The CARP Mobile Sensing Framework– A Cross-platform, Reactive, Programming Framework and Runtime Environment for Digital Phenotyping

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Mobile sensing – i.e., the ability to unobtrusively collect sensor data from built-in phone sensors – has long been a core research topic in Ubicomp. A number of technological platforms for mobile sensing have been presented over the years and a lot of knowledge on how to facilitate mobile sensing has been accumulated. This paper presents the CARP Mobile Sensing (CAMS) framework, which is a modern cross-platform (Android / iOS) software architecture providing a reactive and unified programming model that emphasizes extensibility, maintainability, and adaptability. Moreover, the CAMS framework supports sensing from wearable devices such as an electrocardiography (ECG) monitor, and configuring data transformers. The latter allows to transform collected data to a standardized data format and to implement privacy-preserving data transformations. The paper presents the design, architecture, implementation, and evaluation of CAMS, and shows how the framework has been used in two real-world mobile sensing and mobile health (mHealth) applications. We conclude that CAMS provides a novel cross-platform application programming framework which has proved mature, stable, scalable, and flexible in the design of digital phenotyping and mHealth applications.

CCS Concepts: • Human-centered computing \rightarrow Ubiquitous and mobile computing; • Software and its engineering \rightarrow Development frameworks and environments; • Applied computing \rightarrow Health informatics.

Additional Key Words and Phrases: mobile sensing, wearable sensing, context-aware computing, mobile health, mHealth, digital phenotyping, sensors, electrocardiography, ECG, eSense

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1 INTRODUCTION

Research in mobile sensing – i.e. the collection of data from sensors in mobile technologies – has shown that indicators of behavioral, social, psychological, and health status can be derived by collecting continuous and realworld data and applying advanced algorithms to it [21]. A significant body of research has been applying mobile sensing to health and wellness applications [5], including, for example, the EmotionSense [23], BeWell [22], and StudentLife [35] systems that classify physical activity, sleep, and social interaction based on sensor data. Studies in mental health have demonstrated correlations and predictive power between phone-based features on physical activity, mobility, social activity, phone usage, and voice data on the one hand, and mental health symptoms in e.g., depression [31], bipolar disorder [14, 17], and schizophrenia [7] on the other. In health sciences, mobile and wearable sensing has been defined as central to the 'Precision Medicine Initiative' [12]; genotypic information is

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only powerful if phenotypic information is also available [4]. Using wearable and mobile devices, the prospect of testing intervention strategies in a large population becomes appealing. For example, the 'MyHeartCounts' study on cardiovascular mobile health has recruited 40,000 smartphone users [26]. This use of everyday mobile and wearable technology for collecting behavioral, psychological, and health data has been termed 'digital phenotyping' [19, 20, 27], which can be defined as: *continuous and unobtrusive measurement and inference of health, behavior, and other parameters from wearable and mobile technology.*

In order to support easier deployment and configuration of mobile sensing studies, a number of research projects have aimed at providing more general-purpose support for mobile sensing, including support for configuration of sampling protocols, accessing low-level sensor data, and handling and storing this data. Most of this research has focused on providing easy-to-use *platforms* for collection of data from mobile phones and storing this in a cloud-based infrastructure. These platforms typically have the options to configure a sampling protocol or 'study', enroll a set of participants, deploy the study onto the participants' mobile phones and automatically collect data in a cloud infrastructure, which can be accessed from a web portal. Contemporary examples of this approach include Purple Robot [32], Sensus [37], the AWARE Framework [15], the Beiwe Research Platform [33], mCerebrum [18], RADAR-base [28], and LAMP [34] which all are quite elaborate and mature by now. These platforms are designed for research and target experimental behavioral researchers as end-users; the goal is to allow researchers to easily configure a study, enroll participants, deploy the study on the participants' phones, and collect the data automatically with as little interaction with participants as possible.

However, we have found that often there is a need for designing custom-purpose apps for particular domains and patient groups, and to be able to add support for mobile and wearable sensing to such special-purpose apps. Often the motivation for participants to engage in these studies relies on that 'there's something in it for them' [6], which again means that the app should not be designed with the researcher in mind, but the participant. Therefore, there is a need for having a mobile and wearable sensing programming framework that allows researchers to easily add data sampling to their own app during design and implementation.

For this purpose we have designed, implemented, evaluated, and released the CARP Mobile Sensing (CAMS) programming framework. This framework is part of the overall CACHET Research Platform (CARP) and has been evolving over six major releases, and has been used in the design and implementation of two released mHealth apps for mental health and cardiovascular diseases. Similar to other platforms, CAMS is a state-of-the-art mobile sensing platform with support for collection of a wide range of data types (see Table 4 for an overview), and with support for various non-functional features like privacy protection and adaptive sensing. But CAMS also has a set of unique design goals and novel technological contributions:

- Reactive application programming interface (API) The CAMS programming API is designed to be simple, yet expressive for the programmer. It supports a modern reactive, stream-based programming model allowing for non-blocking sensing and data processing. This is important in order to avoid interference of data sampling with the responsiveness of the app.
- Unified sensing CAMS has a unified sensing concept for both on-board and off-board (e.g. wearable) sensing. This allows for a unified way to set up and use data sampling in the app without the need to consider differences in the underlying operating system (OS) or device.
- Cross-platform CAMS supports a unified programming API and programming language for both Android and iOS programming. Hence, the same code base and programming API is used to develop apps for both Android and iOS.
- Data Management CAMS has extensive support for different data sampling, transformation, storage, and upload methods. A uniform approach to data transformation is adopted, which supports both privacyenabling transformations as well as transforming data to make it comply with official data standards.

- Extensible Most importantly, CAMS is highly extensible in a number of ways: it allows for implementing new data sampling methods (including both phone sensing, external wearable devices, and cloud-based services); it supports creation of new data transformers (both for privacy reasons and data standards), and it allows for creating custom data managers, which can upload data in a specific format to specific servers (or other kinds of data offloading).
- **Maintainable** CAMS integrates with a publicly available online build and dependency management system which allow for easy access to CAMS libraries and for sharing custom libraries amongst a CAMS programming community.

The basic scenario CAMS seeks to support is to allow programmers to design and implement a custom crossplatform mHealth app, which focuses primarily on providing functionality to the patient. To this end, CAMS enables programmers to add mobile sensing capabilities in a flexible and simple manner to application-specific code bases. This includes configuring collection of health and behavioral data like ECG, location, activity, and step count; formatting this data according to different health data formats; using this data in the app (e.g. showing it to the user); and uploading it to a specific server, using a specific API (e.g. REST), in a custom format.

2 EVALUATION OF RELATED FRAMEWORKS

The design of CAMS followed a user-centered design methodology – with users being programmers – in which we first did a thorough assessment of existing frameworks for mobile sensing, including installing the most mature frameworks and using these for system development. We interviewed fellow researchers and industrial software engineers, who had been using some of these frameworks and solicited their experience. Our starting point was that we wanted to use an existing framework in our research, and wanted to find the 'best fit'. Unfortunately, our research found none of the existing frameworks adequate for our purpose, and this was the reason and motivation for creating CAMS. This section outlines which mobile sensing platforms and programming frameworks already exist and discusses some of their strengths and shortcomings based on our review.

