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mQoL Lab: Step-by-Step Creation of a Flexible Platform to Conduct Studies Using Interactive, Mobile, Wearable and Ubiquitous Devices

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Abstract

Human subject studies with mobile users are widely used to understand, and model, human aspects such as behaviours and preferences, in the lab and in the wild. These studies usually employ mixed methods, collecting data by active participation and passive sensing using interactive, mobile, wearable, and ubiquitous devices. Researchers rely on a software platform to design and execute their studies, but existing solutions require a steep learning curve, allow little control, and offer limited guarantees. Our research lab built the *mQoL Lab* platform using open source technologies, and evolved it to a durable and reliable software ecosystem in over ten mobile subject studies along eight years across three countries. In this paper, we share the acquired experience via tangible artifacts such as requirements, architecture, design, step-by-step support, configuration scripts, and recommendations for researchers to construct a software platform supporting mobile subject studies. The paper is especially relevant for researchers embracing short-term to longitudinal, observational or intervention-based studies, leveraging mixed methods, including multiple devices, and tens to hundreds of simultaneous participants.

Keywords: mobile studies, mobile platform, mixed methods, passive sensing, mobile interaction, wearable devices, data collection

1. Introduction

Human subject studies with mobile users in the wild, i.e., outside the research lab, are widely used as a method to better understand human behaviours which occur in the context of daily life, or intervene with behaviors, in case of intervention-based studies. These studies usually imply the use of mixed methods, e.g., qualitative self-reported outcomes referred to as "Participant Provided Outcomes" (inspired by "Patient Reported Outcomes" or PROs from the taxonomy of clinical outcomes [30]) leveraging methods such as Ecological Momentary Assessment (EMA) [33], Day Reconstruction Method (DRM) [23], or longer multi-item surveys. The studies also involve quantitative,

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technology-reported outcomes (TechROs [30]) from data collected passively [9] by interactive, mobile, wearable, and ubiquitous (IMWU) devices. Typically, researchers utilize a software platform to conduct the mobile subject studies. Some platforms are paid-per-use, open source, or custom-made by their research group. Selecting or developing a platform to conduct studies appropriately is a nontrivial task, especially for research labs with limited access to software engineering resources or expertise.

Existing platforms partially address this shortcoming by providing off-the-shelf products, or stand-alone components, rich in functionality for mobile subject studies, such as smartphone sensor data collection or survey administration. However, they require a steep learning curve which involves the exploration of the feature set, only a fraction of which is often needed, or used in a study. Also, because they are offered as is, there are few guarantees for support and troubleshooting. Additionally, because mobile subject studies collect personal data, they are inherently subject to strict ethical and legal regulations, such as the General Data Protection Regulations (GDPR) in the EU, or the Health Insurance Portability and Accountability Act (HIPAA) in the USA. Research labs require robust and flexible infrastructures to satisfy changing needs on a timely manner. However, without coordinated planning, and a suitable technical infrastructure, labs resort to creating disparate infrastructures which are difficult to maintain and reuse. As a result, attempts to build platforms result in artefacts which fall short from bringing long-term benefits.

Our research lab conducts mobile subject studies collecting behaviour and health-related data from IMWU devices (e.g., smartphones and wearables) to support behaviour assessment. To this end, our lab has incrementally developed the *mQoL Lab* platform [11], a robust and flexible ecosystem based on a combination of open source dependencies and custom components since 2011. We deployed and used instances of our platform to conduct mobile subject studies in parallel, within separate research areas, study populations, mixed methods, technical environments, device heterogeneity, and data security regulations mandated by ethical protocols in Switzerland, Denmark and the USA.

The main contribution of this paper is the description of the *mQoL Lab* platform to conduct mobile subject studies. Over time, we revised the platform to support studies matching our growing research needs. We therefore find it relevant to describe and share its overall architecture with the community. This paper presents the architecture of the platform and provides key insights for designing, developing, maintaining, and evolving a platform by following these guidance. Our lessons learned and guiding advice are relevant for researchers who are preparing to conduct mobile subject studies involving simultaneous participants (tens to hundreds), from a few days to several years, by employing qualitative, quantitative, or mixed research methods, potentially across geographies.

