been associated with increased respiratory rate and respiratory variability [63]. The emergence of ARR as the most robust predictor of stress in our study is unique in the literature, where a growing number of studies have pointed to TST, HRV, HR, and sleep stages as the primary sleep measures that are associated with stress. The absence of studies focused on ARR and stress from literature using wearables to detect mental health changes may be due to the low variance in this measure across and between individuals and the need for serial measures over extended periods to detect relationships. ARR has been referred to as a neglected vital sign due to its importance in health assessment, but relatively minimal focus in the literature [64].

We explored the relationship between stress and the distribution of sleep measures (i.e., min, 5%, 25%, mean, 75%, 95%, and max). The relationship between ARR on prediction of PSS was most robust for average values of ARR. While lowest heart rate, rMSSD, percentage of deep sleep, percentage of REM, and bedtime start time emerged as potentially important sleep measures for predicting PSS, they were not robust predictors when time-invariant individual traits were added to our models (*SI Appendix* Table S5). The current study focused on raw sleep measures that could be extracted from the Oura ring's longest sleep period per night, and it will be important for future studies to evaluate additional sleep variables, such as daytime naps, which have been associated with mental health in college students [36].

Longer term studies with further investigation of temporal correspondence between stress and sleep measure deviations may provide better understanding of causal relationships as well as how individual factors affect these relationships. To our knowledge, there is no published evidence of large, randomized control trials of long-term behavioral interventions targeting stress in college students with continuous wearable data. These studies could provide more insight into whether reductions in stress influence ARR and other sleep measures over time. Future research could also evaluate the potential impact of mobile app-based interventions following the detection of sleep disturbances.

There are limitations to the present study. The Oura ring has shown comparable results to polysomnography in sleep duration, sleep latency, and total wake up times, but has shown less accuracy with sleep stages [26], [45]. While sleep data was taken nightly, surveys were collected on a weekly basis; aggregation of an individual's sleep measures could have introduced bias. Second, we do not have stress or sleep data before participants moved to college and therefore cannot assess the influence of beginning college on stress and sleep measures. Potential confounders also exist in our data. We did not account for participants taking medications (e.g., beta-blockers) [65] or sleep disorders (e.g., sleep apnea) [66] which affect sleep. Additionally, we did not account for physical activity or substance use that may influence sleep measures, including caffeine, marijuana, and alcohol use. Compared to previous studies on first-year college students [8]–[10], this cohort got substantially more sleep pointing to potential differences in this population from other college-aged groups.

This study would benefit from inclusion of additional cohorts to assess the influence of these traits and applicability of these results to a broader population, given that our sample was predominantly female, white, and were not first-generation college students (Table 1). Expanding this window of analysis may identify whether the link between ARR and PSS holds prior to the beginning of college and throughout the college experience. Given the bi-directional relationship of stress and sleep, further analysis of the onset of stress, its duration, and the temporal relationship to any sleep disturbances may provide greater clarity on whether ARR can be used to predict stress in this population. During exploratory analyses, we detected significant differences in sleep and stress measures during the Thanksgiving break, and therefore we omitted this week from the current analysis. Utilizing school breaks as a quasi-experimental study for the influence of reduced academic stressors on sleep is a worthwhile area for future study.

The first year of college is a particularly important period for understanding sleep patterns and stress. As students transition to a time during which they have more autonomy, they establish sleep habits in the context of increased academic pressure, changes in their social milieu, and the development of coping behaviors. The present work highlights the potential utility of monitoring nightly ARR, suggesting that this relatively unexplored measure may signal concerning levels of stress for this population. As the demand for mental health services grows, determining which wearable-derived sleep measures provide information about well-being and can predict worsening mental health in young adults is an important area of study.

