Using iOS for Inconspicuous Data Collection: A Real-World Assessment

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ABSTRACT

Mobile Crowd Sensing (MCS) is a method for collecting multiple sensor data from distributed mobile devices for understanding social and behavioral phenomena. The method requires collecting the sensor data 24/7, ideally inconspicuously to minimize bias. Although several MCS tools for collecting the sensor data from an off-the-shelf smartphone are proposed and evaluated under controlled conditions as a benchmark, the performance in a practical sensing study condition is scarce, especially on iOS. In this paper, we assess the data collection quality of AWARE iOS, installed on off-the-shelf iOS smartphones with 9 participants for a week. Our analysis shows that more than 97% of sensor data, provided by hardware sensors (i.e., accelerometer, location, and pedometer sensor), is successfully collected in real-world conditions, unless a user explicitly quits our data collection application.

CCS CONCEPTS

• **Human-centered computing** → Ubiquitous and mobile computing design and evaluation methods; Ubiquitous and mobile computing systems and tools; Ubiquitous and mobile devices.

KEYWORDS

Mobile Crowd sensing; Effective Data Collection; Real-world Assessment; Mobile Sensing Toolkit; iOS

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1 INTRODUCTION

Mobile Crowd Sensing (MCS) is a method for collecting data from distributed mobile devices, and understanding social and behavioral phenomena through sensor data analysis. Nowadays, the smartphone is widely used all over the world [3] and it is used as a mobile sensing platform in various human subject research [2, 4, 8, 9, 13, 15] including health care, public health, and cultural anthropology. For supporting researchers, several mobile sensing platforms [5, 7, 18] were developed and used successfully. For example, the AWARE Framework [5, 10] is an open-source cross-platform (Android and iOS) mobile sensing platform. The framework allows us to collect data from hardware- (e.g., accelerometer, gyroscope, and ambient-noise), software- (e.g., battery level, screen usage, and network condition), human- (Experience Sampling Method: ESM) sensors with a simple application installation and joining a designated study by reading a QR code or URL.

Data collection quality depends greatly on the sensors selected and user compliance [10]. Additionally, the latest mobile OSs aggressively terminate or suspend an application running in the background for maximizing battery life. Therefore, data collection is significantly affected if the application is not running effectively. Our goal is to assess the data collection in realistic conditions, specifically on iOS as it has a greater number of limitations than on Android. We define a "realist condition" as when a researcher distributes an application to a participant's smartphone for collecting data and the data from selected multiple sensors is automatically transferred from the device during a designated deployment, even if the user is not actively using the research application.

In this paper, we assess the data collection quality on off-the-shelf iPhones in realistic conditions for identifying potential data collection issues. For accessing the quality in the realistic conditions, we deliver *AWARE-iOS* to 9 volunteers and collect 6 sensors' data from their iPhones for a week. As a strategy to maximize data collection quality, we use "ESM+SPN (Silent Push Notification)" as seen in our previous work [10]. Our results demonstrate that more than 97% of sensor data provided from hardware sensors are successfully retrieved using ESM+SPN unless the user explicitly quits the application.

The contributions of our paper are as follow:

- We conducted a week-long in-the-wild deployment with 9 participants;
- We demonstrate that the data collection quality is higher with "ESM+SPN", resulting in more than 97% data retrieval success, when compared to previous controlled conditions;
- We determine the impact on battery life in-the-wild for our data collection setup.

2 RELATED WORK

MCS is a method widely used in various human subject sensing researches. With the availability of smartphones, the opportunities for using MCS are growing rapidly. This section describes existing MCS-based research and the sensor data collected. In addition, we arrange the existing tools and their data collection performance in controlled and realistic conditions.

EmotionSense [13] detects individual emotions and verbal interactions between social group members from the sensors (e.g., microphone, GPS, and accelerometer) on off-the-shelf smartphones. Similarly, StudentLife [15, 16] tackled the measuring of hidden stress and strain in students' lives based on data such as sleep, activity, mood, sociability, and mental well–being gathered by smartphones. MCS-based research usually collects sensor data from hardware sensors (GPS, Accelerometer, and Ambient noise), and software sensors (Screen events, Battery level, and Network), and human-input sensor data from off-the-shelf smartphones for analyzing data. The human input data usually is collected through ESM or Ecological Momentary Assessment (EMA) mobile-based surveys.

