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AWARE-Light: a smartphone tool for experience sampling and digital phenotyping

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Abstract

Due to their widespread adoption, frequent use, and diverse sensor capabilities, smartphones have become a powerful tool for academic studies focused on sampling human behaviour. While packing many technological advances, the need for researchers to develop their own software packages in order to run smartphone-based studies has resulted in a clear barrier to entry for researchers without the financial means, time, or technical knowledge required to overcome this technical barrier. We present AWARE-Light, a new smartphone application for data collection from study participants, which is accompanied by a website that provides any researcher the possibility to easily configure their own study. To highlight the possibilities of our tool, we present a research scenario on digital phenotyping for mental health. Furthermore, we describe the methodological configuration possibilities offered by our tool, and complement the technical configuration possibilities with recommendations from the existing literature.

Keywords Smartphone sensing · Experience sampling · Ecological momentary assessment · Scientific software · Digital phenotyping · Self-report · AWARE · Smartphone · In-the-wild

1 Introduction

The promise of smartphones as a revolutionary research instrument emerged around the year 2010, presenting a future in which researchers have access to extensive participant samples, advanced but low-cost sensors, and 'in the wild' data collection techniques [1, 2]. Smartphones enable continuous sensor data collection (e.g. GPS, accelerometer), as well as the repeated collection of manual participant input — a method known as the experience sampling method (ESM) or ecological momentary assessment (EMA) [3, 4]. As stated by Miller in his 'Smartphone Psychology Manifesto', 'Smartphone research will require new skills in app development and data analysis and will raise tough new ethical issues, but smartphones could transform psychology even more profoundly than PCs and brain imaging did' [5].

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While smartphones have since seen a steady adoption, use of these devices as a research instrument has remained mostly exclusive to those with the technical knowledge or means required to create and maintain complex software packages [1, 4]. To support researchers in non-technical domains, e.g. Psychology and Medicine, a number of recent initiatives have aimed to reduce this technology gap. For example, Rough and Quigley present Jeeves — 'a visual language to facilitate ESM application creation' [6]. Using a visual 'block-based' environment, researchers can combine triggers, actions, and variables to create logical statements (e.g. send a questionnaire after receiving a text message). In addition, researchers can enable the collection of certain sensor sources and specify the sampling rate of each sensor. Another tool is Sensus [7], which allows researchers to create mobile (crowdsensing) studies through a mobile application as opposed to a website. Similar to Jeeves, various sensor data can be collected, and a range of ESM questionnaire types can be defined. Finally, Samply is a very recently published application which provides researchers a flexible mechanism for sending mobile notifications, which can subsequently be configured to point to online survey pages (e.g. Qualtrics, Google Forms) [8]. All of the aforementioned tools are open-source and can be used at no extra

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cost by researchers. The existence of this variety of tools, all of which required extensive development efforts, highlights the different needs and preferences among researchers to run mobile ESM studies.

The application presented here builds on the established and widely used AWARE framework [9]. AWARE, in continuous development for over 10 years, has been used for in situ deployments by hundreds of researchers around the world and has received technical contributions from a global network of collaborators. While providing a scalable and advanced sensor data collection framework that extends beyond the possibilities or goals of the aforementioned systems, AWARE requires substantial technical knowledge to implement study-specific applications (e.g. Java for Android) as well as server admin expertise to set up a web server and deploy the required software. Very often, we would be approached by researchers in non-technical fields asking us how they can collect smartphone sensor data during an experience sampling study: as highlighted above, plenty of tools for ESM on smartphones exist, but they do not tend to collect sensor data and are limited in their questionnaire sampling configuration. For this reason, we decided to develop a tool that enables non-technical researchers to access the advanced capabilities of AWARE's mobile sensing framework.

In this article, we present the design considerations of our software platform — AWARE-Light. Our platform consists of two elements. First, the AWARE-Light website, available at https://www.aware-light.org, provides researchers an easy-to-use tool to setup and configure their studies. Second, an Android application that participants install on their smartphone. We outline the functionality of our system through the use of a realistic study design — highlighting the type of study that our platform enables. Following, we present the five steps leading up to a fully configured study through AWARE-Light. We conclude with a discussion on the future impact of accessible smartphone sensing platforms.

2 Software design considerations

During our early design phase, we implemented a basic mobile application for the creation of smartphone sensing studies. Our motivation for doing so was to allow researchers to directly test their experiment in a similar fashion as to how it would be presented to participants, directly on the mobile device. A preliminary evaluation highlighted that the creation of a questionnaire and various sensor configurations is cumbersome to perform on a mobile device. For this reason, we settled on developing a web application that enables researchers to specify a study, and an Android application that can load the specification and actually conduct the study.

