ESTIMATING ANXIETY BASED ON INDIVIDUAL LEVEL ENGAGEMENTS ON YOUTUBE & GOOGLE SEARCH ENGINE

Anis Zaman  
Department of Computer Science  
University of Rochester  
Rochester, NY 14627  
azaman2@cs.rochester.edu

Boyu Zhang  
Department of Computer Science  
University of Rochester  
Rochester, NY 14627  
bzhang25@u.rochester.edu

Vincent M. Silenzio  
Department of Urban-Global Public Health  
Rutgers University  
Jersey City, NJ 07302  
vincen.t.silenzio@rutgers.edu

Ehsan Hoque  
Department of Computer Science  
University of Rochester  
Rochester, NY 14627  
mehoque@cs.rochester.edu

Henry Kautz  
Department of Computer Science  
University of Rochester  
Rochester, NY 14627  
kautz@cs.rochester.edu

July 2, 2020

ABSTRACT

Anxiety disorder is one of the most prevalent mental health conditions, arising from complex interactions of biological and environmental factors and severely interfering one’s ability to lead normal life activities. Current methods for detecting anxiety heavily rely on in-person interviews. Yet, such mental health assessments and surveys can be expensive, time consuming, and blocked by social stigmas. In this work, we propose an alternative way to identify individuals with anxiety and further estimate their levels of anxiety using private online activities histories from YouTube and Google search engine, platforms that are used by millions of people daily. We ran a longitudinal study and collected multiple rounds of anonymized YouTube and Google search log data from volunteering participants, along with their clinically validated ground-truth anxiety assessment scores. We then engineered explainable features that capture both the temporal and semantic aspects of online behaviors. We managed to train models that not only identify individuals having anxiety disorder but also can predict the level of anxiety comparable to the gold standard Generalized Anxiety Disorder 7-item scores with a mean square error of 1.87 based on the ubiquitous individual-level online engagements.

Keywords  First keyword · Second keyword · More

1 Introduction

According to the World Health Organization (WHO), 1 in 13 people suffers from anxiety globally, making it one of the most prevalent mental health concerns. In the United States, it is the second leading cause of disability among all psychiatric disorders [1]. Nearly 40 million people (age 18 and older) experienced an anxiety disorder in any given
year, yet only 35.9% of those suffering received treatments\[ 7\]. A study in 2017 reported that the level of anxiety among young adolescents has been gradually increasing in recent years \[ 2\].

In particular, the population most vulnerable to anxiety disorder is the students in high school and early college years. A report by the American College Health Association in 2018 stated that 63% of college students in the US felt overwhelming anxiety during the last 12 months, and only 23% of these students were either diagnosed or treated for an anxiety disorder by a professional mental healthcare provider \[ 3\]. During the early days of college, students are separated from their traditional support system and find themselves in challenging social and academic settings such as living with roommates, developing independent identities, making new friends, managing heavy workloads, etc. All these experiences induce spikes in anxiety from time to time \[ 4\], and this psychological distress increases during the first few semesters of college \[ 5\]. Furthermore, it has been reported that anxiety disorders are significantly associated with other medical and psychiatric comorbidities \[ 6\] and can eventually cause a great financial burden on the society, an expenditure estimated to exceed 42 to 47 billion dollars \[ 1\]. Despite such a high prevalence of anxiety in young adolescents, current methods for detecting anxiety disorders consist of self-assessment surveys and in-person interviews, which can be time-consuming, expensive, lack precision, and hampered by factors such as fear, concealing information, and social stigma related with the mental health issue.

Engagements in online platforms are major components in the lives of young adults \[ 7\]. On average, an internet user spent the equivalent of more than 100 days online during the last 12 months \[ 8\]. It has been reported that 81% of U.S internet users aging between 15 to 25 use YouTube \[ 1\] frequently. Besides, an average internet user uses Google search at least once a day, and many search dozens of times a day \[ 9\]. Extensive studies have been done trying to correlate mental health issues with popular public social media data such as Facebook and Twitter, yet they may fail to cover people who interact infrequently with social media or post false positive impressions publicly \[ 10\]. In contrast, individual level search and YouTube logs are ubiquitous and private for each user and is less likely to be subject to self-censorship. A group of researchers has shown that search logs can be used as a proxy for detecting both population \[ 11\] \[ 12\] and individual level \[ 13\] mental health issues. We draw inspirations from prior works and hypothesize that private Google search engine logs and YouTube histories can leave a detailed digital trace of the mental health states of users and be used as a proxy to assess the level of anxiety for individuals.

In this work, we propose a framework that leverages individual level online activities logs, in particular, Google search and YouTube activity histories, to identify individuals with an anxiety disorder and further predict their level of anxiety. We ran a longitudinal study to gather two rounds of data, with 5 months in-between, from a college population. During each round, participants shared their anonymized online histories along with their answers to a clinically validated questionnaire for measuring Generalized Anxiety Disorder (GAD-7) \[ 14\]. We then engineered an explainable low-dimensional vector representation that captures different aspects of one’s online activities. Using these feature representations, we are able to accurately detect and predict the level of anxiety from online activities with simple models. Unlike \[ 13\] who focused on detecting mental health issue such as self-esteem from Google search histories, our data incorporates both Google search as well as YouTube activities history and our two rounds of data facilitate both the detection and prediction task. Furthermore, we conduct our experiment with a setup that fits possible real-world applications. We envision our work as an important step towards helping caregivers better understand and engage with their patients without additional burden through ubiquitous computing methods.

In summary, this work is unique in that (i) we are the first to run a longitudinal study where individual level Google search and YouTube histories along with gold-standard clinically validated anxiety assessment are gathered; (ii) we present explainable features that capture various aspects of online activities (temporal, semantic, etc.); (iii) using these features, we managed both detect and predict the anxiety level of a given individual with high performances, showing that ubiquitous private online logs contains strong signals that can potentially be a proxy to assess mental health issues; (iv) our pioneered two rounds of data and light-weight experiment setup has a strong societal implication and can empower care providers to estimate the anxiety levels of patients remotely without having to visit the clinic.

### 2 Related Work

Public social media, blogs, and forums have become one of the most popular data sources employed by researchers to study the prevalence of mental health conditions. For instance, \[ 15\] showed that the usage of social media sites correlates with user depression and anxiety. Tweets, one of the most explored social media platform, has been used to detect depressed individuals \[ 16\] and identify language related to depression and PTSD \[ 17\] \[ 18\] \[ 19\] \[ 20\] \[ 21\]. In 2015, Tsugawa et al. showed that Twitter activities contained signals for assessing the extent of depression \[ 22\]. Other researchers have shown that Tweets contain significant signals for other mental health concerns such as insomnia \[ 23\].

\[ \text{https://www.statista.com/statistics/296227/us-youtube-reach-age-gender/} \]

---

\[ \text{https://adaa.org/understanding-anxiety} \]
suicidal ideations [24], etc. Besides Twitter, [25] have shown that Facebook status can be used to predict postpartum depression. Schwartz et al. demonstrated that Facebook usage can be used to estimate continuous depression scores [26]. Other researchers have leveraged data from Reddit to study mental distress among adolescents [27]. [24] identified shifts in language may indicate future suicidal ideations. De Choudhury provides a comprehensive overview of the role of social media in mental health researches [28] and evaluation methodologies [29]. Social media users constitutes only a fraction of the general population, and a small number of them, with particular personalities or demographics, typically acts out in social media that may reveal signs of mental health struggles. Hence, findings based on social media platforms may not generalize to the majority of the population.

