Sensei: Sensors for Emotional Well-Being

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Problem Statement

According to the World Health Organization, “1 in 5 people in the world will be affected by mental or neurological disorders at some point in their lives” [9]. One such mental health disorder on the rise is depression, “currently ranked fourth among the 10 leading causes of the global burden of disease, [and] it is predicted that by the year 2020, it will have jumped to second place” [1]. Although most depression is treatable, fewer than 50% of those affected in the world (and fewer than 10% in many countries) receive such treatments. Barriers to effective treatment include a lack of resources, lack of trained health care providers, social stigma associated with mental disorders, and inaccurate assessment [5]. Our project idea is to leverage current research on computational algorithms used to detect and assess mental well-being, by building an application on a wearable device to passively collect biometric user data, evaluate risk for depressive mood, and introduce subtle micro-interventions through a wearable interface. Our goal is to help those suffering from depression self-adjust their mental states.

Types of Depressive Disorders (DSM-5)

Depression is a mental illness that involves the body, actions, behaviors, moods, and thoughts. Depression affects the way an individual eats and sleeps, the way one feels about oneself, and the way an individual thinks about things. Without treatment, symptoms can last for weeks, months, or years. However, appropriate treatment can help most people with depression.

The Diagnostic and Statistical Manual of Mental Disorders (DSM) is a guideline for the diagnosis of mental illness. It lists the criteria required for an individual to be diagnosed with a mental illness. One of the changes in the DSM-5 is Bipolar disorders and depressive disorders are now separated. There is no longer a chapter called “Mood Disorders” with both disorder types listed. Mania is the distinguishing symptom of bipolar disorder; without mania, the disorder would be considered depressive disorder.

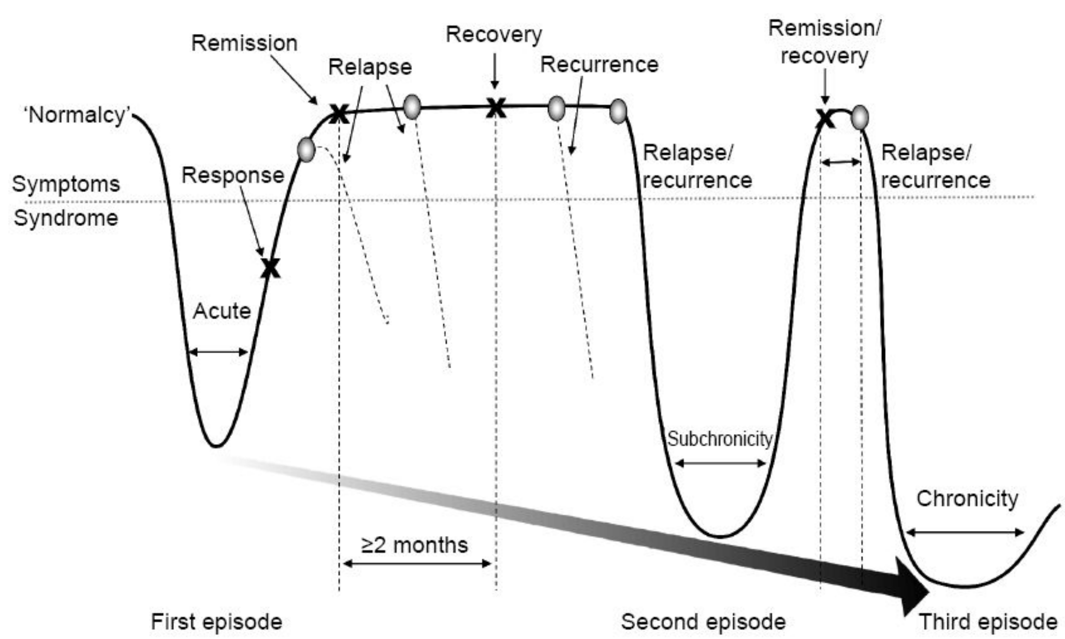
According to the latest 5th version of the DSM, there are now four main depressive disorders:

