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Smartphone Usage and Sleep Disturbance and Their Link to Mental Health in College Students

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ABSTRACT

The growing prevalence of mental health issues on college campuses is a rising issue. With depression and anxiety disorders running rampant, understanding the relationship between behaviors found amongst college students, such as increased smartphone usage and sleep disturbance, and mental health disorders may shed light on potential solutions and mitigation strategies. This study assessed depression via the Patient Health Questionnaire-8 (PHQ-8), anxiety via the General Anxiety Disorder-7 (GAD-7), sleep disturbance using the Patient Reported Outcomes Measurement System (PROMIS) Sleep Disturbance scale (short form), smartphone usage, and demographics in college students as a means to investigate the relationship between smartphone usage, sleep patterns, and mental health. The survey resulted in 285 valid responses, and through statistical and machine learning analysis it was found that depression was significantly and positively associated with anxiety, sleep disturbance, and perceived smartphone usage while anxiety was significantly and positively associated with depression, sleep disturbance, perceived smartphone usage, and actual smartphone usage time. Finally, it was found that the parameters discussed above could be used in a binary logistic regression model to predict the presence of depressive symptoms in new participants with 78.1% accuracy (sensitivity 0.638, specificity 0.861). With a specificity on par with other widely used and accepted depression evaluation scales, such as the PHQ-9, this model displays the potential value in assessing anxiety, sleep disturbance, and screen time when evaluating depression in college students.

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Chapter 1

Introduction

Over the past few decades, smartphones have become an integral technology in the lives of many. Be it for entrainment or productivity, the uses and applications of these devices is vast, and woven into the existence of all aspects of life. In specific, this dependency and attachment can be seen in ample prevalence in the lives of college and university students. According to a study published by Impact Journal regarding smartphone usage in college students, these impacts extend beyond just effecting entertainment in areas such as learning behavior and socialization (Alson & Misagal, 2016). In the recent years, as COVID-19 has run rampant around the world, the use of smartphones to stay connected in a time of widespread isolation and confinement has further changed the dynamic relationship students have with their smartphones.

In addition to these unique smartphone usage behaviors, varied sleep patterns have also been observed amongst students. One study on Chinese medical students even found that anxiety was significantly associated with problematic smartphone use and sleep disturbance, further exacerbated by the COVID-19 pandemic (Song et al., 2022). With mental health disorders having long been prevalent amongst college students, looking at associations to such vulnerability is an ongoing battle, yet to be fully understood (Hunt & Eisenberg, 2009).

The objective of this study is to explore the association between factors such as smartphone usage, sleep disturbance, and mental health among college and university students. Moreover, the goal is to apply logistic regression analysis to understand if the demographics, smartphone usage, and sleep patterns of college students can accurately classify and predict depressive symptoms. This study not only contributes to the field of clinical psychology in understanding factors associated with depression in 18-24 year old's, but also provides value at the intersection of smartphone software development and mental health awareness.

Chapter 2

Motivation

Discussion about mental health issues in college students has become increasingly common in the past few years. Yet despite such conversation, rates of certain disorders, such as depression, continue to climb (Wang et al., 2018), with many universities reporting increased mental counseling rates amongst students as well. The Spring 2020 Health Assessment at Penn State further brought to light concerning statistics about its student population at University Park. It identified l9% of students as being officially diagnosed with an anxiety disorder, with a total of 24% of students being affected by this disorder (Penn State Student Affairs, 2020). Additionally, another 14% of students have been officially diagnosed with a depression disorder, with 19% in total being affected (Penn State Student Affairs, 2020). Of these students, 11% were diagnosed with having both anxiety and depression (Penn State Student Affairs, 2020). Furthermore, 66% of students reported being sleepy during the day on three or more days in the school week (Penn State Student Affairs, 2020). Such anxiety, depression, and sleep disturbance also ranked as the third, fifth, and seventh most impactful issues negatively effecting academic performance in the past 12 months.

As such rates have increased, smartphone usage and addiction in college students has followed a similar trajectory, growing steadily. To make matters worse, studies have shown significant associations between smartphone usage and depression, anxiety, and stress-like symptoms (Kil et al., 2021). To further worsen this cycle, college students have been found to be of some of the most vulnerable to addictive behavior as a result of smartphone usage (Roberts et al., 2015). Thus, as smartphone ownership amongst college students in the U.S. surpasses the

285 million mark by 2023 (Kil et al., 2021), understanding the impacts of such devices is crucial in ensuring the mental wellbeing of students.

Chapter 3

Literature Review

In the last few decades as smartphones became a staple in everyday society, looking into the impacts and relationships such usage has with sleep and mental health has gained momentum. While the causality amongst these three factors still widely remains unclear, their relationships have gained clarity in recent times. This chapter looks at previous studies related to both the topics investigated and tools used in this thesis. The following literature discussed focuses on the current landscape and standards of mental health evaluation, specifically regarding depression and anxiety, as well as the relationships currently understood between smartphone usage, sleep patterns, and mental health.

3.1 Depression Evaluation

One of the most widely accepted and used methods of assessing depression in adults is the Patient Health Questionnaire 9-item scale (PHQ-9) (Maurer & Darnall, 2012). This questionnaire, adapted in 1999 from the full PHQ developed in the 1990s, focuses on evaluating and classifying depression into one of five severity categories. It does this by associating a score with each of the nine criteria for depression outlined in the fourth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-IV), consistent with the DSM-V, each being scored from “0” to “3”, with a score of three on any respective question being the most prevalent or severe (Kroenke et al., 2001). The development of this questionnaire greatly improved the normalization of depression screening as this new abbreviated questionnaire takes up to five minutes to complete and provides a sensitivity of 61% and specificity of 94% when detecting depression (Maurer & Darnall, 2012). Additionally, the PHQ-9 maintains reliability in distinguishing between depression, even as severity increases, when compared for accuracy against a more extensive evaluation approach consisting of the 20-item Short-Form General Health Survey, a reported sick days and clinic visits, and review of symptom-related difficulty (Kroenke et al., 2001). Other versions of the PHQ also exist, such as the PHQ-8, PHQ-4, and PHQ-2. The PHQ-8, for example, only varies from the PHQ-9 in that it withholds item nine aimed at assessing thoughts of self-harm and suicide, with one study finding a correlation of 0.997 between the two (Razykov et al., 2012).

Other tools used to assess depression also exist, yet pose various drawbacks and incompatibilities when looking at young adults in the 18-24 year-old population. The popular Generic Depression Scale (GAD), both short five-item and longer 15-item versions, also provides relativity high sensitivity and specificity yet is more catered to older populations with questions such as, "are you basically satisfied with your life?" (Maurer & Darnall, 2012). Additionally, the American Geriatrics Society recommends using the GAD-15 as a follow-up test after testing positive for depression from an initial screening using the PHQ-2 (Maurer & Darnall, 2012).

