An Open-Source Mobile and Wearable Sensing Platform for Bridging Passive Sensing and Active Sensing

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Abstract

Mobile sensing frameworks have substantially reduced the engineering burden of in-the-wild behavioral data collection, yet important gaps remain in how passive sensing is integrated with active self-reporting through Ecological Momentary Assessment (EMA), such as context-sensitivity of EMAs, decline of participant compliance in long-term studies, and the engineering burden required to mitigate these problems. We present EnPULSE, an open-source mobile and wearable sensing platform that addresses these gaps by providing high-level context sensors, smartwatch-based microEMA, a configurable trigger system, and a web-based dashboard through which researchers can configure and monitor studies without coding. We demonstrate the overall architecture and key features of our platform.

CCS Concepts

• **Human-centered computing** → **Ubiquitous and mobile computing systems and tools**; • **Software and its engineering** → *Development frameworks and environments*; • **Applied computing** → Health informatics.

Keywords

mobile sensing; wearable sensing; context-sensitive EMA; microEMA

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1 Introduction

The performance, usage, and sensing capabilities of smartphones and smartwatches have advanced substantially in recent years, enabling the in-the-wild collection of rich behavioral data through these devices and facilitating the study of human daily behaviors [9]. However, constructing such data collection pipelines from scratch has imposed a considerable burden on researchers, who have often had to re-implement the collection infrastructure for each new study [5]. To address this issue, a number of mobile sensing frameworks have been proposed to support data collection across diverse configurations and to alleviate the engineering burden placed on researchers [17]. These platforms typically support two complementary modalities: passive sensing, which continuously captures objective contextual signals such as mobile device usage, location, and physiological measurements without user engagement, and active sensing, which captures subjective experience through user input, most commonly via Ecological Momentary Assessment (EMA). Both modalities are indispensable for mobile health (mHealth) research, as passive data alone cannot reliably reveal a participant's subjective experience [16], whereas active reports in isolation lack the contextual grounding necessary for proper interpretation.

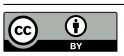
Although existing mobile sensing frameworks have matured considerably with respect to passive sensing, important gaps remain in how passive and active sensing are integrated in long-term, in-the-wild deployments. We identify three such gaps.

The first gap is the integration of active and passive sensing in real time. Triggering EMAs based on the user's current context enables researchers to capture user experiences in close temporal proximity to events of interest, thereby reducing recall bias and increasing the likelihood of compliance [4, 25]. Although numerous studies have developed bespoke pipelines to support context-sensitive EMA (CS-EMA) [1–3, 27], the CS-EMA functionality offered by existing platforms remains largely confined to low-level sensor values or a narrow set of contexts, thereby weakening the intention of connecting actual human behavior and EMA triggering.

The second gap is the integration of the two modalities over time. Unlike passive sensing, active sensing requires participants' effort, and compliance with it tends to decline over the course of long-term deployments. This makes active sensing data sparse and unrepresentative [26], and only a few passive data points can be paired with active data. A widely adopted mitigation strategy to prevent a decrease in compliance is microEMA delivered via a smartwatch, which substantially lowers the interaction cost per prompt [11, 15, 22]. However, most general-purpose sensing frameworks continue to rely on multi-question, smartphone-based EMAs, and the few platforms that do support wearable microEMAs lack broader passive sensing capabilities or context sensitivity [13, 19].

The last gap is the engineering burden imposed on researchers. To mitigate the two gaps described above, researchers have to implement custom components such as CS-EMA and microEMA on top of existing platforms. This partially negates the principal

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Table 1: Comparison of EnPULSE with representative mobile sensor data collection platforms.

Feature	**AWARE** [6]	**RADAR-base** [23]	**Experiencer** [13]	**EnPULSE**
Smartphone passive sensing	✓	✓	✗	✓
Smartwatch passive sensing	Requires plugin [20]	✓	✓	✓
Smartphone-based EMA	✓	✓	✗	✓
Smartwatch-based microEMA	✗	✗	✓	✓
Context for CS-EMA	Low-level only	Low-level only	Physical activity + Low-level	3 high-level context sensors
High-level context derivation	Server-side	Server-side	Not specified	On-device
Study configuration	Web dashboard	Web dashboard	JSON	Web dashboard

benefits that sensing frameworks are intended to provide, namely, reduced engineering burden and improved reproducibility.

To address these requirements, we propose EnPULSE, an open-source mobile and wearable sensing platform that tackles the three gaps above through the following key features:

- **High-level context sensors** that extract semantically meaningful context from raw sensor data with low latency using on-device processing, enabling timely CS-EMA triggering.
- **Smartwatch-based microEMA** that is designed to reduce per-response burden and maintain compliance over time.
- **A configurable trigger system** that allows researchers to customize bindings between high-level context conditions and actions such as EMA or microEMA delivery.
- **A web-based visual dashboard** for configuring sensor modalities, EMA questions, and trigger conditions, removing the need for researchers to write additional code.

