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Research Article

Computerized experience-sampling approach for real-time assessment of stress

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Abstract

The incredible advancement in the ICT sector has challenged technology developers, designers, and psychologists to reflect on how to develop technologies to promote mental health. Computerized experience-sampling method appears to be a promising assessment approach to investigate the real-time fluctuation of experience in daily life in order to detect stressful events. At this purpose, we developed PsychLog (http://psychlog.com) a free open-source mobile experience sampling platform that allows psychophysiological data to be collected, aggregated, visualized and collated into reports. Results showed a good classification of relaxing and stressful events, defining the two groups with psychological analysis and verifying the discrimination with physiological measures. Within the paradigm of Positive Technology, our innovative approach offers for researchers and clinicians new effective opportunities for the assessment and treatment of the psychological stress in daily situations.

Keywords: experience-sampling method, pervasive computing, psychological stress, psychophysiology, heart rate variability.

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1. Introduction

The incredible enhancements in the field of Information and Communication Technologies (ICTs) are dramatically affecting our daily individual and social life. Nowadays, the technological progress has enabled the development of devices that are not only increasingly sophisticated, but also low-cost and user-friendly. As recently suggested by Riva and Colleagues [1], the advancement in the ICT sector has challenged technology developers, designers, and psychologists to reflect on how to develop technologies to promote mental health. In this perspective, Positive Psychology appears to be a promising framework to develop ICTs that foster positive emotions, promote engagement in empowering activities and support connectedness between individuals, groups, and communities to social and cultural development. Indeed, Positive Psychology is the scientific study of well-being to understand human strength and virtues and to promote them to allow individuals, communities, and societies to thrive [2-6]. This progressive convergence between the objectives of Positive Psychology with enhancements of ICTs has led toward a new paradigm, namely Positive Technology. Positive Technology is an emerging discipline that could be defined as the scientific and applied approach to the use of advanced technology for improving the quality of our personal experience [1,7]. Within this framework, self-tracking appears to be a fast-growing trend in the field of e-health that consists in the "regular collection of any data that can be measured about the self such as biological, physical, behavioral or environmental information. Additional aspects may include the graphical display of the data and a feedback loop of introspections and self-experimentation" [8]. This approach is enabled by the fecund convergence between ICTs and wearable biosensors, which allow personal health data to be collected, aggregated, visualized, collated into reports and

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shared [9]. Self - tracking is rooted into the experience sampling approach, originally a paper-and - pencil methodology developed by Csikszentmihalyi and Larson [10]. As underlined by Ebner-Priemer and Trull [11], different terms have been used to refers to real-time assessment of psychophysiological data: Ambulatory Assessment [12-14], Ecological Momentary Assessment [15], Experience Sampling Method [16], Real-Time Data Capture [17], and Day Reconstruction Method [18]. These assessment methodologies, although arose from different research paradigms, have in common the continuous recording of psychological and physiological data or indices of behavior, cognition or emotions in the daily life of individuals. Barrett and Barrett [19] effectively defined real-time assessment procedure as a "window into a daily life" since participants provide self-reports of their momentary thoughts, feelings and behavior across a wide range of daily situations in ecological contexts. This approach appears particularly promising for the assessment of psychological stress. Assessing and monitoring emotional, cognitive and behavioral dimensions of human experience, both in laboratory and in natural setting, in fact, have a crucial role in the research and treatment of psychological stress.

According to Cohen and Colleagues [20], "Psychological Stress" occurs when an individual perceives that environmental demands tax his/her adaptive capacity. In this perspective, stressful daily experiences could be conceptualized as a continuous person-environment transaction [21,22]. Every day, in fact, individuals are continually invited to deal with several situations or circumstances (for example, being fired from work or having trouble with parents or partner) that provoke anxiety and psychological discomfort. In this perspective [20-22], a stressful event [23,24] occurs when a person isn't able to effectively cope with a challenge that is perceived to exceed his/her skills. Physiological measures can also give further information to a psychological definition of stress, but there are still few studies, above all in everyday situations, considering the relation between these two dimensions.

