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Analysing Data Collection Mechanisms Used by Health and Wellness Applications

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ABSTRACT

Background

There has been a steady rise in the availability of health wearables and built-in smartphone sensors which can be used to collect health data reliably and conveniently from end-users. Given the feature overlaps and user tendency to use several apps, these are important factors impacting user experience (UX). However, there is limited work in analysing the data collection aspect of mHealth apps.

Objective

There are thousands of health and wellness applications available today with overlapping features that are mostly data-driven. In this paper, our focus is to first analyse what data mHealth apps across different categories usually collect from end-users and how these data are collected. This is important to guide the development of a common data model from current widely adopted apps. This would also inform what built-in sensors and wearables a comprehensive mHealth platform should support.

Methods

In our empirical investigation of mHealth applications, we identified app categories listed in a curated mHealth app library which was then used to explore the Google Play Store for health/medical apps that were then filtered using our selection criteria. We downloaded these apps from a mirror site hosting Android apps and analysed them using a script we developed around the popular AndroGuard tool. We analysed the use of Bluetooth peripherals and built-in sensors to understand how a given app collects health data.

Results

We retrieved 3,251 applications meeting our criteria, and our analysis showed that 10.7% of these apps requested Bluetooth access. We found 50.9% of the Bluetooth Service universally unique identifiers (UUIDs) to be known in these apps, with the remainder being vendor specific. The most common health-related Bluetooth Low Energy (BLE) services using the known UUIDs were Heart Rate, Glucose and Body Composition. App permissions show the most used device module/sensor to be the camera (20.5%), closely followed by location (18.4%), with their highest occurrence in the 'staying healthy' app category.

Conclusion

We found that not many health apps used built-in sensors or peripherals for collecting health data. The small number of the apps using Bluetooth, with an even smaller number of apps using standard BLE services indicate a wider use of proprietary algorithms and custom services which restrict device use. The use of standard profiles could open this ecosystem further and could provide end-users more options for applications. The relatively small proportion of apps using built-in sensors along with a high reliance on manual data entry suggests the need for more research into utilizing sensors for data collection in health and fitness applications which may be more desirable and improve end-user experience.

INTRODUCTION

Background

mHealth applications support health delivery by use of mobile devices, such as mobile phones, wearables and other wireless devices [1]. Several mHealth systems have been created for various applications such as drug dosage reference [2], [3], weight management [4] and monitoring cardiac health using wearable devices [5]. These mobile applications collect or generate health insights from three sources – external devices (Bluetooth or WiFi based sensors), built-in smartphone sensors and manual data entry.

By 2017, it was estimated that more than 300,000 health applications were available in app stores, with the market growing 25% each year [6], [7]. The use of mobile apps along with wearables and external sensors have enabled self-monitoring of one's health. They unobtrusively collect physiological data to provide better health outcomes and can also play an important role for patients living in remote areas with limited access to healthcare [4]. mHealth applications have been classified either as active or passive [8] - the former generate/derive health data using sensors while the latter rely on manual user input.

The mHealth domain has seen a steady rise of smart wearable and fixed devices [9] that can be used for gathering more detailed and accurate insights into people's health [10]. According to Forbes, their demand is expected to grow each year by around 20% by 2022 [11]. This introduction of sensors has also opened up new avenues for healthcare where these devices can continuously monitor one's health without manual interference. This constant monitoring can also help detect anomalies that may not manifest during a visit to a healthcare professional, and can permit caregivers to remotely monitor their patients [12]–[14]. Several wearables have been developed for specific support in the mHealth domain and are augmented by novel solutions, such as virtual reality implemented on mobile devices [15]. Built-in sensors such as inertial measurement units (IMUs), microphones, cameras and GPS modules can also provide insights into one's health and have been previously used for managing conditions such as sleep apnoea [16]. Bluetooth Low Energy (BLE) has been widely adopted for transferring data, and several applications have been developed that pair BLE devices with smartphones for fetching health insights. The popularity of BLE and the availability of low-cost BLE devices has opened up new avenues for continuous health monitoring in a more user-friendly manner [12]. Such sensors provide an effective platform for collecting real-time metrics conveniently and less intrusively, which may be useful in medical research [17]. They have recently also been suggested for use in low-cost mHealth systems such as those for diagnosing pneumonia [18]. Similar suggestions have also been made for physiological measurements such as heart and respiration rate, blood oxygen

