DESIGNING A SMARTPHONE APPLICATION TO PREDICT ADOLESCENT DEPRESSION WITH MACHINE LEARNING

THE SOCIAL AND ETHICAL IMPLICATIONS OF SMARTPHONE APPLICATIONS USING ARTIFICIAL INTELLIGENCE IN MENTAL HEALTH CARE

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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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While adolescent depression has become increasingly prevalent in recent years, many 10 to 20-year-olds with depression do not receive proper treatment (Gledhill & Garralda, 2013, p. 741; Kalb et al., 2019, p. 1; Mojtabai, Olfson, & Han, 2016, p. 6). According to Mojtabai et al. (2016), “little progress has been made in narrowing the mental health treatment gap for adolescent depression” (p. 6). In their research, Gledhill and Garralda (2013) found that untreated depression in pre-teens and teens persists, and sometimes grows worse over time (p. 741). Kalb et al. (2019) studied emergency department visits for psychiatric purposes and found that the number of adolescents using emergency services for mental health reasons increased from 2011 to 2015. The authors also found an increase in suicide attempts and self-harm related visits for adolescents (p. 1). The increase of depression, suicide attempts, and self-harm indicates an imperative need for 10 to 20-year-olds to receive more mental health treatment.

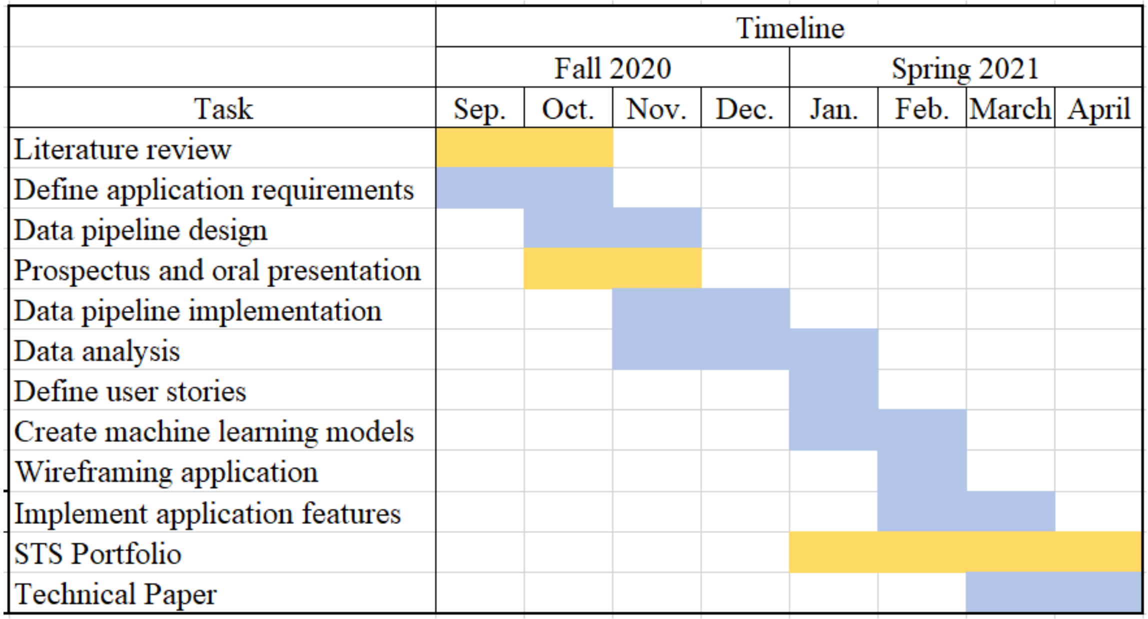
As the rate of adolescent depression has increased in recent years, so has adolescent smartphone usage. According to Anderson and Jiang’s report for the Pew Research Center (2018), 95% of teens have smartphone access, with 45% reporting they are “almost constantly” online (p. 2). These statistics represent a significant increase from 2015, in which only 73% of teens had smartphone access, and 24% said they used the internet as frequently (pp. 7-8). Some parents fear that increased mobile phone use in pre-teens and teens could lead to diminished mental health, since studies indicate social media as a major cause of anxiety and depression (Koh, 2020, p. 1). As schools move online due to the coronavirus pandemic, students will spend more time using mobile devices, especially for socializing (Koh, 2020, p. 3). Adolescent reliance on smartphones could introduce a new, powerful treatment option: mobile mental health apps.

