Machine Learning, Wearable Computing and Alzheimer's Disease

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Final Project Report

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Care Ecosystem
Navigating Patients and Families Through Stages of Care

Table of Contents

Chapter 1: Individual Technical Contributions

1 Introduction

1.1 Project description and context

Our capstone project hopes to pave the way towards a more cost-effective healthcare solution for patients with Alzheimer's disease that would allow patients to live independently at home for as long as possible. Using Bluetooth Low Energy (BLE) SensorTags from Texas Instruments to monitor key aspects of a household such as the stove, the medicine box or the shower, we will be able to monitor the patient's daily habits. With this data and the help of machine learning algorithms, we will then be able to model the patient's behavior. In this manner, patients will be able to live independently most of the time without constant monitoring from the caregivers, and caregivers can respond in the shortest amount of time possible when the need arises. Additionally, with the information on the patient's behavior, physicians will be able to track the disease progression over time and make more well-informed treatment recommendations.

The monitoring system is split into 3 main subsystems – data collection, data storage and data analysis. Data collection is done via the SensorTags which will sense the activities of the patient with various sensors. The data is then passed to the smart watch that is worn by the patient, which is then passed to the smart phone. Periodically, the smart phone uploads the collected data onto the cloud server where all the data of the many patients are stored securely. Machine learning scripts in the cloud server then processes the information to model the patient's behavior.

1.2 Knowledge domains

Prior to our team joining Prof. Bayen, there was already a team working on Care Ecosystem. Care Ecosystem is a program initiated by the UCSF Memory and Aging Center that aims to assist caregivers of patients with Alzheimer's disease in various ways through passively monitoring and collecting data on the patient's behavior. At that point in time, the Care Ecosystem app did not have much support for the SensorTags. Instead, it was used mainly to locate the position of patients around the house via the help of Estimote Bluetooth beacons, and could pinpoint which room the patient was in up to an accuracy of 95%.

In addition to the Care Ecosystem app, a summer intern, Cyril Tamraz, worked on the SensorTags and created an app for it. Using the app, he was able to collect data of various activities such as opening a door or drawer, and recognize those activities using machine learning. When we first took over the development of the SensorTags, we extended the functionality of his app before integrating support for the SensorTags into the Care Ecosystem app.

1.3 List of associated tasks

The project consists of 3 main tasks. The first part of the project involves making sure that we are able to get data from the SensorTags accurately and reliably. These SensorTags communicate with the smart watch via Bluetooth technology and it is imperative that the data collected by the SensorTags are transmitted reliably and accurately from the SensorTags to the smart watch. Chong Wee and I jointly handle this part of the project. Between the two of us, I worked mainly on the hardware and Bluetooth communication between the SensorTag and smart watch, while Chong Wee worked more on the software app and data collection framework. Once we have the data on the smart phone, the next step would be to be able to aggregate the data on a remote server so that the data can be processed. Phoenix handled the creation and organization of this server. Lastly, once the data have been transmitted to the remote server, we will then run the data through machine learning algorithms in order to gain meaningful insights. Both Ludovic and Marie took charge of this portion. Figure 1 illustrates the different tasks and who was initially involved in carrying them out.