2.1 Mobile Sensing Research Platforms

A number of mobile sensing *platforms* exist, i.e. systems which are built and used for data collection via mobile phones but are not designed to be extended or used as programming frameworks. These systems typically follow the same model: they have a standard mobile phone app (sometime different apps for different data types) which can be configured to collect different types of data, which is uploaded to a cloud-based infrastructure. Often the phone app runs in the background and passively samples sensor data while also asking users to fill in surveys or input other user-generated data, such as subjective stress score. The most prominent and mature examples of such platforms include (in chronological order) EmotionSense [23], AWARE [15], Purple Robot [32], Beiwe [33], Sensus [37], mCerebrum [18], RADAR-base [28], and LAMP [34]. Most of these systems only support sampling data from built-in phone sensors (e.g. accelerometer data, step count, location, etc.), but a few like RADAR-base and mCerebrum also support data collection from wearable devices. Many of these systems only support Android, with the exception of AWARE, Beiwe, and Sensus, which also come with an iOS client app. Most of the platforms included here are to a large degree released as open source¹ and the more recent ones (AWARE, Sensus, mCerebrum, Beiwe, and RADAR-base) are actively maintained and used in different studies. However, even though the source code is available and in principle anyone can access most of them, they are challenging to extend and use without a team with a strong technical background [34]. In the phone client apps there are a lot of code dependencies which makes them complicated to build, and there is often no clear separation of the sensing part from user interface (UI) concerns, which makes it hard to reuse the sensing part of the client code.

¹Some platforms – like RADAR-base – keep integration to wearable devices as closed source.

2.2 Mobile Sensing Programming Frameworks

In contrast to mobile sensing platforms, mobile sensing *programming frameworks* are designed to be used by software engineers and app developers to include support for mobile and wearable sensing in their own code base. In contrast to mobile sensing platforms – where the end-user is mainly the researcher running a study – the end-user of a programming framework is the software developer designing and implementing a mobile sensing or mHealth app.

There has been surprisingly little research on providing such 'pure' mobile sensing programming frameworks. Two of the original examples include Funf [2] and the EmotionSense Libaries [24], which are Java-based libraries for Android sensing. They are very similar, providing support for configuration of data sampling from on-board mobile phone sensors and uploading it as files to a server. We did an interview with a software engineer who had been using Funf to add data sampling to a research app. He was satisfied with Funf in many respects but also found it rather "*low-level*" and "*inflexible*" in the sense that it only supports very low-level sensor sampling and has no support for extension, i.e. 'framework hooks' which can be used to 'hook' into the programming framework and extend it for your own application purpose. Moreover, neither the Funf or the EmotionSense libraries seem to be maintained anymore.

PrivacyStreams [25] is a more recent example of a programming framework for mobile sensing, which focuses on providing a modern reactive programming model and privacy protection of data sampling. In some respects, PrivacyStreams is similar to the design of CAMS: PrivacyStreams has an expressive, user-friendly, and welldocumented programming API, provides a modern reactive programming model, and supports sampling of different types of data which can be reused and transformed in a pipeline architecture. The dedicated focus on privacy protection 'at the source' is also a core feature of the framework. However, instead of hooking into a standard stream model (like the ReactiveX² model which is also available for Java), PrivacyStreams has designed its own stream model, which adds extra overhead for the programmer who has to learn a completely new programming model. Data transformation in PrivacyStreams is also limited to stream operations like mapping, filtering, sorting, selecting, etc., and does not provide any hooks for transforming data into specific data formats, such as health data formats like Open mHealth (OMH). Finally, PrivacyStreams is not designed to be extensible and has no direct API support for adding new sampling modalities, data transformation, or data management and upload functionality³. PrivacyStreams is implemented in Java and only supports Android.

Some of the mobile sensing platforms claim that their open source code can be used in the development of custom apps – most notably AWARE and Sensus. We have investigated this as well. When using AWARE, there is good support for setting up a study and sampling data, and AWARE can be extended with custom 'plugins' which can be loaded in the AWARE client app. AWARE also comes with an API and tutorials for how to use AWARE in a standalone app for both Android and iOS. This allows for data collection which uses a consistent data format across iOS and Android. As such, we found AWARE to be a very stable and mature framework. We did an interview with a programmer who had used AWARE in a custom app and who had found it useful, especially on Android. He argued, however, that even though the programming API is available on both iOS and Android, he found them very different and inconsistent and therefore for all practical purposes they are two distinct APIs. Moreover, he argued that it was difficult to fit AWARE into the commercial technology stack of the company and their custom app since there is no direct support for data transformation to their proprietary data formats and uploading data to a different server than AWARE's, which they did not want to install and maintain as part of their setup. Hence, in the end the programmer ended up not using AWARE and instead collected data directly

²http://reactivex.io

³PrivacyStreams is open source and of course one can check out the code and add all sorts of additional functionality. However, the main argument is that the framework itself does not support extensibility, such as loading and registering new sampling mechanisms, data transformation, and data upload modules.

from the OS API, formatted it according to their own data format, and uploaded it to their own server with its own custom REST API.

As for Sensus, we interviewed two researchers who had implemented an app using Sensus. The support for cross-platform (both iOS and Android) data sampling was found very useful, but they argued that the Sensus architecture was difficult for them to use in app development. Basically, the developers had to retrieve the Sensus app source code, disable the Sensus UI code and build a new custom UI for the new app – they labeled this approach as 'hacking' the existing app. Moreover, they found that Sensus is strongly tied to Amazon Web Services (AWS) in terms of data upload and there was no simple way to upload data to other servers.

2.3 Summary

Most of the available software for mobile sensing is tied to a dedicated client and back end infrastructure, which are often designed and build for specific research purposes. These platform are great for non-programmers and clinical researchers for engaging in digital phenotyping and many of these express a high degree of maturity in terms of features, maintenance, robustness, documentation, and support. However, these platforms are not designed as programming frameworks to be extended and used in other custom applications by 3^{rd} party developers. Our literature and code review of the most mature mobile sensing programming frameworks combined with interviews with programmers with hands-on experience in using them for application development revealed a set of shortcomings. Except for Sensus, there are no cross-platform frameworks available, and the Sensus programming model turned out to be hard to use. And even though the AWARE client exists on both Android and iOS, the AWARE programming framework is very inconsistent across Android and iOS. Android-based frameworks like Funf, the EmotionSense libraries, and PrivacyStreams provide programming APIs, but on a very low level requiring the application programmer to implement a lot of higher-order functionality for data management him/herself. But most importantly, all of the frameworks had very limited 'hooks' for extensibility, which significantly hampered the ability to implement new sensing capabilities, data formatting, transformation, management and upload. Hence, it was very difficult to tailor and use these frameworks for building custom mHealth applications for specific diseases and disorders.

3 CAMS APPLICATION PROGRAMMING MODEL

The main purpose of CAMS is to provide a unified and reactive programming API for cross-platform sensing. How code is written hence plays a core role in the framework. Therefore, a natural starting point is to see how CAMS is used from an application programmer's point of view. CAMS is implemented in Flutter, which is a cross-platform software development toolkit for building natively-compiled mobile applications for iOS and Android. Flutter uses the Dart programming language, which is a modern object-oriented, reactive, non-blocking language. This section outlines how mobile sensing can be added to a Flutter app.