Conclusions

The present work indicates that average respiratory rate (ARR) from wearable devices may be a useful metric for detecting stress in first year college students which is a population with an increased risk for mental health burden. Over 500 first-year students showed high perceived stress scores (PSS) and minimal variation in their average respiratory rate over the course of their fall semester of college. The major strength of the present work is that after considering multiple factors that are well-known to influence stress in young adults, there was a persistent significant relationship between PSS and ARR. After accounting for demographic and psychological traits, each additional breath per minute, increased the odds of moderate-to-high stress 1.25 times (by 25%) in that week of the fall semester. The present findings call for more research on the utility of wearable data to identify which young adults are at greatest risk for high stress given the implications for increased morbidity and mortality associated with mental health for this population.

Materials and Methods

Enrollment. All participants were enrolled during the fall semester of their first year. Participants were recruited during orientation, through student mailing lists, and in-person events. After expressing interest in the study, participants were asked to complete basic demographic questionnaires, which were used to screen for eligibility. Study criteria included being a first-year student between the ages of 18-24 years, being enrolled full-time (at least 12 credits), and owning a smartphone. After eligibility screening, participants were invited to attend a lecture which provided in-depth information about the study. Participants were required to complete a comprehension assessment with completely correct answers before being able to provide written informed consent through RedCAP. This study protocol was reviewed and approved by the University of Vermont Institutional Review Board.

After enrollment, participants attended an in-person event to complete sizing for their Oura ring. After receiving their Oura ring, participants were asked to complete a baseline survey and fill out weekly surveys for seven weeks. At the end of the semester, participants completed an exit survey.

Stress measure. The PSS-10 is a ten-item measurement tool that assesses the degree of how individuals perceive situations in their lives as uncontrollable, unpredictable, and overloaded relative to their subjective coping abilities (e.g., how often could you not cope with things that had to be done) [67]. Items are rated on a 5-point Likert-type scale (0=never to 4=very often) (*SI Appendix*). Six items are considered the negativity subscale, and four items relate to a positivity subscale. These items relate to feelings and thoughts during the previous month. The PSS-10 is widely used internationally [67]. The PSS-10 has internal consistency, with α of 0.91, and has also been widely validated across cultures [68]. The PSS-10 is not a diagnostic instrument, and there are not any clinically established cut-offs. However, it has been used as a screening tool, and scores above 14 have been considered a moderate level of stress. The average PSS-10 score was 16.08 (*SD*=6.15) for our sample. Consistent with previous studies, we converted this score to a binary outcome variable at the threshold of 14 for moderate-to-high stress.

Sleep measures. To quantify sleep, the Oura ring uses a combination of accelerometer data, heart rate, heart rate variability, and pulse wave amplitude variability with machine learning models to calculate sleep duration, including those for deep sleep (N3), light sleep (N1+N2), rapid-eye-movement sleep (REM), and proportion of time in bed awake. The Oura ring has a high association with polysomnography (PSG) for measuring total sleep time (TST), sleep onset latency (SOL), and wake after sleep onset (WASO) [33].

For each night, we used information recorded by the Oura ring about the sleep period with the longest duration (i.e., naps were not included). The measures from the Oura ring that we used in our models are given (*SI Appendix* Table S1). Since the total duration of sleep is the sum of the durations for the light, REM, and deep sleep stages as estimated by Oura, we did not include the duration of light sleep as an input to our models as it was highly collinear to TST, REM, and deep sleep durations.

In addition to the raw values, we also compute median-adjusted values for participants. For a given individual, the adjusted measurements are $x_{\mathrm{dev},k} = x_k$ - median($\{x_1, x_2, \ldots, x_n\}$) where k=1, 2, …, n is the k^{th} night measurement of measure x.

In order to compare the weekly survey measures to the daily Oura sleep data, we aggregated the daily measurements at a weekly level. For every user, we consider weeks where there were at least three days where sleep data was recorded. For each week, we take the following statistics for the values in that week: minimum, the 5th, 25th, 50th (median), 75th, 95th percentiles, and the maximum. By using these summary statistics as inputs to our model, we input a reduced representation of the sleep measures distribution for each participant for each week. We performed the same aggregation procedure on the adjusted daily values to adjust for within-individual variation.

