HEAL: A Health Analytics Intelligent Agent Platform for the acquisition and analysis of physiological signals

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***Abstract*—Effectively caring for patients suffering from chronic diseases is a challenging and costly task. There is a need to decrease the cost of treating these chronic patients, while increasing the quality of the care provided to the patients. Mobile health (mHealth) technologies such as remote monitoring, telemedicine, and home-based monitoring have become effective tools shifting the focus towards a more patient-centric healthcare. In this paper we present HEAL, an intelligent healthcare analytics and personal agent platform. The HEAL personal agent enables on-the-go continuous monitoring of covert and overt signals from patients. The HEAL agent consists of a pipeline that aggregates signals from devices and sensor types. The platform collects motion profiles, and user annotation for performing activity recognition and stress level detection. We evaluate the HEAL platform on patients suffering from essential hypertension and show that an intelligent personal mobile agent is capable of monitoring, analyzing and tracking the characteristics of hypertension management.**

***Index Terms*—Mobile health platform, Essential Hypertension, Healthcare analytics**

I. Introduction

Essential Hypertension (EH) is a highly heterogeneous disorder with a multifactorial etiology arising out of a combination of physiological, environmental and behavioural factors [1]. Recent data from epidemiological studies indicate that due to its high prevalence and long-term risks of developing life-threatening cardiovascular diseases, EH has become an important global health challenge. A 2005 life-expectancy study by Franco et. al [2], using the data from the famous Framingham Heart Study, estimated that hypertensives males and females had 5.1 and 4.9 years lower expected longevity compared to their normotensive counterparts.

Unhealthy lifestyle has been identified as an important risk factor for essential hypertension. Evidence from randomized control studies indicate that patients suffering from hypertension and elevated blood pressure should follow lifestyle modification techniques such as maintaining a weight-reducing diet, restricting alcohol, and practicing regular physical exercise [3]. The relationship between daily social, environmental, and psychological factors such as stress and workload with high blood pressure and hypertension has also been well established in research [4], [5]. The global INTERHEART study of 24,746 adults from 52 countries demonstrated that patients suffering from myocardial infarction reported higher (statistically significant) presence of psychosocial stress factors in their daily lives [6]. Due to the importance of lifestyle choices and daily stress, continuous monitoring and management of these factors are integral steps for improving patient care and disease management [7], [8].

Continuous monitoring, care and management of such patients is a challenging task. The multifactorial nature of the treatment management, especially related to lifestyle changes often requires involvement of an entire healthcare team including doctors, nurses, community health workers, and the patient's family. While monitoring the lifestyles of geriatric and other patients who are mostly confined to their homes is often achievable, monitoring adult patients, who are studying or working, is more challenging. Also, while it has been shown that team-based care interventions has the potential for effective hypertension management [9], the cost per patient could be extremely high and hence may not be sustainable and scalable. Therefore, there is a need to decrease the burden of the primary care physician in treating such patients, while increasing the quality of the care provided to the patient.

Wearable and mobile health platforms which can automate some parts of the care management process have shown to lower costs [10], [11] while increasing treatment adherence [12], [13] and improving patient outcomes [14]. Wearable and mobile health platforms have been shown to be effective for the management of a multitude of diseases including obesity, diabetes, bipolar disorder, and anxiety.

In this paper we present HEAL - an intelligent mobile health analytics platform, which can automate the day to day management and care of patients suffering from chronic diseases. The HEAL personal agent platform can track and analyze multiple covert and overt signals of a patient to personalize chronic care management. We apply the HEAL mobile personal agent technology to patients suffering from essential hypertension and show that an intelligent personal mobile agent is capable of monitoring, analyzing and tracking several characteristics of hypertension management.

II. Platform Overview

The Health Analytics (HEAL) Intelligent Agent platform (Fig. 1) consists of three components:

Empatica wristband: The Empatica E3 [15] wristband, developed by Empatica (www.empatica.com), is a bluetooth enabled wearable device capable of recording physiological and motion signals that can be used to monitor the health and well-being of a user. It is unobtrusive with a small form factor and can be worn on the wrist like a watch, making it ideal for ambulatory recording of physiological signals in the wild.

