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Detecting Longitudinal Trends between Passively Collected Phone Use and Anxiety among College Students

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Keywords

Anxiety · Phone use · Location · Longitudinal trends · College students · Passive sensing

Abstract

Introduction: Existing theories and empirical works link phone use with anxiety; however, most leverage subjective self-reports of phone use (e.g., validated questionnaires) that may not correspond well with true behavior. Moreover, most works linking phone use with anxiety do not interrogate associations within a temporal framework. Accordingly, the present study sought to investigate the utility of passively sensed phone use as a longitudinal predictor of anxiety symptomatology within a population particularly vulnerable to experiencing anxiety. ***Methods:*** Using data from the GLOBEM study, which continuously collected longitudinal behavioral data from a college cohort of $N = 330$ students, weekly PHQ-4 anxiety subscale scores across 3 years (2019–2021) were paired with median daily phone use records from the 2 weeks prior to anxiety self-report completion. Phone use was operationalized through unlock duration which was passively curated via Apple's "Screen Time" feature. GPS-tracked location data was further utilized to specify whether an individual's phone use was at home or away from home. Within-individual and temporal associations between phone use and anxiety were modeled within an ordinal mixed-effects logistic regression framework. ***Results:*** While there was no significant association between anxiety levels and either median total phone use or median phone use at home, participants in the top quartile of median phone use away from home were predicted to exhibit clinically significant anxiety levels 20% more frequently than participants in the bottom quartile during the first study year; however, this association weakened across successive years. Importantly, these associations remained after controlling for age, physical activity, sleep, and baseline anxiety levels and were not recapitulated when operationalizing phone use with unlock frequency. ***Conclusions:*** These findings suggest that phone use may be leveraged as a means of mitigating or coping with anxiety in social situations outside the home, while pandemic-related developments may also have attenuated this behavior later in the study. Nevertheless, the present results suggest promise in interrogating a larger suite of objectively measured phone use behaviors within the context of social anxiety.

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Introduction

Anxiety, broadly defined as a multifaceted emotional state characterized by excessive or uncontrollable feelings of apprehension, unease, and nervousness, represents a prevalent mental health concern [1]. Anxiety disorders encompass a variety of more specifically defined conditions, including, but not limited to, generalized anxiety disorder (GAD), social phobia, post-traumatic stress disorder (PTSD), and obsessive-compulsive disorder (OCD) [2]. Recent statistics accentuate the prevalence of anxiety disorders, with current estimates suggesting that the lifetime prevalence of anxiety disorders among adults in the USA is roughly 31% [2]. It is particularly imperative to acknowledge the unique challenges confronted by college students, with common sources of anxiety including the transition to new social situations, rigorous academic coursework, and the novel experience of living away from home [3, 4]. These stressors may render college students especially susceptible to heightened anxiety levels; for instance, recent research suggests that roughly a quarter of college students experience mild-to-severe anxiety symptoms [5]. Furthermore, the COVID-19 pandemic introduced an unprecedented layer of stress, with many works unveiling elevated anxiety levels associated with the pandemic within both broader [6, 7] and college populations [4, 8]. This elevated prevalence of anxiety is especially alarming given anxiety disorders are often comorbid with depression and other impairments to quality of life, including sleep loss and financial difficulties [3, 9, 10]. The widespread detrimental health impacts of anxiety thus underscore a need to robustly detect anxiety symptoms, thereby facilitating more complete identification and timely treatment of at-risk individuals.

A novel way to monitor anxiety symptomatology is via personal device (e.g., smartphone) usage. An estimated 96% of Americans aged 18–29 own smartphones [11]; thus, smart/mobile phone use (hereafter referred to as "phone use") presents as a highly representative data channel which can be leveraged to unobtrusively monitor behavior and track anxiety symptom trajectories. Along these lines, many academic works have explored theories connecting anxious symptoms with phone use. Works within this literature specifically refer to problematic phone use, defined as an inability to regulate one's phone usage, which often negatively impacts one's daily life and is a condition to which college students may be more vulnerable [12]. Historically, problematic phone use has been viewed as a behavioral addiction with similar defining features as drug or gambling addictions (i.e., withdrawal, tolerance, loss of control), thereby conceptualizing anxiety as a symptom of this addiction. However, there is a dearth of empirical evidence affirming phone use as an addiction within the literature [13]. Other frameworks conceptualize problematic phone use as an outcome of different psychosocial pathways. In particular, the excessive reassurance pathway postulates that problematic phone use is driven by a desire to maintain relationships and seek reassurance from others, with heightened general/social anxiety symptoms functioning as one factor that may increase the need for reassurance [13]. This and similar theoretical perspectives have been employed to link phone use with anxiety empirically [14]. For instance, a meta-analysis including nearly 10,000 college students across 13 studies revealed a pooled correlation of $r = 0.34$ between mobile phone addiction severity and anxiety levels [12]. Accordingly, there is both a theoretical and empirical precedent to further probe the influence of phone use behaviors on anxiety symptom changes.

In light of these pathway perspectives which avoid categorizing phone use strictly as a behavioral addiction, it is important not to overpathologize this behavior as addictive or problematic [15]. More fine-grained, data-driven research is needed to move beyond broad framings of phone use and gain a greater appreciation for how anxiety-related symptoms may manifest across varying gradations of use. Relatedly, while some works aim to operationalize the severity of problematic phone use through administering standardized self-report questionnaires [12, 16], these screening tools are often not an objective measure of true phone usage due to the biases inherent in self-reporting. Indeed, a recent meta-analysis found only a moderate correlation ($r = 0.38$, i.e., 14% overlapping variance) between self-reports and objective measures of digital media use (e.g., screen time) [17] – a signal lower than expected given these measures capture the same underlying construct. Thus, in order to draw accurate conclusions about the associations between phone use and anxiety, it is paramount to employ more objective metrics that can surmount these systematic biases and associated underreporting [18]. Furthermore, much of the existing literature linking phone use with anxiety utilizes cross-sectional studies, which estimate associations at a given point in time [12, 16, 19]. While there are benefits to cross-sectional approaches, longitudinal studies – which assess associations over a period of time – may offer more accurate and personalized insights into mental health dynamics, given that they allow for the separation of between-person (i.e., population-level) and within-person (i.e., person-specific) associations, as well as the establishment of temporal precedence [20]. Accordingly, the phone use and anxiety literature would greatly benefit from works that leverage more objective means of data collection within a longitudinal framework.