The web application is based on MeteorJS, a free and open-source isomorphic JavaScript framework based on NodeJS. As such, it is easily extendable and follows modern web practices. We provide a live version of the web application — which does not store any information persistently — but researchers can also deploy it locally if necessary. As software systems are inevitably discontinued due to changing research interests or financing, we hope this allows the work to remain relevant for researchers in the coming years.

Given our focus on experience sampling, we have updated the AWARE framework to support a diverse range of ESM configurations based on prior work as well as our own experiences. For example, we introduced the possibility for researchers to define notification expiry time (i.e. specifying the time after which the notification is dismissed). Dependent on the research question set out to answer, the time between notification arrival and questionnaire completion might be of importance — prior studies have used a wide range of expiry times, for example Langer et al. used a relatively long expiry time of 2 h [10] whereas Van Berkel et al. used a 15-min expiration time [11]. Furthermore, we added new ESM question types (e.g. scale, numeric input) previously unsupported on the AWARE platform. We also introduced the possibility to configure an optional questionnaire expiration threshold (i.e. the maximum time allotted to answer a questionnaire), as sometimes seen in ESM studies (see e.g. [12]). Finally, the questionnaire scheduling was enriched, and when using a signal contingent contingency (i.e. random timing of alerts), researchers can configure an 'inter-notification time': the minimum time in between ESM questionnaire notifications. Such an inter-notification time can prevent the stacking of survey notifications when combined with a notification expiry time [4]. These new study configuration options are naturally included in the presented application and allow for an extensive flexibility in methodological design. This highlights a major benefit of building our work on top of an existing and extendable framework.

Figure 1 provides an architectural overview of the primary actors (researcher and participants) and actions in an AWARE-Light study.

2.1 Security and privacy

In the past, we have worked with non-technical researchers who were concerned about the handling of smartphone sensor and ESM data. In some cases where sensitive data was handled, researchers were adamant that data is not directed through third-party services, often to comply with institutional, state, and national regulations. For this reason, our tool only provides a smartphone client application, and researchers need to provide their own database server. No other server is involved in data handling, and all communication takes place over encrypted channels using SSL over

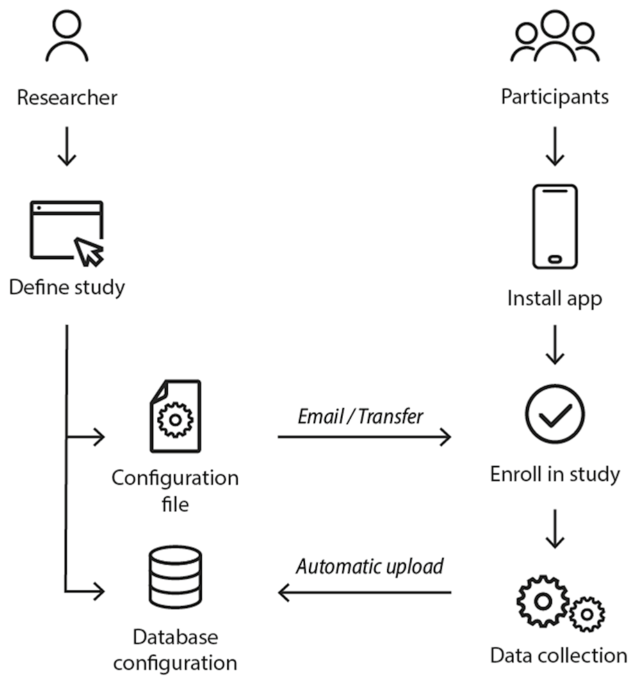

Fig. 1 Architectural overview of the primary actors and actions in AWARE-Light

SHA-256 RSA encryption. Naturally, a secure data storage is critical to ensure participant's privacy.

Furthermore, it is important that participants are informed of the data collected. AWARE-Light therefore follows the guidelines provided by the Android OS, and provides a description and permission notification for each activated sensor when enrolling in a potential study. We consider participant consent to be a continuous event, rather than only of importance during study registration. Therefore, we make use of the required persistent notification in Android to remind the participant that they are part of an active study. As a persistent notification, it does not disappear and cannot be dismissed. This serves to continuously remind participants that they are enrolled in a study and that sensor data is being collected. Interacting with this notification brings the user to our mobile app.