To accurately analyze real-time interaction between environmental demands and individual adaptive capacity and to precisely detect stressful events during the daily life situations, it is fundamental to use a real-time multimodal assessment.

As above described, recent progress in biosensor technology and, on the other hand, the incredible diffusion of ICTs have led to ubiquitous and unobtrusive recorder systems that allow naturalistic and multimodal assessment [9,19,25-27].

Computerized experience sampling method comprising a mobile-based system that collects psychophysiological data appears to be a very promising assessment approach to investigate the real-time fluctuation of experience in everyday life in order to detect stressful events.

At this purpose, we developed PsychLog (http://psychlog.com) a free open-source mobile experience sampling platform that allows psychophysiological data to be collected, aggregated, visualized and collated into reports [28,29]. Our mobile-based system collects physiological data from a wireless wearable electrocardiogram equipped with a three-axial accelerometer. Moreover, the application allows administering self-report questionnaires [30] to collect and investigate participants' feedback on their daily experience in its various cognitive, affective and motivational dimensions.

In this study, we proposed and tested the use of PsychLog to investigate the fluctuation of experience during a week of observation and to detect, on the basis of psychophysiological real-time assessment, both stressful and relaxing events that normally occur during daily activities in ecological contexts.

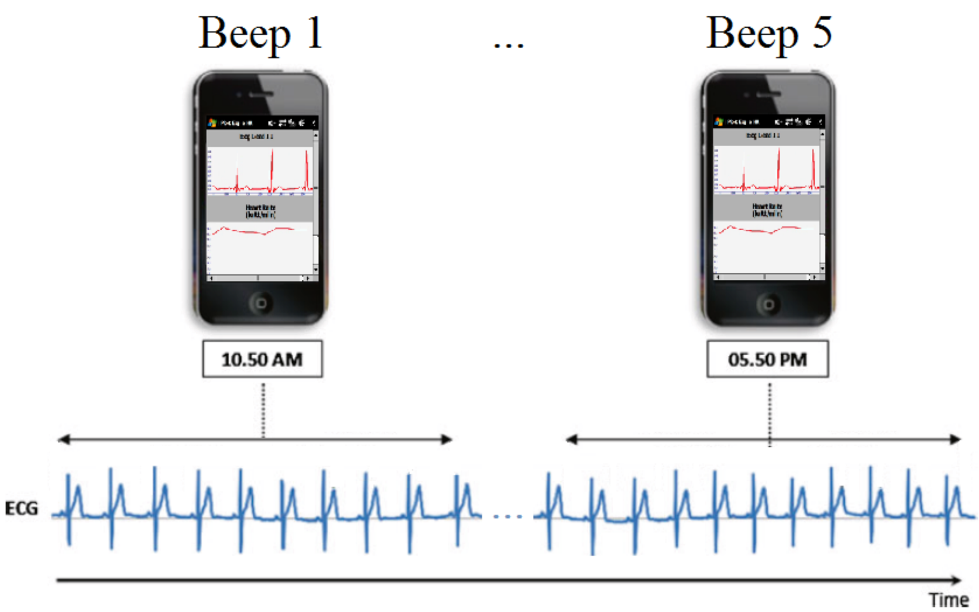

Figure 1. PsychLog: The sensing computing and visualization modules

2. Materials and methods

2.1. Participants

Participants were six healthy subjects (2 males and 4 females, mean age 23) recruited through opportunistic sampling. Participants filled a questionnaire assessing factors that might interfere with the psychophysiological measures being assessed (i.e. caffeine consumption, smoking, alcohol consumption, exercise, hours of sleep, disease states, medications). Written informed consent was obtained by all participants matching inclusion criteria (age between 18-65 years, generally healthy, absence of major medical conditions, completion of informed consent).

2.2. Tools

In our study we used PsychLog (http://psychlog.com), a mobile experience sampling platform that allows the collection of psychological, physiological and activity information in naturalistic settings [28,29]. The system consists of three main modules.

The survey manager module allows configuring, managing and administering self-report questionnaires. Triggers can be launched with a fixed schedule or randomly during a day.

