Using Mobile Sensors to Expand Recording of Physical Activity and Increase Motivation for Prolonged Data Sharing in a Population-based Study

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Abstract

Regularly conducted population cohort studies contribute important new knowledge to medical research. A high participation rate is required in these types of studies in order to claim representativeness and validity of study results. Participation rates are declining worldwide, and re-searchers are challenged to develop new data collection strategies and tools to motivate people to participate.

The last years of advances in sensor and mobile technology, and the widespread use of activity trackers and smart watches, have made it possible to privately collect physical activity data, in a cheap, easy and prolonged way. The unstructured way of collecting this data can have other applications than just showing users their activity trends.

In this paper, we describe our plans for how to use these pervasive sensors as new tools for collecting data on physical activity, in a way that can motivate participants to share more information, for a longer time period and with a renewed motivation to participate in a population study.

Keywords

Cohort studies, Motor Activity, Fitness Trackers, Heart Rate, Photoplethysmography

1 INTRODUCTION

The Tromsø Study is the longest running population-based study in Norway. Inhabitants in the municipality of Tromsø have participated for the last 40 years. The first survey took place in 1974, where the aim was to understand and develop strategies to prevent the high incidence of cardio-vascular disease in Norway (Jacobsen et al., 2012, Njølstad et al., 2016). Altogether seven surveys have been conducted to date. The data collection has gradually expanded with more comprehensive questionnaires, additional measurements and clinical examinations as well as extended biological sampling. The multiple surveys over a long period of time comprises a unique collection of health data and repeated measurements. In total, 45,150 participants have attended at least once and 18,420 participants have attended three or more times.

An additional strength has historically been the high attendance rate, which for the first five studies was between 72 and 79%. The last two studies however, have only achieved an attendance rate of 65%. Figure 1 shows the attendance rate for all seven surveys in the Tromsø Study, as well as the declining tendency of participation. This tendency is not unique to the Tromsø Study. Participation rates for population studies have declined for decades worldwide (Hartge, 2006).

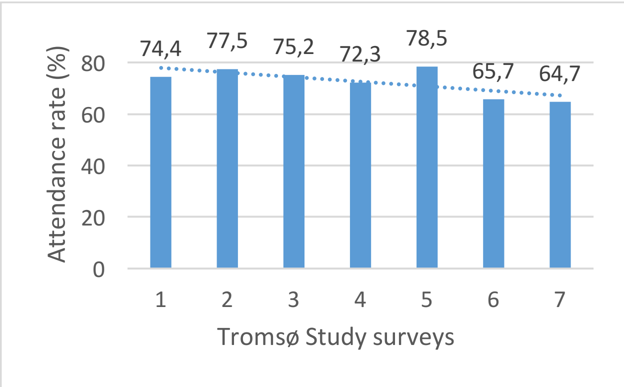

Figure 1. Attendance rates, Tromsø Study surveys.

In addition, lower participation rates are observed in the youngest and oldest age groups respectively. Younger people are less motivated to participate in health surveys and old people participate less, not only due to disease and frailty, but also because of increased intrusiveness and time demands. Figure 2 shows the attendance rate of the different age groups in the last four surveys. The first two age groups only have three pillars because only people above 40 were invited in the last survey.

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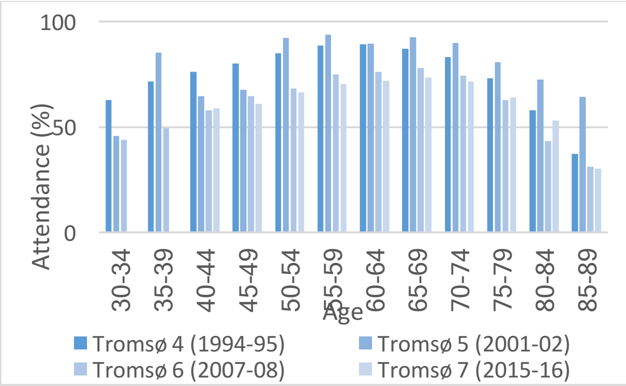

Figure 1. Attendance rate, survey 4 to 7, grouped by age.

The declining tendency in participation rate and the low attendance rate in the younger age groups emphasizes the need for new data collection tools and strategies.