Recent developments in passive sensing technology have provided access to vast datasets on human behavior, including phone use. Passive sensing technologies, such as wearable devices (i.e., smartwatches) [21, 22] and smartphones [23], collect a wide array of information from individuals, including physiological (e.g., heart rate, movement, sleep) and behavioral (e.g., phone usage, location) data. In particular, passively collected phone use (e.g., screen time) has been employed with success as an objective measure of an individual's true phone usage over time [18, 20]. Importantly, many recent works have leveraged phone use and passively collected data as digital phenotypes, or non-intrusive and remotely collected biomarkers, to more conveniently monitor anxiety symptoms [24]. When paired alongside completed anxiety questionnaires, digital phenotyping may provide more objective and frequent accounts of anxious behavior as opposed to solely relying on retrospective reports [22, 25] which may be subject to recall biases [26]. Broadly speaking, passive sensing technologies have been successfully employed for identifying and monitoring anxiety symptoms [27–29], particularly within artificial intelligence-based predictive frameworks [30, 31]. Given the austerity of anxiety if left untreated [32], it is critical to promote digital phenotyping as a means of better facilitating the identification, intervention, and treatment of anxiety [33]. In total, passive sensing technologies provide an objective, promising, and effective means of documenting anxious pathology over an extended period of time.

There is limited literature in which passively sensed phone use is utilized as a digital phenotype for anxiety symptoms over time. Moreover, these works are conflicting in their findings: one study of $N = 384$ US residents ages 18–35 found that past-week phone use measured objectively with Apple's "Screen Time" feature weakly positively predicted anxiety [20]; another study of $N = 101$ college students revealed a negative association between passively collected weekly phone unlock frequency and anxiety [34]; and a third study of $N = 60$ adults observed that neither phone use duration nor frequency across 2 weeks was predictive of subsequent anxiety symptoms [35]. Considering this sparse and inconclusive literature, the present study sought to contribute additional insight through the analysis of longitudinal data derived from the college context, where anxiety symptomatology may be particularly relevant. Furthermore, the present study explores whether phone use at different locations differentially influences anxiety symptoms, given prior works observing that better mental health outcomes are associated with spending more time in nature and away from urban settings [36, 37], visiting different locations more frequently [35], and spending less time indoors [38].

The current work leveraged smartphone data from the GLOBEM study, a research endeavor that curated multi-year passive mobile sensing datasets from college students in the USA [39]. This study was conducted in four 10-week waves during the spring of each year from 2018 to 2021. Two primary data modalities were collected: survey data and passively collected sensor data. The survey data included weekly administered questionnaires to capture more recent changes in mental health, including depression, anxiety, stress, and positive/negative affect. Sensor data were obtained from a mobile app installed on participants' smartphones and included continuous measurements of location, activity, sleep, phone usage (screen time), Bluetooth scans, and call logs. Apropos of the present study's goals, the GLOBEM study facilitated the longitudinal analysis of the association between phone use and anxiety, given the temporal breadth (4 years of data collection) and granularity (phone use tracked continuously and anxiety measured weekly over 10 weeks) of data. Particularly, such a longitudinal analysis could provide evidence that changes in phone use behavior temporally precede changes in anxious symptomatology. Furthermore, the GLOBEM study offered the unique capability to combine passively collected phone use and location data to examine the association between phone use and anxiety at different locations.

The present study aimed to probe a longitudinal association between individual passively collected phone usage profiles and anxiety symptoms within a college environment. The goal of interrogating these associations was to ascertain whether phone use could serve as a reliable proxy for monitoring individual anxiety symptoms over time, particularly within the vulnerable demographic of college students. Moreover, this exploratory work sought to provide a useful methodological reference for future research within larger and more diverse contexts that may be able to further disentangle any trends and build interventions tailored to addressing phone use and anxiety-related psychopathology. Thus, the study was driven by the following hypotheses:

1. There are both significant (either positive or negative) cross-sectional and longitudinal relationships between phone usage and anxiety symptoms.

2. The longitudinal relationship between phone use and anxiety will differ based on the location of phone use (i.e., at home vs. away from home).

Methods

Cohort Summary and Data Collection

The present study leveraged data from the GLOBEM study, a large study conducted over a 4-year period from 2018 to 2021, with each year considered one wave. Data were collected for 10 weeks each year from N = 497 unique students (totaling 705 person-years) at a Carnegie-classified R1 university in the USA [40]. The current work utilized two datasets from the GLOBEM study: SurveyData and FeatureData. The SurveyData consisted of multiple validated clinical self-report questionnaires assessing mental health, physical health, and overall well-being. The majority of these surveys were administered at the beginning and end of each 10-week wave of the study; however, some surveys, including the PHQ-4, were assessed on roughly a weekly basis. For the PHQ-4, the SurveyData contained aggregate scores for both anxiety and depression subscales (see PHQ-4 subsection) as well as the date of completion for each student, resulting in over 5,400 unique PHQ-4 records across the duration of the study. Moreover, PHQ-4 data were paired with phone use and location data stored in Feature Data, which was collected from a mobile app installed on participants' smartphones and modeled after the AWARE framework [41]. The app continuously collected location, phone usage (screen status), Bluetooth scans, and call logs from participants and was compatible with both iOS and Android [39]. However, only data from waves 2 to 4 (2019–2021) were used in the present study as PHQ-4 data were not collected during the first year. Thus, data were available and used for N = 330 unique participants (542 person-years). Additionally, person-level demographic information was not made available in the public data repository for the GLOBEM study to maintain participant anonymity; however, the characteristics of the overall study sample were reported and are characterized by a high representation of females (58.9%), immigrants (24.2%), first-generation college students (38.2%), and those with disability (9.1%), along with broad racial representation, including Asian (53.9%), White (31.9%), Hispanic/Latino (7.4%), and Black/African American (3.3%) [39].