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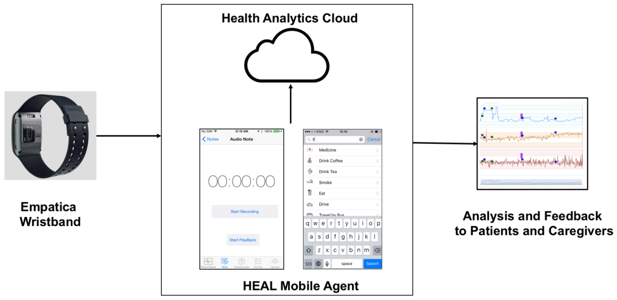


Fig. 1: The 3 components of the HEAL platform: The Empatica E3 wristband, the HEAL intelligent agent, and the HEAL cloud.

HEAL intelligent agent: The HEAL intelligent personal agent is a custom companion application designed to reside on the user's smartphone. This personal companion application is capable of recording and securely uploading physiological signals from the Empatica E3 wristband to the server. The companion features of the personal agent allow continuous and momentary collection of user annotations through both speech and text. It also acts as an agent to elicit information by prompting the user to answer regular questionnaires regarding his or her daily stress and workload.

The HEAL cloud - The Health Analytics cloud is the server component of the HEAL Intelligent Agent platform. All the individual HEAL mobile companions upload their data to the HEAL cloud. The HEAL cloud encrypts and stores the data for secure access. At the back-end, it stores, parses, structures, cleans and runs machine learning algorithms on the data to learn about the user's behaviour including the user's activity and stress levels. The cloud also provides a web visualization platform which can be accessed by the user to be used as a reflective life-logging and monitoring tool. If access is provided, it can also be used by the healthcare team, family members or doctors for keeping track of the well-being of the user/patient.

III. The Empatica E3 wristband

The Empatica E3 (Fig. 2) has one motion sensor and three integrated sensors for recording physiological signals. These sensors report the following physiological and motion signals: a) Blood Volume Pulse (BVP): The E3 reports BVP at a 64 Hz rate. b) Electrodermal Activity (EDA): EDA is reported at a 4 Hz rate. c) Inter Beat Interval (IBI): IBI is reported as a time-IBI pair. d) Skin Temperature: Skin Temperature is reported at a 2 Hz rate. e) Tri-Axial Acceleration: XYZ Acceleration of the wristband is reported at a 32 Hz rate. When active, the E3 can continuously record and stream these signals to a smartphone (Android or iOS) over the bluetooth low energy (BLE) protocol. On a single charge the E3 device lasts for about 10 to 12 hours in streaming mode, making it ideal for ambulatory data collection during a typical workday.

Fig. 2: Empatica E3 wristband – wearable, lightweight, wireless, multi-sensory data acquisition device.

IV. The HEAL Intelligent Agent

The HEAL intelligent agent runs on any iOS device that supports the bluetooth low energy (BLE) protocol (iPhone 4s and up). The HEAL intelligent agent has four main functions:

- To continuously store and upload the physiological and motion signals being streamed from the Empatica E3 wristband.
- The agent also records the data from the sensors (tri-axial accelerometer, gyroscope, and location sensor) on the smartphone.
- The agent transmits the data for analysis to the HEAL cloud.
- The agent elicits information from the user using multiple strategies including predefined questionnaires, list-based activity annotations, and free open text and voice notes.