2.2 Maintainability

The constant and high-paced changes to mobile operating systems require continuous upkeep of mobile instrumentation frameworks. As such, the development of such frameworks commonly comes to a halt after a period of time — thereby greatly diminishing their value to the greater research community. With the increasing reliance and impact on scientific software, researchers have raised questions and concerns with regard to the sustainability and maintainability of these tools [13]. To alleviate some of these concerns, we chose to extend a currently existing platform. This way, AWARE-Light will automatically benefit from the updates as developed for the main AWARE framework (and possibly vice versa). In addition, given the open-source and modular structure of AWARE-Light, it can be ported to work for other frameworks.

3 Research scenario

We outline the functionality of our system with the use of a realistic scenario for an intended end-user of our system.

One emerging research area for smartphone sensing is mental health. Traditional mental health care can be affected by certain subjectivity in assessments and patient recall accounts of behaviour. Furthermore, once a clinical therapy session is complete, there is no simple way to monitor a patient's contexts and behavioural patterns in their day-to-day life. Such continuous information would be of tremendous value to both patient and clinical care providers.

An increasingly prevalent idea to overcome this challenge is to collect from an individual's smartphone usage patterns and sensor data that can be quantitatively and objectively analysed to detect/predict their psychological states and mental health, a process often referred to as 'digital phenotyping' [14]. Smartphones are a prime device to realise this idea of personal sensing given their omnipresence, unobtrusiveness, and frequent use. It is well-established that there are certain links between behaviour and mental health conditions. For example, reduced physical activity, emotional responsiveness, and enjoyable social interactions are well documented symptoms of depression [15, 16]. With digital phenotyping, it is posited that such behaviours can be inferred from smartphone sensing data, which in turn could be indicators of depression. For example, a reduction in geolocation diversity could be measured with a smartphone's GPS and its accelerometer could be used to detect an excessive or abnormal reduction in physical activity and increase in sedentary behaviour. Similarly, decreases in social interaction could be inferred from quantities of incoming and outgoing communication as well as application usage. These are but some simple examples and there are a variety of possible connections to explore between smartphone usage/sensor data and user behaviours and contexts.

Using AWARE-Light to collect participant smartphone data, our group is currently working with youth mental health institute Orygen on a digital phenotyping study involving young people (16–25 years of age) experiencing clinical depression. Data collection for this study involves collecting the following items over an 8-week period for each participant:

1. A set of pre-trial and post-trial quantitative psychometric measures, including inter alia the Quick Inventory of Depressive Symptomatology (QIDS-SR) questionnaire [17].
2. Midday and evening daily ESMs displayed by AWARE-Light to obtain snapshot information about participants' positive and negative affect, sleep quality, loneliness, social activity, anxiety and worry levels, and substance use.
3. Data collected from smartphone sensors using AWARE-Light: application usage, keyboard input (masked or unmasked options), communication (calls and text messages), geolocation, ambient light, network traffic and usage, screen events, and screen interaction.

Our specific aim in conducting this study and collecting this data is twofold. Firstly, this study will involve evaluating the feasibility, safety, and acceptability of obtaining smartphone sensing data from people in this mental health cohort. Secondly, we will explore associations between the sensing data collected via smartphones, ESM, and pre-/post-psychometric results, with the aim of constructing preliminary machine learning models that predict ESM and psychometric outcomes based on input features derived from smartphone sensing data. For example, by extracting various features from raw geolocation coordinates (e.g. location variance, total distance travelled, number of location clusters, and location entropy), we can investigate how such features might be used to predict scores for the QIDS-SR depression measure. Similarly, features extracted from communication and social engagement sensors, such as call/text logs and application usage, can be investigated in relation to the UCLA loneliness measure. Such models can establish relationships between smartphone-inferred behaviour and mental health, ultimately removing the need for traditional manual psychometric assessment. Furthermore, behavioural and contextual information about an individual, obtained via their smartphone, could be used to inform a 'detect and deliver' system that recommends personalised digital mental health interventions to users in situ, during relevant moments of their day [18].

4 Study creation

To define and configure a study through AWARE-Light, a researcher completes five steps. We detail these five steps below, and include recommendations from the literature where they are relevant to study parameters.

4.1 Study and server details

First, a researcher provides general details about the study, including the name of the responsible researcher and the message that participants are shown before they provide informed consent to enroll in the study. At this step, the researcher also needs to provide details of the database server where there data will be stored, as well as the details of a sufficiently privileged database user. The system checks to see whether those details are correct by attempting to connect to that server. Upon connection, the system also initialises the database (e.g. tables, data types) and creates a database user with the minimally appropriate credentials (INSERT) so that participant devices can subsequently insert data to the database.