In the last two surveys, self-reported data on physical activity (PA) were collected using questionnaires. Accelerometers were used to collect accurate objective data on PA. Heart rate (HR) data was collected from standard electrocardiography (ECG), combined ECG- and accelerometers, and via blood pressure measurements.

In the latest survey (Tromsø 7), 6,300 participants carried the ActiGraph wGT3XBT accelerometer for one week. A subsample of 700 participants carried the CamNtech Actiwave Cardio for one day, to collect accurate data on HR and heart rhythm, using a single lead ECG. Six questions related to PA (sedentary behavior, leisure-time and occupational PA, and PA frequency, intensity and duration) were included in the questionnaire. Data from Tromsø 6 show that self-reported moderate-intensity leisure activity was over-reported compared to objectively measured data (Emaus et al., 2010). Results from Tromsø 7 are not yet available, but similar conclusions are expected.

PA is an important health indicator and is used as a predictor, endpoint and adjustment variable. It is of interest to investigate new approaches for collecting PA and HR data, over a longer period of time.

For the next population study, we plan a new approach for collecting PA and HR data. In 2016, a total of 102 million wearable fitness trackers were sold worldwide (International Data Corporation (IDC), 2017). These devices use the same technology as accelerometers used for PA measurements in research studies. Wearable fitness trackers are cheaper, often have additional sensors, are less intrusive, and many study participants use them al-ready. ActiGraph, Actiwave Cardio and similar devices are validated tools for measuring PA and HR. However, some studies indicates that wrist worn fitness trackers (Dooley et al., 2017, Evenson et al., 2015, Reid et al., 2016) and HR monitors (Stahl et al., 2016, Wallen et al., 2016) are accurate as well. In these studies, various wrist worn devices were compared using different tools for validation, including pedometers (Yamax CW-700) and accelerometers (ActiGraph GT1M/GT3X/GT3X+, Actical) for PA, and ECG or HR chest straps (Polar T31, Polar RS400 HR) for HR.

Most wearable fitness trackers use a 3-axis accelerometer to calculate PA; including step counts, energy expenditure and energy intensity. This is the same technology used in accelerometers-based research instruments (e.g. ActiGraph product line). For HR monitoring a different technology is used, compared to ECG waveform recorders (e.g. Actiwave cardio). Photoplethysmography (PPG) is an optical technique used to detect HR by monitoring changes in blood volume beneath the skin (Allen, 2007), and is the most common solution for tracking accurate HR (Stahl et al., 2016) in wrist worn wearables. In addition, more and more modern wearables have a built in gyroscope, GPS, magnetometers, barometers, light sensors and others. These additional sensors can further improve data quality.

In 2016, the top five brands sold about 57% of all fitness trackers (International Data Corporation (IDC), 2017). Fitbit (22%), Xiaomi (15.4%), Apple (10.5%), Garmin (6.1%), Samsung (4.4%) and many of the smaller brands, collects and stores fitness data in online cloud based health repositories. Many of these repositories have a publicly available Application Programming Inter-face (API) we can use to access this data, if given permission by the user. Many brands can also synchronize with Apple Health Kit and/or Google Fit, two of the biggest online cloud repositories for health data. When connecting a wearable sensor to a smart phone, mobile applications can access these sensors, either directly or indirectly through affiliated cloud services. This also makes it possible to collect both historical and live fitness data.

One important limitation with most wearable devices, e.g. fitness trackers, is that they will not expose raw sensor data directly. Instead, they use custom brand and/or device specific algorithms to calculate common metrics, e.g. step count. These derived metrics are in most cases the only data available through device APIs.

In this paper, we will describe our plans for how to collect historical and live PA and HR data from participants in past and future studies, using mobile pervasive sensors. In addition, we will discuss issues regarding participant motivation.

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2 METHOD

The goals of this project are to 1) investigate how we can motivate participants to share data over a longer period, and 2) whether this solution can be used as an additional source of health data and as a potential new tool for collecting this type of data in population-based studies.

Our plan for how to collect historical data using wrist worn fitness trackers, was thoroughly described in a previous paper (Henriksen et al., in press). In this paper, we will expand on our initial plan, describe alternative approaches, and focus on system architecture and requirements.

