MIND: A Tool for Mental Health Screening and Support of Therapy to Improve Clinical and Research Outcomes

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ABSTRACT

Routine experiences of daily living invoke particular patterns that can be detected in online activities. Every time an individual carries out any activity on the internet some kind of metadata, reflecting the user's preference, is created and stored. The generated metadata, a latent bi-product of high volume user interactions, is rich, has the potential to be mined for understanding one's current mental state. For example, Google logs every search query made on Google Search, Maps, and YouTube. Closely monitoring these experiences and events, along with the history of online activities, can inform systems to provide early diagnosis and detection of depression, anxiety, and related problems. A growing body of research focuses on using social media for identifying signals associated to various mental health phenomena. However, interventions based on such sources tend to have high false positive rates and may lead to inaccurate diagnosis. In this work, we propose a framework, MIND, that can leverage large amount of passively sensed online engagements history to estimate mental health assessments on depression, anxiety, self-esteem, *etc.* MIND is designed to use these otherwise ignored data, with informed consent from the subject. We envision that MIND has the potential to be easily be integrated into applications in clinical and research settings to help caregivers make informed assessments about individuals during and in between appointments and other health sector contacts.

CCS CONCEPTS

• **Applied computing → Health informatics**; • **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

mental health prediction, therapeutic tools, online behavior, mobile sensing

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1 MOTIVATION

One in five US adults experience some form of mental illness each year [1] and 50% of all lifetime mental illness begins by age 14 [12]. The most common forms of mental illness include depression, anxiety, low self-esteem, and self-harm ideation. Despite the prevalence of mental illness, the National Institute for Mental Health estimates that only about 40% of the people who suffer from mental illness receive a diagnosis and treatment [20]. Moreover, mental health plays a fundamental role affecting the natural history and outcomes of almost every medical illness, and contributes greatly to the costs of care and to the overall economic impact of illness and disease [26]. There is much interest, therefore, in the potential for technology to support screening for mental illness and for improving mental health therapy.

An increasing portion of our time is spent online: in fact, the average internet user spent the equivalent of more than 100 days online last year [24]. Many researchers and organizations have therefore suggested that people's online behavior can be analyzed for mass mental-health screening. For example, researchers have shown that automated linguistic analysis of social media posts can expand the scope of suicide prevention [25]. In fact, Facebook has been using such methods to find posts from users who are at high risk, and then sending the information to a Community Operations team who may effect an intervention [9]. Similarly, recent external research studies using Facebook data and validated with electronic health records have shown that a broad array of health conditions can be predicted, especially for mental health conditions such as anxiety, depression and psychoses [19].

There are, however, serious ethical and practical problems for the use of online behavior data for mass mental health screening. In a research context, screening individuals for any health condition without their consent is in general a violation of the Federal and State policies for the Protection of Human Subjects, and in even in non-research contexts, could violate health information privacy laws (e.g. HIPPA). One practical problem is that the mental-health signal that machine learning can derive from online behavior is inevitably noisy, and thus there will be many false positive and false negatives. False positives can lead to the waste of resources and the possible stigmatization of healthy individuals, while false negatives fail individuals who are in need of help. An even greater practical problem is that the outputs of most of the systems that have been designed to date are not directly actionable: mental-health professionals require more than just a classification or score for an individual from a black-box algorithm before making an intervention.[1]

We believe that there is an important and common setting where all of these problems are overcome even with current methods for analyzing online behavior: namely, an outpatient clinic where patients are being treated for diseases that have a high co-morbidity with mental illness. Subjects can provide informed consent for having data about their online behavior analyzed, thus overcoming this important ethical concern. Because the population is known to be at risk, the online behavioral signal can be expected to be less ambiguous, thus helping alleviate the first practical concern. Finally, because the clinic setting brings health professionals into the loop, the outputs of the system can be designed to provide helpful information about the patient to the therapist and care team both prior to the initiation of therapy and on an ongoing basis during the course of therapy, thus addressing the concern about actionability.