Smartphone applications for mental health treatment may present a solution to the issue of increasing depression diagnoses (Burns, 2011, p. 2; Chandrashekar, 2018, p. 4). Since teens use smartphones at high rates, these applications would provide accessible treatment for 10 to 20-year-olds with depression. Mobile phones provide the capability to collect massive amounts of data about a patient, and behavioral lifestyle data describing social interactions, location patterns, and schedules can predict the mental health and well-being of patients (Abdullah, 2016, p. 538; Cornet & Holden, 2018, p. 121; Harari et al., 2016, pp. 839-842). Therefore, mobile phone applications for treating depression could collect data about patients and harness it to predict patients' mental states. According to Chandrashekar (2018), the U.S. National Institute of Mental Health has "pointed to mental health apps as cost-effective and scalable solutions to addressing the mental health treatment gap" (p. 4).

Mobile mental health applications may employ artificial intelligence (AI) and machine learning (ML) to use patient data to make predictions about a patient's current or upcoming mental state. The goal of artificial intelligence is "to build machines that are capable of performing tasks that we define as requiring intelligence, such as reasoning, learning, planning, problem-solving, and perception" (Luxton, 2016, p. 2). Smartphones using machine learning technology have the potential to recognize a patient's typical behaviors and associated mental state (Abdullah et al., 2016, p. 538; Burns et al., 2011, p. 2). In their study, Abdullah et al. (2016) showed that automated sensing could feasibly predict patient rhythmicity, an important factor in identifying depression (p. 538). Some applications may use AI output to initiate interventions with patients when they show behavior that deviates from the patient's norm (Abdullah et al., 2016, p. 541; Burns et al., 2011, p. 2; Cornet & Holden, 2018, p. 127; Harari et al., 2016, p. 841). With knowledge of patient behavior, artificial intelligence technology could tailor treatments for patients based on their individual characteristics (Graham et al., 2019, p. 13; Luxton, 2016, p. 16).

The project aims to study artificial intelligence technology in smartphone applications that treat adolescent depression. In this endeavor, it is crucial to analyze the effect of leveraging AI on patient well-being. The technical project plans to create an application, called Moodring, to monitor and predict depression in adolescents using machine learning. The STS research paper intends to examine the social and ethical implications of applying AI in mobile apps to mental health care using the Actor Network Theory approach. These tightly coupled topics seek to provide pre-teens and teens with important insights about their mental illness through mobile apps and to examine the consequences of applying artificial intelligence to mental health care.

Professor Afsaneh Doryab in the Department of Engineering Systems and Environment leads the technical project team composed of five undergraduate Systems Engineering students. Figure 1 on page 6 shows the timeline for the project, which encompasses two semesters and concludes with a technical paper, included in the STS portfolio. The undergraduates will jointly write the technical paper and submit it to the Systems and Information Engineering Design Symposium (SIEDS) in April. In addition to the technical paper, the STS portfolio will include this prospectus, the sociotechnical synthesis, an abstract, and the STS research paper.



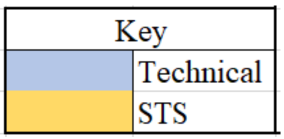


Figure 1: Project Timeline in a Gantt Chart. This figure depicts the proposed tasks and timeline for the technical and STS projects. (Bonaquist, 2020).

DESIGNING A SMARTPHONE APPLICATION TO PREDICT ADOLESCENT DEPRESSION WITH MACHINE LEARNING

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.