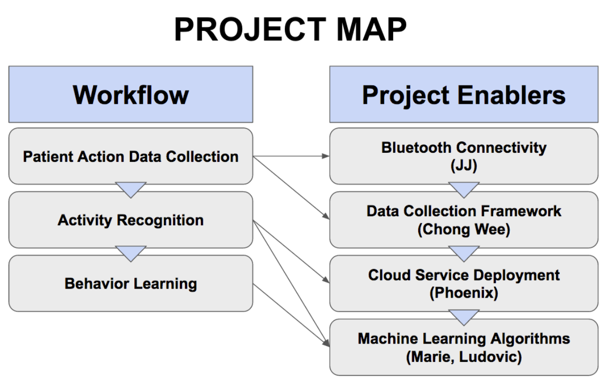

Figure 1.1. List of associated task breakdown

2 Individual Technical Contribution

2.1 Implementing multiple concurrent Bluetooth connections

When we were first presented with the project, we were told that the smart watch could only connect to one SensorTag at a time. This posed a huge challenge to us because it meant that the data collected by other SensorTags that were not connected would be lost, and the loss of data would adversely impact the accuracy of the behavior modeling algorithms. This is largely due to the fact that our behavior-learning algorithm relies heavily on recognizing the patterns in the continuous streams of readings reported by the SensorTags. Therefore, losing information would mean that we would not have the necessary data needed to correctly and accurately model the behavior of the patients, and this will affect the accuracy of our machine learning algorithm. The initial proposed solution was to modify the firmware of the SensorTag to implement a storage buffer on the SensorTag such that when the SensorTag is not connected to the smart device, it will store its data in the buffer. The smart watch will then cycle the Bluetooth connection through the different SensorTags in range periodically in order to retrieve information from the buffer of each SensorTag.

While this approach seemed feasible, none of us were comfortable with modifying the firmware of the SensorTag and were not sure how long it would take. Furthermore, without support for data collection from the SensorTags, the rest of the team will not be able to move far with their parts either. With so much uncertainty on a crucial part of the project, we decided to try an alternative solution. Chong Wee and I recognized that our smart phones were able to connect to more than one Bluetooth simultaneously, so it seemed like each smart device could definitely connect to more than one SensorTag. So, we began to experiment with the existing Android application that was built for Android smart phones.

It turned out that each smart phone could actually maintain connection with up to 7 SensorTags. The reason why it was thought that multiple connections were not possible was because there was no support for it in Cyril's SensorTag app. In Cyril app, there are many different activities defined that will collect data specifically for that activity. For example, one activity defines was to collect data for recognizing the opening and closing of a door. Once that activity has been chosen, the app will then scan for available SensorTags and connect to the first one that is detected. As a result, the user is not able to select the specific SensorTags he/she wants to connect to.

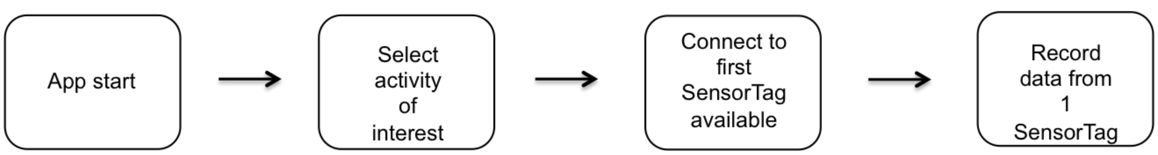

Figure 2.1 Cyril's application's operation flow

In order to support multiple SensorTag readings, Chong Wee and I modified the design of Cyril's app. We added the functionality to specifically request for a scan for available SensorTags. Once the scan has completed, the app will notify the user of a list of available SensorTags, and the user can either choose to connect to one of the SensorTags in the list, or all of the SensorTags.

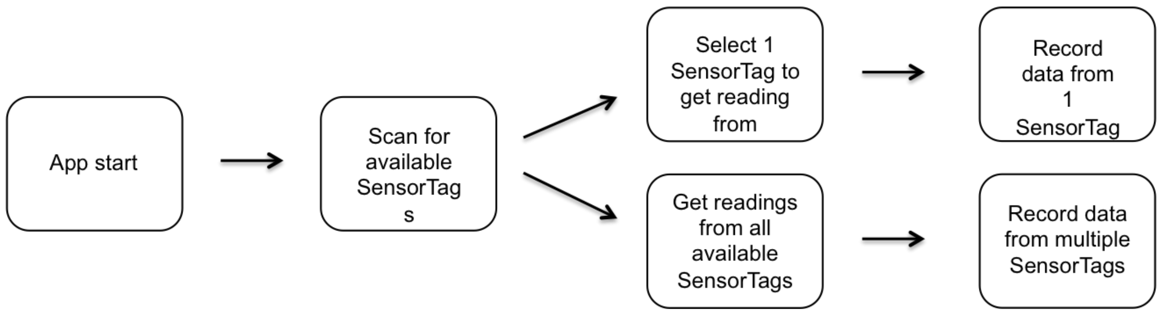

Figure 2.2 Application operation flow with support for multiple SensorTag connections