Measures

PHQ-4

The PHQ-4 is a short self-report measure of both anxious and depressive symptomatology. Originally published in 2009, the questionnaire has four items, with two corresponding to anxiety-related constructs from the GAD-2 [42] and two corresponding to depression-related constructs from the PHQ-2 [43]. Each item is measured on a Likert scale from "0" to "3," indicating the frequency over the last 2 weeks in which an individual experienced the given symptom (0 = "Not at all"; 1 = "Several days"; 2 = "More than half the days"; 3 = "Nearly every day"). This study focused on two anxiety-related items: "Feeling nervous, anxious or on edge" and "Not being able to stop or control worrying." The composite scores for these two items range from 0 to 6, with a score of "3" typically being used as the cutoff for experiencing clinically significant anxiety symptoms [42].

Given the PHQ-4 incorporates the items from the GAD-2 for assessing anxiety, this study capitalized on the documented benefits of the GAD-2 for detecting anxiety. The GAD-2 has had success as a screener for generalized anxiety disorder within a primary care sample (sensitivity = 0.86, specificity = 0.83) using a cutoff score of "3" [44]. Along with this, the criteria included in the GAD-2 for detecting generalized anxiety disorder have also shown efficacy in screening for panic, social anxiety, and post-traumatic stress disorders [44], with one study obtaining successful results using the tool as a shorter, more general screen for anxiety disorders (sensitivity = 0.65, specificity = 0.88) [42]. Moreover, internal consistency has repeatedly been shown to be high (Cronbach's alpha ≥0.85) among college students [45], the population of interest for the present study.

RAPIDS Phone Use and Time at Home

The present study operationalized an individual's phone use as the duration of all unlock episodes (i.e., the time when the phone is unlocked) for a given day. An individual's phone usage was collected using the Reproducible Analysis Pipeline for Data Streams (RAPIDS) software [46]. RAPIDS is open-source software built in R and Python and was designed with the intention of facilitating the collection of smartphone and wearable data for the extraction and creation of digital phenotypes. Among the many benefits of RAPIDS include the consistency, efficiency, and time-zone agnostic nature of data collection, the maintenance of data privacy, and the ability to extract behavioral features for specific time segments (e.g., hours, days, intervals) [46]. For more information on the collection of phone unlock duration, see the RAPIDS documentation for phone screen features at https://www.rapids.science/1.9/features/phone-screen/.

Given that one aim of the present study was to examine the association between phone use and anxiety both holistically as well as more specifically at different locations, additional information was extracted from RAPIDS to estimate and compare an individual's phone use while at and away from home. In particular, this study leveraged the RAPIDS phone location data stream, with their feature extraction methods based on Doryab et al. [47] and Canzian and Musolesi [48]. Location-based features in this study (see Data Preprocessing subsection) were derived from the "timeathome" RAPIDS feature, which estimates an individual's (daily) time spent at home. An individual's "home" location was calculated by first using location data from 12:00 a.m. to 6:00 a.m., then applying a clustering algorithm (DBSCAN or OPTICS) to aggregate and determine the center of the biggest cluster. Once the representative home location was identified, RAPIDS calculated the time, in minutes, that an individual spent at this location each day, as well as the time, in minutes, an individual spent on their phone at this location each day. These two features were leveraged in subsequent preprocessing of the raw data.

Data Preprocessing

All raw data was read into the R statistical software (v4.2.1) for preprocessing and downstream modeling. Some participants were included in multiple waves and had distinct identifiers in each wave. To effectively model and assess changes in anxiety symptoms over time, each participant was reassigned a single, unique identifier across all waves. Next, three passive sensing features – daily phone unlock duration, time spent at home, and phone unlock duration at home – were utilized to create new

Table 1. Summary statistics of predictor variables included in model

Variable	Wave (year)	Median (IQR)	Wilcoxon p value
Phone unlock duration	W2 (2019)	0.164 (0.093)	W2–W3: <0.001*
	W3 (2020)	0.211 (0.151)	W2–W4: <0.001*
	W4 (2021)	0.212 (0.130)	W3–W4: 0.012*
Phone unlock duration at home	W2 (2019)	0.204 (0.146)	W2–W3: <0.001*
	W3 (2020)	0.248 (0.189)	W2–W4: <0.001*
	W4 (2021)	0.237 (0.165)	W3–W4: 0.021
Phone unlock duration away from home	W2 (2019)	0.117 (0.081)	W2–W3: <0.001*
	W3 (2020)	0.006 (0.076)	W2–W4: <0.001*
	W4 (2021)	0.073 (0.131)	W3–W4: <0.001*
Age	W2 (2019)	19 (1)	W2–W3: <0.001*
	W3 (2020)	20 (1)	W2–W4: <0.001*
	W4 (2021)	20 (2)	W3–W4: <0.001*

The individual values for all variables (aside from Age) reflect 14-day medians prior to each PHQ-4 collection for a given individual and are interpreted as proportions of time in a day (0-1). Age is reported in years. *Significance ($p < 0.05$) is denoted with an asterisk.

features which captured phone use at different locations. First, an individual's daily time spent away from home was calculated by subtracting their time spent at home from the total time in a day (i.e., 1,440 min). Similarly, an individual's daily phone use away from home was calculated by subtracting their phone use at home from their total phone use. From these, three features were created to represent the daily proportion of time (range 0.0–1.0) an individual spent with the phone unlocked (1) in total (at all locations), (2) at home, and (3) away from home by dividing phone use at each respective location by the time spent at each location. Note that, for a small sample of days (~2% of >35,000 daily observations) across all participants and waves, the duration of phone unlock time at home exceeded an individual's time spent at home. In these instances, time spent at home and phone unlock duration at home were set equal such that the calculated proportions were capped at 1.0.