Finally, the Beck Depression Inventory (BDI) in its revised version as of 1996, the BDI-II, is also widely used to assess the severity of depression in individuals, in accordance with DSM-IV depression criteria (Beck at al., 1996). Consisting of 21 questions and generally taking around 10 minutes to complete, this scale varies in both duration and content from both the GAD and PHQ (American Psychology Association, 2011). In a study comparing the PQH-9 and BDI-II, indication of advantages of the former were identified through both the increased brevity and content, which is based on the diagnostic criteria for depression" (Titov et al., 2011).

3.2 Anxiety Evaluation

With anxiety being the most prevalent mental health disorder, having a way to effectively recognize and treat anxiety disorders has been crucial (National Alliance on Mental Illness, 2017). Like depression evaluation, various scales and methods have been developed for assessing anxiety, all with unique structures, reliability, and validity. Some of the most common scales include the Generalized Anxiety Disorder 7-item scale (GAD-7), the State-Trait Anxiety Inventory (STAI), the Beck Anxiety Inventory (BAI), and the Hospital Anxiety and Depression Scale – Anxiety (HADS-A) (Julian, 2011).

The GAD-7 is a 7-item self-rated scale used to assess generalized anxiety disorder symptoms. Due to its brevity, only taking one to two minutes to complete, and ease of scoring, the scale gained traction in primary care settings, helping to increase both awareness and recognition of generalized anxiety (Anna Freud National Centre, n.d.). Also, like the PHQ-9, the GAD-7 provides scoring on a “0” to “3” scale, with a score of three on any respective question as being the most severe. In a study regarding the psychometric properties of the GAD-7 using a primary care sample, it was noted that a cutoff score of 10 resulted in an optimal sensitivity and specificity, being 89% and 82%, respectively (Spitzer et al., 2006).

Due to various reasons, other anxiety assessment scales provide potential downside when evaluating an 18-24 year old population found at colleges and universities. According to a study by Julian regarding common measures of anxiety, the STAI and BAI are seen to be much longer in length and duration compared to the GAD-7, consisting of 40 questions taking about 10 minutes on average and 21 questions taking five to 10 minutes on average, respectively (Julian, 2011). Additionally, unlike the GAD-7, the BAI and HADS-A report a total anxiety score rather than a more granular severity rating.

3.3 Currently Understood Relationships

The relationship between smartphone usage, mental health, and sleep have gained clarity in recent years. A 2021 study in the Journal of Affective Disorders found that all three had significant positive correlations at the 0.01 level (two tailed) in Chinese Medical students, with sleep disturbance and anxiety having the strongest Spearman correlation of 0.579 (Song et al., 2022). To further understand the relationship amongst the three, a hierarchical linear regression was also performed, revealing that "sleep disturbance might partially mediate the effect of problematic smartphone use on anxiety" (Song et al., 2022). Furthermore, in order determine the statistical significance of this mediation, structural equation modeling was employed, proving that in addition to having a direct influence on anxiety, problematic smartphone usage patterns also significantly indirectly impacted anxiety through sleep disturbance in its sample population (Song et al., 2022). The article even cites evidence that a potential contributing factor impacting this indirect effect is the use of smartphones prior to sleep, altering the body's natural circadian clock and thus amplifying such sleep disturbance (Song et al., 2022). This study is an important milestone as for the first time it shed light on both the direct and indirect impacts smartphone usage has on anxiety.

Another study titled, "Sleep Disturbance and Psychiatric Disorders" took a deeper look into diagnosis, relationships, and potential causality between sleep patterns and various mental health disorders. It looks at the consequential effects of the often-overlooked occurrence of good sleep. The study argues that conditions affecting sleep quality such as insomnia share a bidirectional relationship with a plethora of mental health conditions (Freeman et al., 2020). Furthermore, it asserts that sleep disturbance remains the most influential causal factor in these conditions. Thus, it argues that these residual mental health disorders can be treated, in part, by treating sleep-affecting disorders such as insomnia first (Freeman et al., 2020). By stating, “intervening on sleep at an early stage might be a preventive strategy for the onset of clinical disorders”, the study establishes a potential causal relationship between sleep disturbance and various mental health conditions (Freeman et al., 2020).

Chapter 4

Hypothesis & Methods

4.1 Hypothesis

The literature discussed in Chapter 3 provides a sound basis of evidence supporting the connection between smartphone usage, sleep disturbance, and various mental health disorders. While widely accepted scales such as the Smartphone Addiction Scale, and its corresponding short version, have been implemented in order to assess smartphone usage and addiction, this area of research has yet to study in-depth these correlations backed by the collection of raw smartphone usage. Furthermore, even though statistical analysis in this space, including the cited literature, has begun to mathematically correlate such variables, classification and predictive models are still in their infancy.

This study hypothesizes that (1) sleep disturbance, smartphone usage time, perceived smartphone usage, and anxiety are positivity associated with depressive symptoms in college students and (2) student depression can be accurately classified and predicted by weighting the relative impacts of demographic information, anxiety, sleep patterns, and smartphone usage behavior in a logistic regression.

4.2 Study Design and Sample

This cross-sectional study is based on survey distributed by a student and various faculty at Penn State University from January to March of 2022, the first half of the spring semester. To ensure fairness and participant safety, ethical guidelines were adhered to in accordance with the

Penn State University and its residing Institutional Review Board (IRB), after being deemed as exempt research. The self-administrated survey was distributed via REDCap, a secure web-based interface for validated data entry hosted by Penn State. The only identifier collected via the survey was an email, optimally provided, at the end of the survey. This was provided by participants if they wanted to be entered in a randomized gift card drawing with 10 gift cards, worth $30 each, being distributed in total to incentivize participation. The survey took users approximately 10-15 minutes to complete, being disseminated across various department listservs and the principal investigator's LinkedIn as a link to the web-based questionnaire. Participants were first required to complete a downselection page on the survey, ensuring that they satisfied the three participant criteria: they are between the ages of 18-24, they are a current student at a college or university, and that they use an iPhone on a regular basis.

