A Mobile Data Collection Platform for Mental Health Research

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ORIGINAL ARTICLE

A mobile data collection platform for mental health research

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Abstract Ubiquitous computing technologies offer exciting new possibilities for monitoring and analyzing user's experience in real time. In this paper, we describe the design and development of Psychlog, a mobile phone platform designed to collect users' psychological, physiological, and activity information for mental health research. The tool allows administering self-report questionnaires at specific times or randomly within a day. The system also permits to collect heart rate and activity information from a wireless electrocardiogram equipped with a three-axial accelerometer. By combining self-reports with heart rate and activity data, the application makes it possible to investigate the relationship between psychological, physiological, and behavioral variables, as well as to monitor their fluctuations over time. The software runs on Windows mobile operative system and is available as open source (http://sourceforge.net/projects/psychlog/).

Keywords Ecological momentary assessment · Wearable sensors · Electrocardiogram · Accelerometer · Smart phones

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1 Introduction

In recent times, there has been growing interest toward the use of experience sampling procedures in research and clinic. Experience sampling method (ESM), also known as ecological momentary assessment (EMA), is a naturalistic observation technique that allows capturing participants' thoughts, feelings, and behaviors at multiple times across a range of situations as they occur in the natural environment [1, 2]. Thanks to its flexibility and the possibility of adapting questions to the goals and motivations of the researcher, ESM has been used with adolescent and adult populations for decades to understand areas such as mood, social interactions, and time use [3]. This approach has been also widely applied in the clinical field, i.e., for improving the comprehension of psychological mechanisms of change [4]. Advances in ubiquitous computing systems offer new opportunities for extending the potential of ESM [5, 6]. Actually, the main goal of ubiquitous computing vision is the development of sensor-based model of the activities that people engage in, and the contexts in which they occur [7] In particular, ESM can benefit from the convergence between two important trends in ubiquitous computing: the rise of smart phones and advances in wireless wearable biosensors. Smart phones are essentially programmable mobile phones, which provide advanced computing ability and communication functionalities enabled by powerful processors, high inbuilt storage capability (expandable via flash memories), large screen, and Bluetooth/Infrared local connectivity. These advanced capabilities enable the researcher to unobtrusively record a variety of behavioral data in real time. As pointed out by Raento [8], since the phone is an integrated part of both the individual and the social life, it provides access to domains of behavioral data not previously available without either constant observation or reliance on self-reports only. Moreover, smart phones are equipped with sensing capabilities (i.e., positioning, accelerometer, proximity, ambient light detector, compass, etc.), which enable detection, recognition, and identification of a number of activity and context information. These data can be used as objective corroborative measures for the analysis and interpretation of subjective self-reports. The second emerging trend in the ubicomp field is wireless wearable biosensors. Thanks to advances in miniaturization and wireless communications, research in this area has gained momentum in the last decade, enabling the development of monitoring devices that are used in ambulatory treatment, in home care, and in hospitals [9]. Different wireless body sensors exist today at various stages of maturity, which can be used for measuring physiological signals such as heart rate, arterial blood pressure, arterial oxygen saturation, respiratory rate, temperature, and cardiac output [10, 11]. Information gathered from these sensors can be complemented with data from wireless pedometers and accelerometers for activity recognition [12, 13]. Thus, the rapid convergence of smart phones and wireless body sensors, pushed by the emerging field of mobile health (or m-health), gives ESM researchers the unprecedented opportunity of integrating the analysis of experiential responses with physiological and activity variables, extending the heuristic potential of this approach [14]. In this paper, we present the design and implementation of such a smart phone-based platform, designed for research and clinical applications in mental health. In the first section, we introduce the main characteristics of ESM and present related work about computerized versions of this procedure. Next, we provide an overview of the system and its ongoing deployment in the field of momentary stress assessment. Finally, we discuss open technical issues and future research directions.

1.1 Experience sampling method

The most important motivation for the development of ESM is the recognition that behavior and experience do not occur in a vacuum but are constantly affected by context. If this assumption is correct, then the best possible way to generalize experimental findings is to sample experience and behavior in the contexts in which they naturally occur. In a typical ESM study, participants carry with them for 1 week an electronic beeper and a booklet of self-report forms. Whenever they receive an acoustic signal, they are expected to fill out a form. Usually, ESM form contains open-ended questions about situational variables such as place, activities carried out, social context, and subjective variables investigating the quality of experience in its various cognitive, motivational, and affective components. Thanks to repeated sampling, after a standard ESM session, a number of sheets are collected from each participant, thus providing a rich databank on the quality of daily experience of each individual [15]. A researcher interested in using ESM can select between three types of protocols: (a) interval contingent, (b) event contingent, and (c) signal contingent [16, 17]. In the *interval-contingent* protocol, participants provide ESM responses at predetermined intervals (e.g., every hour) or at the same time daily. In the *event-contingent protocol*, participants respond only when the event of interest takes place. In the *signal-contingent* protocol, participants are prompted to respond by a signaling device at randomly selected time points in the day. The choice of sampling protocol depends on the object of the study. Some protocols are easier to implement and less burdensome to participants than others (e.g., once daily diary); other factors include the number of observations per day (typically between 1 and 10) and the length of the sampling period (typically between 3 and 30 days).

