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Depression deconstructed: Wearables and passive digital phenotyping for analyzing individual symptoms

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A R T I C L E I N F O

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A B S T R A C T

Wearable technology enables unobtrusive collection of longitudinally dense data, allowing for continuous monitoring of physiology and behavior. These digital phenotypes, or device-based indicators, are frequently leveraged to study depression. However, they are usually considered alongside questionnaire sum-scores which collapse the symptomatic gamut into a general representation of severity. To explore the contributions of passive sensing streams more precisely, associations of nine passive sensing-derived features with self-report responses to Center for Epidemiologic Studies Depression (CES-D) items were modeled. Using data from the NetHealth study on N=469 college students, this work generated mixed ordinal logistic regression models to summarize contributions of pulse, movement, and sleep data to depression symptom detection. Emphasizing the importance of the college context, wearable features displayed unique and complementary properties in their heterogeneously significant associations with CES-D items. This work provides conceptual and exploratory blueprints for a reductionist approach to modeling depression within passive sensing research.

Depression is characterized by extreme sadness or despair, which manifests as a myriad of symptoms, including a lack of interest in daily activities, changes in sleep patterns or weight, loss of energy or concentration, and recurrent feelings of worthlessness or suicide (Ramón-Arbués et al., 2020). As the most prevalent mental disorder, depression can have a great individual burden and heighten the risk for other health outcomes, including myocardial infarction, fibromyalgia, and chronic fatigue (Goodwin, 2006). A global meta-analysis revealed that the onset of symptoms in nearly half of all depressive cases occurs before the age of 25 (Solmi et al., 2022), emphasizing the need to understand the etiology of depressive symptomatology in early adulthood. Accordingly, the college years represent a key developmental period for depression and thus may serve as an invaluable context in which to study depressive symptom manifestation (Liu et al., 2019). Moreover, the prevalence of depression among college students is on the rise. In a population of more than 150,000 students across 196 campuses, depression prevalence increased from roughly 25%–30% between 2009 and 2017 (Lipson et al., 2019). Concurrently, the prevalence of suicidal ideation nearly doubled, rising to 10.8% within this time frame (Lipson et al., 2019). Furthermore, the prevalence of depression may have risen as high as 41–44% among college students during the COVID-19 pandemic (Eisenberg et al., 2021; Lee et al., 2021). Reflective of the critical period of depression onset, this high prevalence within the college setting warrants further specialized attention. Given the far-reaching and integrative impact depression has on other health outcomes, this work aimed to move beyond monolithic analyses of severity and specifically explore symptom-level signals of depression among college students. This effort echoes a growing realization in the literature that depression is not a consistent syndrome and that pervasive use of sum-scores from clinically validated questionnaires hinders the ability to garner insight (Fried & Nesse, 2015). Such a paradigm shift to symptom-level inquiry will facilitate the identification of unique depression profiles which can contribute to personalized diagnosis, prognosis, and intervention protocols (Fried et al., 2017; Fried & Nesse, 2015).

Leveraging data from ubiquitous and unobtrusive wearable technology utilized by 1 in 4 American undergraduates (Vogels, 2020), this research builds from and complements a rapidly growing literature to

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provide a more detailed presentation of how digital translations of behavior can be used to detect various aspects of the depressive state. Many recent works have employed passive sensing modalities for the detection of depression, including wearable devices (e.g., smartwatches) (Jacobson et al., 2019; Makhmutova et al., 2021) and smartphones (Jacobson & Chung, 2020). Importantly, passive sensing offers a promising means of non-intrusively and remotely collecting data from an individual—commonly referred to as digital phenotyping—to facilitate convenient monitoring of depressive status (Mohr et al., 2020). When paired alongside established depression inventories, digital phenotypes offer more objective and frequent assessments of depressive symptomatology (De Angel et al., 2022). Within the passive sensing literature, three primary data streams have emerged as potent indicators of depressive levels: heart rate/pulse, physical activity/movement, and sleep (De Angel et al., 2022). From these, an array of variables that quantify the physiology and behavior captured by these sensing streams have been previously associated with depression. For instance, a meta-analysis found that higher sleep variability, along with lower physical activity time and step counts, were associated with higher depressive severity (De Angel et al., 2022). Moreover, in a longitudinal study specifically conducted on college students, heart rate variability was found to be a significant predictor of depression severity (Jacobson & Chung, 2020). Collectively, the literature sets an important precedent to focus on pulse-, movement-, and sleep-based features for the modeling of depression-related outcomes; however, studies frequently consolidate the presentation of depression into an overall severity score, as determined by the psychometrically validated questionnaire utilized (De Angel et al., 2022). Remarkably, despite the item-level nature of these tools, symptom-based investigations are typically absent from passive sensing studies, masking the phenomenological nuances of depression and limiting insight into the utility of wearable sensor data.

Unlike within passive sensing research, depression symptomatology is modeled and explored in great depth within the network analysis literature. The network framework embodies depression as an integrated system of symptom components which influence one another and are dynamic in nature (Borsboom, 2017; Fried et al., 2017). This is contrary to the traditional top-down approach embodied by a single, sum-score latent variable operationalization. Studies operating under the network symptom framework have uncovered trends with important theoretical and practical implications. In one work, loneliness was found to be a critical "gateway symptom" for depression, first activated by bereavement, but in turn activating several other symptoms in a causal chain, thereby offering novel insight into key mechanistic pathways of depression manifestation (Fried et al., 2015). More broadly, another study on over 3400 depressed patients found that non-clinical symptoms of depression such as sympathetic arousal and panic/phobia were more important in driving overall depression severity than traditionally recognized symptoms such as hypersomnia and agitation (Fried et al., 2016). In addition to encouraging broader symptom coverage in research, this work highlighted the inherent bias of symptom equivalency in traditional approaches—the (incorrect) notion that symptoms are interchangeable indicators of the same underlying disorder (Schmittmann et al., 2013). Item-level modeling offers a way to overcome this innate limitation and place empirically substantiated emphasis on one or more aspects of depression for further scrutiny. Bolstered by the added ability of passive sensing data to capture minute changes in behavior over time, it stands to reason that symptom-level investigations within this realm of data collection have the potential to further deepen our understanding of how depression manifests within and across individuals.

Inspired by efforts in network science and the current gap in passive sensing research, this study sought to leverage a large, temporally rich passive sensing dataset of college students to model depression more granularly. Serving as this study's data source, the NetHealth Project is a prominent and well-utilized research endeavor (Faust et al., 2020; Fridmanski et al., 2022; Kılıç et al., 2022; Wang et al., 2021) that facilitated the collection of a variety of mental health outcomes in conjunction with passively collected features. Developed and administered at the University of Notre Dame, the NetHealth Project followed a cohort of undergraduate college students from the time they entered Notre Dame in the Fall of 2015 through the Spring of 2019. The study makes publicly available several densely represented streams of data, headlined by daily passively-sensed pulse, movement, and sleep data collected via Fitbit. Additionally, varying combinations of validated questionnaires were administered throughout its duration, assessing several facets of physical and mental health at different intervals, notably the Center for Epidemiologic Studies Depression Scale (CES-D) which is commonly paired with passive sensing data (De Angel et al., 2022). Occurring roughly 4–6 months apart, these self-report questionnaires served to bookend eight distinct study "waves" within which wearable sensor data was collected. Germane to the current goals of this research, the NetHealth Project offers an invaluable opportunity to interrogate the associations of prominent passive sensing data streams more deeply with individual depression symptoms within a large, risk-prone college student cohort.