The aim of the present study was to understand how variation in day-to-day phone usage is associated with anxiety levels; accordingly, all individual PHQ-4 records were paired with the median value for each of the three phone use duration features within the 14-day window prior to the date of PHQ-4 completion. A 14-day window was selected to align with both the questionnaire prompts regarding symptom endorsement over the past 2 weeks, along with prior research which paired passive sensing features with mental health constructs [22, 49]. Furthermore, the median value for daily phone use duration was selected to capture a representative value of an individual's phone use over the 14-day window. Median (instead of mean) allowed for an ability to mitigate the influence of any skew or outliers in day-to-day phone use. Of the 497 people in the full dataset, $N = 330$ (66.4%) had passively collected phone use data and corresponding PHQ-4 episodes during at least one of Waves 2–4. Note that because some participants ($N = 136$; 27.4%) were included in multiple waves, participants had a mean (SD) of 7.9 (1.6) PHQ-4 records within a given wave and 12.4 (6.5) records across all waves, compared to a median (IQR) of 8 (2) records within a given wave and 9 (9) across all waves. Furthermore, note that compliance was quite high among members of the final sample, with 79% having zero missing daily total phone use records and >54% having zero missing location-based phone use records. Specific definitions for each variable are provided in the next subsection, and summary statistics for each variable are provided in Table 1, with Wilcoxon ranked sum test p values provided between study waves.

Analyses and Modeling Approach

The present study implemented an ordinal mixed-effects logistic regression model for predicting self-report PHQ-4 anxiety subscale scores, which were reported on a scale of 0–6. The implementation was performed using the cumulative link mixed model (*clmm*) function found in the *ordinal* R package [50] and the link set to "logit" to specify that the model should give proportional odds for each level of the outcome variable. All other default hyperparameters were used. The random effects of time and participant were specified for each individual within the dataset. Time, phone use at home, phone use while not at home, and total phone use were modeled as fixed effects alongside their interactions. Age was also included as a demographic control variable given that technological engagement/phone use may vary by age [51]. Moreover, age is included as a covariate as participants varied in their ages at the time of recruitment, and participants recruited in later waves were not necessarily older than participants recruited at the earlier waves. Nevertheless, there was a moderate relationship (Spearman ρ = 0.53) between age and time. To decrease model complexity and ameliorate issues with convergence, all predictors were scaled to have a range of 0–1, and the PHQ-4 anxiety scores were binned into "no anxiety" (0), "low anxiety" (1–2), "moderate anxiety" (3–4), and "high anxiety" (5–6). These thresholds were chosen to reflect the interpretations of the individual scores on the PHQ-4 anxiety subscales (e.g., score ≥3 indicates potentially clinical anxiety levels) [42].

The full model specification and associated variable definitions are as follows:

$$\begin{aligned}\text{PHQ-4\_anxiety} = {} & \text{Time*PhoneUse} + \text{Time*PhoneUse\_Home} \\ & + \text{Time*PhoneUse\_NotHome} + \text{Age} \\ & + \left(\text{Time}\middle|\text{Participant}\right)\end{aligned}$$

PHQ-4_anxiety: the binned sum of the two anxiety items of the PHQ-4 (0 = raw score of 0; 1 = raw score of 1–2; 2 = raw score of 3–4; 3 = raw score of 5–6). *Time*: the time (in years) elapsed from the first day of the first wave of the study considered in the present analyses to the date of the current PHQ-4 assessment. *PhoneUse*: the median proportion (0–1) of time spent with the phone unlocked out of all minutes in a day for the 14 days prior to the current PHQ-4 assessment. *PhoneUse_Home*: the median proportion (0–1) of time spent with the phone unlocked out of all minutes *spent at home* in a day for the 14 days prior to the current PHQ-4 assessment. *PhoneUse_NotHome*: the median proportion (0–1) of time spent with the phone unlocked out of all minutes *spent away from home* in a day for the 14 days prior to the current PHQ-4 assessment. *Age*: the age (in years) at the beginning of a given wave of the study. *(Time|Participant)*: indicates random slopes of time with random intercepts specified for each participant in the study.

Note that the model formula above allows for the estimation of the effects for each variable individually as well as for the specified interactions. Model fit was assessed by calculating Nakagawa's R^2 for mixed-effects models with the *performance* library [52], which provides estimates for the marginal (variance attributed to fixed effects) and conditional (variance attributed to fixed/random effects) R^2 values. Significance was determined using a threshold of $p < 0.05$ for model coefficients, and model coefficients were interpreted as odds ratios with 95% confidence intervals. To provide a visual representation of the relationship between phone use and anxiety, the *effects* [53] and *ggplot2* [54] R packages were subsequently utilized to extract the fitted estimates from the model and plot the predicted anxiety score over time for different levels of phone use, respectively.

Model Covariates

In response to an anonymous reviewer's comment, additional variables that may influence anxiety symptomatology were also accounted for in the modeling framework. One such potential confounder is physical activity, with a meta-analysis finding evidence that increased physical activity volume (i.e., product of duration and intensity) is associated with lower anxiety symptomatology and lower anxiety prevalence [55]. Physical activity was operationalized with an individual's daily total step count. Along with physical activity, insufficient sleep is commonly experienced comorbidly among individuals with anxiety and is something that exacerbates anxiety symptoms [56]. Accordingly, sleep was operationalized with an individual's total daily duration of sleep minutes. In line with the aforementioned preprocessing measures, the median value of each covariate across the 14-day window prior to each PHQ-4 record was calculated for use in modeling. Furthermore, the GLOBEM study administered the Trait version of the State-Trait Anxiety Inventory (STAI; [57]) prior to the beginning of each wave; these data were included as a covariate in the present modeling framework to account for baseline anxiety levels. To facilitate model convergence, all new covariates were scaled to have a range of 0–1.