3.1 Code Example

Listing 1 shows how sampling can be added to a Flutter app. This basic example illustrates how sampling is configured, initialized, started, and used in four basic steps: (i) a study is defined (line 4–19); (ii) the runtime environment is created and initialized with this study configuration (22–23); (iii) the stream of sampling events is consumed and used in the app (26–28); (iv) data sampling is started (31) and can be adapted at runtime (34). In the following, we shall dig into the details of how this is achieved by the CAMS framework.

```
i import 'package:carp_mobile_sensing/carp_mobile_sensing.dart';
void sensing() async {
   Study study = Study('ex-1', 'user@gmail.com',
```

```
name: 'A simple example study',
5
        dataEndPoint: FileDataEndPoint()
6
         ..bufferSize = 500 * 1000
7
          ..zip = true
8
          \dots encrypt = false
9
      ...dataFormat = NameSpace.OMH
10
      ..addTriggerTask(
11
12
          ImmediateTrigger(),
          Task('One Common Sensing Task')
13
             ..measures = SamplingSchema.common().getMeasureList([
14
               ConnectivitySamplingPackage.BLUETOOTH,
15
               ConnectivitySamplingPackage.CONNECTIVITY,
16
               SensorSamplingPackage.ACCELEROMETER,
17
               SensorSamplingPackage.GYROSCOPE
18
             ]));
19
20
21
    // create and initialize the sampling runtime with the study
    StudyController controller = StudyController(study);
22
    await controller.initialize();
23
24
    // subscribe to events from the controller
25
    controller.events.listen((Datum datum) {
26
     // use the collected data in the app, e.g. show it in the UI
27
28
    });
29
      . . .
    // when ready, start sampling
30
    controller.start();
31
32
    // pause / resume sampling
33
34
   controller.pause();
35 }
```

Listing 1. A simple Dart program setting up phone sensing in CARP Mobile Sensing (CAMS).

3.2 Software Domain Model

The CAMS domain API consists of three main parts: study, sampling schemes, and data points.

3.2.1 Study. Fig. 1 shows the Study part of the CAMS domain model, which specifies how a sampling study is defined and configured. A Study consists of a set of Triggers, which points to a set of Tasks, which defines a set of Measures to be done. Compared to other sensing frameworks (which typically just have a list of measures), this model may seem a little over-complicated. However, each type has a specific purpose:

- **Study** The Study holds the entire definition of the study to be done. As shown in Listing 1:4–9 a Study object defines the id, username, name, and DataEndpoint of the study. The data endpoint specifies where to 'hand over' the data to. For example, to a file or a cloud-based infrastructure. This will be discussed further in section 4.4.
- **Trigger** A Trigger defines *when* sampling is done and hence describes the temporal configuration of a study. CAMS comes with a set of built-in triggers, including triggers that starts sampling immediately (the ImmediateTrigger used in Listing 1:12), a trigger than runs periodically with a fixed period

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Fig. 1. The domain model of Study in CARP Mobile Sensing (CAMS).

(PeriodicTrigger), a trigger that can be scheduled on a specific date and time or following a recurring pattern (the ScheduledTrigger and RecurrentScheduledTrigger), and a trigger that starts when a certain sampling event happens, such as when the phone enters a certain geofence (the SamplingEventTrigger).

- **Task** A task is a bundle of measures to be done simultaneously once initiated by a trigger. For example, a task can specify to sample accelerometer and gyroscope data when triggered during a tremor assessment for Parkinson. In Listing 1:13-19, one task sampling Bluetooth, connectivity status, accelerometer, and gyroscope data is defined.
- Measure A measure defines *what* to measure, i.e. the specific data stream. A measure is a configuration of the type of data to collect, which during runtime maps to a specific probe that can collect this type of data. Since CAMS follows a reactive programming model, all sampled data is collected in *streams* by listening to the underlying sensors. Measures often need detailed configuration, such as specifying the scanning frequency for Bluetooth. However, this low-level configuration is often irrelevant to the user (programmer) of CAMS and can therefore be abstracted away using a SamplingSchema. In Listing 1:14, the common sampling schema is used to get a set of measures with the most 'common' configuration. Sampling schemes are further described in section 3.2.2.

The Trigger concept is a powerful construct, as it allows configuring the detailed scheduling of measures into separate Tasks. For example, *interval-contingent* and *event-contingent* Ecological Momentary Assessments (EMAs) [36] can be designed by triggering a survey measure using a ScheduledTrigger and SamplingEvent Trigger, respectively. More advanced scenarios include: 'start sampling of Bluetooth and Wifi when entering the home of the user' or 'trigger an assessment of Parkinson's Disease symptoms every day at 8pm'. The Parkinson's Disease assessment task could collect measures like a survey, a tremor test (using Inertial Measurement Unit (IMU) sensors), photoplethysmogram (PPG), ECG, and ambient light [8]. A study can be specified in two ways: programmatically using the CAMS domain model API (as shown in Listing 1:4–19) or using a JSON file.

3.2.2 Sampling Schemes. In order to hide the complexity of configuration of measures, CAMS offers the abstraction of a SamplingSchema, which can be used to set up a study in a much more convenient manner. A sampling schema defines a specific configuration of a measure – for example that the bluetooth measure should scan for proximal bluetooth devices every 10 minutes for 5 seconds (as suggested in the StudentLife study [35]). A SamplingSchema can be created with a default sampling configuration called the common schema. In Listing 1:14 the SamplingSchema.common() constructor is used to get a list of measures with the 'common' or default⁴ configuration. In addition to the default sampling schemes, programmers can defined custom schemes for specific purposes that can be reused. For example, in the power consumption studies of CAMS (see section 5.1), two sampling schemes for the two studies were defined, each resembling the studies of AWARE and mCerebrum

⁴The keyword default is reserved in Dart and hence could not be used.

as reported in the literature. Sampling schemes are defined for each sampling package, which are described in section 4.3.

3.2.3 Data Points. A data point holds sampled data and consists of a header specifying the DataFormat and a body, called Datum. The DataFormat specifies the namespace and the type of the data being sampled. For example, carp.bluetooth specify a data point of type bluetooth in the carp namespace, whereas omh.bloodpressure specify a blood pressure measure in the Open mHealth (OMH) namespace. The Datum class defines the specific data point value. For example, the BluetoothDatum holds the Bluetooth device name, id, type, power level, and RSSI signal strength. Similarly, the BloodPressureDatum holds information on the systolic and diastolic blood pressure, and the body position of the measurement⁵.

3.3 Data Transformation

In order to support the design of custom mHealth apps, the ability to transform data into another format is useful for several reasons. First, transformation may be needed to support a specific data format when uploading to a certain data storage. For example, if uploading data to the mCerebrum Cortex server, we need to comply to the mCerebrum data schemes. Second, transformation is useful when data is to be saved in an standardized format, such as the Open mHealth (OMH) or Fast Healthcare Interoperability Resources (FHIR) data schemes. Third, transformation may be needed for *privacy* reasons and can be used to anonymize data prior to upload.