Mixed-effects models. We used longitudinal mixed-effects models, also known as multilevel models, hierarchical linear models, or random effects models, to analyze our data due to the nested structure of panel data where repeated measures are taken [69]. These models account for within-individual and between-individual variability [70]. We used these models to predict PSS as a continuous and binary outcome measure. The fixed effects represent the average relationship between time-invariant traits and stress across the entire population [71]. In our models, we assessed demographic factors (Model 1), psychological factors (Model 2), and their combination (Model 3). These models handle missing and unbalanced data more effectively compared to traditional regression methods.

Data, Materials, and Software Availability. This is an ongoing study. Participants may be enrolled in future stages of the study, and therefore the data are not available publicly at this time. At study conclusion, a de-identified dataset will be available in an online data repository. If you have interest in additional analyses, please contact the corresponding author.

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Figures and Tables

Time-varying independent		Mean (SD)	Spearman's rho	Kendall's tau b
(1) Total sleep time (hrs)		7.31 (0.85)	-0.0205	-0.0138
(2) Deep sleep (%)		32.15 (9.70)	-0.0395**	-0.0265**
(3) REM sleep (%)		20.41 (7.09)	0.0555***	0.0378***
(4) Efficiency (%)		87.76 (4.39)	0.0082	0.0056
(4) Wake up count (times)		8.25 (2.37)	-0.0545***	-0.0390***
(5) Sleep onset latency (min)		9.90 (3.75)	-0.0536***	-0.0371***
(6) Lowest heart rate (bpm)		55.30 (7.32)	0.1395***	0.0961***
(7) Average Respiratory Rate (breaths/min)		15.55 (1.57)	0.0847***	0.0584***
(8) Bedtime Start Time (min past midnight)		29.41 (76.31)	0.0639**	0.0435**
(9) Skin temperate deviation (degrees C)		0.12 (0.17)	0.0332	0.0225
(10) RMSSD (ms)		67.72 (33.09)	-0.0993***	-0.0677***
Time-invariant independent				
(6) Gender			0.1964***	0.1073
	Male (*n*=137)	13.88 (7.36)		
	Female (*n*=339)	17.03 (7.08)		
	Non-binary (*n*=31)	18.77 (7.06)		
(7) Race			0.0136	0.0053
	White (*n*=443)	16.29 (7.35)		
	Non-white (*n*=64)	16.49 (7.04)		
(8) First generation status			0.0038	0.0013
	Yes (*n*=47)	16.38 (7.08)		
	No (*n*=460)	16.31 (7.33)		
(9) Mental Health Diagnosis			0.3090***	0.1764
	Yes (*n*=217)	18.93 (7.05)		
	No (*n*=290)	14.37 (6.88)		
(10) Exposure to Trauma			0.1575***	0.0909
	Yes (*n*=262)	17.43 (7.33)		
	No (*n*=245)	15.16 (7.11)		

Table 1: Demographics and fall semester sleep and stress characteristics of first-year college students. Proportions, averages, standard deviations, and correlations of baseline individual traits and sleep measures with perceived stress scores (PSS). The p-value is the significance of the feature to PSS **** p<0.01, ** p<0.05.*