For accelerating MCS-based research, various mobile sensing frameworks for Android [1, 5, 11, 13, 14, 17] and iOS [6, 7, 15, 18] have been created. With a decade-long existence, AWARE Framework [5] is an open-source mobile sensing framework and support for collecting these three types of sensors by just installing a client application onto a smartphone or importing the library into a sensing application, and has been utilized in several research efforts successfully (https://awareframework.com/science/).

Though stable sensing in-the-wild is an important factor in a mobile sensing framework, most of these frameworks have been not been assessed for sensor data collection quality in realistic conditions, or are assessed under controlled environments. In comparison to Android, iOS has strict rules when an application is running in the background [10]. Unfortunately, this means a higher risk of data loss. SensingKit [7] and AWARE [5, 10] have conducted battery life assessments per sensor condition, however, the assessments do not take into account multimodal sensing conditions nor external factors driven by in-the-wild deployments (e.g., users turn off sensors at will, more physical activity performed by the user, and so on.). In addition, Xiong et al. [18] conducted a case study using Sensus, however, the evaluation does not assess data collection quality during the study. While providing data loss risks and prevention methods can help to plan and manage an MCS study, these risks are not clear and a guideline for sustainable MCS study in-the-wild condition is nonexistent.

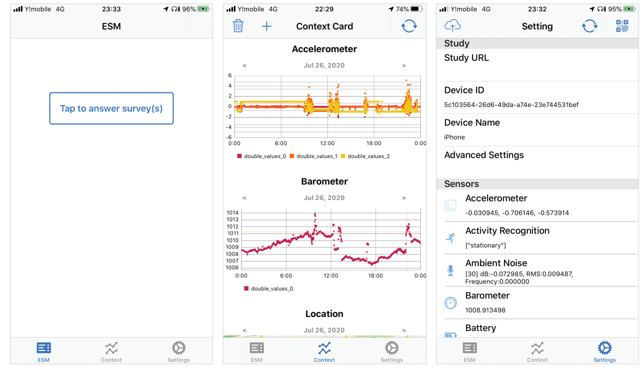


Figure 1: Screenshots of AWARE Client iOS V2

3 SUFFICIENT SENSOR DATA COLLECTION ON SMARTPHONES

Mobile sensing research for monitoring human activities needs to collect sensor data, include hardware, software, and human-data, on smartphone 24/7 as possible. The existing mobile sensing frameworks have measured performance such as battery consumption, data collection, and data upload as a benchmark [5, 7, 10]. For example, our prior research [10] shows that battery life of *AWARE-iOS* varies between 15–34 hours due to the selected number of sensors and sensing frequency. Four case studies were conducted (BASELINE, ESM, SPN, and ESM+SPN) that indicates ESM+SPN allows us to collect nearly 100% data even if the smartphone uses Low-Power Mode and received memory warning more than 10 times per day.

However, the existing basic performance measurement and case studies do not evaluate sensing quality, battery life, and potential risks under in-the-wild conditions. Although the quality of data collection by using off-the-shelf smartphones fluctuates due to the sensing configuration and device condition [10], sensing performance in an in-the-wild condition has not been established. Ensuring the sensing performance in an in-the-wild condition before starting a sensing study helps to design a study and reduce the stress of study management.

In this paper, we assess a data collection performance by using off-the-shelf iOS smartphones in a realistic condition. As a tool of mobile sensing, we use AWARE Framework for iOS (*AWARE-iOS*). AWARE Framework [1] is a cross-platform mobile sensing platform. That is composed of the library, client, and server. *AWARE-iOS* [10] is a mobile sensing library for iOS in AWARE Framework. The library allows us to collect multiple-sensor data. The collected sensor is saved into local storage and uploaded to *AWARE-Server* when the device has a WiFi connection and the battery is being charged. Figure 1 is a screenshot of client application (AWARE Client iOS V2) which is based on *AWARE-iOS*. This application can be download via AppStore or GitHub. Mainly the application has three main screens: ESM, CONTEXT, and SETTING. A user can import data collection settings via the QR code reader on SETTING, and see the data on CONTEXT. In addition, *AWARE-iOS* supports ESM. This client application provides a scheduled survey via the ESM page when the trigger occurs.