By trying an alternative solution that we thought would be easier to implement and better to experiment with, we were able to avoid having to dive into modifying the firmware of the SensorTags which could potentially prove to be very complicated. Additionally, instead of cycling through the different SensorTags periodically, we were able to stream data from the various SensorTags simultaneously. This meant that we did not have to concern ourselves with the many problems that could arise from connecting to and disconnecting from the SensorTags in rapid succession. Most importantly, with the initial support for data collection, we were able to gather preliminary results and move the project forward.

2.2 Indefinite advertisement of SensorTag Bluetooth connectivity

In the previous version of the firmware that came pre-installed on the SensorTags, each unit only began advertising its Bluetooth availability for 30 seconds. If no device connects to the SensorTag during these 30 seconds, the SensorTag will automatically shutdown. This is not ideal because our end goal is to have the SensorTag passively collect activity data around a house as the patient walks around, and as a result different SensorTags will be connected to and disconnected at various points of the day. Thus, the SensorTags must always be ready for a Bluetooth connection whenever the smart watch is in range, and this meant that the SensorTag had to be turned on indefinitely. After modifying some parameters in the firmware code, I was able to enable this feature. With this feature implemented, we were one step closer to a fully automated system, where patients can roam freely in their houses without having to manually connect to the SensorTags.

2.3 Design of smart watch to SensorTags connection algorithm

Since the smart watch is only able to connect up to 6 SensorTags, we needed a way to manage the connections such that only data from relevant SensorTags was being streamed to the smart watch. In order to understand the implementation of the connection algorithm, it is important to first understand how the Care Ecosystem app handles Bluetooth connections.

1. After a successfully starting all the different services of the app, a callback function, mLeScanCallback, is attached to the Bluetooth scan routine.
2. Every minute, the Bluetooth scan routine is started and scans the smart watch's surroundings for available SensorTags for 6 seconds.
3. During the 6 seconds, if an available Bluetooth connection is discovered, the callback function is invoked. The callback function is invoked for every

available Bluetooth connection discovered, SensorTag or not. The callback function checks if the Bluetooth connection is associated with a SensorTag, and if a SensorTag connection has been discovered, stores the connection details of the SensorTag so that it might connect to it later.

Once all available SensorTags have been detected and stored, the connection algorithm then decides which SensorTags are relevant and attempts to connect to them. Initially, we decided that since the purpose was to monitor that patient's activities, it would make sense to connect to the SensorTags in order of proximity – we should connect to the 3 closest SensorTags. We decided to only utilize 3 out of the 6 Bluetooth connections that the smart watch can make because too many Bluetooth connections slows down the smartwatch and causes it to operate very slowly. We envision this to change as smart watches get equipped with better and better processors. Every time an available Bluetooth signal is discovered, the callback function also reports the associated received signal strength indicator (RSSI) value. Although the RSSI value is not perfectly positively correlated with the distance between the smart watch and SensorTag, and can be affected drastically by obstacles in between, we decided to use it because there was still a strong correlation between RSSI values and distance assuming a perfect line of sight.

Using the RSSI value as an indicator of priority, the connection algorithm is as follows:

1. In the callback function, if the available Bluetooth connection belongs to a SensorTag, the SensorTag's unique Bluetooth address and RSSI value is stored in a priority queue.

2. The priority queue sorts the Bluetooth connections based on RSSI value, giving the highest RSSI value the highest priority.
3. At the end of the 6 seconds scanning phase, the smart watch will initiate Bluetooth connections to the top 3 SensorTags based on priority.
4. During the next scan cycle, if the top 3 priority SensorTags are still the same, then the Bluetooth connection is maintained. Otherwise, the app checks if the SensorTags that are currently connected are in the top 3 priority. If a currently connected SensorTag is not in the top 3 priority, it is disconnected from and the app connects to a SensorTag that is in the top 3 priority but is not currently connected. In this way, the app does not make unnecessary connections and disconnections.