1) Major Depressive Disorder: “The most commonly diagnosed form of depression, which is typically defined by symptoms such as "depressed mood, loss of interest, weight loss [and] loss of energy for at least two weeks continuously. Major depression affects about 6.7% of the U.S. population over age 18, according to the National Institute of Mental Health -- although women are 70 percent more likely to be diagnosed with major depressive disorder than men.” [8]

2) Persistent Depressive Disorder (Dysthymia), including chronic major depression: "Persistent depressive disorder appears very similar to major depressive disorder -- losing interest in normal daily activities, feeling hopeless and worthless and experiencing lessened productivity. However, it's less severe; it stretches for longer durations and fewer people are diagnosed. While the prevalence of [persistent depressive disorder] is somewhat controversial, it could be anywhere from 1 to 3 percent [of the population]." [8]
3) Disruptive Mood Dysregulation: "A diagnosis for children between the ages of 6 and 18, Hunt says, who "display a variety of symptoms surrounding the inability to effectively manage their emotions -- more so than a typical child in the same developmental stage." This subtype was created to help clinicians describe a child's depression without prematurely diagnosing him or her with bipolar or some other disorder." [8]
4) Premenstrual Dysphoric Disorder: "women "experience one or more mood swings, marked irritability, marked depression, marked anxiety and/or decreased interest, lethargy, change in appetite, change in sleeping habits, sense of being overwhelmed and physical symptoms." Various studies estimate that 3 to 8 percent of women meet the criteria for PMDD." [8]

Targeting a specific disorder would help us to initially hone our algorithm and scale to other disorders in the future. Since Major Depressive Disorder is the most commonly diagnosed depressive disorder, we decided this would be a larger issue and more worthwhile to focus our efforts on.

Phases of Depression and Treatment



(Kupfer, 1991)

There are several stages in the severity of depression ranging from symptom-level to chronic. Treatment may involve a combination of psychotherapy, medications and patient education. The treatment of Major Depressive Disorder has been divided into three phases: acute, continuation and maintenance. [7]

In the acute phase, the goal is to get the patient into a state with minimal symptoms, known as remission. Typically, selective serotonin reuptake inhibitor (SSRI) antidepressant drugs are prescribed, which take four to six weeks to take effect. If, after eight weeks, the reduction in severity is less than 25 percent, that antidepressant is considered to offer no improvement. The physician and patient establish a baseline of untreated symptoms to begin with. This acute phase of treatment may take six to 10 weeks.

After the patient is in a state exhibiting minimal symptoms, the continuation phase begins. Doctors continue to try and eliminate remaining symptoms and restore the patient to his or her normal functioning level and prevent recurrence of further depressive episodes. During this time, the levels of antidepressant therapy and psychotherapy are maintained. If there is no relapse after six months, medication might be discontinued gradually. The continuation phase of treatment could last six to 12 months.

The maintenance phase is most important for patients with chronic or regular episodes of depression. During this time, patients should be monitored regularly and antidepressant therapies are sometimes restarted. The maintenance phase can last one to three years.

Current and Prior Technology / Science Research

According to the DSM-5, a Major Depressive Episode includes at least 5 of the following symptoms occurring over the same 2-week period:

Must include either:

1) Depressed mood most of the day, nearly every day, as reported by self (i.e. I feel sad or empty) or others (i.e. he appears tearful)
2) Markedly diminished interest or pleasure in all, or almost all, activities most of the day, nearly every day.

Can Include:

3) Significant weight loss or gain, or decrease or increase in appetite nearly every day.
4) Insomnia or hypersomnia nearly every day (difficulty or delay in falling asleep or excessive sleep).
5) Psychomotor agitation (such as pacing, inability to sit still, pulling on skin or clothing) or retardation (such as slowed thinking, speech or body movement) nearly every day that can be observed by others.
6) Fatigue or loss of energy nearly every day.

7) Feelings of worthlessness or excessive, inappropriate, or delusional guilt nearly every day.
8) Diminished ability to think or concentrate, or indecisiveness, nearly every day.
9) Recurrent thoughts of death (not just fear of dying), recurrent suicidal ideation without a specific plan, or a suicide attempt or a specific plan for committing suicide.

