**An Analysis of Mental Health Systems**

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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

Mental illness remains a large public health crisis in the United States. Specifically, the United States has witnessed an increase from 2018 to 2019 in serious mental illness, irrespective of the age group (McCance-Katz, 2020). However, this crisis revolving mitigation and assessment of mental illnesses (whether depression, anxiety, or other disorders) is not experienced in the US solely. In 2017, one in every seven Indians[1] experienced mental illness (Sagar et al., 2020). A group of researchers from France concluded from a literature survey that depression was on the rise in France from the 2000s to 2010s (Fond, Lancon, Auquier, & Boyer, 2019). One well-known disorder that occurs among those with mental illness is major depressive disorder, referred to colloquially as depression.

Depression is a specific mental illness that is described as “a mood disorder that causes a persistent feeling of sadness and loss of interest” (“Depression (Major Depressive Disorder) -

[1] referring to residents of the South-east Asian subcontinent

Symptoms and Causes," 2018). Depression has affected more than an expected 264 million individuals globally, second behind only anxiety in persons affected (James et al., 2018). Thus, it is germane to investigate treatment approaches for depressive disorders. Current popular approaches include talk therapy, where an individual receives guidance from a mental health professional, along with medication, which is sometimes used in concert with talk therapy. However, treatment of mental illness is complex; predicated on various circumstances that make each treatment program unique to each individual.

One of the difficulties encountered with treating mental illness among practitioners, with depression in particular, is ensuring treatment is commensurate with the maturity of the individual. For example, it can be readily intuited that young individuals (one example being teenagers) possess less emotional maturity than adult counterparts. This presents a need for mental health professionals to create treatments productive with low maturity in the adolescent case. Specifically, we see that adolescents are more reticent than adults are when discussing mental health (personal communication, Ana Radovic, fall 2020). A way to circumvent this reticence is through another treatment approach via mobile applications. Mobile applications present a wide variety of benefits that are not seen via other approaches, one particular strength being reduced communication required to communicate emotional state and instructions. However, little work exists on characterizing the benefits, challenges, and overall formulation of mobile mental healthcare as a system.

We can illuminate the benefits of mobile mental healthcare (belonging to a larger family of study as human-machine interaction) through a technique known as systems analysis. Systems analysis has its roots grounded in fields such as management consulting, however this approach can be applied readily to socio-technical systems and their associated entities. We seek to consider major actors in this system: adolescents and parents, healthcare providers, and mobile health solutions. By performing systems analysis on this socio-technical system, we will show the feasibility to derive new insights, recommendations, and phenomena about their interactions and objectives. Our findings will determined with a priori knowledge (Baehr, n.d.). This will provide further directions to research and guide practitioners on when to employ mobile health solutions.

## Motivation

Various conditions motivate the need for further research in adolescent mental health technologies, specifically current events, and novel challenges targeting adolescents. Current events that may impact mental health will focus on the impacts from the Coronavirus pandemic. Novel challenges are a family of social issues that target adolescents today, such as the advent of new social media outlets.

The present physical and social conditions imparted by the COVID-19 pandemic have caused the complexification of assessments of this nature. We must consider numerous factors: ranging from sudden loss of in-person traditions and celebrations, along with isolation/quarantine protocols as possible aggravating factors in the depression rates throughout the world. Likewise, the pandemic presents the “COVID fatigue” paradigm, where individuals are exhausted from living a restricted lifestyle due to public health measures and other stressors (Michie, West, & Harvey, 2020). Both of these families of factors (stratified by short and long term in nature, respectively) underscore the need for further research into mental healthcare systems.

We can also express the motivation for mental health technologies as a byproduct of depression experienced by survivors of the illness. That is, mental health mobile applications could be seen as a treatment medium for a side effect of Coronavirus. The investigation on phenomena between COVID-positive individuals (both hospitalized, under self-care, and recovered) and mental illness is inchoate, however, work exists on such analysis (Kong et al., 2020; Mazza et al., 2020; Taquet, Luciano, Geddes, & Harrison, 2021; Zandifar et al., 2020; J. Zhang et al., 2020). A qualification is that much of the current research on "COVID survivor depression" is with adult patients, and more work is needed to investigate potential differences with the corresponding adolescent case. Coupled with uncertainty on the virus' transmission dynamics, mobile applications may provide promising results to support telehealth visits while ensuring the safety of the clinician providing mental healthcare.