ESM and EMA hold several advantages over traditionally used assessments of psychological phenomena, including the ability to assess the temporal relationship between variables, high ecological validity, and highly detailed information on subjective experience [18]. Thanks to these features, such techniques have been widely used to study a wide range of psychological disorders, including mood disorders and mood dysregulation, anxiety disorders, substance use disorders, and psychosis [15]. This approach holds also promising potential in clinical psycho-pharmacological research. Reports by clinicians are the most commonly used method to study outcomes in this field. However, one shortcoming of this approach is that objectivity of clinician's information can be reduced by the familiarity of the clinician with the patient. Further, there is a lack of standardized procedures to gather information from the subject, so that evaluations are based on heterogeneous information across participants. ESM can improve the sensitiveness of measurement of many of the common outcomes measured by studies in clinical psycho-pharmacology, such as mood and anxiety, as well as to investigate patterns of social interaction in a way that is not possible with the current methodology [19]. For example, ESM has been effectively used to assess effects of antidepressant treatment on the quality of life and related aspects of daily experience [20].

1.2 Computerized experience sampling procedures

In the past, ESM-based studies have been mainly done via paper and pencil measures. However, in the last decade, computerized versions of this technique have been introduced, which allows collecting data by handheld electronic devices [21]. Handheld-based ESM tools have opened up new opportunities for more complex and sophisticated experience sampling protocols that expanded upon the various approaches to collecting self-report data [18]. Computerized experience sampling procedures have several advantages over pen-and-paper approaches. For example, they allow the researcher to precisely control the timing of self-report administration; to objectively control compliance rates; and to reduce the chance of human error when managing the data [18]. Further, computerized experience sampling procedures can take advantage of latest advances in computational recognition and sensing technologies, to automatically detect events that can trigger data collection [14]. Intille and colleagues at MIT have recently developed a personal digital assistant-based version of the ESM [6]. The procedure, called context-aware experience sampling, offers the possibility to assess user's experience not only through the standard time-based protocol but also according to the participant's location, by means of information provided by a GPS plug-in. Thanks to this automatic logging approach, researchers can design experiments collecting self-reports, i.e., only when the participant is near a location of interest. Moreover, users can answer via audio recording or by taking a picture with a camera [6]. A recent evolution of this context-aware approach is the MyExperience platform, which has been developed to run on smart phones in order to take advantage of the increasing number of sensors embedded in these devices [22]. MyExperience supports 50 built-in sensors including GPS, GSM-based motion sensors, and device usage information. The sensor events can be used to trigger custom actions such as to initiate wireless database synchronization, send SMS messages to the research team, and/or present in situ self-report surveys. An interesting feature of the application is that self-reports cannot only be triggered by time but also by additional sensor data gathered from the environment (e.g., GSM cells), the devices position (acceleration), or the phone activity. However, the creation of the studies requires at least basic programming skills, since it is done by editing XML files [5].

1.3 Design requirements

Starting from this background, our main goal was to design and develop a smart phone-based tool to collect users' psychological, physiological, and activity information for mental health research. To collect requirements, we carried out several focus groups with researchers and clinicians interested in the potential applications of this tool in their practice. Findings from interviews with prospect users were integrated with the analysis of related work in the field of computerized experience sampling [21]. Results of this analysis allowed identifying a few specific needs:

- *inexpensive*: since experience sampling studies are usually low-budget projects, the tool should be inexpensive and run on low-cost mobile devices;
- *simple*: the tool should be quick to learn and use, both for researchers (primary users) and for study's participants (secondary users);
- *integrated*: In most cases, handheld-based ESM tools force participants to carry another mobile device along with their personal one. It would be even more convenient if such tools would run on participants' phones [22, 23];
- *customizable*: researchers/clinicians with no programming skills should be able to develop their own customized data capture protocols;
- *unobtrusive*: the application should not interfere with normal mobile phone usage;
- *open source*: this feature was not suggested by prospect users, but from project's developers. Open source licensing allows end users to review and modify the source code for their own customization and/or troubleshooting needs. Although most prospect end users of our application lack programming skills, providing the source code offers more possibility to fit the evolving needs of the research community.

1.3.1 Activity and physiological sensing

An emerging need in mental health research (and in social sciences in general) is the possibility of collecting objective correlates of participant's subjective experience [8]. Within experience sampling studies, physiological and physical activity information can provide researcher with corroborative measures that can be used to contextualize self-reported feelings and thoughts. Unfortunately, it is not feasible to collect and analyze all participants' physiological variables in natural environments. Thus, it is necessary to identify a subset of highly informative measures. Heart rate (HR) responses and in particular the heart's beat-to-beat variability (HRV) are commonly used measures in psychophysiological research. In particular, HRV is a useful psycho-physiological marker, because it directly reflects the natural variability of heart rate in response to affective and cognitive states [24]. Cardiac functioning is mediated by the autonomic nervous system (ANS), with both the sympathetic and parasympathetic ANS' branches innervate the myocardium. The dynamic interaction between the branches reflects the ANS' capacity for regulated emotional responding, contributing to an individuals' ability to function effectively within changing environments. HRV studies carried out with healthy individuals have shown that negative mood is correlated with sympathetic dominance, whereas positive mood is associated with a shift toward parasympathetic activity [25]. Further, HRV and its mathematic transformation of into power spectral density (PSD) have been used to characterize a number of psychological illnesses, including major depression and panic disorders [26]. When respiration signal is recorded, it is also possible to calculate respiratory sinus arrhythmia (RSA) [27, 28].

2 System's overview

PsychLog is a mobile data collection platform that allows gathering and analyzing psychological, physiological, and behavioral information from users in naturalistic settings. The system's architecture is composed of three main modules: the *survey manager module*, the *sensing/computing* module, and the *visualization module*, as illustrated in the PsychLog system's flowchart (Fig. 1).

