MoodRing: A Mobile Application for Monitoring Adolescents' Depression

(Technical Report)

Comparative Impacts of Virtual and In-Person Socialization on Adolescents

(STS Paper)

A Thesis Prospectus Submitted to the

Faculty of the School of Engineering and Applied Science University of Virginia ● Charlottesville, Virginia

In Partial Fulfillment of the Requirements of the Degree Bachelor of Science, School of Engineering

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Fall, 2020

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction:

The technical and STS sections of this paper will both deal with interactions between technology and adolescents. Recently, the use of technology by adolescents has increased drastically and become a part of daily life with 85% of 14-year-old adolescents owning a cell phone (Odgers, 2018). Adolescents today have lived their entire lives exposed to technology including social media, online games, and the internet at large. The Coronavirus pandemic in 2020 has increased reliance on technology as it has become a necessity for both school and almost all other daily social interactions. The current events and long-term trends of technology usage emphasize the importance of understanding both the positive and negative impacts of technology use on adolescents. The technical and STS sections of this paper will investigate two distinct but linked aspects of that broader topic

Collectively, both sections of this paper seek to highlight certain elements of how adolescents interact with technology. The technical project is focused on the development of a singular application that can achieve a positive result through the leveraging of existing relationships between adolescents' and technology. Contrastingly, the STS paper will take a broader look at how adolescents use technology for socialization and how those usages were shaped by societal factors and compare to in-person socialization. Together the two sections will help shed light on the existing and future interactions between adolescents and technology.

Technical Project: A Mobile Application for Monitoring Adolescent's Depression

The typical approach to collecting behavioral data on patients relies on asking participants to estimate the frequency and duration of their behaviors (Harari et al., 2016, p. 839). This approach to patient self-monitoring, accomplished mainly via survey data, serves as a major tool for diagnosing and tracking depression (Burns et al., 2011, p. 3). However, self-monitoring for depression symptoms presents several shortcomings. Patients with depression may be less likely to fill out surveys, since symptoms of depression include fatigue and lack of motivation (Substance Abuse and Mental Health Services Administration, 2016, Table 29). Likewise, patients not actively experiencing symptoms may not feel that self-monitoring is necessary. These issues are further exacerbated in adolescent patients who might be reluctant to share survey information with parents or healthcare providers.

Due to the various shortcomings of self-monitoring, the current mobile applications for adolescent mental health care do not provide optimal user experience and lack accuracy regarding mental state forecasts. The smartphone application, Moodring, would avoid self-monitoring issues by not requiring active input from patients to track and predict mental health states, facilitated by two paradigms known as passive sensing and machine learning. According to Cornet and Holden (2017), passive sensing describes "the capture of data about a person without extra effort on their part" (p. 120). On smartphone apps, passive sensing collects patient data throughout the day, without patients noticing (Cornet & Holden, 2017, p. 120; Frost, Doryab, Faurholt-Jepsen, Kessing, & Bardram, 2013, pp. 133-134).

The approach to monitoring adolescent depression with passive sensing builds on previous applications designed to combat depression. In 2011, Burns et al. created "Mobilyze!," which used machine learning models to predict patient mood, emotion, and motivational state based on a variety of sensor values from smartphones (p. 1). In 2013, “Monarca” successfully estimated mood in adults with bipolar disorder using only sensor data (Frost et al., p. 142). Currently, “Monsenso” monitors patients via mobile phone sensors and relays the data to both patients and health care providers (Monsenso, 2017, pp. 1-2). The technical project team plans to extend these approaches to adolescents with depression, who may be ideal candidates due to their high levels of smartphone use.

The team will use quantitative data from passive sensing coupled with machine learning to identify and forecast depression symptoms, and provide suggestions to alleviate symptoms. The team will use the AWARE framework, an open source programming framework that collects mobile phone data, to conduct passive sensing and capture features such as location, screen time, phone calls, and distance travelled (AWARE, 2020). Using this sensor data, the team will engineer other useful features that may indicate signs of depression, such as amount of sleep, number of hours spent at home, and frequency of communication with peers (Harari et al., 2016, p. 840).