Another consideration for studying mental health systems is the current decline in the well-being of adolescents. Reasons for this include the rise of social media and use of e-cigarette products. Note, these two circumstances are not collectively exhaustive, but are all-common due to their incipience.

Social media can prove burdensome to users, particularly due to the image exuded by users on platforms like Instagram or TikTok. Examples of this concept are posts of opulent lifestyles portrayed by celebrities and influencers, with expensive transportation (jets or cars) or merchandise. A simpler case is a user seeing their peers living a much happier or memorable lifestyle. Showing only happy moments on social media fosters a perception of a quixotic culture, creating further distance to those who cannot attain such an image. A disadvantageous relationship between social media use and odds of depression in adolescents have been identified (Lin et al., 2016). Coupling these two pieces of information, we can postulate that the unhealthy images portrayed on social media may increase chances of depression in teenage users.

Another factor that may contribute to a greater amount of adolescent depression is the novelty associated with e-cigarettes. E-cigarettes are popular among teenagers, especially due to the different flavorings of nicotine available. Only recently were refillable e-cigarette flavorings banned in the United States, with circumvention still possible with disposable variants (Kaplan, 2020). Numerous studies have shown negative associations between depression (and other mental illnesses) and increased use of e-cigarettes (Lechner, Janssen, Kahler, Audrain-McGovern, & Leventhal, 2017; Lee & Lee, 2019; Leventhal et al., 2016). Given the modernity of e-cigarettes, we see that their use can exacerbate teenage depression, motivating investigation into further treatment mediums.

This brief "motivational context" survey motivates investigation into adolescent depression technologies. Specifically, present events and novel inhibitors to well-being (specifically, social media and e-cigarettes) were our foci. To get a further view of the current work in mobile health (mHealth) specifically, we will perform a survey of the mobile applications and associated assessments.

## Literature Survey

Promising results refer to previous research done on the mobile health (mHealth) principle, where there were benefits witnessed by the users, whether that be satisfaction with the software artifact or possible improvement in treatment of the underlying mental illness.  Current innovations in the field are found as two major artifacts: data collection and analysis or application combined with "human-in-the-loop" trials. Data collection refers to a family of processes and technologies that aid the collection of information from the mobile device. Data analysis involves converting the aforementioned "collected" data from its raw form (mostly in the form of numbers) into interpretable insights. These two steps are often interdependent. Data application is the creation of applications (mostly mobile apps) to facilitate the two former stages. Lastly, “human-in-the-loop” trials are showing the efficacy of the latter three stages (or a combination of them) by performing an experiment on users, and recording possible benefits.

In the area of the data collection and analysis, we witness various frameworks, mostly for feature extraction. Feature extraction is a paradigm that is well described by this example from “In our medical diagnosis example, the features may be symptoms, that is, a set of variables categorizing the health status of a patient (e.g. fever, glucose level, etc.)” (Guyon, Gunn, Nikravesh, & Zadeh, 2008, p. 2).   From the aforementioned example, we can describe feature extraction as methods of deriving system insights (usually quantitative) from state variables of that given system. In the context of mHealth, the system would be the user’s emotional state, with the state variables being various sensors and interactions with the device. Examples of specific frameworks that facilitate this paradigm are found in the referenced work (Bardram, 2020; Ferreira, Kostakos, & Dey, 2015; Hossain et al., 2017; Vega et al., 2020). Other information streams from (Bardram, 2020) include artifacts by Apple and Google (“Google Fit | Google Developers,” n.d.; “HealthKit | Apple Developer Documentation,” n.d.). These frameworks assist in the process of taking data from mobile sensors, giving information about user behavior. However, these do not focus on the representation of the data back to the user.