A. Signal Storing and Streaming

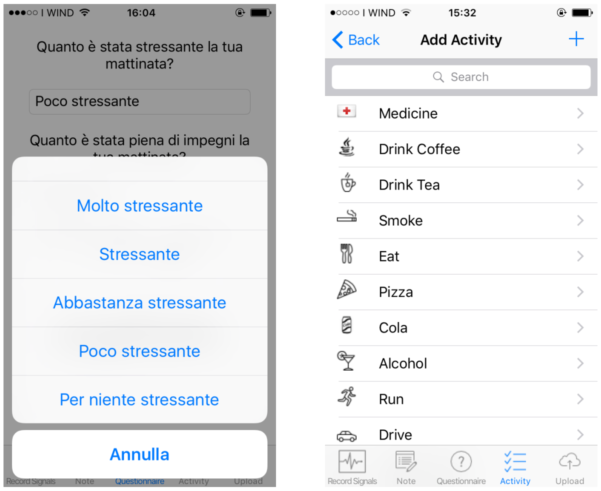
The HEAL intelligent agent connects to the E3 device and continuously records the physiological signals in a time-value pair format. The HEAL intelligent agent uploads the data to the cloud in two steps:

(1) ***Streaming mode***: Whenever the HEAL intelligent agent is actively collecting the data (the E3 wristband is connected to the agent), the agent down-samples the data and uploads it to the HEAL cloud, once every minute in a json format. This down-sampled version of the data is used for live visualization of the physiological and activity signals.

(2) ***Bulk mode***: At the end of the day, the user can upload the entire signal stream to the HEAL cloud. This upload can also be triggered automatically if the HEAL agent detects that the user has not manually uploaded the data for some time (2 days). Since this data can be quite large, at the time of the upload, the data for each session is compressed and a MD5 (Message-Digest algorithm 5) checksum for the file is calculated. The compressed file along with its checksum is uploaded to the server.

B. Overt Signal Acquisition

The HEAL platform uses both interval-contingent and event-contingent recording strategies. In interval-contingent recording, data are collected at pre-determined regular intervals, which in our case is once every three hours (once



(a) Reporting the Stress Level (b) Add a new activity

Fig. 3: The HEAL Companion for recording anticipated and perceived stress and workload and activity. The interface is in Italian for ratings and English for activities, which was sufficient for the use case with Italian patients.

when the user first wears the device at the beginning of the day, after three hours, and at the end of the daily data collection). In event-contingent reporting, users can record a report every time he or she experiences a stressful event. Using these strategies the HEAL platform collects the following overt signals: (1) Periodic Structured Information in the form of **anticipated and perceived stress and workload questionnaire**; (2) Spontaneous Structured Information in the form of **event annotations**; (3) Spontaneous Structured Information in the form of **user diaries**.

1) Anticipated and Perceived Stress and Workload Questionnaire: The HEAL intelligent agent uses interval-contingent strategies to periodically record user's stress and workload level (Fig. 3a).

- *Anticipated Stress and Workload Reporting:* This is a user report of the level of stress and workload for the upcoming period.
- *Perceived Stress and Workload Reporting:* This is a user report of the level of stress and workload perceived for the period which has passed.

At the beginning of the day the user is asked to record the **anticipated stress** and **anticipated workload** levels for their morning session. The Stress annotations are obtained on a five point Likert scale as follows (see Fig. 3a): a) Not at all stressful (per niente stressante) b) Little stressful (poco stressante) c) Moderately Stressful (abbastanza stressante d) Quite stressful (stressante) e) Very Stressful (molto stressante).

Around noon, the users are presented with the same questionnaire again, but this time they are required to assess how their morning really was (perceived stress and workload), and provide their prediction (anticipated stress and workload) for the afternoon. Similarly, at the end of the afternoon, they are asked to assess their afternoon.

2) Event Annotations: The HEAL intelligent agent encourages the user to annotate events and activities during the day. These annotations are also used later to ground the automatic activity recognition done on the analytics cloud. Analysis of these activities can also be used to identify the stress inducing activities in the user's everyday life.

3) User Diaries: Experiences are inherently temporal in nature. If not recorded, over a period of time most people tend to forget the exact nature of the event and the emotions it invoked at the time. Diaries are self-reports intended to capture daily events, interactions, mood and reflections. Diaries are a popular tool for life-logging for memory aiding and recollection [16]. The reflective nature of the process of writing and reading one's own diary has been shown to increase self-awareness about physical activity or emotional states in different situations.