Through our research, we have identified five indicators of depression detectable through wearable sensors: social interaction, mobility, sleep patterns [3], phone usage [6], and nocturnal temperature [2]. Current applications that aim to improve mood or mental health suffer from low adherence and engagement rates due to the obstructive and time-consuming nature of experience sampling methods [4]. Thus, we aim to passively gather sensor data using open source APIs or platforms and apply researched-backed algorithms to assess depression risk based on these indicators. Wearable devices can interpret these indicators to prompt users at the time they are slipping into depression, so they can actively self-adjust to overcome a depressed state of mind.

As part of this project, we will be working with EECS Ph.D. candidate Pablo Paredes and incorporate into our application the research he has conducted on what he calls “PopTherapy” together with the MIT Media Lab and Microsoft Research [10]. PopTherapy involves investigating the potential of smartphones as a pervasive medium to provide crowd therapy, wherein Paredes and his colleagues came up with a micro-intervention authoring process that focuses on repurposing popular web applications as stress management interventions. This authoring mechanism was combined with a machine-learning based intervention recommender system that introduced micro-interventions to individuals to understand the effects on their temporal circumstances. In their study, they found that participants that received the micro-interventions displayed higher self-awareness of stress, lower depression-related symptoms along with a tendency toward constructive coping behaviors. It is in our interest to combine this research along with the sensor data we gather into the product that we are calling Sensei.

Sensei: The Product

Our solution is to build a system to monitor and collect user data, infer early signs of potential depressed mood and suggest micro-interventions. There are three distinct parts to our system:

First, we will use sensing equipment to passively collect user data; this will be a combination of smartphone capabilities and wearable biometric sensors. Data collected from the smartphone includes voice analysis using microphone, colocation using Bluetooth analysis and WiFi registration patterns, call logs, personal calendar activity, and GPS receivers to track mobility patterns. Wearable data collection includes 3-axis accelerometer and gyroscope for movement and sleep tracking, PGP sensor for heart rate monitoring, EDA sensor to measure GSR.

By relying heavily on sensor data for analysis as opposed to user reported data, we hope to develop a relatively unobtrusive system that seamlessly integrates into users' daily routines and can be run in the background without their conscious exertion or effort.

For mobile sensing we have opted to use the Android platform, which is the most widely used mobile OS. While wearable hardware is still to be determined, our top choice is the Basis – Peak, but unfortunately it lacks an SDK or API so data will have to be harvested manually. The Samsung Gear S is our second choice but limits our sensing capability to mobility, sleep and heart rate. Our third choice is the Pebble Watch with customized "Smartsnaps" to add additional sensors.

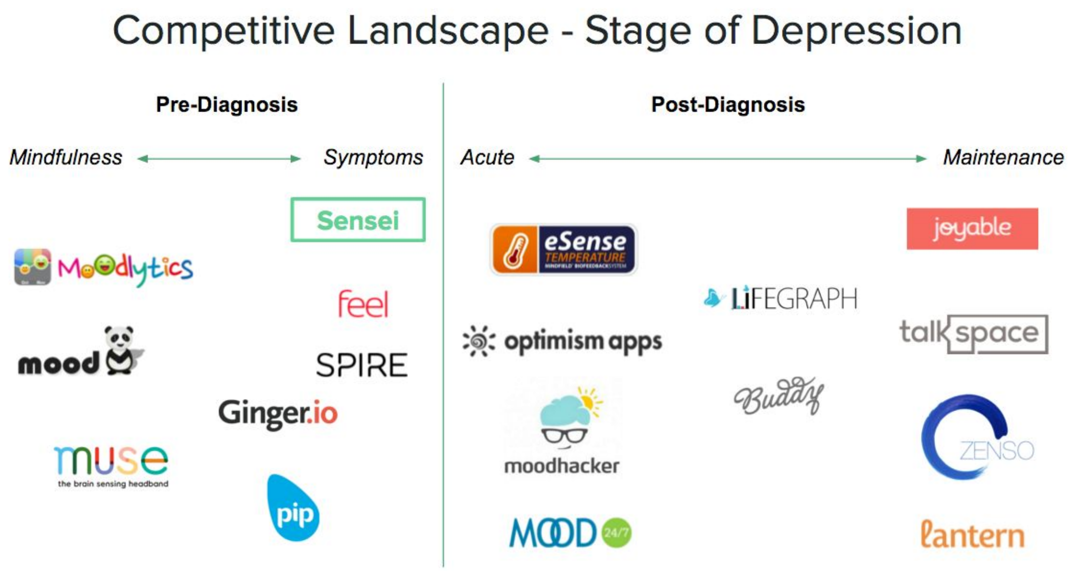
The second part of our solution is to build an Android application to collect and analyze the sensing data and assess the mood of the user. Luckily, there is a plethora of social and behavioral research using sensors. We plan to use EmotionSense, a set of open source smartphone libraries to collect and query the sensor data and incorporate passive experience sampling studies. EmotionSense also includes libraries to trigger notifications based on sensor events, and this code can be adapted for use in a wearable APK. We plan to have an initial working prototype of this application ready by January 2016.