saturation and blood pressure for application in health interventions [19]. Recent works in this area include using such BLE devices for managing diseases ranging from asthma [20] to managing tissue pain and mobility issues [21]. Several studies have reviewed mHealth apps and explored them from various perspectives, such as their impact on health outcomes [22], usability [23], and even the use of integrated smartphone sensors for monitoring health conditions [16]. Despite limitations around accuracy of the apps and peripheral such as measurement errors caused by darker skin tones and higher body mass index [24], and poor energy expenditure estimations by apps [25], they remain mostly well-received [26].
Wisniewski et al. [27] conducted a study in 2019 around the attributes of health apps where they selected 120 top rated apps from Google and Apple app stores in different categories and evaluated them manually. Their study revealed that most applications came under the category of 'self-monitoring of health or diagnostic data by client' apps (WHO classification 1.4.2) [1] indicating a higher interest in, and availability of self-monitoring apps.

The Use of Built-in and External Sensors

Most smartphones host several built-in sensors such as IMUs and GPS modules and support different wireless communication technologies such as Bluetooth and Wi-Fi. Many mHealth applications provide features such as workout tracking, medication reminders and general health monitoring using external or built-in smartphone sensors while some offer other features that may require manual data entry and include apps such as meal/calorie trackers and weight loss coaches.

Built-in Sensors

A recent assessment of health applications from curated health app libraries indicated that cameras were the most frequently used sensors where they were utilized for assessing one's heart rate and even for automated skin cancer diagnosis [16]. Similarly, the use of microphones was seen in applications that provided respiratory therapy [28], [29]. Algorithms have also been developed for processing IMU readings to monitor movement and activity levels in a non-invasive manner and are now widely used for applications in fall detection and gait analysis for tracking progression of diseases such as Parkinson's disease [30]. These algorithms/functions have been integrated with other data collection mechanisms described below to create complex and robust health applications with a common example being popular fitness trackers that use external heart rate sensors along with the onboard IMUs and GPS modules.

Bluetooth Low Energy

The BLE standard was originally designed with focus on low cost, bandwidth, power consumption and complexity, and has allowed developers to design more affordable products than other wireless technologies such as Wi-Fi and Zigbee [31]. BLE uses profiles to define its functionality which can cover operation procedures such as the Generic Attribute Profile (GATT) which describes procedures for exchanging data between devices and defines data models for the same. As several implementations can be made using GATT for exchanging different types of data, the Bluetooth Special Interest Group (SIG) has defined a set of use-cases and specific profiles that cover required procedures as well as data structures. These have been defined using GATT services and characteristics and include profiles for securely transferring health-related metrics [32] such as heart rate and blood pressure. Given that predefined profiles may not completely cover all applications, the Bluetooth SIG also permits device manufacturers to create their own vendor-specific profiles.

GATT provides a framework for data transfer and device operations and applications based on BLE are required to comply with its specifications [31]. Data are exchanged between devices using the smallest addressable data units described by GATT – attributes. These are identified by 128-bit UUIDs which can also be represented using 16 (uuid16) or 32 (uuid32) bit shortened versions, with all currently SIG assigned UUIDs being the uuid16 type [33]. The attributes are organized into nested blocks - services, which may contain 0 or more related characteristics, which in turn may also contain 0 or more descriptors [31]. As an example, Figure 1 describes the Bluetooth SIG defined heart rate service specification [34].

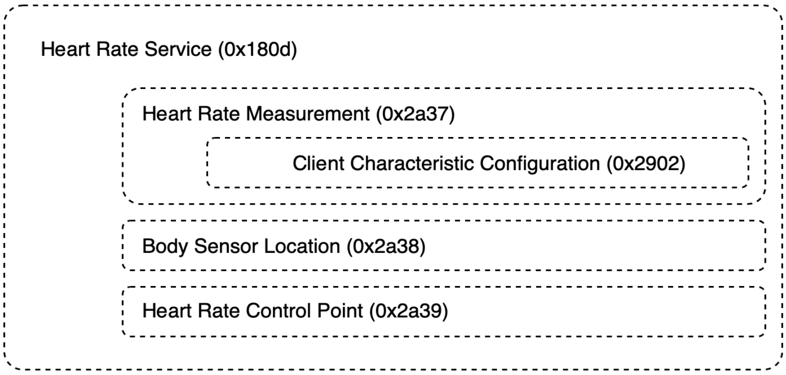

Figure 1: Hierarchy of BLE Heart Rate Service with uuid16 attribute representation (adapted from [34])