CAMS has a very generic model for creating data transformers, which consists of three main parts. First, at the lowest level a DatumTransformer function which can transform a Datum object from one data format to another can be defined. Second, such datum transformers can be organized into a DataTransformer, which hold a set of DatumTransformer functions for a specific data format. Third, data transformers can be registered in the DataTransformerRegistry (see Fig. 2) and used for data transformation at runtime. It is beyond the scope of this paper to describe how to design, register, and use data transformation in CAMS, but a tutorial in the online documentation explains how to do this [10].

CAMS comes with three built-in data transformers: a CARP, an OMH, and a privacy transformer, which can be used in the motivating examples above. For example, listing 1:10 shows how the data format can be specified for a study. In this case, all data points will be transformed into the OMH data format by using the built-in OMHDataTransformer.

The built-in PrivacyDataTransformer defines a set of functions that can obfuscate data points. If privacy is enabled, this schema is used to obfuscate data points when collected and before any other data transformation or upload is done. A common strategy in other mobile sensing frameworks is to support privacy 'by default' by scrambling data at the source, i.e., when data is being sampled. For example, Funf, Sensus, AWARE, and mCerebrum all perform one-way hashing of sensitive data like telephone numbers and email addresses. However, since the original data might be needed, CAMS does not enforce any scrambling of data. Instead, more flexibility is provided by considering privacy protection part of data transformation.

3.4 Extending the CAMS Domain Model

Since CAMS is designed as a highly extensible programming framework, all CAMS domain model classes can be extended for domain-specific purposes. Specifically, the Study, Trigger, Task, Measure, SamplingSchema, Datum, and DataTransformer classes – including the built-in implementations of these – are extensible. Section 4.3 describes how to create new sampling packages in CAMS by extending core classes in the API.

⁵See https://www.openmhealth.org/documentation/#/schema-docs/schema-library for definitions of the Open mHealth (OMH) data schemes.

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Fig. 2. The overall runtime architecture and main components of the CARP Mobile Sensing (CAMS) framework consist of three main layers – runtime, sampling packages, and data managers – which build on top of Flutter plugins and the processes and services in the native OS. Sampling is controlled from the study controller and down to the OS whereas data flows from OS sensors, external wearable devices, and web services up towards the data managers.

4 CAMS RUNTIME ARCHITECTURE

Fig. 2 shows the overall layered software architecture of CAMS. The CAMS runtime model consists of three main layers: the core runtime, data managers, and the sampling packages, which again build on top of a set of Flutter plugins which access processes and services in the underlying OS, external wearable devices, and cloud-based services. This runtime architecture is designed to achieve the non-functional software architecture goals of being highly extensible, cross-platform, and maintainable.



Fig. 3. The initialization of the CAMS runtime.

4.1 Runtime

As illustrated in Fig. 2, the CAMS runtime make extensive use of registries in which different components can be registered and retrieved at runtime. These registries are core to the extensibility of the framework since they allow for adapting and extending how data is acquired, transformed (including anonymization), stored, and uploaded.

As shown in Listing 1:22, the StudyController is the main runtime component responsible for executing a study, handling sampling packages, transforming data (including applying any privacy transformer), and uploading it to a data manager. Fig. 3 shows how the StudyController is created and initialized. On creation it (i) creates a StudyExecutor, (ii) looks up a data manager in the DataManagerRegistry based on the type of data endpoint, (iii) looks up a privacy transformer in the DataTransformerRegistry, and (iv) looks up a transformation scheme (also in the TransformerSchemaRegistry) based on the study's data format (e.g. omh). After the study controller is created, the study executor and data manager are initialized. Note that the data manager is given the events stream, which carries all the sampled data, and the data manager then subscribes (listens) to all data point events.

Once initialized, the StudyExecutor is responsible for executing the data sampling as specified in the Study domain model. It is beyond the scope of this paper to describe how this is done in detail ⁶, but in short, execution entails looking up appropriate sensing Probes in the ProbeRegistry and collecting data according to the timing specified by the triggers. Listing 1:31 shows how sampling is started.

⁶This is described in the online CAMS documentation [10].

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4.2 Adaptive Sampling

Data sampling can be adapted at runtime. This includes pausing and resuming sampling (Listing 1:34), as well as adjusting the study configuration including its measures, which in turn will adjust the probes' sampling configuration while the sampling is running. Adaptive sampling is a very generic property of CAMS which is also used for power-aware sampling. Each SamplingPackage defines a set of default sampling schemes that specify how sampling should be done at different battery levels: normal, light, minimum, and none. At runtime, these sampling schemes are used for adjusting sampling; when the battery level decreases / increases to certain thresholds, the runtime environment will adapt the sampling by using an appropriate sampling scheme (battery level in parenthesis): normal (100%–50%), light (50%–30%), minimum (30%–10%), and none (10%–0%).

4.3 Sampling Packages

A core mechanism for enabling the high extensibility and robustness of CAMS is the sampling package model and API. A sampling package is responsible for specifying what data it can collect, the format of this data, and how data is acquired. A sampling package typically handles the collection of a set of related measure types. For example, the connectivity sampling package collects data on connectivity status, wifi, and bluetooth. New sensing capabilities can be added to CAMS by creating a new SamplingPackage implementing the following classes:

- SamplingPackage the overall specification of the sampling package, specifying which measures it can collect, factory methods to get the default SamplingSchemas, a list of datum transformation functions, including default privacy-preserving functions.
- Measure specifies what to collect (i.e., the measure type) and how (i.e., the configuration of the probe).
- Datum specifies the format of the collected data.
- Probe the concrete implementation to collect data from the underlying OS or external services using one or more Flutter plugins.

It is beyond the scope of this paper to describe how these classes are implemented but an online tutorial explains this and provides an example [10].

In Fig. 2, the built-in sampling packages are shown in green, whereas the external packages are shown in purple. External packages are only loaded if they are used in the app. This modular design of CAMS has a number of benefits, including decreasing app size, reducing dependencies to only those packages needed, and not having to ask the user for permission to access data sources that are unused. The sampling package concept also provides a strong modularization model for adding *external* sampling to an app. For example, real-time ECG data collection from the Movisens EcgMove4 device is implemented as a separate sampling package, which encapsulates the low-level details of handling this device and its data formats. Similarly, support for user surveys has been implemented as a sampling package.

Sampling packages are Dart libraries, which can be released as Flutter packages on Dart pub.dev⁷. This means that they can be downloaded and added to a Flutter app as needed when the app is built. It also means – in contrast to most other sensing frameworks which has all the probes built-in – that an app developer only needs to download and add sampling packages which are needed for his/her specific app. Hence, if context information is not needed for an app, the context package is not linked and used. This also means that application programmers can share CAMS sampling packages with each other via the official Dart code sharing infrastructure, which includes continuous quality assessment of the code. Table 4 in Appendix B shows a list of currently available sampling packages and their measures.

⁷https://pub.dev

4.4 Data Managers

As shown in Fig. 3, during the creation of the study controller, a DataManager is retrieved from the DataManager Registry based on the specified data endpoint type, which again is specified as part of the study (see Listing 1:6). This data manager then subscribes to the events stream and is responsible for handling incoming data. As shown in Fig. 2, CAMS currently supports a file data manager and data managers for cloud storage on Firebase and the CARP backend. Note that the three cloud-based managers (shown in purple) are available as external Flutter plugins, which means that they are only downloaded and linked, if used. Hence, an app would typically use only one of these.