A large body of work on mental health leverages mobile phone sensors [30, 31, 32]. For example, depressions [33, 34, 35, 36], anxiety [37, 38, 39], moods [40, 41, 42], stress [43, 44], schizophrenia [45, 46], etc are just to name a few. Many have proposed mobile apps for helping users manage stress and anxiety [47, 48, 49, 50] and evoking positive emotions [51, 52]. [53, 54] provides an extensive overview on the usage of mobile applications in psychotherapy and effective delivery methods for tackling mental health related phenomena through smartphones. Smartphone applications for tackling mental health issues have several limitations: (i) not every mental health patient have access to smartphones; (ii) any interventions delivered via apps is less likely to be as effective as face-to-face sessions with a therapists [55]; (iii) the app may fail and require developers to constantly keep it updated, which is costly and not sustainable.

An alternate data source that can capture in-the-moment thoughts/feelings of a broad range of people is probably search engine logs which can help fill in the gap for continuous monitoring applications [56]. Researchers have used population level search engine logs via the Google Trends platform to monitor depression and suicide related behaviors [57, 58, 59, 60], demonstrate the effects of geographic location on depression [61], identify seasonality in seeking mental health information [62], show heavy usage for detecting diseases [63] such as screening pancreatic cancer [64] etc. A comprehensive review of usage of Google Trends in the healthcare domain has been provided by Nuti et al. [65]. Unlike population level online engagement logs in Google Trends, individual level activity history from Google Takeout, the data we leveraged in this study, is more likely to fit the fabric of one’s daily life experiences.

3 Data

The longitudinal data collected for this work consisted of individual level Google search logs, YouTube history, and clinical survey responses that are very personal and sensitive in nature. Similar to Zaman et al., we leveraged a cloud based data collection process using Google Takeout[13], a web interface that enables user of Google products to export their Google search and YouTube activity history [13]. Our cloud based data collection pipeline, see Figure 1 has been thoroughly reviewed by the Institutional Review Board (IRB) of our institution.

3.1 Study Recruitment Procedure

Participation was voluntary and one needed to be at least 18 years and have a Google account to qualify for the study. The study spanned 5 months from August, 2019. The recruitment procedure was designed as an one-on-one interview. During the recruitment, participants answered a series of questions that capture incidences of anxiety and recent stressful life events in addition to their GPA, gender, demographics, and the level of social/academic engagements on campus.

[13] http://takeout.google.com/or
A PREPRINT - JULY 2, 2020

Following that, participants signed in to Google Takeout using their Google account and initiated the Google search and YouTube activity history data download process. Before the data was shared with the research team, all sensitive information such as name, email, phone number, physical/internet protocol (IP)/media access control (MAC) address, social security, financial information (banking and credit card) etc was redacted and anonymized using Google’s Data Loss Prevention (DLP) API [66, 67, 68].

In total, we collected two rounds of data. The recruitment procedure mentioned above was performed twice during both the rounds. In August, 2019, 104 college students (all > 18 years old and used Google services in English) participated in the first round. For the rest of the paper, we will refer this round of data as the *first-round* data.

Five months later, we followed up with 72 individuals and collected their Google and YouTube activity history again, along with the survey responses for the second time. For the rest of the paper, we will refer to data collected in the second round as the *follow-up* data. Therefore, there are in total 72 people participated in both rounds and 104 – 72 = 32 people participated only in the *first-round*. The overall recruitment timeline and participant statistics are shown in Figure 2. All participants were compensated with $10 Amazon gift cards at the beginning during each round of participation. About 34% of our participants are male and 68% female. Table 1 presents a comprehensive breakdown of the demographics and anxiety labels of the study population.

---

**Table 1**: Study population breakdown: (a) Gender and Race of the participants. (b) Distribution of subjects with/without anxiety during the first and the follow-up rounds, computed based on the survey response via the GAD-7 questionnaire.

| Gender | Race | Mean Age | # participants | # anxious individuals | # not anxious individuals | Total |
|-------|------|----------|----------------|-----------------------|----------------------------|-------|
| Male  | White| 20.99    | 36 (34.6%)     | 60                    | 44                        | 104   |
| Female| Black/African American | 46 (44.2%) | 46 | 40 | 32 | 72  |
| Female| Other | 46 (44.2%) | 12 (11.6%) | 40 | 32 | 72  |

Figure 2: Timeline and participants for two rounds of data collection. There are in total 104 unique individuals participated in the study, and 72 of them participated in both the *first-round* and the *follow-up*. 
3.2 Ground Truth via Survey

The ground truth about one’s anxiety disorder was measured using the Generalized Anxiety Disorder (GAD-7) \cite{14}, a clinically validated questionnaire (7 questions) which has been reported to be quite accurate in accessing the severity of anxiety \cite{69}. The questions in GAD-7 were prefixed with a text for the temporal context, for example, *Over the last six months, how often have you been bothered by the following problems?*. The responses were compiled to compute an anxiety score. The 21 points scale GAD-7 is a commonly used in clinical diagnosis where score of 5, 10, and 15 are treated as cut-off for mild, moderate and severe anxiety levels, respectively. Further followup and evaluation are recommended for someone with anxiety score greater than 9 \cite{70}, and we use the recommended score of 9 as a cut-off to label individuals with anxiety disorder. For the rest of the paper, any individual with GAD-7 score > 9 is labelled as *Anxious* and someone with score ≤ 9 is labelled as *Not-anxious*. Figure 3 shows the distribution and changes of anxiety scores for all the participants who participated in both the first-round and the follow-up. We observed that the anxiety score increased for 22 individuals, decreased for 32 people, and remain unchanged for 18 participants, shown in Figure 3. It is worth noticing that, only 9 participants had a change in GAD-9 score which was clinically meaningful (the absolute value of the change ≥ 5) during the 5 months of study.

3.3 YouTube & Google search History

For this study, we collect individual level online engagement logs from YouTube and Google search engine using the Google Takeout interface. Google ties all online activities using the Gmail address associated to the person. The Takeout platform aggregates user engagement logs from all different sources and make it available for easy accessibility. This means that as long as someone is logged into his/her/their Google account in mobile phone, personal laptop, and iPad, all engagements from these sources are aggregated under a unified email of that person. For every person, the online activity history spanned (on average) over 5.7 years. In total there were 1,966,400 Google searches and 1,055,847 YouTube interactions were made by all the participants.

Every engagement on YouTube and Google search engine is timestamped along with the information whether it is the result of watching or searching (the raw search query). For YouTube activity logs, we use the YouTube API to extract meta-data about the videos that has been watched, which includes the title, category of the video, video length, rating, number of likes, number of dislikes, etc. Any video living in the YouTube ecosystem has an associated category

\footnote{https://www.mdcalc.com/gad-7-general-anxiety-disorder-7}
Figure 4: Example online activities distribution from a participant over a week, including both Google search and YouTube activities. Each row is a day, and each '|' bar represents a single online activity. The bars on the right side show the daily total online activities for each day. It is worth noticing the burstiness of daily online activities.

label to it, and this enables us to get more context about the video. For Google search activities, we label every search query using the content classification feature of the Google Cloud NLP API\footnote{https://cloud.google.com/natural-language/docs/classifying-text}. Given a query, the API returns one or more possible category labels for the text along with a confidence score. When applicable, we select the category label with the highest confidence. The API returns a hierarchical label for every query, and we consider the root level in the hierarchy as the category label for the query. For instance, for a query $q$, if the label from the API is "/News/Sports", we consider “News” as the category for $q$. The comprehensive list of all the categories for both search queries and videos are listed here [71][72].