While designing the connection algorithm, there were several factors that we considered. Because the scan interval was set at 1 minute, it is possible that we could miss out on data collection from relevant SensorTags because the scanning interval is too long. Imagine a scenario where a patient who is in his bedroom and the smart watch is connected to 3 SensorTags in the bedroom. He decides to use the bathroom and finishes using the bathroom within 1 minute. Since the smart watch was not connected to the SensorTag used to sense flushes, this activity will be undetected.

While we could decrease the interval between scans, this would be at the expense of the battery life of the watch. Currently, the watch is able to last about 12-16 hours on a single charge, which is barely enough for a day’s use, and so shortening the battery life of the smart watch further would be undesirable.

Another solution that we contemplated would be to first define a list of SensorTags that the smart watch should connect to first as long as the SensorTags' RSSI values are above a certain threshold. These SensorTags would thus be connected to first before the SensorTags in the priority queue. Such SensorTags could include ones that detect a toilet flush, or detect if the patients have taken their medication, or any activity that is deemed to be of high importance. However, because we were limited by the amount of time we had, we decide to focus our efforts on collecting more data so that we could build the behavior modeling algorithms instead of refining the connection algorithm. This is however a potential solution and may be experimented on by future teams that work on this project.

3 Concluding Remarks

This Capstone project has undoubtedly been the biggest project that I've worked on. When we were first handed the project, it seemed like there were so many components to work with that we were initially really lost. However, under the patient and professional tutelage of Prof. Alex and George, we were able to produce great results in implementing the system. While we did not achieve our initial goal of reaching patient trials by the end of the academic year, we successfully implemented the system in Ludovic's house and have collected much data that would prove relevant to improving the system. I believe that our team has successfully built the foundations to creating a robust system that would benefit Alzheimer's patients at large.

Because the system implemented in Ludovic's house is only a subsystem without the smart watch, where we used multiple smart phones as hubs to connect to multiple SensorTags, more testing needs to be done with the full system in place where the user wears the smart watch. This is important as it will help us uncover bugs on the software side, as well as use cases that we might not have thought of while designing the app. Additionally, the connection algorithm should be refined to include other forms of priority besides proximity, such as the priority list that I described at the end of section 2.3.

All in all, this has been an extremely enjoyable project because it was extremely challenging and reaching the milestones that we set initially was really fulfilling.

Chapter 2: Team Engineering Leadership Paper

4 Problem Statement

Given the prohibitive cost of nursing facilities and dedicated care for Alzheimer's Disease patients (Hurd, et al. 2013:1332), our project aims to design and develop an affordable (under $1,000) system for tracking and monitoring patients in their own homes. Using inexpensive and commonly available sensors, wearable devices and smartphones, the system constantly gathers information about the patient's daily routine and relays it to a centralized server. This is where machine learning algorithms are used to build up knowledge of the patient's behavior over time, before applying analysis to flag any potential anomalies. In doing so, this system will allow patients to stay safer in their own homes and provide medical practitioners with updates on the progression of their patient's condition. In the following sections, we shall analyze the industry that our project operates within, discuss the technology strategy that we adopted and highlight the intellectual property concerns we have.

5 Industry, Strategy and Intellectual Property

5.1 Industry Analysis

For industry analysis, we reference Porter's Five Forces (Porter, 1979) and performed an analysis on each of the forces with regard to the industry for technology-integrated home-based care solutions for Alzheimer's Disease patients. Porter's framework allows us to compare the relative strengths and weaknesses of the following forces: Threat of New Entrants, Bargaining Power of Customers, Bargaining Power of Suppliers, Threat of Substitutes and Intensity of Rivalry. In doing so, we gain clarity in the profitability of the industry in general and how the stable state might appear in the long term.