2.1 Approaches

We are considering several approaches for data collection. We can collect *historical data* from brand-specific or open cloud based health repositories, like Google Fit or Apple HealthKit. We can collect *live data* from the same repositories, retrospectively, or in some cases, by accessing the sensors data directly and extracting derived metrics. We can collect *raw sensor data* from a limited number of devices, and create custom algorithms for measuring various types of activity. We can create a *custom device*, and create custom algorithms for activity detection. A final approach is to use *third party aggregators.* These approaches have different benefits and drawbacks, and combinations of approaches are possible.

The main benefit of accessing data collected by this type of wrist worn wearables is the long period of which it can be collected. The common drawbacks for all these approaches are the unstructured nature of this data and the not well-known validity of the various devices used by participants for collecting this data.

Historical data

In ongoing projects where PA and HR have already been collected using ActiGraphs/Actiwave Cardios or similar devices, some participants may have worn a personal fitness tracker, by coincidence, during the data collection period, and synchronized this data to their phones. Depending on which device they wore and were their data was eventually stored, it may be possible to download this data in order to complement existing data for those participants.

The main benefits of this solution is that the data is already collected. Except ethical approval, recruitment issues and similar matters, the only additional *technical* requirement is to have the participants install an application on their phone and agree to share their data. This data can then be shared with the research project, retrospectively and automatically. The main drawbacks are that only some participants will have this data, and some will not agree to share the data they have. In addition, for some participants it may be difficult to install this application and set it up correctly.

Live data

In future studies, we can improve on the limitations described earlier. Participants who already have a fitness tracker will be asked to install the same application, but because it is done at the beginning of the project, it may be easier to have them accept this. In addition, they can be provided with assistance to set it up properly. Participants, who does not own a fitness tracker, can be equipped with a suitable device for the duration of the study. An additional benefit with this approach is that for some systems, it is possible to access derived sensor data directly, i.e. without connecting to the cloud repositories. This makes it possible to continuously collect and transfer data for individuals who does not want to upload this data to brand specific or open health repositories, but are willing to share their data for research purposes.

Raw sensor data

In the two previous described methods, data retrieved from clouds and sensors are derived from raw sensor data. This raw data is processed through proprietary algorithms, written by device vendors. These algorithms change over time in an effort to improve them. However, when and how they change these algorithms are generally not reported. An alternative to relying on unknown algorithms is to create our own. The benefit of using this approach is that we have full control of how sensor data is interpreted. The drawbacks are that it will be a more complex solution, and few devices currently support this approach.

Custom device

Because there is a limited number of devices that supports direct access to raw sensors signals, another option is to make our own custom device. The benefits are that we can include only the sensors we need, and we will get full access to sensor signals. Drawbacks include, having to create our own algorithm for all activity types we want to measure, and working with hardware requires additional time and efforts and will be more expensive as a final solution. More expensive because of the need to produce enough devices for *all* participants. We may avoid some of these drawbacks by cooperating with existing device vendors.

Third party aggregators

Another way of improving on the limitations with the various vendor algorithms is to use third party aggregators, that can help standardize metrics received from different vendor APIs. Validic and HumanAPI are two examples of such services. These services can be expensive, but they make it possible to collect data from many different devices and normalize this data into comparable values. Not all devices and brands are currently supported.

2.2 Motivation

It does not matter how good the solution is if participants are unwilling to use it. We foresee two motivational challenges with this system. The first challenge is to motivate participants to install an application on their private phones. Because smart phone often contains a large part of a person's digital life, it is natural and smart to be conscious about which applications to install. The second challenge, and the area we will work with the most, is to motivate participants to keep sharing their personal health data over several months and even years. It is necessary to find the motivational factors that maximizes usage. These factors will be defined through the system requirements. As part of the requirement process, we are planning to conduct a study where we will investigate what could motivate potential participants to use this system. As in many modern software projects where the end goal is clear, but how to get to that goal is unclear, we are planning an agile and iterative approach during implementation. Pilot participants will test each iteration and give feedback on what they think does and does not work.

Because of the declining participation rates in population-based studies, an additional challenge will be to motivate people to participate in the study in the first place. By including attractive features in this system, we believe that potential participants will want to contribute in order to get access to this system. Exactly what these features may be is something we will try to find out in the aforementioned study.