Whereas in the past AWARE provided researchers with a limited storage solution for their research data, this often raised concerns regarding data responsibility, ethics, and regulation, as well as additional hosting costs for AWARE's dashboard. For this reason, we adopted an alternative approach with AWARE-Light, whereby we do not to provide any server or intermediary component to researchers.

4.2 Questions

Next, AWARE-Light allows researchers to define the questions presented to their study participants. Questions consist of at least two elements, the question title, typically the actual question as shown to the participant, and the question type (including free text input, single choice (radio), multiple choice (checkbox), Likert, quick answer buttons, scale, and numeric). For e.g. the multiple choice question type, researchers are able to define the presented answer options. Optionally, the researcher can provide additional instructions for the participant and configure the notification timeout (i.e. time after which the notification is dismissed) and expiration time (allocated maximum time to answer the question). An example of the question configuration is shown in Fig. 2.

4.2.1 Recommendations

In line with the conceptual considerations of the experience sampling method, questions typically focus on the *current* experience of the participant rather than asking them to *reflect* on past events [3]. This follows from the motivation to minimise retrospective bias introduced by the participants.

A recent study by Eisele et al. on questionnaire length and sampling frequency compared participant compliance and response quality of 30- and 60-item questionnaires presented three, six, or nine times per day [19]. Their results indicate that participant burden increased and compliance decreased with the longer questionnaire. In ubiquitous computing, questionnaire length is typically significantly shorter

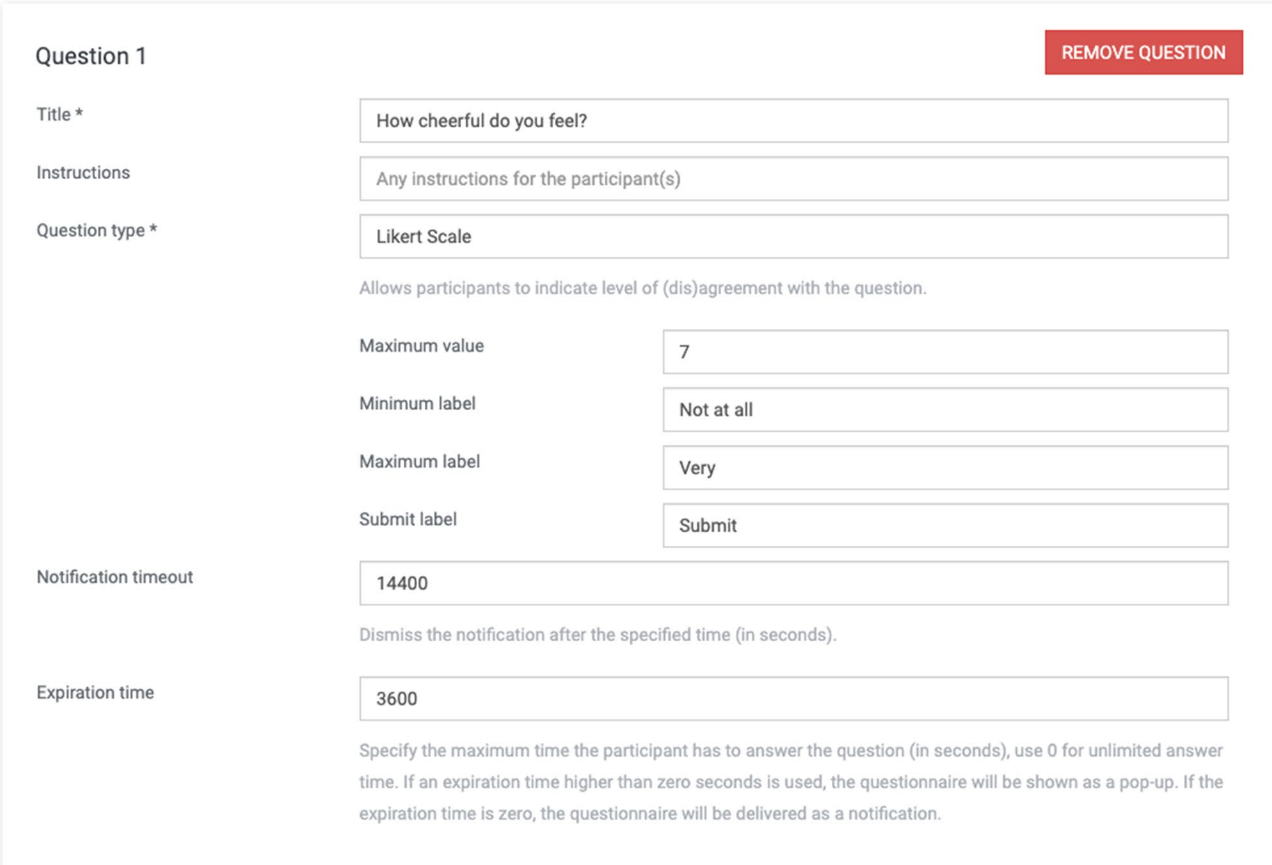

Fig. 2 Example of a Likert question configuration in AWARE-Light, highlighting Likert configuration, notification timeout, and question expiration time

and suggested to remain brief [20]. Other recommendations on questionnaire length focus on the time required by participants to complete the questionnaire. Consolvo and Walker suggest that researchers ensure that participants can complete the questionnaire within 2 min [20], Hektner et al. make a similar suggestion of 2–3 min [21].

