Pervasive Persuasion for Stress Self-Regulation

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***Abstract*—This article reports on coupled smartwatch and smartphone pervasive apps enabling stress self-regulation. Stress, the physiological responses of an organism to demanding conditions, can be both beneficial and harmful. Beneficial stress, or eustress, enhances physical or mental abilities while harmful stress, or distress, can result in reduced abilities, anxiety, or depression. Pervasive computing enables stress self-regulation, that is, the ability to benefit from eustress while avoiding, or limiting, distress. This article first reports on Stila Computed Stress, a stress estimate computed after an original model from pulse rates delivered by smartwatches. It then describes how Stila Computed Stress is combined with users' activity reports and pervasively delivered on their smartwatches and smartphones. It further reports on a real life evaluation pointing to the pervasive apps' persuasiveness, that is, their capacity to enhance stress self-regulation.**

***Index Terms*—Computed Stress, Smartwatch, Fitness Tracker, Heart Rates, Behavior Change, Pervasive Computing**

I. Introduction

This article reports on the Stila smartwatch and smartphone apps that collect pulse rates and activity reports from their users, compute from the pulse rates stress estimates using the original model Stila Computed Stress, and deliver activity-related stress estimates thus enabling the apps' users to better regulate their stress.

Stress [1], the manifold physiological responses of an organism such as increased energy and raised attention to demanding conditions, can be beneficial in which case it is called eustress. Eustress enhances physical or mental abilities like an acute attention and strengthens the resilience of students passing examinations [2]. Stress can also be harmful, in which case it is called distress. Distress often results in reduced abilities, anxiety, or withdrawal behaviors commonly referred to as depression [3]–[5].

Stress self-regulation is the highly desirable ability to benefit from eustress while avoiding, or limiting, distress. Stress self-regulation, like other abilities, must be learned, especially by people confronted with new tasks and new responsibilities like students. This article reports on a research exploiting the potential of pervasive computing to enable stress self-regulation. The research has been motivated by an observed need among students for a better stress self-regulation: 49% of high school students, especially female students, have reported continuous or high stress [6].

The standard approaches to stress detection rely on electrocardiography (ECG), galvanic skin response (GSR) and accelerometers to detect stress with dichotomous outputs [7]–[9]. They require many sensors what make them invasive and sometimes even obtrusive: They cannot be applied in everyday life and are therefore hardly appropriate for stress self-regulation. Furthermore, their heavy equipment may turn them into stressors. There is therefore a need for non-invasive, non-obstructive and pervasive stress detection methods.

Computed stress [10] denotes a stress estimate computed from limited physiological data, typically heart rate variability (HRV) [11]. HRV has been shown to be a convenient basis for computed stress [10]. Many studies have been devoted to specifying and investigating various HRV-based computed stress models referring to heart rate changes over time or to changes in heart rate frequencies. These models mostly rely on linear or non-linear features [12]–[15]. Unfortunately, heart rates can so far not be measured in a non-invasive manner.

Wrist-worn fitness trackers and smartwatches with photoplethysmography (PPG) sensors are promising for a non-invasive stress detection because they rely on passive sensing for providing pulse data that can be exploited for analyzing heartbeat intervals. Photoplethysmography (PPG) and Pulse Rate Variability (PRV) have been shown to be reliable alternatives to HRV for healthy subjects [16].

This article first describes the Stila Computed Stress model that uses PRV pervasively collected through PPG with fitness trackers and smartwatches. It further describes how Stila Computed Stress estimates have been combined with users' activity reports and pervasively delivered to the users using the original coupled Stila smartwatch and smartphone apps (http://stila.pms.ifi.lmu.de) designed after the principles of persuasive systems: Self-monitoring, simulation, reduction, tailoring, personalization, and tunneling [17]. This article finally reports on a real life evaluation of the pervasive Stila apps involving 86 participants over 15 days. A first group of 43 participants used only the Stila smartphone app while a second group of 43 participants used both the Stila smartphone app and the Stila smartwatch app. The main finding of the evaluation is the persuasiveness in the sense of the capacity to enhance stress self-regulation of the pervasive apps: The participants using both the smartwatch and the smartphone apps were significantly more engaged than the participants using only the smartphone application ($p = 0.01$).