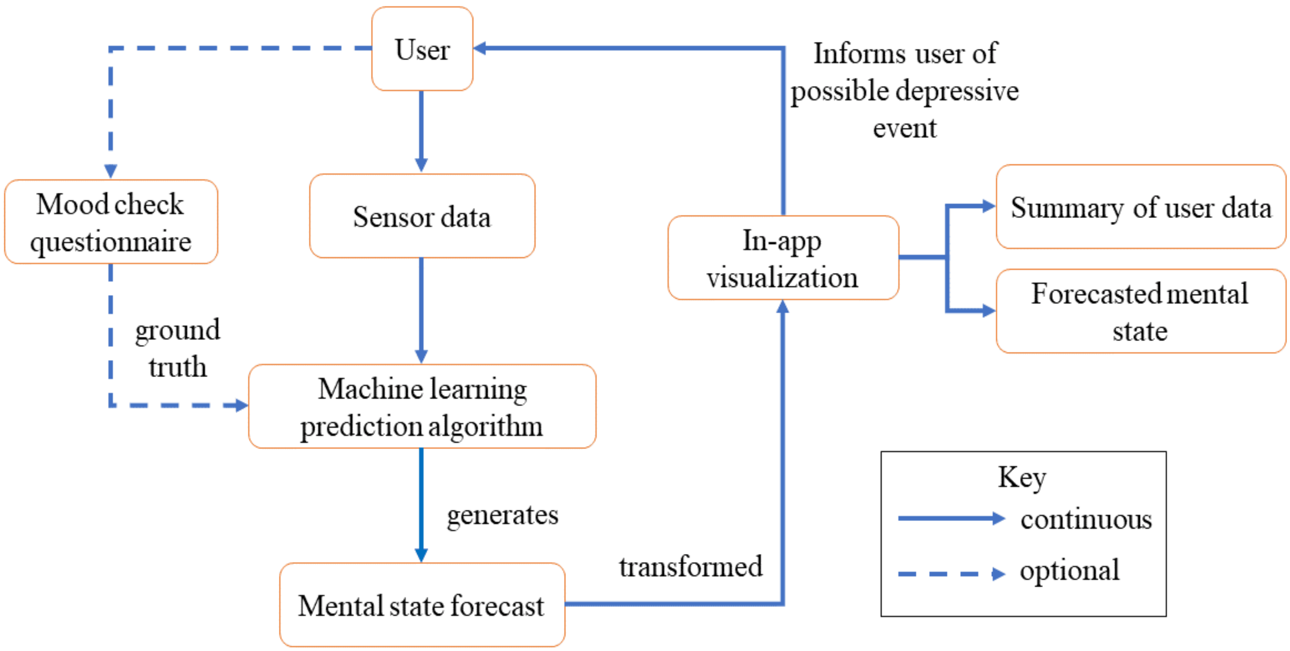


Figure 2: Moodring Concept Map. This figure lays out how Moodring will collect data and relay information to the user. (Adapted by Bonaquist (2020) from Singh, 2020).

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.

THE SOCIAL AND ETHICAL IMPLICATIONS OF SMARTPHONE APPLICATIONS USING ARTIFICIAL INTELLIGENCE IN MENTAL HEALTH CARE

Certain domains of health care have already adopted artificial intelligence technology. AI has been particularly successful at using pattern recognition to detect cancer and assist radiologists and ophthalmologists looking for subtle irregularities in patients (Graham et al., 2019, p. 2). However, the sectors of health care currently using AI differ significantly from the field of mental health care. Graham et al. describe how mental health care clinicians are "more hands-on and patient-centered in their clinical practice than most non-psychiatric practitioners, relying more on 'softer' skills, including forming relationships with patients and directly observing patient behaviors and emotions" (p. 2). The introduction of a new technology may affect the already sensitive relationship between mental health patients and their doctors (Luxton, 2016, p. 19).

