Establishing a Home Sensing Platform in the Field of Technological Healthcare

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Introduction

In the year 2017, Internet of Things (IoT) devices outnumbered living human beings on Earth for the first time (Meulen, 2017). As more of the world comes online and data is considered an ever more valuable resource, the number of IoT devices is sure to accelerate in the coming years. The primary function of these devices is to collect and act on information about the physical environment through the use of embedded sensors and wireless communication protocols (ITU, 2012). Internet of Things devices collect data in many industries including transportation, manufacturing, and even agriculture, where they are used to present data and trends that enable users to make decisions that are informed by data. These same principles can be applied to long term healthcare programs. By using IoT devices to track and analyze human behaviors in the home environment, these sensors can provide data driven insights that inform personal healthcare, caretaking, and treatment.

The Coronavirus pandemic of 2020 has solidified the need for tele-medicine. Suddenly, people must weigh the perceived risk of infection at a doctor's office against getting help for minor issues or chronic disease care. As a result, people are flocking to available solutions for virtual medicine (Koonin et. al, 2020). IoT devices can supplement remote healthcare work by providing a long-term view of behavior in the home. Incorporating the use of sensors in the home is done to capture data and construct patterns for Activities of Daily Living (ADLs). These activities, such as eating, bathing, and moving about, are the activities that are fundamental to independent living. Sensor platforms are also used to gather information related to more complex Instrumental Activities of Daily Living. These IADLs reflect behaviors that are responsible for a good quality of life like cooking, driving, and communicating (Guo & Sapra, 2020). Measurement of these activities is important to understand how people are affected by their chronic conditions (Edemekong & Bomgaars, 2020). Once sensors are placed around a home, the sensors capture daily activity information and store collected health data that can be used to assist medical care programs in diagnosis, treatment, and care. Home technology platforms that track activities of daily living have been deployed in research capacities at several universities. University research programs, such as TigerPlace at the University of Missouri, aim to utilize technology to provide ADL data to medical staff and ultimately to improve the lives of program participants (Rantz et. al, 2013). These programs rely on home technology platforms to drive action in care. By establishing a secure pipeline of information, Internet of Things devices can inform medical staff of changes in behavior and identify patients of concern who may require further investigation.

This thesis explores how home sensor platforms can be leveraged in the context of care for chronic conditions. In order to understand the needs of such a system, a platform has been developed and deployed at the Georgia Tech Aware Home, an authentic home used as a test bed to conduct home-related research, to collect data in a research setting for the Emory and Georgia Tech joint Cognitive Empowerment Program (Kientz et. al, 2008). The goal of this program is to generate insight into the care of Mild Cognitive Impairment using large scale data collection. The design of home sensing platform of the program and how the platform has been utilized are investigated in this paper. Throughout the course of that investigation, several key insights are derived from lessons learned about collecting and using home sensor data in the context of care for chronic conditions.

Background

The field of technological healthcare is relatively new. Technology enables doctors and other medical staff to increase engagement with their patients and provides timely opportunities for health data collection (Alexandru, Ianculescu & Coardos, 2018). This stronger relationship can be enabled through virtual consultation, distribution of medical literature, and collection of patient data. Data collected about a patient empowers medical professionals to create a more personalized approach to medicine as the data provides a holistic view of patient life (Chawla & Davis, 2013). Home data collection is a recent approach to the field of technological healthcare, but it has already been established that high frequency data collection in the home of individuals can reduce sample sizes needed to test a hypothesis regarding health outcomes (Dodge et. al, 2015). Given this utility, it is clear that the use of home sensing in research scenarios shows promise in the future of healthcare. By providing data related to behaviors in the home, home sensing platforms can empower every stakeholder of the system to make better decisions. This data allows researchers to confidently test hypotheses that can impact treatment plans and lead to a better understanding of the impact those treatments have on patients. In the future, home sensing could enable physicians to focus on learning about specific patients and specific diseases, using targeted data, rather than gathering large cohorts of patients for medical trials.