2.1 Survey manager module

The survey manager application allows configuring, managing, and administering self-report questionnaires. Surveys are used to collect participants' feedback on his/her quality of experience in its various cognitive, affective, and motivational dimensions. The type of survey to be administered depends on the study's goals. The researcher can easily customize the questionnaire items by modifying the .txt document saved in the program directory. To ensure maximum flexibility in the management of surveys, the application offers several configuration options, as shown in Fig. 2. The configuration menu is protected by a password to avoid that participants modify the study design. Once authenticated, the researcher defines the schedule of self-reports by setting a *trigger*. Triggers can be launched with a fixed schedule or randomly during a day. If the researcher chooses a fixed schedule, also called interval-contingent sampling [16], participants make their reports at fixed times throughout the day. With a variable schedule, also known as signal-contingent sampling [17], observations are taken at random times within a day. The researcher defines the probability for the trigger event by entering a value between 0 (never) and 1 (always). When trigger goes off, the user hears a beep and a notification message is displayed. Upon hearing a beep, the participant has two options: (a) to accept the questionnaire, by clicking on the "ok" button; (b) to refuse the questionnaire, by clicking on the "skip" button. If the participant takes no action, the notification trigger expires after a pre-defined time and the application records a default data indicating no response. In this way, it is possible to measure participants' compliance to program's instructions, which is a useful information in clinical research studies. If the participant accepts the questionnaire, the survey is displayed on the screen, one item at time. For each item, the user can either select a pre-defined response (for closed-ended questions) or entering a text (for open-ended questions). When an item is displayed on the screen, the participant can: (a) move to the next question (by clicking on the "next" button); (b) step back to the previous question (by clicking on the "previous" button) or (c) skip the question. It is also possible to log response time for each item. This option can be useful, i.e., for measuring specific cognitive variables and observing their fluctuation within the day.

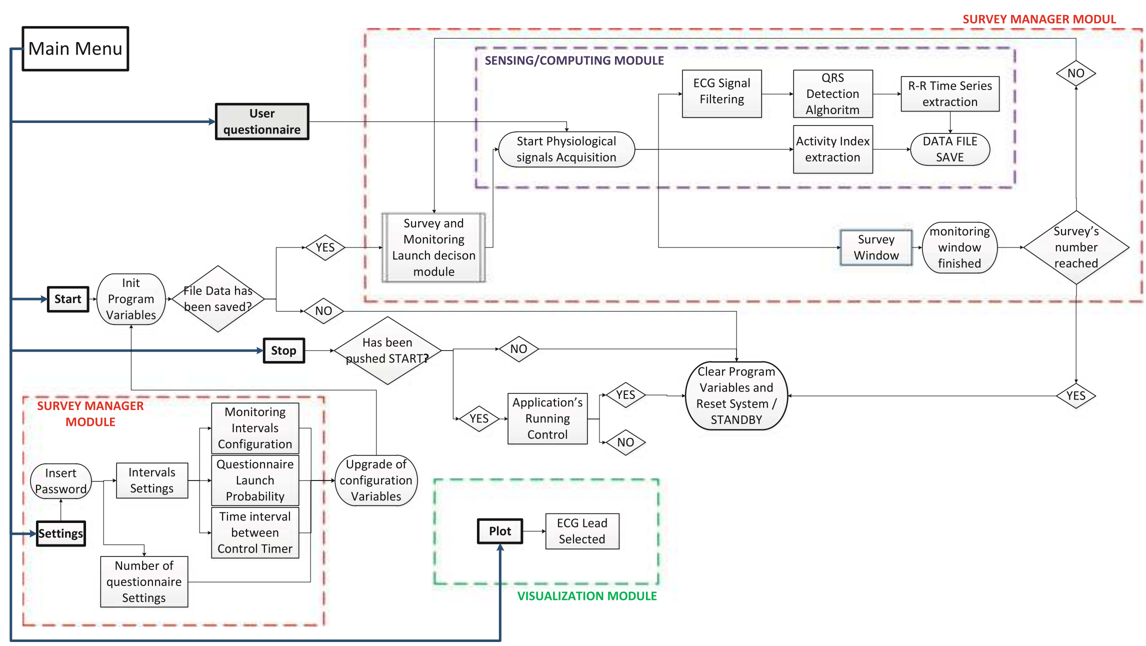

Fig. 1 PsychLog system's flowchart

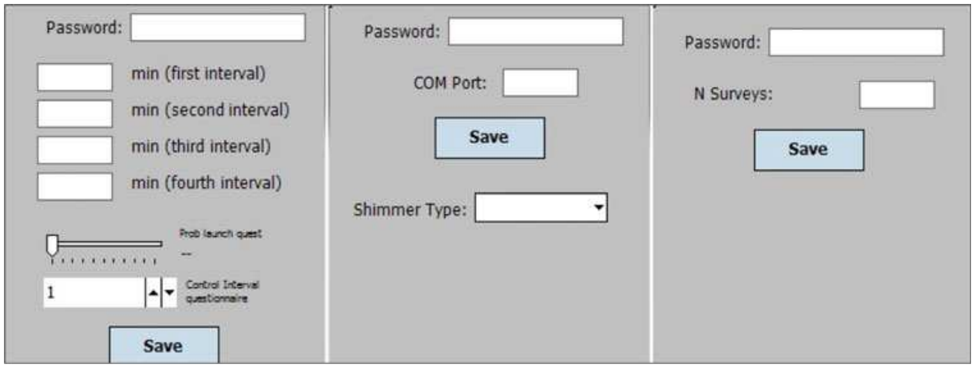

Fig. 2 PsychLog system's configuration. From left to right: trigger configuration; ECG sensor configuration; survey configuration