The original contributions of this article are as follows:

- Stila Computed Stress, an original stress estimate

- The coupled pervasive Stila smartwatch and smartphone apps that pervasively inform on stress levels
- A real life evaluation pointing to the persuasiveness of the pervasive Stila apps

This article is structured as follows. Section I is this introduction. Section II is devoted to related work. Section III describes Stila Computed Stress. Section IV presents the Stila smartwatch and smartphone apps. Section V reports on a real life evaluation of the Stila apps. Section VI is devoted to the evaluation's findings. Section VII is a conclusion.

II. Related Work

The research reported about in this article is related to stress estimates from heart and pulse rates, pervasive stress monitoring, persuasive computing for behavior change, persuasive mobile applications, and addiction to pervasive devices or apps.

a) Stress Estimates From Heart and Pulse Rates: Heart rate variability (HRV) is the fluctuation over time of heartbeat intervals. HRV expresses the strength of the autonomic nervous system, more precisely of the sympathetic and parasympathetic nervous systems, at a given time: A lower (higher, resp.) value in HRV indicates a higher (lower, resp.) stress level [11]. PRV has been shown to be a reliable alternative to HRV for healthy subjects [16]. HRV scores refer to the following parameters:

- NN or RR: Time between two successive heart beats
- meanRR: Average of RR (or NN) over a time span
- RMSSD: Root of the mean square of the difference of successive NN (or RR)
- SDNN: Standard deviation of NN (or RR)
- NN50: Number of pairs of successive NN (or RR) differing by more than 50 ms
- pNN50: Proportion of NN50 over a time span divided by the total number of NN (or RR) in that time span

Using a mental sensor measuring artificially imposed stress Taelman et al. [18] observed that pNN50 and meanRR are lower when mental tasks are performed than during rest.

Li et al. [19] estimated stress with 89% accuracy during mental arithmetic task using PPG raw data collected from Huawei Watch 2 smartwatches. Their approach consists in deriving PRV in 1.5 min intervals, in using an elastic net based on a differential feature vector and the subjective stress reported by the subjects, and in assuming a linear dependency between the pulse variability differential and the stress level differential of a subject.

b) Pervasive Stress Monitoring: Egilmez et al. [9] designed the UStress system for investigating the subjective stress of college students using both pervasive custom-made wrist-worn and pervasive LG Urbane 2 smartwatches measuring the galvanic skin response (GSR) and pulse rates at a 5 Hz sampling rate. Invasive chest-band Polar H7 and GSR sensors were used to verify the accuracy of the stress estimates computed from pervasive GSR and pulse rate data. In a laboratory study with 9 participants, stress was shown to be accurately detected using the pervasive devices collecting GSR and pulse rate data (F-measure of 88.8%).

StudentLife [20] is an Android smartphone app estimating its users' stress from the correlation between continuous smartphone sensing and self-reported stress and mood. The smartphone sensors used by StudentLife are the accelerometer, the microphone, the light sensor, and the GPS locator. A field study with StudentLife has shown that students having more frequent and longer conversations at day time are less likely to feel stressed.

Elite HRV [21] is a smartphone app which relies on a chest strap (like Polar H10 HRM) for computing HRV scores. It helps athletes to reach their optimal training intensity. Note that a chest strap is invasive and inappropriate in everyday life.

Health apps for smartwatches (mostly provided by the smartwatch vendors, like Samsung S Health, LG Health, and Apple Health) also provide stress estimates. To the authors' knowledge, so far neither the computed stress model of these apps has been disclosed, nor studies on the models' accuracies have been published.

c) Persuasive Computing For Behavior Change: Fogg defines in [22] a persuasive technology as "any interactive computing system designed to change people's attitudes or behaviors" as well as the three roles that computers can take: Tool, media, and social actor.

Torning and Oinas-Kukkonen provide in [23] an overview on the design of persuasive systems based on the systems developed between 2006 and 2008. Tailoring, tunneling, reduction and social comparison are reported in this overview as the most widespread forms of persuasion technique. Oinas-Kukkonen and Harjumaa stress in [17] the aspects of process model and system features that are key in designing persuasive systems.

Fogg introduces in [24] the behavior model FBM for persuasive design which considers three principal factors: Motivation, ability, and triggers. FBM states that increasing the motivation or the ability of an individual with a trigger event at an appropriate time point is likely to result in this individual adopting the target behavior.