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

Table 1: Participants' Devices

#	Device	OS	RAM	Storage Size (Free)
D1	iPhone XR	13.3	3GB	128 (2) GB
D2	iPhone XS	13.3.1	4GB	64 (8) GB
D3	iPhone XS	13.3	4GB	64 (1) GB
D4	iPhone XS	13.3	4GB	256 (141) GB
D5	iPhone XS	13.3	4GB	256 (54) GB
D6	iPhone 11	13.3	4GB	128 (63) GB
D7	iPhone 11	13.3.1	4GB	128 (82) GB
D8	iPhone 11	13.3.1	4GB	256 (22) GB
D9	iPhone 11 Pro	13.3.1	4GB	64 (5) GB

4 EXPERIMENTAL SETUP

As an experiment in realistic conditions, we collect human daily activities and emotions by using a data collection application on a smartphone. The application collects sensor data (hardware-, software, and human-sensor) and events on the smartphone automatically in the background. Based on the collected data, we assess the performance of data collection and battery consumption in the realistic condition.

4.1 Sensors and Participants

In this experiment, we use the same set of sensors and configuration as in Nishiyama et al. [10]. The configuration contains the following hardware-, software-, and human-sensors:

- Pedometer (every 10 minute)
- Locations (every 3 minute, 100 meter accuracy)
- Accelerometer (5 Hz)
- Weather (every 10 minute)
- Battery consumption (every event)
- Screen (every event)
- ESM (three times in a day)

For ESM, the application delivers a questionnaire at 9 AM, 3 PM, and 9 PM. The ESM contains a Photographic Affect Meter (PAM) [12]. A participant needs to select an image that represents his/her own feeling when the ESM is delivered. The collected data is saved into the local-storage in the application and uploaded when the device connects to WiFi and is charging the battery. In addition, our server sends a silent push notification every 30 minutes to the application continuously. This makes sure the application is able to remain active in the background.

Table 1 shows a list of OS and devices for each participant. We recruited 10 volunteers who are students at Keio University and have an iOS smartphone. A participant's smartphone was damaged during this study, resulting in our final 9 participants.

4.2 Experiment Procedure

The participants installed AWARE Client iOS V2 as a sensing application from AppStore onto their personal smartphone before joining the study. Each participant read instructions of the experiment and set up the application independently. The participant can enable the sensor configuration just by reading a QR code from the SETTINGS page. In addition, we requested that each participant conduct the following tasks:

- Answer surveys provided three times (9AM, 3PM, and 9PM) in a day
- Do not use Low-Power Mode as possible
- Set location access to "Always"
- Allow Push Notifications

At the end of the experiment, we conducted a survey on perceived battery consumption, application usage, and frequency of notifications during the study. No reward was used in this experiment.

Table 2: Estimated Amount of Sensor Data

Sensor Name	Hour	Day	Week
SPN	2	48	336
ESM	—	3	21
Location	20	480	3,360
Pedometer	6	144	1,008
Accelerometer	18,000	432,000	3,024,000
Weather	6	144	1,008

4.3 Estimated Amount of Sensor Data

Table 2 shows the estimated amount of sensor data (number of records) during this one week study. In this evaluation, we compare this ideal amount of collected sensor data (Table 2) to what was actually collected in an hour, day, and week.

Battery and Screen sensors do not record sensor data periodically, as they are event-triggered. Thus we can not estimate the amount of event during a time window. These sensor data are not used as a data source for measuring the data collection rate.

5 RESULT

This section organises the results by application usage, data collection rate, and battery consumption analysis.