As the GATT structure is strictly enforced for all BLE-compatible devices, any client application that intends to exchange data with them needs to either discover each exposed service or be aware of relevant services and characteristics. For specific use-cases, applications would require UUID descriptions in their code for connecting with peripherals and identifying the services and subsequently reading exposed characteristics. With that, an analysis of Android packages to extract these UUIDs would help us to not only identify those applications using peripherals to collect health metrics, but also the use of standard and vendor-specific services. Applications have been previously analysed for identifying the use of BLE peripherals, but the focus of existing works in the domain has been around security assessment and identifying vulnerabilities [35]. Tools such as BLEScope [35] and BLECryptracer [36] have been created for the same but they have not been used in identifying the types of services supported by health applications.

Objectives

Recent exploration of the domain has also revealed interconnectivity and convenience as two factors impacting user experience [37]. This is even more important today given the thousands of health apps with overlapping features and the user tendency to use more than one app [2]. Although they are mostly data-driven, there is limited work around the analysis of existing mHealth apps to identify **what data are collected and how**, an understanding of which can help develop better health apps and eventually improve technology adoption. Our objective was therefore to analyse a set of free mHealth applications to investigate the use of peripherals along with built-in sensors as an indicator of the collected data and provided features.

METHODOLOGY

The Google Play Store is the official hub for downloading Android applications and offers over 100,000 mHealth applications [38]. Given the availability of several curated health app repositories, we explored the app categories described in one major curated app list – MyHealthApps [39]. Through a search on the Play Store using terms identified from this library, we identified applications that we then downloaded and analysed. Figure 2 shows a high-level overview of the methodology which is then discussed in detail below.