The third part of our solution is behavioral intervention, which will be crucial to the success of our product. The specific interventions will be derived from the existing research that Pablo Paredes has done around cognitive behavioral therapy; additionally, we plan to conduct expert interviews and user studies to uncover new and novel approaches to digital mental health management, keeping in mind recent research surrounding neuroplasticity. Paredes' research on PopTherapy will allow us to use a machine-learning algorithm to better match interventions to specific users.

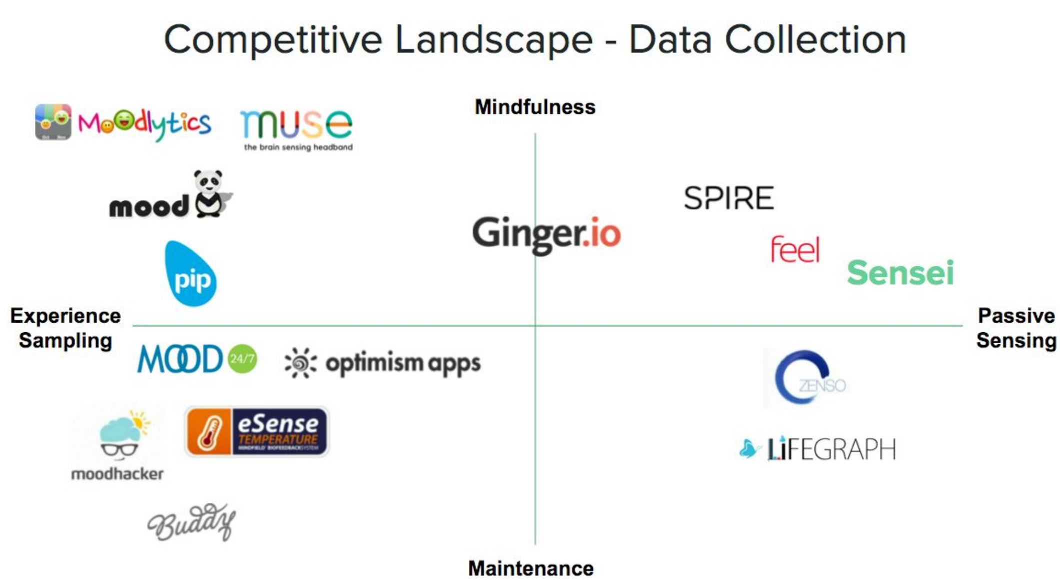
Industry Landscape and Differentiation

There exists a very large industry with respect to the treatment of depression and the symptoms that lead up to it, so we had to carefully consider where our solution would best fit itself in this landscape. The tools available to address the symptoms of depression run the gamut from consumer mood trackers and wearable sensors all the way to medical tools such as telemedicine (helplines) and behavioral tracking and intervention applications.