4.3 Data Validity Analysis

Shortly after the distribution of the survey solely through the principal investigator's LinkedIn, the database received an influx of various rounds of suspicious data. The first red flag was the influx of four rounds of dozens of surveys all submitted within the spacing of a minute successively. Additionally, within these groupings, each survey contained the exact same, illogical, reported information for weekly phone usage, amongst other data points, being highly unlikely. Finally, after investigating the performance of the LinkedIn post, being the only avenue of distribution at that time, it was found that the number of surveys submitted was multiple times higher than the amount of clicks the survey had received. Thus, after investigating the correlated content and submission timings, validated by the survey traffic, it was proposed that automated 'bot' software had recognized and exploited the survey. In order to stop the submission of this false data, Google's reCAPTCHA feature was promptly turned on in REDCap, appending an "I'm not a Robot" page to the start of the survey. This immediately stopped the entry of additional automated data, further supporting the theory that the previous 60 suspicious survey entries were in fact generated by 'bot' software. All 60 survey responses were then removed.

In addition, a logical examination of the data revealed remaining entries with illogical daily average screen time. While up to 24 hours of smartphone use per day is theoretically possible, a threshold of a daily average of 12 hours of screen time per day was set to ensure only logistical responses were tracked and so outliers were removed. The 12-hour threshold was obtained by factoring in other primary functions into a 24-hour day such as sleeping and eating which were found to occupy more than seven hours (Kamenetz, 2016) and one hour (Hamrick, 2021) respectively for the average student. Then, an additional four hours for all other common primary functions was estimated, ranging from activities such as showering, using the restroom, attending class, completing schoolwork, walking, and socializing. This resulted in a 12-hour maximum of reasonable smartphone use per day and the elimination of 37 entries in total.

4.4 Participant Demographics

In addition to data pertaining to the mental health, sleep, and smartphone usage of the participants, demographic data was also collected. The general demographic parameters collected included academic standing (1st year, 2nd year, 3rd year, 4th year, graduate student, or other), academic institution (Penn State or other), and area of study. The remaining five demographic datapoints were collected due to their identification in related literate as having a correlation to depression or anxiety. These included gender, impacts of financial stressors over the past two weeks (not at all, several days, more than half the days, or nearly every day), and the binary yes or no presence of family depression, anxiety, and suffering from chronic physical conditions.

4.5 Mental Health Evaluation

The mental health state of participants was evaluated by assessing both depression and anxiety. The depression of students was assessed using the Patient Health Questionnaire 8-item scale (PHQ-8). This eight-item version of the PHQ was used as it avoided the risk of complications associated with positive responses to item nine, with recommended reporting for further suicide risk assessment by an expert. The anxiety of students was assessed using the Generalized Anxiety Disorder 7-item scale (GAD-7). Both were selected based on the benefits described in Chapter 2, mainly being the brevity and reliability associated with each. Additionally, both consist of Likert-type questions with “Not at all” scoring 0, “Several days” scoring 1, “More than half the days” scoring 2, and “Nearly every day” scoring a 3. This provided additional consistency and ease for participants.

4.6 Sleep Disturbance Evaluation

Sleep disturbance was evaluated via a modified version of the PROMIS Sleep Disturbance scale (Short Form), presenting participants with eight questions. Unlike the PHQ-8 and GAD-7 which target symptoms over the past two weeks, this scale simply evaluated sleep disturbance over the past week. While the questions presented were exact to the original

PROMIS Sleep Disturbance scale (Short Form), the response choices were limited to the same four options presented in the PHQ-8 and GAD-7, scoring from 0 to 3 rather than 1 to 5. This was done to increase survey usability and consistency. To ensure consistency with the scale's cutoff points for assessing sleep disturbance, the 4-point modified scale was then converted into a compatible 5 points scale when scoring, ensuring a uniform distribution while maintaining the same minimum potential score of 1 and maximum potential score of 5. As a result, a 0 mapped to a 1, 1 to 2.333, 2 to 3.667, and 3 to 5. Then, per the original scale, a standardized T-score was found using the summed score of all eight questions.

4.7 Smartphone Usage Evaluation

Smartphone use was evaluated through both self-reported raw phone usage data as well as through perceived phone usage (PPU) via select questions adapted from the Smartphone Addiction Scale (SAS). In order to standardize the raw usage data collected, students were only able to participate if they regularly use an iPhone. By implementing such criteria, the study survey was able to tap into the tracking automatically done via the iPhone's iOS platform in the form of its "Screen Time" feature. By digging into the settings of each participants iPhone, per a set of written and visual instructions, users where then prompted to report various elements of usage, ranging from areas such as usage content, physical phone interaction, and raw usage time. Specifically, participants were requested to input their daily average screen time, most used application category, second most used application category, third most used application category, daily average number of iPhone pickups (or the number of times a user picked up their phone), and finally daily average number of notifications. These datapoints were reported for two consecutive weeks, all tracked and aggregated by iPhones for easy access and reporting.

In addition to this raw smartphone usage data, PPU was measured via eight Likert-type questions, with six taken from the Smartphone Addiction Scale (SAS). The specific six questions used from the SAS were selected based on their high content validity index, ranging from 0.714 to 1 (Kwan et al., 2013), and relevance to the study at hand. The additional two questions assessed perceived usage relative to peers, asking participants if they believe they use their smartphone and receive more notifications than their average peer. All eight questions, with five answers choice in total, were scored from 1 to 5 and then summed, providing a raw smartphone disturbance sentiment score.

4.8 Data Cleaning

Excel was used primarily to perform preliminary data cleaning, such as finding any observable patterns and inconsistencies. This step allowed for the identification of automated data as well as illogical values, as discussed earlier in this chapter. Additionally, Excel was used to standardize all variables that used Likert-based scales to mitigate potential effects due to differences in each respective scale. The data after this stage was used to generate the summary statistic of the participants.

R Studio software was used to further refine the data. All missing numeric datapoints were imputing using respective variable means while entries containing missing categorical data were removed. This provided a dataset with no missing entries used in the logistic regression as well as to generate numeric correlations amongst certain variables.

4.9 Statistical Analysis

The data analysis for this study was performed in R Studio. Preliminary data exploration allowed for the generation of descriptive statistics, used to visualize distributions across the various datapoints collected. Spearman correlations were used to evaluate the connection between depression, anxiety, sleep disturbance, PPU, and smartphone usage time. Next, after a binary logistic regression with depression as the dependent variable was run on all variables after the initial removal and aggregation of certain variables, a stepwise regression was then conducted to downselect variables of non-significance. Finally, to mitigate any bias when evaluating model performance, testing and training sets were derived from an 80/20 split ratio from the cleaned dataset. The respective accuracy, sensitivity, and specificity of the reduced model was then calculated after running 20 replications derived from different randomly generated splits.

Chapter 5

Dataset

This chapter provides a high-level overview of the volume of data obtained from the survey in addition to the various parameters collected. The categorical variables are described and further defined by the levels, or categories, that each contains. The numeric variables are described as well for consistency in variable definition throughout the remainder of the thesis.