2. Characterizing Human Subject Studies

2.1. Constituents and Data in Human Subject Studies

Human subject studies usually have three constituents: two "actors" - participants and researchers - and the "system". Fig. 1 shows the study participants on the left hand side, and the researchers conducting the study on the right hand side. The system is depicted in the middle, as it enables the data collection from participants, by using artefacts such as IMWU devices, and data analysis by the researchers. For instance, in human-computer interaction, during mobile subject studies, the collected data pertains to the interaction between the participant and the artefacts in context; in behavioural science, the collected data pertains to the participant behaviours in context, as measured by the artefacts.

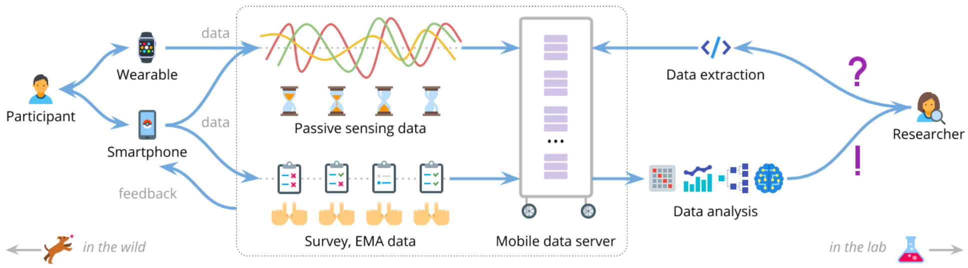

Fig. 1: Overall data flow of a generic human subjects study with mobile users

In mobile subject studies, researchers typically incorporate both qualitative and quantitative data. Qualitative data is usually collected from surveys (whose outcomes rely on scoring of a validated scale). Smartphones can facilitate the collection of data from surveys.

Quantitative data is usually obtained as TechROs collected through passive sensing by IMWU devices (often from the context of daily life). For example, commonly used data from the smartphone itself includes: position and orientation, applications usage, notification events, screen events, network connectivity, ambient light, ambient temperature, battery level, as well as more personal traces such as recognized physical activity, geographical location, ambient sound, calls, messages, audio and video. Data from wearable devices can be of physical (e.g., steps, energy expenditure, distance, and duration of physical activity as well as sleep) and physiological (e.g., electrodermal activity, heart rate, heart rate variability, respiration, glucose levels) nature, as well as other types [35]. After the data collection, researchers typically perform extraction and analysis on both qualitative and quantitative data by following, for example, an iterative hypothetico-deductive approach [28].

2.2. Requirements of Mobile Subject Studies

This section describes common requirements for a research platform to conduct mobile subject studies. These requirements illustrate important functionalities associated with the three constituents identified in Fig. 1: the participants (R1-R4), the system (R5-R8), and the researchers (R9-R11). Instead of using a strict software engineering requirements decomposition, we present them as a combination of functional and non-functional requirements in Table 1. In this context, functional requirements refer to the scope of the system, and stem from study objectives, and researcher investigation experience. Non-functional requirements stem from necessary system properties (e.g., usability aspects for participants and researchers) and researchers' need for gradual automation within the system.

We do not claim that the list of requirements of the *mQoL Lab* is exhaustive. Instead, the requirements emerged over time in the following four life stages of the platform:

Stage 1: Our research began in 2010, in Switzerland, by instrumenting smartphones with a sensor data-logger (acceleration, location, network, screen, applications used, battery state, among others) for brief periods, covering requirements R1, R7, R8 and studies [6, 7, 14, 20, 21, 22].

Stage 2: Then, in 2017, as we were repeating steps for every study in Switzerland and the USA, we evolved the sensors data-logger into a platform that allowed parallel studies with separate configurations, covering requirements R2, R3, R4, R6, R9 and studies [4, 12, 13].