Diaries have been shown to be very effective in gaining a deep insight into a patient's well-being, and can be used by a therapist for learning about the patient's behaviour and routines. They can also be used for tracking medicine adherence and compliance to treatment regimes. In psychology research, diaries have been shown to be an effective tool in monitoring and promoting psychological recovery for patients suffering from various symptoms like anxiety, depression, and stress [17], [18].

One of the main challenges of diary-keeping is the need to carry around a physical diary, and finding the right place and time to record one's thoughts. The growth in the usage of mobile phones in our lives has resolved this problem – it provides an easy interface to write or speak to. The HEAL mobile companion encourages the user to maintain a multimodal diary – the user can either take frequent written notes or record speech about his or her feelings, current state, and elicit about the surroundings, and how his day is.

V. The Health Analytics Cloud

The analysis and machine learning for the intelligent agent is performed on the Health Analytics (HEAL) cloud. The HEAL cloud has three parts - (1) Data Processing Engine (2) Analytic Engine (3) Visualization Dashboard (see Fig. 4).

A. Data Processing Engine

The data preprocessing engine performs the various subtasks involved in preparing the data and signals for feature extraction and machine learning performed by the analytic engine. It consists of four components:

Data aggregation and verification: The data from the intelligent agent application is uploaded to the Health Analytics cloud. The backend uses a mysql database to store all the structured data. The signals and the audio themselves are stored on the disk, and their references are saved to the respective database tables.The json files from the streaming data are parsed and entered into the mysql database for continuous visualization through the HEAL dashboard. For the end of the day data, the compressed files are decompressed and their validity is checked against their md5 checksum. In

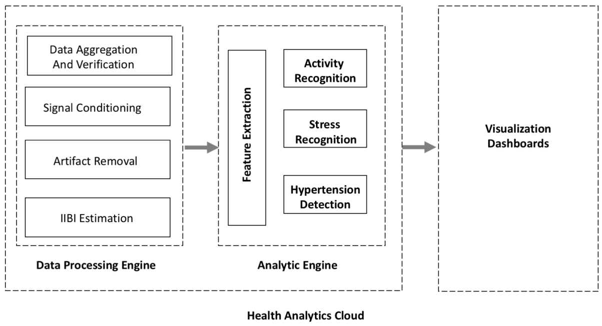


Fig. 4: The Health Analytics Cloud Pipeline. The pipeline consists of the (1) Data Processing Engine (2) Analytic Engine (3) Visualization Dashboard

case a problem is detected, a message is returned to the HEAL application to re-compress and upload the file which did not match the checksum. The same step is taken for the audio files uploaded from the HEAL intelligent agent.

Signal Conditioning: The signal conditioning module is responsible for signal processing. Physiological signals recorded by the Empatica E3 collected during everyday ecological settings suffer from a variety of artifacts and noise. The electrodermal activity (EDA) and skin temperature signals are passed through a low pass filter and detrended. The accelerometer signal is used for active noise cancellation from the blood volume pulse (BVP) signal which is used in the inter-beat-interval (IBI) estimation module.

Artifact Removal: Physiological signals are highly susceptible to artifacts which can limit their usage for identification of the mental state of the user. These artifacts can be generated due to a variety of factors such as local pressure, nervous fidgeting, vasoconstriction due to cold weather, change of posture, or gross body movements. It is therefore extremely important to apply effective signal processing methodology for artifact removal before further analysis of these signals. The HEAL data processing unit identifies and removes such artifacts using the approaches described in [19], [20].

Inter-beat Interval Estimation: The time-series of the Inter-beat Interval is an extremely important signal stream used to generate a clean Blood Volume Pulse (BVP) signal (Fig. 5). The BVP signal is used to extract Heart Rate Variability (HRV) features. Heart Rate Variability (HRV) is the measure of the variations of the time-interval between heart beats, and can be used to estimate the hearts ability to adapt to the autonomic neural regulation. A reduction of heart rate variability has been accepted as a correlate for stress among individuals [21] and in several cases is associated with increased risk of cardiovascular mortality [22], [23]. This module estimates the interpolated inter-beat-interval signal from the conditioned blood volume pulse (BVP) signal. The IBI estimation is performed using the data and approaches described in [20], [24].