5.1 Dataset Overview

In total, 467 responses were collected from the survey distributed. Of those, 85 did not pass the downselection criteria, 60 were identified as being automated by 'bot' software, and 37 reported daily average screen times over the 12-hour threshold. This left 285 usable datapoints, with 81% of the data observed and 19% missing. In total, 24 variables were tracked. Table 1 outlines the 16 categorical variables tracked.

Table 1. Categorical Variables Collected

Variables	Description	Levels Count	Levels
Grade	Academic Standing at the time of survey completion	6	1^{st} year, 2^{nd} year, 3^{rd} year, 4^{th} year, Graduate Student, Other
Gender	Participant's gender	3	Male, Female, Other
School	Current attending college or university	2	Penn State, Other
Major	Area of study	18	Art, Business, Communication, Engineering…

Family. Depression	Does anyone in the participants immediate family suffer from a depression disorder	2	Yes, No
Family.Anxiety	Does anyone in the participants immediate family suffer from an anxiety disorder	2	Yes, No
Chronic.Pain	Does the participants suffer from a physical condition	2	Yes, No
Depression	PHQ-8 depression evaluation	5	No-minimal depression, Mild depression, Moderate depression, Moderately Severe depression, Severe depression
Anxiety	GAD-7 anxiety evaluation	4	No-minimal anxiety, Mild anxiety, Moderate anxiety, Severe anxiety
Sleep	PROMIS Sleep Disturbance (Short Form) sleep evaluation	4	No-slight sleep disturbance, Mild sleep disturbance, Moderate sleep disturbance, Severe sleep disturbance
W1.Category.1	Most used application category in participant’s current week	12	Creativity, Education, Games, Entertainment, Social …
W1.Category.2	Second most used application category in participant’s current week	12	Creativity, Education, Games, Entertainment, Social …
W1.Category.3	Third most used application category in participant’s current week	12	Creativity, Education, Games, Entertainment, Social …
W2.Category.1	Most used application category in participant’s previous week	12	Creativity, Education, Games, Entertainment, Social …
W2.Category.2	Second most used application category in participant’s previous week	12	Creativity, Education, Games, Entertainment, Social …
W2.Category.3	Third most used application category in participant’s previous week	12	Creativity, Education, Games, Entertainment, Social …

Of the 24 variables collected, eight were defined as numeric as outlined below in Table 2.

Table 2. Numeric Variables Collected

Variables	Description
Financial.Stressors	The standardized score of the severity of financial stressors facing the participant
Perceived.Phone.Usage	Referenced as PPU above, the standardized raw score of the participant's perceived smartphone usage. Larger PPU indicated perception of "worse" smartphone usage behavior and increased addition
W1.ScreenTime	The participant's daily average raw screen time, in hours, in the current week
W1.Pickups	The daily number of times the participant picked up their smartphone in the current week
W1.Notifications	The daily number of notifications the participant received on their smartphone in the current week
W2.ScreenTime	The participant's daily average raw screen time, in hours, in the previous week
W2.Pickups	The daily number of times the participant picked up their smartphone in the previous week
W2.Notifications	The daily number of notifications the participant received on their smartphone in the previous week

Chapter 6

Analysis

In order to get a holistic understanding of the variables at hand and the interactions between them, a 3-part analysis was conducted. This included:

1. Generating summary statistics of participant demographics
2. Correlating the variables of focus being sleep disturbance (sleep), smartphone usage (AveScreenTime), perceived smartphone usage (Perceived.Phone.Usage), anxiety (anxiety), and depression (depression)
3. Developing a binary logistic regression with depression as the response variable (outcome)

To determine correlation, a Spearman correlation analysis was conducted. It is important to note that in this analysis, sleep disturbance, anxiety, and depression were all used in their continuous numeric states, prior to their conversion into severity categories based on the raw score thresholds outlined in each respective assessment scale. Through this analysis, both the strength and direction of association between each variable was determined through the assessment of their monotonic relationships.

6.1 Logistic Regression Process

As a means of using the collected data to create a model capable of predicting if a participant displays depressive symptoms, a binary logistic regression was employed. This classification methodology, also known as a logit model, allows for the prediction of a dichotomous outcome variable, in this case being depressive symptoms are present (1) in a participant, or they are not (0). Prior to performing a usable regression, additional data preparation was required, as discussed below.

6.1.1 Depression Re-Classification

The five depression severity categories identified in the PHQ-8, outlined in Table 1, were first converted into a binary classification of either displaying depressive symptoms or not. To do this, a cutoff score of 10 was identified, with all raw scores below being classified as not displaying depression and raw scores above as being classified as displaying depressive symptoms.

6.1.2 Variable Reduction

Due to the high degree of both variables and respective levels in comparison to the volume of observed data entries, both variable and factor-level reduction was necessary. As a means of variable reduction, natural groupings were identified. Due to the cross-sectional nature of the study, screen time (W1.ScreenTime & W2.ScreenTime), pickups (W1.Pickups & W2.Pickups), and notifications (W1.Notifications & W2.Notifications) were averaged over the two tracked for each participants. Additionally, the variables corresponding to the second (W1.Category.2 & W2.Category.2) and third (W1.Category.3 & W2.Category.3) most used application categories for both weeks were removed due to their over granularity for the scope of the study. This resulted in an overall loss of 7 variables, bringing the initial number of predictors down to 17.

6.1.3 Level Reduction

Natural cutoff points in addition to grouping were identified in order further reduce the complexity of predictors, given the small dataset. In this study, a "level" is defined as the number of categories, or states, for each factor variable. Gender was dichotomized into "male" and "female" after only one observation of "other" was deleted. Grade was also split into either "undergraduate" and "graduate" after deleting the two entries indicating "other", reducing the variable from six to two levels. Next, with application categories "social", "entertainment", and "games" making up 87% and 86% of the most used application categories for weeks one and two respectively, the remaining levels and entries associated with them were deleted, reducing W1.Category.1 and W2.Category.1 to three levels each. Finally, with the relatively limited dataset, level reduction was necessary for major, initially containing 18 levels and eventually consolidated into four. "Engineering", "Earth and Mineral Sciences", "Information Sciences and Technology", and "Sciences" were grouped into a new "Science and Engineering" level. "Business" remained pure in comprising the "Business" level. "Medicine", "Nursing", and "Health and Human Development" were aggregated into a "Health" level. The remaining 10 initial levels, comprising 19% of observed datapoints, were aggregated into an "Other" level. In the end, this aggregation and pointed variable filtering allowed for a more viable model to be created.