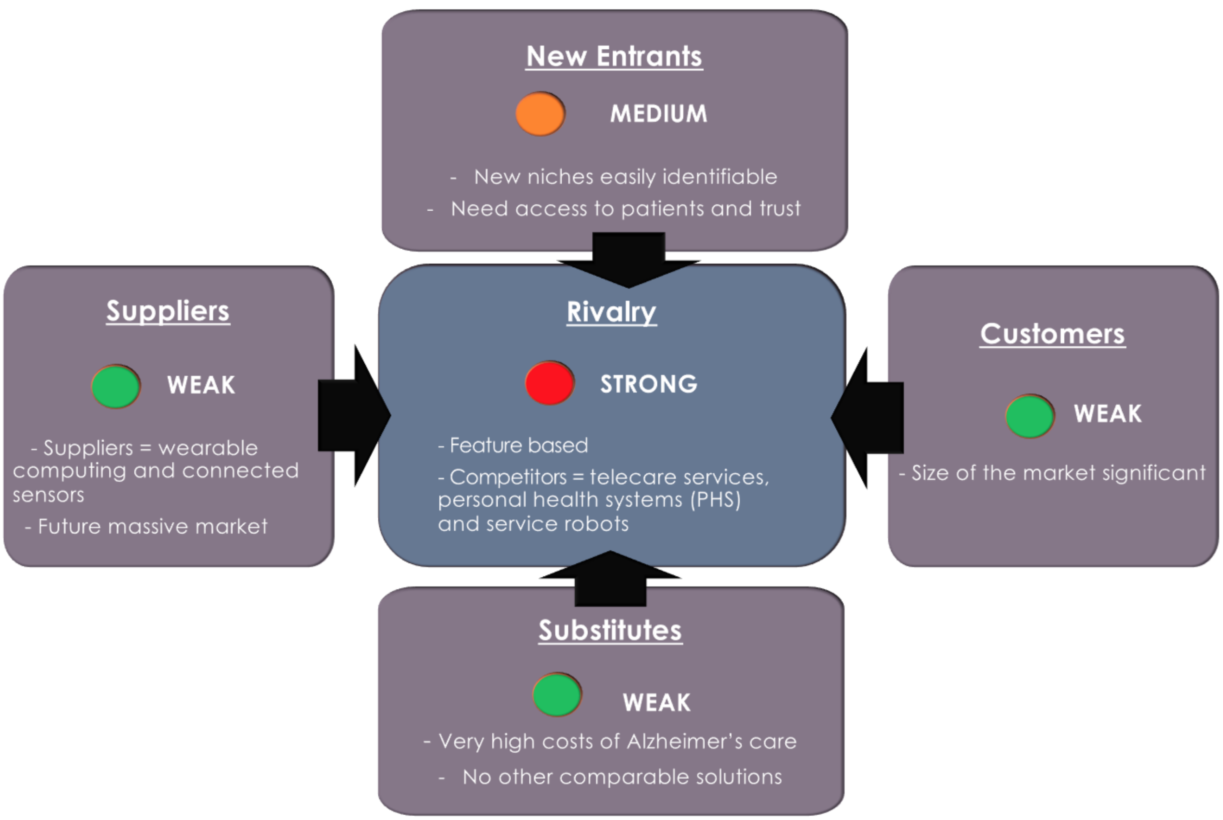

Figure 5.1 Porter's five forces on technology-integrated home-based case industry

For the threat of substitutes, we assess that the force asserted is extremely weak. According to a paper published by the New England Journal of Medicine, the average annual financial cost of Alzheimer's care in 2010 was $28,501 (Hurd, et al. 2013:1332). Out of that, 48.6% was attributed to payments made to nursing home care (Hurd, et al. 2013:1332). By allowing Alzheimer's patients to live at home independently as long as possible, they will be able to save a substantial amount of the financial cost associated with Alzheimer's care. Moreover, nearly 18 billion hours of unpaid care was provided to Americans with Alzheimer's Disease in 2014 (Alzheimer's, A. 2015). Through the use of technology to replace dedicated caregiving, our solution provides a game-changing alternative to Alzheimer's Disease patients. Specifically, our solution is significantly more cost efficient (under $1,000 compared to $28,501) and reduces the human intervention needed by existing solutions by doing away with a dedicated caregiver. Hence, we believe that the threat of substitutes to the industry is weak.