The team will create a machine learning model to provide greater insight into the adolescent’s mental state based on features most relevant to the patient. The application will relay this prediction, as well as a summary of the relevant features, to the patient in a dashboard. This approach allows for an individualized experience for each adolescent and provides an opportunity to understand how behaviors contribute to their mental state. If the patient wants to fill out a questionnaire about their mood, they may do so to provide a basis of comparison for the machine learning model, referred to as the ground truth. However, the application will not require any questionnaire data in order to summarize and forecast a patient’s mental health status.

The anticipated deliverable for the team's technical project is a minimum viable product of the smartphone application Moodring. Figure 2 on page 9 shows the flow of information between the application and the patient. The application will continually process sensor data, forecast mental state, and provide visualizations for the patient. Initially, the team will develop the application using sensor data from their own smartphones to provide a proof of concept of a lightweight app that forecasts mental status and summarizes sensor data. The team will test the accuracy of the application's machine learning predictions using de-identified adolescent patient data from Professor Afsaneh Doryab's previous studies.

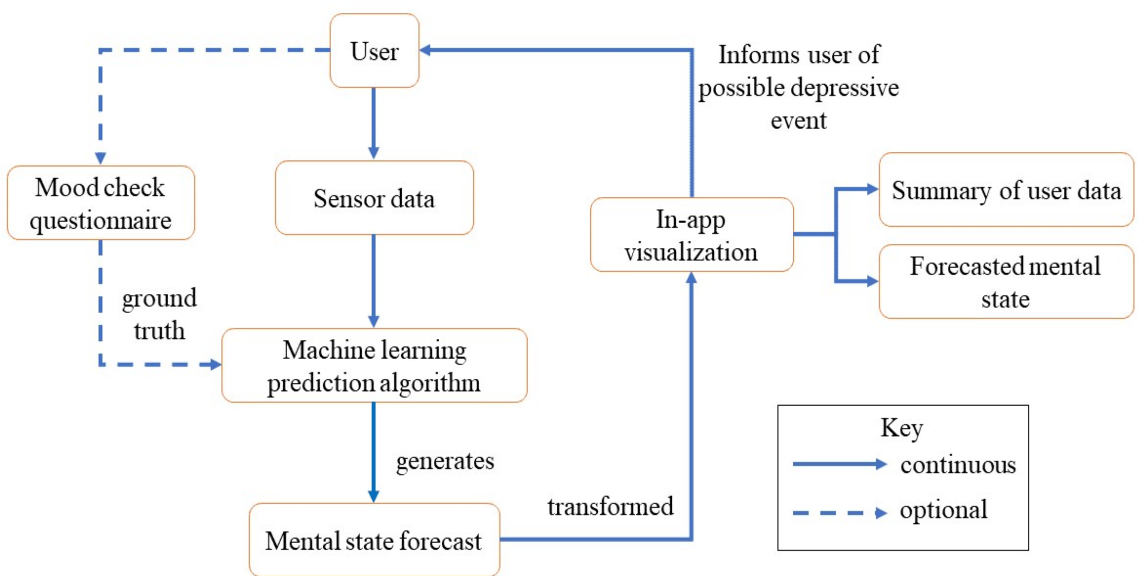

Figure 1: Moodring Concept Map. This figure lays out how Moodring will collect data and relay information to the user. (Adapted by Bonaquist (2020) from Singh, 2020).

The team believes that this combination of technology will be able to provide insight into the adolescent's mental state for several reasons. To start, passive sensing alleviates the burden of self-monitoring from the young patient. Traditional approaches to self-monitoring allow for user bias to decrease the accuracy and integrity of analysis. The deliverable will help circumvent this issue by consistently collecting unbiased, objective data through passively monitoring pre-teens and teens. The forecasting methodology for mental health status under the context of depression in adolescents serves as a novel aspect of the deliverable. Currently, technology that monitors mental health exists, but to the team's knowledge, no other smartphone application projects the depressive states of 10 to 20-year-olds. Another novel and major improvement over present work is that the team's modeling will all occur on the device on which the application is installed, a concept known as on-device machine learning (Dhar et al., 2020, p. 1). On-device machine learning allows greater privacy over existing practices, which use external storage, such as the cloud.