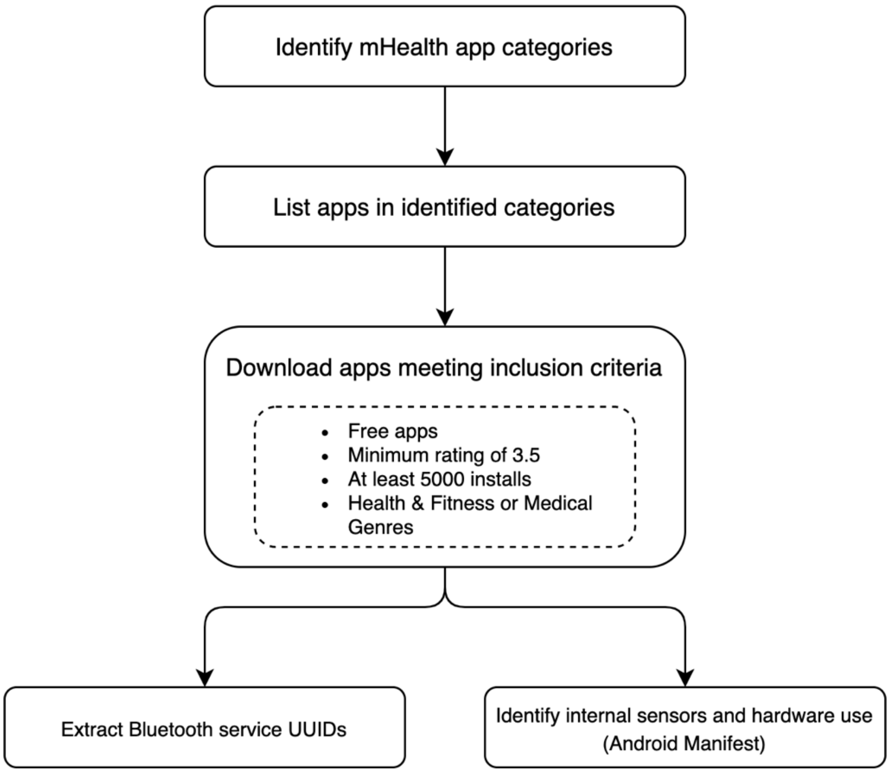

Figure 2: Data collection methodology

Identifying and Collecting mHealth Applications

We referred to the categories and subcategories of mHealth apps defined by the MyHealthApps library to guide our search and we identified 15 categories with their respective subcategories listed in Table 1. We wrote a script around a Play Store scraper [40] that returned applications from the United States with English as the default language and gave us detailed information about the applications, and the results indicated that not all apps matching the search terms were health-related, but also included other genres such as "News & Magazines" and "Tools". Although several apps of interest came under the "Health & Fitness" or "Medical" categories, many were classified under other groups and were excluded from our list. For example, the search term "Blood Pressure" returned a set of 250 apps with 113 Health & Fitness and 89 Medical apps (as of November 2020). Our selection criteria for the applications had the following 4 key conditions to include a large set of more popular, accessible, and quality mHealth apps –

- Free applications
- Rating > 3.5

- Installs > 5000
- Health & Fitness or Medical applications

However, as we also wanted to include comparatively new apps along with well-established ones, we did not consider a minimum number of ratings.

Application Category	*Search Terms (Subcategories)*	*Apps*
Bones and Muscles	11	2745
Breathing and Lungs	6	1493
Cancer	13	3237
Diabetes	5	1247
Endocrine	2	499
Heart, Circulation and Blood	13	3238
Human Immunodeficiency Virus (HIV)	1	249
Kidneys	1	250
Medication	3	749
Mental Health	16	3991
Nervous System and Brain	22	5469
Skin	3	748
Staying Healthy	23	5744
Stomach, Bowel and Continence	14	3493
Senses, Mobility and Learning	24	5728
Total	154	38780

Table 1: Application categories, the number of subcategories and the total number of apps in each category (Nov. 2020)

After filtering the list and removing duplicates, the remaining apps were downloaded to our test machine from a mirror site [41] following which, files except those with the .apk extension were discarded. We investigated the use of built-in sensors such as accelerometers, gyroscopes, GPS modules and even the smartphone's camera modules in the identified apps. By analysing app permissions, it is possible to infer to some extent what features these apps provide, and how data are gathered. We were particularly interested in the use of GPS (coarse and fine location), Bluetooth, Camera, Body Sensors, Microphones and Activity Recognition permissions.

Data Extraction from mHealth Applications

Application Dataset

Our query fetched a list of 38,130 applications (as of November 2020) which were then filtered to remove the duplicates in each app set as well as the ones not meeting the inclusion criteria, giving us a much smaller list of apps for analysis [42] (n=3,330). Of these, 12 apps were not found on the mirror site and 67 returned zip files which were discarded.

Extracting UUIDs from Packages

To analyse the downloaded apps, we used a popular static analysis tool – AndroGuard [43] that allowed us to decompile android packages to extract relevant details. These apps need to be aware of the relevant services, characteristics and descriptors to connect with peripherals. However, apart from statically defined UUID strings, applications can also construct them from a base ID and a shortened version at runtime. Although tracking these IDs may be necessary to identify all possible uses of standard services, not all applications follow this approach. Analysing the downloaded packages with AndroGuard helped us identify –

- The set of permissions and hardware features requested by the applications (to help understand how data is collected by the apps).
- Applications requesting the Bluetooth permission (for identifying applications that may use external peripherals).
- Statically defined UUIDs for apps using Bluetooth (for understanding the use of predefined or vendor-specified profiles).

The use of Internal Sensors

Since access to device hardware and other features may have security implications, Android restricts access by mandating the use of permissions declared in the application's manifest file [44]. AndroGuard was used to identify built-in sensors accessed by the mHealth apps through the declared permissions. Although the Android developer documentation recommends only using permissions necessary for the application to work as one of the best practices [45], some developers may request access to extra sensors and hardware without actually using them - a sign of a poorly developed application. However, such edge-cases were not considered.

iOS Applications

Although iOS applications also contribute to the mHealth application numbers, we limited our search to Android because of technical limitations around downloading these apps and lack of open tools for decompiling and analysing them. However, permission checks could be performed to indicate the types of hardware features used by these apps. We randomly selected 30 applications from the list of Android apps and searched for them on the iOS app store. Of these 30 apps, 25 were available on iOS which were downloaded using Apple's Configurator tool and unpacked to identify the hardware features used in the apps based on the app permissions.