Collection of data in the home provides an enormous amount of information about the behavior of patients, particularly those with chronic conditions that may limit activity outside. The focus of home data collection is to collect information about Activities of Daily Living. These activities, such as sleeping, eating, and walking about the home, been determined as an effective dataset in predicting and tracking health outcomes from a longitudinal health data analysis standpoint (Sonn, Grimbyand & Svanborg, 1996). Collecting data and analyzing Activities of Daily Living from individuals can also enable medical professionals to better understand the personal impact that treatment or disease is having on an individual as reflected in behavioral changes, and then adapt their treatment to address those changes. Specifically, analyzing data related to activities of daily living has already been used to inform personalized healthcare advice which led to better medical outcomes for the individuals studied (Jacobs, 2017). Researchers must balance between protecting extremely sensitive medical information or data and analyzing the behaviors of individuals in their homes in order to achieve better healthcare outcomes. While the benefits of home data collection have been demonstrated thoroughly, the intricacies related to the design of home sensing platforms have not sufficiently addressed privacy concerns thus far. The system defined in this paper seeks to balance the value of medical data collection with values and needs for individual privacy. The goal of this system is to create a reciprocal partnership between researchers and participants, and ultimately, create better health outcomes.

Home data collection platforms, like the system defined in this article, uncover valuable and interesting data about the behaviors that make up much of our daily lives. While privacy considerations have bubbled to the forefront of the design process for many data platforms, datasets collected for medical purposes in the home require a special concern due to the intimate nature of the data collected and regulations protecting medical data, such as HIPAA. In order to navigate the privacy considerations required of home sensing platforms, this article will separate home sensor devices into two categories with an emphasis on privacy: primary and secondary devices.

Primary data collection devices, those that collect video, sound or GPS information, have been found to be very effective in determining a number of different metrics such as balance, falls, and room usage (Stone &

Skubic, 2015). However, these devices can be considered obtrusive and invasive as they collect specific personal information and associate that information with an individual at the data source. These devices provide a clearer understanding of a participant's environment, which is incredibly useful to researchers. Still, that clear understanding comes at a cost to privacy.

Another approach to data collection in the home relies on secondary sensors. This subgroup of sensors collects more generalized, unattributed information on participant interactions with their environment. Examples include presence sensors, traditionally included in home security systems, as well as devices that track doors, temperature and humidity, or power usage. These anonymized data sources provide insight into the lives of participants without directly linking activities to the user at the source of data collection. This approach enhances participant privacy at the cost of being able to clearly attribute behaviors to a specific participant in multiple occupancy dwellings. As with most sensor platforms, innovative analysis algorithms must be employed to extract useful events and behaviors from secondary sensor data. Even so, it has been established that given clever algorithms, secondary data collection devices are a suitable substitute for manually collecting information about activities of daily living (Hayes et. al, 2010). In many situations, secondary sensing paradigms can protect participant security while providing accurate and useful data to researchers. Secondary data collection devices have been combined with analysis to gather health metrics from research participants. When employed in this way, secondary data collection devices were found to be very accurate in otherwise difficult to track situations (Petersen et. al, 2012). As evident in this passage, secondary sensors can provide useful data to researchers much in the same way as primary devices. Based on the limitations and requirements of the study platform built for this paper, the core of the home technology Internet of Things System for the Cognitive Empowerment Program is passive secondary device sensors.

Platform

To understand the demands and requirements of home sensing technology, a platform of smart home and relevant health-centric devices was developed for the Cognitive Empowerment Program. This platform is being used to analyze data and track activities of daily living in the homes of program members. The flagship research platform has been developed and installed in the Georgia Tech Aware Home. This facility provides a prototype testing environment for similar systems that are deployed in Cognitive Empowerment Program members' homes. The home sensing platform is primarily made up of Oregon Health and Science University's Orcatech research platform (Orcatech, n.d.) and the commercial Presence Family Care (PFC) platform (Presence Family, n.d.) by People Power Co. These two systems were combined to form the home technology platform for the Cognitive Empowerment Program due to the variety of devices that each system supported. While the Orcatech system was developed for research purposes and provided many useful health data collection devices, the PFC platform was included to support real time interventions in the home. The data from all devices is processed and stored in HIPAA compliant databases for longitudinal analysis.

The Aware Home platform was designed to support the tracking of several key activities of daily living. After thorough discussion with therapeutic components of the Cognitive Empowerment Program, some critical behaviors were identified as useful to track. The system supports data collection related to sleep patterns, walking speed, weight, activity levels in the home, meal preparation, and presence in the home. To track these activities the system is made up of the following devices: PIR motion sensors, magnetic door sensors, temperature and humidity sensors, smart-plugs, seven day medication trackers, a smart-scale, a bed-mat sleep sensor, and a vehicle sensor that tracks driving related data (See **Appendix B : Sensors** for more detailed descriptions). This article will now detail installation and usage of each of these sensors.