2.2 Sensing/computing module

Thanks to this module, the PsychLog system allows continuously monitoring HR and activity data acquired from a wireless electrocardiogram (ECG) equipped with a three-axial accelerometer. The wearable sensor platform (Shimmer Research^{TM}) includes a board that allows the transduction, amplification, and pre-processing of raw sensor signals, and a Bluetooth transmitter to wirelessly send the processed data. The unit is mounted on a soft-textile chest strap designed to seamlessly adapt to the user's body shape, bringing full freedom of movement. Sensed data are transmitted to the mobile phone Bluetooth receiver and gathered by the PsychLog computing module, which stores and process the signals for the extraction of relevant features. ECG and accelerometer sampling intervals (epochs; Fig. 3) can be fully tailored to the study's design. During each epoch, signals are sampled at 250 Hz, filtered to eliminate common noise sources using Notch filter at 0 Hz and low pass at 35 Hz and analog-to-digital converted with 12-bit accuracy in the ±3 V range. The PsychLog application extracts QRS peaks through a dedicated algorithm [26] and R–R interval time series. The movement information is the variance of the magnitude of the three-axis acceleration vector (Fig. 3, bottom).

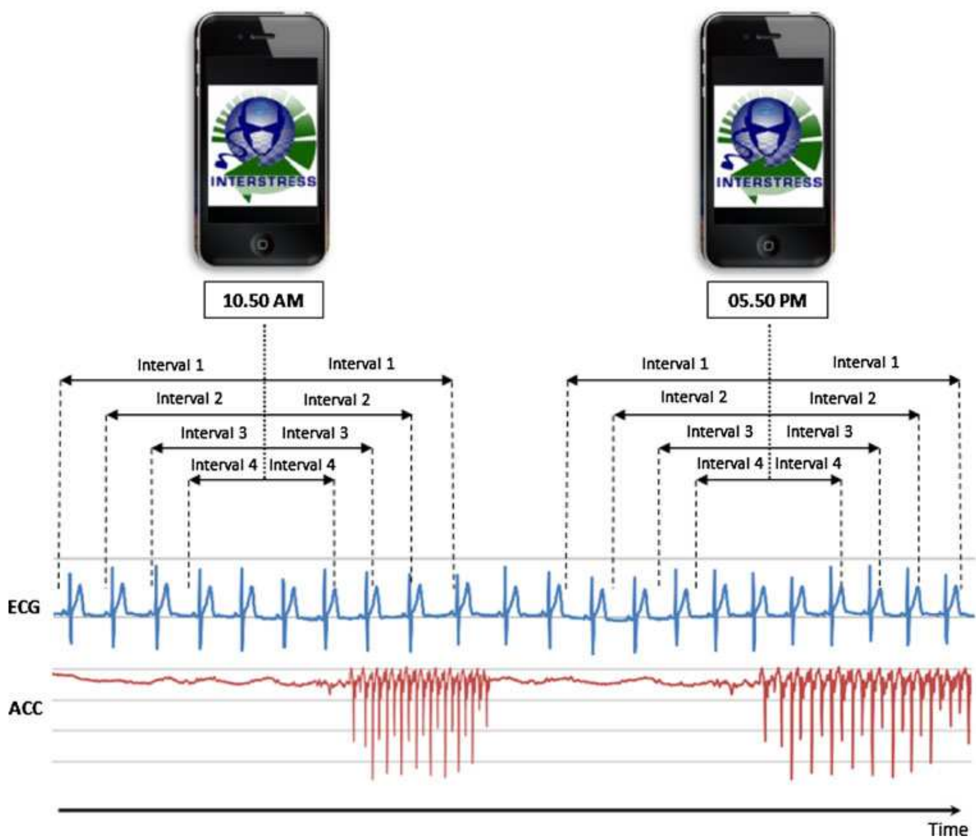

Fig. 3 Sampling intervals' configuration options (*top*); ECG and movement signals (*bottom*)

2.3 Visualization module

The visualization module allows plotting in real time ECG and acceleration graphs on the mobile phone's screen. This feature is useful either for monitoring the ECG data or for checking the functioning of the ECG sensor apparatus. The ECG visualization module was implemented by developing a C# class that uses libraries included in the compact framework 3.5. The class is called by the Signal Processing Module of the application, which provides the array of physiological data. The plot is refreshed every 2 s, and a routine is included that allows auto scaling the signal on the *Y* axis to fit the mobile display size. The visualization module allows the user to choose which ECG lead to plot, as well as the HR plot computed by the Signal Processing Module.

2.4 Data management

Self-reports and sensors data are stored on the mobile phone's internal memory, in separate files, for off-line analysis. Data are stored as .dat (supported by most data analysis programs), .txt, and .csv format. The number of data that can be saved depends on the storage capacity of the device.

2.5 Implementation of the prototype

The PsychLog application was developed on Windows mobile 6.5 platform using Microsoft® Visual Studio 2008 Professional Edition, the. Net Compact Framework 3.5 and the object-oriented language C# 3.0. This platform was chosen because it provides easy access to lower level APIs that are required for the sensor modules. The software is freely available for Windows mobile, and its open-source code (BSD license) can be configured to meet specific experimental or clinical requirements. The prototype application was deployed on a Samsung Omnia II i8000 smart phone.