The initial setting for our work in an outpatient HIV clinic at our university medical center. Our proposed tool will use one's daily online activities to infer about one's anxiety, depression, and self-esteem state. Initially, the data will consist of search engine logs such as Google, YouTube, and mobility data from Google Maps usage history. Once a patient opt-in to use our system, the generated reports can help inform patients and therapists about in-the-moment mental state. More importantly, it can be used by care providers to access the mental state of the patients on days between the scheduled appointments. This opens the door to monitor mental health related phenomena that are known to have complex relationships with other medical conditions such as HIV and AIDS, substance use, and addiction, which in turn has many important implications at the individual and public health levels. Our proposed system will allow a collaboration between medical, mental health, public health, and computer science in implementing an effective system for detection and real-time monitoring of mental health associated with other health conditions.

The framework presented in this paper is novel in that it (i) does not require users to complete diaries or surveys; (ii) fuses data from multiple sources, including search history, YouTube viewing, and Google Maps location history; (iii) allows users to share the metrics with their care provider; and (iv) enables healthcare professionals to not only perform screening but to also gain information about a patient's mental state on days between the therapy sessions.

2 TECHNICAL APPROACH

The data collection and patient recruitment procedure of our cloud based system has already been approved by a Human Subject Review Board. Interested participants are required to be at least 18 years old, able to read and write in English, and have an active Google services account. Qualified subjects are told the purpose, procedure, and goal of the study, and sign a statement of informed consent.

After consent, a participant logs into our data collection system using his or her active Google account. The data collection system downloads the subject's search, YouTube, and Google Maps history to a HIPPA compliant server.[2] During the download process, Google Cloud's Data Loss Prevention (DLP) API is employed to automatically strip names, addresses, phone numbers, credit card numbers, and other personal identifiers from the data stream. Analysis is performed on the secure server and summary information is then made available to the Therapist Dashboard application described below. It is important to note that although explicit identifiers have been stripped from the user data, it is still protected to avoid the possibility of re-identification.

We are interested in identifying both the temporal and contextual components from online activities that can help detect traits, sudden change online activities which can in turn reflect one's in the moment mental state. We employ the Google NLP content classification API[3] to label each web search query along with its time stamp. YouTube history entries are labeled by content category, keywords, timestamp, and viewing duration. We are experimenting with various approaches to turning the Google Maps location history into a set of meaningful dynamic features. A promising approach we are exploring is to use algorithms for inferring place labels such as home, work, store, *etc.*/ from movement logs [15] to convert the GPS-based history to a history of "stays" at kinds of places.

The data thus labeled and summarized is fed into a probabilistic model whose output is a time series of depression, anxiety, and self-esteem scores. The model is an extension of the methods described in Zaman *et al.* (2019). Fig. 1(iii) illustrates how this data could be graphed in the Therapist's Dashboard application described below.

3 USE CASES

The framework presented in this paper will initially provide therapists engaged in behavioral, addiction, substance use, and HIV clinics with a tool to use information about clients' predicted mood disorders (*e.g.*, major depression and generalized anxiety disorder). In addition, the predicted disorder data will be used to help counselors connect directly through the app to patients identified to be at risk, and to facilitate their access to earlier follow-up visits at clinics.

In-clinic Screening: Patients who, after providing informed consent, are found to be at risk for worsening depression or anxiety, would be flagged for review by a designated member of their care team who has been specifically trained in how to understand and use prediction model results.

In addition, model results are then compared with specific clinical outcome measures (*e.g.*, PHQ-9 scores for depression or GAD-7 scores for generalized anxiety disorder) to help inform the creation of similar prediction models for these clinical endpoints.

Finally, counselors will use output data from the models to guide their initiation of specific treatment steps. Those individuals passing specific threshold values will be referred for early or immediate follow up at the clinic or urgent services through a direct link within the interface to the scheduling system and clinic staff.

[1] An exception is the case where an algorithm can provide an unambiguous signal of imminent harm, such as a social-media post where the user declares that they are about to commit suicide.