2.3 System architecture

The architecture is comprised of several existing systems, two new systems and an upgrade to one existing system. **Error! Reference source not found.** shows an overview of the architecture of the proposed solution. White elements represent existing systems we will integrate with in our solution. Grey elements are our contribution to the architecture. Partly grey/white elements are existing systems that must be upgraded to support our solution. Round edged boxes represent mobile phone systems. Regular boxes represent backend/server solutions. Boxes with dashed lines are hardware sensors internal or external to the phone. The figure also shows how each system is connected using arrows. Dashed arrows illustrates new communication lines we must implement.

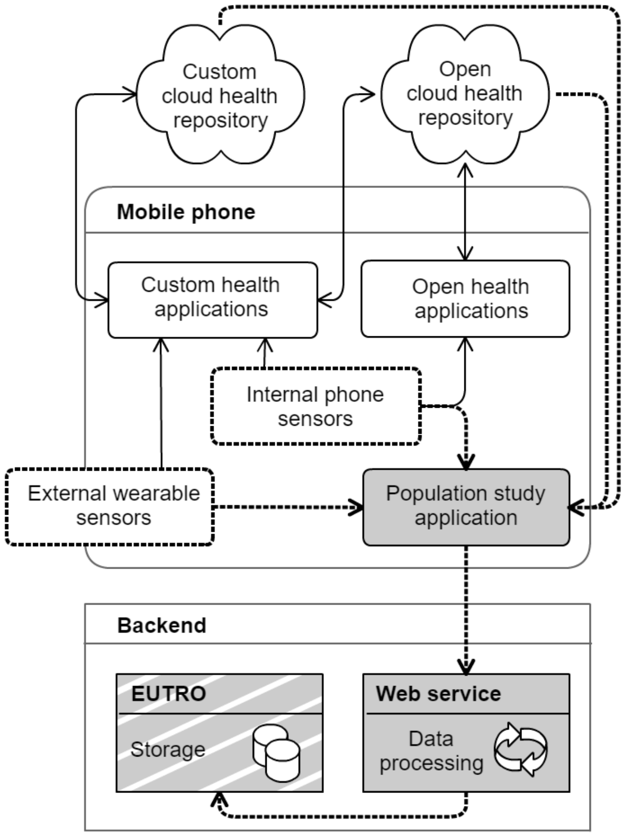

Figure 1. System architecture.

2.4 Existing systems

We have divided existing systems into three categories: 1) cloud repositories, 2) sensor systems and 3) mobile applications. Information travels between these systems differently for iOS-based (iPhone) devices and Android-based devices. In both systems, internal sensors are accessible by installed applications. On Android devices, this is also the case for externally connected sensors running Google's Android Wear. Sensors in the Apple Watch, running watchOS, can only be accesses by the affiliated Apple Health application. This is important because 10% of all fitness trackers are Apple Watches, and the only way to access these sensors are therefore indirectly through the Apple HealthKit cloud repository.

Cloud repositories

Open cloud repositories are services that can be used by any application, service or system to store health and fitness data online. We are only considering Google Fit and Apple HealthKit in our solution, because they are by far the most used systems. There are others, e.g. Microsoft HealthVault, which may be relevant down the line. Our first implementation will target open services.

Custom cloud repositories are online services that are mostly tailored for specific brands. There are several available custom cloud repositories. Depending on brand popularity, we may also have to implement support for some of these services.

Sensor systems

Different smart phones have different sensors. Most modern smart phones have several internal sensors that is relevant when measuring PA. When collecting historical data, we do not access these sensors directly, but rather downloads data from a cloud repository. When collecting live data, we may, in some cases, access these sensors directly and interpret the data in a custom way. Accelerometers, gyroscopes and magnetometers, often packed together into an inertial measurement unit (IMU), are the most important and widespread sensors for detecting PA.

External wearable sensors have the added benefit of giving results that are more accurate because these are generally carried throughout the day. In addition, with PPG-enabled wrist worn wearables, we will also be able to access HR.

Although it is possible to only use internal sensors in this solution, our plan is to focus on wearable external sensors, because they provide data more continuously. However, only a few fitness trackers support GPS, so in most cases this particular type of data must be collected from the phone.

Mobile applications

In our architecture, Google Fit and Apple Health are the only two open health applications considered. These applications will automatically collect data from internal sensors and store it as health information (e.g. step counts, activity intensity, energy expenditure, distance walked, floors, etc.). This information is then uploaded to affiliated cloud health repositories. Users can also view historic data and trends in these applications.