Overall, in each step of the exploratory analysis, custom tools were built and used to automate app downloads, static analysis, data manipulation and management. The data were then checked manually to ensure accuracy.

RESULTS

The Use of Internal Sensors

From the analysed set of 3,251 apps, we found several applications using the coarse ("ACCESS_COARSE_LOCATION") and fine ("ACCESS_FINE_LOCATION") locations suggesting the use of distance tracking as a possible feature. Similarly, several instances of activity recognition for tracking step counts ("ACTIVITY_RECOGNITION") and a few for body sensors ("BODY_SENSORS") were found. Smartphone cameras have also been used widely, as indicated by the presence of over 600 apps that requested the appropriate permission ("CAMERA"). Table 2 lists the number of applications using these permissions while Figure 3 shows the use of different sensors in each subset. We found the camera being more popular across most search categories with GPS following closely, with the highest use seen in the

"Staying Healthy" category. The high use of cameras is consistent with previous app reviews [16] and is discussed in the next section.

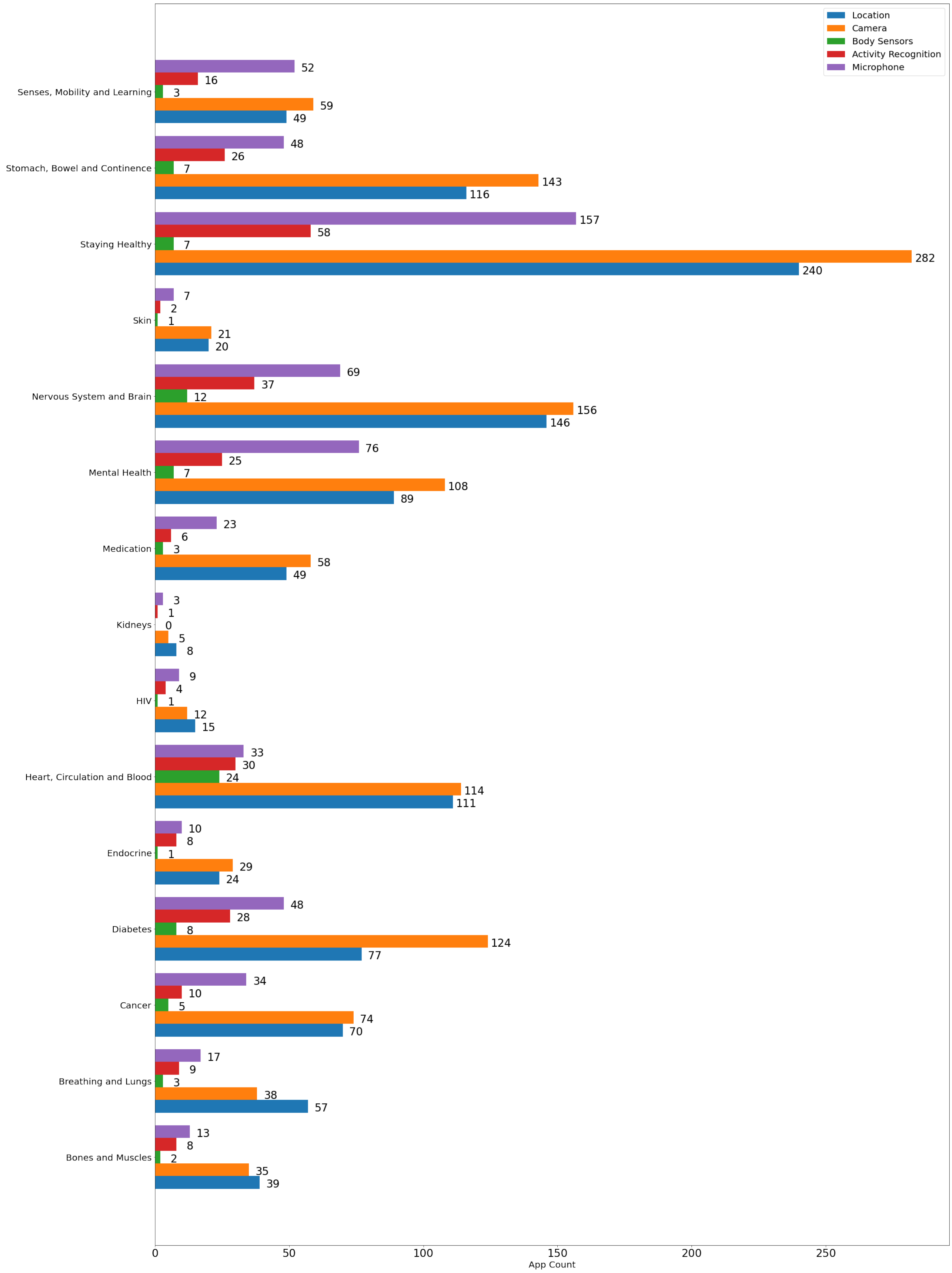

Figure 3: Built-in sensors used in apps across different categories

Permissions (simplified)	*Number of Apps*
Coarse Location	557 (17.13%)
Fine Location	598 (18.39%)
Camera	669 (20.57%)
Body Sensors	36 (1.1%)
Activity Recognition	123 (3.78%)
Audio Recording	340 (10.45%)

Table 2: Applications and requested permissions

The Use of Bluetooth Peripherals