2.6 System's performance evaluation

We tested the performance of PsychLog application on a standard smart phone (Samsung Omnia II i8000) equipped with 32 bit CPU, ARM 11 RISC processor (cache 16 KB) 667 MHz, RAM 256 MB, 1,500 mAh Lithium ion battery, running the operative system Windows mobile 6.5. More specifically, we were interested in assessing the impact of physiological signal acquisition on CPU and battery consumption. The performance test was carried out under four operating conditions: standby; questionnaire; signal acquisition; combined questionnaire; and signal acquisition. In the standby mode, the application runs in background waiting for a trigger event. In the questionnaire mode, the application runs the self-report questionnaire. In the signal acquisition mode, the application wirelessly receives ECG and accelerometer signals from the remote sensor unit, performs pre-processing (filtering, amplification, and feature extraction), and stores data on the internal memory. In the combined mode, questionnaire and signal acquisition run in parallel. As predictable, in both standby mode and questionnaire mode, CPU utilization is very low (0–2%). In the signal acquisition mode, there is a significant increase of resource utilization (48%), which reaches 50% in the combined mode. Findings from this simple test indicate the high impact of sensor acquisition operations on CPU resource utilization. However, remaining processing resources (50%) allow standard usage of mobile phone. This gives the researcher the possibility of monitoring physiological signals when the user is using other functionalities of the mobile phone (i.e., calling, texting, browsing), which can be useful for specific research purposes (i.e., for usability studies, marketing studies, etc.). As concerns the measurement of battery life, several tests were performed varying the duration of sampling epochs in the combined mode. Results showed that the battery is drained in about 5 h under continuous wireless sampling, and the storage capacity needed for a 5-h recording is about 150 MByte. This requires the user to recharge (or change) the battery at least two times during a typical experimental day, which is a significant complication for the research design. However, the PsychLog application provides the researcher with the possibility of optimizing battery life by limiting the signal acquisition epochs to specific events of interest (i.e., 15 min before and after a prompt, see Fig. 3).

3 Pilot study

To test the system, a pilot trial was designed and carried out with the goal of testing the feasibility of monitoring concurrent stress and physiological arousal within subjects' typical daily environments and activities. Previous work has shown that psychological stress is associated with an increase in sympathetic cardiac control, a decrease in parasympathetic control, or both [24, 25]. Associated with these reactions is a frequently reported increase in low frequency (LF, range between 0.04 and 0.15 Hz) or very low frequency (VLF, <0.04 Hz) HRV, and decrease in high frequency (HF, 0.15–0.50 Hz) power. HF power is reported to reflect parasympathetic modulation of RR intervals related to respiration, whereas the LF component is an index of modulation of RR intervals by sympathetic and parasympathetic activity (in particular baroreflex activity) [29]. Furthermore, stressors are often accompanied by an increase in the LF/HF ratio (a measure used to estimate sympathovagal balance, which is the autonomic state resulting from the sympathetic and parasympathetic influences) [29, 30].

The specific objectives of this pilot study were two-fold:

- to test the feasibility (and accuracy) of PsychLog system in monitoring autonomic arousal and psychological stress in ambulatory healthy subjects;
- to test overall user's acceptance of the system (including wearable sensor platform) and level of compliance with the experimental procedure.

3.1 Participants

Participants were six healthy subjects (3 men and 3 women, mean age 22) recruited through opportunistic sampling. Participants filled a questionnaire assessing factors that, in the opinion of the investigators, might interfere with the measures being assessed (i.e., caffeine consumption, smoking, alcohol consumption, exercise, hours of sleep, disease states, and medications). Written informed consent was obtained by all subjects matching inclusion criteria (age between 18 and 65 years, generally healthy, absence of major medical conditions, and completion of informed consent).

3.2 Procedure

Participants received a short briefing about the objective of the experiment and filled the informed consent. Then, they were provided with the mobile phone with pre-installed PsychLog application, the wearable ECG and accelerometer sensor and a user manual including experimental instructions. The application was pre-programmed to collect data over 7 consecutive days, at random intervals during waking hours. At the end of the experiment, participants returned both the phone and the sensors to the laboratory staff. After filling a short usability questionnaire, participants were debriefed, thanked for their participation, and dismissed.

3.3 Psychological measures of stress

Momentary stress was measured using a digitalized version of the ESM. The ESM questionnaire used in this study has been adapted from that used by Jacobs et al. [29] for studying the immediate effects of stressors on mood. The self-assessment forms included open-ended and closed-ended questions investigating thoughts, current context (activity, persons present, and location), appraisals of the current situation, and mood. All self-assessments were rated on 7-point Likert scales. Following the procedure suggested by Jacobs et al. [29], three different stress measures were computed in order to identify the stressful qualities of daily life experiences. Ongoing activity-related stress (ARS) was defined as the mean score of the two items "I would rather be doing something else" and "this activity requires effort" (Cronbach's alpha = 0.76). To evaluate social stress, participants rated the social context on two 7-point Likert scales "I don't like the present company" and "I would rather be alone"; the social stress scale (SS) resulted from the mean of these ratings (Cronbach's alpha = 0.59). For event-related stress (EVS), subjects reported the most important event that had happened since the previous beep, whether or not it was still ongoing. Subjects then rated this event on a 7-point bipolar scale (from 3 very unpleasant to 3 very pleasant, with 0 indicating a neutral event). All positive responses were recoded as 0, and the negative responses were recoded so that higher scores were associated with more unpleasant and potentially stressful events (0 neutral, 3 very unpleasant). In addition to those scales, an item (not included in the original survey) asked participants to rate the perceived level of stress on a 10-point Likert scale. This item was included as a global subjective measure of stress.

3.4 Physiological measures of stress

The QRS peaks and RR interval time series recorded and saved on the PsychLog application were exported and further processed with the software Matlab (version 7.10) in order to compute a set of HRV indexes. To this end, the ECG signal was first elaborated for artifact correction, and then a fast Fourier transform was used to compute the power spectrum in the LF (0.04–0.15 Hz) and HF (0.15–0.50 Hz) bands.