3.3.1 Justification for Using YouTube and Google NLP API:

We used YouTube and Google NLP API for labeling the queries and the videos because we wanted to maintain a unified set of topics that could be applied to consistently label and compare online activities from all individuals. For instance, consider two searches, ‘how to best marinade beef’ and ‘homemade tender BBQ tips’, both the Google NLP and YouTube API will classify them as Food whereas data-driven topic modeling may put these in two different clusters.

4 Online Data Feature Extraction

In this section, we explain how we extracted explainable features from online history logs for each individual. Individual level online engagement logs from YouTube and Google search engine provides an unique opportunity to capture what may be going through one’s mind at any given time. Since online activities are timestamped, one can investigate attributes such as weekday/weekend activity frequency & variance, calculate the contextual and temporal variability of these activities, and estimate daily sleeping/resting duration etc. For example, Figure 4 demonstrates the distribution of activities on YouTube and Google search engine over a week for a specific individual in our dataset. We observe the bursty nature of incidences of these activities which we will leverage to construct features later in the section. On aggregating daily activities we found that there are higher number of interactions on these two platforms at the beginning of the week, and, as the week progresses, the number decreases. One possible explanation for drops in activities during weekends can be that people are probably spending less time interacting on internet and more time relaxing, socializing, and connecting with people around them. Notice that each of the following feature is a scalar and is calculated for each individual participant. In total we have explored five types of features, and each of them as a number of variants, see Section 4.1 to 4.5.

4.1 Activity Mean and Variance

We define the activity mean and variance to measure the overall distribution of an individual’s online interactions on YouTube and Google search engine. We calculate the daily and weekly mean and variance of number of activities on YouTube and Google search for each participant separately, and take the normalized $\log$ of the mean and variance for numerical stability.

4.2 Category Entropy $C_H$

We define category entropy as a measure of how diverse an individual’s online activities are in terms of the categories. This has been motivated by the concept of entropy ($H$) from information theory $[73]$. For an individual $p$, based on
his/her/their online data, we compute category entropy in the following way:

$$H_p(\text{Category}) = - \sum_{i=1}^{m} P_i \times \log(P_i)$$

where 16 = total number of distinct categories in p’s online activities, and $P_i$ is the percentage of activities that belong to category $i$. A high entropy indicates that $p$ interacts more uniformly across different categories online, whereas lower entropy indicates larger inequality in the number of online activities across the categories. Considering that individuals may have different habits during weekdays and weekends, we also calculated the category entropy for weekdays and weekends separately. We include the total, weekday, and weekend category entropy as features for each individual. We denote them as $C^\text{weekday}_H$, $C^\text{weekend}_H$, and $C^\text{total}_H$.

### 4.3 Time Entropy $T_H$

Similar as above, we define time entropy as a measure of how diverse an individual’s online activities are in terms of the when it happen. We define the discrete bins for time entropy as the 24 hours of a day. For an individual, $p$, based on his/her/their online data, we computed time entropy in the following way:

$$H_p(\text{Time}) = - \sum_{i=1}^{24} P_i \times \log(P_i)$$

where $m \in \{0, ..., 23\}$ is the set of 24 hour marks, and $P_i$ is the percentage of activities that happen during hour $i$. A high entropy indicates that $p$ interacts with YouTube and Google search engine more uniformly across different times of a day, whereas lower entropy indicates larger inequalities of numbers of online activities between different hours in a day. Similar to Category Entropy, we obtain the time entropy for weekdays and weekends separately. We denote them as $T^\text{weekday}_H$, $T^\text{weekend}_H$, and $T^\text{total}_H$.

### 4.4 Online Activities Temporality $\{\gamma, \alpha, \beta\}$

We observed that there is a bursty nature of online activities when plotted on the time axis, see Figure 4, which resulted in clusters of online activities regardless of Google searches or YouTube histories. In other words, we can view the incidences of online activities as a Temporal Point Process and investigate individual-level online behaviors from a temporal point of view, such as the Interevent Times (IETs). Inspired by [13], instead of considering the online history as a homogeneous Poisson process, we enrich our temporal feature by assuming dependencies between past activities and the next activity. We envision that every occurrence of an online activity increases the probability of future online activities, and the probability of the next activity decays with time. Hence, such process, called a self-exciting point process, can be modeled by the Hawkes Process [74], and it has been widely used for modeling online data and social media activities at a population level [75]. Specifically, we define a univariate Hawkes Process with an exponential decay kernel as

$$\lambda(t) = \gamma + \sum_{t_i < t} \alpha \beta \exp(-\beta(t - t_i))$$

where $\lambda(t)$ represents the probability (intensity) of an activity occurs at time $t$, $\gamma$ is the background intensity of an activity happens exogenously, $\alpha$ represents the infectivity factor which controls the average number of new activities triggered by any past activity, and $\beta$ is the decay rate where $\frac{1}{\beta}$ represents how much time has passed by, on average, between the previous event and the next event. By fitting the above Hawkes Process to each individual online history log, we obtain a unique set of $\{\gamma, \alpha, \beta\}$ for each participant as features. We keep the notations as $\{\gamma, \alpha, \beta\}$ for this set of features.

### 4.5 Inactivity Period $I$

It has been reported that YouTube is becoming the modern day classroom for students [76] and provides new ways to consume contents for virtually every age groups [77]. However, spending too much time on any platform can lead to internet addiction [78], in particular the YouTube addiction [79] and the compulsive usage of YouTube [80], which are quite prevalent among college population. These previous findings have inspired us consider feature that can be treated as a proxy to capture the time away from internet of each participant, and we call it the inactivity period $I$.

We focus on periods of time when no Google search or YouTube activity was performed of each individual. Given the online activity log of a participant and a duration threshold of $k$ hours, we pick out all the inactive periods with duration longer than $k$ hours and investigate when did they happen mostly. Specifically, for all inactivity periods longer
than \( k \) hours, we calculate the midpoint timestamp of each period and obtain the median and mode of the midpoints. For example, for an 8-hour inactivity period starting at 11 P.M. and ending at 7 A.M., the midpoint time stamp is 3 A.M. We found that, for all our participants and \( k \in \{8, 9, 10\} \), both the medians and modes fall in-between 5 to 7 A.M., which are most likely to be the middle of sleeping periods. Notice that for the inactivity defined here, we are looking for when it occurs most frequently for each individual, and hence it may not be suitable to take the mean and variance of inactivity midpoints. As the medians and modes lay close to each other in our case, we included the modes of midpoints for thresholds \( k \in \{8, 9, 10\} \) for each individual as features. We denote, for threshold \( k \in \{8, 9, 10\} \), the inactivity mode features as \( Z_8, Z_9, \) and \( Z_{10} \).

Overall, we achieved 16 features (including variants) form the online activities (YouTube and Google search engine) of each individual: 2 from Activity Mean & Variance; 3 from each of the Category Entropy \( C_I \), Time Entropy \( T_I \), Online Activities Temporality \( \gamma, \alpha, \beta \), and Inactivity Periods \( I \).

5 Modeling Anxiety

For this study, we recruited 104 individuals in the first-round in 2019 and followed up with 72 individuals after 5 months, see Figure 2. Following the clinical anxiety score cutoff threshold \( [14] \), participants with GAD-7 score \( \geq 10 \) were labelled as anxious subjects and individuals with score \( \leq 9 \) were labelled as non-anxious subjects. Overall, there were 60 out of 104 subjects with anxiety conditions in the first-round and 40 out of 72 participants with anxiety conditions during the follow-up. Given one’s YouTube and Google search activity history, we explore: (i) can we identify individuals with anxiety condition through his/her/their online data? (ii) can we predict anxiety score based on online activities and past anxiety levels?