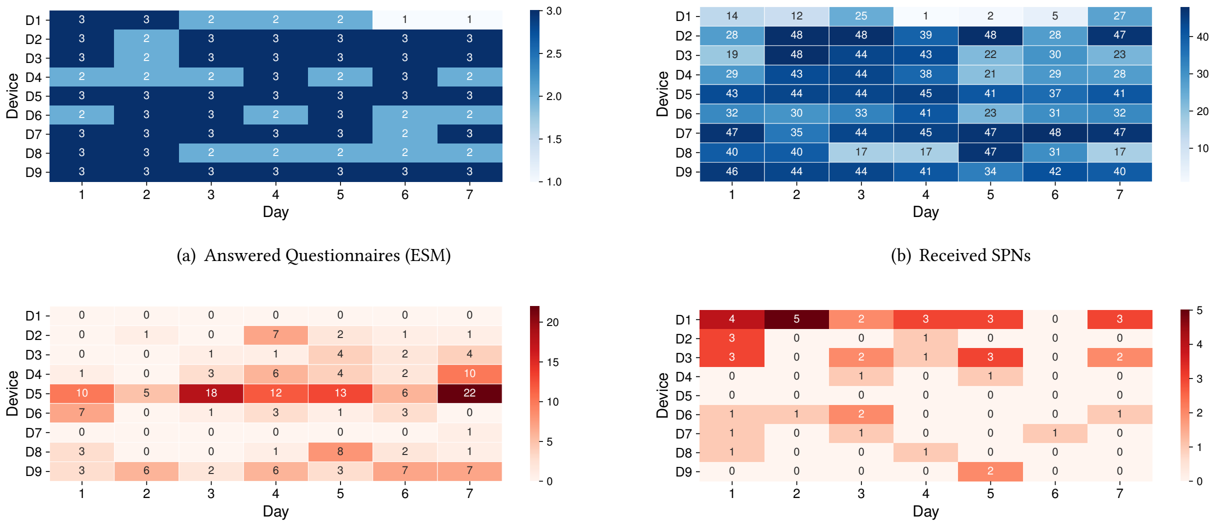
5.1 Application and Device Usage

Figure 2 illustrates application and device usage during the study for each device. Figure 2(a) and Figure 2(b) are events for potentially improving data collection.

The participants answered surveys more than 2 times in a day except $D1$. In addition, the *SPN*s are received more than 10 times in a day except for $D1$. On the other hand, potential events for reducing data collection are shown in Figure 2(c) and Figure 2(d). $D5$ received memory warnings 12.3 times a day on average as shown in Figure 2(c). As shown in Figure 2(d), $D1$ quit or shut down the application 20 times in the week.

5.2 Data Collection Rate

Figure 3 illustrates the data collection rate of each sensor. Each sensor indicates a similar data collection pattern except for $D1$. Pedometer sensor 3(a) collected 99.75% (SD: 0.7) of data except for $D8$. Same as pedometer, 97.89% (SD: 3.08) of location and 97.68% (SD: 3.19) of accelerometer sensor data are collected as shown in



(a) Answered Questionnaires (ESM)

(b) Received SPNs

(c) Memory Warnings

(d) Terminate Events

Figure 2: Number of Device and Application Events Per Day

Figure 3(b) and 3(c). Weather sensor collected 80.49% (SD: 10.65) of data.

Figure 4 shows the number of data sampling events by hour during the study. The data collection rate of $D1$ is less than 40%. This rate is less than other devices, which have about a 95% collection rate. As shown in Figure 2(d), $D1$ quit the application at the early phase, and then the operating system appears to have blocked the application running as a background process.

The battery sensor records battery information when the battery level is changed, therefore the collected data is not periodic. As shown in Figure 4(d), the battery level is frequently changed in the daytime. When a periodic sensor (i.e., location sensor) is not collecting sensor data ($D3$ 00:00–12:00 in Day1) an event-based sensor could not collect its data.

5.3 Battery Consumption

Figure 5 illustrates battery consumption in an hour. This battery consumption (BC) is calculated by Formula 1. b_{start} and b_{end} are battery level at start and end of battery dis-charging event. t_{start} and t_{end} are timestamp (second) of start and end of the dis-charging event. H (=360 seconds) a constant of seconds of hour.

$$BC = \left(\frac{b_{start} - b_{end}}{|t_{start} - t_{end}|} \right) H \tag{1}$$

The median of battery consumption per hour is 8.24% (N:166, Mean:10.1, SD:6.65). Based on the median, the battery life is 12.14 hours in this sensor setting.

However, battery consumption depends greatly on the users. For instance, the minimum battery consumption case of the median is 2.76% per hour ($D2$), but the maximum case is 17.95% per hour ($D4$).

Table 3 shows the result of the questionnaire. Each participant were given three 7-Point Likert-Scale questions. 8 participants (total count of 1, 2, and 3 in Q1) answered that battery is consumed as under normal use. However, 6 participants (total count of 5, 6, and 7 in Q2) feel that the battery consumption does not detract from their activities. In addition from Q3, 5 participants felt that receiving questions three times in a day is too frequent (the total count of 1, 2, and 3 in Q3) for them.