Applications need to "know" the UUIDs of the services exposed by BLE peripherals to communicate with them and transfer data, and we found that 10.7% of the applications requested Bluetooth access. The Bluetooth-SIG permits the use of vendor-specific UUIDs for different use-cases and 50.9% of the discovered UUIDs were known and include service, characteristic and descriptor identifiers. The unknown IDs include vendor specific UUIDs along with those not related to Bluetooth operations; since these are not available publicly, further separation of this set was not possible.

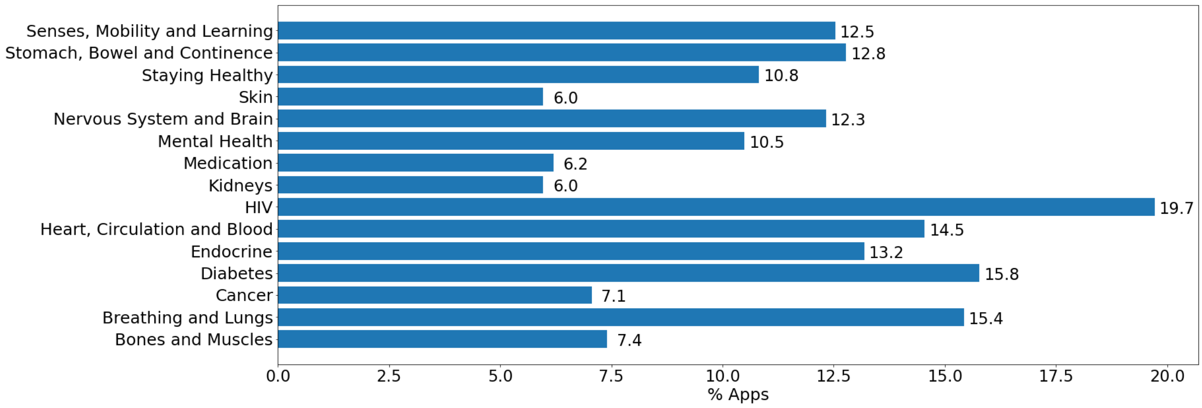

Figure 4: Percentage of apps in each subcategory using Bluetooth

GATT Service	*Number of Apps (out of 3251)*
Heart Rate Measurement	41 (1.26%)
Glucose Measurement	26 (0.79%)
Running Speed and Cadence	14 (0.43%)
Cycling Speed and Cadence	13 (0.39%)
Blood Pressure Measurement	13 (0.39%)
Body Composition Measurement	12 (0.36%)
Weight Measurement	10 (0.30%)

Table 3: Services and the number of applications using them

We mapped the known UUIDs to the apps that used them which allowed us to identify the most commonly used UUIDs and therefore, services. 'Client Characteristic Configuration (00002902-0000-1000-8000-00805f9b34fb)' was found to be the most common with 116 applications using the same. However, not many standard health-related services were identified, and we note that only the Heart Rate Measurement (n=41) and the Heart Rate Service (n=40) UUIDs were found in the top 10, with 1.2% of the analysed apps using these services (Table 3).