The latter set of contributions focuses on mobile apps and studies seeking to apply the frameworks, much like those mentioned above, to deliver insights about a certain wellness aspect of the user. For adult users, we have apps created around the treatment of mental illness. Monarca is an application that focuses on the treatment of bipolar disorder (Frost, Marcu, Hansen, Szaántó, & Bardram, 2011). Although an experiment was performed on Monarca and found to have no significant effects, this paper shows a proof of concept that such methodologies are viable (Faurholt-Jepsen et al., 2015). One example that discusses the use case for young adults, specifically college students is found are StudentLife (Wang et al., 2014). One of the benefits of this study was the finding of a trend, in this case, that University students would gradually decline in well-being throughout an academic term. The last major group to consider includes children and teens. The motivation for specific investigation and attention to the adolescent case will be the focus of the work. Some examples of prior work include a survey on the mobile health interventions for internalizing disorders (Buttazzoni, Brar, & Minaker, 2021). To investigate the efficacy of these apps, experimental papers have been written (Baumel, Muench, Edan, & Kane, 2019; Carlo, Hosseini Ghomi, Renn, & Areán, 2019; R. Zhang et al., 2019).

## Systems Analysis

The first step of the systems analysis is to identify goals of the system (Gibson, Scherer, Gibson, & Smith, 2016, p. 28). However, to aid this process, we will first define and detail each stakeholder group. The major stakeholders are the teenager, the caregiver, the clinician, and the application developer. We define the teenager (also generalizable to be a patient of any age) as the primary subject of a therapy medium. The caregiver is someone who is either (a) supporting the needs of the teenager, or when discussing adults who are autonomous (b) an individual who is part of their everyday life. For the sake of ease, we consolidate teenager and caregiver to be the same person. The clinician is a professional who prescribes palliative steps for treating a given illness, in this context, mental illness to the teenager/patient. Lastly, a third party not directly involved in the treatment loop is the developer, the party that writes and tests the code; responsible for the “life” of the application. A qualification to the coming work is that the novelty does not lie in the metrics derived (due to their simplicity and triviality), however, the contribution lies in showing the feasibility of systems analysis being possible for mental health systems.

We can now readily identify primary, high level goals by the various perspectives of a mental healthcare organization. Within the three groups, teenager and physician can be considered “user” groups, that is, groups who directly interface with the technologies discussed. The last group, the developer, although not directly using the app, contributes to its development in a unique fashion detailed below. We present one high-level goal and accompanying example to show the efficacy of systems analysis.

For the teenager, a goal is improving their depression. Iterating, a more granular goal could be to pursue a treatment medium that blends well with their everyday life. The current stigma against mental illness would motivate discrete treatment mediums, an example being that teenagers would not need to miss a travel sport tournament to see a somnologist for a sleep study, but rather examine sleep’s effect through phone sensors. Another stakeholder parallel to the teenager is the professional healthcare provider, often a physician.

The physician has the top-level goal of using mHealth to improve care, for both the patient and them alike through the presence of more information. To elucidate this further, the computational algorithms for predicting mental health states can remove much uncertainty in deciding care programs. With future research, researchers can create decision support frameworks that integrate mHealth system metrics with predicted psychological scale changes, such as PHQ-9 (for depression) (Kroenke, Spitzer, & Williams, 2001). Another metric is GAD-7 for anxiety (Spitzer, Kroenke, Williams, & Löwe, 2006). These are survey questions that allow practitioners to evaluate the severity of the associated mental health condition. Likewise, the clinician will have a lower-level objective of gaining further insights from their patient.

Applications of this nature will allow for mapping of habits to certain times of day (e.g., watching videos on the phone thirty minutes before bed each evening). These insights will allow for more individualized feedback, without the associated errors of subjectivity with human judgment.

Lastly, the developer serves a unique role, as the arbitrator of the three aforementioned parties. Their primary objective will be to create a lightweight and fuss-free application that meets the three others are functional requirements. Another goal will be to resolve conflicting objectives between the three former stakeholders (the users). An example of a conflict would be a clinician wanting to see a prediction on depression scores for a teenager, while the teenager would not want to see such specificity, accounted for by coming work (Bonaquist et al., in press). By creating an “optimal” representation in a way that minimizes a need for sacrifices from any group, the developer resolves these conflicts. Although these are a limited subset of a larger set of goals, this will inform the system development and evaluation.