Stage 3: Afterwards, the sensing capacity from smartphones increased, but hardware and software restrictions and policies (from Google and Apple) limited access from development frameworks, which forced updates to the platform. At the same time, adoption and measurement accuracy of wearable devices for daily life outcomes made significant progress. Thus, in 2018 we updated the platform to support a set of consumer-friendly wearable devices, covering updates to requirements R4, R7, R8 and studies [10, 26, 29, 36].

Stage 4: Finally, driven by recent data protection regulations in different countries (specifically, Switzerland, USA and Denmark), in 2019, we enhanced the platform to easily allow re-instantiations, covering requirement R5, R6, and partly R11, with a completed study [2]. Re-instantiations enabled us to deploy the platform to the Stanford University Hospital where we are currently conducting a study for clinical patients collecting longitudinal data from multiple sources: self-reports, peer-reports [2], and technology-reports (mobile application and wearables simultaneously).

2.3. Existing Platforms for Mobile Subject Studies

Research using mobile devices is naturally growing, as smartphones become more ubiquitous. Some researchers created their own mobile applications to record passive data, especially from Android smartphones [34, 1, 27, 8]. Moreover, some research groups developed mobile applications, as well as larger platforms made available for other researchers [16, 27, 24]. Table 2 depicts some of the most popular mobile sensing solutions used in previous research. The systems listed there have slightly different focus areas, but share the common goal to support research in mobile sensing. The first two solutions (AWARE [16] and Sensus [27]) are sufficiently equipped to support mobile subject studies (we label them as mobile frameworks in Table 2). For instance, they work in multiple operating systems (Android and iOS) supporting both passive and active data collection. SensingKit [24] is a specialized library that simplifies the interaction with on-board smartphone sensors. The other solutions in Table 2 are not actively maintained.

Table 1: Requirements and their corresponding motivations for mobile subject studies

	Requirement	Motivation
	Requirements for study participants	
R1	Participants can provide consent and take part in studies at home, over the internet (functional).	Participants should be minimally required to have access to a web browser. For most studies, they are (additionally) required to own an IMWU device, such as their own smartphone or wearable. At times, they receive a device in temporary or permanent ownership. More than 65% of participants prefer being able to contribute to the study at home, over the internet [5].
R2	Participants can control presence in a study (functional).	Participants should receive clear information about the institution, purpose, contributions, and data collected from the study. They should be able to start, pause, resume, stop, and delete their participation from the study at any time, and at no cost. Trust in the research is an important factor for participation in studies [5]. Transparency minimizes concern and confusion while giving informed consent to participate [15].
R3	Participants can control data provision (functional).	Participants should receive clear information about the collection, storage, and analysis of their data as part of the study. They should be able to start, pause, resume, stop, and delete their data at any time and at no cost. For example, participants should be able to answer or skip surveys and authorize/deauthorize IMWU devices. Allowing control and authorization is a determinant factor for individuals to participate in studies [15].
R4	Participants can contribute to studies in the lab and in the wild (functional).	Participants should be able to contribute to a study (either in the wild or in the lab) by providing passive sensing (e.g., using a smartphone or wearable device), active involvement (e.g., answering surveys), or a combination of both, depending on the measured outcomes of the study [31] defined by the researcher.
	Requirements for study researchers	
R5	The mobile data server can be easily re-instantiated (non-functional).	The mobile data server should allow deployment on Linux-based host environments with minimal *a priori* dependencies. Components should use as much as possible free-of-charge, widely-used, secure, and open-source technologies. Deployment should take only a couple of days in a new environment, with minimal learning curve.
R6	The mobile data server can unify in-study data from the same participant (non-functional).	The mobile data server can pseudo-identify participants across their data sources (e.g., by assigning each participant a random identifier and separating it from personally identifiable data, such as a set of demographic data points). Data from multiple sources can be aligned in time. Internal identification is necessary to retrieve and delete information about participants.
R7	The mobile data server can support offline data (non-functional)	Mobile clients should be temporarily self-standing while collecting data in geographically remote experimental settings, and eventually synchronize with the server.
R8	The mobile data server can manage the participant data within safety requirements (non-functional).	Data management includes collection, storage, extraction, and analysis. These processes should be compliant with regulatory bodies, and data protection regulations. Security and privacy concerns are an important factor for participants to share their data [25, 18], e.g., by supporting participant consent, and their right to withdraw from the study at anytime.
	Requirements for the system	
R9	Researchers can manage separate features in studies with minimal programmatic changes (functional).	Researchers should be able to add, modify, and remove features for each study. Study editing should be possible while the study is in progress, to adapt to preliminary findings in the study. For example, researchers should be able to change survey questions, or swap IMWU devices. Researchers should be able to reuse features across multiple studies. Meeting this requirement enables quick iterations of hypothesis and deduction.
R10	Researchers can administer interventions (functional).	Researchers should be able to reach anonymous participants, either manually or automatically, potentially from real-time data analysis (e.g., by means of push notifications).
R11	Researchers can analyze in-study data (functional).	Researchers should be able to programmatically extract data for a study by using, e.g., queries. The data extracted should allow visualization, summarization, statistics, and machine learning processes, which can start on the platform and continue to a capacity limit which depends on the host environment. Researchers should be able to monitor participant retention and engagement with the study, to assess data quality.

