IoT in the Wild: An expedition of discovery for remote monitoring.

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ABSTRACT

Free-living assessment and remote monitoring is important for healthcare researchers. Moving research beyond the laboratory provides habitual environments for remote assessment that allows research to remain agile even when facing uncontrollable external factors e.g., the SARS-COV-2 pandemic. Emergent technologies have the potential to make this form of assessment feasible by providing accessible and affordable mechanisms for conducting free-living research. This paper presents findings from a study that was halted due to the pandemic, but this work highlighted a series of challenges that may present themselves to researchers conducting similar work. By transparently reporting the challenges and solutions rather than just methods, it is hoped that the lessons learned from this study could provide researchers with greater awareness in future studies.

CCS CONCEPTS

• **Applied computing** → *Health informatics*; • **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**.

KEYWORDS

Remote sensing; Application Programming Interfaces (API); Wearable Health Technologies (WHT); Indoor Environmental Quality (IEQ); Internet of Things (IoT)

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1 BACKGROUND

Daily patient management and personalised health interventions are important areas of investigation. Clinic/lab-based assessments with state-of-the-art equipment provide accurate data under supervised/idyllic conditions (e.g. good lighting, even terrain). Yet, these environments can be a limitation as they not representative of everyday living conditions and those being studied are conscious of being observed [6]. Free-living assessment can be useful here as it provides a range of habitual challenges that people normally face [5] to increase measurement variability that provide greater insights to better assess health conditions. Yet, moving beyond the lab presents unique challenges to researchers that can often be under reported - especially when piloting projects [12].

Research-grade monitoring equipment used in laboratories makes free-living monitoring challenging due to its high cost and (often) uni-modal configuration [8]. Longitudinal deployment is also often unfeasible for free-living assessment, because the complexity of the equipment either requires researcher intervention for setup or is disruptive to daily living [1]. Deployment in free living conditions also lacks environmental context that would be available to researchers in supervised laboratory conditions.

Emergent, disruptive, and accessible sensor technologies are reducing the costs associated with remote sensor deployment [3], which is increasing feasibility of remote free-living assessment. These technologies have a range of applications for remote healthcare monitoring with wearable health technologies (WHT) and passive environmental monitoring. For example, Fitbit can provide affordable and direct mechanisms for free-living monitoring that have potential to provide new digital biomarkers in research [7]. Whereas, environmental sensors can be used to monitor Indoor Environmental Quality (IEQ) *(the measurement of Air Quality and Thermal/Acoustic/Visual Comfort)*, with potential to provide environmental context to free-living research. Poor IEQ can impact general health [10], so augmenting those data with information from WHT can provide a wider health context [2]. However, multimodal data capture from many different devices can create unique challenges even in laboratory settings, these can be exacerbated during remote deployment. This depends on devices having remote access capabilities, but also ensuring environments have suitable communication/connectivity infrastructures. Moreover, many systems/devices are tied to closed eco-systems that can be challenging to utilise within research [4].

Here, we present challenges that were identified in a pilot study which aimed to gather data from remotely deployed WHT and IEQ devices via an Internet of Things (IoT) platform. Lessons were learned from the setup and mobilisation of the project that could be useful to future researchers aiming to conduct remote monitoring with off-the-shelf devices.

2 STUDY SETUP

The purpose of the pilot study was to capture data from a variety of remote devices in order to explore possible links between WHT outcomes and IEQ. The primary aim for the pilot was to examine collection protocols while aggregating data from different off-the-shelf devices within a single/n-of-1 (female, 44 years) home and office setting. N-of-1 methods were chosen as they can inform many types of research, but are useful in exploratory research and pilot studies for monitoring individuals longitudinally to gain a wider context on health outcomes and patterns of behaviour, when compared to group-based studies [11]. Ethical consent was granted by Northumbria Research Ethics committee (REF: 17141) and the participant gave written informed consent before the study commenced.

2.1 Technologies and outcomes

The health and environmental outcomes, and the devices used to capture them, are listed in Table 1. WHT outcomes were measured using a Fitbit Charge 3 and IEQ outcomes were measured using a Netatmo Healthy Home Coach and a Foobot Air Quality Monitor. Each device was configured to use the participant's smart-phone (Apple iPhone 11) where data were synced periodically to the proprietary mobile apps. Data were then accessible from a cloud account and could be accessed via the web platform, integration apps *(e.g., Alexa and If This Then That, IFTTT)* and proprietary APIs.

