Behavioral Sensing App Development

Team # **31**

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Behavioral Sensing App Development - Final Report

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Behavioral Sensing App Development - Final Report

Executive Summary

The objective of this project was to explore the detection of daily-life behavioral markers using Global Positioning Systems (GPS) data and phone-usage sensors, and their use in identifying depressive symptom severity.

This is an ongoing research project that Team 31 was on-boarded into at the start of this semester. The team's responsibilities were to help design and develop an Android application that can determine the correlation between GPS data and depressive symptoms in students at Purdue University.

The project life cycle was as follows: The first step was to develop an Android application that can collect and store GPS data. This was implemented by Brian Huang— a Junior in Computer Science who was already a part of the research team when Team 31 was on-boarded. The second step was to conduct research on the current literature on mobile sensing. The third was to incorporate the functionality of collecting and storing GPS data via the application. The next step was to analyze the collected GPS data in R following a methodology outlined in a study from Saeb et al (2015) that will be discussed later in the report. The last step for the design team was to create an interactive User Interface (UI) for the application in Adobe XD and carry out Moderated Usability Testing (MUT) on it.

Team 31 was able to work with Brian to create a functional, stable, and robust android application that can collect GPS data from smartphones and store it in a local directory on the phone. The functioning application is live right now and works seamlessly on stock Android 8, 9, and 10.

Additionally, Team 31 was able to follow the methodology outlined in Saeb et al. (2015) to write an R program that is able to correlate GPS data to depressive symptoms. The specific metrics that the correlation is based on will be discussed in the Results section.

Lastly, Team 31 was able to develop a functional mock UI for the android application using Adobe XD. The UI can be overlayed onto the application to make it easier for the coder to implement it. The team was also able to recruit five participants to carry out Moderated Usability Testing on the UI.

Introduction

The competitiveness and challenges of a college education in the United States is at an all-time high. Evidence suggests that this group has greater levels of stress and psychopathology than at any time in the nation's history. According to mental health research conducted by the National Alliance on Mental Illness (NAMI) [1]: one in four students have a diagnosable illness, 40% do not seek help, 80% feel overwhelmed by their responsibilities, and 50% have become so anxious that they struggled in school. The statistics uploaded by NAMI are enough to reason that today's college students are arriving on campuses without adequate mental health aid resources to assist them, given the increasing prevalence of mental health challenges in this demographic. Purdue University is no exception. The center for Counseling and Psychological Services at Purdue University has been facing bottlenecks while trying to accommodate the students. Purdue Exponent reported that "Students wait weeks for therapy" [2]. Team 31 was tasked with creating an Android mobile application that would allow users to assess their mental state by studying the GPS data, as well as other metrics, collected from their smartphones.

The business need for this project was not concerned with increasing the profit margin or optimizing manpower, it sought to lay the groundwork for a mental health improvement initiative at Purdue University. With the end goal of making students a Purdue University mentally healthier by assisting them in understanding behavioral patterns. The Behavioral Sensing App team proposes an Android application to aid Generation Z students affected by this mental health crisis. However, this will not be a typical application that the user 'actively' uses. As of now, the idea is the develop a dormant application that sits in the user's phone and passively gathers and analyses data from their smartphones. The user data will be the input to a Behavioral Sensing algorithm. For context, the Institute of International Studies at UC Berkeley defines Behavioral Sensing as "Integrating Sensors into Social and Behavioral Research "[3]. The sensor, in this case, is the user's smartphone.

This is an ongoing project that was initiated last semester, Spring 2019, by a team of Multi-disciplinary Engineering (MDE) majors. The application was planned to have a system of intervention that alerts a handful of the user's trusted parties if it deems the user requires attention. These trusted parties will be termed the "Circle of Trust" within the application. This circle is going to be configurable contact details that the user inputs while registering on the application. After gathering enough data and establishing a baseline pattern of use, deviations from this individualized pattern could trigger these alerts, facilitating opportunities for users to interact with human sources of psychological comfort. Due to the complexity of this problem, the design team has identified stakeholders for this project as individuals with mental illnesses themselves, people who are close to individuals with mental illnesses, CAPS; Dr. Susan Prieto-Welch, Dr. Nan Kong, and Dr. Denny Yu.

The proposal for this project was submitted by three parties belonging to Purdue University. The following named individuals are the primary points of contact for the higher-level picture for the project. Namely, Dr. Susan Prieto-Welch, Ph.D., HSPP - Counseling Center

Director of CAPS (The Counseling and Psychological Services at Purdue University) with a clinical orientation in psychodynamic/object-relations, humanistic and cognitive-behavioral. Dr. Nan Kong, Ph.D. in Industrial Engineering - a professor of Biomedical Engineering and an expert on Artificial Intelligence. Last but not least, Dr. Denny Yu, PhD. in Industrial & Operations Engineering - a professor of Industrial Engineering and the subject matter expert on Human Factors Engineering. The motivation for this project stems from the fact that the lines at CAPS are too long along with the fact that Prof. Kong and Prof. Yu want to understand mental health better through this application. The clients' combined vision was to create an ecosystem consisting of users who understand their own mental health better through this application.

Problem Statement

The formal problem statement at this stage of the project is as follows:

At the start of this semester, there was no app that could track smartphone usage data (like GPS data and application usage data) that had been linked to depressive symptoms and was capable of behavioral sensing

The specific design problem the team was concerned with was to help design and develop an application that can gather relevant data from users' smartphones and use that to enable better Behavioral Sensing. This problem was divided into two main parts. The first part was that, as of then, there was no mechanism to identify and gather relevant data from users' smartphones that can be used to study mental health. The latter half of the problem was that even if this data existed, how does one label or categorize it? How does one say that certain data reflects deterioration in mental health while some other data signals mental health improvements? The clients refer to this aspect of the problem as "Anomaly Detection". How does one identify anomalies, aberrations, and changes in mental health through data? What are the criteria for detection? How does one justify these criteria? Questions like these are what the design team inched closer towards answering.

System Model

The current state of the app was almost entirely conceptual. The previous team created a very strong design foundation for the app (called *initi8*), with extensive research to back it up. This includes storyboards, interviews, and detailed descriptions of their final design idea. However, a total of only ~200 lines of code was produced in the end. This code was mostly just setting up the app environment as well as a graphic user interface, with no functionality in terms of collecting user data and applying behavioral sensing. Screenshots of the current app are provided below.

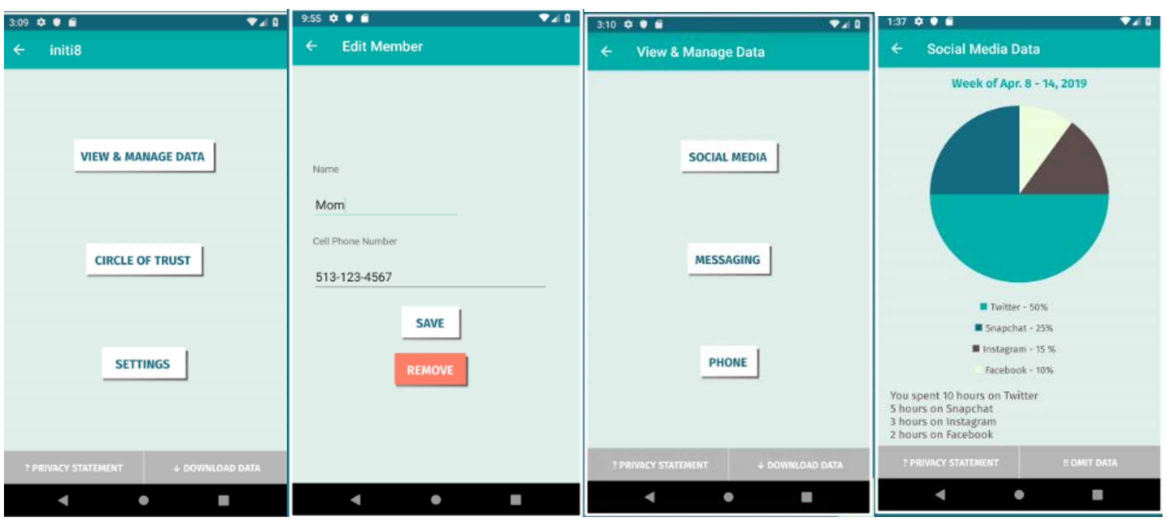


Figure 1 - initi8 User Interface - Preliminary System Model

Figure 1 screenshots showed the layout of the aforementioned “Circle of Trust” as well as a page to monitor social media usage. However, the only functionality was signing up for the app. The lack of preliminary workable data collection and analysis was of utmost concern.

The current system model did not draw from mock drafts of the UI created by the previous team. Team 31 decided to focus most efforts primarily on data collection. In order to build the app, Dr. Nan Kong allowed the team to partner with Brian Huang, an undergraduate computer science student also interested in behavioral sensing research.

Upon further discussion with Brian Huang, Team 31 identified constraints that would affect data collection. The phone operating system and version were discovered to be the most important constraints. The preliminary initi8 UI was designed for Android devices. Brian defined that an android system with an SDK version 21 and above would allow the app to run stably. For the scope of the semester projects, these technical constraints will be set, but later on, the app is planned to run on multiple operating systems as well as older Android versions.

As the usage increases across devices, this app will function within the social system that connects those in need of mental health help to help themselves. A literature review from Guillver et al. (2010) identified the key barriers between those two entities. These include: “stigmatizing attitudes towards mental health consumers and shame, poor mental health literacy, self- dependence, lack of trust in help sources and hopelessness. However, one of the most significant factors in help-seeking was having the capability to understand the symptoms of a mental health difficulty and communicate it with others” [4]. Tackling any of these key barriers would be helpful in improving access to mental health help. However, one of the highest interests is the last: the difficulty in understanding mental health and sharing it with others. This is the factor that the Circle of Trust would be ameliorating, by fostering conversations about the sensitive subject with a trusted friend.