In terms of the bargaining power of customers, we assess this to be weak. There are around 47.8 million people in the US aged 65 or older, representing 15% of the total US population (IBISWorld, 2015). Since Alzheimer's Disease and other dementias are highly correlated with age, nearly 5.1 million senior Americans are expected to be afflicted by Alzheimer's Disease (Alzheimer's, A. 2015). Given the size of the market, it is unlikely that any one single group of customers can assert significant pressure on the industry. Furthermore, the high cost of substitutes mentioned previously, such as nursing homes and dedicated caregivers, further erodes the bargaining power of customers.

Next, we argue that the bargaining power of suppliers is weak as well. Since the industry depends heavily on off-the-shelf wearable computing and connected sensors (a subset of the Internet of Things category), we shall examine these suppliers in detail. Firstly, it is predicted that 33% of adults in the US shall own a wearable device by 2017, and the smartwatch will lead this growth by taking an increasingly larger share of the smart devices (The Wearables Report: Growth trends, 2016). Secondly, it is also predicted that the worldwide market for IoT solutions will grow from $1.9 trillion in 2013 to $7.1 trillion in 2020, and will be the world's most massive device market, equivalent to double the size of all of the other smart devices market in 2019 (Internet of Things - HorizonWatch 2015 Trend Report, 2016). These trends are immensely beneficial to our industry since the prevalence of smartwatches and connected sensors represents substantial competition between suppliers, lowering the bargaining power that individual suppliers may possess over our industry.

As for intensity of rivalry within the industry, our team anticipates strong competition from the different players, namely telecare services, personal health systems (PHS) and service robots. According to Pols (2012:11), 'Telecare' is an "umbrella term referring to the technical devices and professional practices applied in 'care at a distance', care that supports chronically ill people living at home". It is a passive, unsophisticated technology that requires the patient to initiate a call to the telecare center in times of need. A second form of technology integrated home-based care solutions can be generally termed as Personal Health Systems (PHS). This refers to any home-based ICT system that collects, monitors and manages health-care related information (Codagnone 2009:8; Schartinger et al. 2012:1; Abadie et al. 2011:11-14). In contrast to telecare, PHS is an active technology comprised of motion sensors, on-furniture sensors (e.g. chairs, beds, doors) and video cameras (activated only during emergencies for privacy) to monitor patients in their own homes. At the forefront of technology-integrated patient care, there have been attempts to introduce service robots to the patient care activity chain. Compagna and Kohlbacher (2015) investigated instances of service robots in patient care facilities, identifying possible applications in logistical activities to reduce caregiver workload and therapy enhancement through multimedia entertainment.. In summary, given the myriad solutions offered in this industry, we foresee that the rivalry would be strong and features-based, where companies innovate to provide more timely and accurate monitoring for both patients and caregivers.

Lastly, the threat of new entrants is the most uncertain force to this industry. While intellectual property could form significant barriers to entry, the diversity of solutions available means that a new entrant could easily identify a new niche to operate within. Nevertheless, we believe that access to patients and trust formed between patients and companies could be a key barrier formed by the incumbents. Once an incumbent has cornered a sizeable portion of the market, the reputation and trust it has built up would be its key weapon against any new entrant. Thus, we feel that there is a medium threat in the form of new entrants.

5.2 Technology Strategy

Based on Naeem Zafar's framework for determining the quality of a product idea (Zafar, 2010), we assessed our project's suitability for product creation. While this framework is meant to evaluate a product idea at its incubation phase before proceeding to development, we have applied it retrospectively to determine its suitability for transition from an academic project to a full fledged commercial product.