Focusing on the item-level CES-D scores, along with passively collected pulse, movement, and sleep data over four years, this study implemented a series of models to individually quantify associations between each of the 20 CES-D items and a small representative suite of passive sensing features. Importantly, the items of the CES-D can be attributed to unique depression symptoms, and these symptoms in turn constitute broader and phenomenologically distinct aspects (or more precisely, factor analytic loadings onto latent factors) of depression: somatic symptoms, negative affect, anhedonia, and interpersonal difficulties (Carleton et al., 2013). Practically speaking, the revelation of significant associations between passively collected features and symptom-level items may facilitate more informative monitoring and targeted intervention of depression.

With this in mind, the present study aimed to examine the associative profile of passive sensing features in terms of their ability to detect item-level magnitudes of self-report depression symptomatology against the backdrop of college life. This research hypothesized that passive sensing streams (pulse, movement, sleep) will vary in their magnitude and ability to signal for each depression symptom as captured by the multifaceted CES-D. Echoing success in the literature, we hypothesized that each stream will prove to be statistically significant ($P < 0.05$) in its association with one or more symptom-level items of depression, which in turn map to broader constructs or CES-D factors (anhedonia, negative affect, somatic, interpersonal). Moreover, streams will likely overlap in terms of shared symptom detection capabilities; however, mutually exclusive detection of symptoms may emerge, highlighting uniquely insightful capabilities of the stream. The goal was to interpret findings with the dynamics of the college lifestyle in mind and highlight trends that may be useful for future research or intervention efforts that seek to monitor depression with wearable technology on this vulnerable subset of the population.

1. Methods

1.1. Cohort summary and data collection

The present study used two of the publicly available datasets from the NetHealth Project: Basic Survey Data and Fitbit Data (http://sites.nd.edu/nethealth/). The Basic Survey Data contained questionnaire responses from a total of $N = 722$ students beginning college at the University of Notre Dame in the Fall of 2015. Students were enrolled in the NetHealth study over three phases which spanned from the Summer of 2015 through the Spring of 2016, meaning that a subset of participants did not have data for the second and/or first waves of data collection. Additionally, some participants did not complete all subsequent questionnaires after enrollment in the study. Administered questionnaires included a variety of clinically established mental health, physical health, and social-psychological questionnaires to assess constructs such as exercise self-regulation, diet self-efficacy, self-esteem, loneliness, anxiety, and depression. The Basic Survey Data reported item-level responses to these questionnaires at each wave of collection, totaling over 3000 unique variables. Each questionnaire was not administered at every wave; particularly, the CES-D was only administered at waves 1, 2, 4, 6, and 8. The item-level CES-D scores were paired with data passively collected via FitBit, which originally contained over 330,000 unique daily records of pulse, movement, and sleep activity combined across all individuals and waves. After preprocessing (see "Data preprocessing and descriptive statistics" below), the data consisted of a fairly large, representative sample of undergraduate students in the United States (N = 469, 50.7% female, 65.2% White, 13.4% Latino/a, 9.2% Asian American, 6.0% African American, 6.2% Foreign/Other). This sample consisted of an average of 702.8 (standard deviation = 375.67) per-person records for step count, 704.57 (standard deviation = 375.82) per-person records for activity minutes and heart rate, and 671.40 (standard deviation = 409.13) per-person records for sleep across all eight waves of the study with an accompanying average of 2.17 (standard deviation = 1.05) CES-D records across the five waves in which this questionnaire was completed. Supplemental File 2 contains additional summary statistics on per-person days represented (mean = 11–12 days) and completion rates (mean = 80–88%).

1.2. Measures

1.2.1. CES-D

The CES-D is a short self-report measure of depressive symptomatology originally published by Radoff in 1977 (Radloff, 1977). The 20-item survey asks an individual to rate how often in the past week they experienced specific symptoms of depression (Table 2). CES-D item responses range on a Likert scale from "0" to "3", indicating the frequency to which that item was experienced by the participant (0 = "rarely or none of the time"; 1 = "some or a little of the time", 2 = "occasionally or a moderate amount of the time", 3 = "all of the time"). Systematic review and meta-analysis has indicated that the CES-D exhibits acceptable screening accuracy for detecting depression (median sensitivity = 0.85, median specificity = 0.72) with no significant differences in screening sensitivity between clinical cohorts and the general population (Vilagut et al., 2016). Moreover, internal consistency has repeatedly been shown to be high (Cronbach's alpha≥0.85) across different national and ethnic groups (O'Halloran et al., 2014; Radloff, 1977; Roberts, 1980; Yang et al., 2015).

Research into the factor structure of the CES-D has been conducted across a wide array of populations, both clinical and non-clinical, and the four-factor model proposed at its inception (Radloff, 1977) is frequently supported in these efforts (Blodgett et al., 2021; Cosco et al., 2020; C. S. Johnson et al., 2008; Schafer et al., 2022; Williams et al., 2007). However, deviations from the constituency and number of latent variables have been reported as well. To date, over 20 alternative solutions have been proposed, ranging from one to four factors (Carleton et al., 2013). For example, there is some empirical support for a three-factor, 14-item solution that calls for the removal of socially-focused items and a careful re-appraisal of several somatic items due to symptomatic overlap with other conditions (Carleton et al., 2013).

Evidence for differing latent factor structures in the literature stems in part from the idiosyncrasy in symptom presentation across sociodemographic groups and thus suggests that treatment of the CES-D as a monolithic representation of depression is not ideal. Latent factors afford nuance in framing depression phenomenology and can be leveraged alongside individual items for explanatory insight. Likewise, in the current study, participant responses to each of the 20 items of the CES-D were kept separate as ordinal variables in modeling, interpreted as stand-alone symptoms, and contextualized within the original (and frequently supported) four-factor latent variable structural solution: negative affect (seven items), anhedonia (four items), somatic activity (seven items), and interpersonal challenges (two items). Keeping in line with the analytical goals of this work, which were inspired by previous bottom-up approaches to modeling mental health constructs, CES-D sum-scores were not considered in the current investigation.