The bulk of the Cognitive Empower Program Sensing Platform is made up of motion and door sensors. Across the two platforms there are fourteen Orcatech motion sensors, four Orcatech door sensors, seven Presence Family Care motions sensors, and eight Presence Family Care door sensors. Installation procedures in participants' homes typically place motion sensors so that high-use rooms in the home are instrumented by both systems. Room-level motion data from key places like the bedroom, bathrooms, kitchen, living area, eating area, entryways and exits provide insights on activity levels within the home. In addition to standard motion sensors, four of Orcatech's motion sensors are placed in sequence to form a "sensor line" in many participant homes. These sensor lines are used to collect a naturalistic observation of gait speed in the home (Hagler et. al, 2010). Door sensors are placed on all exterior entries as well as appliances such as the fridge and microwave doors. Perimeter door sensors are used to estimate occupancy of the home. Sensors that are attached to appliances are used to identify meal-preparation, cooking, and mealtimes. These sensors are paired with the hub device of their platform. The data they transmit is a timestamped alert of motion or a change in door state. That data is then stored long term on platform databases.

Participant homes are outfitted with two Orcatech medication trackers that collect and store data on when medication is being taken. The medication trackers utilized by this system have seven doors, each corresponding to a day of the week, and emit data about when each of these doors open and close. This data is returned as a single time-stamped hexadecimal code that is processed to determine which compartment was opened. A smart-scale that reports weight and heart rate is installed in order to collect information about fluctuations in participant weight with respect to their treatment. An emFit under-mattress sensor is installed to gauge duration and quality of sleep of participants and caretakers. The data reported by this sleep sensor is intended to aid medical staff in reducing sleep disruptions of participants. These devices send data to their platform databases, where information is then processed and stored long-term for data analysis.

The People Power Co. platform includes a number of small sensors including a touch sensor that is attached to a daily use item, four temperature and humidity sensors, and a few smart plugs. These devices are placed in locations that capture activities of daily living. For example, a smart plug will capture TV usage by analyzing when power is flowing through it to a TV set. Meanwhile, humidity and temperature sensors can be deployed near showers to gather an understanding of daily bathroom routines. These devices are focused on detecting the impact that treatment has on the participant’s daily lives.

Home systems are inventoried and activated before installation. During the installation process, two members of the lab join a participant at their home for three to four hours to explain and install the system. One member of the lab addresses participant questions while another takes room measurements and installs devices taking note of their location. After installation, lab members will visit twice in the first quarter and once quarterly after to discuss home sensing technology with participants and repair any problems. Upon installation, devices begin transmitting and storing data to their respective databases. This information is processed before being stored in a longitudinal regulation-compliant program member database for the Cognitive Empowerment Program.

This data provides information to therapeutic staff from Emory about patient condition and treatment adherence. This program is intended to scale to ninety participant homes over the timeframe of the project. Collecting data from program members' homes will provide accurate aggregated data about the progression of Mild Cognitive Impairment. This information will allow researchers to better understand the daily impacts that chronic conditions can have on people and which treatments work best. This system can create an enormous amount of behavior rich data. Analysis of that data will unlock its potential to accelerate the rate of medical research.

Data Collection

The platform that has been prototyped in the Aware Home and deployed in participant homes includes all of the sensors outlined above. The data collection for these sensors is performed by two platforms, Orcatech and Presence Family Care, as well as several standalone web-connected devices. As a result of this, data is collected in a variety of database locations. Oregon Health and Science University's Orcatech offers data storage, as well as a research API to access data from their custom devices (See **Appendix A: Terms** to find definitions for technical terms). The People Power Presence Family Care system enables teams to store data on the company architecture and access it with a variety of microservices written in Python. In order to better enable Cognitive Empowerment Program participants and researchers to access data being collected in the home technology components, a single repository of information is being created. Here, data from the home can be combined with data collected from other aspects of the Cognitive Empowerment Program to monitor progression of illness or to prompt a participant or care partner with an alert. This regulation-compliant Amazon S3 database will be accessed with a custom research API. In order to enable distribution of the data collected in the home environment, data collection scripts were developed to aggregate home data from all devices deployed.