	Model 1			Model 2			Model 3		
Variable	**Coef. (OR)**	**SE**	**95%**	**Coef. (OR)**	**SE**	**95%**	**Coef. (OR)**	**SE**	**95%**
Intercept	-3.26** (0.04)	1.46	[-6.12, -0.41]	-3.66** (0.03)	1.43	-6.47, -0.85	-3.78*** (0.02)	1.43	[-6.58, -0.99]
Gender (male)	*Reference*						*Reference*		
Gender (female)	1.56*** (4.77)	0.39	[0.80, 2.32]				1.23*** (3.43)	0.37	[0.50, 1.96]
Gender (nonbinary)	1.69** (5.42)	0.80	[0.12, 3.26]				0.77 (2.17)	0.77	[-0.74, 2.29]
Non-white	0.36 (1.43)	0.51	[-0.65, 1.37]				0.68 (1.97)	0.50	[-0.30, 1.66]
First-gen	0.16 (1.18)	0.59	[1.00, 1.32]				0.025 (1.03)	0.57	[-1.09, 1.14]
MH Diagnosis				2.06*** (7.83)	0.36	[1.35, 2.77]	1.95*** (6.99)	0.36	[1.24, 2.65]
Trauma Exposure				0.673*** (1.96)	0.34	[0.02, 1.33]	0.68** (1.97)	0.33	[0.03, 1.33]
ARR	0.25*** (1.28)	0.10	[0.06, 0.44]	0.27*** (1.31)	0.09	[0.09, 0.45]	0.22** (1.25)	0.09	[0.04, 0.40]
Random Intercept	2.86	1.46	[2.24, 3.65]	2.82	0.35	[2.22, 3.59]	2.85	0.348	[2.25, 3.62]
Random slope	0.649	0.08	[0.52, 0.82]	0.64	0.08	[0.50, 0.81]	0.63	0.08	[0.50, 0.80]
LR chi-square (df=1)	6.98***			9.05***			5.85**		
Wald statistic	27.93***			51.73***			61.66***		

Table 2. Results of mixed effects multi-linear regression analyses for outcome of moderate-to-high stress (PSS>=14) in the past week. For each of the models, the full model includes the addition of average respiratory rate (ARR). The likelihood ratio (LR) compares the null model to the full model fit. Model 1 includes baseline demographic factors. Model 2 includes baseline psychological history. Model 3 includes both baseline demographic traits and psychological history. The p-value is the significance of the feature to the outcome of moderate-to-high stress (PSS>=14) *** *p<0.01,* ** *p<0.05.*

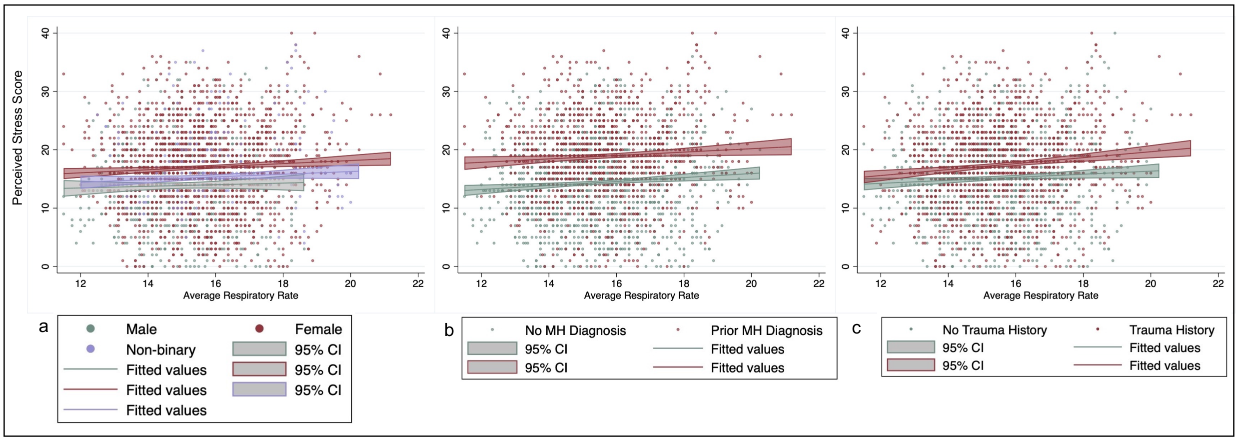

Figure 1: Average respiratory rate (breaths per minute) is associated with higher perceived stress score (PSS) in the first semester of college. There are significant differences in PSS for individual traits: a) Gender, b) Mental Health Diagnosis, and c) History of Traumatic Exposures.