The sensing/computing module allows continuously monitoring heart rate and activity data acquired from a wireless electrocardiogram (ECG) equipped with a three-axis accelerometer. The wearable sensor platform (Shimmer Research™) includes a board that allows the transduction, the amplification and the pre-processing of raw sensor signals, and a Bluetooth transmitter to wirelessly send the processed data. 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) can be fully tailored to the study's design.

During each epoch, signals are sampled at 250 Hz and filtered to eliminate common noise sources using Notch filter at 0 Hz and low pass at 35 Hz and analogue-to-digital converted with 12-bit resolution in the ±3 V range. The application extracts QRS peaks through a dedicated algorithm and R-R intervals [31,32]. These intervals are then transformed to a tachogram, i.e. the series of R-R intervals durations as a function of the interval number.

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.

Psychological and physiological 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.

In this study, we used standard smartphone (Samsung Omnia II i8000) equipped with 32 bit CPU, ARM 11 RISC processor (cache 16KB) 667 MHz, RAM 256 MB, 1500 mAh Lithium ion battery, running the operative system Windows mobile 6.5.

PsychLog platform implementation, architecture, and technical aspects were discussed further in a previous research [33].

2.3. Procedure

Participants were provided with a short briefing about the goal 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. Subjects were asked to wear biosensor for one week of observation. PsychLog was pre-programmed to beep randomly 5 times a day each day (between 10 AM and 10 PM) to elicit at least 35 experience samples over the 7-days assessment period. 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 and thanked for their participation.

2.4. Psychological Assessment

Psychological stress was measured by using a digitalized version of an ESM survey adapted from that used by Jacobs and Colleagues [28,30] for studying the immediate effects of stressors on mood. The self-assessment questionnaire included open-ended and closed-ended questions (rated on on 7-point Likert scales) investigating thoughts, current context (activity, people, location, etc.), appraisals of the ongoing situation, and mood. Following the procedure suggested by Jacobs and Colleagues [30], three different scales were computed in order to identify the stressful qualities of daily 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 = 0.699). 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 = 0.497). For Event-Related Stress (ERS), subjects reported the most important event that had happened since the previous beep. Participants then rated this event on a 7-point scale (from – 3 very unpleasant to 3 very pleasant, with 0 indicating a neutral event). All positive responses were coded as 0, and the negative responses were coded so that higher scores were associated with more unpleasant and potentially stressful events (0 neutral, 3 very unpleasant).

In addition to those scales (not included in the original survey), we introduced an item asking participants to rate the perceived level of stress (STRESS) on a 10-point Likert scale. In particular, to rate the gap between challenge and skills, we used two specific items: (1) an item assessing the perceived level of ongoing challenge (CHALLENGE) on 7-point Likert; (2) an item evaluating the perceived level of skills (SKILLS) on 7-point Likert.

2.5. Activity

ECG biosensors used by PsychLog application has also an integrated three-axial accelerometer.

This accelerometer permits the computation of activity indexes used to establish the macro movements of a subject during the recording of ECG. It is useful, for example, to avoid to detect signals when she/he is running.

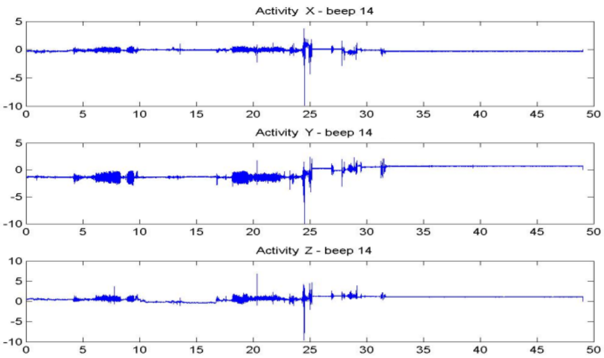

Figure 1. Raw signal from accelerometer.