Table 1: Outcomes measured with remote sensors

	Netatmo	Foobot	Fitbit
Temperature	✓	✓	-
Humidity	✓	✓	-
CO2	✓	-	-
eCO2	-	✓	-
PM2.5	-	✓	-
VOCs	-	✓	-
Outdoor Pollution	-	✓	-
Noise	✓	-	-
Steps	-	-	✓
Calories	-	-	✓
Distance Travelled	-	-	✓
Heart Rate	-	-	✓

2.2 Study setting

IEQ sensors were placed in the participant's home and on their desk within their office in a multi-occupant office on a university campus. The study was initially designed to run through spring 2020 for 8 weeks. The study was mobilised on 18 March 2020, but was subsequently halted on 23 March due to COVID-19 UK lockdown restrictions.

3 TAMING THE WILD: LESSONS LEARNED

Irrespective of the project being halted due to COVID-19, a series of challenges had to be addressed within the setup and mobilisation of technology that could be useful to future researchers. Pilot projects are often only reported, when successful, as a means to support future work, but the outcomes *(whether positive or negative)* can be of benefit to future researchers [12]. This section outlines what steps were taken to mitigate and/or overcome the impact of these challenges.

3.1 Integrator Apps: Limited data access

Consumer grade IoT devices are typically marketed to highlight a multitude of options to connect data. Cross-platform mobile support, web-based access from a browser, and tight integration with smart home platforms (e.g., Amazon Alexa) make these devices appealing. However, those data can often lack detail suitable for robust health assessment. IFTTT provides a mechanism to integrate multiple platforms and an example use case includes taking data from Fitbit and logging it to Google Sheets. However, data from Fitbit that is exposed to IFTTT is either captured as a daily summary of the previous day's activities or triggered when outcomes, *e.g. sleep, steps, calories*, are above/below a threshold. Thus, it is not possible to capture intra-day data from these services or make requests for data during a specific time period. Furthermore, consumer activity monitors utilising accelerometers (the same sensors used by clinicians to detect sensitive spatio-temporal gait characteristics [5]) will rarely output raw (sample level) data. Instead, data are processed and output as e.g., step count.

3.2 Proprietary APIs: Restrictions and regulations

Data captured from proprietary hardware are often stored in the manufacturers closed eco-system. Although these eco-systems may provide access to backlogs, resulting data are often collated to e.g., hourly aggregations [4]. Data access varies by device, manufacturer, data type and is also dependant on the level of authorisation. Data are often synced to a mobile device, web-based platform or both but there is often a requirement for software development to create apps that can interface with the proprietary API and provide authenticated requests for data.

IEQ data from the Netatmo and Foobot devices were accessible via an API key setup within the associated account for each device. Data were collected using Azure Function Apps (developed in .NET Core version 3.1) which made periodic authenticated calls to the respective APIs (Figure 1). An Azure function app was also used to obtain data from the participant's Fitbit, but an intermediary API (developed in PHP using the Simple API framework) was used to provide an authentication layer that the Function App could use to fetch data.

Azure Function apps communicated with the proprietary APIs. Initially these were developed in Python, but it became apparent

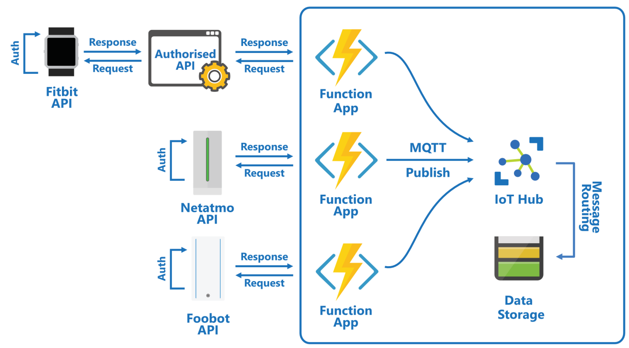

Figure 1: System Architecture for extracting data from proprietary APIs using Azure Function Apps.

when hosting the app that Azure can only host Python-based Function Apps on Linux. However, Linux hosted apps require an additional service plan to be set up, incurring additional costs. Therefore, apps were subsequently developed in .NET Core and hosted on a Windows server.

3.3 Data Security: Authentication and protection

Under General Data Protection Regulation (GDPR), Fitbit provides access to historical data via the Web API only. To access intraday data there was a requirement to make an additional ethical application to Fitbit outlining the purpose of the data collection, as well as indicate how the data would be collected, used, stored and managed. Within this process it became apparent that using Azure Function Apps to directly communicate with the Fitbit API was not appropriate. Fitbit authentication protocol requires an application to be developed with a specific callback that is protected by a Secure Sockets Layer (SSL). That enables Fitbit users to securely connect their accounts and authorise the application to access specific health outcomes.