6.1.4 Baseline Case Selection

The last step before running a logistic regression was choosing a baseline case, or referent, for the outcome variable, in this case being "depression". With all output coefficients, or log-odds, of the regression representing a linear combination of the predictors with respect to the baseline, setting a reference point was necessary. For this study, a baseline of displaying no depressive symptoms (PHQ-8 score <10) was chosen as it not only represented the majority of the participants, but also corresponded to the "negative" outcome for depression classification. For additional consistency, the baseline for all other categorical variables was set as the most frequent level for each.

6.2 Logistic Regression Equation

A logistic regression works by predicting the likelihood of a class with respect to its default case, in this thesis being the lack of depressive symptoms (0) in a participant. In order to obtain the classification qualities found in logistic regression modeling, a logistic function is used. Thus, while the outcome variable, depression, is no longer a linear combination of its predictors, the log-odds of depression is, as seen in the logit form. Through some manipulation, this logit form can also be displayed in probability form, both of which are shown in Figure 1.

Logit Form

Probability Form

$$\ln\left(\frac{P(Patient = 1)}{P(Patient = 0)}\right) = \beta_0 + \beta_1 x \quad \Longleftrightarrow \quad P(Patient = 1) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}$$

Figure 1. Logistic Regression Forms

Chapter 7

Results

The data obtained in the survey was used to explore an overall breakdown of participant demographics, understand the correlation of certain variables, and construct logistic regression models whose details are discussed in this chapter. Summary statistics are presented first broken down by variable type, being categorical and numeric. Next, the correlations between depression, anxiety, sleep disturbance, perceived phone usage, and actual phone usage is discussed. Finally, the output and performance of the logistic regression modeling is presented.

7.1 Summary Statistics

The overall breakdown of participants by categorical variables is found in Table 3. For viewing and consolidation purposes, "Majors" were grouped into four levels and the second and third most used categories for weeks one and two were dropped, as discussed in Chapter 6. Of the observed data, the majority of participants were male 149 (55%) while 121 (44.6%) were female. The academic standing of participants was heavily skewed towards undergraduates 244 (90%) and academic focus towards science and engineering fields 162 (61.1%). The majority of participants for both week one 118 (57.3%) and week two 106 (53.5%) reported that "social" applications were most frequently used when measured by raw screen time. Finally, severity for depression, anxiety, and sleep disturbance symptoms were all right tailed, with lower-level severity experienced by the highest number of participants and highest severity experienced by the fewest. For each variable, the percent of missing values from the 285 observed and validated entries is tracked.

Table 3. Summary Statistics of Categorical Variables (N=285)

Variables	N (%)	Percent Missing (%)
Grade		4.91
Undergraduate	244 (90.0)	
Graduate	25 (9.2)	
Other	2 (0.7)	
Gender		4.91
Male	149 (55.0)	
Female	121 (44.6)	
Other	1 (0.4)	
School		4.56
Penn State	254 (93.4)	
Other	18 (6.6)	
Major		7.02
Business	19 (7.2)	
Health	33 (12.5)	
Science & Engineering	162 (61.1)	
Other	51 (19.2)	
Family. Depression		5.26
Yes	128 (47.4)	
No	142 (52.6)	
Family.Anxiety		5.96
Yes	146 (54.5)	
No	122 (45.5)	
Chronic.Pain		5.61
Yes	59 (21.9)	
No	210 (78.1)	
Depression		10.53
No-minimal	102 (40.0)	
Mild	78 (30.6)	
Moderate	42 (16.5)	
Moderately Severe	23 (9.0)	
Severe	10 (3.9)	
Anxiety		13.68
No-minimal	109 (44.3)	
Mild	64 (26.0)	
Moderate	43 (17.5)	
Severe	30 (12.2)	
Sleep		14.04
No-slight disturbance	180 (73.5)	
Mild disturbance	44 (18.0)	

Moderate disturbance	16 (6.5)	
Severe disturbance	5 (2.0)	
W1.Category.1		27.72
Entertainment	30 (14.6)	
Games	32 (15.5)	
Social	118 (57.3)	
Other	26 (12.6)	
W2.Category.1		30.53
Entertainment	30 (15.2)	
Games	35 (17.7)	
Social	106 (53.5)	
Other	27 (13.6)	

The overall breakdown of participants by numeric variables is found in Table 4. Per discussion in Chapter 6, screen time, pickups, and notifications were averaged over the two weeks tracked for each participant, denoted below as "AvgScreenTime", "AvgPickups", and "AvgNotifications", respectively. Of the observed data, the average participant used their smartphone 5.66 hours per day, on average, with a standard deviation of 2.07 hours. Furthermore, the average Pickups to Notifications ratio for participants over the two-week span was 1.08 pickups/notification.

Table 4. Summary Statistics of Numeric Variables

Variables	**Units**	**Mean**	**SE**	**Median**	**Min**	**Max**	**Missing (%)**
Financial.Stressors	0-1 Scale	0.23	0.016	0.33	0.00	1.00	5.61
Perceived.Phone.Usage	0-1 Scale	0.44	0.012	0.44	0.00	0.97	16.49
AvgScreenTime	Hours/Day	5.66	0.152	5.31	0.01	10.61	35.09
AvgPickups	Pickups/Day	130.35	4.429	135.75	2.00	332.50	33.33
AvgNotifications	Notifications/Day	151.81	9.964	127.00	2.50	1478.50	32.98

7.2 Correlations

The result of a Spearman correlation analyses is displayed in Figure 2, with the correlation coefficients displayed in text and relative statistical significance indicated by circle size and color intensity. As seen, anxiety, sleep disturbance, and perceived phone usage were all significantly and positivity correlated with depression (P<0.001). Additionally, sleep disturbance and perceived phone usage were significantly and positivity correlated with anxiety (P<0.001) while screen time was to lesser significance (P<0.01). Perceived phone usage and daily average screen time were both significantly and positivity correlated (P<0.001). Lastly, while daily average screen time was significantly and positivity correlated anxiety, no significance in correlation was detected with either depression or sleep disturbance.