1.2.2. Fitbit

Participants were given a Fitbit HR upon joining the study, and these devices were upgraded to Fitbit Charge 2s in the Winter of 2018 for students continuing the study. All participants periodically synced their device with the Fitbit cloud, and the NetHealth Project coordinators retrieved the corresponding data with an API. Fitbit devices passively collect data with two sensors: a 3-axis accelerometer and a heart rate sensor. The accelerometer was used to measure all raw movement-based features; the heart rate sensor was used to measure pulse; and the combination of the two sensors was used to obtain sleep features. The project coordinators aggregated all step- and pulse-based measurements at the daily level, whereas they allowed individuals to have multiple sleep episodes in a given day (e.g., nap), only combining sleep periods into one if less than 30 min separated two sleep periods marked as distinct by the Fitbit.

1.3. Data preprocessing and descriptive statistics

All data from the Basic Survey Data and Fitbit Data were read into R (v4.2.1) for exploration and preprocessing. Because the outcomes of interest—participant item-level responses to the 20-item CES-D questionnaire—were only collected at five timepoints and therefore marked the end of waves 1, 2, 4, 6, and 8, only passive sensing data from these waves were considered in analysis. From the Fitbit Data, nine features were derived to represent three ubiquitous data streams within passive sensing implementation and research: pulse, movement, and sleep. The goal was to capture basic aspects of day-to-day behavior with only a few non-redundant, uniquely representative features. Of these nine, one feature captures pulse, four features capture movement, and four features capture sleep. Table 1 provides a complete list of these features along with their associated definitions. These features were calculated for a given individual using wave data across the 14 days prior to beginning a given wave's surveys. The time of day at which each participant began or completed a given wave's surveys was not factored into the 14-day window utilized for feature calculation; thus, same-day data from participants beginning the surveys in the evening was not utilized, but rather data starting from one day prior. Despite the 7-day recall of CES-D item prompts, a window of 14 days was selected to increase the statistical robusticity and stability of the summarized behavioral features. Moreover, this 14-day window for data collection and analysis, along with thresholds for designating high and low daily step counts and hypo/hypersomnia, were selected from existing literature leveraging similar passive feature constructions to predict depressive severity to good effect (Makhmutova et al., 2021).

Of the 722 students in the full dataset, N = 469 had passive sensing data collected during at least one of waves 1, 2, 4, 6, and 8 and had corresponding CES-D questionnaire data. Of these 469 participants, some were missing one or more days of passive sensing data within the 14-day windows under consideration (between 2 and 3 days on average). However, all available data for each individual was leveraged to generate their summative passive features. The final preprocessed dataset is available as Supplemental File 1.

Prior to modeling, values for each of the nine passive sensing features, as well as the 20 CES-D item responses, were compared between "early college" (waves 1, 2, 4, collected during students' first and second years of study) and "late college" (waves 6 and 8, collected during students' third and fourth years of study) stratifications of the data using the Wilcoxon rank-sum test. Any differences between these groups among either the digital signals or self-report depression scores, in addition to being of interest in their own right, justified the necessity to

Table 1
Definitions and summary statistics of passively sensed features.

Feature Stream	Feature	Definition	Summary Statistic	Early College (n = 671	Late College (n = 345	Wilcoxon P-value	
Pulse	Heart Beat Rate	Median daily heart rate value	Mean (SD)	74.28 (7.53)	73.48 (7.54)	0.117	
			Median (IQR)	74.35 (11.01)	73.22 (10.03)		
Movement	Activity Ratio	Median daily ratio of non-sedentary (active) minutes to sedentary minutes	Mean (SD)	0.38 (0.14)	0.35 (0.15)	0.034	*
			Median (IQR)	0.37 (0.16)	0.35 (0.17)		
	Step Count	Median daily step count	Mean (SD)	11,999 (3443.6)	11,544.7 (3584)	0.030	*
			Median (IQR)	11,735 (4007)	11,314 (4614.5)		
	High Step %	Percentage of total days with greater than 10,000 steps recorded	Mean (SD)	64.61 (24.89)	59.34 (27.48)	0.005	*
			Median (IQR)	69.23 (35.71)	64.29 (40.11)		
	Low Step %	Percentage of total days with fewer than 5000 steps recorded	Mean (SD)	8.59 (12.45)	9.33 (13.41)	0.367	
			Median (IQR)	7.14 (14.29)	7.14 (14.29)		
Sleep	Sleep Minutes	Median length of distinct sleep episodes	Mean (SD)	376.9 (76.85)	398.5 (62.60)	<0.001	*
			Median (IQR)	388.5 (88)	409 (76)		
	Hypersomnia %	Percentage of total days with more than 10 h of sleep recorded	Mean (SD)	1.77 (4.75)	1.84 (4.35)	0.517	
			Median (IQR)	0 (0)	0 (0)		
	Hyposomnia %	Percent of days with less than 5 h of sleep recorded	Mean (SD)	25.43 (21.39)	20.00 (18.93)	<0.001	*
			Median (IQR)	21.43 (29.81)	16.67 (21.90)		
	Bedtime Variability	Day-to-day variation in an individual's time to bed	Mean (SD)	3.57 (2.32)	3.30 (2.27)	0.062	
			Median (IQR)	3.29 (3.78)	2.98 (3.73)		

Note: Each passively-sensed feature was constructed by considering a given individual's data for the 14 days prior to taking the CES-D at a given wave. All percentages are based on the fraction of (participant-agnostic) 14-day windows in which the behavior occurred and relevant only to High Step %, Low Step %, Hypersomnia %, and Hyposomnia % features. P-values reflect results of the Wilcoxon rank sum test comparing the distribution of each passive feature between early and late college stratifications of the data. Groups were considered significantly different (*) if $P < 0.05$.

Table 2
Structure and summary of CES-D items.