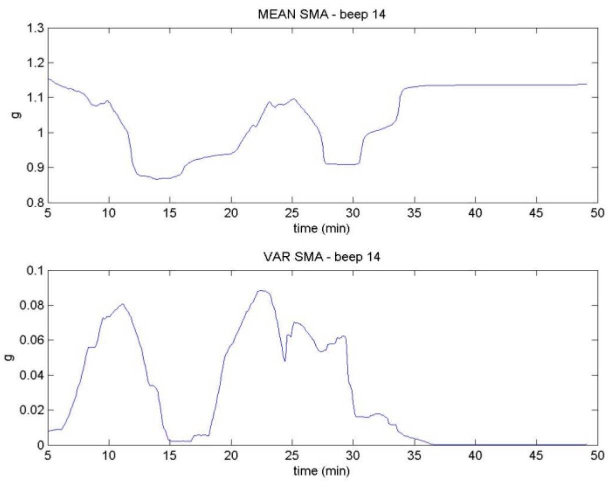

Figure 2. Mean and variance values of SMA index related to the previous five minutes of activity.

SMA index [34,35], in particular, has been calculated in order to establish when subject was not in movement. In this way, we calculated ECG indexes, avoiding the periods in which the subject was running, walking, or also moving too much (figure 1 and 2).

Signal-magnitude area (SMA) is calculated according to:

$$SMA = \sum_{i=1}^{n} (|x(i)|) + (|y(i)|) + (|z(i)|). \quad \textbf{(1)}$$

where x(i), y(i), and z(i) indicate the acceleration signal along the x-axis, y-axis, and z-axis, respectively.

2.6. Cardiovascular indexes

Cardiovascular activity is monitored to evaluate both voluntary and autonomic effect of respiration on heart rate, analyzing R-R interval from electrocardiogram. Furthermore standard HRV spectral methods indexes and similar have been used to evaluate the autonomic nervous system response [36].

From ECG each QRS complex is detected, and the normal-to-normal (NN) intervals (all intervals between adjacent QRS complexes resulting from sinus node depolarisations) are determined to derive the most common temporal measures, including RMSSD, the square root of the mean squared differences of successive NN intervals, and NN50, the number of interval differences of successive NN intervals greater than 50 ms [36]. In general, RMSSD are estimate of short-term components of heart rate variability.

This experiment aimed at testing the feasibility of monitoring concurrent stress and physiological arousal within subjects' typical daily environments and activities. Previous works have shown that psychological stress is associated with an increase in sympathetic cardiac control, a decrease in parasympathetic control, or both [31,32]. Associated with these reactions is a frequently reported increase in low frequency (LF, range between 0.04-0.15 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) [31,32,36]. 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) [36].

Although the time domain methods, especially RMSSD method, can be used to investigate recordings of short durations, the frequency methods are usually able to provide results that are more easily interpretable in terms of physiological regulations [36].

Spectral analysis has been performed by means of autoregressive (AR) spectral methods with custom software. The AR spectral decomposition procedure has been applied to calculate the power of the oscillations embedded in the series.

The rhythms have been classified as very low frequency (VLF, <0.04 Hz), low-frequency (LF, from 0.04 to 0.15 Hz) and high frequency (HF, from 0.15 to 0.5 Hz) oscillations.

The power has been expressed in absolute ($LF_{RR,}$ and HF_{RR}) and in normalized units. For example RR series: LF_{nu} and HF_{nu} as 100 * LF_{RR} / (σ^2_{RR} - VLF_{RR}) and 100 * HF_{RR} / (σ^{2}_{RR} - VLF_{RR}), where σ^2_{RR} represents the RR variance and VLF_{RR} represents the VLF power expressed in absolute units [31,32,36].

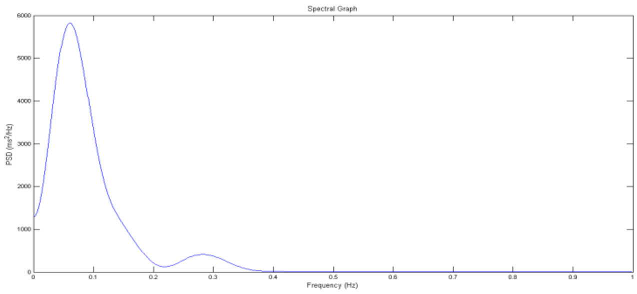

Figure 3. LF (in the range 0.04 - 0.15) is the first slope and HF (in the range 0.15 - 0.4) is the second slope. This is the typical situation of a stressed subject.