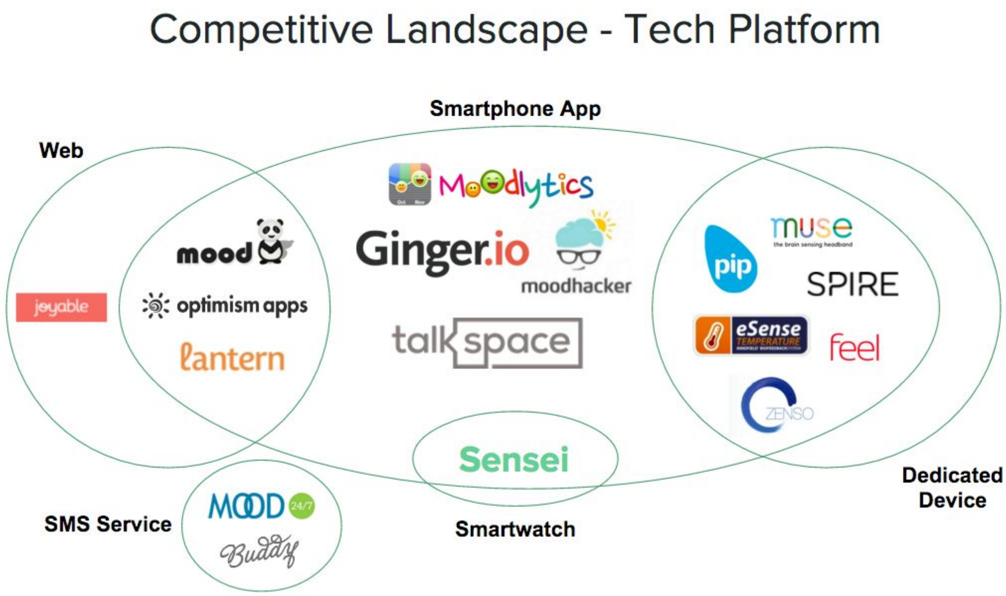
One of the first dimensions we considered was to assess the stage of depression where it would be best to introduce our kind of solution. As seen in the graphic below, you can classify existing applications based on the degree of severity of depression, from when a user is becoming mindful of their mood to when they start displaying the symptoms of depression up until they are diagnosed and require regular therapy and treatment to manage the depression. It can be seen that there are a representative number of applications for each of these levels, and we feel that Sensei would be well-positioned right before a user is diagnosed but after they start showing symptoms of depression that would be detected by Sensei's sensors and machine-learning algorithms.



The next dimension we considered when it came to positioning Sensei was that of data collection. Many of the existing applications on the market rely on active collection of data from the user, prompting them to answer surveys and make subjective assessments of their mood at a given time of day, or for them to take a measurement of a certain biometrics such as heart rate variability or body temperature. One of the key issues we found with the active sampling approach was that users do not have a good baseline to assess their mood whenever subjective assessments are required, thus jeopardizing the accuracy of behavioral tracking. The same can be said for active collection of biometrics.