Factor	Item	Definition	Summary Statistic	Early College (n = 671)	Late College (n = 345)	Wilcoxon P-value	
Somatic	DEP1	I was bothered by things that usually don't bother me.	Mean (SD)	0.47 (0.68)	0.44 (0.67)	0.487	
			Median (IQR)	0 (1)	0 (1)		
	DEP2	I did not feel like eating; my appetite was poor.	Mean (SD)	0.39 (0.68)	0.48 (0.72)	0.016	*
			Median (IQR)	0 (1)	0 (1)		
	DEP5	I had trouble keeping my mind on what I was doing.	Mean (SD)	1.03 (0.88)	1.01 (0.81)	0.991	
			Median (IQR)	1 (2)	1 (2)		
	DEP7	I felt that everything I did was an effort.	Mean (SD)	0.81 (0.92)	0.71 (0.87)	0.131	
			Median (IQR)	1 (1)	0 (1)		
	DEP11	My sleep was restless.	Mean (SD)	0.84 (0.84)	0.86 (0.82)	0.519	
			Median (IQR)	1 (1)	1 (1)		
	DEP13	I talked less than usual.	Mean (SD)	0.74 (0.76)	0.66 (0.73)	0.117	
			Median (IQR)	1 (1)	1 (1)		
	DEP20	I could not get going.	Mean (SD)	0.60 (0.80)	0.60 (0.75)	0.509	
			Median (IQR)	0 (1)	0 (1)		
Negative Affect	DEP3	I felt that I could not shake off the blues even with the help from family or friends.	Mean (SD)	0.43 (0.76)	0.44 (0.74)	0.818	
			Median (IQR)	0 (1)	0 (1)		
	DEP6	I felt depressed.	Mean (SD)	0.46 (0.76)	0.42 (0.72)	0.435	
			Median (IQR)	0 (1)	0 (1)		
	DEP9	I thought my life had been a failure.	Mean (SD)	0.22 (0.51)	0.21 (0.52)	0.521	
			Median (IQR)	0 (0)	0 (0)		
	DEP10	I felt fearful.	Mean (SD)	0.59 (0.82)	0.45 (0.68)	0.029	*
			Median (IQR)	0 (1)	0 (1)		
	DEP14	I felt lonely.	Mean (SD)	0.82 (0.88)	0.76 (0.79)	0.465	
			Median (IQR)	1 (1)	1 (1)		
	DEP17	I had crying spells.	Mean (SD)	0.28 (0.60)	0.31 (0.62)	0.315	
			Median (IQR)	0 (0)	0 (0)		
	DEP18	I felt sad.	Mean (SD)	0.74 (0.77)	0.72 (0.73)	0.977	
			Median (IQR)	1 (1)	1 (1)		
Anhedonia	DEP4	I felt I was just as good as other people. (reverse)	Mean (SD)	0.81 (0.94)	0.76 (0.89)	0.510	
			Median (IQR)	1 (1)	0 (1)		
	DEP8	I felt hopeful about the future. (reverse)	Mean (SD)	0.92 (0.90)	0.88 (0.84)	0.604	
			Median (IQR)	1 (1)	1 (1)		
	DEP12	I was happy. (reverse)	Mean (SD)	0.70 (0.78)	0.69 (0.76)	0.847	
			Median (IQR)	1 (1)	1 (1)		
	DEP16	I enjoyed life. (reverse)	Mean (SD)	0.68 (0.80)	0.64 (0.76)	0.462	
			Median (IQR)	1 (1)	0 (1)		
Interpersonal	DEP15	People were unfriendly.	Mean (SD)	0.38 (0.63)	0.39 (0.65)	0.899	
			Median (IQR)	0 (1)	0 (1)		
	DEP19	I felt that people disliked me.	Mean (SD)	0.58 (0.77)	0.48 (0.74)	0.025	*
			Median (IQR)	0 (1)	0 (1)		

Note. P-values reflect results of the Wilcoxon rank sum test comparing ordinal CES-D item responses (0–3) between early and late college stratifications of the data. Groups were considered significantly different (*) if $P < 0.05$.

control for the effect of college tenure (seniority) in downstream modeling.

1.4. Modeling framework

Since each outcome of interest was an individual response on the Likert scale (0–3), and the data consisted of repeated measures for a subset of the cohort, a mixed-effects ordinal logistic regression (MOLR) approach was selected for modeling using the *ordinal* package in R (v4.2.1). Twenty independent MOLR models (one for each CES-D item) were constructed with an identical set of nine passive sensing features. Each passive sensing feature was standardized with $\mu = 0$ and $\sigma = 1$ for parity of scale, ease of interpretation, and to facilitate model convergence. Time was controlled by modeling the wave of each data point as a binarized (early college or late college) fixed effect. Participant ID was treated as a random intercept. Accordingly, each model was of the following form:

itemScore ~ time_{EL} + HeartBeatRate + ActivityRatio + StepCount + HighStep% + LowStep% + SleepMinutes + Hypersomnia% + Hyposomnia% + BedTimeVariability + (1 | id)

The estimated slope and significance of each variable, defined at the $P < 0.05$ threshold, along with effect size (Cohen's D), associated odds ratios, and their profiled 95% confidence intervals were calculated across each model. Importantly, odds ratios of significant variables in the MOLR setting were interpreted in the following general manner: "One standard deviation change in the independent variable is significantly associated with [a percentage] increased/decreased odds in a higher frequency endorsement of the depression outcome item, controlling for all other independent variables and individual variability." Moreover, due to how estimation is performed in MOLR, higher frequency on the ordinal scale is defined as anything greater than the lowest class (herein, Likert score 0), and thus does not distinguish smaller (e.g., 0 versus 1) from larger (e.g., 0 versus 3) differences. More precisely, the odds ratio in the ordinal setting is akin to a logistic implementation, whereby it is represented as an increased/decreased odds in a higher frequency outcome endorsement of *any* degree (the collapsed positive class) above the reference (the negative class).

1.5. Ethics statement

All data utilized in the current work was collected from a previous observational study approved by the University of Notre Dame's IRB after a full board review under protocol number 17-05-3912. All participants had provided written informed consent prior to taking part in the study.

2. Results

2.1. Descriptive statistics of dataset

Table 1 indicates that five of the nine passive sensing features (Activity Ratio, Step Count, High Step %, Sleep Minutes, Sleep Hyposomnia %) were found to be statistically significantly different ($P < 0.05$) between early college and late college stratifications of the data. Similarly, Table 2 indicates that endorsement of poor appetite (DEP2), feeling fearful (DEP10), and feeling disliked (DEP19) were significantly different ($P < 0.05$) between early college and late college stratifications of the data. No other CES-D item responses were found to differ significantly as a function of stratification. Nonetheless, results suggested the importance of controlling for seniority in all models (see Methods).

2.2. Significant features among mixed-effects ordinal logistic regression models

All passive sensing features, except for Sleep Hyposomnia %, were found to be associated with a statistically significant odds of endorsing higher or lower frequency of at least one CES-D item. Moreover, with the exception of feeling people were unfriendly (DEP15), all CES-D items were significantly associated with at least one passive sensing feature. Echoing descriptive statistical analyses, DEP2, DEP10, and DEP19 were the only outcomes found to be statistically significantly associated with being earlier or later in one's college career, controlling for all passive sensing features. Table 3 provides a summative list of all significant associations organized according to passive sensing stream and constituent features. Estimated effect sizes among significant associations were small to moderate, with average magnitudes of 0.29, 0.23, and 0.23 among pulse, movement, and sleep features, respectively. Fig. 1 maps all of these associations to accentuate patterns of significance and primarily organize findings by passive sensing stream. For reference, the statistical interpretation of every significant association is provided in Supplemental File 2.

Focusing on patterns in item overlap and organized primarily by CES-D factor (somatic, negative affect, anhedonia, interpersonal), Fig. 2 presents unique and shared item-level significance across the passive sensing streams. Some notable trends include: (i) no overlap in somatic items between movement- and sleep-based features, with restless sleep (DEP11) uniquely significant to the sleep stream, (ii) a high proportion of negative affect item overlap among the three passive sensing streams, with the self-perception of life being a failure (DEP9) uniquely shared across all three streams, (iii) a high proportion of anhedonia item overlap between the three passive sensing streams, with only one stream-unique item related to movement being negatively statistically associated with hopefulness for the future (DEP8), and (iv) High Step % was the only feature tied to an interpersonal item, highlighting a link between lower overall levels of daily movement and feeling disliked by others (DEP19) through a statistically significant negative association.