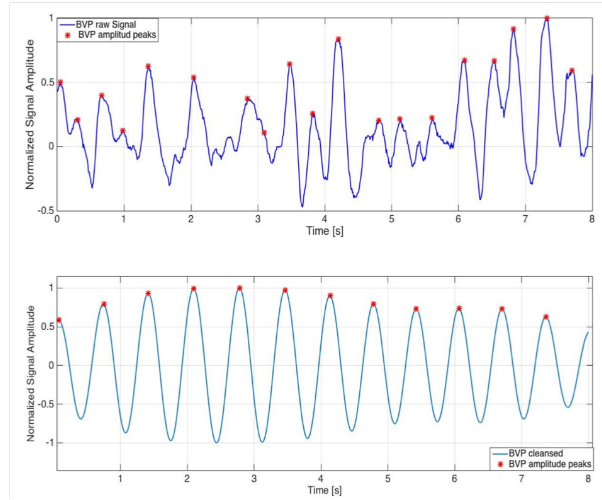


Fig. 5: Raw and Clean BVP signal after processing through the Inter-beat Interval Estimation module of the Data Processing Engine of HEAL

B. Analytic Engine

The analytic engine is responsible for the extraction of features and further analysis of the processed signals. It applies machine learning algorithms for performing activity recognition, stress recognition and hypertension detection. The analytic engine prepares the data to be visualized. The analytic engine consists of the following modules:

Feature extraction: The feature extraction module extracts various features from the physiological, motion, and user profile data. The nature, and number of extracted features depends on the downstream task performed by the module (activity recognition, stress recognition and hypertension detection modules) which utilises these features. For example, for the activity recognition tasks, features are extracted from the motion signals (accelerometer and gyroscope), and the hypertension detection module mostly uses features from the physiological signals. While most downstream tasks use a combination of the multiple features extracted by this modules, some of the individual features themselves can be quite informative. For example, the density plot of the detrended, and normalised mean skin conductance level (SCL) of normotensive and hypertensive patients demonstrate how their daily skin conductance vary.

Activity recognition: This module performs activity recognition using the accelerometer and gyroscope signals recorded from the smartphone. The goal is to add context for the analysis of the physiological signals. The type and amount of daily activity contributes to the daily stress levels of the users. Factors such as long commute hours and commuter stress are highly correlated with workplace aggression. Both driving a car [25] and taking a train [26] to work have been shown to increase the stress response of an individual. Longer commuting times have also been demonstrated to decrease the tolerance for frustration [27].

The HEAL activity recognition system was trained using

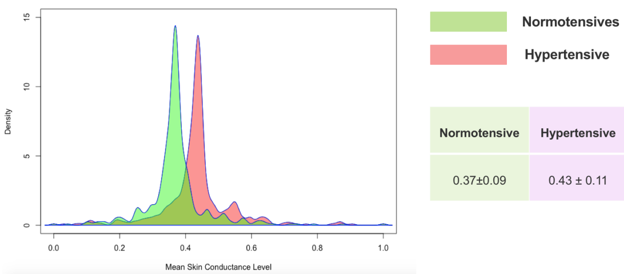


Fig. 6: Density plot of the of the detrended, and normalised Mean Skin Conductance Level (Mean SCL) of Normotensive and Hypertensive Subjects