Table 1 summarizes how EnPULSE compares to existing mobile sensing platforms.

2 EnPULSE: System Architecture and Implementation

In this section, we describe the overall architecture of EnPULSE and detail three of its key features: high-level context sensors based on on-device processing, smartwatch-based microEMA, and a configurable trigger system.

2.1 Overview

EnPULSE consists of four main components: the EnPULSE Android Library, the EnPULSE Android Application built on top of the library, a backend server, and a web-based visual dashboard. Figure 1 illustrates the overall structure of the platform.

The **EnPULSE Android Library** (Fig. 1(a)) is the bottom-most layer of the platform. The library retrieves physiological data from the Samsung Health Sensor SDK and the Samsung Health Data SDK and device- or interaction-related data from the Android API. The EnPULSE Android Library includes 29 sensor modules capable of collecting data from smartwatches and smartphones[1]. It also provides built-in support for smartphone EMAs and smartwatch-based microEMAs (see Section 2.3 for details), in the form of a sensor module. To manage the data collection state for multiple sensors at once and to continuously collect data using background services, the controller module implemented inside the library can be used. Firebase authentication module, trigger module (see Section 2.4 for details), and definitions for sensor data and configuration storage are also included.

The **EnPULSE Android Application** (Fig. 1(b)) is a user-level application built on top of the EnPULSE Android Library. Two versions of the application are provided: one for smartphones and one for smartwatches. Both applications continuously collect sensor data in the background and store the data in local storage. The smartwatch application primarily handles wearable sensing and microEMA delivery, while the smartphone application downloads study configurations from the server, displays collected data from both phone and watch, collects mobile sensor data, and delivers EMA. The smartphone application also manages operations on collected sensor data, including exporting to a comma-separated value (CSV) file, automatically or manually uploading to the backend server, and deleting from local storage. The two apps synchronize data over Bluetooth Low Energy (BLE).

The **backend server** (Fig. 1(c)) uses a self-hosted Supabase instance. The PostgreSQL database included in Supabase is used to store participant information, study configuration, and collected sensor data. To protect participants' data, it uses PostgreSQL's row-level security policies, ensuring that each researcher and participant can only access data they are authorized to view, modify, or delete. Firebase connected to Supabase is used to provide single-sign-on-based participant authentication.

The **visual dashboard** (Fig. 1(d)) is a web-based interface that allows researchers to generate and modify study configurations, including sensor modalities to be collected, EMA questions and schedules, and trigger conditions and actions. Configurations can be exported and imported as JavaScript Object Notation (JSON) files to support reproducibility across studies. For ongoing data collection studies, the dashboard also provides a data visualization view, which is designed following the rationales suggested by Jung et al. [12], enabling researchers to monitor collected data. It provides an overview panel that helps researchers check how much data is collected in a 2-hour time slot for each participant and sensor. Also, to help researchers infer why data is missing, comparison of data over three different axes is supported: between sensors, between participants, and between days.

[1]For the list of supported sensors, refer to https://github.com/Kaist-ICLab/EnPULSE/tree/main/tracker-library