CAMS supports the creation of new data managers – or extending the existing ones – for special-purpose data management. This is done by implementing two base classes: DataEndPoint – specifies how a data endpoint is to be configured and DataManager – implements the details of how to store or upload data from the events stream. Moreover, if such data managers are release at Dart pub.dev, they would be available for other programmers using CAMS. Again, it is beyond the scope of this paper to describe how these classes are implemented, but a tutorial in the online CAMS documentation goes into more details and provides an extensive example [10].

4.5 Implementation and Availability

CAMS is implemented in Flutter v1.7 using Dart v2.4. Flutter is a cross-platform toolkit for building nativelycompiled applications for mobile, web, and desktop from a single codebase [16]. Dart is a modern object-oriented, reactive programming language optimized for non-blocking UI programming with a mature and complete asyncawait event-driven code style, paired with isolate-based concurrency model. The implementation of CAMS particularly exploits three core aspects of Dart: (i) the asynchronous non-blocking programming style using the Future construct, (ii) the event-driven reactive stream model using the Stream API, and (iii) access to native OS processes via the PlatformChannel API.

Note that the Flutter plugins shown in Fig. 2 are not part of CAMS, but are 3^{rd} party plugins available from the Dart packages repository. The CARP team contributes to this library of Flutter plugins and has released several. However, they are designed to be general purpose and are not specific to CAMS – CAMS-specific use of these plugins happens in the Probe implementation in the different sampling packages.

CAMS has been designed, implemented, and tested over the course of six major releases and the core framework and all of its associated plugins, sampling packages, and data backends have been released on the Flutter pub.dev software package repository. The framework has been downloaded and used a number of times. We are getting issue reports and feature request from outside our lab, so others are seemingly using it. Appendix A provides an overview of all the online CAMS resources, including API documentation and online tutorials.

5 EVALUATION

5.1 Technical Evaluation and Benchmarking

In order to evaluate and benchmark CAMS, a set of technical evaluation studies were performed in which the performance of CAMS was compared to the AWARE framework [15] and the mCerebrum platform [18]. All studies used the latest released version (November 2019) of the Android client apps of AWARE (v4.0.815), mCerebrum (v2.0.14), and CAMS (v0.6.2). The main purpose of these technical studies was to investigate whether the cross-platform runtime environment of Flutter comes with any significant performance penalties compared to native Android sensing frameworks.

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Fig. 4. Comparing battery consumption of AWARE and CAMS during two tests: Test #1 – AWARE and CAMS running concurrently for 24 hours. Test #2 – AWARE and CAMS running independently for 24 and 36 hours respectively.

5.1.1 Memory. On Android, the size of the Android Application Package (APK) files for the AWARE, mCerebrum, and CAMS clients are 6.1 MB, 34.1 MB⁸, and 38.8 MB respectively. In comparison, the size of the 'Hello World' app provided by Flutter is 35.1 MB; it thus seems cross-platform support in Dart/Flutter comes at the cost of an initial payload of 35 MB. Hence, the additional size of adding CAMS sensing capabilities to an app is in the order of 4 MB. In order to investigate working memory usage, the CAMS client app was tested using the Android Profiler [3] over the course of two hours. This revealed a stable memory footprint in the range of 45–49 MB while running in the background. In comparison, the runtime memory consumption of mCerebrum is 80 MB and 50 MB for AWARE. Hence, there seems to be no memory penalty in using Flutter and hence CAMS.

5.1.2 Battery. Power consumption and battery life are major concerns in mobile sensing [18, 21]. Therefore, CAMS was subjected to two power consumption tests: one mimicking a typical sensing scenario, and another focusing on high-frequency data collection. Following the evaluation strategy in Hossain et al. [18], we compared CAMS to AWARE and mCerebrum. However, in contrast to the power consumption tests done in the Hossain et al. [18] study which only lasted one minute, our studies ran for up to 36 hours in real-world sensing scenarios. All tests were done on Android, using a Samsung Galaxy A3, Android OS level 8.0. Power consumption statistics were collected using the AccuBattery Pro app [1], which is based on the research of Choi and Lim [11]. Power-aware sampling adaptation was disabled in CAMS. Data was stored locally on the phone using the default storage mechanism of the apps (AWARE uses a database and mCerebrum and CAMS use files).

The purpose of the first study was to compare AWARE to CAMS by sampling data from as many sensors/probes as possible over an extensive period of time. The common set of data types supported by both apps was identified

⁸mCerebrum consists of several apps which are designed for different purposes and installed as needed. The minimum setup for mobile sensing are three apps: the mCerebrum app (17.8 MB), the PhoneSensor app (7.6 MB) and the DataKit app (8.7 MB) – in total 34.1 MB



Fig. 5. Battery consumption during the high-frequency test comparing AWARE, mCerebrum and CAMS. 17-hours runtime.

and each app was configured to collect this data at the same sampling frequency. The following sensors were used (sampling period in parentheses, when applicable): accelerometer (200ms), gyroscope (200ms), light (200ms) applications, battery, bluetooth (60s), communication, location, screen, wifi (60s), activity (60s), and weather (60m). During a first test, the two client apps were running concurrently for 24 hours in order to be subject to identical sensing scenarios. During a second test, the two apps ran independently during two different periods (24 hours for AWARE and 36 hours for CAMS). Activities during the two tests included a mixture of office work, walking, driving, and sleeping. Fig. 4 shows the result of these two tests. During the first test (#1), power consumption of the two apps is very similar, while AWARE seems to consume slightly more power initially. During the second test (#2) where data collection ran independently, we found no significant difference in power consumption. This study shows that the energy drain from both frameworks is small (below 12 mAh).

The second study was inspired by the test done by Hossain et al. [18] focusing on high-frequency data. Even though CAMS is not designed specifically for high-frequency sampling (like mCerebrum is), it is still of interest to see how it performs under high load. Therefore, a test scenario similar to the test done by Hossain et al. was created in which the following data were collected at the same frequency: accelerometer (20ms/50Hz), gyroscope (20ms/50Hz), and light (20ms/50Hz). All three apps (AWARE, mCerebrum, and CAMS) ran concurrently in order to collect data under identical circumstances. Again, in contrast to the mCerebrum study which only lasted 10 minutes, this study ran for 17 hours involving sensing during a heterogeneous set of real-wold activities as in the first study. Fig. 5 shows the result of the study comparing the power consumption of the three apps over the 17 hours study. We observe that the power consumption profile is identical for the three apps, while AWARE and mCerebrum seem to be consuming slightly more power. All three apps was restarted during this long-term test, which can be seen in the graph: AWARE was restarted around midnight on the 13th, CAMS at 8 in the morning on the 14th, and mCerebrum at 10 on the 14th. These restarts result in a significant peak in power consumption.

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Fig. 6. Sampling coverage. Top: Android Samsung A3, sampling period 09:00–08:00. Bottom: iPhone XP, sampling period 10:00–08:00. Numbers in cells indicate sampling coverage; 1 indicates 100% coverage, i.e. that all expected data points were collected. Note that the app_usage, light, and memory measures are not available on iOS (see Table 4) and hence not collected on the iPhone.