Smartphone apps that use AI to treat mental health patients follow a common design. A typical application passively collects data from the patient's smartphone sensors, then uses the data to identify the behaviors associated with mental health state (Abdullah, 2016, p. 538; Cornet & Holden, 2018, pp. 121-127; Harari et al., 2016, p. 839). Many apps suggest changes to behavior or initiate interventions with patients when they appear to engage in behaviors that harm their mental state (Abdullah et al., 2016, p. 541; Burns et al., 2011, p. 2; Cornet & Holden, 2018, p. 127; Harari et al., 2016, p. 841) Although mobile phone applications using artificial intelligence aim to help mental health patients by analyzing their behaviors and enacting change, the adoption of these applications must be thoroughly considered. Smartphone applications with AI capabilities may bring many benefits to mental health patients, but they will also create consequences.

POWER IN THE PATIENT-DOCTOR RELATIONSHIP

The introduction of applications using artificial intelligence technology to mental health care will surely affect the relationship between patients and their doctors. Power dynamics may already cause tension in the patient-doctor relationship, so power is an especially important topic to consider in smartphone applications for treating mental health (Carr, 2020, p. 125). According to Carr (2020), “The use of power in mental health systems is vital to remember for any data-driven mental health technology, and underlines the need to use AI ethical frameworks and codes of conduct in the field” (p. 125). Since AI technology relies entirely on patient data, this sensitive relationship regarding power should be investigated.

Mental health patients undergoing treatment may feel that their doctor has the upper hand in the relationship, especially if the patient needs the doctor’s approval for some purpose (Carr, 2020, p. 125). Patients using smartphone applications to monitor their data and predict mental health outcomes may find themselves at one of two extremes. Some may agree with the results of the application and enjoy the access to unbiased data regarding their condition (Hurtado-de-Mendoza, Cabling, & Sheppard, 2015, p. 329). These patients may feel empowered by artificial intelligence technology, since they can track their progress without the help of their doctor. However, patients who disagree with the results of AI technology may feel even more powerless. Not only must they rely on their doctor, but they must also depend on a surveillance technology which they may find obtrusive (Hurtado-de-Mendoza et al., 2015, p. 328). Both of these reactions to the introduction of AI technology in mental health care require careful consideration, as they may influence the dynamics of power and trust between patients and their doctors.

BIASED DATA

The success of artificial intelligence depends entirely on the data provided. Biased data creates biased output, which could lead to inaccuracies and discrimination. In smartphone apps using AI, biased data could produce erroneous outputs that harm patients. If patients perceive themselves as healthy, but receive a substandard mental health assessment from the app, they could understandably feel discouraged (Carr, 2020, p. 126; Frost et al., 2013 p. 137) According to Carr (2020), data from monitoring devices such as smartphones “excludes the contextual information needed to assess mental health such as the interpersonal, cultural, social, economic and environmental influences” (p. 126). The collection of data that imperfectly represents a patient could result in unnecessary or incorrect mental health interventions. These interventions could make patients distrust the technology and their doctor, or set the patient back in terms of their mental health state.

Additionally, mobile applications that are built using training data from parties other than the patient pose a risk. The lack of representation of different groups can create bias in algorithms. As Schönberger (2019) has noted, any underlying bias in a dataset will be reproduced in the output of an algorithm trained on the dataset (p. 176). If artificial intelligence methods utilize large samples of training data, the developers must ensure that the data does not contain biases against any particular group. Without this condition, AI technology intended to help patients may result in propagating societal biases based on race, gender, or other factors.

INTELLIGIBILITY, DECISION MAKING, AND LIABILITY

Patients and doctors may struggle to understand how artificial intelligence systems in smartphone applications produce output. Schönberger (2019) describes how AI systems appear “opaque” since end users usually could not explain how algorithms classified a particular input (p. 177). Without proper training, many AI algorithms appear to be a “black box.” Patients and doctors analyzing the output of artificial intelligence will not know how to point out biases or incorrect results from AI systems that they do not understand. Since AI technology in mental health care may produce sensitive output for patients, the lack of transparency in models may cause patients even more harm.