[2] Email and messages are not collected. We believe such data is too highly sensitive to be used, however carefully such a system is designed.

[3] https://cloud.google.com/natural-language/docs/classifying-text

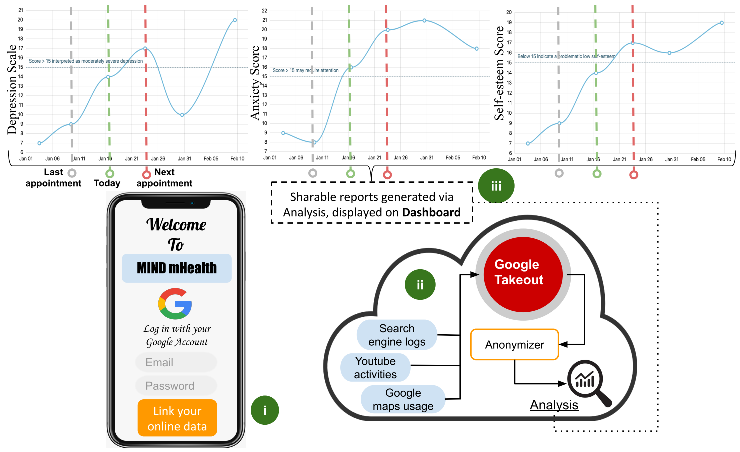

Figure 1: MIND mHealth App Framework: (i) following informed consent, participants link their online activities data by logging in using their active Google account; (ii) participants' data are transferred directly into a cloud-based Anonymizer for pre-processing and removal of protected health information (PHI) and potential identifiers before being downloaded by the research team for analysis; (iii) shareable reports are generated for presentation via user Dashboards designed for specific groups of users (e.g. counselors)

Therapist's Dashboard: Patients who are receiving mental health therapy may be asked by their therapist if they would consent to have the system download and analyze their online data on a weekly basis. When preparing to meet with a consented patient, the therapist would review the application dashboard, see Fig. 1(iii), in order to note spikes and other changes in the patient's estimated level of depression or anxiety since the patient's last session. The therapist could use this information when conversing with the patient in order to uncover stressors and other issues that might otherwise go unmentioned by the patient. For example, the therapist might note that the dashboard indicated the patient was engaging in online behavior associated with high stress on a particular day in the past week, and ask if the patient agreed with that assessment and if so what was happening at that time in the patient's life.

4 RELATED WORK

Researchers have proposed mobile apps for helping users manage stress, anxiety [17, 18, 21, 22] and virtual reality to evoke positive emotions [2, 23]. [8, 16] provides an extensive overview on usage of mobile applications in psychotherapy and effective delivery methods for tackling mental health related phenomena through smartphones. It has been found that usage of mobile application to deliver Cognitive behavioral therapy has resulted in significant improvements in outcomes for patients with depression [27].

Over the years, the research community has taken initiatives towards designing tools for reducing depression and dysfunctional thinking [10], improving user's attention [14], helping people living with HIV for regular engagement in care [7] *etc.* Researchers have also integrated wearable sensing devices, such as smart watches, to collect real-time data [11], provide feedback [6, 13], help regulate emotions, and improve cognitive performances [4, 5].

The majority of the proposed systems ask some form of engagement or inputs from time to time from users, which often results in a low app retention rate. Eventually people stop using the app. Furthermore, few of these applications allow users to share the metrics from the app with their care providers. One potential reason can be that care providers are not aware of the existence of such systems, and even if they are aware, there is not sufficient evidence of their success to support clinician buy-in and uptake.

5 ETHICAL CONSIDERATIONS

There are many ethical challenges posed by the use of automatically acquired online behavioral data, most prominently the profound risk to individual privacy when dealing with such sensitive clinical issues as mental health, HIV/AIDS, and the use of illicit substances. These have been a direct focus of the work of some colleagues [3], and so we are especially sensitive to these concerns. Our principal approach to address these complex challenges is to limit the collection of user data to patients who explicitly opt-in and then provide ongoing follow-up confirmation of informed consent. This approach, while not explicitly dealing with data privacy issues *per se*, does help to address several aspects of the ethical challenges around informed consent. In addition, within our collaborating clinical settings, research addressing substance use, mental health, and HIV is conducted exclusively using a community-based participatory research (CBPR) model. CBPR and related approaches are designed to help assure that clinical and population health research is carried out in a manner that is both responsive to community needs, as well as in direct guidance and leadership of research by community members, health providers, and other stakeholders.