3. Data analysis

In order to detect both stressful and relaxing events, Activity-Related Stress Scale (ARS), Social Stress Scale (SS), Perceived Stress Scale (STRESS), Challenge Scale (CHALLENGE) and Skill Scale (SKILLS) were within-subjects standardized. Event-Related Stress Scale wasn't standardized so it was classified as follows: 0 = no stress; 1= low stress; 2 = medium stress; 3 = high stress.

We proposed the classification in Table 1 to define stressful and relaxing events.

Table 1. Classification of relaxing and stressful events

		Value
STRESS	Zscore(STRESS)	> 1
	Zscore(ARS)	> 1
	Zscore (SS)	> 1
	ERS	> 1
	Zscore(CHALLENGE) & Zscore(SKILLS)	> 1 & < - 1
RELAX	Zscore(STRESS)	< - 1
	Zscore(ARS)	< - 1
	Zscore (SS)	< - 1
	ERS	= 0
	Zscore (CHALLENGE) & Zscore (SKILLS)	< - 1 & > 1

Hierarchical structure of the experiment data makes traditional forms of analysis unsuitable. Subjects are measured at many time points during each day, across seven days. Traditional repeated-measures designs require the same number of observations for each subject and no missing data. Multilevel models are appropriate to analyze such data above all because the existent dependencies due to repeated measurements are included in the parameter estimates. Moreover, also other dependencies existing in the data can be taken into account.

Because the ESM entries are nested within seven days within participants, we estimated the psychophysiological indexes on events (Relax or Stress), with hierarchical linear analysis, an alternative to multiple regression suitable for our nested data. We referred to two levels in the model: beep-level and subject-level. Our model was based on binary logistic, specifying Binomial as the distribution and Logit ($f(x)=\log(x / (1-x))$) as the link function.

Using a mixed hierarchical model we inferred the dichotomised event (Relax or Stress) on the basis of physiological parameters. In this sense we used these indexes to predict relax or stress condition indicated by subjects. The analysis aimed at finding statistically significant parameter for the estimation of a model designed to predict relaxing and stressful events. More, a linear discriminant analysis (LDA) has been used to verify if a set of physiological measures (RMSSD, NN50, and HF Power) was able to discriminate between the two groups (Relax and Stress).

4. Results

The six participants completed a total of 213 ESM reports. Aggregated over participants' means, mean Perceived Stress was 2.99 (S.D. = 1.50), mean Activity-Related Stress was 3.35 (S.D. = 0.72), mean Social Stress was 3.34 (S.D. = 1.40), mean Challenge was 2.99 (S.D. = 1.92), mean Skills was 4.58 (S.D. = 1.86), and frequencies for Event-Related Stress was: 88% no stress, 4.2% low stress, 3.1% medium stress, and 4.7% high stress.

A total of 31 events (14.55 % of total events) have been identified, 18 relax events (8.45 %) and 13 stress events (6.10 %) among the six subjects. For each one of these events we calculated two temporal HRV indexes, namely RMSSD and NN50, and one spectral HRV index, i.e. HF power.

In Table 2, means and standard deviations are reported per each index on the basis of events' group (Relax or Stress).

A linear discriminant analysis (LDA) has been used to verify if the physiological indexes (RMSSD, NN50, and HF Power) were able to discriminate between the two groups (Relax and Stress) defined on the basis of the questionnaires, as above defined. Tests of equality of group means are showed in table 3. More, results showed a 0.622 Wilks' Lambda (Chi-square: 13.070, df: 3, $p < .005$) with 77.4% of original grouped cases correctly classified (see table 4).