According to Jacobson (2004), the adoption of new technologies in health care stimulates malpractice liability lawsuits (p. 20). New technologies introduce opportunity for errors, which can harm patients and result in malpractice suits against doctors (Jacobson, 2004, p. 20). If doctors cannot understand the output of AI in smartphone apps, they may not adopt the technology because they will not want to risk errors that result in malpractice liability litigation. Some mobile applications using AI suggest serious decisions, such as patient interventions or plans to change patient behavior, and doctors may not accept liability for such decisions, especially if doctors do not understand how the recommendation was formed.

In the words of Carr (2020), “scrutiny is needed at all times for AI, and it has been strongly argued that humans should not delegate decision making responsibility to ‘machines alone’” (p. 126). Similarly, Luxton (2016) expresses that he intends the technology presented in his book on artificial intelligence in mental health care to assist doctors in treating patients, not replace them (p. 18). While it may be tempting to rely entirely on smartphone applications utilizing AI for some mental health services, this technology should serve only as a tool to help healthcare professionals and patients. Without scrutiny of the decisions of artificial intelligence, the output may lead to negative outcomes for mental health patients.

SECURITY

By nature, artificial intelligence technology requires a wealth of data. To monitor, predict, and identify mental illnesses, AI technology may use very sensitive patient data, such as location, sleeping habits, and phone use (Cornet & Holden, 2018, p. 129). According to Harari et al. (2016), data security is necessary from collection to storage to sharing data between health care professionals (p. 850). If patients do not feel that their data is safe, they may reject the idea of using smartphone apps with artificial intelligence as treatment. Additionally, patients should have maximum control over their data to assure their privacy is respected (Harari et al., 2016, p. 850). Patients should know who has access to their data and should be able to change that access as needed in order to maximize trust in AI.

BENEFITS

Despite these concerns, smartphone applications using artificial intelligence could provide worthy benefits to mental health care patients. First of all, AI offers the opportunity to collect and monitor patient data. Allen (2020) points out how this data means that "psychiatrists could have more information about how their patients are doing than they currently get from seeing patients for 30 min every three to six months" (p. 4). From such data, AI has the ability to identify irregularities in patient behavior. Changes in factors like sleep, phone use, social contact, and exercise may help identify a patient's mental health status. Monitoring can help both the patient and the doctor better understand the manifestation of the patient's illness. Mobile phones can increase the amount of data patients see about their health, helping patients assess and monitor their individual goals (Frost et al., 2013 p. 137; Luxton, 2016, p. 16).

Artificial intelligence technology via smartphones can provide an accessible medium for those seeking mental health treatment. According to Luxton (2016), "nearly 80 million Americans reside in areas without a sufficient number of mental healthcare practitioners to meet the needs of those communities" (p. 15). Artificial intelligence technology can help close the gap between the number of mental health patients and available mental health care providers (Chandrashekar, 2020, p. 4; Luxton, 2016, p. 15). Since mobile applications using AI can provide doctors with an understanding of patient behavior, these applications could reduce the amount of time doctors need to evaluate each patient. Lastly, patients may gain more autonomy over their treatment plans, as Luxton describes how AI has "the potential to greatly improve health outcomes among care seekers by customizing their care" (p. 16).

ACTOR NETWORK THEORY APPROACH

Actor Network Theory (ANT) presents an approach to consider the "interconnected character of the social and technical" (Law & Callon, 1988, p. 285). According to Law and Callon (1988), ANT investigates the way actors create roles to fulfil the needs generated by technology and other actors (p. 285). The STS research aims to use the Actor Network Theory approach to explore how best to utilize smartphone applications with AI in mental health care. In a similar manner to Hurtado-de-Mendoza et al. (2015) ANT analysis on digital pills, the STS research will explore how patients react differently to artificial intelligence technology depending upon circumstances within their network (p. 332).