5.1 Notations and Definitions

First, we introduce the notations for the rest of the paper. The feature vectors for the first-round are extracted using the top 12 months of data (the grey box in Figure 2) before the completion of the first-round survey. We denote this by \( x_1 \in \mathbb{R}^{16} \). Unless mentioned specifically, \( x_1 \) is the concatenation of all 16 scalar features in Section 4 in the same order for each individual. The corresponding GAD-7 scores, gathered via the survey (the green box in Figure 2) during the first-round, are denoted as \( y_1 \). Similarly, for the follow-up round, the feature vectors are extracted solely from the 5 months of online history data (the blue box in Figure 2) in-between the first-round and the follow-up, and we denote it as \( x_2 \in \mathbb{R}^{16} \). The corresponding GAD-7 scores, provided in the follow-up survey, (the magenta box in Figure 2), are denoted as \( y_2 \). Therefore, there are in total 104 \((x_1, y_1)\) pairs from first-round and 72 \((x_2, y_2)\) pairs from follow-up (see Figure 2 & Section 5.1).

5.2 Classifying Individuals with Anxiety

Here, we treat the problem as a binary classification task: given the online activity history, we aim to identify if the subject has anxiety condition. Assuming online activity histories are independent for every person, we consider 104 + 72 = 176 segments \((x_1 \text{ and } x_2)\) of online history in total, regardless of which round or from whom they are collected, as observation data with respective anxiety scores as labels. Formally, we are interested in \( P(y \mid x) \), where \( y \) is the binary anxiety label we cull from the GAD-7 scores.

We trained logistic regression (LR), linear support vector machine (SVM), and random forest (RF) classifiers on this task and performed stratified 5-fold cross-validations, respectively. Since the performances of LR and linear SVM were comparable, we report the performance of LR. However, RF significantly outperformed the other two with an average F1 score of 0.83 \( \pm \) 0.09 and ROC AUC of 0.91 \( \pm \) 0.06. The detailed precision, recall, and F1 scores for each class/average are reported in Figure 2. In Figure 5 we present the average ROC curve with standard deviations of the RF.

5.2.1 Data Dependency between Two Rounds

As mentioned in Section 5.1 and Figure 2, 72 participants are involved in both the first-round and the follow-up. For these 72 people and their \( 2 \times 72 = 144 \) segments of online data from two rounds of collection, the dependency between the data coming from the same person may not be negligible. It is possible that, for the same participant, neither the online behavior nor the anxiety level changes significantly, i.e., \( x_1 \approx x_2 \) and \( y_1 \approx y_2 \) for the same subject. Therefore, in order to make sure that the supervised model does not leverage such dependency trick to perform well, we manually make sure that, for these 72 participants, all their 144 segments of data belongs to the training set, and the test set is composed of single-time participants only. The stratified random data splits are then performed on single-time participants, taking into account the class label distribution already existed in the 144 subjects.
Figure 5: ROC curves for Random Forests to classify individuals with anxiety. We carried out a stratified 5-fold cross-validation. The grey area represents ±1 standard deviation.

| 5-fold cross-validation | Not-anxious | Anxious | Avg.     |
|-------------------------|-------------|---------|----------|
| Precision               | <0.81 ± 0.12> (0.68 ± 0.12) | <0.86 ± 0.07> (0.74 ± 0.05) | <0.84 ± 0.10> (0.71 ± 0.09) |
| Recall                  | <0.80 ± 0.11> (0.59 ± 0.14) | <0.87 ± 0.09> (0.79 ± 0.11) | <0.84 ± 0.10> (0.69 ± 0.13) |
| F1 score                | <0.80 ± 0.10> (0.62 ± 0.10) | <0.86 ± 0.07> (0.76 ± 0.06) | <0.83 ± 0.09> (0.69 ± 0.08) |

Figure 6: The metrics of RF and LR on the anxiety classification task. We carried out a stratified 5-fold cross-validation. The values after the ± sign represent the standard deviations. Numbers inside () represents LR and <> represents RF.

5.3 Predicting Anxiety for Individuals

In this section, we consider the anxiety score prediction task: **we aim to estimate the exact GAD-7 score for an individual.** Concretely, given the two rounds of data, we aim to predict the GAD-7 score in the follow-up round given the entire individual online history data and the GAD-7 score from the first-round. Formally, this task is regarded as a regression problem, and we are interested in \( P(y_2 | x_1, x_2, y_1) \).

**Features for the regression task:** for predicting anxiety scores \( y_2 \) in the above setup, we only consider the weekday/weekend Time & Category entropy \( \{C_{\text{weekday}}, C_{\text{weekend}}, T_{\text{weekday}}, T_{\text{weekend}}\} \), the Temporality parameters \( \{\gamma, \alpha, \beta\} \), and the Inactivity Periods with thresholds of 9 and 10 hours \( \{I_9, I_{10}\} \) as input features. Thus, for the rest of the section, \( x_1, x_2 \in \mathbb{R}^9 \) for all individuals.

We hypothesize that the change in online behaviors may preserve information about the change in one’s anxiety level, and in order to leverage this in the anxiety prediction task, we define the following processed feature vectors for the
regression models:

\[
\Delta x = x_1 - x_2 \in \mathbb{R}^9
\]
\[
x_{gp} = [\eta \odot x_2, (1 - \eta) \odot \Delta x] \in \mathbb{R}^{2 \times 9}
\]
\[
x_{reg} = [\eta \odot x_2, (1 - \eta) \odot \Delta x, y_1] \in \mathbb{R}^{2 \times 9 + 1}
\]

where the square bracket indicates concatenation, \( \eta \in [0, 1] \) is a hyperparameter, and \( \odot \) denotes an element-wise multiplication. \( x_{gp} \) is a trivial modification of \( x_{reg} \) by slicing out the last entry \( y_1 \) and keeping only the online data features.

We chose \( \eta = 0.9 \) and fed the \( x_{reg} \) as inputs. We first performed this task with two most common regression models: Ordinary Least Squares regression (OLS) and Gradient Boosting regression (GB). The GB outperformed OLS significantly. It achieved an average mean square error (MSE) of 2.29 \( \pm \) 0.25 and coefficient of determination (\( R^2 \)) of 0.81 \( \pm \) 0.06 in the GAD-7 anxiety scores predicted, see Table 2.

Instead of merely looking for the best prediction given by maximum likelihood estimations, it is crucial to access the uncertainty over the model and take a Bayesian perspective, especially given we are working with healthcare applications with limited sample size. Moreover, it would grant much flexibility if the regression is not limited to parametric linear form but in a functional space with non-linearity, investigating the distribution of functions. Therefore, we performed the regression task with a non-parametric Bayesian method, the Gaussian Process (GP) \[81\]. We define our regression function as \( f(x_{reg}) \), and it follows the GP below:

\[
f(x_{reg}) \sim GP(m(x_{reg}), k(x_{reg}, x'_{reg}))
\]
\[
m(x_{reg}) = y_1
\]
\[
k(x_{reg}, x'_{reg}) = \exp\left(-\frac{\|x_{gp} - x'_{gp}\|^2}{2\ell}\right)
\]
\[
y_2 = f(x_{reg}) + \epsilon \text{ where } \epsilon \sim N(0, \sigma)
\]

where the mean function \( m(x_{reg}) \) is a deterministic function that returns the corresponding previous anxiety score \( y_1 \) for each data point. The covariance matrix is obtained by an exponential quadratic kernel \( \ell \) over all pairs of pure individual online data, \( (x_{gp}, x'_{gp}) \). It entails that, given any pair of individuals, the closer the distance between their online features in the vector space, the greater the correlation between their anxiety scores \( y_2 \) (close to 1), and vice versa (close to 0). \( \ell \) is a hyperparameter that controls the length scale between data points: the greater the \( \ell \), the smoother the function. We further assume that the true \( y_2 \) equals to the function prediction plus an independent unknown Gaussian noise \( \epsilon \), and \( \sigma \) is the hyperparameter for the noise distribution. The above GP gave us a prior belief over the possible regression functions. The intuition is that, in the output space of our function \( f(x_{reg}) \), the future GAD-7 anxiety scores, \( y_2 \), are normally distributed with a mean of the previous anxiety scores, \( y_1 \), and the correlations between different \( y_2 \) values are determined by the similarities between online activities \( x_{gp} \) from the input space.