Table 2. Group Statistics

		Mean	Std. Deviation	Valid N (listwise)
RELAX	Zscore(RMSSD)	.2175527	.78903922	18
	Zscore(NN50)	.3686125	.80597461	18
	Zscore(HF_pwr)	.4263368	.81428263	18
STRESS	Zscore(RMSSD)	-.4225023	.73893069	13
	Zscore(NN50)	-.5293378	.62354657	13
	Zscore(HF_pwr)	-.5657602	.57913531	13
TOTAL	Zscore(RMSSD)	-.0508575	.82114721	31
	Zscore(NN50)	-.0079473	.85235392	31
	Zscore(HF_pwr)	.0102961	.87036922	31

Table 3. Tests of equality of group means

	Wilks' Lambda	F	df1	df 2	Sig.
Zscore(RMSSD)	0.847	5.233	1	29	0.03
Zscore(NN50)	0.721	11.236	1	29	0.002
Zscore(HF_pwr)	0.673	14.085	1	29	0.001

Table 4. Classification Results. Overall, 77.4% of original grouped cases correctly classified

	Condition	Predicted Group Membership: Relax	Predicted Group Membership: Stress	Total
Original	Relax	72.2 %	27.8 %	100.0 %
	Stress	15.4 %	84.6 %	100.0 %

As explained in data analysis, because the ESM entries are nested within seven days within participants, we estimated the psychophysiological indexes on events (Relax or Stress), with hierarchical logistic analysis, an alternative to multiple logistic regression suitable for our nested data. Results show, a statistical significant hierarchical regression model for RMSSD (Beta: 1.177; St. Dev.: .5839; $p < .044$), and a quasi statistical significant for HF power (Beta: .888; St. Dev.: .4612; $p < .055$). The RMSSD method is preferred to NN50 because it has better statistical properties [36].

5. Discussions and Conclusion

Recent progress in the sophistication and feasibility of biosensor technology and the remarkable spread of ICTs have led to ubiquitous and unobtrusive recorder systems that allow naturalistic and multimodal assessment of psychophysiological parameters [19,25,26]. Computerized experience sampling method comprising a mobile-based system that collects psychophysiological data seems to be a very promising assessment approach to investigate the real-time fluctuation of the quality of experience in daily contexts. Since psychological stress could be defined as a continuous person-environment transaction [20-22], this integrated and mobile assessment offers the opportunity to analyze the real-time interaction between challenges and skills occurring in daily life situations.

In this study, we proposed and tested the use of PsychLog [28] (http:// psychlog.com) a free open-source mobile experience sampling platform, aggregated, visualized and collated into reports, to investigate the fluctuation of individual' experience [16,29] and to detect, on the basis of psychophysiological real-time assessment, stressful events that normally occur during daily activities and situations.

Analysis has been set selecting two events groups (Relax and Stress) on the basis of psychological questionnaires. Then, an hierarchical logistic analysis, an alternative to multiple logistic regression suitable for our nested data and a discriminant analysis between the two groups, showed that physiological measures have been able to predict the groups selected on psychological basis. These results seem to indicate that a relation between physiological patterns and psychological behavior exists. Being true these results, we would be able to predict particular events on physiological basis, i.e. without having to ask subjects about their own states.

Within the paradigm of Positive Technology, our innovative approach offers for researchers and clinicians new effective opportunities for the assessment and treatment of psychological stress in daily environments.

The advantages in using a mobile psychophysiological stress assessment are potentially several: (a) it is possible to evaluate the continuous fluctuation of the quality of experience in ecological contexts; (b) it is possible to schedule the timing and the modality of psychophysiological monitoring; (c) it allows a multimodal assessment, comprising psychological, physiological, behavioral and contextual data; (d) it permits the detection of stressful events in daily life; and (e) it provides the opportunity of giving immediate, graphical and user-friendly feedback. In this perspective, a mobile self-tracking could be conceived as a persuasive technology [37] that allows individuals to accurately monitor their mental health and check their progress with encouraging and motivating feedback enhancing self-efficacy [38].

Finally, as a consequence of the detection of a stressful event, PsychLog may offer the chance to deliver real-time and effective Ecological Momentary Interventions [39-41] or a mobile biofeedback training [27,42] to provide real-time support for mental health in the natural context, when it is most needed. In conclusion, as for any new tools, much more research is necessary to evaluate our approach.

Acknowledgements.

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