While no uniform recommendations exist on notification expiry time, it is recommended to expire notifications before a new notification arrives in order to prevent ‘notification stacking’ [4].

4.3 Schedule configuration

Once the ESM questions are defined, researchers can then configure the schedule with which the questions are presented. AWARE-Light allows the researcher to define multiple schedules, and to select which questions are assigned to each schedule. Currently, AWARE-Light allows for three types of questionnaire schedules to be used:

- Set schedules, triggers the schedule at an exactly defined point in time, e.g. at 08:00.
- Random triggers, triggers the schedule at a random timepoint between a given start and end time.
- Repeat intervals, triggers the schedule repeatedly in accordance with a specified interval.

An example of the schedule configuration is shown in Fig. 3.

4.3.1 Recommendations

Prior work has assessed the effect of different scheduling techniques on participant responses. The aforementioned work by Eisele et al. found no effect of notification frequency [19]. Van Berkel et al. found that sending a notification upon smartphone unlock resulted in higher response rates than time-based schedules [11]. No difference was found between a randomised and an interval-based notification schedule.

While the use of interval-based notifications (e.g. every hour between 08:00 and 18:00) enables a more straightforward time-related statistical analysis, it also comes with potential downsides. Scheduled notifications will typically repeatedly capture the same context (e.g. going to work, end