In order to assess the performance of our GP over the held-out test set, we first obtained the predictive posterior:

\[
P(f(x_{test}) \mid f(x_{train}^{\text{reg}}), x_{train}^{\text{reg}}, x_{test}^{\text{reg}})
\]

over all the regression functions conditioned on (after observing) the training set. This conditioning operation is in a sense that, after generating functions from the GP prior, we filter out those that violate the training examples. It has an efficient closed form solution given in \[81\], Chapter 2.2. After that, we sampled 100 functions (traces) from the posterior from Equation 11 and used them to make predictions on the test set. We report the average MSE and \( R^2 \) of the 100 functions, and such process is repeated for each fold of the cross-validation. We finally report the average performance over the 5 folds in Table 2. Our GP achieved an average MSE of 1.87 \( \pm \) 0.14 and \( R^2 \) of 0.88 \( \pm \) 0.05 in the GAD-7 anxiety scores predicted.

Table 2 summarizes the average performances and standard deviations of the above models in the stratified 5-fold cross-validation. Furthermore, as mentioned in Section 5.2, only 9 subjects had changes in GAD-7 anxiety scores (\( \geq 5 \)) that is clinically alarming. Thus, we conducted another 5-fold cross-validation but kept all these 9 subjects in the test set. We observed a good flexibility of \( x_{reg} \) in capturing such significant changes in GAD-7 since the performances are comparable to the average scores for all models, see Table 2, the bottom sub-table.

6 Discussion

It has been reported that, every year, approximately 60% of all people with mental health conditions receive no treatment [56]. The inability to identify patients in need of care and deliver treatments on-time are major failure points in the
Inferring mental health conditions such as anxiety from online behavior is challenging. The Curse of Variability: variability in assessing one’s level of anxiety. For example, some individuals may choose not to use any online platforms and research on the web, which may result in a false positive image. Furthermore, one may not be near a computer due to the wide array of subjective and external factors, such as seasonality, environment, etc., which add questionable variability to the image. To the best of our knowledge, we are the first to study and demonstrate that it is feasible to identify whether one is experiencing anxiety and estimate his/her/their exact anxiety score using individual level YouTube and Google search engine history logs. Finally, because of the longitudinal study design, we had access to ground truth anxiety score at multiple time points and were able to compare our model performances with gold standard clinical metrics.

Integration into Existing Healthcare Systems: the anxiety assessment framework presented in this paper can be initially set up in clinical endpoints such as behavioral clinics. Therapists involved with patients suffering from various mental health conditions can use the output of the model as additional information about their patients. The predicted anxiety assessments can be leveraged to connect patients with the right counselor/expert. For example, some patients may come to the clinic for a drug addiction problem and, following their informed consents, the counselor runs our model which outputs that the patient may have been experiencing severe anxiety during the last 4 week. In this case, our anxiety classification setup from Section 5.3 may be applicable. The patient may be flagged for review by designated members of the caregiver team who are specifically trained to handle patients with anxiety as well as addiction problems.

Furthermore, our anxiety estimation setup from Section 5.3 can be used as a guideline to initiate specific treatment steps. Most importantly, counselors can use the model on a weekly basis to monitor anxiety levels of their patients remotely (based on their online engagements) in-between sessions/follow-up visits. This enables caregivers to note abnormal spikes in the estimated level of anxiety comparing to the last visit. Healthcare providers can then either schedule an immediate follow-up or use this information when engaging with the patient to uncover stressors and other issues that may otherwise go unmentioned during the next appointment. For example, a therapist could bring up the online behaviors of the patient during the past weekend, which were associated with high stress and anxiety symptoms, and ask if the patient agreed with the assessment and, if so, what was happening in his/her/their lives at that time. Besides, such anxiety estimation setup is not one-shot fixed: it can and should be compared with professional clinical measures, as more patients came in, to help improve the future performance of the model.

Table 2: The performances of OLS, GB, and GP on the anxiety prediction task. We carried out a standard stratified 5-fold cross-validation first. We then conducted another 5-fold cross-validation but kept all the subjects with significant changes in GAD-7 anxiety scores in the test set. The values after the ± sign represent the standard deviations.

| Model   | MSE      | $R^2$    |
|---------|----------|----------|
| OLS     | 9.13 ± 3.65 | 0.47 ± 0.25 |
| GB      | 2.29 ± 0.25  | 0.81 ± 0.06  |
| GP      | 1.87 ± 0.14  | 0.88 ± 0.05  |

| Model   | MSE      | $R^2$    |
|---------|----------|----------|
| OLS     | 9.27 ± 3.48 | 0.39 ± 0.28 |
| GB      | 2.27 ± 0.23  | 0.79 ± 0.09  |
| GP      | 1.86 ± 0.15  | 0.87 ± 0.07  |

The Curse of Variability: Inferring mental health conditions such as anxiety from online behavior is challenging due to the wide array of subjective and external factors, such as seasonality, environment, etc., that add questionable variability in assessing one’s level of anxiety. For example, some individuals may choose not to use any online platforms while experiencing anxiety. Someone may be very concerned about his/her/their significant other’s anxiety disorder and research on the web, which may result in a false positive image. Furthermore, one may not be near a computer...
or mobile device when he/she/they are experiencing anxiety, and hence a framework such as ours may miss out on capturing signals that may be associated with anxiety. Besides, how people conduct searches on YouTube and Google search engine is subjected to change over time. One possible way to address such high variability is to incorporate longitudinal studies on large populations. However, such studies require time and can be expensive.

**The Prevalence of Uncertainty:** We acknowledge that any mental health sensing system, such as our anxiety assessment framework, even under the most ideal circumstances, will likely have some degree of error and uncertainty. The trade-off between accuracy and uncertainty should be considered prior to designing a mental health sensing system. Lim et al. and Kay et al. have explored questions around how much uncertainty is acceptable, how much accuracy is sufficient, and how to best mitigate the uncertainty [83][84]. There are open questions such as the cost of misclassification, how derived models around mental health indicators can be integrated in the current system need more attentions. A clear guideline needs to be set through discussions among therapists, clinicians, and computer scientists

**Privacy & Ethical Considerations:** Building an anxiety monitoring system using individual-level YouTube and Google search engine activity logs presents a series of concerns around privacy and personal safety. Due to the sensitive nature of the data collected in this study, it is important that significant appropriate human subject protection protocols are in place. Hence our study protocol has been rigorously reviewed and approved by the Institutional Review Board of our institution to address these concerns. Despite these measures, we acknowledge that ethical challenges will arise if and when applications based on our methods are deployed in the real world.