6 DISCUSSION

6.1 Potential Risks of Data Collection

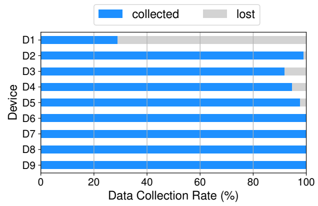
The experimental results show that ESM+SPN allows us to collect more than 97% of data from hardware sensors, unless a user explicitly terminates the application (Figure 3), also visible in Figure 2(d).

For instance, the data collection rate of $D1$ is lower than other devices. In addition, 8 out of 9 participants have terminated the application voluntarily or involuntarily in their daily life (swiping it away) more than one time. That is a potential risk for reducing data collection, therefore the study designer has to closely monitor app termination events, and set forth mitigation methods.

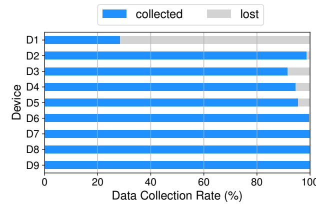
In addition, the free storage space of $D1$, $D2$, and $D9$ is less than 5GB (see Table 1). An application cannot store any data to the local-storage if there is no space available. Especially for a long-term study, a study organizer should check the free-storage size before starting the study to ensure safe data collection.

The weather sensor lost 20% on average in the case of $D2-9$. The weather sensor collects data through RESTful APIs. On iOS, using the internet connection in the background is restricted, resulting in the HTTP request being canceled by the OS, beyond the researcher's control. A researcher who wants to use a sensor that needs to use the internet connection in the background needs to consider the unstable internet connection in the background condition and potentially postpone the request to a later time or retry again.