The Orcatech system consists of both custom devices and commercial offerings. The Oregon Health and Science University created the system and host data collected by the devices. To access these devices, a RESTful

API is documented on the Orcatech API wiki. Custom devices, including motion sensors, door sensors, and medication trackers, must be accessed directly from the Orcatech API. The current solution for collating data from custom Orcatech sensors relies upon custom services written in Javascript. The data collected from the Orcatech API is returned in JavaScript Object Notation (JSON). Each device records a variety of inventory metadata followed by a list of events. The events collected by each sensor are processed into separate data sources as time series comma separated values for simplified analysis. Both JSON and CSV data outputs will be collected and stored in a Cognitive Empowerment Program database.

Sleep tracking and vehicle analytics are monitored by external web applications. Sleep tracking information is collected via REST API similar to Orcatech data described above. It is processed, packaged and stored in the same location as general Orcatech data. Vehicle analytic information such as average speed, sudden braking, and trip duration is accessed using an On-Board Diagnostic (OBD) tool offered by Automatic. The data from that application is accessed with participant account information and stored in the Cognitive Empowerment Program database. The data collected from the Automatic OBD tool can provide important information about how driving habits change in response to disease progression. In the future, this real time flow of driving data will enable better analysis of events in the home in response to vehicles entering or leaving.

The Presence Family Care system provides a data storage solution called the data cube. Once configured, this solution allows near synchronous local and remote storage. Initially, data is hosted on the hub device as the hub reads in events from various sensors. This local caching of home data enables the Presence Family Care system to allow for real-time data interactions. At a regular interval, data from the hub device is uploaded to a remote cloud storage version of the data cube for long-term storage. The long-term storage solution provides several data access micro-services written in Python. These services are currently used to collect information about device data. When prompted with home identification information and device type, the data cube provides CSV data files with associated inventory and accounting information. That data is then uploaded to the Cognitive Empowerment Program database for long-term analysis and use.

Limitations of Data Collected

Continuous collection of sensor data in the home is largely a new frontier that has yet to reach maturity. The research system described in this paper is an archetype of soon to be widespread smart home sensor platforms. The design philosophy behind the Cognitive Empowerment Program Home Technology platform was to protect program member privacy at the cost of data fidelity. This section will discuss some of the limitations of the data collected for the Cognitive Empowerment Program, as well as the devices considered and their tradeoffs. It will conclude by discussing how data collected from this system and other similar systems can be processed to enable its use in medical research.

With concern for member privacy as a key design consideration, the research platform design group focused on using secondary data collection devices within the home. The two devices that make up the majority of the platform, motion and door sensors, provide limited unattributed binary data about related behavior in the home. Secondary data collection devices have two major limitations when deployed in smart home platforms: attribution and recognition. When deployed in multi-occupancy homes, secondary sensors do not provide information about which occupants are responsible for the data collected. In single occupancy homes, visitors can introduce similar stochastic noise into the behavior data set. These gaps in data are considered attribution errors and are a major limitation that is present in secondary data collection devices. The second major limitation for secondary data collection devices is activity recognition. While data is powerful, by itself the low fidelity data provided by this smart home system can be difficult to interpret. Data collected by sensors attached to appliances throughout the home can provide hints about user behavior in the home, but oftentimes the data must be paired with powerful algorithms to extract usable information from the pool of data. This process is known as recognition, as it refers to the difficulty of recognizing behaviors usually from patterns in the data.

During the design process, these limitations were considered, and many data collection techniques were analyzed as potential solutions. Primary data collection techniques such as gathering video and audio data from the home environment were investigated, but ultimately did not make it into the final research system. Two specific systems, occupancy and sleep tracking, were initially designated to be captured with primary data collection devices. For occupancy measurement, the research team investigated several real time location aware systems for room occupancy. Ultimately the team chose to use motion sensors to protect member privacy.

Likewise, sleep tracking originally involved the usage of a low-quality infrared camera. Privacy concerns about video sensing in the bedroom led to the usage of the bed mat pressure sensor instead.