Table 2: Overview of popular mobile sensing solutions and general characteristics

Name	Platform	Research Methods	Mobile Framework	Maintained†
AWARE, 2015 [16]	Android, iOS	Smartphone sensors, EMA	Yes	Yes
Sensus, 2013 [27]	Android, iOS	Smartphone sensors, EMA	Yes	Yes
SensingKit, 2016 [24]	Android, iOS	Smarphone sensors	No	Yes
Paco, 2014 [19]	Adnroid, iOS	EMA	No	Fair
Ohmage, 2015 [34]	Android, iOS	Smartphone sensors, EMA	No	No
Funf, 2011 [1]	Android	Smartphone sensors, EMA	No	No
Emotion Sense,2013 [27]	Android	Smartphone sensors, EMA	No	No
Research Stack, 2016 [8]	Android	EMA	No	No

† Self-assessed by the authors as of May 2020.

Existing platforms such as AWARE [16] suffer from high specificity in terms of their ability to integrate with other platforms, while others such as Sensus [27] are too stringent: customization involves considerable effort. Libraries such as SensingKit [24] cannot support mobile subject studies on their own. All are provided on an *as-is* basis, with limited support and timely troubleshooting. Furthermore, libraries not actively maintained are at risk of obsolescence due to the rapid evolution of mobile operating systems.

This paper makes a unique contribution by sharing a set of instructions and guidance from our experience on numerous studies and experiments. We argue that researchers with long-term goals in mobile studies will benefit from creating a robust and flexible platform of their own, which can be modified in time to support changing research needs.

3. The *mQoL Lab* Platform

3.1. Architectural Design Overview

Conceptual Model: Considering the mobile data server of Fig. 1, each component (depicted in magenta), consists of two layers, robust and flexible, that we illustrate in Fig. 2. For each component, a set of permanent core features forms a robust layer (depicted in green). The features in the robust layer are connected across components (low coupling). The robust layer serves as the foundation of the architecture. In each component, a set of transient features (high cohesion) forms the flexible layer (depicted in yellow). By connecting and disconnecting the flexible features to their corresponding robust features in their component (high cohesion), researchers can adapt the platform to changing research needs. Fig. 2 illustrates this separation in layers, that all together fit the requirements in section 2.