the data, features and algorithm presented in [28]. The activity recognition module identifies six activities - Walking, Standing, Sitting, Driving, Travelling by bus, and Travelling by Train and segments the signal data using continuous labels. ***Stress recognition***: The stress recognition module uses the daily stress annotations collected from the users as explained in Section IV-B1, and was trained using the approach explained in [19]. The Stress recognition system was trained using features extracted from physiological signals (time and frequency domain features from EDA, HRV, Skin Temperature), and activity profile features (total commute time, time spent on each activity type during the segment), among others. The training and evaluation of the system was performed using a “Leave One Subject Out” (LOSO) cross validation scheme for all classification tasks, and achieved an average F-measure of 0.91 when combining features from all signal streams.
Hypertension detection: One of the goals of the HEAL platform is to detect, track and monitor patients suffering from Essential Hypertension. The most common technique for the diagnosis of essential hypertension is the detection of high-blood pressure using brachial cuff-based measurement devices. However, these devices are cumbersome to use on a regular basis and commonly not regularly used by otherwise healthy people. Due to the recent increase in popularity of wearable devices capable of recording physiological signals, the goal of the HEAL platform is to enable patients who use wear such devices to be able to continuously monitor their well-being, and possibly lead to early detection of hypertension. The Hypertension detection module was trained on data and algorithms reported in [20]. The module, using a combination of features extracted from electrodermal activity, and heart rate variability signals was able to achieve an F-measure of 0.83 using the Adaboost classifier under a LOSO evaluation scheme.

C. Visualization Dashboard

The HEAL Dashboard can act as a visualization, annotation and analysis platform for both users/patients as well as the care team. The dashboard visualizes the near real-time streaming physiological signal data and overlays the context to it by adding the patient supplied notes, and the annotations on the signal timeline. Each user/patient can view and edit their data. They can also provide more context or delete information which they might consider private. This can be used as a reflective tool by the patient to perceive their physiological response to the various stressors in their life (Fig. 7).

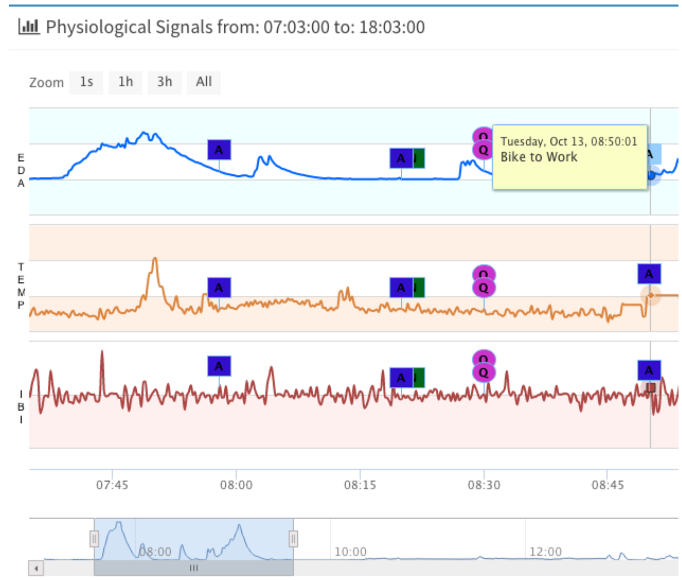


Fig. 7: HEAL Dashboard visualizing the physiological signals (electro-dermal activity (EDA), skin temperature (TEMP) and Inter Beat Interval (IBI). The user annotations (audio and text notes) and responses to the daily questionnaires are overlaid on the graph to provide context to the signals.

The healthcare team has access to the data to keep track of the most important vital signs of the patients during the day (Fig. 7). In the streaming mode, they can see minute by minute update of the physiological signals of the patients. They also have access to summaries and visualizations highlighting differences between different patient groups. In figure Fig. 8 we can see the summary of the data collection for a Hypertension detection study carried out at the Centro Ipertensione Ospedale Molinette.