When someone uses platforms such as YouTube and Google search engine, he/she/they never intend the personal data to be used by mental health assessment systems. Hence, some individuals may choose not to share their sensitive data and refuse to participate. It is important to ensure that participants, at all times, have the choice and control over their data and can choose to exclude themselves from such studies at will. Participants need to be explicitly informed about how their online engagement logs will be de-identified and analyzed, what type of information it may reveal about the user, and the accrued benefits to the patients and the therapists/care providers from mental health clinics. To address these concerns, we employed an opt-in model for volunteering study participation. In addition, we conducted one-on-one interviews for each participant during the recruitment procedure so that the research team can (a) take the time to clearly explain the purpose and the outcome of the study and (b) explicitly inform the participants about the existence of such sensitive data and how they reserve full control over the information shared such as limiting data access or deleting data. Yet, one big limitation of employing opt-in model is that it may significantly limit the number of volunteering participants for the study. Besides, the opt-in procedure may introduce participation bias in terms of study recruitment and the awareness of subjects. To limit recruitment bias, we have adapted generic wordings, such as “help us learn about mental health using online data”, in our study advertisements without specifically mentioning anxiety.

Another remaining issue is that whether and when it is ethical to intervene in the life of an individual on the basis of online data signals associated with anxiety, which may not always be accurate. We believe that the ultimate decision regarding intervention must be made by therapists, care providers, and experts who understand both anxiety and the power and limitations of an automated anxiety assessment system.

Finally, we acknowledge that YouTube and Google search history logs are personal and sensitive information, and many may feel reluctant to share such data for assessing anxiety. The strongest push back may come especially from the population who have histories of mental health-related complications such as anxiety, depression, etc. However, organizations such as Ascension, the second-largest health system in the United States, and Google have already begun aggregating individual-level health records with online activities logs to build systems that help patients and healthcare experts [85]. Therefore, it is imperative that strict measures are in place to ensure patient privacy, the possibility and consequence of data breach, preventing harmful entities from misusing such personal information for monetary benefit [86].

**References**

[1] Harvey A Whiteford, Louisa Degenhardt, Jürgen Rehm, Amanda J Baxter, Alize J Ferrari, Holly E Erskine, Fiona J Charlson, Rosana E Norman, Abraham D Flaxman, Nicole Johns, et al. Global burden of disease attributable to mental and substance use disorders: findings from the global burden of disease study 2010. *The lancet*, 382(9904):1575–1586, 2013.

[2] Susanna Calling, Patrik Midlöv, Sven-Erik Johansson, Kristina Sundquist, and Jan Sundquist. Longitudinal trends in self-reported anxiety. effects of age and birth cohort during 25 years. *BMC psychiatry*, 17(1):119, 2017.

[3] American College Health Association. American college health association-national college health assessment ii: Undergraduate student reference group data report fall 2018. *Silver Spring, MD: American College Health Association*, sep 2018.
[4] Christine Purdon, Martin Antony, Sandra Monteiro, and Richard P Swinson. Social anxiety in college students. *Journal of Anxiety Disorders*, 15(3):203–215, 2001.

[5] Colleen S Conley, Jenna B Shapiro, Brynn M Huguenel, and Alexandra C Kirsch. Navigating the college years: Developmental trajectories and gender differences in psychological functioning, cognitive-affective strategies, and social well-being. *Emerging Adulthood*, 8(2):103–117, 2020.

[6] E Jane Costello, Helen L Egger, and Adrian Angold. The developmental epidemiology of anxiety disorders: phenomenology, prevalence, and comorbidity. *Child and Adolescent Psychiatric Clinics*, 14(4):631–648, 2005.

[7] Andreas M Kaplan and Michael Haenlein. Users of the world, unite! The challenges and opportunities of social media. *Business horizons*, 53(1):59–68, 2010.

[8] The Next Web. Digital trends 2020: Every single stat you need to know about the internet. [https://thenextweb.com/podium/2020/01/30/digital-trends-2020-every-single-stat-you-need-to-know-about-the-internet] (2020). Accessed: 2020-02-07.

[9] GlobalStats. Search engine market share worldwide. [https://bit.ly/382vgWD] (2019). Accessed: 09-04-2019.

[10] Oren Gil-Or1, Yossi Levi-Belzm, and Ofir Turel. The “facebook-self”: characteristics and psychological predictors of false self-presentation on facebook. *Frontiers in Psychology*, 6:99, 2015.

[11] Natalia Adler, Ciro Cattuto, Kyriaki Kalimeri, Daniela Paolotti, Michele Tizzoni, Stefaan Verhulst, Elad Yom-Tov, and Andrew Young. How search engine data enhance the understanding of determinants of suicide in india and inform prevention: observational study. *Journal of medical Internet research*, 21(1):e10179, 2019.

[12] Alberto Jimenez, Miguel-Angel Santed-Germán, and Victoria Ramos. Google searches and suicide rates in spain, 2004-2013: correlation study. *JMIR public health and surveillance*, 6(2):e10919, 2020.

[13] Anis Zaman, Rupam Acharyya, Henry Kautz, and Vincent Silenzio. Detecting low self-esteem in youths from web search data. In *The World Wide Web Conference*, pages 2270–2280, 2019.

[14] Robert L Spitzer, Kurt Kroenke, Janet BW Williams, and Bernd Löwe. A brief measure for assessing generalized anxiety disorder: the gad-7. *Archives of internal medicine*, 166(10):1092–1097, 2006.

[15] Elizabeth M Seabrook, Margaret L Kern, and Nikki S Rickard. Social networking sites, depression, and anxiety: a systematic review. *JMIR mental health*, 3(4):e50, 2016.

[16] Munmun De Choudhury, Michael Gamon, Scott Counts, and Eric Horvitz. Predicting depression via social media. In *ICWSM*, page 2, 2013.

[17] Andrew G Reece, Andrew J Reagan, Katharina LM Lix, Peter Sheridan Dodds, Christopher M Danforth, and Ellen J Langer. Forecasting the onset and course of mental illness with twitter data. *Scientific reports*, 7(1):1–11, 2017.

[18] Glen Coppersmith, Mark Dredze, Craig Harman, Kristy Hollingshead, and Margaret Mitchell. Clpsych 2015 shared task: Depression and ptsd on twitter. In *Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*, pages 31–39, 2015.

[19] Philip Resnik, William Armstrong, Leonardo Claudino, Thang Nguyen, Viet-An Nguyen, and Jordan Boyd-Graber. Beyond lda: exploring supervised topic modeling for depression-related language in twitter. In *Proceedings of the 2nd Workshop on Computational Linguistics and Clinical Psychology: From Linguistic Signal to Clinical Reality*, pages 99–107, 2015.

[20] Daniel Preotiuc-Pietro, Johannes Eichstaedt, Gregory Park, Maarten Sap, Laura Smith, Victoria Tobolsky, H Andrew Schwartz, and Lyle Ungar. The role of personality, age, and gender in tweeting about mental illness. In *Proceedings of the 2nd workshop on computational linguistics and clinical psychology: From linguistic signal to clinical reality*, pages 21–30, 2015.

[21] Ted Pedersen. Screening twitter users for depression and ptsd with lexical decision lists. In *Proceedings of the 2nd workshop on computational linguistics and clinical psychology: From linguistic signal to clinical reality*, pages 46–53, 2015.

[22] Sho Tsugawa, Yusuke Kikuchi, Fumio Kishino, Kosuke Nakajima, Yuichi Itoh, and Hiroyuki Ohsaki. Recognizing depression from twitter activity. In *Proceedings of the 33rd annual ACM conference on human factors in computing systems*, pages 3187–3196, 2015.