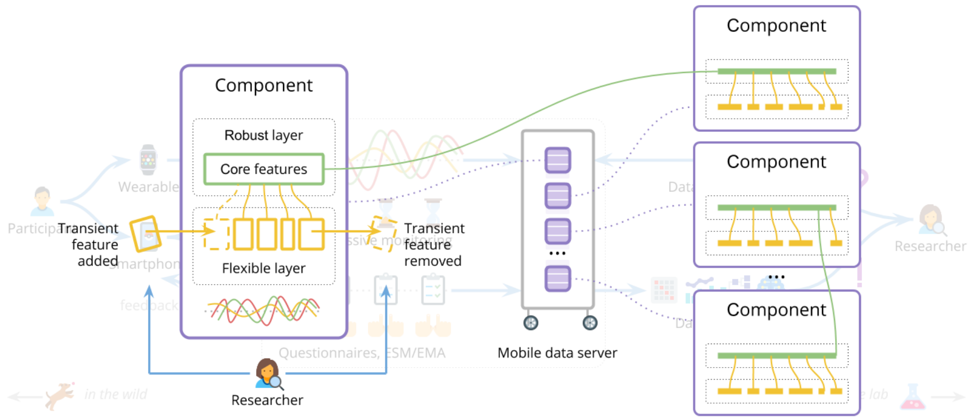

Fig. 2: Conceptual model of the *mQoL Lab* platform facilitating mobile subject studies

Architectural Design: The architectural design of the *mQoL Lab* platform focuses on the system constituent from Fig. 1, and is depicted in Fig. 3. This design consists of two blocks, clients and servers, grouping components (red rectangles for clients, and blue rectangles for servers), e.g., mobile apps and application server. Each component is tagged with the technology of *mQoL Lab* choice (e.g., `parse server`, `Android`). But researchers can leverage the architectural design even if they choose other technologies (see Section 3.2).

For example, the functionality of collecting TechRO data from passive sensing can be partitioned into a robust layer and a flexible layer (Fig. 2) as follows. Most wearable manufacturers (such as Fitbit and Withings implemented in *mQoL Lab*) require a reference to our platform in their Application Programmable Interface (APIs), which they use to (1) identify our platform in the informed consent, (2) authorize our platform for data collection, and (3) notify our platform about new data. Also, many wearable manufacturers use the same authorization protocol (OAuth 2.0), and communication style (REST [17]). The robust layer consists of a web client feature and a web server feature, collectively, a web application, for participants to choose the wearable type they own, and initiate the authorization. The web application (1) conducts authorization flows, (2) stores the grants used to collect the data, and (3) sends the data to the data storage component. The flexible layer includes device/manufacturer specific features. For example, servers implement pagination for data collected (a Fitbit API feature), or notification of new data (a Withings API feature). Currently, we are implementing data collection features for Garmin and Polar wearables as features in the flexible layer. These features reuse a minimally changed robust layer.

Supported Study Designs: The architecture in Fig 3 enables researchers to conduct short or longitudinal studies, inside or outside the lab, observational or including interventions, collecting passive or active data from participants,