3.5 Data analysis and results

Out of 220 beeps, participants filled 214 reports (98%), of which 197 were included in the analysis (90%). A total of 220 ECG sampling were recorded (100%), and 205 were included in the analysis (93%). Given the repeated sampling, Lykert-type scales data were standardized (mean = 0; SD = 1) on each participant's weekly mean for every variable before performing the analyses. ESM data can be aggregated at the report level (the unit of analysis is the individual diary entry) or at the subject level (the unit of analysis is the participant). In the present study, most of the analyses were conducted using the subject-level aggregation, because this approach avoids problems related to unequal weights and produces more conservative significance tests [31]. The following table provides the correlations between stress measures described before.

As can be seen from Table 1, all scales measuring stress (ARS, SS, and EVS) are significantly correlated between them and with the item ("STRESS") measuring the global perceived level of stress, suggesting high internal consistency of the instrument. In order to measure the quality of the ECG signal provided by the PsychLog application, the number of detectable artifacts was measured [32]. To this end, we used custom-designed algorithms in order to detect R-peaks. To perform RR detection, we followed the guidelines of the Task Force of the European Society of Cardiology and North American Society of Pacing and Electrophysiology [33]. Artifacts were then detected by visually inspecting the resulting ECG plot including the R markers identified by the custom-designed algorithms. A total of 220 ECG plots were included in the analysis. Of them, 13 ECG plots were completely artifacts free; 154 had up to three artifacts; 53 ECG had between four and eight artifacts; none had more than eight artifacts. Table 2 provides the correlations between HR and psychological measures of stress in different time segments, where $t = 0$ indicates the instant of the beep event (only significant correlations are reported). The analysis shows that increases in HR are positively correlated with EVS and the item ("stress"), which measures the global perceived level of stress. Note that correlations are significant (or close to significance) in all temporal segments that were considered.

However, it must be noted that HR is a global index of arousal, which does not necessarily reflect psychological stress. In order to identify specific correlates of mental stress, a more detailed analysis of cardiovascular indexes is required [29]. For the objectives of the present work, we were specifically interested in examining whether the ECG signal processed by the PsychLog system is sufficiently accurate and artifact free to detect meaningful correlations between self-reported psychological variables and HRV indicators of stress. To address this issue, we performed a detailed analysis of 7-day ECG recordings and ESM entries of a specific participant (female, 24 years old, university student). A total of 31 ESM entries were filled by this subject during the 7-day session; of them, 29 were included in the analysis and 2 were discarded because incomplete or incorrectly compiled. The measure of psychological stress included in this analysis was the "self-reported stress" rated on a 10-point Likert scale. HRV was analyzed in the frequency domain, yielding estimates of spectral power in low (LF) and high (HF) frequency bands, as well as the LF/HF ratio. Since LF/HF ratio is affected by physical exertion, we used the acceleration module computed by PsychLog to identify the level of physical activity. Events below the median magnitude (0.19) of the combined 3-axis acceleration vector were classified as "low activity". Then, the LF/HF ratio was computed from the ECG signal of low-activity events. The resulting LF/HF scores were then correlated with stress ratings. The Pearson correlation performed on $n = 17$ events resulted in a positive and moderate relationship between the two variables ($r = 0.564$, $p < 0.02$). Perceived psychological stress was significantly associated with an increase in the LF/HF ratio, suggesting increases in the relative predominance of sympathetic nervous system activity during stressful periods of the day. Figure 4 illustrates an exemplification of the psycho-physiological profiles of three specific events extrapolated from the dataset. In (a), the participant was attending a morning lesson at the university and was with other people (classmates). The event is rated as moderately stressful on three out of four scales considered. The HRV profile of this event is characterized by a predominance of the LF component on HF component. In (b), the participant was "unsuccessfully studying" at home and was in company of her mother and her dog; the event is rated as highly stressful on all scales. The HRV profile of this event shows a marked predominance of the LF component on HF component. In (c), the subject was involved in a typical leisure activity (watching television) and was in company

Table 1 Summary of correlations between psychological stress scales

		ZARS	ZSS	EVS	STRESS
	N	195	190	156	195
ZARS	Pearson correlation	1	0.416**	0.166*	0.290**
	Sig. (2-tailed)		0.000	0.038	0.000
	N	195	190	156	195
ZSS	Pearson correlation	0.416**	1	0.355**	0.237**
	Sig. (2-tailed)	0.000		0.000	0.001
	N	190	191	157	190
EVS	Pearson correlation	0.166*	0.355**	1	0.248**
	Sig. (2-tailed)	0.038	0.000		0.002
	N	156	157	157	156
STRESS	Pearson correlation	0.290**	0.237**	0.248**	1
	Sig. (2-tailed)	0.000	0.001	0.002	
	N	195	190	156	197

* $p < 0.05$, ** $p < 0.01$

Table 2 Summary of correlations between measures of psychological stress and heart rate (HR)

	EVS	STRESS
ZSS		
Pearson correlation	0.355**	0.237**
Sig. (2-tailed)	0	0.001
N	157	190
EVS		
Pearson correlation	1	0.248**
Sig. (2-tailed)		0.002
N	157	156
STRESS		
Pearson correlation	0.248**	1
Sig. (2-tailed)	0.002	
N	156	197
HR (time frame: −12 to −8 min)		
Pearson correlation	0.151	0.168*
Sig. (2-tailed)	0.066	0.021
N	149	189
HR (time frame: −8 to −4 min)		
Pearson correlation	0.175*	0.176*
Sig. (2-tailed)	0.031	0.014
N	153	193
HR (time frame: −4 to 0 min)		
Pearson correlation	0.173*	0.205**
Sig. (2-tailed)	0.032	0.004
N	155	195