A 2016 study from Chandrasekara categorized these factors into three dimensions following the popular behavioral framework known as the Theory of Planned Behavior (TPB). These three dimensions are Attitudes, Subjective Norms, and Behavioral Control and are visualized below [5].

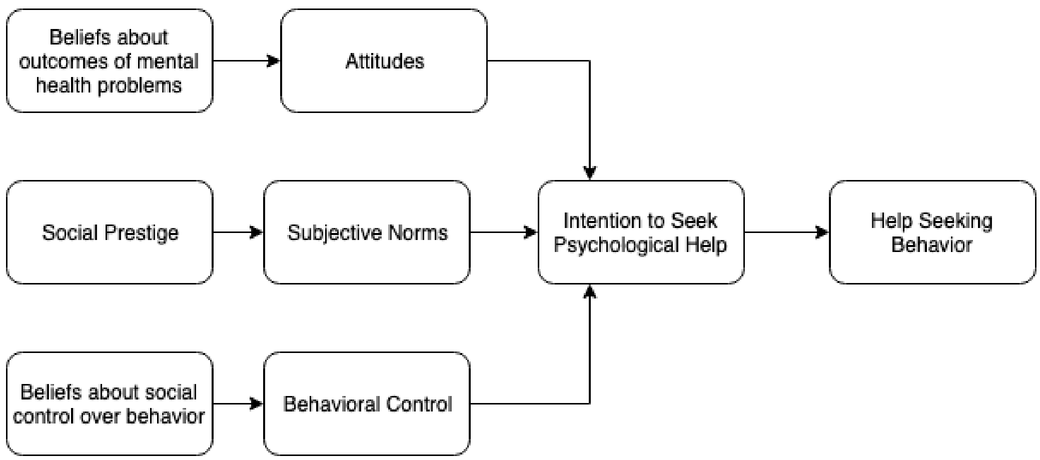


Figure 2 - TPB Model of Help-Seeking

When visualizing these factors that influence a person's "help-seeking behavior", it can become clear where the planned app will have its place. Ideally, the user-controlled app will have positive influences on all three factors in order to promote help-seeking behavior.

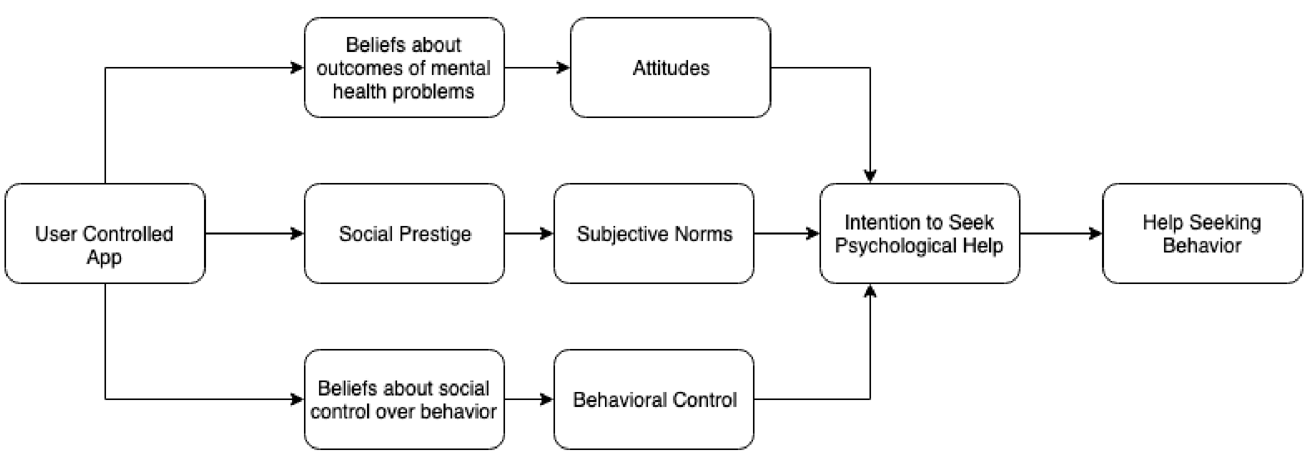


Figure 3 - TPB Model with App

The dimension the app is most suited to affect is within “Subjective Norms”, or the “social influences to engage or not to engage in a given behavior” [5]. This speaks to the aforementioned barrier of communicating mental health problems in an unstigmatized manner, which the Circle of Trust facilitates. App influences on the other two dimensions are potential improvements for the further work.

Methodology

Database

One of the initial goals set by the clients for Team 31 was to set-up the app's databasing capabilities. However, it was soon discovered that this would be out of Team 31’s control, as a proper research database requires coordination between the professors and ITAP. This is a lengthy discussion and is currently still in progress. Still, Team 31 designed a database and created an ER-diagram that will be discussed later in this report.

Behavioral Sensing - Research

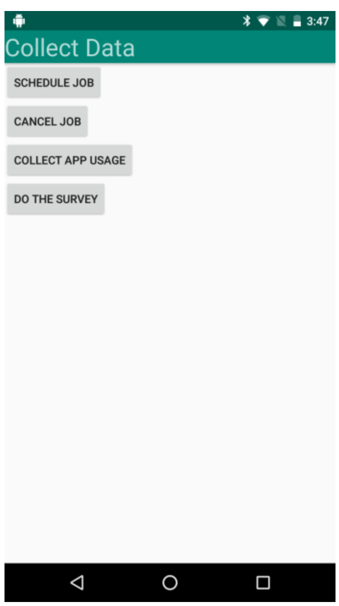
In laying the groundwork for a new system of behavioral sensing through mobile use patterns, a thorough discussion was held with the clients to determine various activities that could be tracked. With direction from Dr. Nan Kong and Dr. Denny Yu, the team narrowed the scope of features that will be implemented within the time frame of the Fall 2019 semester. These features include the collection of GPS data as the main priority followed by the battery usage data of apps on the phone. Previously, the team considered using call and messaging frequency as a metric correlated to depressive symptoms, but after more research, the team discovered in a mobile sensing study that calls and text frequency were the least correlated to mood compared to other metrics [11]. So, at the request of the client, the Team decided to try app usage as a metric that could be possibly linked to depressive symptoms. App usage was also relatively easier to implement according to Brian’s capabilities. Future developments for this project can add additional metrics for functional and research purposes.

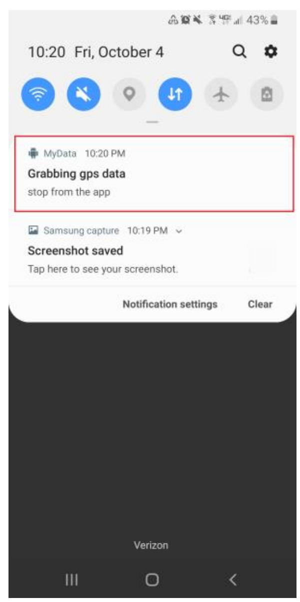
In identifying features of the app for overall development, the team was able to interview Dr. Susan Prieto-Welch, director of CAPS. Her input, as a client and domain expert in psychiatry, has guided the direction of the app in many ways. First, she confirmed the usefulness of using GPS data and app usage data. Second, she reiterated that the Circle of Trust could function as a great method of intervention, though that was not on Team 31’s priorities. Last, she confirmed the use of the PHQ-8 to gauge depressive symptoms. The PHQ-8 is an 8 question test that measures depressive symptoms and is one question shorter than the more standard PHQ-9, dropping the question on suicidality which clinical studies have shown to have very little effect on predictive power [15]. Dr. Prieto-Welch emphasized that there is a liability in knowing someone’s sensitive information, particularly when they are at risk of self-harm so it is in the research project’s best interest to avoid collecting that data.

In search of a method of analysis of GPS data, Team 31 consulted the growing literature on mobile sensing and mental health. Team 31 reviewed around 20 studies published between 2010-2019 that were interested in mental health monitoring through mobile phones. One study, titled “Mobile Phone Sensor Correlates of Depressive Symptom Severity in Daily-Life Behavior” by Saeb et al. (2015), stood out in particular [6]. This research paper examined the depressive symptoms of users in correlation to their GPS data, tackling the same question posed by Team 31. What sets this study apart from the rest of the literature examined was that it provided detailed equations that made their calculations repeatable, and that it was replicated to similar effects by the same authors and another independent research group [7][8]. Furthermore, a 2019 literature review by Fillekes et al. singled out Saeb et al. (2015) as the study they found that contained “the most comprehensive set of mobility indicators" [14]. These mobility indicators are location variance, circadian movement, number of clusters, entropy, and homestay [6]. These five metrics have shown to be statistically meaningful in reflecting mental health status without any manual labeling of the type of location visited, only utilizing latitude and longitude locations.

Pilot Study

A few weeks into the project, Brian developed a preliminary app that could record latitude and longitude every 15 minutes and allow the user to take the PHQ-8.





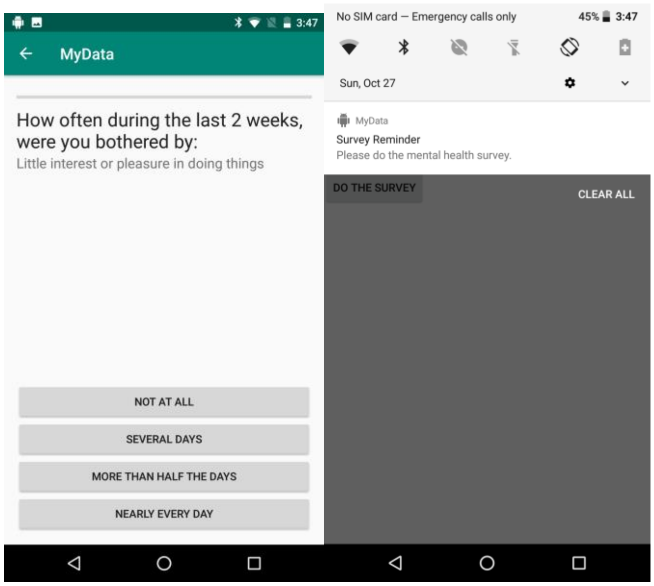


Figure 4. Data Collection UI - Current System Model

From there, Team 31 coordinated a mini-pilot study as requested by Dr. Kong. This pilot-study would ensure the GPS collection could function as intended and recreate the analytical framework found in Saeb et al (2015). Initially, the team sought help to obtain Android devices for pilot testing by coordinating with Lawson's Instructional Laboratory Coordinator, Victory Soe. Lawson could not supply phones, so the Team decided to recruit acquaintances who used Android phones to download the app and leave it running for around 2 weeks. Due to the sensitive nature of mental health, this mini-pilot study could not ethically collect data on depressive symptoms from the subjects who, to reiterate, were generous friends of Team 31.