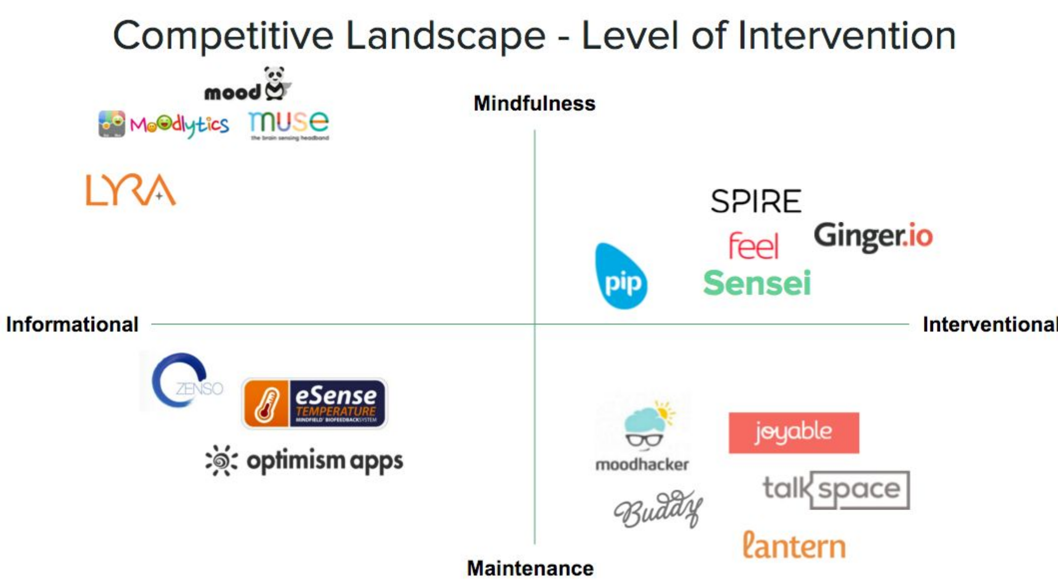


Thus, the strength of our solution lies in the passive sensing of multiple indicators of depression coming from the different sensors available on the user's smartphone and smartwatch. This leads us to the next dimension we considered, which was the technology platform the solution would reside on.



Almost all the competitors have some form of application installed on the smartphone, with some of them utilizing dedicated devices to enhance or collect more accurate sensor data. Our solution is the only one on the market that will be integrated into and will passively collect data from a user's smartwatch, thereby eliminating the need for a dedicated device.

The next key dimension we looked at was behavior modification and at what level it would be acceptable to introduce interventions to alleviate the symptoms of depression the user was



experiencing. In our survey we found that a large number of consumer-level applications already introduced some form of intervention and behavior modification, thus to maintain feature parity our solution would need to employ a similar system.

Finally, we looked at how the current solutions are distributed in the market. A large number of them can be easily downloaded from the application stores on the iOS and Android platforms, while a few are being used primarily for clinical trials or are distributed in partnership with employers and insurance companies.

Key Competitors

After the analysis of the existing landscape of depression application across different dimensions, we narrowed down our focus to three key competitors in the market that employ the three key parts of our solution - passive sampling of sensor data, personalized analytics of user data and behavioral modification through micro-interventions. These three competitors are Ginger.io, Spire and Feel.

The first competitor we looked at is Ginger.io, which is a smartphone application that markets itself as providing personalized mental health care for anxiety and depression. Built on top of social sensing research done in the MIT Media Lab, the app analyzes data from the smartphone's location and communication sensors to understand user movement, smartphone usage and communication patterns and whether these indicate of depression. Ginger's business model hinges on using the data collected by the service and selling this to health care providers, while keeping it free for patients and users. The benefit for the healthcare provider is that they can tailor their care plans to the patient's diagnosis or risk profile.

From a user standpoint, the key advantage of our solution over Ginger's is that Sensei will be employing a larger number of sensors and will be tracking a greater number of depression indicators, thereby increasing the number of data points and accuracy of the machine learning algorithms Sensei will employ. Ginger also requests the user to occasionally provide subjective assessments of their mood (at least once a day) to supplement the data it collects from the mobile phone's sensors. Our solution will reduce the need for experience sampling due to its reliance on a larger number of sensors as indicators of depression.

The second key competitor is Spire, which bills itself as a personal mindfulness coach that employs a smartphone application and a dedicated clip-on device that monitors a user's breathing patterns. The device, called a Spire Stone, retails for $149.95 and passively collects data on the frequency and magnitude of each of the user's exhaled and inhaled breaths. Based on this breath analysis, the application sends notifications to the user in the form of breathing exercises whenever it detects tension or stress in the user's breathing pattern.

Spire's business model relies on revenue generated from sales of the Stones, which is the final monetary transaction they have with each customer. Spire does not sell the data to health care providers or insurance companies, unlike Ginger's approach.