3. Discussion

The current study leveraged longitudinal, densely collected wearable sensor data from a large publicly available dataset on a college student cohort to explore the capability of passive sensor data on pulse, movement, and sleep to signal for self-report item-level endorsements of depression symptom severity. Using the CES-D and a well-recognized four-factor analytic solution to its items, along with a small representative suite of nine passive sensing features, this work built a series of mixed-effects ordinal logistic regression models to profile and compare how strongly passive sensing modalities associate with different aspects of the depressive state. Nineteen of the 20 items in the CES-D were significantly associated with at least one passive sensing feature. Pulse (heart rate) presented as the most versatile and potentially useful stream to individually capture depressive symptoms. Additionally, daily movement operationalized through a threshold of high step count (>10,000 steps) was found to be effective in detecting several aspects of depression symptom severity, especially anhedonia. Aligning with prior empirical observations for pulse and movement-related information, the results reflected the heterogeneous, differential, and complementary value of data streams to detect components of depression and highlighted how the unique aspects of college may influence interpretation and utility.

Through initial descriptive statistical analysis of the data, a few significant differences arose between less senior and more senior students in the cohort. For passively sensed data, the results from Table 1 suggest that more senior students slept longer (with a *per diem* median difference of approximately 21 min of sleep; $P < 0.001$) and had a lower rate of hyposomnia (with an approximately 5% lower proportion of days with less than 5 h of sleep; $P < 0.001$). Movement was also significantly

Table 3
Summary of significant results.

Stream	Feature	Outcome Factor	Outcome Item	β	*P*-value	Cohen's D [95% CI]	OR [95% CI]
Pulse	Heart Beat Rate	Somatic	DEP1	0.33	<0.001	0.35 [0.17, 0.54]	1.39 [1.17, 1.64]
			DEP2	0.38	<0.001	0.39 [0.21, 0.57]	1.46 [1.22, 1.74]
			DEP5	0.21	0.012	0.23 [0.05, 0.41]	1.23 [1.05, 1.45]
			DEP7	0.29	<0.001	0.32 [0.14, 0.50]	1.34 [1.13, 1.57]
			DEP20	0.29	0.005	0.26 [0.08, 0.44]	1.34 [1.09, 1.63]
		Negative Affect	DEP3	0.34	<0.001	0.35 [0.17, 0.53]	1.41 [1.18, 1.68]
			DEP6	0.28	0.003	0.27 [0.09, 0.45]	1.33 [1.10, 1.61]
			DEP9	0.38	0.002	0.28 [0.10, 0.46]	1.46 [1.14, 1.88]
			DEP17	0.43	<0.001	0.32 [0.14, 0.50]	1.53 [1.21, 1.95]
			DEP18	0.20	0.022	0.21 [0.03, 0.39]	1.22 [1.03, 1.44]
		Anhedonia	DEP4	0.23	0.001	0.24 [0.06, 0.42]	1.26 [1.06, 1.51]
			DEP12	0.21	0.033	0.20 [0.02, 0.38]	1.23 [1.02, 1.42]
Movement	Step Count	Somatic	DEP2	0.40	0.020	0.21 [0.03, 0.40]	1.49 [1.06, 2.08]
			DEP7	0.37	0.016	0.22 [0.04, 0.40]	1.45 [1.07, 1.96]
			DEP13	0.37	0.016	0.22 [0.04, 0.40]	1.45 [1.07, 1.97]
	Activity Ratio	Negative Affect	DEP10	0.24	0.032	0.20 [0.02, 0.38]	1.27 [1.02, 1.57]
	Low Step %	Negative Affect	DEP9	−0.46	0.003	−0.27 [-0.45, −0.09]	0.62 [0.46, 0.86]
			DEP14	−0.27	0.008	−0.25 [-0.43, −0.07]	0.76 [0.63, 0.93]
			DEP18	−0.21	0.031	−0.20 [-0.38, −0.02]	0.81 [0.66, 0.98]
		Anhedonia	DEP16	−0.31	0.004	−0.27 [-0.45, −0.09]	0.73 [0.59, 0.90]
	High Step %	Somatic	DEP2	−0.52	0.002	−0.29 [-0.47, −0.11]	0.59 [0.43, 0.82]
			DEP7	−0.34	0.022	−0.21 [-0.39, −0.03]	0.71 [0.53, 0.95]
		Negative Affect	DEP6	−0.36	0.037	−0.19 [-0.37, −0.01]	0.70 [0.50, 0.98]
			DEP10	−0.39	0.017	−0.22 [-0.40, −0.04]	0.68 [0.49, 0.93]
		Anhedonia	DEP8	−0.53	<0.001	−0.32 [-0.50, −0.14]	0.59 [0.44, 0.79]
			DEP12	−0.35	0.037	−0.19 [-0.37, −0.01]	0.71 [0.51, 0.98]
			DEP16	−0.40	0.018	−0.22 [-0.40, −0.04]	0.67 [0.48, 0.93]
		Interpersonal	DEP19	−0.38	0.024	−0.21 [-0.39, −0.03]	0.68 [0.49, 0.95]
Sleep	Sleep Minutes	Somatic	DEP11	0.31	0.019	0.22 [0.04, 0.40]	1.37 [1.05, 1.78]
	Bedtime Variability	Somatic	DEP1	0.21	0.026	0.20 [0.02, 0.39]	1.23 [1.03, 1.49]
	Hypersomnia %	Negative Affect	DEP3	0.17	0.029	0.20 [0.02, 0.38]	1.19 [1.02, 1.39]
			DEP9	0.28	0.009	0.24 [0.06, 0.42]	1.32 [1.07, 1.62]
			DEP14	0.26	0.001	0.30 [0.12, 0.48]	1.29 [1.11, 1.51]
		Anhedonia	DEP4	0.23	0.004	0.27 [0.09, 0.45]	1.26 [1.08, 1.47]
			DEP12	0.18	0.027	0.20 [0.02, 0.38]	1.21 [1.02, 1.42]
			DEP16	0.22	0.010	0.24 [0.06, 0.42]	1.24 [1.05, 1.47]

Note. Results are primarily organized by passive sensing stream and feature (independent variables). All features were simultaneously used to predict CES-D depression item scores across 20 independent, mixed ordinal regression models. The table provides an exhaustive list of significant associations ($P < 0.05$). Sleep Hyposomnia % was not found to be significantly associated with any item outcome. DEP15 was not significantly associated with any feature. The 95% CI around the estimated ORs were obtained by profiling the likelihood function, thus not assuming a normal distribution. OR = Odds Ratio; CI = Confidence Interval.

different between groups, reflecting a less ambulatory (with a difference of more than 400 in median daily steps; $P = 0.03$) and generally more sedentary (with a lower median daily ratio of non-sedentary-to-sedentary activity minutes; $P = 0.034$) day-to-day among the more senior students. This finding of a less active lifestyle among older students is supported by other longitudinal studies of similar size. For example, the University Life Study conducted at Penn State University ($N > 700$) found a significant decline in physical activity across seven semesters of student tenure (Small et al., 2013), while another study of nearly 500 midwestern university students observed that younger students tended to score higher in several indicators of physical activity relative to their older peers (Buckworth & Nigg, 2004). The literature is comparatively more scant in terms of sleep behavior, especially within longitudinal contexts. However, the current results differ from a semester-long study on 820 U.S. undergraduates that found that freshmen slept 20 min longer on average than upperclassmen (Liguori et al., 2011). Currently, there is no surmounting empirical data in the literature to suggest a dominant trend in either direction, and it is possible that factors such as academic workload, extracurricular obligations, social factors, or other unaccounted cohort idiosyncrasies influence these patterns.