VI. Conclusion

In this paper we present the HEAL health analytics personal agent platform for the tracking and care-management for chronic conditions. We presented a) an intelligent personal agent platform for on-the-go continuous monitoring of covert and overt signals and b) a pipeline which combines various physiological signal streams, motion profiles, and user annotations for on-the-go activity and stress recognition. The HEAL intelligent agent platform streamlines the collection, annotation, and automatic analysis of the diverse signal streams. The HEAL intelligent agent platform has the potential to change the care-management for chronic conditions by empowering patients and improving the detection and subsequent self-management of diseases such as hypertension. By providing patients with an updated view of their signals,

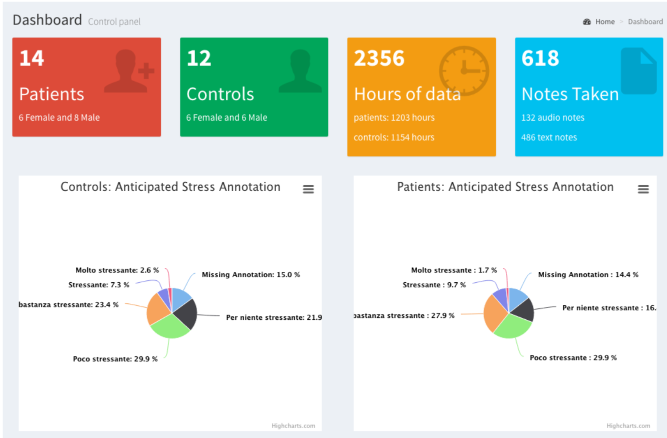


Fig. 8: One screen of the HEAL overview dashboard for doctors. The top part of the dashboard provides an overview of the patient population distribution, the number of hours of physiological signals collected, and the total number of annotations in the form of audio and text notes. The bottom part shows the distribution of the anticipated stress annotations by the two patient populations.

it can help engage and empower patients, making the task of primary care physicians and care teams easier.

References

1 Carretero, O. A. and Oparil, S., "Essential hypertension: part i: definition and etiology," *Circulation*, vol. 101, no. 3, pp. 329–335, 2000.

2 Franco, O. H., Peeters, A., Bonneux, L., and De Laet, C., "Blood pressure in adulthood and life expectancy with cardiovascular disease in men and women: life course analysis," *Hypertension*, vol. 46, no. 2, pp. 280–286, 2005.

3 Dickinson, H. O., Mason, J. M., Nicolson, D. J., Campbell, F., Beyer, F. R., Cook, J. V., Williams, B., and Ford, G. A., "Lifestyle interventions to reduce raised blood pressure: a systematic review of randomized controlled trials," *Journal of hypertension*, vol. 24, no. 2, pp. 215–233, 2006.

4 Wiernik, E., Pannier, B., Czernichow, S., Nabi, H., Hanon, O., Simon, T., Simon, J.-M., Thomas, F., Bean, K., Consoli, S. M. *et al.*, "Occupational status moderates the association between current perceived stress and high blood pressure: evidence from the ipc cohort study," *Hypertension*, pp. HYPERTENSIONAHA–111, 2013.

5 Gilbert-Ouimet, M., Trudel, X., Brisson, C., Milot, A., and Vézina, M., "Adverse effects of psychosocial work factors on blood pressure: systematic review of studies on demand-control-support and effort-reward imbalance models," *Scandinavian journal of work, environment & health*, pp. 109–132, 2014.

6 Rosengren, A., Hawken, S., Ôunpuu, S., Sliwa, K., Zubaid, M., Almahmeed, W. A., Blackett, K. N., Sitthi-amorn, C., Sato, H., Yusuf, S. *et al.*, "Association of psychosocial risk factors with risk of acute myocardial infarction in 11 119 cases and 13 648 controls from 52 countries (the interheart study): case-control study," *The Lancet*, vol. 364, no. 9438, pp. 953–962, 2004.

7 Rainforth, M. V., Schneider, R. H., Nidich, S. I., Gaylord-King, C., Salerno, J. W., and Anderson, J. W., "Stress reduction programs in patients with elevated blood pressure: a systematic review and meta-analysis," *Current hypertension reports*, vol. 9, no. 6, p. 520, 2007.

8 Linden, W., Lenz, J. W., and Con, A. H., "Individualized stress management for primary hypertension: a randomized trial," *Archives of Internal Medicine*, vol. 161, no. 8, pp. 1071–1080, 2001.