Due to the speedy nature in which a functional app was rolled out along with the aforementioned database roadblock, the app stored its data as a character string on a ".txt" file on a public folder on the Android phones, as compared to the more standard private folders which require "rooting" the Android software to access. Although this is less secure, it made the data extractable from the test subject's phones. Figure 5 shows a data flow diagram depicting how the data for this pilot-study was collected. Test-subjects emailed Team 31 their data, which would then be loaded onto the Team's computers, and plugged into R Studio, where plotting and analysis were conducted.

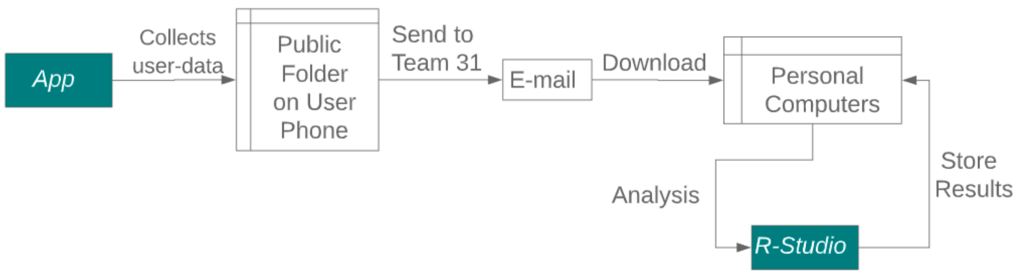


Figure 5 - Current Data Flow Diagram

In the future, this data flow diagram should look very different. Once a secure Purdue database has been acquired by our clients, then the app should automatically record user data into it. This would also allow the data on the phone to be stored in a secure, hidden folder like most app data is. Additionally, the app should be able to communicate with analytical research results to incorporate them into any app functions as desired. This is shown in Figure 6.

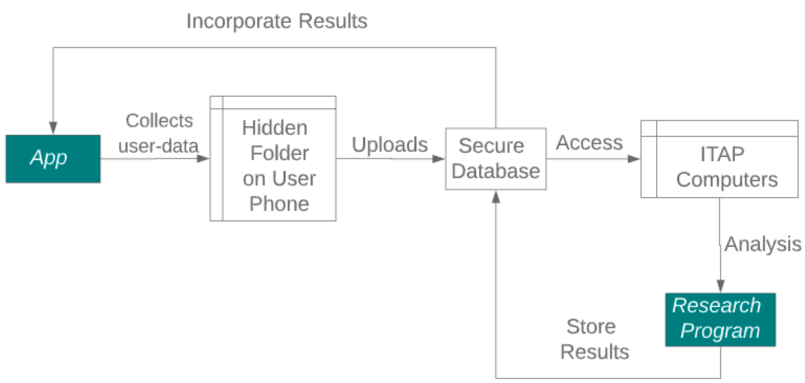


Figure 6 - Future Data Flow Diagram

Results

Database

The ER-diagram shown in Figure 7 was designed to achieve Third Normal Form, a popular standard for databases that ensures integrity and reduces redundancy [12]. The center table “COT” represents the Circle of Trust, and stores a unique UserID of each user along with the info for each person in the Circle. The UserID serves as the foreign key for the other tables, which store the collected phone data and PHQ scores. The table named Phone_Feature represents further modifications to the app that will collect more data for each user. As the discussion between Dr. Kong and ITAP continues, this diagram will function as a clear, workable format the end-goal.

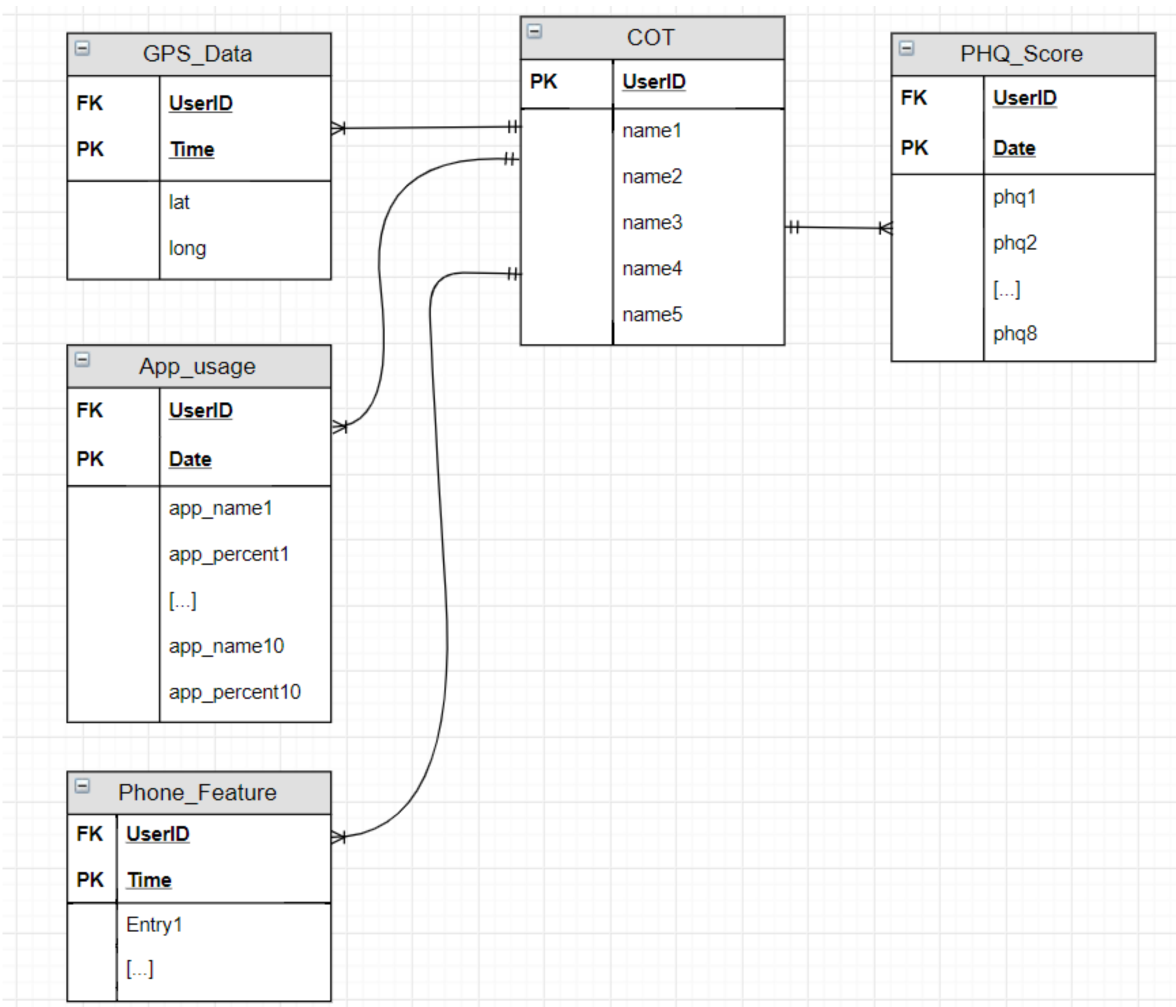


Figure 7 - ER Diagram of Future Database

GPS Data Analysis

Four acquaintances of Team 31 were recruited in the mini-pilot study. However, initial test subjects used buggy and inconsistent versions of the application. This was useful feedback for Brian, who worked to make the GPS collection more reliable across different versions of Android. Because of this development cycle, the timeframe needed for workable data, and the different versions of Android amongst the subjects, only one user's dataset was worth analysis. Although more datasets were desired, having only one is suitable for the purposes of this project which was to help develop the app and reproduce the analytical framework found in Saeb et al (2015). The data analyzed came from a Purdue student whose GPS location was tracked for just over 2 weeks and was collected in a text file as described in the Methodology section. The data was then loaded into R Studio, parsed and reformatted as a data frame in which timestamp, longitude, and latitude were separate columns. By default, the timestamp on each of the 15-minute intervals was not designated as AM or PM, so all timestamps were converted into military time in R. This was reported back to Brian who changed the app for future use so this step would not be necessary. After that conversion, the hour of the day was plotted against the data point number to ensure continuity in data collection as seen in Figure 8.