The difference between an open health application and a custom health application is that the first is meant to be used by any device, and the second is meant to be used by a specific brand of devices. Sensor data from externally connected sensors are not automatically stored in open health applications, but it is possible for the affiliated custom health applications to also forward sensor data to the open health application, and ultimately to the cloud.

2.5 New systems

We have defined two new systems, and identified one existing system that must be upgraded. The new systems includes 1) a mobile application (population study application) and a backend web service (WS). The existing system is a backend data storage (EUTRO) solution. We will pre-sent a high-level list of the core functional requirements and non-functional requirements related to motivation. Only the major must have requirements are included, as defined in the MoSCoW method (Agile Business Consortium, 2014), a technique used in agile development for task prioritizing.

Population study application

Participant must install the population study application on their smart phone, and allow it to connect to the cloud repository they use. We plan to support Android and iOS devices.

The main purpose of this application is to download health data from relevant sources and forward this data to a backend WS. In order to allow participants full autonomy over their data, they can specify what types of data they want to share and from which period they want to share it.

For Android phones, it is possible to write a background service that regularly uploads new data to the WS. For iPhones, this is not possible. An alternative approach is to use notifications to ask participants to regularly start the application and actively share new data. This limitation requires participants to engage with the application several times during the collection period. It is therefore essential that the application is easy to use and helps trigger participant motivation to keep sharing their data.

Functional requirement

- The mobile application must be able to correctly identify the user as a participant in the Tromsø Study.
- The mobile application must be able to connect to and download data from relevant cloud repositories using appropriate APIs
- The mobile application must be able to access available internal phone sensors and external connected sensors, and record live PA and HR data.
- The mobile application must be able to transfer collected data and sensor meta data to the online WS.
- The users must be able to decide which type of data they want to share.
- The user must be able to decide what period they want to share data from, including historic and future data.
- The user must be able to see an overview of the data they have shared.
- The users must be able to withdraw their consent for the use of specific data.

Non-functional requirements

- The mobile application must be easy to install, set up and use.
- The mobile application must include design elements that maximizes the period a user is willing to use the application and share data.
- The mobile application must include features that maximize the likelihood of motivating potential users to participate and use the system

Web service

Health data collected from mobile phones cannot be directly transferred to the final data storage for at least two reasons. Firstly, EUTRO contains sensitive data, and opening for direct access by mobile solutions, will be a great security risk. Secondly, some level of processing of the received data is necessary before storing it in a normalized and comparable way. The WS will solve both these issues, placing itself between the several thousand mobile phones and the final storage of the data receive from these phones.

Functional requirements

- The web service must be able to receive data from the mobile application
- The web service must be able to send data and sensor meta-data to a data storage system (EUTRO)
- The web service must be able to process and clean received data before sending it to the data storage system (EUTRO)

Backend data storage - EUTRO

EUTRO is “an IT solution designed to protect and manage biologic material, metadata, data and projects for major health surveys” (UiT - Department of Community Medicine, 2011). EUTRO is a standalone service, created, owned and operated by our own department, i.e. Department of Community Medicine. It is therefore possible to make changes to this system without involving external resources. It is however a complex system that is used by many research projects. Any proposed changes must be well defined and relevant to warrant inclusion. The Tromsø Study uses EUTRO, but other similar data storages can be used, as long as they have an interface for receiving continuous data from the WS.

Functional requirements

- EUTRO must be able to receive health data and sensor meta-data from the WS, and connect it to the correct research project and participant.
- EUTRO must be able to delete data collected from participants using the mobile application, who have withdrawn their consent.

2.6 Ethics

Participating and sharing health data requires informed consent from study participants. We will apply for approval from The Regional Committee for Medical and Health Research Ethics, as well as get approval from the Norwegian Data Protection Authority.

3 RESULTS

Some preliminary results show that in order to get access to data from as many different devices as possible, we will have to make the mobile solution capable of connecting to several APIs.

3.1 Cloud based health repositories

In our previous paper (Henriksen et al., in press) we only described Google Fit and Apple HealthKit, because these are the two largest online repositories for health data used by smart watches and fitness trackers. According to the Vandrico wearable database (Vandrico Inc., 2016), fitness trackers and smart watches are produced by more than 50 companies, several of which has more than one device on the market. In addition, this database does not contain all devices, and several less known brands exists.