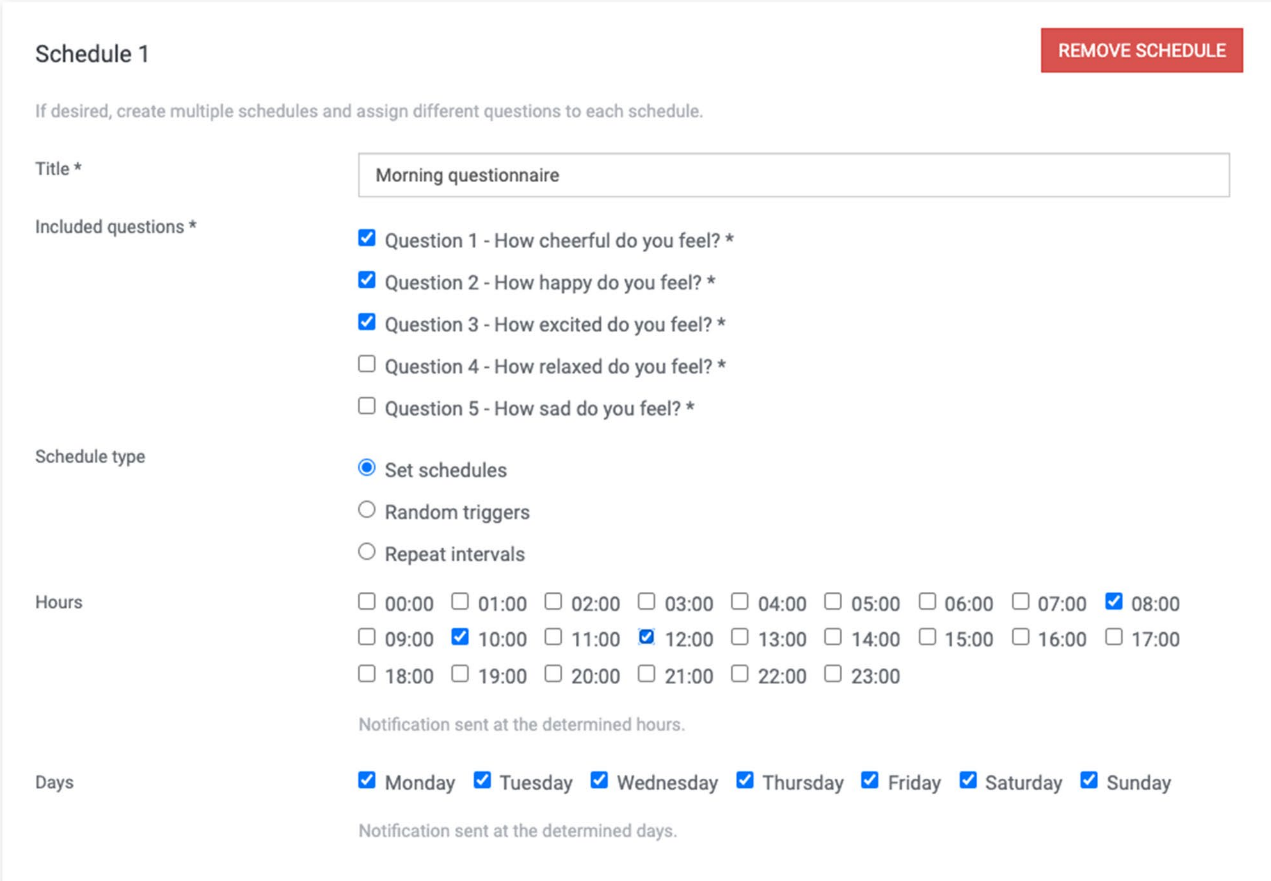

Fig. 3 Example of schedule configuration in AWARE-Light, highlighting a selection of questionnaire items, schedule type, and subsequent configuration of the selected schedule type

of class), reducing the contextual richness of the collected data. Furthermore, participants may begin to anticipate the scheduled notifications and alter their behaviour in anticipation of an upcoming notification [4, 22]. For most research scenarios, a randomised notification scheme is therefore preferred over an interval scheme.

4.4 Sensor data

In addition to the collection of participant-labelled data, AWARE-Light allows researchers to collect a wide range of smartphone sensor data. Sensor data is collected continuously without active participant input. Available sensors include both software sensors (e.g. application use, keyboard) and hardware sensors (e.g. accelerometer, battery level, GPS) — detailed in Tables 1 and 2 respectively. General configuration settings include the ability to synchronise data only over WiFi (reducing mobile data usage) and the frequency with which old data are removed from the device. Additional parameters are available for a number of the sensors. For example, for the GPS sensor, the frequency with which the participant's location is determined as well as the desired accuracy can be configured — allowing the researcher to make a trade off between data richness and battery consumption.

4.4.1 Recommendations

There is often a desire to 'collect as much data as possible' during a study. However, careful consideration is needed to assess the potential impact of data collection on smartphones' battery life. Different sensors have a different impact on battery life, and research has shown that typically 'software' sensors consume less power than hardware sensors [29]. Another consideration is the frequency of sensor collection, since some sensors can generate large amounts of data at high frequency (such as accelerometer), which can potentially fill a mobile device's storage (as well as adding up on the central database storage side) — a problem relevant both on today's smartphones [9] as well as PDAs in the past [30]. AWARE-Light also provides an option whereby those initialising the configuration file can select whether to

Table 1 Overview of software sensors and their possible usage in a study

Sensor	Description	Example uses in behaviour studies
Application	Application usage and incoming notifications on the device.	The applications an individual is using and the extent to which they are using these applications can naturally provide insights into their behaviour and mental health.
Communication	Communication events and related metadata, such as calls, call duration, and SMS messages, performed by or received by the user.	Quantifying incoming and outgoing communications, missed calls, and call durations, can all serve as potential indicators of sociability and connectedness. Regarding mental health, one example study found that certain reductions in the number and duration of outgoing calls, as well as number of text messages, were associated with relapses of schizophrenia [23].
Installations	Application installations, removal, and updates.	–
Keyboard	Log keyboard input.	The keyboard sensor can record user's keystrokes and in which application the keyboard is being used (does not record passwords). It is well established that natural language processing methods can be used to extract behavioural insights [24]. Despite research showing the potential utility of analysing bodies of text in determining/predicting mental illness [25, 26], there are obvious privacy issues with recording character inputs. Irrespective of semantic content though, there is work showing that typing dynamics alone can provide indications of psychological and cognitive health [27, 28].
Screen	Monitors the screen statuses, such as turning on and off, as well as lock and unlock.	Screen data can be used to know when, how often and in what intervals someone is using their phone. This translates to information of psychological interest, such as diurnal patterns and excessive phone use.
Touch	Logs clicks, long-clicks, and scroll up/down events.	As with points made for the keyboard sensor, screen touch dynamics could provide indications of psychological states. For example, it is conceivable that an agitated state or a manic episode may be preceded by an increased rate of screen interaction.
Telephony	Information on the mobile phone capabilities of the device, connected cell towers, and neighbouring towers.	–
Timezone	Logs user's current timezone.	–