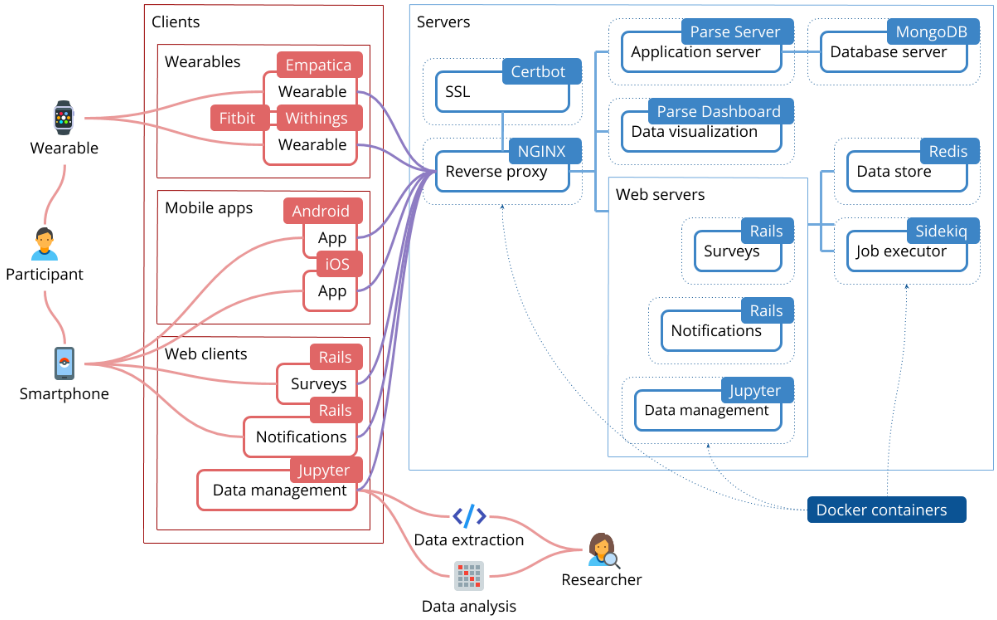

Fig. 3: Architecture of the *mQoL Lab* platform for mobile subject studies

including contextual markers. Table 3 describes study design and methodological aspects that researchers typically consider when selecting a platform. We describe how the the *mQoL Lab* architecture of Fig. 3 enables those aspects.

Table 3: Study design and methodological aspects supported by the *mQoL Lab* architectural

Design Aspect	**Description**
Study scope	The *mQoL Lab* design supports both observational (i.e., findings from data are used to further scientific knowledge) and intervention studies (i.e., findings can trigger interventions to one of more participants based on their collected data). Researchers can include Just-in-Time Adaptive Interventions (JITAIs) [32].
Study location	The *mQoL Lab* design allows both studies in the lab and in the wild. Participants can interact with IMWU devices in both cases.
Study variations	The *mQoL Lab* enables to create study flows with slight variations (e.g., with respect to data sources, frequency of data acquisition, among others). To this end for example, the *mQoL Lab* design allows the assignment of roles to study participants.
Study interactions	Human-device interactions in a study can range from standardized for all participants, to cross-sectional based on population characteristics, to personalized for a specific participant. The last two study interactions are based on data provided by participants.
Device provenance	Smartphones and wearable devices usuually follow standardized communication protocols. This allows the *mQoL Lab* design to support devices irrespective of their manufacturer.
Data collection source	Passive quantitative TechRO data can be collected by IMWU devices regularly carried by participants with them during daily life. The *mQoL Lab* for example includes a data logger for Android-based smartphones called *mQoL Log*. Active qualitative data is collected through mobile clients (such as web views in spartphone apps) where participants can answer surveys. Other connected devices, such as weight scales, can provide additional TechRO data.
Data synchronization	Some manufacturers provide data through an API (e.g. Fitbit, Withings),or via a mobile application through wireless transmission (e.g., NFC, BLE). The *mQoL Lab* design supports offline storage on mobile clients with eventual synchronization to the servers.
Data contextualization	Passive and active data can be augmented with contextual markers collected via *mQoL-log* such as time, location, ambient conditions, or social company (e.g., people around, collected either via wearables, smartphone sensors or self-reports).
Data sampling	Researchers can define sampling rates for passive and active data at the beginning or during a study. Sampling can be continuous or moment-, interval-, event-, and context-based, and it can be constrained to a given location area (geofenced).
Feedback to participants	Feedback can be given in near real-time as well as offline. It can be triggered locally (by using rules in the mobile clients) and remotely (automatically or manually, by the researcher).

3.2. Architectural Design and Implementation Choices

The architectural design of Fig. 3 uses a container-based infrastructure that simplifies the deployment, and allows execution as a distributed system, that supports the fulfillment of the requirements posed on the *mQoL Lab* platform. This choice provides several advantages: (1) the components can be maintained, updated, and run without influencing other components (R9) (cohesion), (2) they adhere to a common protocol of inter-container communication (coupling), and (3) their deployment is reproducible onto any host which allows containerization (R5). For containerization, we selected `Docker`[1] for its ease of use, flexibility, ubiquity, and documentation. A docker image is a software package that includes all its dependencies (e.g. code, libraries, settings). In Fig. 3, each component is represented by a docker image, which describes a docker container able to communicate with other containers at run time. In the remainder of this section, we describe the fundamental components of the *mQoL Lab* platform.