O'Brien suggests in [25] to see user engagement as "a quality of user experiences with technology" and proposes a Process of Engagement that users go through while using a technological artefact. Long-term engagement is especially significant for persuasive wearables since behavior changes can be lengthy processes. Ledger and McCaffrey identify in [26] three key factors towards improving users' long-term commitment to wearables and the services they provide and stress that wearables should encourage the formation of habits of sustained engagement. Such a formation can take place thanks to triggers on the wearable that remind their users of adopting a certain behavior.

d) Persuasive Mobile Applications: Affective Health is a mobile system aiming at relating its users' daily activities with their memories and with their subjective stress. It detects certain bodily reactions and visualized them on smartphones.

In a Wizard of Oz experiment conducted in laboratory, visualizations of stress feedback were investigated that aim at causing no additional stress [27]. The experiment's findings are that feedback visualizations leaving interpretations open, stress retrospectives, and an updatable feedback are desirable.

Several studies have investigated the impact of engagement on behavior change. Consolvo et al. [28] report on increasing users' engagement via goal setting with a cellphone software so as to encourage individuals to increase their physical activity. Dennison et al. [29] report that the ability to track behaviors, to set goals, and to get advices and information "on the go" are desirable features of apps fostering health-improving behavior changes.

Ashbrook et al. report in [30] on an investigation of the impact on device access time with both stored in pocket and on-body devices. They report that 78% of the total reaction time is spent only for reaching in-pocket devices.

e) Addiction to Pervasive Devices or Apps: Van Deursen et al. report in [31] on the influence of usage types, emotional stress, social stress, self-regulation, age, and gender on an addictive smartphone use and that an habitual smartphone use is an important contributor of addictive smartphone behaviors and that a process-related smartphone use is a strong determinant for developing both a habitual and an addictive smartphone use.

Elliot et al. report in [32] that the more participants pursue avoidance goals, the higher the decrease in their subjective well-being. An avoidance goal is a goal like "avoid distress" or "don't drink alcohol" which expresses an interdiction.

III. Stila Computed Stress: A Pervasively Computed Stress Estimate

The Stila smartphone app uses either a Fitbit fitness wristband with a continuous pulse tracking or a Wear OS by Google smartwatch equipped with the Stila watch app as pulse rate providers.

The pulse rate stream is preprocessed into 10 min intervals starting at the beginning of each day. A stress estimate is computed for each of these intervals. RMSSD (defined above in the section II1) is used as an approximation of HRV/PRV (see Section II1). The rational is that RMSSD, in contrast to other HRV measures such as pNN50, can be considered robust against noise and missing data because it expresses the cumulative differences between the time points of consecutive heartbeats.

The following equations, where T is a scaling constant (T = 20), C_{pop} is a translating constant, and $\widehat{X}$ denotes an estimate of a variable X, define Stila Computed Stress, short SCS:

$$\widehat{RR}_i = 60/PR_i \tag{1}$$

$$\widehat{RMSSD} = \sqrt{\frac{\sum_{i=1}^{n}(\widehat{RR}_i - \widehat{RR}_{i-1})^2}{n-1}} \tag{2}$$

$$HRV_{\text{Score}} = ln(\widehat{RMSSD} \times 10^3) \times T \tag{3}$$

$$SCS = C_{pop} - HRV_{\text{Score}} \tag{4}$$

These equations are explained as follows:

(1) converts a pulse rate (PR_i) at time i into an estimate of RR_i.

(2) gives an estimate of RMSSD. n is the number of pulse rates in the time interval considered.

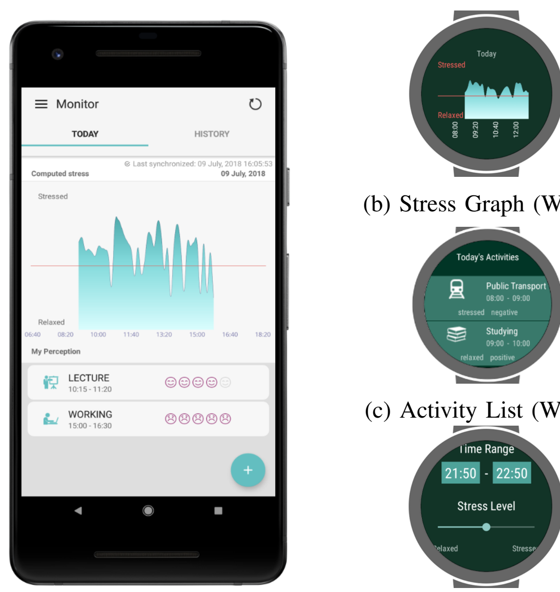
(3) derives a HRV score from $\widehat{RMSSD}$. T is a constant ($T = 20$) upscaling the values of HRV_{Score} to the range 10-110.