An additional ethical concern is that prediction model results do not yet rise to the level of reliability, robustness, and reproducibility normally required of clinical data. Crudely put, without something as rigorous as FDA review and approval, such data are not appropriate for direct incorporation into medical records. This means that collaborating members of the clinical team involved in this research require additional training to understand the data provided by our prediction models, including how it is generated and the limitations of both these models and of this general approach. Ultimately, this collaborative approach also enables the project design team to learn from the feedback provided by the collaborating clinicians, and to incorporate this into the ongoing design progress.

Finally, with respect to human subjects protection concerns such as privacy and confidentiality, it is crucial that any work such as this maintain full compliance with all regulatory requirements. Work such as this also raises concerns around the potential for data to be reverse-engineered by combining it with additional data sets, using novel machine learning methods, etc. This implies an important need to limit the types of data collected, the length of time that data is needed to be kept, and to incorporate state-of-the-art approaches such as disseminated data storage and data analysis. In short, attention to these and other ethical challenges is an ongoing process.

6 PLANNED STUDIES & FUTURE DIRECTIONS

We are collaborating with other researchers and clinicians at our universities' medical centers to include this work in clinical settings so that we can test the effectiveness of the system. At the moment, we are concurrently conducting data collection and data analysis studies within outpatient HIV & Behavioral Health specialty clinics, an outpatient general Mental Health & Wellness clinic, and with a population of non-at-risk subjects from a general campus population. We have built a predictive engine for depression, low self-esteem, and suicide ideation that employs user search history data, and are working on integrating YouTube viewing and location history data. Collecting these forms of diverse online activities from different sources can lead to incomplete or missing data because not everyone uses all the Google products in daily basis. To address these technical data challenges we have employed a rigorous data pre-processing pipeline to clean and complete the data for accurate analysis. Finally, the mental health therapists on our team are guiding the design of the Therapist's Dashboard application. We plan to have an end-to-end version of the system completed and pilot studies underway by the end of this year.

REFERENCES

[1] Substance Abuse. 2018. Mental Health Services Administration.(2017). Key substance use and mental health indicators in the United States: Results from the 2016 National Survey on Drug Use and Health (HHS Publication No. SMA 17-5044, NSDUH Series H-52). Rockville, MD: Center for Behavioral Health Statistics and Quality. *Substance Abuse and Mental Health Services Administration. Retrieved from https://www. samhsa. gov/data* (2018).

[2] Judith Amores, Xavier Benavides, and Pattie Maes. 2016. 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*. 2–2.

[3] Stevie Chancellor, Michael L Birnbaum, Eric D Caine, Vincent MB Silenzio, and Munmun De Choudhury. 2019. A taxonomy of ethical tensions in inferring mental health states from social media. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*. 79–88.

[4] Baek-Hwan Cho, Jeonghun Ku, Dong Pyo Jang, Saebyul Kim, Yong Hee Lee, In Young Kim, Jang Han Lee, and Sun I Kim. 2002. The effect of virtual reality cognitive training for attention enhancement. *CyberPsychology & Behavior* 5, 2 (2002), 129–137.

[5] Jean Costa, François Guimbretière, Malte F Jung, and Tanzeem Choudhury. 2019. BoostMeUp: Improving Cognitive Performance in the Moment by Unobtrusively Regulating Emotions with a Smartwatch. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 3, 2 (2019), 1–23.

[6] Richard Wayne DeVaul. 2004. *The memory glasses: wearable computing for just-in-time memory support*. Ph.D. Dissertation. Massachusetts Institute of Technology.