Along with phone use duration, other works have found relationships between phone use frequency and anxiety [34]. As a means of examining whether any associations existed between an alternative operationalization of phone use and anxiety, an identical version of the present modeling framework was created, with the only difference being that the features corresponding to phone use instead represented the 14-day median values for phone unlock frequency (rather than phone unlock duration), in total and at/away from home. Phone unlock frequency was operationalized via taking an individual's daily total counts of phone unlock episodes and dividing this value by the number of minutes spent at each location, meaning that the values are interpreted as "unlock episodes per minute." The median values of total phone unlock frequency and phone unlock frequency at/away from home across the 14-day window prior to each PHQ-4 record were calculated for use in modeling, and these values were also scaled to have a range of 0–1.

Results

Descriptive Statistics

Summary statistics for the variables included in the modeling framework, broken down by the wave/year of the study, can be found in Table 1. Total phone unlock duration significantly increased by ~5% from Wave 2 to Waves 3–4, with participants roughly spending a median of 21% of the time across 14 days with their phones unlocked. More precisely, phone unlock duration at home increased significantly by around 4% from Waves 2–3, then decreased slightly by ~1% from Waves 3–4, nevertheless increasing from initial levels at Wave 2. Strikingly, these findings show that individuals were spending a median of 20–25% of their time on their phones while at home across all waves. Furthermore, phone unlock duration away from home significantly declined from Waves 2–3, falling from a median of ~12% to a median of <1%, then significantly increasing back to a median of ~7%. Overall, median phone unlock duration away from home was considerably lower than either median phone unlock duration at home or in total. Note that Wave 3 of the study occurred in 2020 during the initial stages of the COVID-19 pandemic, suggesting a role of pandemic-related events (e.g., stay-at-home orders) in influencing phone use in total and at/away from home.

Figure 1 displays the proportion of completed PHQ-4 surveys for which participants scored a given level of

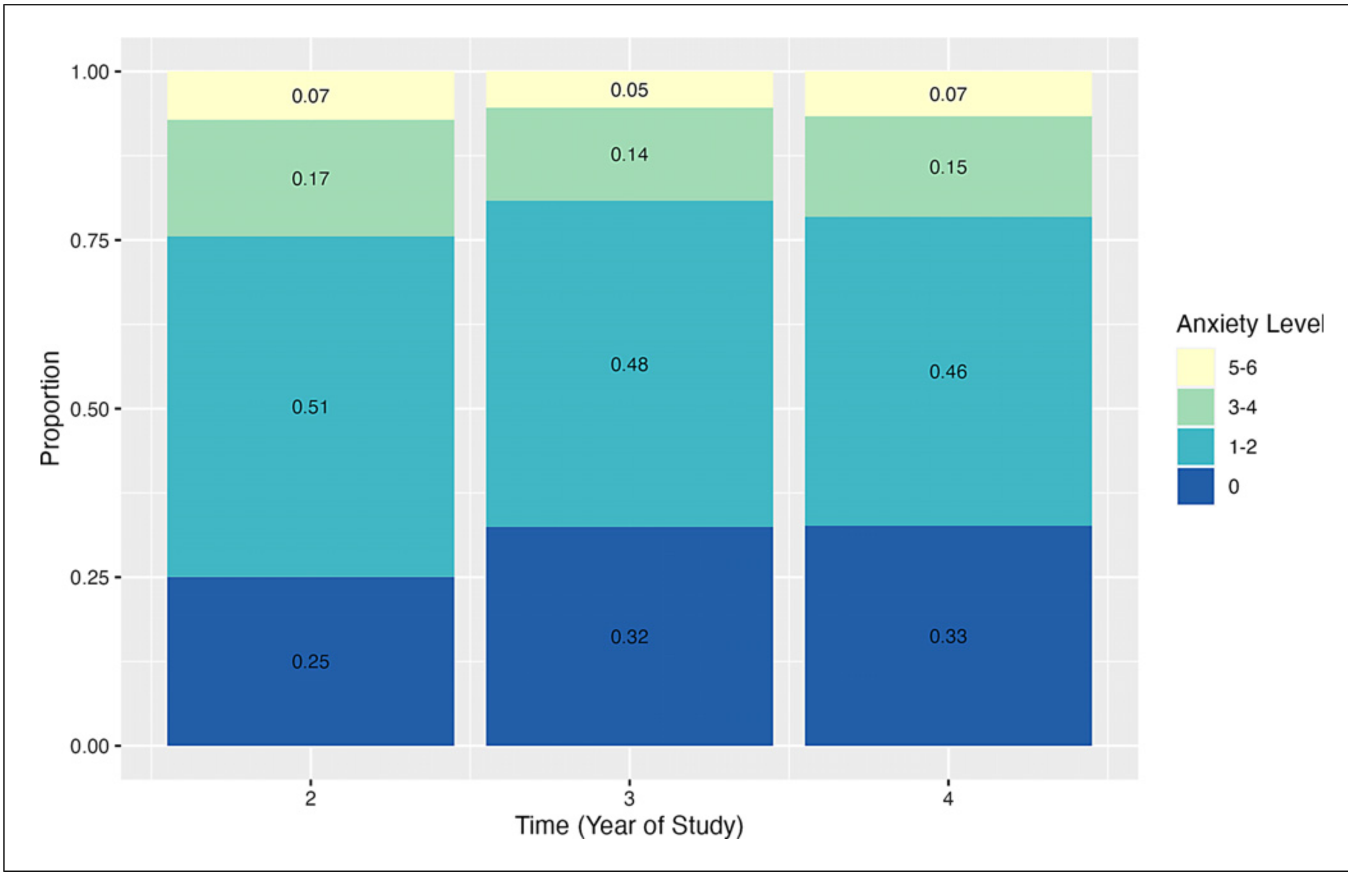

Fig. 1. Distribution of anxiety levels across study years. The stacked bar plots depict the relative proportion of anxiety severity on the PHQ-4 anxiety subscale. Each stacked plot represents a wave/year whose proportion sums to 1.0.

anxiety severity across each of the three waves. Of note, roughly half of recorded observations were a "1" or "2" on the PHQ-4 anxiety subscale across each wave, suggesting that around half of individuals had at least one symptom of anxiety at any point in the study. Along with this, the proportion of records with score ≥3 varied between 0.19 and 0.24 across waves, which, taken together, suggest that around a fifth or more of individuals were experiencing above a clinically significant anxiety level at any given wave in the study. Furthermore, less than a third of recorded observations were at an anxiety level of "0" across all three waves, suggesting that the majority (≥67%) of participants experienced some level of anxiety symptoms.