Based on these two studies we can conclude that the cross-platform CAMS framework performs equivalently to native Android sensing platforms (AWARE and mCerebrum) and support for cross-platform sensing does not seem to come with a penalty in terms of increased power consumption.

5.1.3 Sampling Coverage. A third technical parameter to address is sampling coverage, i.e., to what degree does CAMS collect data points compared to what is expected. For example, if the sampling frequency for location is set to 30 s, 120 location data points are expected per hour. Sampling coverage can only be calculated if ground truth is know, i.e., if we know the expected number of data points. Ground truth can be established if sampling is periodic (set to a fixed frequency) – such as sampling light at a certain frequency – but cannot be established if sampling is event driven – such as activity recognition.

Fig. 6 shows the result of a 24-hour coverage test executed on the Android Samsung A3 (top) and an iPhone XP (bottom). The test includes most of the periodic measures in CAMS, for which ground truth can be established via a known sampling frequency: location (0.5s), wifi (1s), light (1s), noise (1s), app_usage (5s), memory (1s), weather (10s), and air_quality (10s) (see Table 4). Coverage is calculated per measure on an hourly basis as the ratio of collected data points compared to the expected number. Overall, the results in Fig. 6 reveal that sampling

coverage on both Android and iOS is close to 100% for all measures supported by the respective OSs. Hence, we can conclude that CAMS provides full coverage in data sampling using an identical study configuration across both platforms.

5.2 Application Studies

CAMS has been used in the development of two real-world mHealth apps. These apps have been developed by five experienced developers from the same lab as the authors of CAMS, but they are not co-authors of CAMS or this paper. Table 1 shows an overview and programming background of the programmers. All were involved in implementing mobile sensing support in one of the two apps, and one programmer added mobile sensing support for a third app (not discussed in this paper). As part of the the user-centered design of CAMS, they were asked to take notes while using CAMS, especially regarding the usability and usefulness (pros and cons) of the API and online documentation. Table 2 shows overall statistics on the two apps, including the number of data points collected and uploaded via CAMS. This illustrates that CAMS was used in non-trivial apps for collecting a non-trivial amount of mobile sensing data, while also illustrating two very different ways of using CAMS.

5.2.1 MUBS. MUBS is an app supporting Behavioral Activation (BA) [30], which is a therapy form that emphasizes planning of small, achievable activities as part of treatment for depression. MUBS was released in the winter of 2019 and is available on both the Google and Apple app stores. At the time of writing, 174 users have registered for MUBS, and ca. 25 users use it at least once on a weekly basis, with a peak use during a clinical study. There are 56% Android and 44% iOS users, illustrating the cross-platform nature of CAMS. The majority of users were from the app's home country (45%) and the United States (US) (38%). According to the logs, none of the MUBS users encountered any crashes, illustrating the stability of the app and hence also CAMS.

The software architecture of MUBS follows the 'InheritedWidget' architecture [13], and sensing is added to the app via a sensing utility class. MUBS uses CAMS to collect data on location, steps, weather, activity, screen, and app usage. Once sampling is started it runs continuously. All data is uploaded to a Firebase cloud database using the FirebaseDatabaseDataManager plugin. An activity recommendation algorithm is implemented as a Firebase function, which utilize the data being uploaded in real-time. Fig. 7 (right) shows the collection of data points collected via CAMS over time. Since a strong relationship between location and depression has been shown [9, 29], MUBS collects location at similar high sampling frequency (every 30 secs.). As shown in Table 2, MUBS has now been running for 305 days (Jan. 27–Nov. 28) and close to 600,000 data points have been collected and uploaded to Firebase. The large standard deviations (SD) in terms of data points per day and user reflects that MUBS was used more extensively during clinical trials.

5.2.2 mCardia. mCardia is an app for monitoring cardiovascular diseases (CVDs). Compared to MUBS, mCardia utilizes CAMS beyond just sensing and is a proof of concept of several of its core features, including extensibility. First, using the prepackaged CAMS phone sampling packages, location, activity, steps, noise, air quality, and general phone usage is collected. Second, collection of *high-frequency* data from a wearable ECG device is implemented by *extending* CAMS with a sampling package for collecting data from the Movisens EcgMove4⁹ device. This device collects heart rate (HR), heart rate variability (HRV), metabolic activity level, steps, and tap markers. Support for the EcgMove4 device is implemented via two Flutter plugins: a generic movisens_flutter plugin which can access data from the device over Bluetooth Low Energy (BTLE) using the Android API provided by Movisens, and a MovisensSamplingPackage which uses the movisens_flutter plugin to collect data via CAMS. Third, *user surveys* about heart problem events such as feeling dizzy or having chest pains are collected. An event can registered by 'double tapping' the Movisens device and later the details can be filled in on the phone. Fourth, in order to collect data in a standardized way for later reuse and cross-validation, data collected in

⁹https://www.movisens.com/en/products/ecg-sensor/

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Fig. 7. Left: the user interface of the MUBS app for Behavioral Activation (BA). Right: the collection of data points collected via CAMS in the MUBS app since its release in February 2019.

mCardia is *formatted* according to the OMH data schemes (where they exists). This is done simply by specifying the study's data format as the OMH namespace, as shown in Listing 1:10. All data is uploaded to the CARP cloud using the CarpDataManager. Finally, the software architecture of mCardia follows the Business Logic Component (BLoC) pattern [13], in which sensing is handled in a centralized sensing BLoC component that separates mobile sensing from the rest of the app. This allows the app to *access the data in real-time* using the events stream. This is used to display data in real-time in the user interface, as shown in Fig. 8, which shows minute-for-minute HR, HRV, tap markers, metabolic activity level, active time, steps, and sleep.

Currently, Movisens only provides an Android API and mCardia is hence mainly useful for Android users. However, if Movisens releases an API for iOS, support for iOS users would also be available without any changes to the mCardia implementation. Moreover, the plugable architecture of CAMS allows for supporting other HR or ECG devices by implementing appropriate sampling packages, which can be directly linked and used in the app.

At the time of writing, initial pilot tests of mCardia are ongoing. Cardiovascular disease monitoring typically runs over 24–48 hours, and seldom more than 4 days. As shown in Table 2, the app collects high-frequency data from the EcgMove4 device and phone – up to 15,000 data points per user every 24 hours. Our tests show that the app runs stable during these conditions. Different strategies for increasing robustness and scalability of CAMS have been implemented based on input from the programmers of mCardia, including buffering of data on the phone prior to upload.



Fig. 8. The mCardia app for cardiovascular disease (CVD) monitoring – (i) the homepage of the app showing an overview of the data being collected via CAMS (HR, HRV, metabolic level, physical activity, and sleep) – (ii) the list of events registered via tapping the device and sampled via the CAMS Movisens sampling package – (iii) the Movisens EcgMove4 device for ECG monitoring.

Table 1. Programmers using CAMS. PE: Programming Experience – MPE: Mobile Programming Experience – FPE: Flutter Programming Experience – Apps: Number of mobile app releases.