Sensei plans to compete head on with Spire by not requiring a separate dedicated device to operate, while also looking at other indicators beyond the user's breathing patterns. According to a 2014 white paper from Endeavour Partners, it was found that roughly 57% of wearable users lose interest in wearing their devices within 12 months. Sensei avoids this by integrating into the existing smartphone and smartwatch setup of the user.

The final competitor we are looking at is Feel, which is a wristband that aims to track and measure a user's emotions throughout the day. The wristband comes with four integrated sensors that track biosignals such as galvanic skin response, blood volume pulse and skin temperature, which are sent to a smartphone application over Bluetooth which visualises the data and provides the user with personalized recommendations similar to that of the first two competitors.

We believe that while this wristband does take into consideration a larger number of biosignals, it suffers from the same weakness as Spire in that it requires a dedicated device to operate. As of December 2015, the startup behind Feel, Sentio Solutions, is still raising the capital needed to mass produce their wristband. They have not launched their product in the market nor have they set any price point. All activity so far has been to promote their product at various industry conferences and events, while courting investors to back the company.

Our research found a similar product to Feel called Olive, which was also a wristband that attempted to assist users with stress management. The startup behind Olive took a different approach and launched with a crowdfunding campaign on Indiegogo in 2014, which raised $180,000 and allowed them to have some initial traction with users. However, as of May 2015, the company has shut down their operations due to the lack of a strong business model required to sustain the production of a dedicated device, and refunds have been issued to their backers on Indiegogo. We feel that the challenges faced by these startups to come up with robust revenue streams to fund the manufacturing of their devices strengthens Sensei's positioning in the market, as our solution does not require a separate device to operate and deliver value for the end user.

Value Proposition

The value proposition of Sensei is simple: we offer an unobtrusive, accurate way for users to ward off symptoms of depression through personalized, timely micro-interventions that reduce stress and anxiety in their daily lives.

Sensei is unobtrusive - there is no additional device that the user needs to purchase, our solution leverages the user's existing smartphone and smartwatch to collect data. This passive sampling of data is invisible, the user does not need to disrupt their daily routines to input data into the system.

Sensei is accurate - our solution makes full use of the multiple sensors on their smart devices to collect multiple data points, which gives the platform a larger amount of data to train machine learning algorithms on compared to existing solutions.

Sensei is personal - through the usage of the user's personal data across multiple devices, they will receive individualized reports tailored to their profiles and personalized to meet their emotional needs.

Sensei is timely - our solution leverages the research coming from UC Berkeley EECS, MIT Media Lab and Microsoft to introduce micro-interventions at the most appropriate time for small, simple behavioral interventions to ward off depression.

Risks and Mitigation Plans

We have identified several risks that could jeopardize Sensei's adoption in the market, along with mitigation plans to address each of them. The first key risk is the accuracy of the logic behind the algorithms that determine whether or not a user is showing symptoms of depression. False positives can lead to misdiagnoses and mistreatment, so the key mitigation for this is to conduct extensive testing to improve accuracy. As we are positioning Sensei not as a tool to diagnose depression but only to introduce micro-interventions, we feel that the risk is manageable enough as long as proper testing is done.

Another key risk is the protecting the privacy of user data and making sure it does not fall into the wrong hands. This requires the use of encryption and privacy settings to ensure that the user has full control into who can view their data. On the back-end, any user data used for training machine-learning algorithms must be anonymized and stripped of all personally identifiable information.

The final major risk we have considered is protecting the safety of our users, especially from self-harm. One possibility is that we might have users who display suicidal tendencies, and a possible way of mitigating this is through implementing safeguards within the application such as notifying ‘in case of emergency’ contacts when such behavior is seen by the platform.

Future Plans

As was mentioned in our product introduction, a working prototype of the application will be ready in January 2016. From there, we will be using an iterative design approach to develop the micro-intervention feature, running design experiments from February through April 2016. We plan to have a POC implementation incorporating all three features of our product by May 2016.

While we get our product ready for testing, we are already working on the business model to ensure the viability of our product in the market - narrowing down our target customer segments, exploring multiple revenue streams and looking at partnerships with key players in the healthcare industry such as insurance companies, clinicians and employers of our target customers.

Resources

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