(4) specifies Stila Computed Stress (SCS). C_{pop} is a constant ($C_{pop} = 110$) shifting the SCS values in the range 0-100. A low (high, resp.) HRV_{Score} yields a high (low, resp.) SCS.

In short, Stila Computed Stress is obtained by a linear transformation of a RMSSD estimate computed from RR estimates derived from pulse rates.

IV. The Stila Smartwatch and Smartphone Apps User Interfaces

The Stila smartwatch and smartphone apps have two purposes: To inform their users on their stress (by displaying their Stila Computed Stress) and to collect from their users activity reports (so as to relate stress and activities). The apps aim at fostering stress awareness so as to foster stress self-regulation.



(a) Stress Graph (Phone) (b) Stress Graph (Watch) (c) Activity List (Watch) (d) Reporting an Activity

Fig. 1: Stila's Stress Information and Activity Reporting

a) Phone App: Figure 1a first shows the Stila Computed Stress graph: The horizontal axis is a time line and the vertical axis gives the computed stress observed for every 10 min interval. The horizontal red line indicates a computed stress value of 50 in a range of 0 to 100. The vertical axis has no scale so as to both sustain pre-attentive comparisons and prevent exact value comparisons deemed harmful to stress self-regulation.

Figure 1a also shows an activity list. A new activity can be added by pressing a button what opens an activity report, that is, a short questionnaire using which a user can name an activity, her perceived stress level and feeling during that activity as well as a few other information. A smiley expresses the perceived feeling during an activity. One to five smileys express the perceived stress level (1: low to 5: high).

The compound Stila Computed Stress graph and activity list have been designed after the simulation principle of [17] so as to incite users to compare their computed and perceived stress levels and to relate these levels with their activities thus fostering their stress self-regulation. Every three hours, a notification reminds of reporting activities.

The Stila smartphone app can be used with a Fitbit wristband acting as pulse sensor from which the pulse data are fetched by the user over a Fitbit cloud service. As a consequence, the Stila Computed Stress graph cannot be automatically updated in real time but instead periodically requiring a user intervention. The Stila smartphone app can also be used with a smartwatch in which case the Stila Computed Stress graph is automatically updated in real time without user intervention.

b) Smartwatch App: The Stila smartwatch app offers color customizable digital and analog watchfaces. It collects pulses at adjustable rate (1 Hz, 0.2 Hz, and 0.1 Hz) and synchronizes the recorded pulse rates with the Stila smartphone app which processes them, determines the Stila Computed Stress for every 10 min interval, and synchronizes with the Stila smartwatch app. Figure 1b shows how the Stila Computed Stress graph is rendered on a smartwatch.

The activity list is both-way synchronized between the Stila smartwatch and smartphone apps. Because of the limited size of a smartwatch display, it is rendered on a smartwatch in a separate scrollable view – see Figure 1c. Figure 1d shows an activity report with its associated user-reported stress level. The user can access the further information by scrolling down. The activity report questions are the same on the smartwatch and smartphone apps. A live recording of an activity can be started with a play button and ended with a stop button allowing for a precise and easy tracking of an activity time range.

When the Stila Computed Stress crosses a threshold, a stress event is registered. After the computed stress has returned to a normal level, a notification is sent to the user suggesting to report on her perceived stress and on the activity that caused it. This way, notifications are triggered only "at rest" and do not cause stress.

The Stila smartwatch app has been designed after Fogg's behavior model (FBM) [24] based on the same self-monitoring and simulation principles as the Stila smartphone app and enhanced with further reduction, tailoring, tunneling, and personalization principles [17]. Thus, compared with the Stila smartphone app, the Stila smartwatch app increases the user's ability to examine her stress in real time and to comfortably report on her activities and perceived stress levels during her activities.

The results of the studies [31], [32] mentioned above in Section II have been considered by designing the Stila apps: The Stila apps do not send messages that could trigger an addictive smartphone use and do not rely on their users setting avoidance goals.