Mixed-Effects Ordinal Logistic Regression Model

Model estimations from the mixed-effects ordinal logistic regression model, including standard errors and variable significance, can be found in Table 2. Only two variables had estimates that were statistically significant (p value <0.05): phone use unlock duration away from home and the interaction of time with phone use unlock duration away from home. Note that because the present modeling framework is a form of ordinal logistic regression, the coefficients can be interpreted as odds ratios (ORs). For ease of interpretation, the ORs in Table 2 were divided by 100 prior to exponentiating to interpret as percentage changes (0–100) rather than proportional changes (0–1). Thus, the OR for phone use unlock duration away from home is 1.043, implying that a 10% increase in the 14-day median phone use unlock duration while not at home (all other variables equal) increased the odds of endorsing a higher level of anxiety on the PHQ-4 by roughly 43%. While the model suggests that higher phone use away from home is significantly associated with higher anxiety, it also provides evidence that this association attenuates over time: the OR for the interaction of time with phone use unlock duration away from home is 0.972, implying that for each successive year of

Table 2. Results from mixed-effects ordinal logistic regression model

Variable	Estimate	Standard error	p value	Odds ratio (95% CI)[a]
Time	0.219	0.24	0.368	1.002 (0.997, 1.007)
Phone unlock duration	0.284	1.847	0.878	1.003 (0.967, 1.040)
Phone unlock duration at home	1.402	1.092	0.199	1.014 (0.993, 1.036)
Phone unlock duration away from home	4.242	1.285	<0.001*	1.043 (1.017, 1.070)
Age	0.067	0.140	0.635	1.001 (0.998, 1.003)
Time*phone unlock duration	0.514	1.257	0.682	1.005 (0.981, 1.030)
Time*phone unlock duration at home	−1.098	0.753	0.145	0.989 (0.975, 1.004)
Time*phone unlock duration away from home	−2.836	0.890	0.001*	0.972 (0.955, 0.989)

Table values correspond to the results from the ordinal mixed-effects logistic regression model estimated in R and described further in the “Analyses and Modeling Approach” subsection. [a]Model coefficients are divided by 100 prior to exponentiating to interpret odds ratios as percentages rather than proportions. *Significance (p < 0.05) is denoted with an asterisk.

the study, the odds of endorsing a higher level of anxiety with a fixed 14-day median phone use unlock duration away from home (all other variables equal) decreased by 2.8%. Taken together, the significant findings suggest that higher phone use away from home may have been associated with higher anxiety levels earlier in the study, but over time this association had weakened.

Figure 2 provides a visual representation of the significant results from the mixed-effects model, which reveal that phone use duration away from home exhibited significant associations with anxiety levels both on its own and in its interaction with time. Each stacked bar plot in the figure depicts the predicted probabilities for each anxiety severity level generated by the model. These results are stratified by wave/year (x-axis), as well as by high phone use away from home (>75th percentile; top plot) and low phone use away from home (<25th percentile; bottom plot). Looking at only the bar plots at Time = 2, high phone use has considerably higher probabilities for all non-zero anxiety levels relative to low phone use, implying that the model associated higher phone use with higher anxiety levels. Specifically, high phone users were predicted to exhibit clinical anxiety symptoms (i.e., Anxiety Level ≥3) 20% more frequently than low phone users at Time = 2. However, examining these trends across all years, the predicted probability for Anxiety Level = 0 in the high phone use group increases considerably, whereas the probability of Anxiety Level ≥3 decreases considerably, and the predicted probabilities in the low phone use group remain relatively stable. Overall, the plots depict that the association between high phone use and higher anxiety severity attenuates over time, reaffirming the findings discussed above and shown in Table 2 and suggesting that individuals with higher phone use at Time = 4 have a higher probability of no anxiety symptoms (Anxiety Level = 0) than individuals with lower phone use.

Additional Modeling with Covariates

The present modeling approach was repeated with addition of the covariates outlined in the Methods . Descriptive statistics for the additional covariates can be found in the online supplementary Table S1 (for all online suppl. material, see https://doi.org/10.1159/000540546). The full results from the model can be found in the online supplementary Table S2. Importantly, after controlling for physical activity, sleep, and baseline anxiety levels, the significant associations between phone use away from home and anxiety remained and did not change much in magnitude, both cross-sectionally (OR = 1.035) and longitudinally (OR = 0.975). Of these covariates, only baseline anxiety scores were significantly associated with PHQ-4 anxiety scores (OR = 1.069). The full results from the modeling approach including phone use frequency and covariates can be found in the online supplementary Table S3. Interestingly, aside from baseline anxiety levels (OR = 1.070), none of the other covariates, nor any of the phone use frequency features, were significantly associated with anxiety levels.