The following step in the systems analysis will be to “establish criteria for ranking alternative candidates” (Gibson et al., 2016, p. 30). Alternatives in this context are certain candidate implementations of a given application. For brevity, we will have each user group present one-sample criteria that best represent their interests, and then we can perform a brief computational experiment with arbitrarily initialized values. Note, the developer group is being included, as we assume a tradeoff exists with respect to software costs or development time.

For the adolescent, mentioned earlier was a hypothesized predilection toward discreet treatments. One way to measure such a thing would be through a metric of taking the product of three terms: a “disruptiveness” factor, dot produced with the number of minutes spent on the app. We assume that the app will be used a fixed number of times per day, making the equation “disruptiveness index” to be as noted in Equation (1). (This represents a traditional weighted sum.)

$$D = \begin{bmatrix} d_{morning} \\ d_{noon} \\ d_{evening} \end{bmatrix} \cdot \begin{bmatrix} t_{morning} \\ t_{noon} \\ t_{evening} \end{bmatrix} \tag{1}$$

Our next metric will allow us to gauge the doctor’s value of integrating mobile applications into treatment regimens for their patients. This can be done by witnessing an improvement through a sample pool of participants through the depression and anxiety scores (Kroenke et al., 2001; Spitzer et al., 2006). In particular, we can consider individuals who can decrease their mental health categories over a desired time horizon as a success, and anyone who increases their score can be considered a “failure case.” (Note, the term failure is being used to show the binomial nature of this formula, not any of the author’s opinions on any parties being discussed). The denominator is a physician’s total number of patients who are receiving this treatment. The numerator represents the number of patients who use the mHealth technology in their treatment program and witness a benefit (a decrease in scores). This metric will be referred to as “proportion of improvements.”

$$p = \frac{n_{I_t \geq 1}}{N} \tag{2}$$

Our following metric will be the cost of the software artifact. Cost is important, as it can represent a tradeoff between the following factors: time to develop, maintenance and renovations support, and quality of the application. These three factors, in particular, present large sociotechnical importance to any mental healthcare application. Time to develop can present an urgency on releasing this technology (or a given attribute implemented). If other products exist that can supplant a given proposed application, we can relax this constraint. Maintenance and support are important, as technology is constantly changing. If we witness new technologies that could integrate well into the assessment of adolescent mental health, whether wearable devices or future integration with medical delivery devices (e.g., transdermal insulin controllers). Lastly, quality remains an important aspect of the application. Frequent bugs, crashes, or corruption of neighboring data will frustrate the user, and thus reducing their engagement and willingness to try the novel methodologies.

With all the metrics formulated, the following step is “rank alternatives” while considering factors referred to as “nonperformance concerns” (Gibson et al., 2016, p. 32). Assume that we have developed three prototypes, performed usability studies and created the following aggregates detailed in the following table. The first and third metrics are means, provided by averages disruptions and improvements of all participants in this dummy experiment. Without further normalization nor weights, there does not exist a closed form solution. Given equal tradeoffs between these three variables, we can determine application 1 is preferred (demonstrated in the Appendix).

**Table 1**

Alternatives in Applications For The Given Systems Analysis

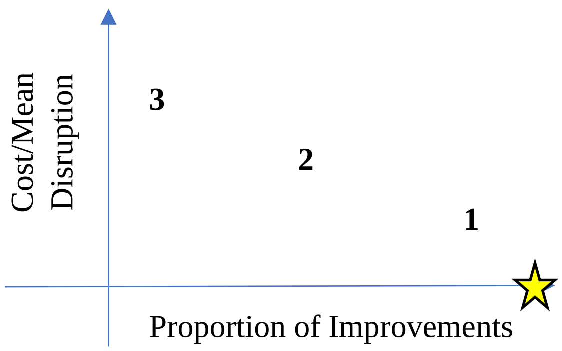
| | Mean Disruption | Cost (millions USD) | Proportion of Improvements |
|---|---|---|---|
| Application 1 | 10 | 1 | 0.9 |
| Application 2 | 20 | 2 | 0.8 |
| Application 3 | 30 | 3 | 0.7 |

*Note*. This table shows the benefits and costs of each of the given applications

To cope with the associated uncertainty, we can conduct a Pareto analysis to visualize the tradeoff. A Pareto analysis allows us to visualize the tradeoffs between differences in a given set of alternatives. At this point, we would address items like "effects on nonusers" (Gibson et al., 2016, p. 32),  however this will be left for future work. As shown in Figure , Applications 2 and 3 are not as good as Application 1, as Application 1 performs better on all measures. An optimization to quantify this is in Appendix A.  Our last two steps of "iterate" and "action" (Gibson et al., 2016, pp. 34–35) would involve repeating this multiple times.