V. Evaluation: How Persuasive are the Stila Apps?

A quantitative and qualitative evaluation was devoted to investigating whether the coupled Stila smartwatch/smartphone apps are more persuasive than the smartphone app alone.

a) Setting and Data Collected: 86 participants aged 18 to 61 (mean age: 31) were recruited online (among others on *Reddit* and the *Quantified Self Forum*). They were awarded no compensations. 43 participants, the watch group, were instructed to use the Stila smartwatch and smartphone apps. 43 participants, the phone group, were instructed to use the Stila smartphone app and fitness wristbands (Fitbit PurePulse). The fitness wristbands collected pulse rates but, in contrast to the smartwatches, did not inform their users on their computed stress and could not be used for reporting activities (what had to be done using the Stila smartphone app). All participants were instructed to use the Stila app(s) during 15 days, to regularly check their computed stress on the Stila app(s) and to report their activities every day using the Stila app(s). They all received the same few email reminders.

The evaluation was based on the participants answers to an online questionnaire (available at http://stila.pms.ifi.lmu.de/experiments/pervasivepersuation.html) sent to all participants at the end of the experiment and on the participants' usage of the Stila app(s) during the experiment. (Usage data were collected with an instance of the Matomo analytics platform deployed for the experiment.)

The online questionnaire was devoted to the participants' subjective appreciation of the Stila app(s). It consisted of 16 statements to rate on a Likert scale from 1 (strongly disagree) to 5 (strongly agree), of 15 questions (on the app(s) usage and demographics) to answer with multiple choices, and of 5 free text fields for comments or feedbacks. 24 participants (watch group 11, phone group: 13) answered the questionnaire.

The Stila app(s) usage data of a participant were UE_1 the total number of apps' visits (for consulting stress estimates or entering activity reports) and UE_2 the total number of activity reports entered over the 15 days of the experiment. In the evaluation, the usage data of the 62 participants (phone group: 33, watch group: 29) are considered who reported at least 4 activities.

b) Variables and their Distributions: The following 8 variables have been used, each of which is either derived from the collected usage data (UE_1 and UE_2) or had been reported, that is, a questionnaire answer:[1]

- User Motivation:
  - UM_1: Number of users per group using the Stila app(s) per day
  - UM_2: Reported initial motivation to use the Stila app(s)

[1]The questionnaire answers and the processed usage data are available at http://stila.pms.ifi.lmu.de/experiments/pervasivepersuation.html.

- UM_3: Reported decreasing interest in the Stila app(s)

- User Engagement:
  - UE_1: Number of visits of a Stila app
  - UE_2: Number of activity reports
  - UE_3: Reported frequency of app(s) visits
- Task Efficiency TE: average time spent in reporting an activity
- Stress Awareness
  - SA_1: Reported stress awareness
  - SA_2: Reported stressor recognition

c) Hypotheses and Statistical Tests: The questionnaire answers' distributions are rather symmetrical suggesting that their normalities can be assumed. Normal distribution make sense since, usually, opinions are evenly spread. The usage data UE_1 (number of apps' visits per user) and UE_2 (number of activity reports per user) distributions are asymmetric leaning to the lower values suggesting that they can be assumed to follow Zipf's (or power) laws. Zipf's laws make sense for usage data since, usually, the longer the time elapses, the more users have given up their use of a novel tool. The normality and skewness of all data samples were tested with a D'Agostino omnibus test (α = 0.01) and Q-Q plots.

The null hypothesis for a variable is that no differences in that variable's values can be observed in the answers of the smartwatch and the smartphone groups.

Since the distribution of a variable which is a questionnaire answer is normal and since the groups consist of 43 participants, the null hypothesis can be tested with a Student's t-test.