Discussion

The present study leveraged longitudinal, passively collected phone usage data from a large college student cohort to investigate the ability of phone use data to

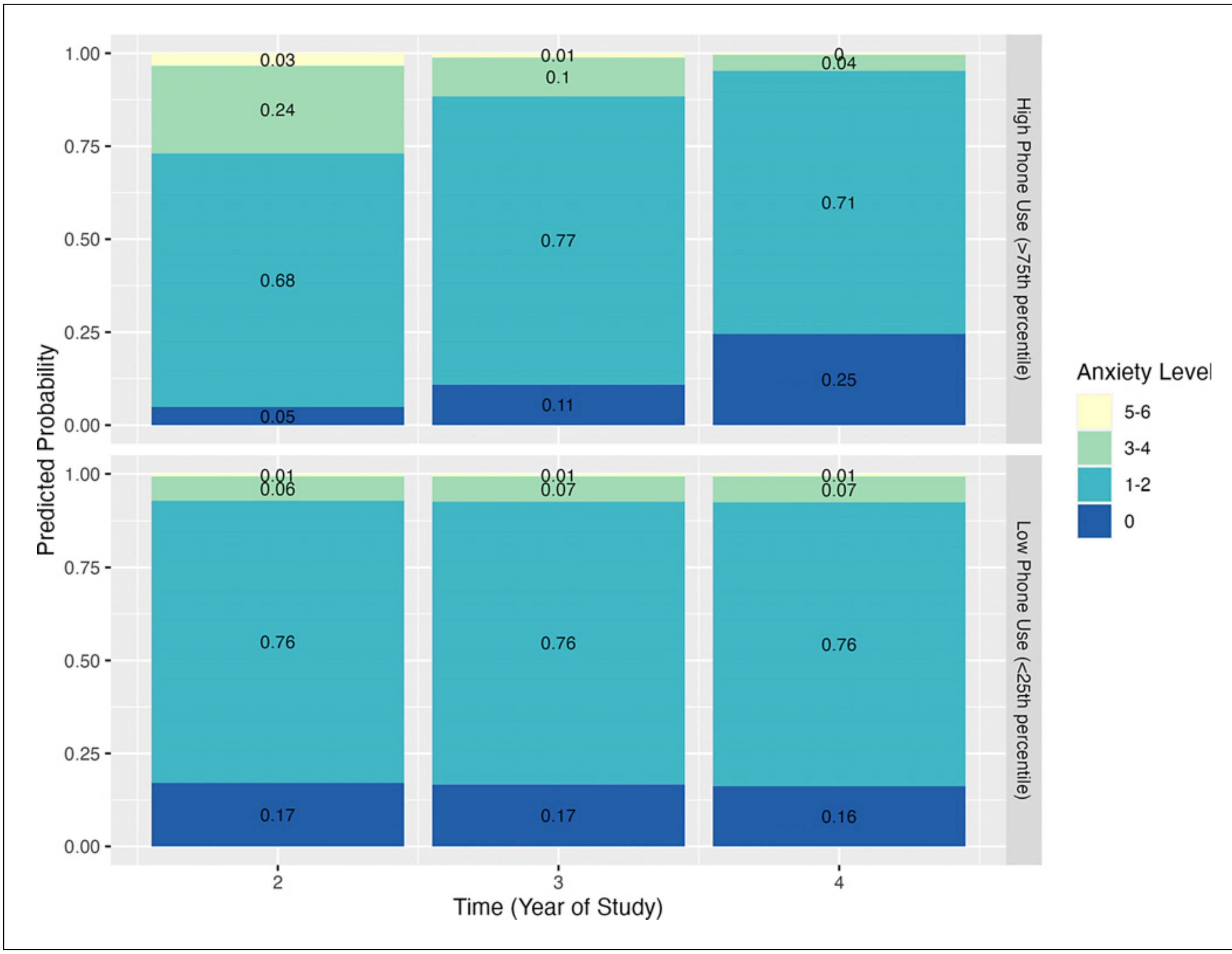

Fig. 2. Predicted probability of anxiety severity level across time for high and low phone use away from home. The stacked bar plots each depict the relative probability of each level of anxiety severity on the PHQ-4 anxiety subscale. The stacked bar plots are stratified into two groups, with the top group corresponding to individuals above the 75th percentile in phone use away from home, and the bottom group corresponding to individuals below the 25th percentile in phone use away from home. Each stacked plot represents a wave/year whose proportion sums to 1.0.

capture fluctuations in individual self-report anxiety symptoms. Using a short, reliable, and commonly employed questionnaire to measure individual anxiety symptomatology, this work implemented a mixed-effects ordinal logistic regression modeling framework to examine associations between location-based phone use and PHQ-4 anxiety subscale scores across 3 years. The high prevalence of anxiety symptoms in the present sample (see Fig. 1) emphasizes both the general need to study and address anxiety within a college setting, as well as to more specifically understand how college students interact with their phones to their benefit (e.g., ameliorating anxiety) or detriment (e.g., as an additional source of anxiety). Results indicated that an increased duration of phone use away from home was significantly associated with greater anxiety severity across all years of study, while this association attenuated throughout the college experience.

In support of the initial hypotheses, significant associations between phone use and anxiety were found which differed based on phone use location. Interestingly, while phone use duration away from home was significantly associated with anxiety, no significance was detected for total phone use duration or phone use duration at home. Moreover, no significant associations were detected between phone use frequency and anxiety symptomatology (see online suppl. Materials). Other longitudinal studies have similarly observed null associations between phone use (both duration and frequency) and anxiety [35, 58]; however, this work is potentially the first to observe null associations with at-home phone use specifically. Along with this, the present study found no significant associations between either age or time and anxiety severity. Other works examining anxiety within a college cohort have observed conflicting changes in anxiety scores throughout the college experience, with these works measuring anxiety scores at semester or yearly intervals [59, 60], while the present work captures anxiety symptomatology on a weekly basis. In light of this, greater resolution in anxiety score measurement (e.g., ecological momentary assessments) may provide the most serviceable ground truths for understanding the temporal associations in college student anxiety levels. Furthermore, the present study found no significant associations between either physical activity or sleep and anxiety severity. Nevertheless, the directionality of these associations aligned with findings from previous studies (e.g., decreased physical activity/sleep are associated with increased anxiety [55, 56]).

Importantly, the two significant associations between phone use and anxiety uncovered by the present modeling framework both included phone use away from home. This finding may point to phone use as a means of mitigating or coping with anxiety when navigating social situations outside the home. Previous works have examined the association between phone use and social anxiety specifically, with one cross-sectional study observing a significant positive association between social anxiety and phone use in group settings [61]. Another work found a significant positive cross-sectional association – but no significant longitudinal association – between social anxiety and problematic phone use [58]. Thus, it is possible that heightened phone use may be a result of a desire to mitigate acute social anxiety symptoms, rather than a pathologic or habitual behavior [61]. Given that this work operationalizes the PHQ-4, which was designed to capture anxiety symptoms more broadly and thus does not specifically measure social anxiety, this same conclusion cannot necessarily be applied to the present findings. Nevertheless, these findings accentuate a need to longitudinally assess phone use in relation to social anxiety, especially considering that such an empirical model may better align with the theoretical models that link phone use with anxiety [13, 58].