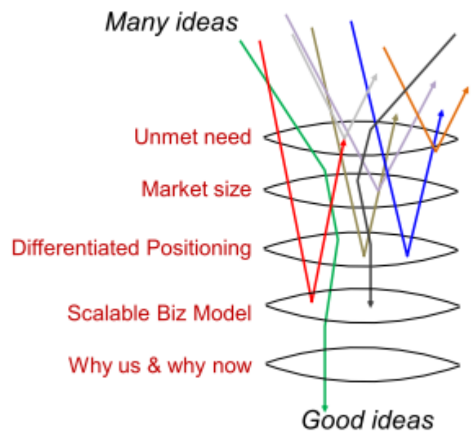

Figure 5.2 Zafar's framework (Zafar, 2010)

Criteria	Score
Unmet Need	A
Market Size	A
Differentiated Positioning	A-
Scalable Business Model	A
Why us	A-
Why now	B+

Table 5.1 Applying Zafar's product idea evaluation framework to the project

To begin with, the framework requires us to consider whether an unmet need exists for the product. Clearly, based on the high costs associated with nursing homes and dedicated care-giving services, Alzheimer's Disease patients have a strong desire to stay at home independently (Score for Unmet Need: A). With an estimated 5.1 million Americans above 65 with Alzheimer's Disease and a further

200,000 below 65 (Alzheimer's, A. 2015), we expect the market size to be relatively large, thereby bringing with it substantial opportunities for commercialization and growth (Score for Market Size: A).

In terms of differentiated positioning, we have investigated potential competitors in terms of telecare systems, PHS and service robots. Our proposed solution can be considered as a form of PHS, considering that it uses sensors to track patient activity. However, our solution has a significant edge over contemporary implementations which are prone to false alarms due to the usage of predetermined thresholds (Neven, 2015). In contrast, our proposed solution makes use of machine learning to recognize patient behavior over time, hence reducing the likelihood of false alarms. By maintaining machine learning as our competitive edge over our competitors, our proposed solution should emerge as the forerunner in this field (Score for Differentiated Positioning: A-).

Next, the framework has prompted us to consider the scalability of the business model. Our proposed solution exploits prevalent off-the-shelf technologies such as wearable computing, IoT and next generation communication infrastructure. Since these components and infrastructure are readily available to our customers, our scalability will not be constrained by them. Furthermore, as our added value comes largely from the machine learning algorithm and server-based processing, we are able to easily scale up our operations by adding server capacity (Score for Scalable Business Model: A).

Lastly, the framework challenges the team to answer why we should be the one to bring such a product to market and why this is the most opportune time to do so. We believe that we are in an excellent position to do so given our relationship with the Memory and Aging Center at University of California San Francisco. This provides us with access to a panel of neurologists, patients, caregivers and healthcare regulators, allowing us to refine the product to best fit the needs of Alzheimer's Disease patients (Score for Why Us: A-). In addition, we believe the timing is appropriate since we are approaching a phase in technology where wearable computing, connected sensors and high bandwidth data communications are becoming ubiquitous, allowing us to deploy our solution at scale in a cost efficient manner. Moreover, the field of machine learning is advancing rapidly and this technology has been proven to produce results when large amounts of data is available (Score for Why Now: B+).

5.3 Intellectual Property

For this project, we are in an unique position with regard to topics on intellectual property. Since our work brings significant benefit to patients, publishing our algorithms and source code in the public domain would greatly benefit the Alzheimer's Disease community or even the greater dementia community. This can be achieved by lowering barriers of entry for companies to join the industry, thereby bringing down the cost of development and spurring further innovations in this area.

On the other hand, given the size of the target market and viability of the product, there are enormous opportunities for commercialization. By retaining the intellectual property and building a commercial product around it, we would be able to introduce a truly differentiated offering to the market, with the potential of achieving sizeable returns to our research and development. Alternatively, should we decide not to bear the risks of bringing the product to market, there are also potential gains to be reaped by licensing the intellectual property to interested parties.

Despite the lure of potential gains, our team firmly believes that such innovation should be propagated to benefit the millions of patients afflicted by Alzheimer's Disease. Through open-sourcing the intellectual property, we hope that like-minded researchers can also contribute towards our effort and allow patients to stay safer in their own homes.

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