Since the distribution of a variable which is derived from the usage data UE_1 and UE_2 follows a Zipf's law, since the smartwatch and smartphone groups could not influence each other, and since the groups consist of 43 participants, the Wilcoxon rank-sum test (or Mann-Whitney U test) can be used for testing the null hypothesis.

p-values smaller than 0.05 were considered significant.

d) Motivation: The watch group rated UM_2 ("My motivation to use the Stila App at the beginning of the study was high") on average 4.6, the phone group 4.5 (p = 0.37). The watch group rated UM_3 ("My motivation to use the App decreased during the study") on average 3.1, the phone group 3.3 (p = 0.33). No differences regarding both the initial motivation and motivation drop between the groups were observed. 41 members of phone group and 36 members of watch group have used Stila apps during the study. The number of daily active users (UM_1) dropped similarly for both groups. At the end of the experiment, each group had 10 members still using the Stila app(s). The user drop can be interpreted as a motivation drop.

e) User Engagement: 63% of the watch group but only 18% of the phone group reported more than two app(s) visits a day. A member of the watch group visited both Stila apps on average 46 times (mean: 46), a member of the phone group only 17 visits (rank-sum: p = 0.01). 38 participants (phone group: 21, watch group: 17) reported activities. A member of the watch group reported on average 37 activities, a member of the phone group 24 (rank-sum: p = 0.05). The watch group reported 75% of activities using the Stila smartwatch app and 25% using the Stila smartphone app.

TABLE I: Evaluation Summary

Variable	Phone Group	Watch Group	p Value
Total Visits(UE_1)	μ: 17 (n=33)	μ: 46 (n=29)	0.01†
Reported Activities(UE_2)	μ: 24 (n=21)	μ: 37 (n=17)	0.05†
Act. Reporting Time(TE)	μ: 16s (n=21)	μ: 19s (n=17)	$\ll$ 0.01‡
Rep. Freq. Visits (UE_3)	often: 18%	often: 63%	–
Init. Motivation (UM_2)	μ: 4.5* (n=13)	μ: 4.6* (n=11)	0.37‡
Motivation Drop (UM_3)	μ: 3.3* (n=13)	μ: 3.1* (n=11)	0.33‡
Stress Awareness (SA_1)	μ: 2.5* (n=13)	μ: 3.5* (n=11)	0.02‡
Stressor Recognition(SA_2)	μ: 2.3* (n=13)	μ: 2.7* (n=11)	0.22‡

*< 3: denied; >3: confirmed
†Wilcoxon rank-sum test, often: more than 2 daily app(s) visits
‡one-tailed t-test, μ: mean, n: sample size

f) Task Efficiency: A member of the watch group spent on average 19 seconds to report an activity, a member of the phone group 16 seconds (t-test: p $\ll$ 0.01).

g) Stress Awareness: The watch group confirmed that "The Stila app(s) helped me to be more aware of my stress levels" (SA_1) with an average of 3.5 and a variance of 1.07 while the phone group disagreed with an average of 2.5 and a variance of 1.32 (p = 0.02). The watch group disagreed with "The Stila app(s) helped me to identify stressors in my life" (SA_2) with an average of 2.7, the phone group also disagreed with an average of 2.3 (p = 0.22). This suggest that the watch group reported a subjective increase in its stress awareness while using Stila apps and that none of the groups were well capable of identifying stressors.

VI. Finding: Pervasiveness Persuades

Table I summarizes the findings reported about above in the section V.

More activities were reported by the watch group than by the phone group even though reporting an activity takes more time with the Stila smartwatch app (due to the smartwatch's small screen size) than with the Stila smartphone app. The pervasiveness of the smartwatch is the likely reason for this discrepancy because up to 78% of the total time needed for reporting an activity with a Stila smartphone app is spent for reaching the device [30].

The watch group also consulted the Stila app(s) more often than the phone group what might be explained by Fogg's behavior model (FBM) [24]. Indeed, the pervasive smartwatch app facilitates perception and therefore fosters stress self-regulation.

The higher pervasiveness of the smartwatch app and the seamless integration of its feedback with the smartphone app are the likely reasons why the watch group reported increases in stress awareness while the phone group did not.

VII. Conclusion

This article has reported on the coupled Stila smartwatch and smartphone pervasive apps enabling stress self-regulation.

The apps rely on the original Stila Computed Stress model that uses pulse rates pervasively collected through PPG with fitness trackers and smartwatches. Through the apps, these estimates are combined with users' activity reports and pervasively delivered to the apps' users. The Stila apps were designed after the principles of persuasive systems.

The pervasive smartwatch app coupled with the smartphone app has been shown in an experimental real life evaluation to better persuade its users to consult their stress and to report on their activities, their feelings and their perceived stress levels during these activities. Thus, the coupled smartwatch/smartphone pervasive apps better foster stress awareness and therefore stress self-regulation than the smartphone app alone does.

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