ID	PE	MPE	FPE	Education	Mobile Tech.	Apps
P1	2-5	0-2	0-2	Master	Xamarin	1
P2	2-5	0-2	0-2	Master	Flutter	3
P3	2-5	0-2	0-2	Bachelor	Native iOS, Flutter	1
P4	2-5	0-2	0-2	PhD	Native Android, React Native	0
P5	2-5	2-5	0-2	Bachelor	Native Android, Native iOS	4

5.3 Programmer Feedback

The feedback from programmers helped identify strengths and suggestions for improvement for the CAMS API and documentation. One common feature highlighted as important by all programmers was the support for building consistent cross-platform mobile sensing apps.

I'm an iOS guy who is turning to Flutter, and the ability to build [data collection] once is very good. It makes life a lot easier that data is collected in the same way and has the same data format. [P3]

The way that CAMS abstracts away the sampling in one unified and simple API is based on continuous input from the programmers and the design goal was to let programmers configure sampling in a standardized manner across iOS and Android. It was highlighted that the design of CAMS and its API became "nicely aligned with the Flutter API and the way Dart code looks" [P1]. For example, the support for reactive programming using the

CAMS events stream fits directly into Flutter and allows for using e.g. the StreamBuilder class when creating reactive UI widgets. In general, the "*deep integration with the Flutter ecosystem*" was seen as an essential feature by the programmers. Specifically, using Flutter's programming model, complying to Dart's official coding and documentation guidelines¹⁰, the use of pub.dev for publishing packages and plugins, and support for Firebase, resulted in a streamlined developer experience.

The design of CAMS as a framework that plugs into the programmers' own app was also perceived as useful.

I've previously done another app using another sensing framework. Compared to this, the use of CAMS is much better. You just add the CAMS flutter plugin and start using it – the design of your app is independent of this. [P1]

The same programmer also provided feedback on the ability to consume CAMS data sampling events in the app (by just listening in on the study controller's events stream), since he found this to be an essential part of CAMS; "... in the other framework, this was not possible at all".

The support for extending CAMS using the sampling package and data manager services was also considered an essential feature of the framework.

We did spend quite some time implementing the Movisens Flutter plugin – we had a lot of issues with undocumented behavior in the Movisens Android API. However, once we had the plugin ready, creating a CAMS sampling package was straightforward. And when adding the Movisens measure to our app, we saw Movisens data floating in immediately. [P4]

The modular design of sampling packages that are loaded on compile time and only included if needed, is a feature implemented as a direct result of programmer feedback. This ability was designed together with the MUBS programmers when Google announced that they are limiting which apps are allowed to ask for permission to access the phone call and SMS logs¹¹. Once the phone_log and text_message_log measures were moved to the communication sampling package, and MUBS did not include this package, the app was approved by Google and released in the Play Store.

During the use of CAMS, the programmers also helped identify limitations of the framework. Firstly, the benefit of Flutter being cross-platform also comes at a cost in terms of not being able to directly access native OS APIs. For example, the Flutter plugin for sensor access has a more limited API compared to e.g. the native Android sensors API. Secondly, some programmers argued that CAMS comes with a fairly complex study domain model including the study, trigger, task, and measure classes (see Fig. 1). However, programmers also liked the flexible and expressive manner a study could be set up, so finding an appropriate balance was important. The sampling schema model was introduced to address part of this complexity. Thirdly, the programmers highlighted that there is a huge difference between *using* CAMS and its built-in features and *extending* it with new functionality. Especially the documentation and code examples should to a much larger extent reflect the difference between using versus extending the framework. This feedback from the programmers has been incorporated in the latest release of the framework and its online documentation (see Appendix A)

6 DISCUSSION

6.1 Meeting the Design Goals

The initial design goals of the CAMS framework were to provide a reactive, unified programming API with a cross-platform, extensible, and maintainable runtime architecture. CAMS provides the programmer with an expressive, yet simple API for configuring a study, executing it via a study controller, and consuming the incoming data as a stream of events in the app which can be mapped, filtered, transformed, saved, and uploaded as specified

¹⁰https://dart.dev/guides/language/effective-dart

¹¹https://android-developers.googleblog.com/2018/10/providing-safe-and-secure-experience.html

	MUBS	mCardia
Total number of users	174	6
Total days running	305	83
Total no. of data points	588, 434	2,021,303
Data points per user (avg. \pm SD)	$3,375 \pm 10,613$	$336,884 \pm 302,427$
Data points per day (avg. ± SD)	$1,928 \pm 2,083$	$24,353 \pm 11,509$
Data points per day per user (avg. \pm SD)	129 ± 229	$14,632\pm2,82$

Table 2. Overall statistics on the CARP Mobile Sensing (CAMS) apps: MUBS and mCardia.

in configured plugins. Sampling can be adapted and controlled (paused/resumed) at runtime and executes in a non-blocking asynchronous manner, preventing it from interfering with the responsiveness of the app and user experience. CAMS provides a uniform programming model to enable sensing of different on-board phone sensors, e.g., location and pedometer, logs (e.g. call log), external wearable devices (e.g. an ECG monitor), and online web services (e.g. weather information). Data sampling is configured via 'measures' and sampling support and data formatting is done via sampling packages. Data upload to different local or remote data back-ends is supported by plugable data managers. By leveraging the Flutter and Dart technology, the app programmer is able to add data sampling that runs cross-platform on both iOS and Android using the same CAMS API resulting in a single codebase.

The most important design goal of CAMS is to support extensibility and the framework has 'hooks' that support adding new sampling measures (via the 'sampling package' concept), adapting sampling (via the 'sampling schemes' concept), transforming and protecting data in different ways (via the 'data transformer' concept), and storing and uploading data in different ways (via the 'data manager' concept). Hence, CAMS allows for in-depth customization, as demonstrated by the two quite different apps, one for mental health and one for cardio-vascular diseases. Moreover, by leveraging the Dart/Flutter package manager ecosystem, CAMS is easily distributed and linked when programmers want to use the framework in their code. This setup also allows third-party developers to distributed and share new packages for extending CAMS, including new sampling packages and data managers.

The evaluation of CAMS shows that using Flutter and Dart for implementing mobile sensing did not come with a penalty or overhead in memory and battery consumption as compared to native mobile sensing apps implemented for Android. A study of sampling coverage on both Android and iOS revealed close to 100% coverage. Hence, if a programmer wants to use Flutter (with all the benefits that come with it), CAMS would be a useful framework for adding mobile and wearable sensing. The implementation and release of two real apps – MUBS and mCardia – shows that CAMS scales to non-trivial apps beyond the framework authors' own apps. In addition, the programmer-centered design of the API and documentation involving five programmers helped to make the framework gradually more useful and usable.

6.2 Limitations

CAMS, as well as the studies presented here, also have a set of limitations. First, even though Dart compiles to native iOS and Android, the Flutter API is different from the native APIs, and the underlying OS features and service cannot be accessed directly. Access to e.g. the location API is limited in Flutter compared to the Android sensor API. This can be solved by using platform channels in Flutter which allow passing messages to/from the host platform, thereby giving access native services and APIs where needed. This, however, implies that when creating a Flutter plugin, OS-specific libraries for both iOS and Android need to be implemented. Hence, the uniform and unified API of CAMS comes with a cost of implementing the need to master three programming ecosystems: Flutter, iOS, and Android.