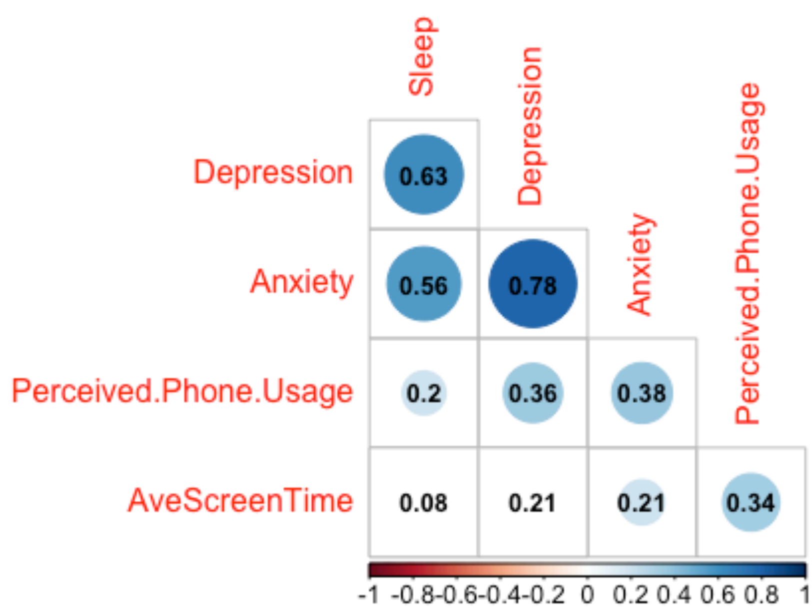

Figure 2. Correlation of Focus Variables

7.3 Logistic Regression Model

Two logistic regression models were run on the 155 usable observations remaining after data preparation discussed in Chapter 6:

1. Model 1: The initial regression model run with all 16 potential variables as predictors and depression as the response. This model displays a high level of complexity which can lead to overfitting.
2. Model 2: The modified logistic regression model after a bi-directional stepwise regression was performed on Model 1. This contains fewer predictors and is less susceptible to overfitting.

Table 5 provides a summary of all variables used in Model 1 which were manipulated from the initial dataset collected, per discussion in Chapter 6.

Table 5. Modified Variables

Original Variable	New State	Manipulation
W1.ScreenTime & W2.ScreenTime	AvgScreenTime	(W1.ScreenTime +W2.ScreenTime)/2
W1.Pickups & W2.Pickups	AvgPickups	(W1.Pickups+W2.Pickups)/2
W1.Notifications &W2.Notifications	AvgNotifications	(W1.Notifications+W2.Notifications)/2
W1.Category.2 & W2.Category.2	N/A	Dropped from dataset
W1.Category.3 & W2.Category.3	N/A	Dropped from dataset

Table 6 displays the variable coefficients of the two binary logistic regression models run with depression as the response. Model 1 permed with an Akaike Information Criterion (AIC) score of 120.89 while Model 2 with an improved score of 105.54. Additionally, all severities of both anxiety and sleep disturbance were statistically significant in both models when predicting depression. Lastly, smartphone usage time also showed statistical significance in predicting depression in both models. Note that "N/A" entries in Model 2 correspond to variables that were downselected and not used when classifying depression.

Table 6. The Binary Logistic Regression of Depression (N=155)

Variables	Model 1	Model 2
AIC	120.89	105.54
Intercept	-5.73**	-5.69**
Grade		
Graduate	-1.23	N/A
Gender		
Female	0.07	N/A
School		
Other	0.59	N/A
Major		
Business	0.46	0.50
Health	2.74**	2.77**
Other	3.51**	3.29**
Financial.Stressors	3.34**	3.11**
Family. Depression		
No	-1.70*	-1.74*
Family.Anxiety		
No	2.37**	2.27**
Chronic.Pain		
Yes	0.114	N/A
Anxiety		
Mild	2.20**	2.12**
Moderate	4.67**	4.66**
Severe	5.87**	6.01**
Sleep		
Mild disturbance	2.24**	2.06**
Moderate disturbance	2.724**	2.54**
Severe disturbance	5.70**	5.77**

Perceived.Phone.Usage	2.71	2.79
W1.Category.1		
Entertainment	-0.79	N/A
Games	-1.35	N/A
W2.Category.1		
Entertainment	0.76	N/A
Games	1.23	N/A
AveNotifications	0.001	N/A
AvePickups	0.01	0.01
AveScreenTime	-0.52**	-0.52**

Significant at the 0.01 level '**' and 0.05 level '*'

Based on Model 2, a final equation was derived, using the variables of significance, for the log-odds of displaying depressive symptoms (1) vs. not displaying depressive symptoms (0).

$$\ln\left(\frac{P(Patient = 1)}{P(Patient = 0)}\right) =$$

$$\begin{aligned} &-5.69 + 2.77\,(major = health) + 3.29\,(major = other) \\ &+ 3.11(financial.stressors) - 1.74\,(family.depression = no) \\ &+ 2.27(family.anxiety = no) + 2.12(anxiety = mild) \\ &+ 4.66(anxiety = moderdate) + 6.01(anxiety = severe) + 2.06(sleep = mild) \\ &+ 2.54(sleep = moderate) + 5.77(sleep = severe) - 0.52(AveScreenTime) \end{aligned}$$

Using the above equation, fitted outcome values for each of the 155 observations were calculated by entering the factor level or value for each variable of significance. Figure 3 visualizes the distribution and frequencies of these predicted probabilities. The dichotomous nature of the model can be seen as predictions heavily cluster around the "0" and "1" probabilities of displaying depressive symptoms.