The complications and consequences of using artificial intelligence in mental health care expand to patients and their families, doctors, developers of the technology itself, and many others. The Actor Network Theory approach will identify the key actors in the potential adoption of applications levying AI by the mental health care field. This approach will examine actors' interactions with objects that have agency, called actants, such as smartphones. It will also consider actors' effects on one another. For example, the way doctors frame AI technology to their patients may affect patient receptivity. Doctors who support applications using AI might be able to frame such apps as tools that empower patients and reduce reliance on doctors. However, not all doctors will necessarily support this technology. According to Allen (2020), a survey of psychiatrists found that only 33% believed artificial intelligence could one day perform a mental status exam (p. 3). The ANT approach seeks to understand such interactions among actors and actants.

Applying the Actor Network Theory approach may address many of the concerns about smartphone applications with artificial intelligence as mental health treatment. The approach can help doctors and patients avoid relying on biased data by identifying where bias might be introduced to the network. Actor Network Theory can also help determine who the responsibility of transparency and security in AI falls on within the mental health care domain. Using ANT, the network that smartphone applications with AI operate in will be mapped out. Understanding the full network that the technology serves could help ensure that artificial intelligence is introduced in the safest way possible for mental health patients.

Currently, the network that smartphones applications using artificial intelligence exist in is not fully understood. However, expectations between doctors and patients, the most prominent actors, create implications to guide the STS research. Figure 3 on page 18 depicts the current expectations between mental health patients, doctors, and smartphone applications harnessing AI. The figure also renders the implications resulting from the different actors' expectations. The STS research will use these implications as a starting point when applying the Actor Network Theory approach.