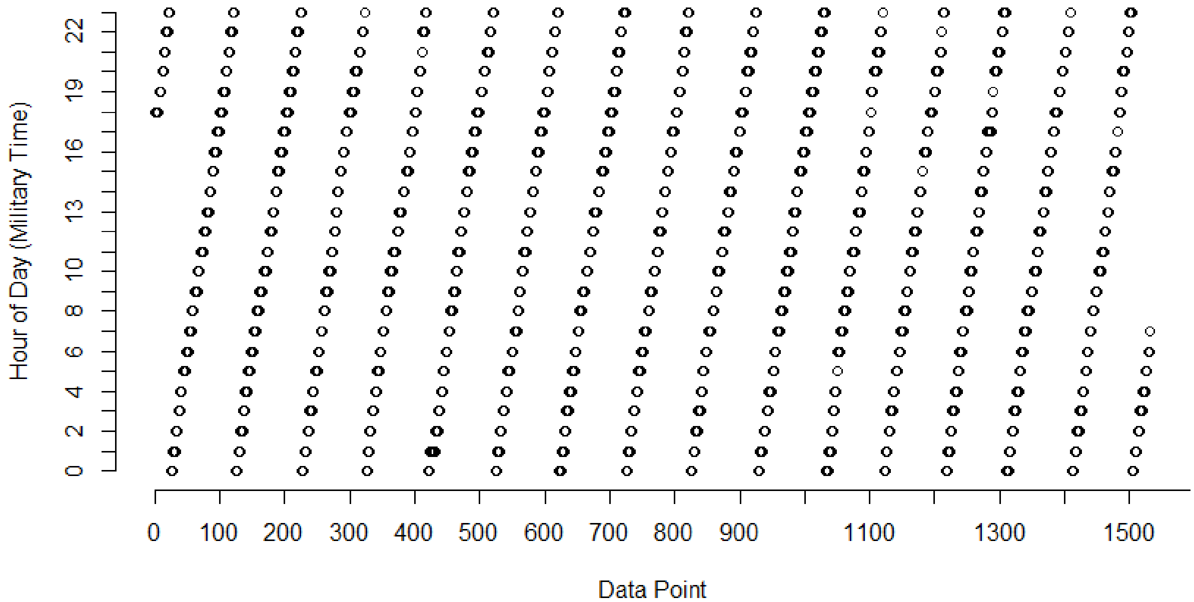


Figure 8 - Hour of Day vs. Data Point Plot

If no blank spaces appeared in the plot, this ensured that data was at least being collected every hour of the day and that the app had correctly functioned in terms of repeated data collection over a two week period.

Next, the optimal amount of clusters was defined for the given dataset. No standardized method was used in observed research papers to define the appropriate amount of clusters for a data set. For example, Saeb et al. (2015) a clustering limit of 500 meters was used, Canzian (2015) used a clustering limit of 200 meters, and Fillelkes (2019) used a density and epsilon radius based algorithm [14]. At the client’s request, Team 31 utilized a modular method of defining the optimal number of clusters called silhouette width clustering that could be applied to any dataset. The silhouette width method (Figure 9) iterates through a range of the number of clusters and identifies the optimal number clusters where the inter distance between data points between clusters is maximized and the intra-distance of points within clusters is maximized.

These distances are normalized to a value range of [-1,1] where 1 represents the most defined separation of clusters. For the tested data set, two clusters were found to be optimal.

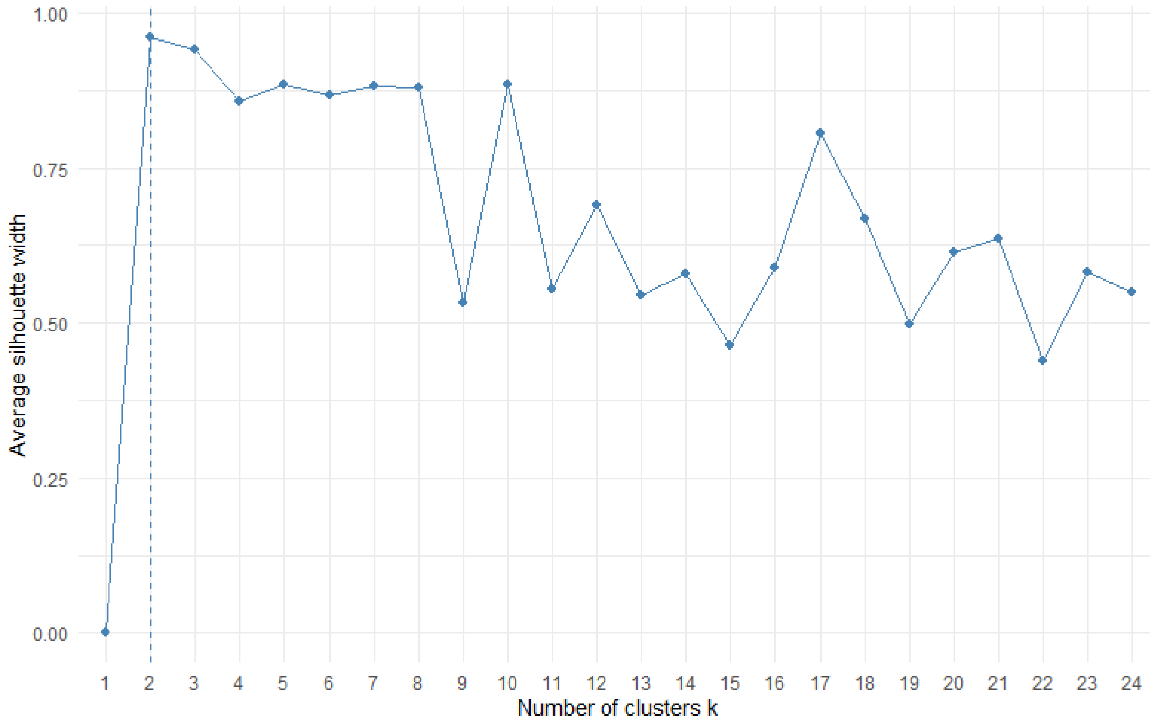


Figure 9 - Silhouette Width Plot

After the optimal number of clusters was defined, the data points were then clustered to that set number using a k-means algorithm, as done so in Saeb et al (2015). For visualization purposes, the dataset along with their respective clusters was plotted. Figure 10 shows the data points, clusters and the relative sizes of the clusters. Figure 11 shows the same data points plotted using the Static Google Maps API.

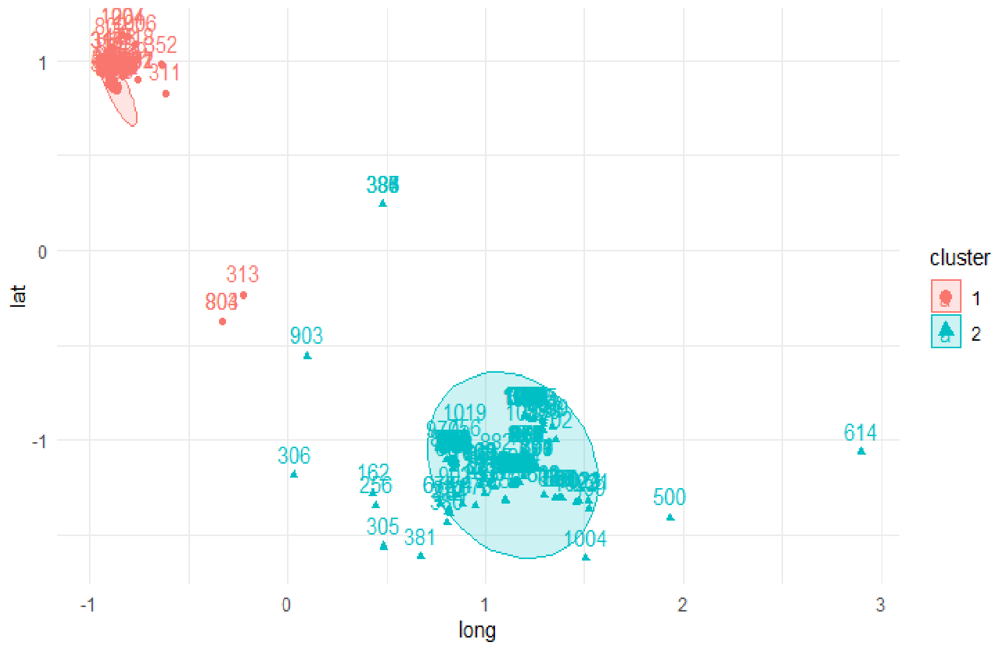


Figure 10 - Cluster Plot of GPS Data

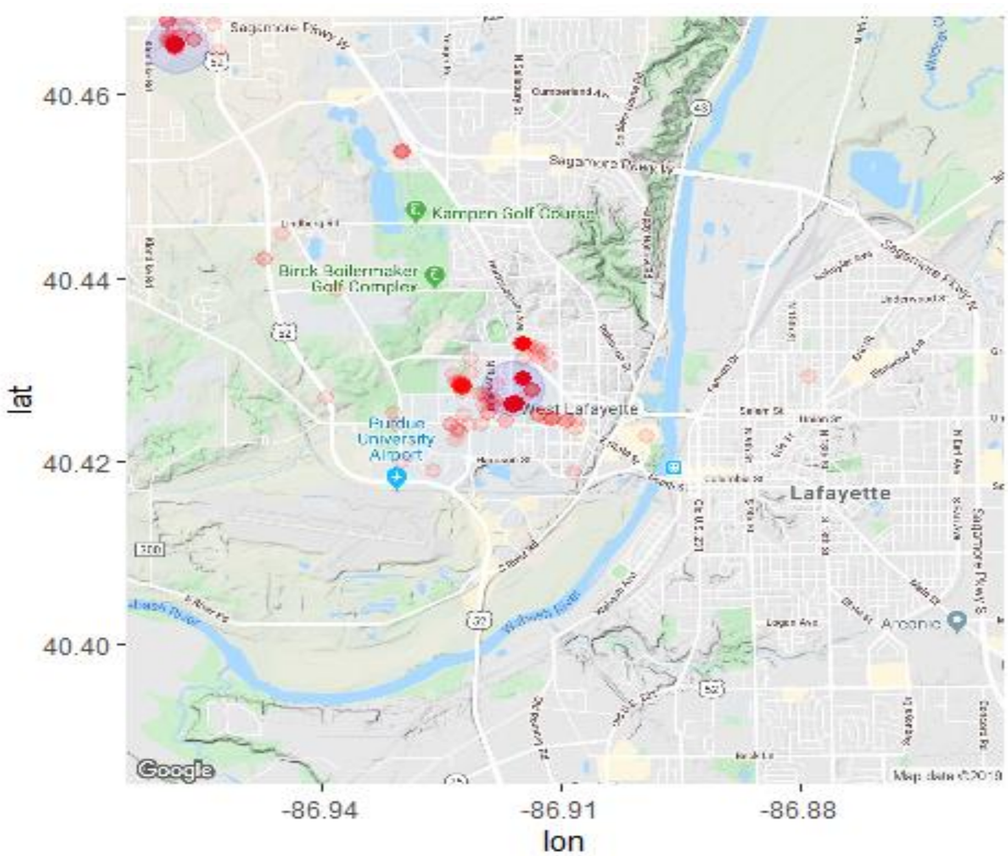


Figure 11 - Closter Plot on Google Maps

After visualization, the analytics outlined in Saeb et. al (2015) was applied to the data to produce the five metrics: location variance, circadian movement, number of clusters, entropy, and homestay.