Second, in terms of technology Dart/Flutter did prove very scalable and robust, as shown in the technical evaluation. However, there are still a few technical limitations and open issues with Dart. Most importantly, there is an unsolved issue in the core Dart runtime, that an app crashes if a Dart isolate accesses a platform channel. This is a limitation for the implementation of CAMS since data sampling almost always relies on a platform channel to access data from the native OS and therefore isolates cannot be used for data sampling. However, this did not seem to be a problem during our technical evaluation and we have not experienced any problems in terms of robustness during the deployment of real-world apps. But – support for runtime isolation of data sampling probes is planned to be implemented, once this issue is fixed by the Dart team.

Third, even though Dart/Flutter is one of the rising technologies for app development, widespread adoption is still limited. Therefore, user involvement in the design of CAMS was limited to five programmers. Even though these were experienced programmers developing real apps for release, the current insight is limited to the involvement of these programmers. Further input from other programmers in the continued enhancement of CAMS will be needed.

7 CONCLUSION

CARP Mobile Sensing (CAMS) is a cross-platform (Android/iOS) mobile programming framework, which in addition to state-of-the-art mobile and wearable sensing provides a modern reactive programming API with a unified approach to data sampling, management, transformation, usage, storage, and upload across different types of data sources and data storage facilities. CAMS provides support for data sampling from on-board mobile sensors (e.g. accelerometer, location, and step counter), from phone logs (e.g. call log), from off-board wearable sensors (e.g. ECG monitor), and web-based services (e.g. weather forecast). All currently supported measures are listed in Table 4 and new measures are continuously being added in the form of released sampling packages. CAMS provides a stream-based API which allows for flexible stream operations, including data transformation and privacy-preserving functions. Most importantly, however, as a programming framework, CAMS is designed to be highly extensible. Many framework 'hooks' for further extension are available, including support for adding new data sampling methods, data transformations (including privacy functions), data storage, and upload to cloud-based servers. As a publicly available framework for Flutter, CAMS leverages the Dart package manager ecosystem for easy code releases and sharing of 3rd-party extensions. On a more general level, the CAMS architecture shows how a framework for mobile and wearable sensing can be designed to be extensible and flexible for different data sampling needs, data formats, data transformation, data management, and different application use cases.

The design of CAMS was informed by a team of programmers and their continuous feedback on the usefulness and usability improved the API and online documentation. In addition, CAMS has been thoroughly evaluated, both technically and in terms of usefulness in mHealth application development. Even though the use of CAMS is still in its early stage – programming frameworks are typically judged by their long-term use – the present results show that CAMS performs similar to native sensing platforms, could be used to build and release two non-trivial and very different mHealth applications, and that programmers found the framework useful and usable. As such, we conclude that CAMS might be a good choice for adding mobile and wearable sensing to cross-platform Flutter apps, using either the default-provided sensing capabilities, or when needing to extend it with support for custom measures and sensors.

The CAMS framework has been released along with detailed online documentation on how to use the framework for adding mobile and wearable sensing to a Flutter mHealth applications, including how to extend and customize CAMS for application-specific data sampling, management, use, transformation, storage, and upload. See Appendix A for details. We hope that others can benefit from using and extending CAMS.

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A ONLINE RESOURCES

CARP Mobile Sensing (CAMS) and its associated sampling and backend packages have been released as Dart packages with online API documentation. An overview of all software packages is available online at https://github.com/cph-cachet/carp.sensing-flutter as well as shown in Table 3 (at the time of writing).

The CARP Mobile Sensing (CAMS) online tutorial on how to use the framework in a Flutter app – including using the different packages – is available at https://github.com/cph-cachet/carp.sensing-flutter/wiki.

Note that these online resources are constantly updated to reflect new additions and enhancements to CAMS.

Component	Description	url
Core		
carp_mobile_sensing	CARP Mobile Sensing (CAMS) in Flutter	https://pub.dev/packages/
		carp_mobile_sensing
Sampling Packages		
carp_communication_	Communication sampling package (phone, sms)	https://pub.dev/packages/
package		carp_communication_package
carp_context_package	Context sampling package (location, activity,	https://pub.dev/packages/
	weather)	carp_context_package
carp_audio_package	Audio sampling package (audio, noise)	https://pub.dev/packages/
		carp_audio_package
carp_movisens_	Movisens Move & ECG sampling package	https://pub.dev/packages/
package	(movement, MET-level, ECG)	carp_movisens_package
carp_esense_package	Sampling package for the eSense ear plug device	https://pub.dev/packages/
	(IMU & button)	carp_esense_package
Backends		
carp_backend	Support for uploading data to a CARP data back-	https://pub.dev/packages/
	end as JSON.	carp_backend
carp_firebase_	Support for uploading data to Firebase as both	https://pub.dev/packages/
backend	zipped files and JSON data	carp_firebase_backend

Table 3. CARP Mobile Sensing (CAMS) software components.

B CAMS MEASURES

Table 4 shows a list of currently available measures in CAMS and which sampling package they belong to. Compared to other frameworks, CAMS covers most of the common set of measures and most of them are available on both Android and iOS, which makes CAMS a good choice for cross-platform implementation of mobile sensing. More packages and plugins are constantly being designed and released at pub.dev. See https://pub.dev/publishers/cachet.dk/packages for an overview of the released CAMS sampling packages and plugins.

Table 4. Measures available in CAMS, their availability on Android and iOS (+: available, -: not available), and which package they belong to. The top part lists the sampling packages built into CAMS; the middle part lists the external sampling packages, and the lower part lists sampling packages for wearable devices. The external packages are available for download at pub.dev

Туре	Android	iOS	Package	Description
accelerometer	+	+	sensors	Accelerometer data from the built-in phone sensor
gyroscope	+	+	sensors	Gyroscope data from the built-in phone sensor
pedometer	+	+	sensors	Step counts from the device on-board sensor
light	+	-	sensors	Ambient light from the phone's front light sensor
device	+	+	device	Basic device information
battery	+	+	device	Battery charging status and battery level
screen	+	-	device	Screen event (on/off/unlock)
memory	+	-	device	Free memory
connectivity	+	+	connectivity	Connectivity status
bluetooth	+	+	connectivity	Scanning nearby bluetooth devices
wifi	+	+	connectivity	SSID and BSSID from connected wifi networks
apps	+	+	apps	List of installed apps
app_usage	+	-	apps	App usage over time
location	+	+	context	Request the location of the phone.
geolocation	+	+	context	Listens to location changes.
activity	+	+	context	Activity as recognized by OS
weather	+	+	context	Current weather and weather forecasting
air_quality	+	+	context	Local air quality from land-based air pollution stations
geofence	+	+	context	Entry/dwell/exit events in circular geofences
audio	+	+	audio	Records audio from the device microphone
noise	+	+	audio	Detects ambient noise from the device microphone.
phone_log	+	-	communication	Log of phone calls in/out
<pre>text_message_log</pre>	+	+	communication	Log of text messages (sms) in/out
text_message	+	+	communication	Text message (sms) events when received
calendar	+	+	communication	All calendar events from all calendars on the phone
survey	+	+	survey	User surveys via the Flutter research_package
movisens	+	-	movisens	ECG-related data from the Movisens EcgMove4 device.
esense_button	+	+	esense	Button press/release events from the eSense device.
esense_sensor	+	+	esense	Sensor events from eSense devices.
health	+	+	health	Wearable device data from Apple Health / Google Fit.