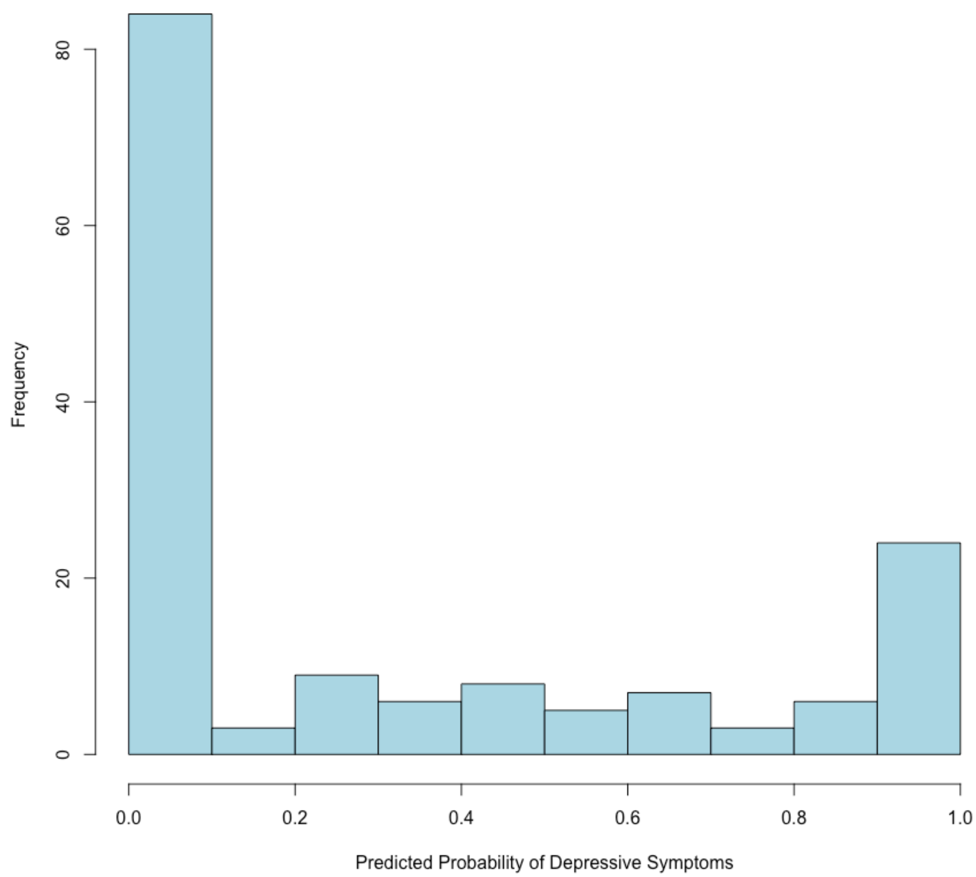

Figure 3. Histogram of Fitted Response Values

The performance of the model was then evaluated by predicting depression outcomes in a test set comprised of 20% of the usable data. The model was thus trained on the other 80% of the data to reduce bias. Note that in order to create truly dichotomous predictions, predicted probabilities of greater than 0.5 were rounded to one while probabilities below 0.5 to zero. The accuracy, sensitivity, and specificity of the model was then calculated, as seen in Table 7, after running the model 20 times using different seed values when randomizing the 80/20 data split.

Table 7. The Performance Evaluation of Model 2

Performance Measure	Mean (95 % Confidence Interval)
Accuracy	0.781 (0.752, 0.811)
Sensitivity	0.638 (0.578, 0.698)
Specificity	0.861 (0.829, 0.893)

To 95% confidence, the accuracy of the model falls between 75.2% and 81.1%, sensitivity between 57.8% and 69.8%, and specificity between 82.9% and 89.3%. The relatively high specificity reveals that the model performs well in predicting when a student doesn't display depressive symptoms while the relativity low sensitivity shows that the model performs worse when predicting if a student truly does display depressive symptoms.

Chapter 8

Discussion

This study set out to investigate the association between depression, anxiety, sleep disturbance, and smartphone usage in college and university students and to explore the use of logistic regression to classify depressive symptom vulnerabilities. As such, this study fills a void in existing research due to the incorporation of weighting various raw phone usage characteristics, such as physical interactions in the form of pickups, notifications, content, and screen time.

8.1 Interpretation and Significance

The summary statistics regarding the participant sample reveals a lot about the smartphone usage patterns of college students. The overwhelming majority of students spend most of their time using applications focused on social media, gaming, and entertainment, in descending order of use. Additionally, the pickup to notification ratio for participants averaged 1.08, meaning that for every notification, the average student picks up their smartphone about once. When combined with the statistically significant correlations of 0.21 and 0.78 between average screen time and anxiety, and depression and anxiety, respectively, a pattern begins to unfold. While causation cannot be linked to correlation, a vicious relationship is present. It poses questions such as:

1. Does increased anxiety result in increased screen time, or vice-versa?
2. Does increased screen time result in increased depression with anxiety as an intermediary?

3. Is most used application category, representing consumed content-type, statistically correlated to notifications, pickups, and screen time?

When looking at the prevalence of those with depression and anxiety symptoms, discrepancies were observed with prior research. While the Spring 2020 Health Assessment at Penn State identified 19% of the campus population as being affected by a depressive disorder, this study found that number to be as high as 60%, comprised of anyone with mild severity and above as classified by the PHQ-8. Based on the same severity threshold, this study found 55.7% of students to be affected by anxiety while the Spring 2020 Health Assessment only identified that number to be 24%. Such discrepancies likely can be attributed to a variety of factors. First, Penn State collected participant data two years prior to the collection of data in this study, with issues such as the COVID-19 pandemic and increased inflation having had time to set in. Secondly, while the cited research didn't provide a demographic breakdown of academic focus or major, this study was heavily skewed by students focused in science and engineering, making up over 60% of participants. Also, females comprised 17.4% less of the participant pool in this study. Finally, more depressed and anxious students could have been more likely to participate in this study than that performed by Penn state. The combination of these timing and demographic differences in addition to the skewed sample set of this study likely account for the variation found in the mental health of students at Penn State.

Next, when looking at the correlations investigated in Figure 1, statistical significance brought to like novel observations. Even though depression, anxiety, perceived phone usage, and screen time were all positivity correlated with one another, screen time only maintained significance in its correlation with anxiety and perceived phone usage. Yet perceived phone usage itself maintained significance with all four other metrics tracked. This reveals the important role a student's perceived phone usage has. Does increased depression or anxiety in an individual create a more negative sense of smartphone usage, or does one's perceived usage and attachment result in diminished mental health? Such questions come to light from these observations.

Finally, logistic regression was successfully employed in order to classify and predict depressive symptoms in students. It is seen that while outside literature, such as that put out by Mayo Clinic, suggests that females are twice as likely to suffer from depression than men, this study suggests otherwise (Mayo Clinic, 2019). The output of both the full and reduced logistic regression found that gender played little to no role in increasing the likelihood of displaying depressive symptoms. In addition to the demographically skewed sample in this study, the statistic cited observed depressive likelihoods between males and females in all stages of life rather than just young adulthood. This provides further explanation for variation as it noted that many causes of the increased depression seen in women appear later in life with conditions such as postpartum depression and menopause (Mayo Clinic, 2019). In the end, a model which can predict the presence of depressive symptoms in new samples was developed, with an accuracy of 78.1%. Given the small sample size, such accuracy is a success. Notably, a specificity of 86.1% was achieved. According to one study on the accuracy of the PHQ-9 using the same cutoff score of 10, the PHQ-9 only obtained specificity of 85% (0.82, 0.88) (Levis et al., 2019).

8.2 Limitations

This study's main limitation was the sample size obtained and its cross-sectional nature. Due to only having participant data from a single two-week snapshot, failing to see changes over time prevented any understanding of causality between variables. Additionally, with other studies in this area providing research built on many hundreds or even thousands of observations, this work's findings is built on 285 valid entries, with only of these 155 observations used in logistic regression after data cleaning and preparation. This limited and skewed sample size also impacts the study's generalizability, preventing the assumption that the model and its associated accuracy to holds true for Penn State students, and more generally college students, as a whole.

The limited sample size can largely be attributed to various elements in the planning and survey design of this study. The survey administered failed to limit both quantity and quality of data input by participants, requiring nearly 67% of the data to be purged before performing the regression analysis. In addition to proactivity setting the limitations discussed, increased time for data collection across increased recruitment methods likely would have also yielded an improved response rate. Finally, such tactics paired with increased incentives for participation would have had a similar effect in increasing the sample size.