[7] Rebecca Dillingham, Karen Ingersoll, Tabor E Flickinger, Ava Lena Waldman, Marika Grabowski, Colleen Laurence, Erin Wispelwey, George Reynolds, Mark Conaway, and Wendy F Cohn. 2018. PositiveLinks: a mobile health intervention for retention in HIV care and clinical outcomes with 12-month follow-up. *AIDS patient care and STDs* 32, 6 (2018), 241–250.

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

[9] Facebook. 2018. How Facebook AI Helps Suicide Prevention. https://bit.ly/35Px0AP. Accessed: 09-04-2019.

[10] David Haldane. 2006. MoodGYM: http://moodgym. anu. edu. au.

[11] Steve Hodges, Lyndsay Williams, Emma Berry, Shahram Izadi, James Srinivasan, Alex Butler, Gavin Smyth, Narinder Kapur, and Ken Wood. 2006. SenseCam: A retrospective memory aid. In *International conference on ubiquitous computing*. Springer, 177–193.

[12] Ronald C Kessler, Patricia Berglund, Olga Demler, Robert Jin, Kathleen R Merikangas, and Ellen E Walters. 2005. Lifetime prevalence and age-of-onset distributions of DSM-IV disorders in the National Comorbidity Survey Replication. *Archives of general psychiatry* 62, 6 (2005), 593–602.

[13] Mina Khan, Glenn Fernandes, Utkarsh Sarawgi, Prudhvi Rampey, and Pattie Maes. 2019. PAL: A Wearable Platform for Real-time, Personalized and Context-Aware Health and Cognition Support. *arXiv preprint arXiv:1905.01352* (2019).

[14] Nataliya Kosmyna, Utkarsh Sarawgi, and Pattie Maes. 2018. AttentivU: Evaluating the feasibility of biofeedback glasses to monitor and improve attention. In *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers*. 999–1005.

[15] Lin Liao, Dieter Fox, and Henry Kautz. 2005. Location-Based Activity Recognition using Relational Markov Networks.

[16] Joyce HL Lui, David K Marcus, and Christopher T Barry. 2017. Evidence-based apps? A review of mental health mobile applications in a psychotherapy context. *Professional Psychology: Research and Practice* 48, 3 (2017), 199.

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

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

[19] Raina M Merchant, David A Asch, Patrick Crutchley, Lyle H Ungar, Sharath C Guntuku, Johannes C Eichstaedt, Shawndra Hill, Kevin Padrez, Robert J Smith, and H Andrew Schwartz. 2019. Evaluating the predictability of medical conditions from social media posts. *PloS one* 14, 6 (2019), e0215476.

[20] NIMH. 2020. Mental Illness. https://www.nimh.nih.gov/health/statistics/mental-illness.shtml. National Institute for Mental Health. Accessed: 2020-02-07.

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

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

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

[24] The Next Web. 2020. 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. Accessed: 2020-02-07.

[25] John Torous, Mark E. Larsen, Colin Depp, Theodore D. Cosco, Ian Barnett, Matthew K. Nock, and Joe Firth. 2018. Smartphones, Sensors, and Machine Learning to Advance Real-Time Prediction and Interventions for Suicide Prevention: a Review of Current Progress and Next Steps. *Current Psychiatry Reports* 20:51 (2018).

[26] Sebastian Trautmann, Jürgen Rehm, and Hans Ulrich Wittchen. 2016. The economic costs of mental disorders. *EMBO reports* 17, 9 (July 2016), 1245–1249.

[27] Sarah Watts, Anna Mackenzie, Cherian Thomas, Al Griskaitis, Louise Mewton, Alishia Williams, and Gavin Andrews. 2013. CBT for depression: a pilot RCT comparing mobile phone vs. computer. *BMC psychiatry* 13, 1 (2013), 49.

[28] Anis Zaman, Rupam Acharyya, Henry Kautz, and Vincent Silenzio. 2019. Detecting Low Self-Esteem in Youths from Web Search Data. In *The World Wide Web Conference*. ACM, 2270–2280.