The desired outcome is for patients and their caretakers to gain an understanding of the factors affecting their mental state. Specifically, patients should learn what behaviors, such as reduced sleep or more time spent at home, contribute to their depression. The research also provides an opportunity to facilitate communication between adolescents, their parents, and care providers. In the mobile app, young patients will control consent over sharing their data summary and mental health forecast with their parents and care providers. This would help those who care for the patient quickly understand the patient's mental state and corresponding influential factors.

The Moodring project is sponsored by the United States National Institute of Health (NIH), and is a collaboration between the University of Pittsburgh, the University of Virginia, and the Pittsburgh-based software company NuRelm. At the University of Virginia, Professor Afsaneh Doryab holds grant 1-R44-MH122067-01 from the NIH. Anna Bonaquist, Meredith Grehan, Owen Haines, Joseph Keogh, and Neil Singh make up the undergraduate team. Throughout the process of developing Moodring, the team will write a technical paper on the project. The team will submit the technical paper to the Systems and Information Engineering Design Symposium in April.

STS Report: Comparative Impacts of Virtual and In-Person Socialization on Adolescents

This paper will apply the Social Construction of Technology (SCOT) framework to demonstrate how virtual socialization methods have developed compared to in-person socialization methods. The basic idea of the SCOT framework is that human activity and societal factors shape the development of technology. This framework can be further broken down into four main concepts: interpretive flexibility, social groups, closure and stabilization, and the wider context (Klein & Kleinman, 2002). All four of these concepts play into how technologies have developed for social interaction.

Interpretive flexibility is the concept that different outcomes of technology design are possible depending on the different social context from which they are developed. The intrinsic value of social interaction has caused technologies to develop that closely mimic in-person reaction as closely as possible. The development of voice and video reflect this desire to mimic in-person interaction. This desire to match existing in-person systems has been exemplified through online schooling during the Coronavirus pandemic with attempts made to recreate a typical classroom experience as much as possible. Other social values such as efficiency and ease of use have also played roles in how communication technologies have developed.

The second component of the SCOT framework is the concept of "relevant social groups". Essentially, there are definable groups each with separate views and feelings related to a technology that share influence over the shaping of that technology. There are a wide number of complex stakeholders and social groups that play into the development of technologies for social interaction, especially when focused on adolescent usage. Parents, teachers. government agencies, and adolescents all have different values that play into how technologies are developed and used.

The third component of the SCOT framework is closure and stabilization which refers to the process by which an artifact's design my multiple relevant social groups will continue until a point is reached at which the technology no longer poses any issues to any of the relevant social groups. At that point the design process is closed and the technology is stabilized. This concept is a bit less clear, partially because technologies for virtual socialization are not closed or stabilized entirely. While certain concepts such as video calling or instant messaging have been established and stabilized as effective tools, the products offered are frequently varying in response to changing societal needs and desires. The Coronavirus pandemic is a major clear example of how changes in societal needs change the uses of technology, but that change can also be seen more gradually as technology and society shift and change naturally.

The final component of the SCOT framework is the wider context. This may involve things such as the connections between subgroups, the wider cultural and technological context, or other broader connections. For example, just looking at each social group as equal overly simplifies complex systems. The power structures between groups are especially important to consider especially in this context where adolescents have much less control than other groups. The Coronavirus pandemic represents a clear example of how external factors can influence social needs and therefore technology.

For the STS research paper, I will be performing more in-depth research on the impacts of socialization of adolescents and various methods of online socialization. This is a very broad topic, but potential topics to focus on include social media, online gaming, and virtual schooling. The topic of online schooling is specifically relevant in the context of the Coronavirus pandemic and has a clear in-person alternative, so I may focus on that specific area provided there is enough available research. The aim of this research is to apply the SCOT framework in order to examine how systems of online socialization have developed as a reaction to societal factors and how they compare to in-person socialization systems. I hope to use primarily academic papers, but may also use some more recent news articles when referring specifically to the impacts of the Coronavirus pandemic.

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