Data phenotyping, the process of drawing expressed insights from raw data, is a critical step in utilizing the sensor data captured by smart home sensors. While recognition and attribution are possible limitations of secondary data collection platforms; phenotyping can be used to help recognize behaviors and even attribute them to certain occupants. There are two main methods for delivering behavioral insights from sensor data. The first method is to analyze the collected data in-depth to determine where patterns might indicate that certain behaviors can be quantified. For example, door sensors that are attached to kitchen appliances like microwaves and fridges can be used to determine time spent preparing meals. To make that connection, the data that the sensors produce must be analyzed and quantified. These sensors produce flat binary data that indicates when an appliance is being opened and closed that can then be combined with algorithms that use that data to determine when a participant is heating food or grabbing a snack from the fridge. Similarly, data from multiple exterior doors can be combined through the use of an algorithm with motion sensor data in the home. While a door open event itself provides very little information, that event can trigger a scan for motion in the home, which then informs home occupancy data. Another method of interpretation for this data is to use machine learning and statistical techniques to find patterns in the aggregated data. A 2018 study of data collection in the home for the treatment of Dementia utilized a Markov Chain to identify patterns in behavior and to detect abnormal patterns (Enshaeifar & Zoha, 2018). By using collected data to develop a model of what a person should be doing on a day-to-day basis, the researchers were able to use motion sensor data and other secondary collection measures to determine when data indicated important home interactions. These data interpretation methods can deliver meaningful insights from home use data. Those insights can then be used to drive treatment direction and to understand the effects that a treatment can have.

Data Visualization

One of the most interesting challenges to address when using smart home data collection to support medical research is creating value for the various stakeholder categories. When deployed, the system should provide actionable information to the program member and their caregivers, as well as to the medical staff involved in the program. Getting detailed information about the built environment and the activities that people do in their environment is only the first piece of empowering home technology. Standardizing the collection of data to a single data source will support future development with this data that is necessary to empower users. During the Spring of 2020, three teams of graduate students in Georgia Tech's Mobile and Ubiquitous Computing course were tasked with utilizing the data collected using this research platform to create useful data visualization tools for the members of the Cognitive Empowerment Program.

The graduate teams were given access to longitudinally collected data from the research platform deployed in the Georgia Tech Aware Home. Due to concerns about patient privacy, the teams were not able to access data collected from program participants, but they were given access to data collected from 4 pilot research platforms. The data that was made available to the design teams included medicine adherence, weight, sleep, and heart rate data. They were also provided with aggregated data collections from motion and door sensors. The teams worked with Aware Home staff to understand the data and develop rules-based approaches to data phenotyping.

Developing interfaces that show critical information in an interesting way is important for increasing the engagement between a program member and their treatment plan. The design teams were able to uncover a few criteria that can help direct future development of visualizing home data. Visualizations of home data should focus on three areas: comparison to a baseline, temporal self-comparison, and aggregate data comparison. Visualizations that provide a comparison to a baseline can help to indicate individual progress or problems in a succinct way. A caretaker or program member can be empowered by a shallow overview of how the program member's recent behavior compares to their expected behavior. These types of visualizations can be used to encourage behavior that will improve treatment outcomes. One design team utilized this principle to enforce medicine adherence using the data visualization shown in figure 1 (Deshpande et. al, 2020).

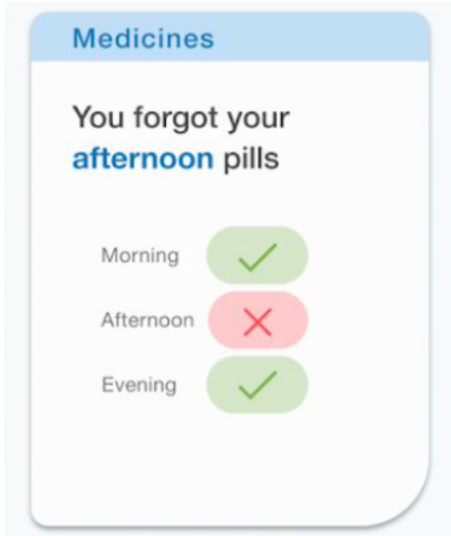

Figure 1: Comparison to expected behavior for medication adherence

Temporal self-comparison is used to reinforce progress towards a goal. Visualizations designed for this concept empower users with information about long term behavioral trends. These trends are critical to understanding the effects of treatment. Continuously collected temporal data can be used to understand treatment effects on weight, average activity levels, and sleep quality. These factors are important indicators of overall health. Trend data is also especially useful to understanding repeated patterns of behavior. Certain data types are especially accustomed to temporal visualization, such as the weight over time line chart in figure 2 (Dua & Do, 2020) . This chart is meant to accentuate fluctuations in weight over time to help program members and caretakers better understand their health data. By providing a baseline comparison as well as trend information, the data collected by the smart scale is easier to understand. Data visualizations like this one make the data collected by smart home platforms more usable and actionable.