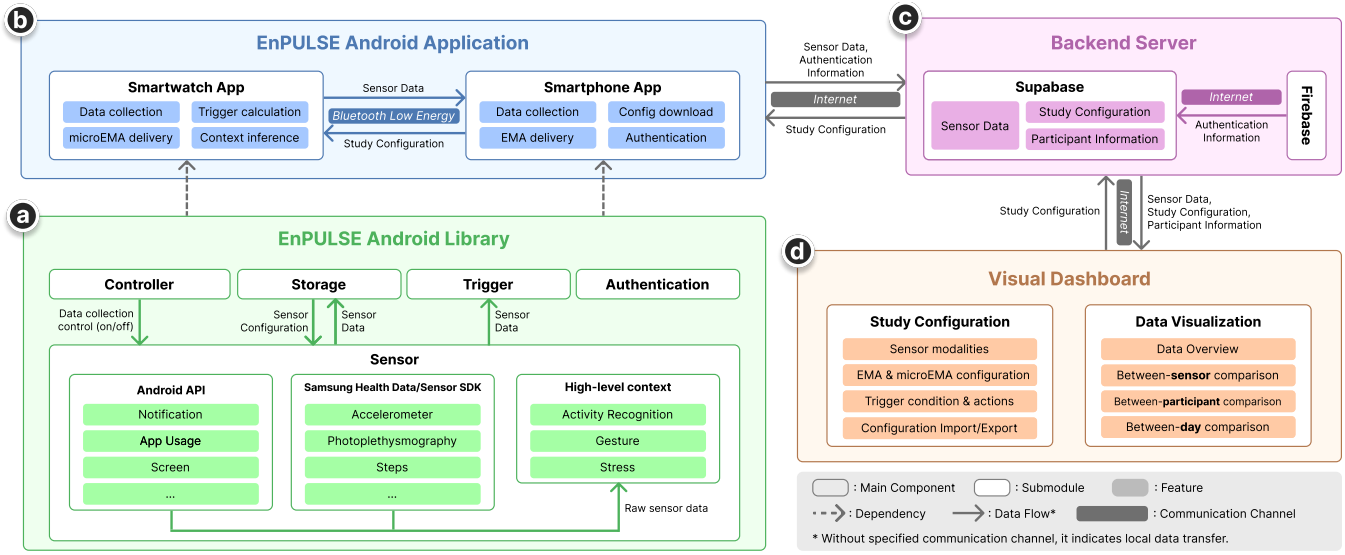


Figure 1: Overview of the EnPULSE architecture. (a) The EnPULSE Android Library provides sensor modules, a controller, storage definition, trigger, and authentication. Sensors can be organized into Android API-based, Samsung Health SDK-based, and high-level context sensors. (b) The EnPULSE Android Application is built on top of the library and consists of a smartwatch app and a smartphone app, which communicate over Bluetooth Low Energy. (c) The backend server is built on a self-hosted Supabase instance and stores sensor data, study configurations, and participant information, with authentication handled by Firebase. (d) The visual dashboard allows researchers to configure studies and monitor incoming data in real time.

2.2 High-Level Context Sensors

As part of the sensor modules in the EnPULSE Library, we implemented high-level context sensors that extract semantically meaningful information from raw sensor data with low latency using on-device processing techniques. By performing inference on the device rather than on the server, these sensors can produce contextual information in near real time. Currently, three high-level context sensors widely used in the mHealth community are implemented: activity recognition, gesture, and stress.

The activity recognition sensor is implemented using the Google Activity Recognition API, which infers the user's current activity type in real time with minimal resource consumption. The sensor produces one of seven activity types: *still*, *walking*, *running*, *on bicycle*, *in vehicle*, *tilting*, and *unknown*.

The gesture sensor is implemented using the WatchHAR model [29]. The model uses inertial measurement unit (IMU) sensor data and voice data to detect the type of gesture and activities on-device and in real time. To minimize privacy concerns and resource usage, voice data is collected and processed only when the model detects an event of interest based on IMU data alone.

The stress sensor estimates the user's stress level using the root mean square of successive differences (RMSSD) of inter-beat intervals (IBI), which is a frequently used indicator of stress derived from heart rate variability [14]. To calculate RMSSD, IBI samples are first filtered based on their status flag (`ibiStatus`) to remove unreliable measurements. Then, feasibility-based filtering is applied by excluding samples whose corresponding heart rate falls outside the physiologically feasible range (BPM < 30 or BPM > 220), followed by median $\pm$ 3 MAD trimming to remove outliers. The window size is set as 60 seconds with 75% overlap [18]. We use the 20th percentile of the participant's observed RMSSD values as a personalized threshold to determine if they are stressed or not [24].

2.3 MicroEMA

EnPULSE supports smartwatch-based microEMA, which is designed to be answered with a small number of interactions. It supports five types of questions: binary, checkbox, radio, short-text, and number scale. It also supports four types of scheduling: fixed time of day, randomized intervals with configurable minimum and maximum interval bounds, event-based triggering via the trigger system described in Section 2.4, and manual triggering by the participant. The set of microEMA questions and their schedules can be configured through the visual dashboard.

We designed the interface of microEMA (Figure 2) so that the required amount of interaction to complete the question is as small as possible, as interactions per EMA are a dominant factor influencing compliance [21]. Also, if possible, multiple interaction modalities are provided. Both the voice and keyboard inputs can be used for short-text questions, and both swiping and touching can be used to select one of the options when answering binary, radio, and number scale questions. This way, participants can choose the interaction style that best fits their context, which can help increase EMA compliance [28]. Also, to prevent recall bias, each microEMA prompt is designed to be answered within a configurable time limit. A visual indicator at the edge of the smartwatch display shows the remaining time, providing participants with awareness of the response window.