For item-level depression scores summarized in Table 2, poor appetite (DEP 2), fearfulness (DEP 10), and feeling disliked by others (DEP 19) were the only CES-D symptoms to differ significantly between freshman/sophomore students and those with junior/senior standing. Poor appetite was the sole somatic CES-D item and was endorsed with a statistically significantly higher frequency in more senior students. Previous work has shown that college students suffer from stressors related to changes in eating habits (Acharya et al., 2018). While these changes are often attributed in part to inadequate support in transitioning from a dependent living situation during high school to a more independent structure in college (Deshpande et al., 2009), it is notable that the current analysis found a heightened frequency in poor appetite self-report among students who have been in school longer and therefore do not necessarily represent this period of transition. Poor appetite potentially suggests a key somatic reaction that transcends collegiate "culture shock" and may entail mounting expectations and responsibilities related to the stress and challenges associated with more advanced coursework or the planning and preparation for the next career step. As work-life balance may become more demanding with increasing seniority, it is possible that negative shifts in eating habits, herein specifically operationalized as "poor appetite," may present as a notable reactive depressive component to stress during college.

Regarding the negative affect and interpersonal factors of the CES-D, fearfulness and feeling disliked by others, respectively, were significantly lower among more senior students. Taken together, these trends may represent a cultivated sense of community belonging, an established confidence in the self, and/or a habituation to college life that encompasses dimensions of "adjustment". To the authors' knowledge, no studies have looked at the longitudinal effects of college life on belongingness; however, many studies have highlighted the critical role belongingness plays in the well-being and performance of vulnerable college minority groups such as Latinos (Hurtado & Carter, 1997), the LGBTQ + community (Duran et al., 2022), and racially diverse women within traditionally male-dominated fields of study (D. R. Johnson,

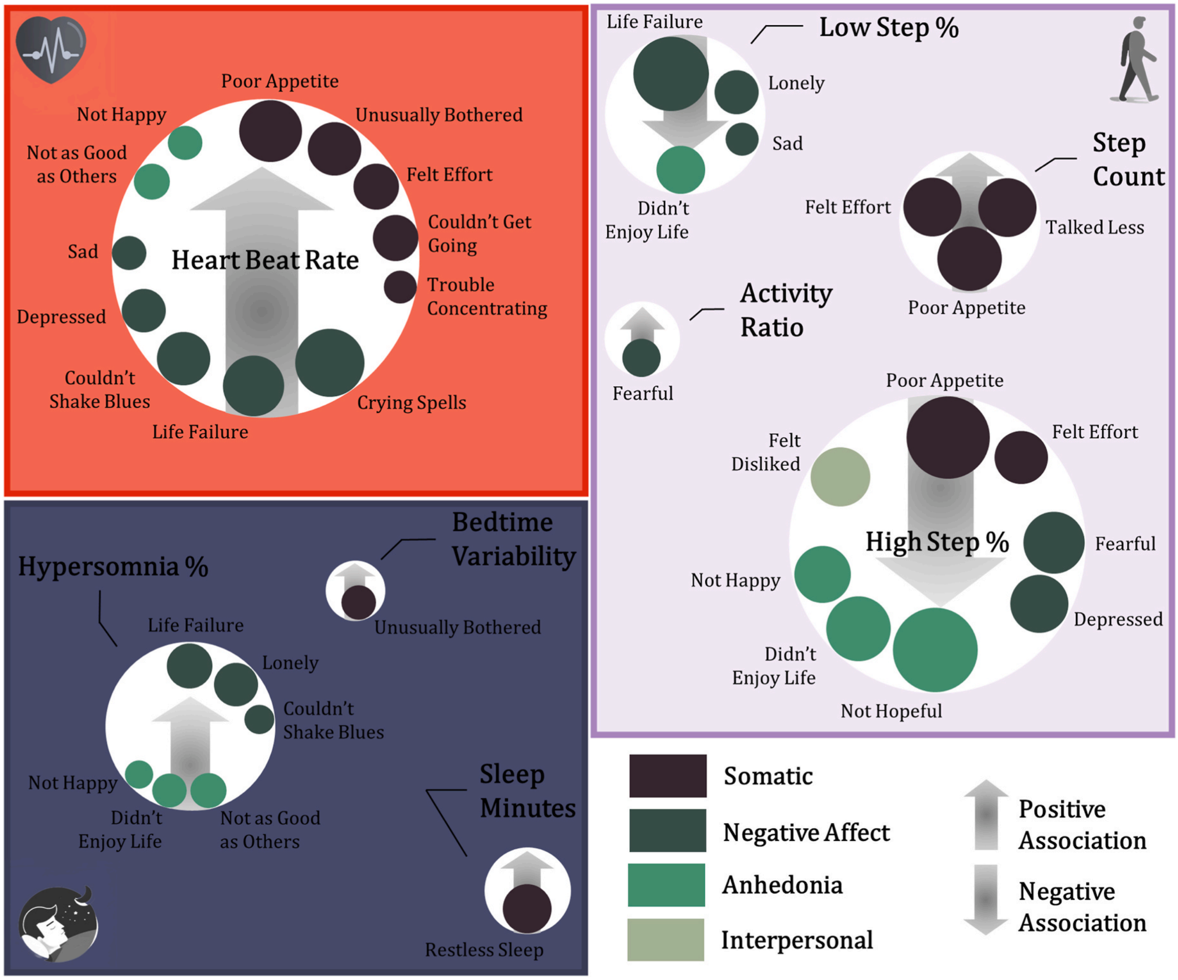

Fig. 1. Relative strengths of association among passive sensing features and CES-D depression items.
Note. Results are primarily segmented by passive sensing data stream (pulse, movement, sleep; large colored boxes). Colored nodes represent the original CES-D four-factor solution membership for each item (somatic, negative affect, anhedonia, interpersonal). Arrows indicate positive or negative directionality of association between the passive sensing feature node and all statistically significant CES-D items contained within. Sizes of all passive sensing feature nodes (white) are scaled relative to one another and are based on the summed absolute values of the significant ($P < 0.05$) statistical associations (β) found among their respective CES-D items. Larger passive sensing feature nodes indicate higher overall relative associations of the passive sensing feature with depression. Sizes of all item nodes are scaled relative to one another and are based on the absolute value of the significant ($P < 0.05$) statistical association (β) found between the CES-D item and passive sensing feature pair. Larger item nodes represent higher strength of association of that item with the passive sensing feature.