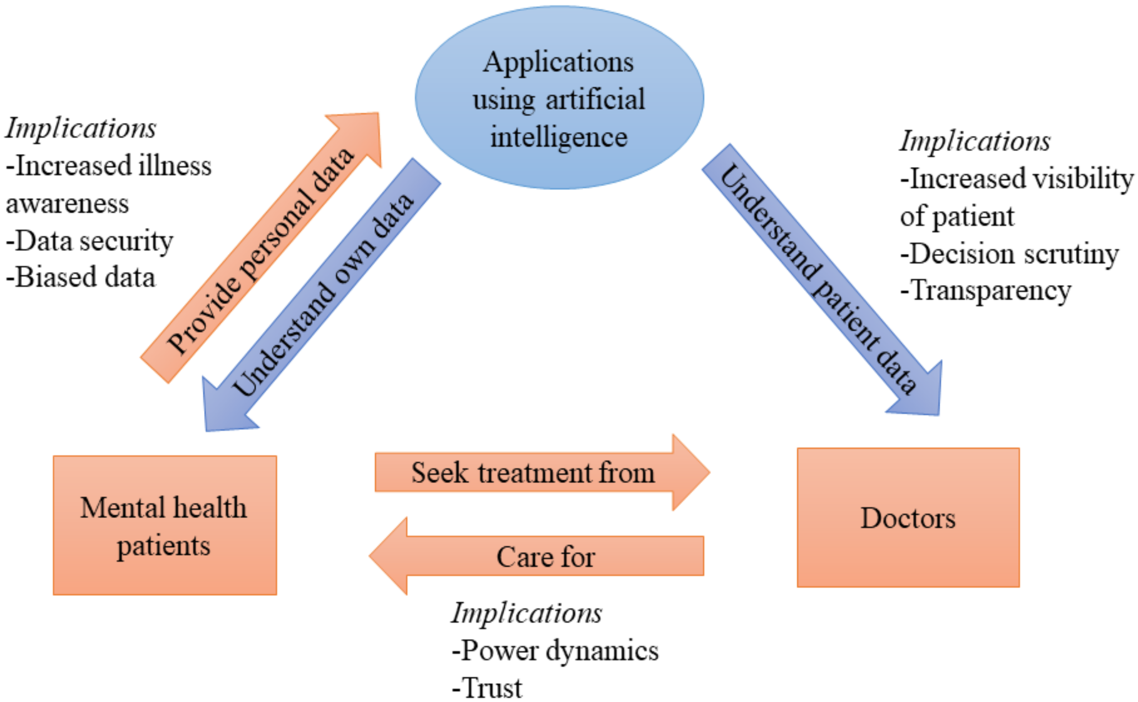


Figure 3: Map of the expectations between patients, doctors, and applications. This figure shows the expectations between the patient, doctors, and application, as well as implications resulting from those expectations. (Adapted by Bonaquist, 2020 from Pinch, Hughes, & Bijker, 1984).

FUTURE RESEARCH

The Actor Network Theory approach seeks to investigate the context surrounding the implications in Figure 3 consider how to best address each implication. Identifying the key stakeholders presents the first challenge in the issue of bringing artificial intelligence technology into the mental health care sphere. Once stakeholders are identified, their interactions with each other and other actants will be mapped. The ANT approach will consider the complications and consequences of smartphone applications using AI, as well as the benefits. While the technical project seeks to create a smartphone app with artificial intelligence, the STS research considers the impact of such technology. Through mapping the situation using ANT, the STS research will identify how to best use applications with artificial intelligence technology without harming mental health patients.

REFERENCES

Abdullah, S., Matthews, M., Frank, E., Doherty, G., Gay, G., & Choudhury, T. (2016). Automatic detection of social rhythms in bipolar disorder. *Journal of the American Medical Informatics Association*, 23(3), 538-543. doi:10.1093/jamia/ocv200

Allen, S. (2020). Artificial intelligence and the future of psychiatry. *IEEE Pulse*, 11(3), 2-6. doi: 10.1109/MPULS.2020.2993657

Anderson, M., & Jiang, J. (2018, May 31). *Teens, social media, & technology 2018*. Retrieved from Pew Research Center website: https://www.pewresearch.org/internet/wp-content/uploads/sites/9/2018/05/PI_2018.05.31_TeensTech_FINAL.pdf

AWARE [Mobile application software]. (2020). Retrieved from https://awareframework.com/

Bonaquist, A. (2020). *Project timeline in a Gantt chart*. [Figure 1]. Prospectus (Unpublished undergraduate thesis). School of Engineering and Applied Science, University of Virginia. Charlottesville, VA.

Burns, M. N., Begale, M., Duffecy, J., Gergle, D., Karr. C. J., Giangrande, E., & Mohr, D.C. (2011). Harnessing context sensing to develop a mobile intervention for depression. *Journal of Medical Internet Research*, 13(3), 1-17. doi: 10.2196/jmir.1838

Carr, S. (2020). 'AI gone mental': engagement and ethics in data-driven technology for mental health. *Journal of Mental Health*, 29(2), 125-130. doi:10.1080/09638237.2020.1714011

Chandrashekar, P. (2018). Do mental health mobile apps work: evidence and recommendations for designing high-efficacy mental health mobile apps. *mHealth*, 4(3), 4-6. doi:10.21037/mhealth.2018.03.02

Cornet, V. P. & Holden, R. J. (2017) Systematic review of smartphone-based passive sensing for health and wellbeing. *Journal of Biomedical Informatics*, 17, 120-132. doi: 10.1016/j.jbi.2017.12.008

Dhar, S., Guo, J., Liu, J., Tripathi, S., Kurup, U., & Shah, M. (2020). On-device machine learning: an algorithms and learning theory perspective. *ArXiv*, 1(1), 1-45. doi:10.1145/nnnnnnn.nnnnnnn

Frost, M., Doryab, A., Faurholt-Jepsen, M., Kessing, L. & Bardram, J. E. (2013). Supporting disease insight through data analysis: refinements of the MONARCA self-assessment system. *In Proceedings of the 2013 International Joint Conference on Pervasive and Ubiquitous Computing*. Retrieved from https://dl.acm.org/doi/10.1145/2493432.2493507