**Figure 1**

*Pareto Frontier of Mock Experiment*




*Note.* These Pareto frontiers shows inherent tradeoffs between each of the proposed applications, adapted from (Singh, 2021)

## Conclusions

We presented a systems analysis of the mobile health (mHealth) paradigm for candidate applications. Motivated by current situations revolving adolescents (who would benefit from such applications) and the current literature supporting the development of mobile mental health applications, we promoted further research into analyzing mental health systems. For future work, practitioners must consider in the systems analysis: ensuring algorithms are free of bias, accounting for "device fatigue," (where individuals are tired after engaging working on devices), and device agnostic implementations. However, many applications are modularly designed, and thus these modifications can occur presently without much delay to software development timelines.

Coming work will discuss the role of a project known as Moodring. Moodring is a data pipeline that is designed for monitoring and prediction of adolescent depression. Likewise, the Sociotechnical Synthesis will describe the possible intersection between the Moodring artifact and the Systems analysis and survey of the literature presented here. However, the work presented here opens up avenues for future papers. This includes a more robust systems analysis, beyond a proof of concept/ "toy" example; incorporating realistic data from past projects. The metric design could be likewise improved, with some form of sensitivity analysis. A software development experience paper describing the development of software artifacts, like Moodring, would inform future teams of potential design decisions and difficulties inherent in the design of mental health applications.

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# Appendix

To formulate a solution, we can use mathematical optimization to find an application that best meets a decision maker's operational objectives. We can walk through the following parts of an optimization problem: decision variables, objective function, and constraints. We will begin by creating our decision variables, which will be as follows, referred to as our $\boldsymbol{d}$ vector, which will be a $n$ element vector.

$$\boldsymbol{d} = [d_1 \quad d_{\dots} \quad d_n] \tag{3}$$

After, we need to normalize our table of alternatives, in order to ensure that no single value can corrupt the analysis due to a difference in units. After, we should assemble a $p\ x\ n$ matrix (where $p$ are the number of min-max normalized metrics, we apply three above), such that the rows are different applications, and columns are the same metric. Note for the Proportion of Improvements, we use the complement $1 - p$ to minimize all three columns.

$$\boldsymbol{v} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & \dots & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \rightarrow \begin{bmatrix} 0 & 0 & 0 \\ 0.5 & 0.5 & 0.5 \\ 1 & 1 & 1 \end{bmatrix} \tag{4}$$

Our constraints will be to ensure that $\boldsymbol{d}$ only contains binary integer variables. Thus, this meets the qualification of creating a binary integer program. We can use this such that each value of $\boldsymbol{d}$ allows for a value to be one if it is selected. Likewise, $\boldsymbol{d}$ should sum to one, to ensure only one application is selected. The below equations describe this.

$$d_i \in \{0,1\}, \forall\ i \in d \tag{5}$$

$$\Sigma d_i = 1, \forall\ i \in d \tag{6}$$

Our weights vector, $\boldsymbol{v}$, will allow us to express the tradeoffs between each of the normalized metrics, and should add to one. (We will assume equal tradeoffs.)

$$\boldsymbol{w} = \begin{bmatrix} w_1 \\ w_{....} \\ w_p \end{bmatrix} \rightarrow \begin{bmatrix} 1/3 \\ 1/3 \\ 1/3 \end{bmatrix} \tag{7}$$

$$\Sigma w_i = 1, \forall\, i \in w \tag{8}$$

Lastly, our objective function will be to minimize the weighted sum selection. We see that application one presents the best option, given our tradeoffs and objective.

$$\min((v \times w)^T \cdot d) \rightarrow [0 \quad 1/2 \quad 1] * [d_1\ d_2\ d_3] \tag{9}$$