2012). This study cannot address these complex associations, but the results nonetheless suggest a general role that the college experience can have on perceptions related to belongingness. In terms of adjustment, however, a large study on more than 5000 college students showed improvement in self-esteem and emotional coping across the latter two years of enrollment relative to the first two years (Conley et al., 2020). Moreover, the results pointed to the first 2 years as a key target for intervention efforts (Conley et al., 2020), echoing the significant differences observed between less senior and more senior stratifications in the current study.

Fig. 1 illustrates the broad symptom association profile grouped by passive stream (panel) and feature (white circle). Starting with the pulse stream, median daily heart rate was significantly positively associated with twelve items that span CES-D factors of somatic, negative affect, and anhedonia. In general, heart rate and associated pulse features have been incorporated into predictive models of depression, suggesting a uniquely informative role in predicting changes in depression severity through time both idiographically and nomothetically within large college student cohorts (Jacobson & Chung, 2020; Wang et al., 2018). Consistent with the current results, other studies have specifically shown that higher heart rate is positively associated with depression symptomatology (Gerteis & Schwerdtfeger, 2016; Schiweck et al., 2021; Schwerdtfeger & Friedrich-Mai, 2009). In one study, resting heart rate was higher in patients with depression after adjusting for psychiatric medications, and some researchers suggested that this higher rate reflects poorer physical conditioning relative to non-depressed individuals (Taylor, 2010). This tie to physical state may be reflected, in part, by the multi-item overlap between heart rate and movement features (e.g., "poor appetite", "everything feeling like an effort"), together indicating that both higher heart rate and lower movement signal more frequent depression symptom endorsement (Fig. 2A).

Of the four CES-D factors, heart rate was primarily associated with somatic and negative affect symptoms. "Being unusually bothered" (DEP1) and "poor appetite" (DEP2) were the most strongly associated somatic symptoms, while "crying spells" (DEP17) and "feeling life had been a failure" (DEP9) were the most strongly associated negative affect symptoms. Focusing on negative affect, research has indicated that the heart rate response to negative emotions is prolonged compared with positive emotions (Brosschot & Thayer, 2003) and that depression is related to both negative affect and elevated heart rate throughout the day (Schwerdtfeger & Friedrich-Mai, 2009). Additionally, items such as "feeling life had been a failure", an "inability to shake the blues" (DEP3),

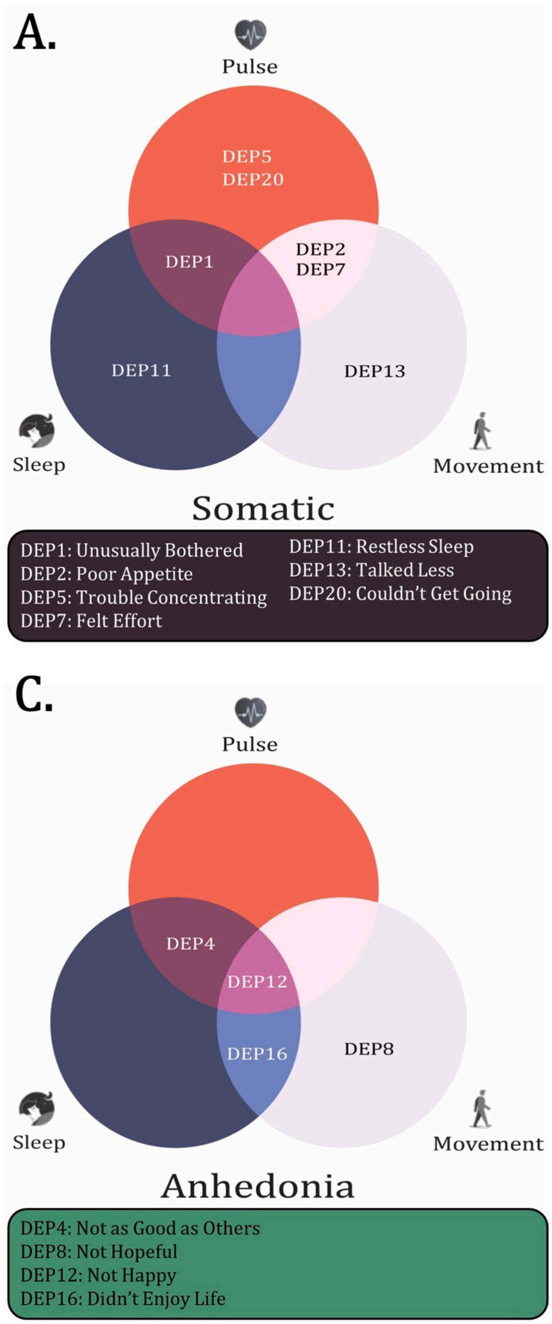

Fig. 2. CES-D item-stream significant association overlap by factor.
Note. Venn diagrams (organized by CES-D factor) show patterns of significant associations ($P < 0.05$) between depression items and passive sensing streams. (A) Somatic factor; (B) Negative affect factor; (C) Anhedonia factor; (D) Interpersonal factor.

being "sad" (DEP18), and being "depressed" (DEP6) could represent manifestations of ruminative behavior which has been shown to spur increases in heart rate (Gerteis & Schwerdtfeger, 2016). Interestingly, the highest increases in heart rate as a consequence of rumination have been found to occur during ambiguous social interactions (Gerteis & Schwerdtfeger, 2016). Day-to-day life on a college campus likely involves several types of interactions with professors, staff, and other students across various settings and contexts that vary on continua of familiarity and formality. Thus, it is possible that some social interactions as a college student may serve to exacerbate heart rate response to ruminative processes that partially define a depressive state.

The overall versatility of heart rate as a signal for depression symptomatology may also be due to its physiological ties to both movement and sleep. Consequently, heart rate may present a singularly powerful marker of the depressive state that implicitly incorporates aspects of both movement and sleep patterns. Movement features themselves mapped to all four CES-D factors (Fig. 1), with "talked less" (DEP13), "fearful" (DEP10), "not hopeful" (DEP8), and "felt disliked" (DEP19) uniquely captured by movement for the somatic, negative affect, anhedonia, and interpersonal factors, respectively (Fig. 2). Moreover, a decreased High Step % was significantly associated with all four factors, meaning that fewer days with more than 10,000 steps signaled feelings of "increased effort", "fearfulness", "hopelessness", "being disliked", and "not enjoying life". While this threshold of daily movement may not necessarily signal depression to the same degree in the general population, the academic responsibilities, social expectations, and active schedules of college students, especially at a top-ranked national university like Notre Dame, may render any lack of considerable daily ambulation a stark contrast to the norm and, thus, an especially telling indicator of poor mental state.