First, location variance was calculated as per the formula in Appendix- Table 3 [6], by finding the variance (the square of the standard deviation) of both latitude and longitude and taking the log of their sum. Perhaps the simplest of the calculated metrics, location variance describes how the user's GPS data is spread out.

Next, a temporal aspect of the user's mobility was captured by calculating their circadian movement. To do so, a Lomb-Scargle periodogram was created for their latitude and longitude, as shown below in Figure 12. The Lomb-Scargle is a form of Least Squared Spectral Analysis which is closely related to Fourier Analysis. Like Fourier Analysis, the Lomb-Scargle decomposes an unevenly sampled time-signal into its component frequencies. The frequencies of interest to Team 31 are the ones between 23.5hr and 24.5hr. As detailed in Saeb et al. (2015) and shown in Appendix - Table 3, summing up the power of those frequencies in the range of 23.5 hr to 24.5 hr creates a metric that captures how well the subject's movement pattern fits into a daily cycle. Saeb et al. (2015) found that a consistent daily movement pattern (i.e. a high circadian movement) was negatively correlated with depressive symptoms.

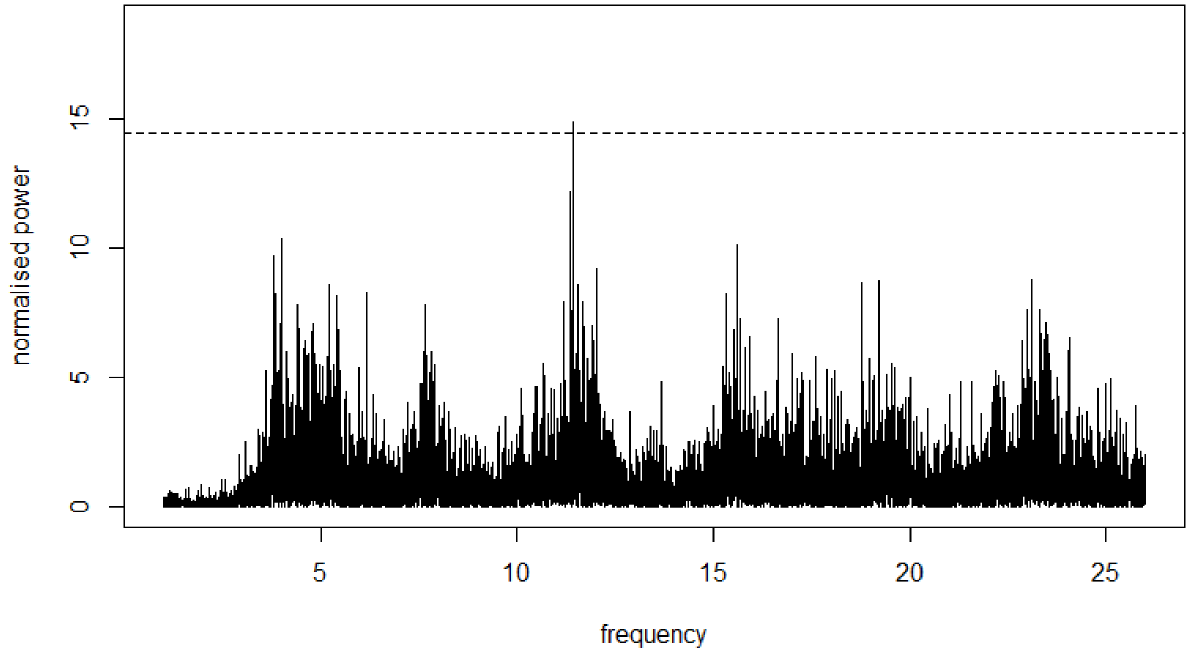


Figure 12 - Lomb-Scargle Periodogram

Third, the optimal number of clusters was calculated with the silhouette method previously described. Fourth, entropy was calculated using the formula in Appendix - Table 3. This metric, which the authors derived from information theory, captures how spread out the user is amongst their clusters. Essentially, as Saeb et al. describe, the higher the entropy, the harder it would be to predict which cluster the user is in. A very low entropy would mean the user is mostly in only one of their clusters. Lastly, the homestay percentage was calculated through a two-step process. First, user data was extracted between the hours of 12:00 AM and 6:00 AM. Within this data subset, the cluster containing the largest amount of data points was defined as the home cluster and the homestay percentage is then calculated as a percentage of total data points that are labeled within that home cluster. A higher homestay percentage was positively correlated to depressive symptoms.

Table 1 below shows the values of these five metrics calculated for the single test subject. Note that both location variance and circadian movement lack units because of the nature of taking a logarithm, which both formulas call for in order to combine latitude and longitude.

Metric	Value	Unit
Location Variance	5.297	N/A
Circadian Movement	2.938	N/A
Number of Clusters	2	clusters
Entropy	0.525	bits
Homestay Percentage	57.805	%

Table 1 - GPS Data Metrics

By replicating previous studies in finding significant GPS metrics correlating to depressive symptoms, Team 31 has reached the current benchmark in terms of data analytics and has also generated a user-friendly UI. However, in terms of app design, functionality, and data storage, Team 31 has only succeeded in creating a functioning prototype that will be continually updated.. Due to the nature of working with sensitive data, full-scale data collection of anonymous users cannot be collected without IRB approval. As this research project continues, other teams of Purdue students will be able to initiate data analytics on multiple users' data over longer time frames than 2 weeks. As long as the project clients are able to recruit Purdue students to refine application development, the project will remain a viable option in terms of providing a helpful resource for Purdue University students suffering from depressive symptoms.

Moderated Usability Testing

Usability testing is the process of watching/tracking an actual user while they use a product to determine if it is navigable. Usability testing is the best way to understand how real users experience your website or app [13]. Team 31 created a user interface (UI) design to satisfy the request of the client to make the application more user-friendly. In the cited article, Nick Babich explains a few ways to carry out usability testing. The design team adopted a method he calls "Moderated Usability Testing" [13].

Moderated usability testing refers to obtaining feedback from live users during a moderated test [13]. Moderators (Team 31 members) sat down with a few users of the current app, facilitated them through tasks, answered their questions, and replied to their feedback in real-time. A list of ordered tasks was provided to the participants. Shown below.

1. Open the UI Prototype #1
2. Click and follow the flow from each button on the Homepage
    a. Survey >> 8 questions of the PHQ-8 Survey
    b. Places >> "Your top 10 places over the past two weeks"
    c. Routine >> "Your top 10 apps over the past two weeks"

Live communication enabled Team 31 to ask questions about the current user experience after those users had used the application for three days. Team 31 members sat down with five users of the current app, facilitated them through tasks, answered their questions, and documented their feedback. Table 2 shows otable feedback received after carrying out MUT on the UI:

Participant #	*Feedback Received*

1	Would prefer a designated back button to make it easier to navigate through the UI
2	Would like to be notified when the PHQ-8 survey is finished; the notification should then redirect the user back to the homepage
3	Have one central button on the homepage to start/stop recording the GPS and app usage data
4	Rename the "Analytics" to "Data Visualization" as it fits better
5	Instead of just showing the charts after clicking the button, create a list of options that the user can click which would all open in a new screen

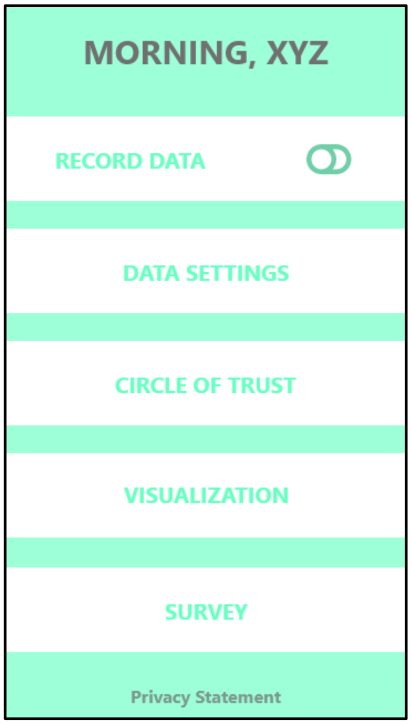
Table 2 - Moderated Usability Testing Feedback

UI Design

The preliminary app that was sent out to the test subjects only consists of minimum functionality. It is not user-friendly and not possible for a test subject to understand how to use the app without training or walkthrough from the test provider. In order to attract more users to use our application, the interface should be self-explanatory, easy to navigate, and user-friendly. The user interface should satisfy several ergonomic principles. Since the application is not fully completed at this moment, the user interface should also leave space for the addition of new functionalities in the future. The goal of the user interface design at this stage was to build a structure for the app interface, build a foundation for future development.

Cyan color was chosen to be the background color, HEX CODE: #9DFFD8. A green theme is found to be comforting to people. Green is calming and relaxing. [16] Although, it may arouse the problems that some people are color blind. Further research on this topic is still needed and is addressed in detail in the Discussion section. Based on the cyan background. White, HEX CODE: #FFFFFF. was chosen to be the background for buttons. It provides a mediocre contrast rate of 1.45. To keep a good theme, the color for the text on the buttons is cyan as well. The color for the title and is dark grey, HEX CODE: #707070. It still remains a good contrast rate of 4.18 with the background.