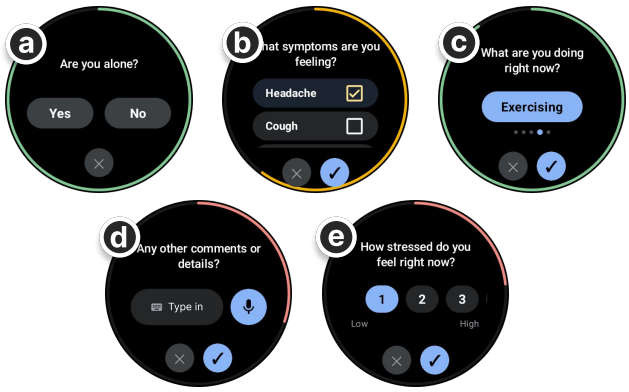


Figure 2: Example microEMA interface for the supported question types: (a) binary, (b) checkbox, (c) radio, (d) short-text, and (e) number scale. The arc at the edge of the display indicates the remaining time until the question expires.

2.4 Trigger

The trigger system in EnPULSE follows the *Sense–Analyze–Act* structure that has been adopted by several prior mobile sensing platforms [7, 8, 10]. First, the system takes inputs from sensors (*Sense*) and evaluates whether the collected values fulfill a researcher-defined condition (*Analyze*). To allow researchers to express a wide range of contextual conditions, the trigger system supports the combination of atomic conditions using `AND`, `OR`, and `NOT`. Then, actions are executed if the corresponding condition is satisfied (*Act*). The actions are either the delivery of an EMA or microEMA, or the broadcasting of Android API's Intent message that can be captured by third-party applications. To prevent overly frequent triggering, which may degrade participants' experience and reduce compliance, a minimum interval between consecutive actions can be set for each trigger action. The trigger conditions and actions can be configured through the visual dashboard without the need to write any code (Fig. 3).

3 Demonstration

In the live demo, attendees can experience the full EnPULSE pipeline through a three-phase walkthrough in which they take on both the researcher and the participant role. Our goal is to showcase the expressiveness and ease of configuration of EnPULSE when defining custom CS-EMA settings, as well as microEMA and the visual dashboard interface.

First, from the perspective of researchers, attendees can watch a video about the visual dashboard. They can see how studies are configured, and data collected from simulated large-scale studies are visualized. Next, the attendees can have hands-on experience in configuring a study using the visual dashboard, composing a custom context-sensitive trigger that binds one or more high-level context conditions to a microEMA action. Finally, acting as study participants, they wear the smartwatch and perform any action. The on-device high-level context sensor running on the smartwatch detects the action in near real time. If the trigger condition is satisfied, the corresponding microEMA will be delivered to the smartwatch.

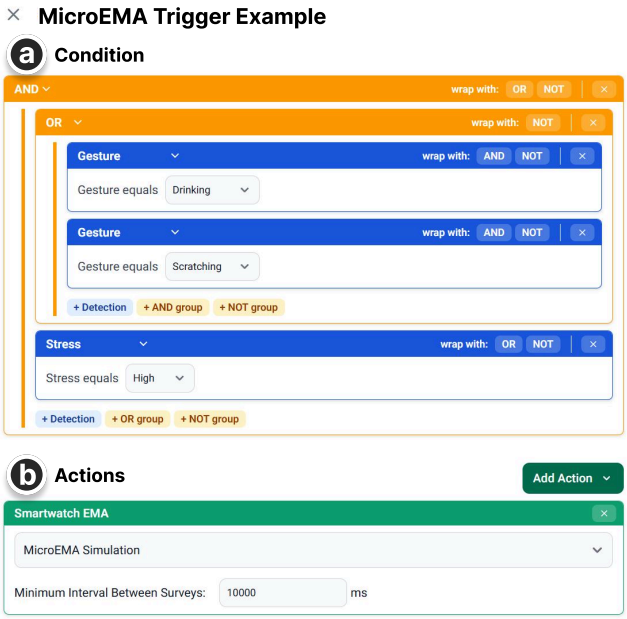


Figure 3: An example trigger configuration in the visual dashboard. (a) The condition is composed of atomic conditions (gesture and stress detections) combined with logical operators. (b) When the condition is satisfied, the configured action (microEMA) is executed.

4 Conclusion and Future Work

We presented EnPULSE, an open-source platform for mobile and wearable sensing. EnPULSE addresses gaps that existing mobile sensing platforms leave in integrating passive and active sensing by supporting high-level context sensors, smartwatch-based microEMA, a configurable trigger system, and a web-based visual dashboard for study management and configuration.

In future iterations, we plan to expand the types of supported high-level context sensors and extend trigger conditions to general sensors to broaden the use cases supported by the platform. Also, formative evaluations will be conducted, such as measuring the energy consumption of each sensor modality, including high-level context sensors, and validating the reliability and effectiveness of EnPULSE through in-the-wild deployment.

We hope EnPULSE will lower the engineering barrier to deploying context-sensitive and microEMA-based mobile sensing studies in mHealth research and contribute to a better understanding of human behaviors through the lens of mobile sensor data. The code is released as open source at https://github.com/Kaist-ICLab/EnPULSE.

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