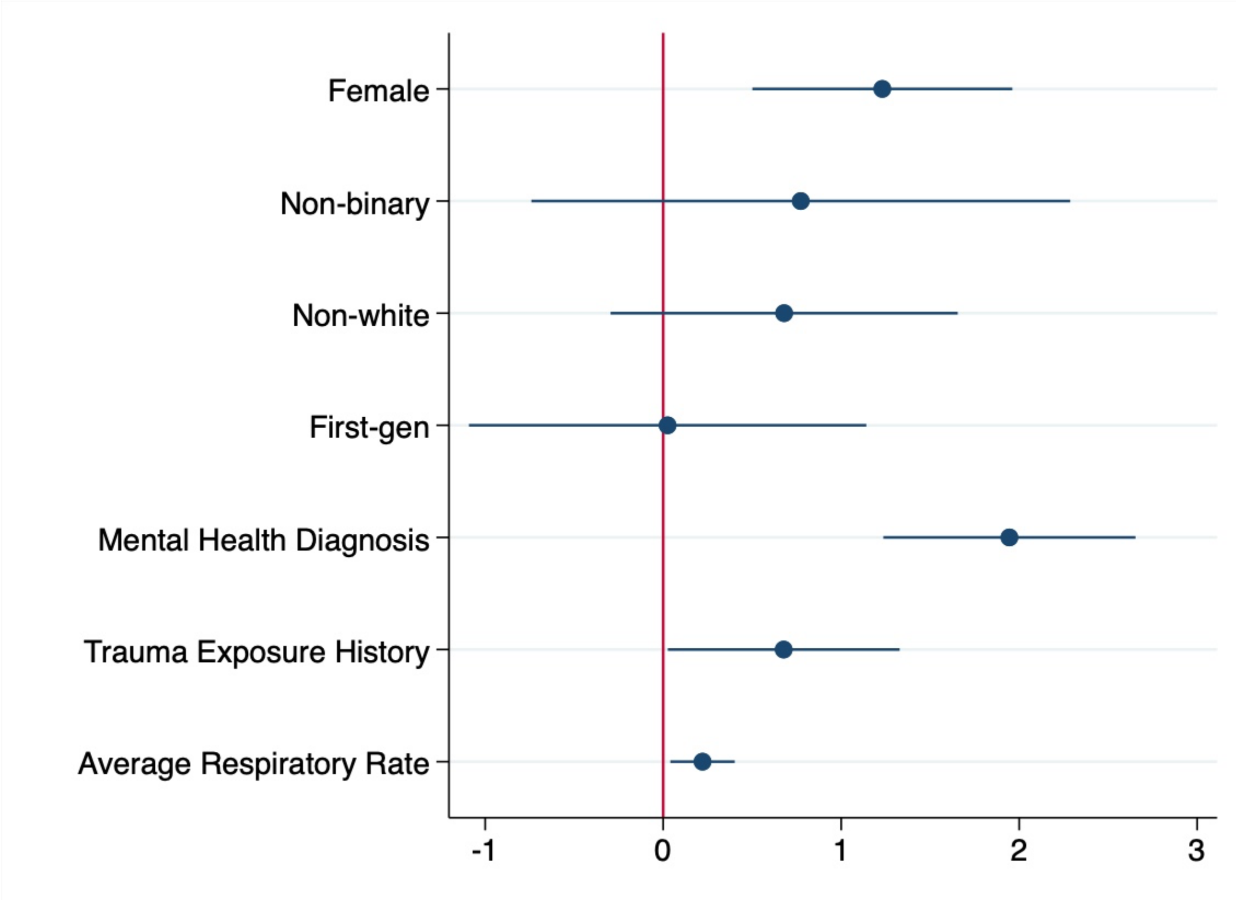

Figure 2: Coefficient plot of the full covariate-adjusted mixed-effect model (Model 3) for moderate-to-high stress (PSS>=14). Being female, a mental diagnosis, a history of trauma exposure, and increased average respiratory rate are significantly associated with an increased odds of reporting moderate-to-high stress.