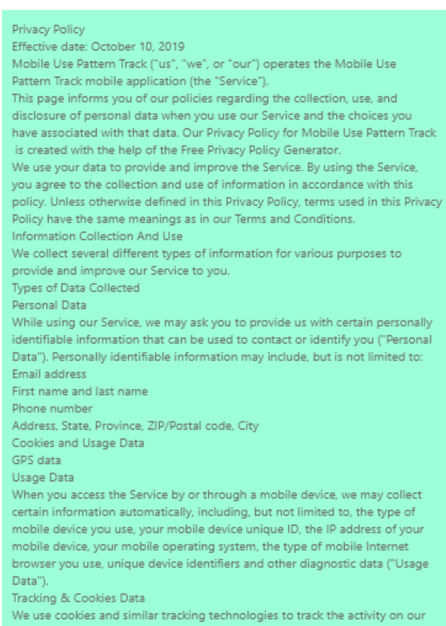
Home Page



The main page in Figure 13 consists of welcoming text, one master button, four major function buttons, and the privacy statement. The welcome message is set to be the time period plus the name of the device recorded in the setting of the phone. The master button should be able to start or end all data recording at once. A toggle switch is chosen at the moment. Four functions are data settings, circle of trust, visualization, and survey.

Figure 13 - Home page

Privacy Statement



The privacy statement is put at the bottom of the page. It is a scrolling page. The text simply copied into this page. The full version of the privacy statement can also be found in the appendix.

Figure 14 - Privacy Statement

Data settings page

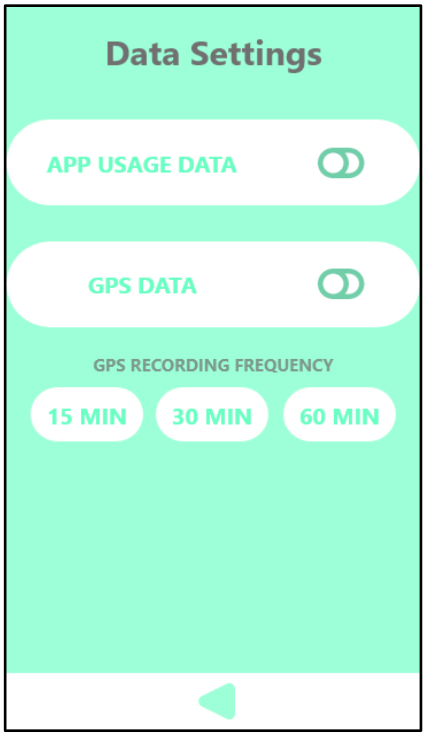
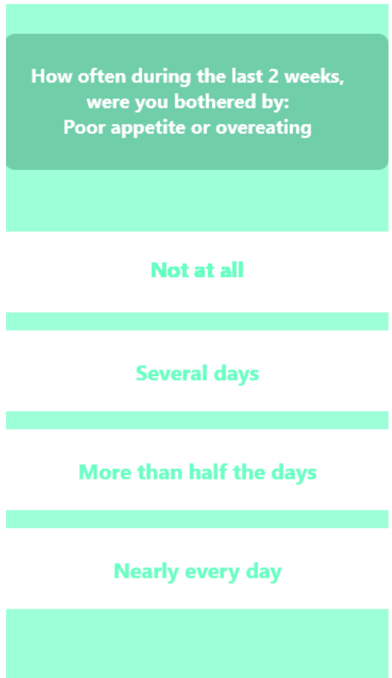


Figure 15 - Date setting page

At the data settings page in Figure 15, the user can choose which type of data they want to share with the team. Team 31 is giving users the right to choose which data to share based on their preferences. A toggle switch is used at this moment. GPS recording frequency can be adjusted to 15-minute intervals, 30-minute intervals, or 60-minute intervals. Note that the intervals will not be the exact time intervals. The actual time interval will be around the selected time interval. The deviation is usually within 1 minute but it varies phone by phone. In the future, if more types of data were to be recorded, they would be added to the data settings page following the same options structure.

PHQ-8 Survey page



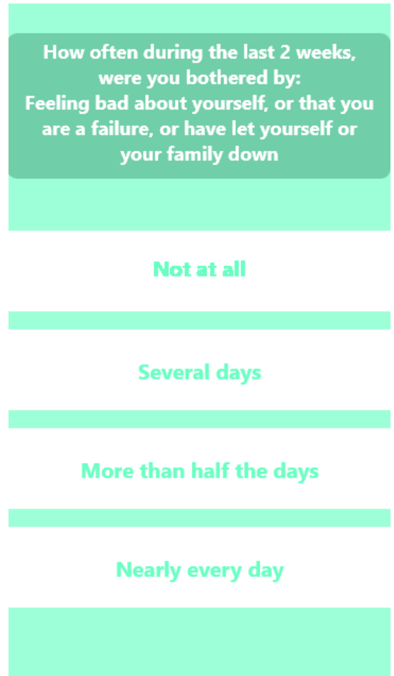


Figure 16 - Eight PHQ-8 questions

Figure 16 shows the eight PHQ-8 survey questions implemented into the UI. Users take the survey when first installing the app, and every 14 days afterward. Once begun, they are supposed to finish all 8 questions. They can not change their answers at this moment to minimize the workload for the coder. The return button to the home page does not show up until all eight-questions are finished. All colors used on this page are still the same as the previous pages except the background color of the survey question. The background color HEX CODE is #70CEA9. The contrast rate is 1.89. Note that only PHQ-8 is chosen instead of PHQ-9 because the ninth question is related to suicidal tendencies. Going into that level will cause too many problems at this moment. More discussion about this topic is in the Discussion section.

Circle of Trust and editing

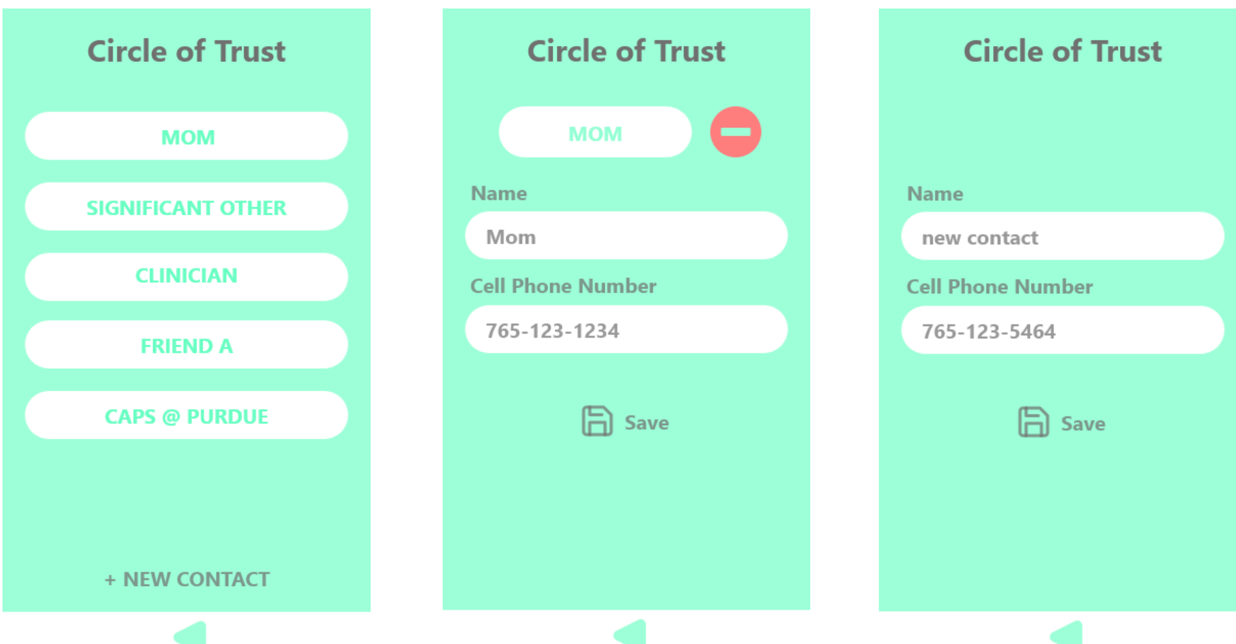
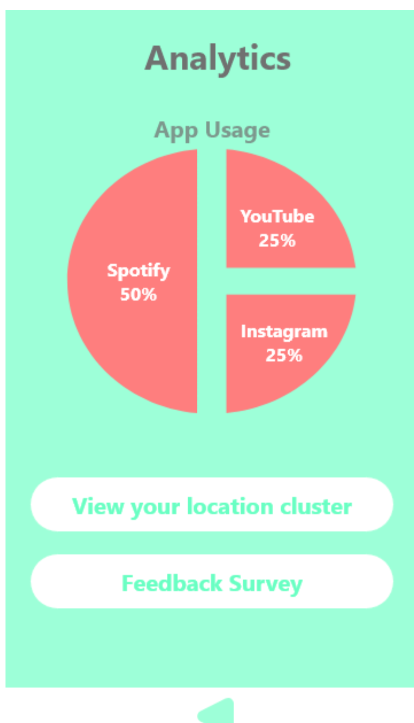


Figure 17 - Circle of Trust feature

Figure 17 shows the intervention method called "circle of trust". At this page, the user will have the ability to add in their trusted contact by clicking "+ NEW CONTACT". At this moment the intervention is notification only. When the app detects a higher score on their PHQ-8, the app prompts a notification to encourage the user to talk to their circle of trust. The notification tab shown on the phone should bring them to the first page where they are encouraged to call them or text them to talk about their life over the past two weeks. Hotlines such as Purdue CAPS and National Suicide Prevention Lifeline will also be put on the page. More discussion of this topic is in the Discussion section.