Gledhill, J., & Garralda, M. E. (2013). Sub-syndromal depression in adolescents attending primary care: frequency, clinical features and 6 months outcome. *Social Psychiatry and Psychiatric Epidemiology*, 48, 735–744. doi:10.1007/s00127-012-0572-z

Graham, S., Depp, C., Lee, E. E., Nebeker, C., Tu, X., Kim, H., & Jeste, D. V. (2019). Artificial intelligence for mental health and mental illnesses: an overview. *Current Psychiatry Reports*, 21(116), 1-18. doi:10.1007/s11920-019-1094-0s

Harari, G. M., Lane, N. D., Wang, R., Crosier, B. S., Campbell, A. T., & Gosling, S. D. (2016). Using smartphones to collect behavioral data in psychological science: opportunities, practical considerations, and challenges. *Perspectives on Psychological Science*, 11(6), 838–854. doi: 10.1177/1745691616650285

Hurtado-de-Mendoza, A., Cabling, M. L., & Sheppard, V.B. (2015). Rethinking agency and medical adherence technology: applying Actor Network Theory to the case study of Digital Pills. *Nursing Inquiry*, 22(4), 326-335. doi: 10.1111/nin.12101

Jacobson, P. D. (2004). *Medical liability and the culture of technology*. Retrieved from Pew Research Center website: https://www.pewtrusts.org/en/research-and-analysis/reports/2004/09/23/medical-liability-influenced-by-technology

Kalb, L. G., Stapp, E. K., Ballard, E. D., Holingue, C., Keefer, A., & Riley, A. (2019). Trends in psychiatric emergency department visits among youth and young adults in the US. *Pediatrics*, 143(4), 1-15. doi: 10.1542/peds.2018-2192

Koh, Y. (2020, March 17). Project digs deeper into teenage smartphone use. *The Wall Street Journal*. Retrieved from https://www.wsj.com/

Law, J. & Callon, M. (1988). Engineering and sociology in a military aircraft project: a network analysis of technological change. *Social Problems*, 35(3), 284-297. doi: 10.2307/800623

Luxton, D. D. (2016). An introduction to artificial intelligence in behavioral and mental health care. In D. D. Luxton *Artificial intelligence in behavioral and mental health care* (pp. 1-26). Cambridge, MA: Academic Press. Retrieved from https://doi.org/10.1016/B978-0-12-420248-1.00001-5

Mojtabai, R., Olfson, M., & Han, B. (2016). National trends in the prevalence and treatment of depression in adolescents and young adults. *Pediatrics,* 138(6), 1-10. doi: 10.1542/peds.2016-1878

Monsenso. (2017, December). *The Monsenso mHealth solution for mental illnesses.* Retrieved from https://www.monsenso.com/downloads-fact-sheets

Pinch, T. J., Hughes, T. P., & Bijker, W. (1984). Adapted by Bonaquist, A. (2020). *Map of the expectations between patients, doctors, and applications*. [Figure 3]. Prospectus (Unpublished undergraduate thesis). School of Engineering and Applied Science, University of Virginia. Charlottesville, VA.

Schönberger, D. (2019). Artificial intelligence in healthcare: a critical analysis of the legal and ethical implications. *International Journal of Law and Information Technology*, 27(2), 171–203. doi: 10.1093/ijlit/eaz004

Singh, N. (2020). Adapted by Bonaquist, A. (2020). *Moodring concept map*. [Figure 2]. Prospectus (Unpublished undergraduate thesis). School of Engineering and Applied Science, University of Virginia. Charlottesville, VA.

Substance Abuse and Mental Health Services Administration. (2016). *DSM-5 changes: implications for child serious emotional disturbance*. Substance Abuse and Mental Health Services Administration (US).