Error! Reference source not found. shows an overview of what level of integration is possible for the top five brands. The second column shows if devices will automatically synchronize to Google Fit and/or Apple HealthKit. The third column shows if devices supports a developer API, that makes is possible to achieve this synchronization by implementing a custom solution, and transferring the data manually.

Brand	Google/Apple automatic integration	Google/Apple manual integration
Fitbit	No	Yes
Xiaomi	Yes	No
Apple	Yes (Apple only)	No
Garmin	No	Yes
Samsung	No	Yes

Table 2: Top five brands Google/Apple integration

Additional brands that supports direct integration with Google Fit or Apple HealthKit includes, *Fossil, Huawei, LG, Michael Kors, Mio, Misfit, Moto, Mushroom Labs, Nevo, Nixon, Sony, Tag Heuer* and *Withings*. Brands that only supports manual integration includes, *Huawei, Jawbone, Suunto, Timex Wellograph*. Some brands appear in both lists because they have multiple devices with different level of support. In addition, several brands do not support either solutions. This list is likely to change as new brands and devices appear on the market. It is also worth mentioning that the list in **Error! Reference source not found.** is a list of the most sold brands worldwide. If this list were for Norway only, it would probably be different. For instance, Xiaomi is a Chinese brand and does not have the same market share in Norway.

As these findings indicate, we will have to implement support for a range of brands using different APIs. In order to make sure we support most devices, we will at least have to implement support for Google Fit, Apple HealthKit, Fitbit, Garmin and Samsung. Implementing support for these five services will make it possible to import data from 19 brands.

4 DISCUSSION

Participation in population studies are declining worldwide and the Tromsø Study is no exception. This is especially true for the younger age groups. Because population studies are important for monitoring and understanding the health status of a population, we must find new ways to motivate the population to participate. There are many reasons for not attending. The number of questions, examinations and test have increased in every Tromsø Study survey, and the amount of time required to attend has increased accordingly. This may affect willingness to participate.

Physical inactivity is an important risk factor for disease, and collecting more data on PA in a population, can help to improve knowledge and understanding of the effects of this behavior. With plans to add additional tools for collecting more data, it is important to do it in a way that does not make it more inconvenient for participants.

A new way of collecting this data has been discussed in the context of already existing mobile sensors, and continuous data collection from these sensors. Several approaches were discussed, highlighting benefits and drawbacks of the different options. Some of these options requires very little extra efforts from participants, and may therefore prove to be a value addition to the data collection regime, without affecting participation rates negatively. In fact, we hope that by introducing these new tools, we can help motivate participants to contribute more data over a longer period, while at the same time make them feel that they benefit from participating. We hope this will drive motivation, to both participate in the study and to participate longer.

We have discussed several ways to collect health data over several months and years, but all include using mobile sensors to measure PA and HR. These sensors could be used for other purposes as well, for instance measuring sleep patterns. For the most part, we are limited to the metrics supported by the various devices, but in future solutions this could be improved and open up new possibilities.

5 CONCLUSION

In order to collect PA and HR from all participants successfully over a period of several months and years, we have identified three possible options.

1. Access historical and live fitness data, using privately owned fitness trackers already worn by participants.
2. Access live fitness data, using one specific fitness tracker available on the consumer market, paid for by the Tromsø Study.
3. Access live fitness data, using a custom fitness tracker, built by and paid for by the Tromsø Study.

The first option requires the least resources and is most likely to result in longer recording periods, because participants wear private devices that they would use even if they did not participate in a study. However, received data will be from different devices with different level of accuracy, and there will be a greater need to implement access for multiple cloud services. The second option is more resource demanding and less likely to result in a very long recording period, because participants will have to wear a new unfamiliar device and recharge it regularly. However, it is easier to handle the data and we only have to implement cloud access for one type of device. A combination of option one and two is also possible, i.e. buy one type of device and ask participants who does not own a fitness tracker to wear this device. The third option is more complex, but allows us to have full access to sensor signals. This option is also less likely to result in a long recording period, for the same reason as in option two.

A combination of option one and two seams, at this point, to be the most viable option. By implementing support for five APIs, we will support at least 19 brands, including the five most popular brands. More brands, future and existing, may also implement support for Google Fit or Apple HealthKit APIs later, increasing availability even more.

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