Data Visualization



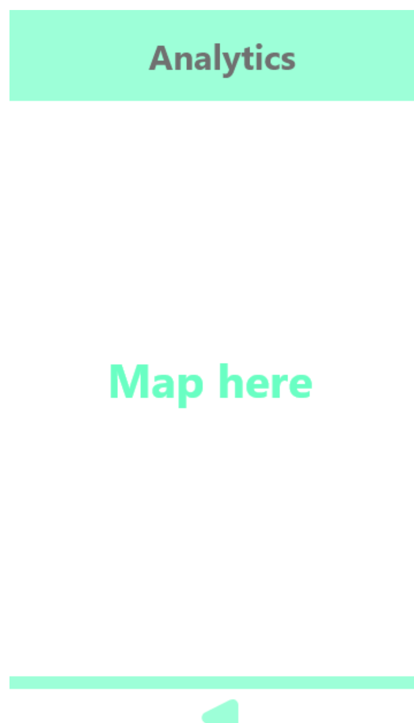


Figure 18 - Data visualization page

Data visualization pages function as an incentive for the user to use the app. The top half shows the top app usage over the past two weeks. The bottom part consists of two buttons. The first button is "View your location cluster" where it brings to another page showing the map showed previously in this report with the dots and clusters on. The second button directs to an external survey that focuses on user feedback and usability of this app. The link for the survey is https://www.surveymonkey.com/r/HN6YSMD.

App Flow Diagram

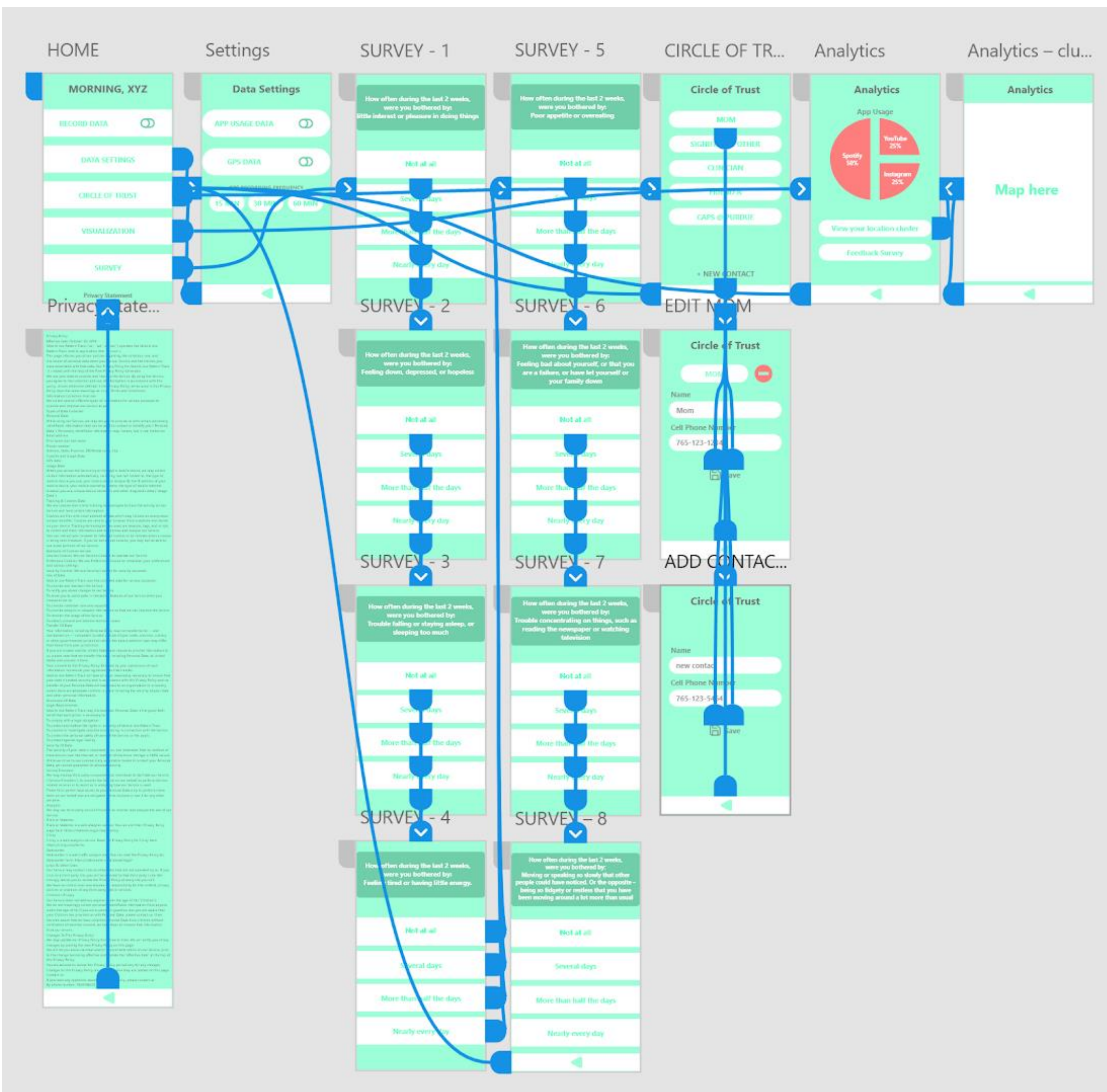


Figure 19 - App flow diagrams

This diagram shows how the app flows at the moment. The inter-relationship between buttons is shown. The entire UI design was done in Adobe XD. The file name is “UI prototype”. The file will be located in Google Drive.

Discussion

Discussion Related to Behavioral Sensing

There are a few concerns regarding the design and validation of the detection algorithm. First, there are too many potential indicators of depressive symptoms. While a metric like recording frequency of text-messaging has been ruled out as previously mentioned, there are many other possibilities. An interesting method involves tracking the decibel level from the microphone, as a measure of social interaction, and accelerometer, to gather more precise mobility data [17].

Second, the data needs to be compared with the user’s historical data and his or her peers’ concurrent data. Changes in activity patterns with respect to mood can vary greatly across users. This was a concern echoed by Dr. Prieto-Welch - it’s possible that a user spending more time at home is actually healthy for their mental state and helps fight depressive symptoms. So, although a generalized model can be used to generally predict significant changes in mood, a personalized model is far more accurate [8]. However, for a personalized model to work it requires a lot of data for the app to be trained. This necessitates that the app is designed for high user-engagement, a problem that is also discussed in this section.

Lastly, the data collected needs to be private, retain the accuracy of the metrics being recorded, and not become overbearing to phone processing capabilities or battery life. As more behavioral metrics are implemented into the app, the need to store student data in a secure database and the need to ensure the sustainable load on a device is kept also become more prevalent. Some users may also feel more comfortable with larger time intervals between recordings. So, as the app is scaled to incorporate more behavioral metrics and users with different devices, a trilemma may exist between agreeable privacy policy, the accuracy of data collection, and battery usage/system load. Close attention to these three development aspects will remain important as development continues.

Discussion Related to UI design

The UI design is using cyan color as the main color at the moment. Colorblind users are the part we neglect during this semester. Possible solutions can be using a new color theme or to build several themes and let the user choose. One of the new version colors should not cause problems for colorblind users. Further, the size and shape of the buttons were chosen arbitrarily as well as font size and font type. More studies can be done on this part regarding usability. The contrast ratio is not high enough and better color choices can be discussed. The text can also have a border with a high contrast color to emphasize the text itself.

Discussion Related to App Development

Another major topic concerning the UX is to have more incentive for users to keep the app. More methods need to be developed as current literature could not provide a workable guide. The studies reviewed by Team 31 all utilized standard research methods of engaging users throughout the research period - that is, mainly, a cash incentive for test subjects. It is also important to find new ways to attract more users to increase the amount of data. One way suggested is to transfer the current app into a “fitness tracking” app. The fitness app can generate fitness and mental health reports bi-weekly which can be a good incentive for the users. Another approach, albeit expensive, could incorporate some cash incentives via coupons from restaurants or shops nearby. These coupons can encourage people to socialize, perhaps with other users of the app. Overall, a creative solution would be needed since long-term user engagement of the app is needed for both unique research avenues and overall training functionality.

Discussion Related to Future Research

With the current capabilities of the app and the R code, it is possible to replicate many of the studies the team has reviewed. Once proper IRB approval has been received, the app can collect GPS data, PHQ-scores, and then, in R, analyze the statistical significance between the GPS metrics and the PHQ-scores. This is already a great opportunity of research since replicating findings, particularly when it comes to psychological science, has been given renewed importance. However, further work could open up many more opportunities for unique studies - specifically, with a functioning Circle of Trust. From Team 31's understanding, there is very little research in mobile sensing that looks at an intervention method and its results. A refined and operating Circle of Trust function incorporated into the app could provide a wealth of research into how effective that method of intervention is.

A more general question still remains with the app's functionality and that is how the PHQ-score would fit in its ecosystem once it is fully running. As a research metric, the idea is simple and previously discussed. However, when the app works as a detector of mental health state, how does one incorporate the PHQ-score? The PHQ-score, or some other psychometric test, would still be needed as a training gauge for any sort of personalized mental health app. Yet, if the user regularly takes the test to reveal their true mental health state, then what is the purpose of any other sort of behavioral sensing? Whether to use the PHQ-8 score as a datum, a target, a reinforcement, or a combination of sorts needs further consideration before implementing a serious method of behavioral sensing and intervention.