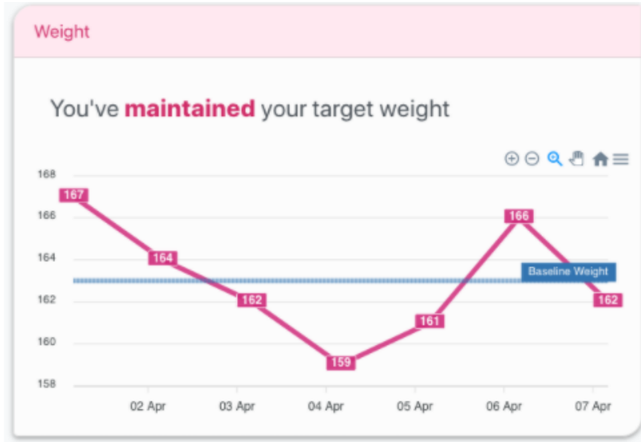

Figure 2: Trend visualization for weight data

Home use data collected for the purposes of medical research and treatment also must serve the needs of the medical researchers and therapeutic staff of the program. One way to deliver value to these stakeholders is through the aggregate comparison of data. Since information about Activities of Daily Living are collected for an entire cohort of program members, data can be compared to help clinicians understand which members need help. An intelligent system would be able to leverage information like average activity level or heart rate data to promote certain participants for further analysis and possible intervention. A snapshot view of activity levels for all members in a cohort could enable medical staff to intervene before a patient is even aware that their condition is causing them to degrade.

Conclusion

The information that home sensing platforms make available can drive great discoveries in the field of technological healthcare. In this research, the data collected by the Cognitive Empowerment Program Home Technology platform was utilized to assist in tracking the progression of Mild Cognitive Impairment. Beyond this program, the lessons learned from designing this platform can be applied to the design and production of other similar platforms. Taking these lessons into account will allow engineers to create more effective aids for patients and medical staff alike.

The limitations discussed in this article apply to any data collection platform and the design priorities of protecting the privacy of the monitored individual must remain front and center. In order to promote proactive privacy in design, system architects must consider any data collected as potentially threatening to participant privacy. A great way to protect the security concerns posed by tracking and analyzing our most intimate behaviors is to focus the design of any platform on the secondary data collection devices defined in this article. These sensors promote patient privacy by removing identifiable behavioral information from the collection equation.

Data collection can serve as an important driver of medical research and treatment development. To do so, this data must be made into useful insights. Rules-based and statistical analysis of data can be used to recognize and attribute important behaviors in the home. To turn these behaviors into actionable information though, the insights must be accessible. The design principles laid out in the data visualization section of this piece can inform the design of behavioral data interfaces. Those principles, paired with large scale data collection and intelligent algorithms, combine to create an incredibly useful addition to medical research.