We analysed the permissions requested in 25 iOS app versions of the selected Android applications. Given that the applications provided the same features, the permissions were not expected to differ and were mostly identical in the main categories of interest – Bluetooth, Camera, Microphone, Activity Recognition and Location ("Multimedia Appendix 1: Android and iOS Permission Comparison"). A few minor deviations were observed on both platforms where some permissions did not match (e.g., 2 Android variants requested NFC which was not available on iOS). We could not analyse the BLE UUIDs in the applications because of the lack of open tools such as AndroGuard on iOS. However, given that both iOS and Android versions of an application would be connecting to similar hardware, the UUIDs are expected to be the same for the same group of applications.

DISCUSSION

End-users tend to deal with multiple mHealth apps to manage their health and wellbeing, with even healthcare providers referring to more than one app as one may not provide all the details they need [2]. These apps do not share a consistent user interface, sensors, nor a common mHealth data model leading to poor overall user experience. To address this problem, there is a need for a comprehensive mHealth data collection model and catalogue of sensors to then develop robust app development guidelines and frameworks. This study represents the first step in this roadmap. We reviewed data collection in 3,251 mHealth apps to understand what health data are collected and how apps collect them with a focus on built-in and external Bluetooth-based sensors.

Data Collection

Our findings indicate that although there is an increasing use of smart wearables and increasing popularity of peripherals, not many applications use them for collecting health data. Similarly, not many applications were found to use built-in smartphone sensors. Our results are consistent with a recent study by Wisniewski et al. where most apps relied on manual entry with limited support for any wearables [27]. Their reliance on manual reviews limited their study to 120 apps for mental health, which we were able to extend by automating the app review process. However, one drawback of our approach is that we cannot conclusively determine where the data were being used or what they were used for.

Our results show 20.6% and 18.4% of the apps used the camera and GPS modules respectively, which also happen to be the most used sensors across each app category, with the highest occurrence in the "Staying Healthy" set. This was expected as this category includes apps around diet and exercise where images and location data may be used for tracking meals and physical outdoor activities. We also expected a similar trend favouring cameras in the 'Heart, Circulation and Blood' category. We were also surprised by the relatively high use of location and images in 'Nervous System and Brain' applications which may indicate the increasing acceptance of these data types in different applications. This can be an indication of useful features, such as scanning an item (e.g., medication) or tracking movement. However, it may also indicate poor application design where access to sensors are requested without actually using them. Unsurprisingly, the lowest occurrence of these sensors was found in more medical applications as opposed to health and fitness apps, where categories such as HIV and Kidneys may not have any use of currently available built-in sensors at all. Apps were also found to use the microphone with the highest occurrence in the "Staying Healthy" category where its use can range from call features to speech analysis to tracking one's sleep.

Given the popularity of health wearables and peripherals, we expected to find a significant number of apps supporting them for passive data collection. However, our results indicate the opposite. We found 10.7% of the apps requesting Bluetooth access, of which, only about half of the discovered UUIDs were found to be the standard Bluetooth services with the remaining unknown. Apart from unrelated IDs, this also indicates that most devices and applications used proprietary algorithms, limiting their compatibility and use [46]. However, of the ones that were known, very few were related to health with the highest occurrence being the Heart Rate Measurement service in 40 apps (1.2%). Vendor-specific IDs (almost 50% of the reported apps using Bluetooth) may be used for any purpose as defined by device manufacturers making it difficult to identify the data transferred through those services. Besides the possibility of the UUIDs not being detected, this suggests that despite the growing popularity of wearables, they are restricted to a few manufacturers with limited applications using proprietary services and formats.

Since we rejected applications with low ratings and downloads, we may also have skipped several bespoke applications used for specific cases or by small groups. These can include applications developed for research studies and specialized devices that may not be widely available. Similarly, as Google restricts search results to 250 items per search term, we were also limited in our app search. The analysed data also indicated the presence of other known health-related services in a smaller number and shows the use of Heart Rate, Glucose and Body Composition as the more common services provided by peripheral devices.