* $p < 0.05$, ** $p < 0.01$

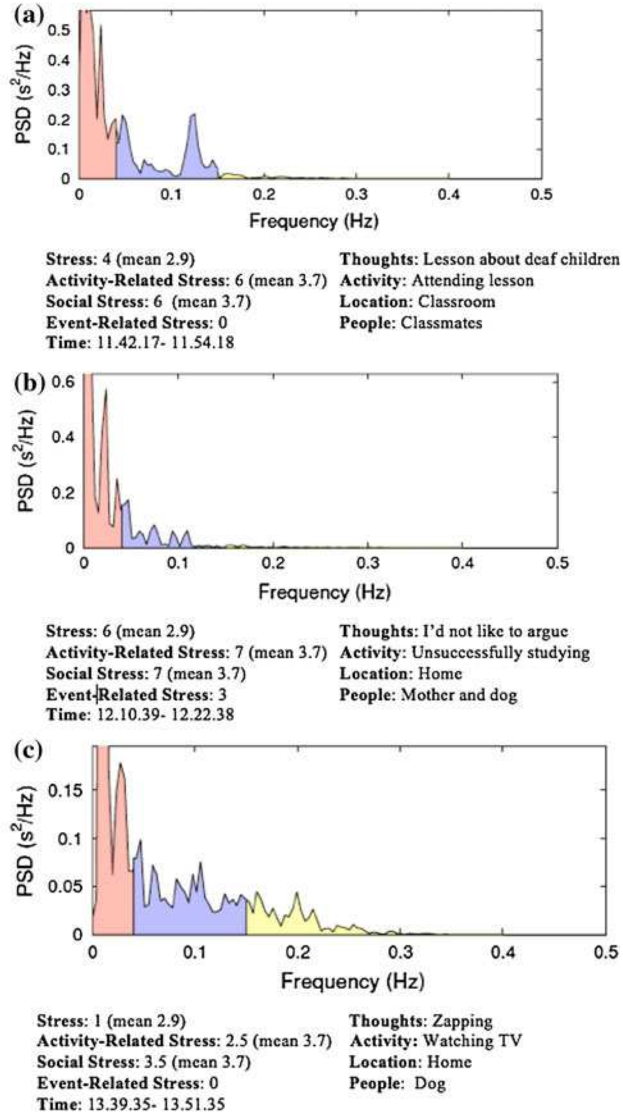

Fig. 4 Psycho-physiological profile of three sample events

of her dog. The event was rated as not stressful on all scales. Compared to the stressful events, the HRV profile of this event shows a higher HF component and a reduced predominance of LF on HF. As concerns aspects related to usability and acceptability, findings showed that all participants found the application very easy to learn and did not report specific difficulties in filling the ESM questionnaires. Specific (minor) technical issues included: problems in switching on the wireless sensor unit; difficulties in recognizing the "beep" tone that precedes the questionnaire; slow functioning of the application during the ECG monitoring; frequent need for recharging the phone and sensors batteries (averagely twice a day).

4 Conclusions and future developments

In this paper, we have described the design and initial deployment of a smart phone-based data collection platform for psychophysiological research. The application allows high flexibility in designing and running sensor-enhanced ESM research protocols and is available as free, open source software. Although PsychLog is less sophisticated than other applications, such as Context-Aware Experience Sampling or MyExperience, it does not require programming skills and can be run on relatively low-cost smart phones running Windows mobile. The application also provides native support for wireless ECG and accelerometer, and its visualization module allows unobtrusively monitoring physiological and activity information in real time. The sensing/computing module can be easily set up and configured to sample data in combination with self-report, allowing the researcher to correlate to behavioral, psychological, and physiological variables, as well as to analyze fluctuations over time. The pilot deployment test results suggest the feasibility and accuracy of using the PsychLog system to monitor the dynamic psycho-physiological profile of mental health constructs such as stress in ecological situations. Furthermore, findings indicated a good level of acceptance by participants of the experimental procedure, (as indicated by the high compliance rate in filling the ESM forms, 98%, and considering that participants did not receive monetary or other forms of compensation for their involvement).

However, there are still technical limitations—with particular reference to efficiency in power and computational resource consumption—that need to be addressed before making PsychLog an useful tool for experience sampling researchers. On the other hand, it is expected that the open source nature of this project will allow the research community to constantly improve its features and provide new sensing capabilities. At the moment, three main features are planned: (a) portability to Android platform; (b) definition and implementation of a client–server architecture to allow remote data management; and (c) extended support to additional psycho-physiological markers (galvanic skin response and respiration rate).