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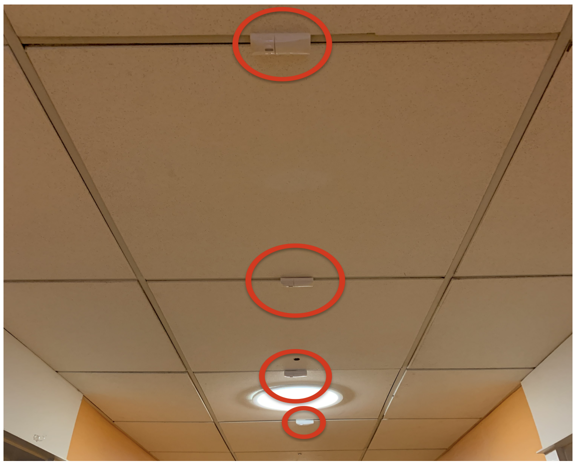
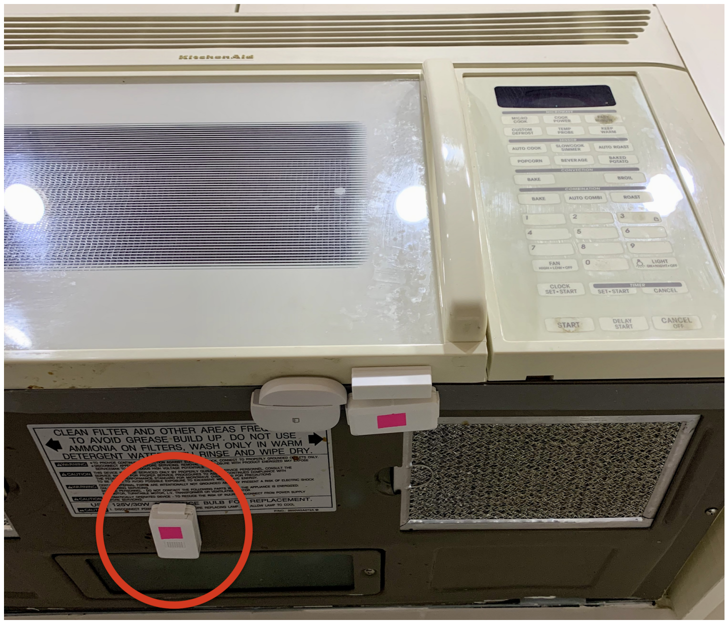
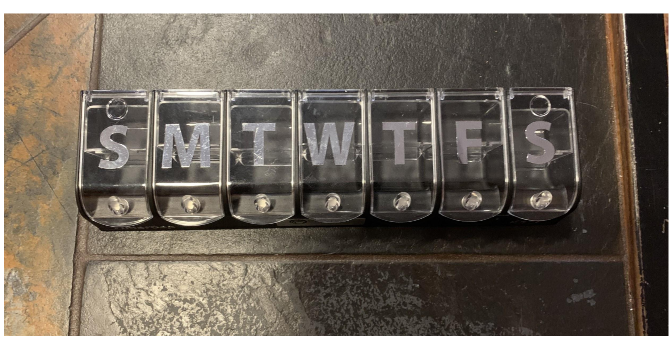
Appendix A : Terms

Term	Definition
API	Application Programing Interfaces are externally available software gateways that allow for data transfer between software applications
CSV	Comma Separated Values are plain text files that contain data delimited by commas and new line characters. Data is often formatted into a CSV file for transfer between applications.
JSON	JavaScript Object Notation is a notation for data transfer in the style of JavaScript Objects. This notation consists of key: value pairs separated by commas. Data is often formatted into JSON for transfer between applications
S3 Database	Amazon's Simple Storage Service is a scalable and inexpensive data storage solution
REST	Representation State Transfer or REST is a widely used architectural style for developing APIs. The REST principles focus on uniform, nested interfaces for accessing data through an API

Appendix B : Sensors

Sensor	Image	Description
PIR Motion Sensor		Often found in home security systems, Passive InfraRed Motion Sensors are low cost, reliable sensors that report on motion within sensor range.
Door Sensor		Door or latch sensors have two components. The components are magnetically connected. This sensor reports door open and close events by reporting when the magnetic connection is established or broken.

Temperature and Humidity Sensor		Temperature and humidity sensors are small devices that continuously report the temperature and humidity of their surroundings. They were used in this system to report events such as a stove heating up or a shower turning on,
Smart Plug		Smart plugs are wirelessly controlled relays that report when devices are turned on and can be controlled remotely to turn on and off devices.
Medication Tracker		The medication tracker used in this platform has seven doors corresponding to days of the week. The device reports open or close events for each door using the small magnets attached to the doors.

Smart Scale		The smart scale used in this platform is a wirelessly enabled scale that reports weight and heart rate upon measurement to its corresponding web application.
Under-mattress Sleep Sensor		The mat seen here is placed beneath a participant's mattress. It then begins reporting on sleep quality, duration and heart rate on a daily basis.
Automatic On-Board Diagnostic Sensor		The Automatic On-Board Diagnostic tool is connected to a participant's vehicle. After configuration this device reports driving data such as average speed, distance and trip duration to the automatic web application.