[23] Sue Jamison-Powell, Conor Linehan, Laura Daley, Andrew Garbett, and Shaun Lawson. I can’t get no sleep: discussing# insomnia on twitter. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1501–1510. ACM, 2012.
[24] Munmun De Choudhury, Emre Kiciman, Mark Dredze, Glen Coppersmith, and Mrinal Kumar. Discovering shifts to suicidal ideation from mental health content in social media. In Proceedings of the 2016 CHI conference on human factors in computing systems, pages 2098–2110. ACM, 2016.

[25] Munmun De Choudhury, Scott Counts, Eric J Horvitz, and Aaron Hoff. Characterizing and predicting postpartum depression from shared facebook data. In Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing, pages 626–638, 2014.

[26] H Andrew Schwartz, Johannes Eichstaedt, Margaret Kern, Gregory Park, Maarten Sap, David Stillwell, Michal Kosinski, and Lyle Ungar. Towards assessing changes in degree of depression through facebook. In Proceedings of the workshop on computational linguistics and clinical psychology: from linguistic signal to clinical reality, pages 118–125, 2014.

[27] Shrey Bagroy, Ponnurangam Kumaraguru, and Munmun De Choudhury. A social media based index of mental well-being in college campuses. In Proceedings of the 2017 CHI Conference on Human factors in Computing Systems, pages 1634–1646, 2017.

[28] Munmun De Choudhury, Scott Counts, and Eric Horvitz. Social media as a measurement tool of depression in populations. In Proceedings of the 5th Annual ACM Web Science Conference, pages 47–56. ACM, 2013.

[29] Stevie Chancellor and Munmun De Choudhury. Methods in predictive techniques for mental health status on social media: a critical review. NPJ digital medicine, 3(1):1–11, 2020.

[30] Min S Hane Aung, Faisal Alquaddoomi, Cheng-Kang Hsieh, Mashfiqui Rabbi, Longqi Yang, John P Pollak, Deborah Estrin, and Tanzeem Choudhury. Leveraging multi-modal sensing for mobile health: a case review in chronic pain. IEEE journal of selected topics in signal processing, 10(5):962–974, 2016.

[31] Nicholas D Lane, Emiliano Miluzzo, Hong Lu, Daniel Peebles, Tanzeem Choudhury, and Andrew T Campbell. A survey of mobile phone sensing. IEEE Communications magazine, 48(9):140–150, 2010.

[32] Rui Wang, Fanglin Chen, Zhenyu Chen, Tianxing Li, Gabriella Harari, Stefanie Tignor, Xia Zhou, Dror Ben-Zeev, and Andrew T Campbell. Studentlife: assessing mental health, academic performance and behavioral trends of college students using smartphones. In Proceedings of the 2014 ACM international joint conference on pervasive and ubiquitous computing, pages 3–14, 2014.

[33] Rui Wang, Weichen Wang, Alex DaSilva, Jeremy F Huckins, William M Kelley, Todd F Heatherton, and Andrew T Campbell. Tracking depression dynamics in college students using mobile phone and wearable sensing. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 2(1):1–26, 2018.

[34] Sohrab Saeb, Mi Zhang, Christopher J Karr, Stephen M Schueller, Marya E Corden, Konrad P Kording, and David C Mohr. Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study. Journal of medical Internet research, 17(7):e175, 2015.

[35] Sohrab Saeb, Emily G Lattie, Stephen M Schueller, Konrad P Kording, and David C Mohr. The relationship between mobile phone location sensor data and depressive symptom severity. PeerJ, 4:e2537, 2016.

[36] Luca Canzian and Mirco Musolesi. Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis. In Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing, pages 1293–1304, 2015.

[37] Jon D Elhai, Jason C Levine, and Brian J Hall. The relationship between anxiety symptom severity and problematic smartphone use: A review of the literature and conceptual frameworks. Journal of Anxiety Disorders, 62:45–52, 2019.

[38] Skyler Place, Danielle Blanch-Hartigan, Channah Rubin, Cristina Gorrostieta, Caroline Mead, John Kane, Brian P Marx, Joshua Feast, Thilo Deckerbach, Andrew Nierenberg, et al. Behavioral indicators on a mobile sensing platform predict clinically validated psychiatric symptoms of mood and anxiety disorders. Journal of medical Internet research, 19(3):e75, 2017.

[39] MILES RICHARDSON, ZAHEER HUSSAIN, and MARK D GRIFFITHS. Problematic smartphone use, nature connectedness, and anxiety. Journal of Behavioral Addictions, 7(1):109–116, 2018.

[40] Robert LiKamWa, Yunxin Liu, Nicholas D Lane, and Lin Zhong. Moodscope: Building a mood sensor from smartphone usage patterns. In Proceeding of the 11th annual international conference on Mobile systems, applications, and services, pages 389–402, 2013.

[41] Hong Lu, Denise Frauendorfer, Mashfiqui Rabbi, Marianne Schmid Mast, Gokul T Chittaranjan, Andrew T Campbell, Daniel Gatica-Perez, and Tanzeem Choudhury. Stresssense: Detecting stress in unconstrained acoustic environments using smartphones. In Proceedings of the 2012 ACM conference on ubiquitous computing, pages 351–360, 2012.
[42] Yuanchao Ma, Bin Xu, Yin Bai, Guodong Sun, and Run Zhu. Daily mood assessment based on mobile phone sensing. In 2012 ninth international conference on wearable and implantable body sensor networks, pages 142–147. IEEE, 2012.

[43] Akane Sano and Rosalind W Picard. Stress recognition using wearable sensors and mobile phones. In 2013 Humaine Association Conference on Affective Computing and Intelligent Interaction, pages 671–676. IEEE, 2013.

[44] Amir Muaremi, Bert Arnrich, and Gerhard Tröster. Towards measuring stress with smartphones and wearable devices during workday and sleep. BioNanoScience, 3(2):172–183, 2013.

[45] Dror Ben-Zeev, Rui Wang, Saeed Abdullah, Rachel Brian, Emily A Scherer, Lisa A Mistler, Marta Hauser, John M Kane, Andrew Campbell, and Tanzeem Choudhury. Mobile behavioral sensing for outpatients and inpatients with schizophrenia. Psychiatric services, 67(5):558–561, 2016.

[46] Dror Ben-Zeev, Christopher J Brenner, Mark Begale, Jennifer Duffecy, David C Mohr, and Kim T Mueser. Feasibility, acceptability, and preliminary efficacy of a smartphone intervention for schizophrenia. Schizophrenia bulletin, 40(6):1244–1253, 2014.

[47] Diana MacLean, Asta Roseway, and Mary Czerwinski. Moodwings: a wearable biofeedback device for real-time stress intervention. In Proceedings of the 6th international conference on PErvasive Technologies Related to Assistive Environments, pages 1–8, 2013.

[48] Pablo Paredes and Matthew Chan. Calmmenow: exploratory research and design of stress mitigating mobile interventions. In CHI'11 Extended Abstracts on Human Factors in Computing Systems, pages 1699–1704, 2011.

[49] Mark Matthews, Jaime Snyder, Lindsay Reynolds, Jacqueline T Chien, Adam Shih, Jonathan W Lee, and Geri Gay. Real-time representation versus response elicitation in biosensor data. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, pages 605–608, 2015.