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Appendices

Gantt Chart

Team Member Resumes

Accounting of hours worked on the project to-date

Objective	Date	Length (hours)
Working on Team Charters	9/1/2019	3
Initial meeting with Client (Professor Kong)	9/5/2019	1
Meeting with Professor Kong and Professor Yu	9/12/2019	1
Working on project proposal presentation	9/13/2019	3
Meeting with coder Brian	9/17/2019	1.5
Meeting with Professor Kong, Professor Yu, and Brian	9/20/2019	0.5
Working on the project proposal document	9/22/2019	6
Meeting with Professor Kong, Professor Yu, and Brian	9/27/2019	1
Meeting with Dr. Welch from CAPS	10/11/2019	1
Working on team assessment	10/17/2019	1
Meeting with Professor Kong, Professor Yu, and Brian	10/18/2019	1
Testing app usability, team meeting	10/21/2019	1.5
Meeting with Brain	10/23/2019	1
Meeting with Professor Kong	10/25/2019	1
Working on UI design	10/28/2019	2
Working on data analysis	10/28/2019	2
Meeting with Professor Kong, and Brian	10/29/2019	1
Working on data analysis	10/30/2019	3
Working on data analysis	10/31/2019	3
Working on data analysis	11/4/2019	3
Meeting with Professor Kong, and Brian	11/5/2019	1
Working on UI design	11/08/09	1
Working on the status report	11/09/09	3

Working on UI design, data analysis	11/11/2019	2
Meeting with Professor Kong, and Brian	11/12/2019	1
Working on data analysis	11/15/2019	3
Working on UI design, data analysis	11/18/2019	3
Meeting with Professor Kong, and Brian	11/19/2019	1
Working on UI design, data analysis	11/20/2019	3
Working on the final poster, slides	11/22/2019	4
Working on final slides	11/26/2019	1
Poster Presentation	12/03/2019	3
Final presentation	12/05/2019	1
Working on the final report	12/08/2019	3

Table 3 - GPS Metric Equations

Metric	Equation
Location Variance	$$\text{Location variance} = \log\left(\sigma_{\text{lat}}^2 + \sigma_{\text{long}}^2\right),$$
Entropy	$$\text{Entropy} = -\sum_{i=1}^{N} p_i \log\left(p_i\right),$$ where p_i is the percentage of time spent at location i, and N is the total number of location clusters.
Circadian Movement	$$E = \frac{1}{i_u - i_L} \sum_{i=i_L}^{i_u} \text{psd}\left(f_i\right),$$ where psd(f_i) denotes the power spectral density at frequency bin f_i, and i_L and i_U represent the lower and the upper bounds of the frequency range of interest, corresponding to 24.5 and 23.5 h periods respectively. We calculated E separately for longitude and latitude, and obtained the total circadian movement as: $$CM = \log(E_{\text{lat}} + E_{\text{long}})$$

Privacy Statement

Privacy Policy
Effective date: October 10, 2019
Mobile Use Pattern Track ("us", "we", or "our") operates the Mobile Use Pattern Track mobile application (the "Service").
This page informs you of our policies regarding the collection, use, and disclosure of personal data when you use our Service and the choices you have associated with that data. Our Privacy Policy for Mobile Use Pattern Track is created with the help of the Free Privacy Policy Generator.
We use your data to provide and improve the Service. By using the Service, you agree to the collection and use of information in accordance with this policy. Unless otherwise defined in this Privacy Policy, terms used in this Privacy Policy have the same meanings as in our Terms and Conditions.
Information Collection And Use
We collect several different types of information for various purposes to provide and improve our Service to you.
Types of Data Collected
Personal Data
While using our Service, we may ask you to provide us with certain personally identifiable information that can be used to contact or identify you ("Personal Data"). Personally, identifiable information may include, but is not limited to:

- Email address
- First name and last name
- Phone number
- Address, State, Province, ZIP/Postal code, City
- Cookies and Usage Data
- GPS data

Usage Data
When you access the Service by or through a mobile device, we may collect certain information automatically, including, but not limited to, the type of mobile device you use, your mobile device unique ID, the IP address of your mobile device, your mobile operating system, the type of mobile Internet browser you use, unique device identifiers and other diagnostic data ("Usage Data").
Tracking & Cookies Data
We use cookies and similar tracking technologies to track the activity on our Service and hold certain information. Cookies are files with small amount of data which may include an anonymous unique identifier. Cookies are sent to your browser from a website and stored on your device. Tracking technologies also used are beacons, tags, and scripts to collect and track information and to improve and analyze our Service.
You can instruct your browser to refuse all cookies or to indicate when a cookie is being sent. However, if you do not accept cookies, you may not be able to use some portions of our Service.
Examples of Cookies we use:

- **Session Cookies.** We use Session Cookies to operate our Service.
- **Preference Cookies.** We use Preference Cookies to remember your preferences and various settings.
- **Security Cookies.** We use Security Cookies for security purposes.

Use of Data
Mobile Use Pattern Track uses the collected data for various purposes:

- To provide and maintain the Service
- To notify you about changes to our Service
- To allow you to participate in interactive features of our Service when you choose to do so
- To provide customer care and support
- To provide analysis or valuable information so that we can improve the Service
- To monitor the usage of the Service
- To detect, prevent and address technical issues

Transfer Of Data

Your information, including Personal Data, may be transferred to — and maintained on — computers located outside of your state, province, country or other governmental jurisdiction where the data protection laws may differ than those from your jurisdiction.
If you are located outside United States and choose to provide information to us, please note that we transfer the data, including Personal Data, to United States and process it there.
Your consent to this Privacy Policy followed by your submission of such information represents your agreement to that transfer.
Mobile Use Pattern Track will take all steps reasonably necessary to ensure that your data is treated securely and in accordance with this Privacy Policy and no transfer of your Personal Data will take place to an organization or a country unless there are adequate controls in place including the security of your data and other personal information.
Disclosure Of Data
Legal Requirements
Mobile Use Pattern Track may disclose your Personal Data in the good faith belief that such action is necessary to:

- To comply with a legal obligation
- To protect and defend the rights or property of Mobile Use Pattern Track
- To prevent or investigate possible wrongdoing in connection with the Service
- To protect the personal safety of users of the Service or the public
- To protect against legal liability

Security Of Data
The security of your data is important to us, but remember that no method of transmission over the Internet, or method of electronic storage is 100% secure. While we strive to use commercially acceptable means to protect your Personal Data, we cannot guarantee its absolute security.
Service Providers
We may employ third party companies and individuals to facilitate our Service ("Service Providers"), to provide the Service on our behalf, to perform Service-related services or to assist us in analyzing how our Service is used.
These third parties have access to your Personal Data only to perform these tasks on our behalf and are obligated not to disclose or use it for any other purpose.
Analytics
We may use third-party Service Providers to monitor and analyze the use of our Service.

- **Piwik or Matomo**
  Piwik or Matomo is a web analytics service. You can visit their Privacy Policy page here: https://matomo.org/privacy-policy
- **Clicky**
  Clicky is a web analytics service. Read the Privacy Policy for Clicky here: https://clicky.com/terms
- **Statcounter**
  Statcounter is a web traffic analysis tool. You can read the Privacy Policy for Statcounter here: https://statcounter.com/about/legal/

Links To Other Sites
Our Service may contain links to other sites that are not operated by us. If you click on a third party link, you will be directed to that third party's site. We strongly advise you to review the Privacy Policy of every site you visit.
We have no control over and assume no responsibility for the content, privacy policies or practices of any third party sites or services.
Children's Privacy
Our Service does not address anyone under the age of 18 ("Children").
We do not knowingly collect personally identifiable information from anyone under the age of 18. If you are a parent or guardian and you are aware that your Children has provided us with Personal Data, please contact us. If we become aware that we have collected Personal Data from children without verification of parental consent, we take steps to remove that information from our servers.
Changes To This Privacy Policy
We may update our Privacy Policy from time to time. We will notify you of any changes by posting the new Privacy Policy on this page.
We will let you know via email and/or a prominent notice on our Service, prior to the change becoming effective and update the "effective date" at the top of this Privacy Policy.

You are advised to review this Privacy Policy periodically for any changes. Changes to this Privacy Policy are effective when they are posted on this page.

Contact Us

If you have any questions about this Privacy Policy, please contact us:

- By phone number: 7654186225

Cognitive walkthrough

A list of ordered tasks was provided to the participants to test and gather data from the functioning prototype of the app. Shown below.

1. Click the APK file in the email, the downloading and installation will begin automatically.
2. Users should read the Privacy Statement carefully.
3. Go into settings, turn on location services all the time. Notice, this may drain your battery, but the app is set to a low frequency to minimized battery drain.
4. Go into settings, turn on background app refresh, cellular data, notifications.
5. Open the app.
6. Take the survey.
7. Click schedule jobs. This will starts collecting your GPS locations at a very low frequency. You can always cancel it by click cancel jobs.
8. After 7 days, the data file stored on your phone will be collected by Team 31.
9. Follow in-app notifications for further instructions.

Risk Assessment

Battery Life and Data Accuracy Trade-Off

The biggest risk with the current approach is the trade-off between battery life and data accuracy. Collecting GPS data entails turning the smartphone's GPS on that consumes substantial battery life. Meaning, the more frequent the data collection, the faster the smartphone's battery will be drained. However, a higher frequency of data collection means more accurate data. The team has proceeded to deal with this trade-off by limiting data collection frequency to 15 minutes, or more.

Privacy

The risk of privacy is a glaring one. GPS data is very sensitive in nature. It can provide the exact location of a person throughout the day. To mitigate this issue, the team has identified two solutions. The team will store the data on a Purdue server and not transfer it to physical hard drives. The team will also come up with a comprehensive privacy agreement that will be provided to new users at the time of registration, along with notifications to let them know that the data collection is in progress.

Collecting enough data

Research suggests that in order to accurately correlate GPS data to depressive symptoms, the data should be collected for a 10-week period [6]. The 10-week period creates a time crunch because this is a semester-long project. Team 31 will try to find a workaround for this issue by reducing the interval for data collection so more data can be gathered in less time.

Schedule

This risk of schedule is also a concern since the research requires participants to complete the PHQ-9, an online assessment consisting of a demographics questionnaire and the PHQ-9, the measure of self-reported depressive symptom severity. And other features need to be extracted from raw data processing, such as location variance, number of clusters, entropy, and homestay. More advanced models need to be constructed in order to evaluate regression and classification models so the team needs to collect enough data within a shorter time and proceed with the data analysis.