8.3 Future Work

Beyond the immediate benefits presented in this work, including an understanding of the relationship between smartphone use, sleep disturbance, anxiety, and depression as well as a relatively accurate model for detecting depression in college students, this research creates the opportunity for future work and expansion. By creating a more robust dataset, various additional possibilities are presented which are discussed below.

8.3.1 Multinominal Logistic Regression

A multinomial logistic regression is a variation of binary logistic regression that allows for multi-class classification. With the outcome variable now having more than two possibilities, more observations are needed to understand the patterns associated with the increased granularity of prediction. Applied to this study, multinominal logistic regression would allow for the prediction of all five depression severities identified in the PHQ-8, rather than using a cutoff point to dichotomize depression as was done in this study. Such a model would be able go beyond predicting the existence of depression by predicting the vulnerability of worsening depressive symptoms.

8.3.2 Machine Learning

Machine learning is the process of using data to generate algorithms with increasing accuracy, similar to how a human brain works. Having more datapoints would allow for more successful machine learning to be applied to the problem at hand as such complexity requires ample observations for the “learning” process. Additionally, doing such would allow for a variety of usable applications of the topics discussed in the paper. For example, if a given participant were to automatically or manually input data corresponding to the parameters in this study on a weekly basis, transforming the dataset from cross-sectional to longitudinal, a machine learning algorithm could begin to pick up on specific individual patterns and trends. Such a model would then be able to understand causality and possess the ability warn participants of their depression vulnerability. This logic can be applied to software and technology-based initiatives to mitigate the potential negative effects smartphones have on users.

Chapter 9

Conclusions

This study displays the positive associations between depression and anxiety, sleep disturbance, smartphone usage time, and perceived smartphone usage in college students. It also demonstrates that the existence of depressive symptoms in college students can be classified and predicted by looking at the relative impact the above parameters have in addition to demographic information. It is suggested that the associations and causal relationships amongst these factors be further investigated in order to intervene on the increasing prevalence of mental health issues such as depression and anxiety disorders at colleges and universities. Furthermore, college students should be made aware of the problematic behaviors exhibited amongst their peers with regards to sleep and smartphone usage behavior. Though causality isn't presented in this study and remains widely unknown, reducing the overall time spent on smartphones, limiting notifications, and cutting down on the time spent on social media-based applications may have a positive result on observed anxiety and depression in college students. While the majority of participants in this study were undergraduate students at Penn State, the results discovered provide a sound basis for similar investigation by other academic institutions. Continuing to understand these associations will better help universities and communities alike to allocate mental health resources for time to come.

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ACADEMIC VITA

BRADY L. FEUER

EDUCATION

The Pennsylvania State University | Schreyer Honors College — **University Park, PA**
College of Engineering | Bachelor of Science in Industrial Engineering — *Class of 2022*

PROFESSIONAL EXPERIENCE

Lockheed Martin — **Valley Forge, PA**
Product Manager | Senior Intern — *Sep 2021 – Feb 2022*
- Oversaw the development of an internally facing dashboard that aggregates, visualizes, and presents programmatic data to senior vice presidents to assess funding, performance, and contract behavior
- Coordinated weekly communication and engaged with international points-of-contact in England and Australia to expand accessibility of leading AI and emerging technologies across Lockheed Martin
- Worked with Directors and Lockheed Martin Fellows to assess the current and future landscape of IRAD and customer-facing contract funding of $250MM for strategic sustainment and growth planning in 2022

Systems Engineer | Intern — *Jun 2020 – Sep 2021*
- Facilitated discussions with various United States Air Force units to prioritize, outline, and design a new user interface tool needed to ease the onboarding and training of end users
- Led a team of 6 software and test engineers by defining timeline, scope, and acceptance criteria which resulted in a 50% reduction in time for both development and integration efforts
- Helped review a Basis of Estimate to support a new multi-million dollar subcontract acquisition geared towards integrating artificial intelligence into existing software

Study Abroad Design Challenge — **San Sebastian, Spain**
Personal Mobility Vehicle (PMV) Product Design | Model and Design Lead — *May 2019 – Jun 2019*
- Determined a new Product Opportunity Gap pertaining to personal motor vehicles by assessing the social, economic, and technical limitations and observing transportation patterns in San Sebastian
- Communicated in Spanish with locals to determine customer needs for increased PMV storage which resulted in 3 iterations of low fidelity prototypes of an ergonomic beverage holder design
- Modeled in PTC Creo to create a functional high-fidelity beverage holder which was 3D printed over a 24-hour period and displayed at a local surf and bike store

Penn State University Department of Industrial Engineering — **University Park, PA**
Analytics and Modeling in Sharing Economy | Lead Researcher — *Aug 2019 – Dec 2019*
- Studied elements of Uber, Lyft, and Airbnb to determine success markers in modern Sharing Economies by analyzing over 50,000 Airbnb host identifications to draw correlations between various metrics
- Utilized analytical modeling on data such as reviews, locations, and availability associated with the Airbnb platform to predict and optimize supply and demand from a service and operational perspective

LEADERSHIP EXPERIENCE

Via Co. — **State College, PA**
Co-Founder — *Apr 2020 – Sep 2020*
- Head the development of an iOS adventure application by focusing on product/market fit, user retention, and scalability through various regression tests as well as user behavior analysis
- Lead a growing team of developers by providing technical mentorship as well as by setting weekly initiatives to excel the startup through the full project lifecycle of design, development, and testing

University Park Undergraduate Association (UPUA) — **University Park, PA**
Director of Governmental Affair — *May 2019 – Mar 2020*
- Directed initiatives and events relating to governmental affairs for an assembly of more than100 students and constituency of more than 40,000 undergraduate students at University Park
- Programmed PSU Votes Week 2019 centered around civic engagement education while transitioning voter registration to an online format for the first time in the history of PSU Votes Drives by utilizing Vote411

- Organized the partnership and cooperation of 14 other student organizations to delegate various responsibility and outreach events for a 300% increase in student voting since 2017

Schreyer Honors College Student Council **University Park, PA**
Presidential Advisory Board *Jan 2019 – Dec 2019*

- Worked with 9 other selected members in order to advise and oversee the work of the president and general assembly of more than 65 Schreyer Honors College Students

SKILLS, HONORS, & INTERESTS

- **Skills:** Skilled in Timeline Development, Valuation, Data Collection & Visualization, Agile Development, Contract Assessment
- **Honors:** IE Academic Excellence Scholarship, The President's Freshman Award, 1st Place for Design Process in EDSGN Showcase
- **Interests:** FinTech M&A, Skiing, Hiking, French Cuisine, Dale Carnegie, Nutrition, Calisthenics