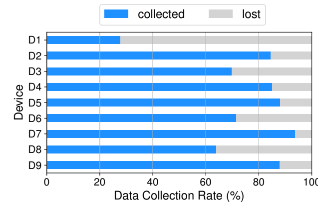
(a) Pedometer Sensor



(b) Location Sensor

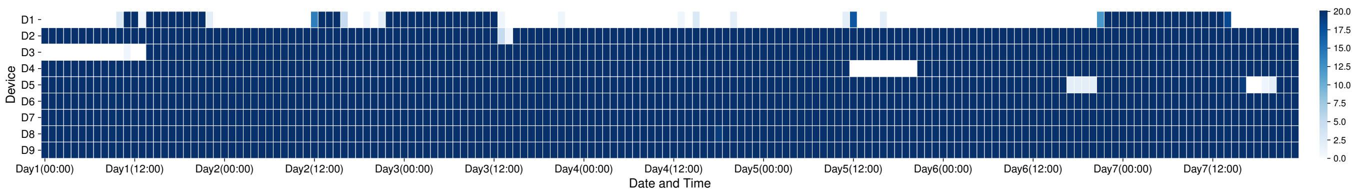


(c) Accelerometer Sensor

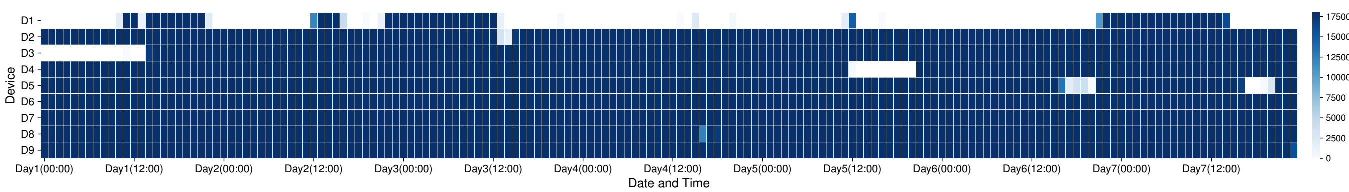


(d) Weather Sensor

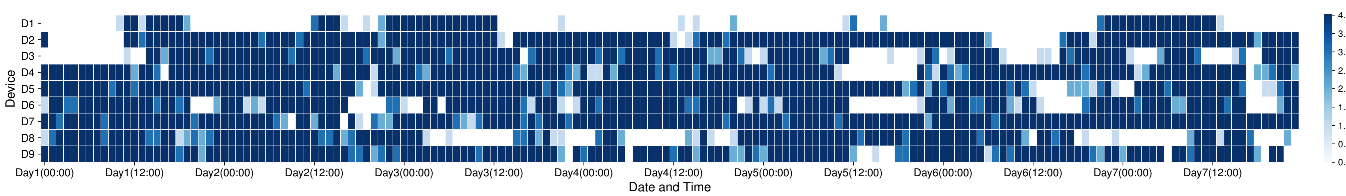
Figure 3: Data Collection Rate



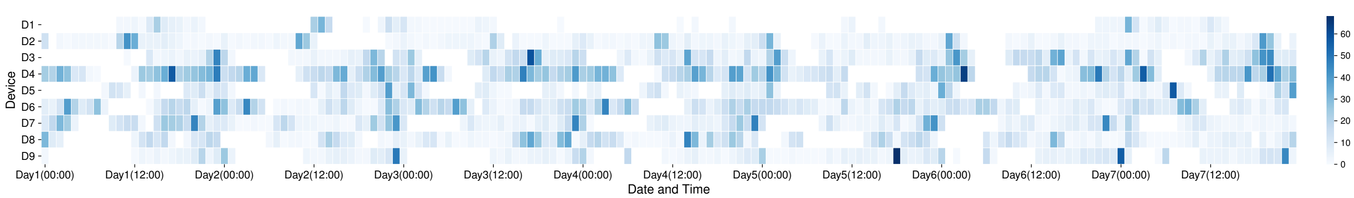
(a) Location Sensor



(b) Accelerometer Sensor



(c) Weather Sensor



(d) Battery Sensor

Figure 4: Amount of Collected Sensor Data Per Hour

6.2 Battery Life and User's Feelings

In our analysis (see Section 5.3), participants felt the research application consumes slightly more battery than usual, but they did not feel it makes a significant impact on their daily smartphone use. However, the battery life changes depend on the sensor settings, as discussed in [10]. Assessing the data collection quality in different sensor combinations are scheduled for future work.

6.3 Limitation

In this paper, we assessed the performance of ESM+SPN mode over a week. However, the sensing mode (i.e., Baseline, ESM, SPN, or ESM+SPN) depends on the study purpose. Each mode has benefits for collecting sensor data. For instance, SPN mode allows us to collect sensor data without ESM. Our sample size is relatively small and the data collection is limited to a week. Effectively, this allowed

Table 3: Result of Questionnaire

#	Question	1	2	3	4	5	6	7	Mode
Q1	How did you perceive the battery life of your smartphone during this study when compared to normal use? 1:Very impacted – 7:No impact at all	1	3	4	0	1	1	0	3
Q2	How much did you feel the battery life has restricted your daily activity? 1:Very restricted – 7:Not restricted at all	1	0	3	0	2	2	2	3
Q3	How did you feel regarding the frequency of ESMs? 1:Too much frequent – 7: Not frequent at all	0	1	4	2	2	0	1	3

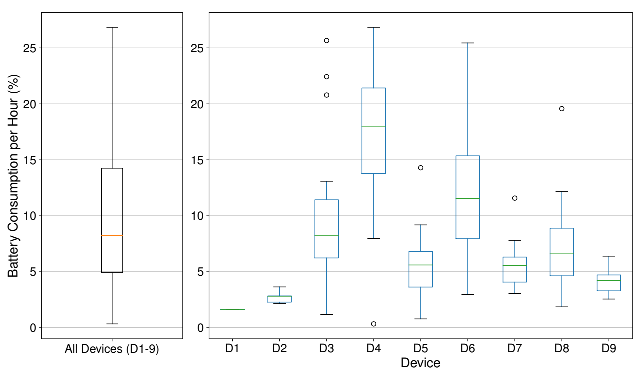


Figure 5: Battery Consumption in an Hour

us to understand the impact that AWARE iOS has on the battery life of iOS devices and whether or not the strategies in place would considerably affect the data collection quality. Our experiment shows that 97% data acquisition is possible with limited battery impact.

7 CONCLUSION

MCS is a method for collecting data from multiple sensors from distributed mobile devices for understanding phenomena, and the method is required to collect sensor data continually from these devices even if the user does not interact with the device. Although several MCS tools for off-the-shelf smartphones have been proposed and evaluated only under controlled conditions, performance data in a realistic condition is scarce. In this paper, we assess the data collection performance of *AWARE-iOS* in realistic conditions through an evaluation with 9 participants for a week. The result shows that 97% of data of periodic collecting hardware sensors are collected in an in-the-wild condition unless the user explicitly quits the application, and the average battery life is not perceived as significant by participants.

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