From a longitudinal perspective, the present findings specifically suggest that the association between phone use and anxiety weakens over time. This diminishing association may be related to the fact that the last two waves of the study overlapped with the beginning of the COVID-19 pandemic (i.e., Waves 3/4 took place in Spring 2020/2021). The results revealed increases in total phone use and phone use at home in Waves 3–4 of the study (see Table 1), which is corroborated by other works finding heightened phone use during the COVID-19 pandemic [51, 62, 63]. However, an opposing trend is found for phone use away from home in Waves 2 to 3, with median time spent on the phone when away from home dropping from 11.7% to 0.8%. This finding, alongside physical restrictions enacted during the pandemic, including stay-at-home orders [64] and mask mandates [6], may suggest that these pandemic-related policies influenced individuals' behaviors, both in terms of leaving their homes and in the nature or degree to which they interfaced with their phone while in public settings. For instance, one work found evidence that students relied more heavily on their phones for academic use and communication with friends during the pandemic [63], which, as this study suggests, may therefore have coincided with a decreased reliance on their phones for mitigating anxiety symptoms. In light of these hypothetical reasons for the observed significant associations, the present study ultimately underscores the importance of conducting additional longitudinal studies to examine these phenomena, given that the observed relationship between phone use and anxiety within this study differed cross-sectionally and longitudinally.

This work has many strengths, the foremost of which is the use of a large, publicly available dataset consisting of unobtrusively collected, ecologically valid, and densely sampled measures. Such data well-positions this work to contribute to a limited literature examining the longitudinal relationship between phone use and anxiety. The longitudinal operationalization of phone use also allowed for insights to be drawn into the influence of phone use on anxiety both over time and at different locations, making this one of the first works to provide insight into these phenomena. Furthermore, this study examines these associations within a college context, a population which is particularly vulnerable to anxiety-related symptomatology. Moreover, the present modeling framework accounted for many common covariates of anxiety, including physical activity, sleep, and pre-existing anxiety symptomatology, which provides stronger support that the uncovered association between phone use duration away from home and anxiety relates to a real social phenomenon rather than a product of random noise.

Considering these strengths, this study has several areas upon which future research could improve. First, this study addressed the ability of phone use to serve as a signal for longitudinal changes in anxiety, rather than anxiety as a signal for longitudinal changes in phone use. While this work establishes a longitudinal association with phone use predicting changes in anxiety severity, future work may consider examining whether anxiety severity can in turn predict changes in phone use behavior [58]. Along with this, given the present significant associations between phone use duration and anxiety away from home, this work suggests a potential role of phone use in individuals experiencing anxiety induced via social interaction. Hence, future research should consider investigating these trends within a social anxiety context, perhaps through utilizing screening tools specifically adapted for detecting social anxiety (i.e., the Social Avoidance and Distress Scale) [65]. Furthermore, given evidence of anxiety symptoms exhibiting nonlinear trends with time [6, 59], it may be worthwhile to recreate this study's modeling framework using a more flexible modeling approach that can capture any nonlinear trends. Nevertheless, the present linear modeling framework prioritized ease of interpretation over fit to align with the exploratory nature of the work. Additionally, while this work establishes an association between phone use duration away from home and anxiety, future work may seek to conduct analyses that explicitly reveal the mechanisms through which phone use duration and anxiety are related.

Other areas for future research pertain to the study sample utilized within the present work. First, due to a lack of data availability, this study was not able to include demographic information (e.g., sex, race, income) as potential covariates within the modeling framework, although it is likely that the selected subsample of the original GLOBEM cohort still consisted of a representatively diverse college student sample. Second, the data preprocessing pipeline outlined in the Methods addressed a small minority of cases where individuals had a daily recorded phone use at home greater than their daily time spent at home. In light of this, it is possible that the passive sensing technology utilized for tracking phone use may exhibit some inaccuracies, which may have biased the associations between phone use and anxiety revealed in this paper. Future work should investigate the accuracy of smartphones for tracking behavioral patterns, in line with what has been done with smartwatches [66]. Third, there was a high prevalence of missing data within the present study sample pertaining to phone use data at different locations (e.g., green, exercise, and study spaces), which did not allow the authors to leverage these data for analysis; nevertheless, future work may benefit from examining the relationship between phone use and anxiety at more specific locations. Finally, the examination of call details and/or type of phone use (i.e., social media/apps) may provide a finer understanding of how phone use may be related to anxiety [67]; however, these data were not readily available within the GLOBEM dataset.

Taken together, this study provides a framework for interrogating longitudinal associations between phone use and anxiety, suggesting that phone use duration may serve as a potential proxy for anxiety-related symptoms. While this work lends itself to drawing interesting conclusions within a college context, future research should seek to extend the present analyses in an attempt to recapitulate the present findings across the broader population or within other vulnerable subpopulations.

Statement of Ethics

Ethical approval and consent were not required as this study was based on publicly available data.

Conflict of Interest Statement

All authors declare neither financial nor non-financial conflicts of interests. All study funders played no role in study design, data collection, analysis, and interpretation of data or the writing of this manuscript.

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Author Contributions

J.A.G.: conceptualization, data curation, methodology, software, investigation, formal analysis, visualization, writing – original draft, and writing – review and editing. D.L.: visualization, writing – original draft, and writing – review and editing. N.C.J.: methodology and writing – review and editing. All authors approved the final version of the paper for submission.

Data Availability Statement

The data utilized in this study were made publicly available by the authors of the GLOBEM study: https://physionet.org/content/globem/1.1/. Preprocessed datasets utilized in the present study may be provided upon reasonable request to the corresponding author.

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