Table 2 Overview of hardware sensors and their possible usage in a study

Sensor	Description	Example uses in behaviour studies
Accelerometer	Acceleration applied to the device, including the force of gravity.	By measuring acceleration, this sensor can detect physical movements and conversely sedentary states. Distinct patterns within the data can be analysed to recognise activities such as running, walking, and standing. The accelerometer has been used in an array of digital phenotyping studies, although one limitation is that the phone may not capture a participant's true level of activity since not everyone carries their phone with them constantly [34].
Barometer	Ambient air pressure.	–
Battery	Battery information and power related events (phone shutting down, rebooting).	Given that demotivational conditions such as depression could result in withdrawal and a lack of phone maintenance, reductions in battery charging could indicate such conditions.
Bluetooth	Smartphone's Bluetooth sensor and surrounding Bluetooth-enabled and visible devices. Includes respective RSSI dB values.	Research has demonstrated the potential use of Bluetooth as a measure of social interaction (a potential indicator of mental health), by detecting how many other Bluetooth devices have been in a smartphone's proximity [35].
Gravity	Force of gravity applied to the the device, provides a three dimensional vector indicating the direction and magnitude of gravity.	–
Gyroscope	Rate or rotation in rad/s around a device's x-, y-, and z-axis.	–
Light	Level of ambient light.	Insofar as exposure to light is associated with health, this sensor is relevant. This sensor can also form part of sleep detection.
Linear accelerometer	Acceleration applied to the device, excluding the force of gravity.	–
Locations	Best location estimate of the users' current location, based on an algorithm that results in minimum battery impact.	One of the main sensors in digital phenotyping research to date, with early research suggesting associations between geolocation information features and depression [36]. The types of locations one visits could also offer mental health insights, though there has been little research on this idea [37].
Magnetometer	Geomagnetic field strength around the device.	–
Network	Information on the network sensors availability of the device. These include use of airplane mode, Wi-Fi, Bluetooth, GPS, mobile, and WIMAX status as well as internet availability.	–
Processor	Processor load.	–
Proximity	Distance to an object in front of the device.	–
Rotation	Orientation of the device as a combination of an angle and an axis.	–
Temperature	Ambient air temperature in Celsius (° C). Not many devices have this sensor available.	–
Wi-Fi	The device's Wi-Fi sensor, current AP, and surrounding Wi-Fi visible devices with respective RSSI dB values.	–

allow study participants to turn off (or back on again) sensors that are initially activated as part of the study. Privacy sensitive data collection has been repeatedly highlighted as a critical element in engaging with participants [31, 32]. This is particularly important for studies that capture privacy-sensitive sensors such as character input, and being able to state this feature can be an important factor in proposing study ethics applications.

For a more extensive overview of methodological recommendations on conducting experience sampling studies, please see Van Berkel and Kostakos [33].

4.5 Deployment

Finally, an overview of the created study configuration is shown for verification. Once verified, the researcher can download the configuration of the study as a .JSON file. This file should subsequently be given to prospective participants. The configuration file can be uploaded on a private server, but also to a public hosting service such as Google Drive.

Next, our client application is installed on participants' Android device. Upon launch, it prompts to enter the URL at which the aforementioned configuration file is located (Fig. 4-A). It then prompts participants to provide consent to join the study, and subsequently the client application enables the questionnaire protocol and starts sensor data collection in line with the configuration. The client application confirms that the participant on-boarded successfully, and offers the option to quit the study at any point (Fig. 4-B). Researchers can introduce changes to the study configuration even after a study has commenced. To do so, a research can simply update the configuration file and post it to the same URL as the original configuration file. The client application periodically checks for changes to the configuration file, and takes action if changes are detected. This allows for easy segmentation of the population in the case of between-groups experiments: a research can maintain multiple configuration files, one per experimental condition.

5 Discussion

The related work shows both a high demand and high expectations for the use of mobile devices by researchers studying human behaviour [1, 5]. Indeed, smartphones can be used as scientific instruments no different from microscopes or ultrasound — enabling us to collect data on the real-world environment of study participants. As with these established scientific instruments, end-users of the instrument are not necessarily those able or responsible for the design, implementation, and maintenance of these methodological tools.