The server block contains the application server component, a data visualization component, multiple web server components, and other components enabling data traffic and network security. The first server-side component is the *application server*, and it can be hosted locally (R4). It exposes the data in the platform as objects. The objects represent the entities used in the clients (e.g., survey questions and answers, passive sensor data), as well as those provided to the researchers via aggregation and data analysis tools (R6). It transfers them seamlessly between the clients and servers and stores them in the *database server*. The application server communicates with the clients and web servers. Furthermore, it allows for application logic hosted in the server to be triggered by the clients, simplifying the deployment of updates, and freeing up processing resources from the clients. For the application server we use `Parse Server`[2]. It represents data objects as (`Parse Objects`), includes software development kits (SDKs) to communicate with mobile applications, libraries to communicate with web servers (we use libraries for `Rails/Ruby` and `Jupyter/Python`) as well as the `Cloud Code` functionality to execute server logic (using `Nodejs`). For the database server, we chose `MongoDB`. The *data visualization* component has a dashboard with elevated permissions to manage the data as objects. We use `Parse Dashboard` which represents the data objects in the `JSON` format.

The server block contains the web server consisting of three web applications: (1) *surveys*, (2) *notifications*, and (3) *data management*. The operations of the web servers are optimized by an in-memory rapid *data store* (implemented using `Redis`) and a concurrent *job executor* (implemented using `Sidekiq`). The *surveys* web application renders dynamic surveys prepared for each mobile study. The surveys can be administered to the participant via conventional web clients (browsers), or through `web views` embedded in mobile applications (R1). The *notifications* web application schedules and dispatches push notifications to the appropriate clients and invites participants to answer the surveys (R10). Researchers can define the scheduling of each survey in a study by using a flexible scheme with time-based triggers [3]. We have chosen to implement the two web applications by using the `Ruby on Rails` web framework. The *data management* web application allows researchers to extract, summarize, aggregate, and visualize data by using a programmatic environment. They can analyze data by using `Jupyter` notebooks (R11) and libraries in `R` or `Python`. This last web application is currently an active area of research and development in the *mQoL Lab* platform.

The server-side network is managed through the *reverse proxy* and *SSL* components. The *reverse proxy* component routes network traffic from the internet directly into the various components. It is simple to use, integrates seamlessly with the other components, and allows the addition of new components (R9). For the reverse proxy component, we use `nginx`[4]. For secure communication over the web (R8), we use the `SSL` component. This component exposes a `HTTPS` certificate from within its container, which also executes `letsencrypt`[5] certificate authority.

In the clients block, our architectural design currently supports three types of clients: mobile applications, wearable devices, and web clients. Mobile applications use the `Parse` SDKs, which simplify the application logic and data transfer. The `Parse` SDKs allow local data storage on the clients prior to eventual synchronization (R7). For passive TechRO data collection, `Android` libraries allow efficient ways to send data from the on-board smartphone sensors to the application server directly (R4), in our case, via the *mQoL Log* component. For `iOS`, Apple Health Kit collects and stores the data locally on the device and exposes it to our mobile apps which send aggregates to the application server (R4). Mobile applications also embed `web views` of the surveys web client (R4). All mobile applications require informed consent from participants before starting the study (R2) and collecting data from any source (R3).

Wearables such as off-the-shelf fitness trackers (e.g., Fitbit, Withings) or research-oriented devices (e.g., Empatica) can be integrated into our platform. Two wearable data collection alternatives are supported at the moment. First, the manufacturer opens a web application where the participant can read and approve the informed consent for data usage

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[1] https://www.docker.com/

[2] https://parseplatform.org/

[3] We provide an example in the public repository https://gitlab.unige.ch/qol/archimwu

[4] nginx is a web server, load balancer, and reverse proxy which requires minimum configuration: https://www.nginx.com/

[5] Certificate Authority provided by the Internet Security Research Group: https://letsencrypt.org/

(R3) and authorize our platform (via Oauth 2.0) to collect data from the wearable devices without revealing their credentials (R8). Second, the wearable device connects to the mobile application in the smartphone (via `Bluetooth`) and regularly synchronizes the data with it, in which case the consent in the mobile app covers the collected data (R3). Then the mobile applications eventually synchronize its data with the application server. The three web clients are part of the three web applications and communicate with their corresponding web servers.