Callbacks are not available in Azure Function Apps and require additional web services to provide an interface to users. Therefore, Function Apps were unsuitable for connecting directly to Fitbit. Consequently, an intermediary API was developed in PHP using the Simple API framework. The API had a single endpoint that could be called by the Azure Function App to provide an authenticated layer required to access Fitbit data.

3.4 Communication and connectivity

IEQ monitoring devices were initially brought to a university campus for testing, with the intention of connecting the devices to the university's WiFi network. However, IoT devices were configured to accept WiFi credentials in the form of a Network Name (SSID) and Password pair and the university used Enterprise WiFi Protected Access 2 (WPA2-Enterprise). This meant that it was not possible to connect the IEQ monitoring devices to the internet via the university network.

The use of 4G SIM card routers overcame these challenges, but they also provided additional protection regarding ethics and governance. Since the intention was to deploy IoT devices both on a university campus and in the participant's home, the sand-boxed environment provided a suitable mitigation against the security risks involved with using IoT devices, which are becoming increasingly targeted by malware [9].

3.5 Remote deployment: Access restrictions

Prior to the UK lockdown there were established procedures within the university to prohibit unnecessary travel or meetings. Consequently, sensors were given to the participant, having been preconfigured prior to deployment. This meant the setup and mobilisation of the study had to be done remotely. However, shortly after deployment, the SIM cards became unresponsive and had to be be reconfigured remotely, by assisting the participant over video conferencing. This was problematic due to the type of SIM card that was used.

Researchers conducting short-term/pilot projects may be inclined to choose a pay-as-you-go (PAYG) SIM card so that they are not constrained with contracts that extend beyond the study period. Unlike contracted SIM cards, which typically have accounts associated to them, PAYG SIM cards are not always designed for use in 4G routers. For example, a TESCO Mobile PAYG SIM card was initially selected, but this had to be switched to another SIM as there was no online access. All configuration of the SIM was done via SMS, which made remote deployment unfeasible. Despite not having a contract, GiffGaff provided online access to the SIM account, which allowed data consumption and renewals to be monitored and managed.

4 DISCUSSION

Although SARS-COV-2 had a major impact on the length of this pilot, some challenges were identified relating to the setup and mobilisation of off-the-shelf, free-living/remote monitoring equipment. Here, solutions to overcome those challenges were presented.

When establishing in-the-wild research projects, it can be useful to understand the pragmatic technical issues once equipment is deployed. Failure to do so can delay research, increased costs, or in-the-field modifications that could increase patient and researcher burden. Here, many challenges occurred during the setup phase. This meant contingencies *(e.g., use of 4G routers)* and alternative solutions *(e.g., use of Azure Function Apps and intermediary APIs)* could be developed before mobilisation. The challenges identified *(e.g., additional ethics from FitBit and procurement of 4G routers)* delayed the project many weeks and had these challenges been foreseen, it may have been possible to conduct the pilot a number of weeks prior to lockdown.

Transparency surrounding project limitations is vital. Nuanced technical challenges may present themselves throughout projects, yet these same challenges could have a greater impact on other researchers with different skill sets. Here, we present notable challenges in a similar technology deployment scenario. It should be noted that lack of control and potential need for remote data access can present challenges specific to individual projects. Proprietary systems or black-boxed eco-systems can exacerbate challenges and often present a need for bespoke solutions requiring software development. For example, details pertaining to the interfacing with an API or development of bespoke software integration.

5 CONCLUSION

Consumer grade monitoring equipment is becoming more accessible and is permeating into multiple disciplines of research including healthcare. Many devices are targeted towards the IoT market and integration with cloud-based services are commonplace. Integration services such as Amazon Alexa, Google Home, or IFTTT can provide access to proprietary platforms, but integration is limited due to consumer focus and are often of little use to researchers. There is a need for software development when creating interactions with proprietary APIs. This may result in a skill requirement that is not readily available in healthcare teams. However, this creates an opportunity for researchers to create bespoke implementations that are able to collect data from multiple data sources for holistic remote monitoring. To do this, it is important for teams to recognise and address the multidisciplinary nature of emergent technologies within healthcare research, as doing so could allow research to remain agile and exploit emergent emergent technologies. It is also important to have complete transparency around the technical development (and challenges involved) to inform the needs of future research teams.

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