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References

1. Larson RW, Csikszentmihalyi M (1983) The experience sampling method. In: Reis H (ed) New directions for naturalistic methods in the behavioral sciences. Jossey-Bass, San Francisco, pp 41–56
2. Stone AA, Shiffman S (1994) Ecological momentary assessment (EMA) in behavioral medicine. Annal Behav Med 16:199–202
3. Barrett LF, Barrett DJ (2001) An introduction to computerized experience sampling in psychology. Soc Sci Comput Rev 19(2):175–185
4. Conner TS, Tennen H, Fleeson W, Feldman BL (2009) Experience sampling methods: a modern idiographic approach to personality research. Social Person Psychol Compass 13(3):292–313
5. Fischer JE (2009) Experience sampling tools: a critical review. In: Proceedings of MobileHCI'09, 15–18 Sept 2009, ACM, Bonn, Germany
6. Intille SS, Rondoni J, Kukla C, Ancona I, Bao L (2003) A context-aware experience sampling tool. In: Proceedings of human factors in computing systems (CHI 03), ACM, New York, USA, pp 972–973
7. Yin J, Yang Q, Pan JJ (2008) Sensor-based abnormal human-activity detection. IEEE Trans knowl Data Eng 20(8):1082–1090
8. Raento M, Oulasvirta A, Eagle N (2009) Smartphones: an emerging tool for social scientists. Sociol Method Res 37:426–454
9. Pantelopoulos A, Bourbakis NG (2011) A survey on wearable sensor-based systems for health monitoring and prognosis. IEEE Trans Syst Man and Cyber 41(1):1–12
10. Asada HH, Shaltis P, Reisner A, Rhee S, Hutchinson RC (2003) Mobile monitoring with wearable photoplethysmographic biosensors. IEEE Eng Med Biol Mag 22(3):28–40
11. Budinger TF (2003) Biomonitoring with wireless communications. Annu Rev Biomed Eng 5:383–412
12. Sun L, Zhang D, Li B, Guo B, Li S (2010) Activity recognition on an accelerometer embedded mobile phone with varying positions and orientations. Lect Notes Comput Sci 6406:548–562
13. Aminian K, Robert P, Buchser E, Rutschmann B, Hayoz D, Depairon M (1999) Physical activity monitoring based on accelerometry: validation and comparison with video observation. Med Biol Eng Comput 37(1):304–308
14. Hicks J, Ramanathan N, Kim D, Monibi M, Selsky J, Hansen M, Estrin D (2010) AndWellness: an open mobile system for activity and experience sampling. In Proceedings of wireless health 2010 academic and research conference, La Jolla, CA, 5–7 Oct 2010 (WH '10). ACM, New York, USA
15. Hektner JM, Schmidt JA, Csikszentmihalyi M (2007) Experience sampling method: measuring the quality of everyday life. Sage, Thousand Oaks
16. Reis HT, Gable SL (2000) Event-sampling and other methods for studying everyday experience. In: Reis HT, Judd CM (eds) Handbook of research methods in social and personality psychology. Cambridge University Press, New York, pp 190–222
17. Wheeler L, Reis HT (1991) Self-recording of everyday life events: origins, types, and uses. J Pers 59:339–354
18. Shiffman S, Stone AA, Hufford MR (2008) Ecological momentary assessment. Annu Rev Clin Psychol 4:1–32
19. Moskowitz DS, Young SN (2006) Ecological momentary assessment: what it is and why it is a method of the future in clinical psychopharmacology. Journal Psychiatry Neurosci 31(1):13–20
20. Barge-Schaapveld DQ, Nicolson NA (2002) Effects of antidepressant treatment on the quality of daily life: an experience sampling study. J Clin Psychiatry 63(6):477–485
21. Barrett LF, Barrett DJ (2001) An Introduction to computerized experience sampling in psychology. Soc Sci Comput Rev Summer 19(2):175–185
22. Froehlich J, Chen MY, Consolvo S, Harrison B, Landay JA (2007) MyExperience: a system for in situ tracing and capturing of user feedback on mobile phones. MobiSys '07. ACM, New York, USA, pp 57–70
23. Khan VJ, Markopoulos P, Eggen B (2009) Features for the future Experience Sampling Tool. In: Proceedings of MobileHCI '09, 15–18 Sept 2009, ACM, Bonn, Germany
24. Berntson GG, Cacioppo JT (2004) Heart rate variability: stress and psychiatric conditions. In: Malik M, Camm J (eds) Dynamic electrocardiography. Wiley-Blackwell, Hoboken, pp 57–64
25. Kimhy D, Delespaul P, Ahn H, Cai S, Shikhman M, Lieberman JA, Malaspina D, Sloan RP (2010) Concurrent measurement of "real-world" stress and arousal in individuals with psychosis: assessing the feasibility and validity of a novel methodology. Schizophr Bull 36(6):1131–1139
26. Pan J, Tompkins WJ (1985) A real-time QRS detection algorithm. IEEE Trans Biomed Eng 32:230–236
27. Jönsson P (2007) Respiratory sinus arrhythmia as a function of state anxiety in healthy individuals. Int J Psychophysiol 63(1):48–55
28. Jönsson P, Hansson-Sandsten M (2008) Respiratory sinus arrhythmia in response to fear-relevant and fear-irrelevant stimuli. Scand J Psychol 49(2):123–131
29. Sloan RP, Shapiro PA, Bagiella E, Boni SM, Paik M, Bigger JT Jr, Steinman RC, Gorman JM (1994) Effect of mental stress throughout the day on cardiac autonomic control. Biol Psychol 37:89–99
30. Jacobs N, Myin-Germeys I, Derom C, Delespaul P, van Os J, Nicolson NA (2007) A momentary assessment study of the relationship between affective and adrenocortical stress responses in daily life. Biol Psychol 74:60–66
31. Larson RW, Delespaul P (1992) Analyzing Experience Sampling data: a guide book for the perplexed. In: de Vries MW (ed) The

experience of psychopathology. Cambridge University Press, New York, pp 58–78
32. Mateo J, Laguna P (2003) Analysis of heart rate variability in the presence of ectopic beats using the heart timing signal. IEEE TransBiomed Eng 50(3):334–343
33. Malik M, Bigger JT, Camm AJ, Kleiger R, Malliani A, Moss A et al (1996) Task force of the European society of cardiology and the North American society of pacing and electrophysiology, heart rate variability: standards of measurement, physiological interpretation, and clinical use. Circulation 93(5):1043–1065