[50] Inmaculada Plaza, Marcelo Marcos Piva Demarzo, Paola Herrera-Mercadal, and Javier García-Campayo. Mindfulness-based mobile applications: literature review and analysis of current features. JMIR mHealth and uHealth, 1(2):e24, 2013.

[51] Giuseppe Riva, Fabrizia Mantovani, Claret Samantha Capideville, Alessandra Preziosa, Francesca Morganti, Daniela Villani, Andrea Gaggioli, Cristina Botella, and Mariano Alcaniz. Affective interactions using virtual reality: the link between presence and emotions. CyberPsychology & Behavior, 10(1):45–56, 2007.

[52] Judith Amores, Xavier Benavides, and Pattie Maes. Psychicvr: Increasing mindfulness by using virtual reality and brain computer interfaces. In Proceedings of the 2016 CHI Conference Extended Abstracts on Human Factors in Computing Systems, pages 2–2, 2016.

[53] Tara Donker, Katherine Petrie, Judy Proudfoot, Janine Clarke, Mary-Rose Birch, and Helen Christensen. Smartphones for smarter delivery of mental health programs: a systematic review. Journal of medical Internet research, 15(11):e247, 2013.

[54] Joyce HL Lui, David K Marcus, and Christopher T Barry. Evidence-based apps? a review of mental health mobile applications in a psychotherapy context. Journal of medical Internet research, 15(11):e247, 2013.

[55] Melvyn WB Zhang, Cyrus SH Ho, Christopher CS Cheok, and Roger CM Ho. Smartphone apps in mental healthcare: the state of the art and potential developments. BJPsych advances, 21(5):354–358, 2015.

[56] David C Mohr, Mi Zhang, and Stephen M Schueller. Personal sensing: understanding mental health using ubiquitous sensors and machine learning. Annual review of clinical psychology, 13:23–47, 2017.

[57] Michael J McCarthy. Internet monitoring of suicide risk in the population. Journal of affective disorders, 122(3):277–279, 2010.

[58] Hajime Sueki. Does the volume of internet searches using suicide-related search terms influence the suicide death rate: Data from 2004 to 2009 in japan. Psychiatry and clinical neurosciences, 65(4):392–394, 2011.

[59] Albert C Yang, Shi-Jen Tsai, Norden E Huang, and Chung-Kang Peng. Association of internet search trends with suicide death in taipei city, taiwan, 2004–2009. Journal of affective disorders, 132(1):179–184, 2011.

[60] John F Gunn III and David Lester. Using google searches on the internet to monitor suicidal behavior. Journal of affective disorders, 148(2):411–412, 2013.

[61] Albert C Yang, Norden E Huang, Chung-Kang Peng, and Shih-Jen Tsai. Do seasons have an influence on the incidence of depression? the use of an internet search engine query data as a proxy of human affect. PloS one, 5(10):e13728, 2010.

[62] John W Ayers, Benjamin M Althouse, Jon-Patrick Allem, J Niels Rosenquist, and Daniel E Ford. Seasonality in seeking mental health information on google. American journal of preventive medicine, 44(5):520–525, 2013.
[63] John Paparrizos, Ryen W White, and Eric Horvitz. Detecting devastating diseases in search logs. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 559–568. ACM, 2016.

[64] John Paparrizos, Ryen W White, and Eric Horvitz. Screening for pancreatic adenocarcinoma using signals from web search logs: Feasibility study and results. Journal of Oncology Practice, 12(8):737–744, 2016.

[65] Sudhakar V Nuti, Brian Wayda, Isuru Ranasinghe, Sisi Wang, Rachel P Dreyer, Serene I Chen, and Karthik Murugiah. The use of google trends in health care research: a systematic review. PloS one, 9(10):e109583, 2014.

[66] Annie Pearl, Andy Kiang, and Joel Bailon. Data loss prevention (dlp) methods by a cloud service including third party integration architectures, October 18 2016. US Patent 9,473,532.

[67] Andy Kiang and Joel Bailon. Data loss prevention (dlp) methods and architectures by a cloud service, January 12 2016. US Patent 9,237,170.

[68] Tae Wan Kim and Seung Tae Paek. Cloud data discovery method and system for private information protection and data loss prevention in enterprise cloud service environment, October 27 2016. US Patent App. 14/728,503.

[69] RP Swinson. The gad-7 scale was accurate for diagnosing generalised anxiety disorder. Evidence-based medicine, 11(6):184, 2006.

[70] Nerys Williams. The gad-7 questionnaire. Occupational medicine, 64(3):224–224, 2014.

[71] Google. Content Categories. https://cloud.google.com/natural-language/docs/categories, 2020. [Online; accessed 12-May-2020].

[72] TechPostPlus. YouTube video Categories list FAQs and solutions. https://techpostplus.com/2019/04/26/youtube-video-categories-list-faqs-and-solutions/, 2019. [Online; accessed 26-April-2019].

[73] Peter S Shenkin, Batu Erman, and Lucy D Mastrandrea. Information-theoretical entropy as a measure of sequence variability. Proteins: Structure, Function, and Bioinformatics, 11(4):297–313, 1991.

[74] Alan G Hawkes. Spectra of some self-exciting and mutually exciting point processes. Biometrika, 58(1):83–90, 1971.

[75] Marian-Andrei Rizoiu, Young Lee, Swapnil Mishra, and Lexing Xie. Hawkes processes for events in social media. In Frontiers of Multimedia Research, pages 191–218. 2017.

[76] Bethany KB Fleck, Lisa M Beckman, Jillian L Sterns, and Heather D Hussey. Youtube in the classroom: Helpful tips and student perceptions. Journal of Effective Teaching, 14(3):21–37, 2014.

[77] Christopher Cayari. The youtube effect: How youtube has provided new ways to consume, create, and share music. International Journal of Education & the Arts, 12(6):n6, 2011.

[78] Alex S Hall and Jeffrey Parsons. Internet addiction: College student case study using best practices in cognitive behavior therapy. Journal of mental health counseling, 23(4):312, 2001.

[79] Sedigheh Moghavvemi, Ainin Binti Sulaiman, Noor Ismawati Binti Jaafar, and Nafisa Kasem. Facebook and youtube addiction: the usage pattern of malaysian students. In 2017 international conference on research and innovation in information systems (ICRIIS), pages 1–6. IEEE, 2017.

[80] Jane E Klobas, Tanya J McGill, Sedigheh Moghavvemi, and Tanousha Paramanathan. Compulsive youtube usage: A comparison of use motivation and personality effects. Computers in Human Behavior, 87:129–139, 2018.

[81] Christopher KI Williams and Carl Edward Rasmussen. Gaussian processes for machine learning, volume 2. MIT press Cambridge, MA, 2006.

[82] Jeffrey A. Hall and Natalie Pennington. Self-monitoring, honesty, and cue use on Facebook: The relationship with user extraversion and conscientiousness. Computers in Human Behavior, 29(4):1556 – 1564, 2013.

[83] Brian Y Lim and Anind K Dey. Investigating intelligibility for uncertain context-aware applications. In Proceedings of the 13th international conference on Ubiquitous computing, pages 415–424, 2011.

[84] Matthew Kay, Shwetak N Patel, and Julie A Kientz. How good is 85%? a survey tool to connect classifier evaluation to acceptability of accuracy. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, pages 347–356, 2015.

[85] Rob Copeland. Google’s ‘project nightingale’ gathers personal health data on millions of americans. The Wall Street Journal, 2019.

[86] Becky Inkster, David Stillwell, Michal Kosinski, and Peter Jones. A decade into facebook: where is psychiatry in the digital age? The Lancet Psychiatry, 3(11):1087–1090, 2016.