Data Sharing

Mobile health devices and applications have been found to be useful for collecting clinical insights [47], which shows their potential not only in personal use but also in clinical applications where integration with electronic health records can help improve health outcomes. Newer applications integrate with frameworks such as Apple Health or Google Fit that allow data aggregation and sharing, but they also require installation of more than one application - a challenge that deters end users. Here, a platform integrating a diverse set of applications, health records and sensors could improve this aspect of mHealth applications with functionality and usability blend in seamlessly, potentially improving health outcomes.

Tools and Dataset

Besides app analysis, our contribution also includes the raw dataset including collected app details along with the extracted data comprising app permissions and identified UUIDs. Our tool for downloading and analysing apps is also included in our repository which is available on Github [48], and would be beneficial for future studies related to mHealth apps analysis.

Overall, our results suggest a more common use of manual entry (where automated data collection is possible) which apart from being less reliable, also degrades user experience leading to more users abandoning health apps[49]. Although usability is subjective, limited support for passive data collection with internal and external sensors can have a negative impact on app experience which can lead to reduced adoption by end users – sidestepping any benefits the apps could offer. Therefore, it is critical to understand the importance of peripherals and built-in sensors in modern health solutions and integrating them in a clinically acceptable manner with health apps.

However, the main limitation of our work arises from automated data extraction where we could not capture more nuanced details such as where the data from these sensors are being used and requires further investigation. Many valid health applications such as reference apps, management apps (weight, diet) and calculators (body composition, drug dosage etc.) may also be classified under other categories such as 'Education' and 'Books & Reference' and were rejected. Similarly, because of the difference of app numbers in each category, comparison between them may be biased.

Given the presence of over 300,000 applications in app stores, analysing them all was not feasible and using a curated app list was a better approach for identifying different apps as they would be closer to the domain than manually searching through thousands of apps. Since more health apps are widely available today for managing one's health, we believe that our results are relevant where accuracy of health data and wider integration would be important for better healthcare delivery. Although app analysis can be performed manually, we chose to automate the process which ignored possible data sources such as developer descriptions and user reviews. Similarly, our results are based on limited app categories where the use of sensors/wearables may not be feasible (e.g., 'Medication' or 'Mental Health'), and we acknowledge that these results may not be generalisable to the entire domain. Therefore, there is also a need to explore new applications of current sensors in these areas for improving data collection.

Given the potential of mHealth applications to improve an end-user's health, adherence to regular use is essential, which can only be ensured if such applications are intuitive and convenient to use. In the larger context of a connected, IoT enabled ecosystem apps would play an important part as an interface. This indicates a need to integrate more peripherals with health applications for collecting user data, which along with built-in sensors could ultimately help improve health outcomes. To that end, we envision a connected ecosystem of mini health applications, sensors and health records as a key mHealth technology of the future. We plan on using these results to develop a single mHealth platform for aggregating several wearables and health apps as mini health services, which we believe would provide a much better experience to end users. We have built a prototype of such a platform with health micro-mHealth apps [50], an introduction to which is planned in our upcoming work followed by a study to understand its impact on user experience and technology adoption.

CONCLUSION

Given that user studies into app experience have highlighted convenience and data interconnectivity/aggregation as important factors, automating data collection can improve user experience, especially in applications needing access to health metrics. However, a limited number of applications in our search were found to do so, indicating the need for more focus on integrating more peripherals and built-in sensors for health applications.

Our analysis of 3,251 applications indicates that less than 10.7% of the apps use smart devices and wearables for gathering health metrics from users. In this set, extracted UUIDs show that very few apps used standard health-related Bluetooth services with the most popular service being Heart Rate Measurement. Several applications were found to use custom services which affects interoperability of devices with different applications. Here, using standard profiles may be beneficial as more applications would be able to interact with these devices, giving end-users more options. Similarly, several applications were found to request access to device hardware features such as the GPS and camera indicating the increasing acceptance of these devices. However, their numbers remain small and indicates the need for more research into utilizing them in health applications.

Although manual entry may be inevitable for some apps, a significant number of apps requiring manual data entry was found in our set, highlighting the need to direct more focus on developing mHealth apps that automate health data collection. As several applications for research and health studies are also published, a better approach for developing and consuming mHealth apps is required. Overall, our findings can guide the design of future mHealth applications and hopefully have a positive impact on improving mHealth data collection in these apps.

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