We provide a public repository `https://gitlab.unige.ch/qol/archimwu` (*Repo*) with steps to bootstrap the foundation of a platform as shown in Fig. 3

3.3. Studies Conducted with the mQoL Lab Platform

Table 4 lists the research studies that leveraged various features of the *mQoL Lab* platform over time. The platform has been incrementally developed, enhanced, and it continues to be used in ongoing studies. The main features of the platform have remained since the early days, undergoing updates due to changes in the Android OS libraries. One novel functionality was added in the process to support an experimental method named Peer-ceived Momentary Assessment (PeerMA) which is being studied in the context of self and peer-based state assessments [2, 3].

Moreover, the process to re-instantiate the complete *mQoL Lab* platform has been validated at a new HIPAA compliant site in the USA during 2019. We accomplished this goal by following the steps outlined in *Repo*. Since then, one study was conducted to validate the stability of the platform, and the second, longitudinal study, used mobile technologies to assess quality of life-related aspects of patients undergoing a liver transplant.

Table 4: Studies conducted using the *mQoL Lab* platform

Study Aims	**Participants (N, t)**	**Methods and Tools**	**Year**	**Location**
Phone proximity [14]	28 x 1 month	DRM, EMA, Survey, Passive sensing	2011	USA
Mobile interaction experience [22]	29 x 1 month	DRM, EMA, Survey, Passive sensing	2012	USA
Intimacy perception [20]	20 x 1 month	DRM, EMA, Survey, Passive sensing	2013	Switzerland
Intimacy perception [21]	22 x 1 month	DRM, EMA, Survey, Passive sensing	2016	USA
Self-efficacy [36]	20 x 1 month	EMA, DRM, Survey, Passive sensing, Fitbit	2017	USA
Stress assessment [6]	25 x 1 month	EMA, Survey, Passive sensing	2018	Switzerland
Sleep assessment [7]	14 x 6 month	EMA, Survey, Passive sensing, Basis Peak	2018	Denmark
Sleep deprivation [10]	1 x 1 month	EMA, DRM, Survey, Fitbit, Glucose Monitor	2018	USA
Smartphone app quality of experience [12, 13]	38 x 1 month	EMA, Survey, Passive sensing	2018	Switzerland
Human state assessment with peers [2, 4]	30 x 1 month	EMA, PeerMA, Survey, Passive sensing	2018	USA, Switzerland
Health and dementia risk assessment [26]	20 x 3 months	Survey, Fitbit	2018	Denmark
Physical activity calibration [29]	31 x 2 years	Survey, Fitbit	2019	Denmark
Social support perception (active)	21 x 2 years	Survey, Fitbit	2019	Denmark
Quality of life in liver transplant patients (active)	15 x 6 months	EMA, PeerMA, Survey, Fitbit	2019	USA

4. Discussion and Concluding Remarks

In this paper, we characterized the main constituents of a mobile subjects study: participants, researchers, and the system. This is an area of active exploration and previous researchers have developed platforms, tools, and solutions to support it, especially those related to passively collecting data from wearables and smartphones. Given the fast pace of research, not all groups have the expertise or resources to design their own platform, and embracing inadequate frameworks, or siloed tools poses a high risk of obsolescence. Researchers with long-term goals in mobile sensing will benefit from building a reliable and scalable architecture that supports their growing needs. We described the *mQoL Lab* architecture that has evolved with more than ten studies over eight years; we focused not only on explaining the architecture, but also on the rationale of the underlying components of the architecture, offering practical and technical details that developers can use in the process of designing and building their platforms.

As future work, we plan to extend the contribution presented in this paper with videos, tutorials and code snippets that researchers can follow in a more hands-on manner with the aim of helping the community effectively.

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