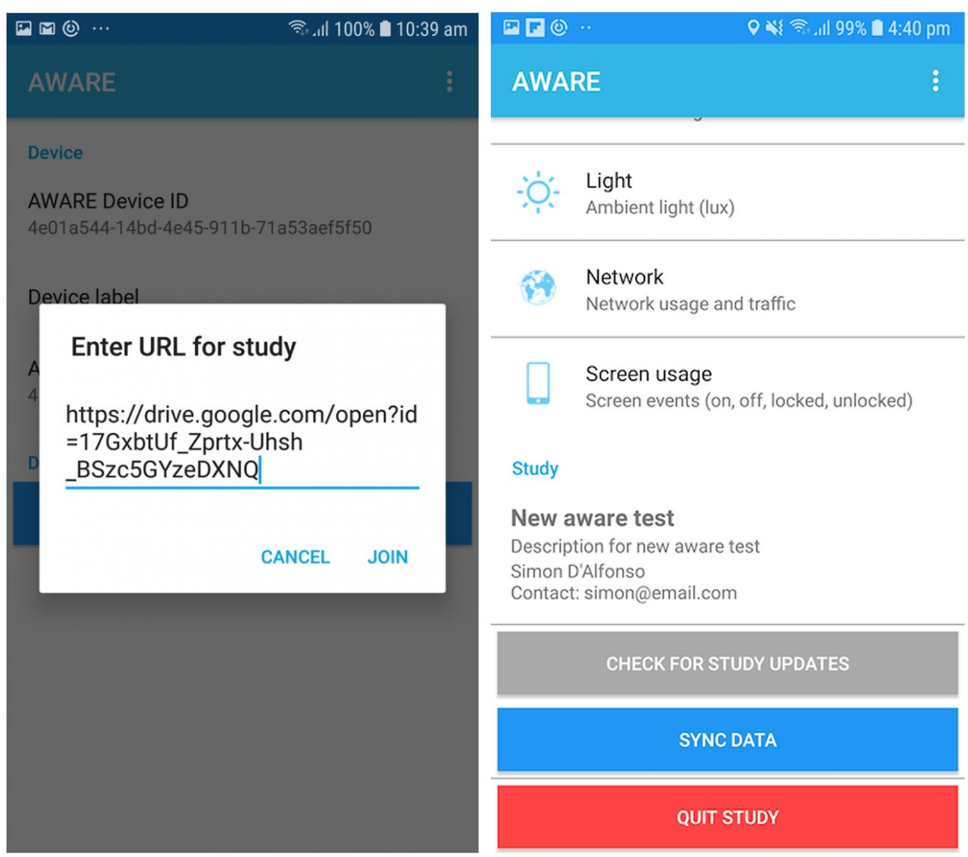

Fig. 4 Screenshots of the AWARE-Light smartphone application, showcasing the sign-up procedure for study participants

Miller makes a distinction between four types of smartphone sensing studies [5]:

- Data collected through telecom providers.
- Pre-programmed mobile devices (e.g. PDA's) distributed by the researcher to participants.
- Distribution of a particular smartphone model and custom-made application to participants.
- Distribution of a mobile software application through an application store.

The application presented in this paper targets the latter two, recognising the fact that smartphone ownership is both wide spread and increasing every year [38].

In his 'Smartphone Manifesto', Miller states that 'The question is not whether smartphones will revolutionize psychology but how, when, and where the revolution will happen' [5]. While Miller concluded with these words in 2012, numerous reports from the literature stress that this revolution has not arrived to all [4, 6]. This provides barriers to time-pressed or less technical researchers to conduct in situ studies. As such, the development of accessible and alternative smartphone sensing tools paves the way for more researchers to collect data from their participants as they are living their real life. Arguably, such data can provide more realistic and ecologically valid representations of participants' daily reality.

5.1 Future work

The frequent and often substantial changes to the Android ecosystem make the maintenance and upkeep of mobile instrumentation software a challenging task. Support for iOS devices is a long-term objective of our project. We publicly release the source code of AWARE-Light under the Apache License 2.0, and make it available on the project's GitHub page (https://github.com/awareframework/AWARE-Light-Configurator). In doing so, we hope to engage in the project's development with members of both the UbiComp/HCI community and those typically outside of the Computer Science domain. We welcome both suggestions and technological contributions to support the development of new functionalities.

6 Conclusion

We set out to develop and present a tool for the creation of smartphone sensing studies that is available and accessible to all researchers, regardless of their discipline, technological background, or financial restrictions. The software that we present here, consisting of a website for the creation and configuration of studies and a smartphone application for in situ participant data collection, is open source, and we warmly welcome any feedback, suggestions, or contributions from the community. During the development of this tool, we ensured flexibility in the code base, allowing for the possibility for others to port the toolkit to a different (mobile) sensing framework if desired — further increasing the longevity of the presented work. We hope that AWARE-Light removes the barriers for researchers who have previously considered but ultimately come short in conducting a smartphone sensing study.

Declarations

Conflict of interest The authors declare no competing interests.

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