A study of over 2000 adolescents found that physical activity has a reciprocal, bidirectional association with depression, where increased activity led to decreased depressive severity and *vice versa* (Stavrakakis et al., 2012). Interestingly, the significance of these associations was specific to affective symptoms (Stavrakakis et al., 2012). Other studies have also shown associations between measures of anhedonia and walking frequency in university students (Leventhal, 2012), aligning with the association of increased anhedonia symptom endorsements with lower High Step % (Fig. 1). An association of physical activity on affective symptoms was also observed with the negative affect factor associations in the current analysis. Consistent with other research on negative affect, reactivity, and stress mitigation (Puterman et al., 2017; Schultchen et al., 2019), fewer days with a high step count (>10,000 steps) were associated with an increased endorsement in the negative affect items of "depression" and "fearful". However, the findings also indicate that fewer days with less than 5000 steps (i.e., higher ambulation) were associated with increased feelings of being "lonely", "sad", and "feeling like life had been a failure". This latter set of associations is counterintuitive, and there is no empirical or theoretical precedent available to offer a satisfactory explanation. Broadly, however, it is possible that movement, aside from being an especially useful marker for depression holistically, is a data stream that may be both highly contextual and potentially heterogeneous in its dynamics with respect to the depressive symptom milieu, warranting further study.

From the sleep stream, Hypersomnia % (oversleeping) was positively associated with the most items, capturing aspects of heightened negative affect and anhedonia (Fig. 1). However, Hyposomnia % (sleep deprivation) was not found to be significantly associated with any CES-D item. This does not align with prior research which has found sleep deprivation to be associated with increased negative affect, including loneliness (Altena et al., 2020; Franzen et al., 2008). The significance of oversleeping in the present analysis is reminiscent of atypical depression rather than depression, where sleep deprivation is more commonplace (Łojko & Rybakowski, 2017). Nevertheless, the ability of oversleeping to signal for negative affect and anhedonia items is not entirely surprising as differences between depression and its atypical variant are mostly based on the timing of onset, duration, and persistence of these items rather than the items themselves. The prominence of the Hypersomnia % feature and the concomitant lack of representation of the Hyposomnia % feature in the results may be due to two factors. First, the demands and stresses of college life lead to a prominence of sleep deprivation among American students (Gilbert & Weaver, 2010). Hyposomnia may not be a useful feature to capture depression in this setting as physiological response can be confounded by student behavioral and social norms. Second, items of the CES-D were modeled, not depression as a whole. The ability of hypersomnia to flag for components of depression such as "loneliness," an "inability to shake the blues," and "not feeling as good as others," for example, does not necessarily equate to an ability for hypersomnia to behaviorally signal for depression in totality. Taken together, the results suggest that unlike pulse, sleep may not be a suitable stream to independently leverage when modeling depression. This may be especially true considering that sleep-related problems are often a primary disorder rather than secondary to depression (Gilbert & Weaver, 2010). Ultimately, insights for depression gleaned from sleep data may be more valuable when considered in combination with pulse and/or movement streams.

Supporting the study's hypotheses, the results suggested that pulse, movement, and sleep are capable of informing depression symptomatology. Despite this, there are important limitations. First, only five CES-D questionnaires were administered across four years with imbalanced student representation across waves. This precluded an ability to more granularly model college advancement. While the grouping of data into "early" and "late" college designations revealed interesting trends, future work will undoubtedly benefit from assessments at more frequent intervals. Second, the item-level approach to modeling, while providing the ability to systematically explore a complex construct, has a drawback of being less clear. Depression is best understood as a network of interrelated symptoms that may have one or more symptoms in common with other disorders (Borsboom, 2017). Due to this, the capacity to extend item-feature associations into a broad commentary on depression is limited. CES-D items have overlapping constructs such as anxiety and chronic stress. Consequently, an association between "unusually bothered" and bedtime variability, for example, may be interpreted as the ability for sleep data to indicate an anxiety phenotype that is part of a wider depressive state, anxiety itself, or ruminative behavior that is not clinical in nature. While the item-level approach to modeling passive sensing data is useful, it should be used with caution when extrapolating to depression as a whole since items are best thought of as components in broader interrelated systems of phenomena. Third, the chosen four-factor structure of the CES-D is only one possible solution. Nonetheless, this study encourages future exploratory work that leverages alternative structures of the CES-D as well as items from other validated tools. Fourth, the passive features were intended to represent each stream of behavioral data in a straightforward, non-redundant, and parsimonious manner. Accordingly, operationalization of pulse, movement, and sleep was not exhaustive. Aspects such as sleep quality, exercise, and heart rate variability were not considered in the current analysis. Future research could benefit from examining these factors to build a more comprehensive understanding of the relationship between depression symptomatology and digital phenotypes of day-to-day behavior. Additionally, more complex deep learning models which leverage large suites of passive sensing-based features to predict symptom outcomes can be employed to capitalize on performance at the expense of interpretability. Fifth, the operationalization of median sleep duration, as well as hypersomnia and hyposomnia rates, was based on the length of individual sleep episodes which did not distinguish shorter naps from main sleeping events. Future research may consider the total amount of sleep by combining all sleep episodes for a given day, or only focus on the main sleep episodes for feature derivation. Lastly, this study focused on a college student population which comes with unique environmental considerations that may influence patterns in passive symptom detection. Despite the importance of studying depression in this vulnerable group, the results are not likely to be generalizable to the broader population.

The modern explosion of wearable devices and passive sensing data is a boon for developing explanatory, predictive, and preventative models of mental disorder. Depression is a complex state characterized by dynamic interactions of symptoms over time, and thus, it greatly benefits from data sources that not only continuously monitor behavioral changes but also provide digital representations of behavior that serve as surrogates for symptomatology. The search for digital markers can benefit from framing depression at a level of phenomenological reductionism that facilitates an understanding of the marginal and unique contributions of sensing streams, ultimately shedding light on the optimal types and combinations of signals for depression as a whole. This work thus serves as a conceptual and exploratory springboard for further research that focuses on item-level treatment of mental health within the passive sensing domain.

CRediT authorship contribution statement

Damien Lekkas: Conceptualization, Data curation, Methodology, Software, Investigation, Formal analysis, Visualization, Writing – original draft, Writing – review & editing. **Joseph A. Gyorda:** Conceptualization, Data curation, Software, Investigation, Writing – original draft, Writing – review & editing. **George D. Price:** Visualization, Writing – original draft, Writing – review & editing. **Nicholas C. Jacobson:** Methodology, Writing – review & editing, All authors approved the final

version of the paper for submission.

Declaration of competing interest

None

Data availability

All data generated and analyzed during this study is included with this published article as a supplementary information file.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.brat.2023.104382.

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