9 Carter, B. L., Rogers, M., Daly, J., Zheng, S., and James, P. A., "The potency of team-based care interventions for hypertension: a meta-analysis," *Archives of internal medicine*, vol. 169, no. 19, pp. 1748–1755, 2009.

10 Piette, J. D., List, J., Rana, G. K., Townsend, W., Striplin, D., and Heisler, M., "Mobile health devices as tools for worldwide cardiovascular risk reduction and disease management," *Circulation*, vol. 132, no. 21, pp. 2012–2027, 2015.

11 Darkins, A., Kendall, S., Edmonson, E., Young, M., and Stressel, P., "Reduced cost and mortality using home telehealth to promote self-management of complex chronic conditions: a retrospective matched cohort study of 4,999 veteran patients," *Telemedicine and e-Health*, vol. 21, no. 1, pp. 70–76, 2015.

12 Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., Patel, V., and Haines, A., "The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: a systematic review," *PLoS medicine*, vol. 10, no. 1, p. e1001362, 2013.

13 Wenze, S. J., Armey, M. F., and Miller, I. W., "Feasibility and acceptability of a mobile intervention to improve treatment adherence in bipolar disorder: a pilot study," *Behavior modification*, vol. 38, no. 4, pp. 497–515, 2014.

14 Hamine, S., Gerth-Guyette, E., Faulx, D., Green, B. B., and Ginsburg, A. S., "Impact of mhealth chronic disease management on treatment adherence and patient outcomes: a systematic review," *Journal of medical Internet research*, vol. 17, no. 2, 2015.

15 Garbarino, M., Lai, M., Bender, D., Picard, R. W., and Tognetti, S., "Empatica e3a wearable wireless multi-sensor device for real-time computerized biofeedback and data acquisition," in *Wireless Mobile Communication and Healthcare (Mobihealth), 2014 EAI 4th International Conference on*. IEEE, 2014, pp. 39–42.

16 Kalnikaite, V., Sellen, A., Whittaker, S., and Kirk, D., "Now let me see where i was: understanding how lifelogs mediate memory," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 2010, pp. 2045–2054.

17 Aitken, L. M., Rattray, J., Hull, A., Kenardy, J. A., Le Brocque, R., and Ullman, A. J., "The use of diaries in psychological recovery from intensive care," *Critical Care*, vol. 17, no. 6, pp. 1–8, 2013.

18 Ghosh, A., Stepanov, E. A., Danieli, M., and Riccardi, G., "Are you stressed? detecting high stress from user diaries," in *Cognitive Infocommunications (CogInfoCom), 2017 8th IEEE International Conference on*. IEEE, 2017, pp. 000 265–000 270.

19 Ghosh, A., Danieli, M., and Riccardi, G., "Annotation and prediction of stress and workload from physiological and inertial signals," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*. IEEE, 2015, pp. 1621–1624.

20 Ghosh, A., Torres, J. M. M., Danieli, M., and Riccardi, G., "Detection of essential hypertension with physiological signals from wearable devices," in *Engineering in Medicine and Biology Society (EMBC), 2015 37th Annual International Conference of the IEEE*, 2015.

21 Berntson, G. G. and Cacioppo, J. T., "Heart rate variability: Stress and psychiatric conditions," *Dynamic electrocardiography*, pp. 57–64, 2004.

22 Tsuji, H., Larson, M. G., Venditti, F. J., Manders, E. S., Evans, J. C., Feldman, C. L., and Levy, D., "Impact of reduced heart rate variability on risk for cardiac events the framingham heart study," *Circulation*, vol. 94, no. 11, pp. 2850–2855, 1996.

23 Nolan, J., Batin, P. D., Andrews, R., Lindsay, S. J., Brooksby, P., Mullen, M., Baig, W., Flapan, A. D., Cowley, A., Prescott, R. J. *et al.*, "Prospective study of heart rate variability and mortality in chronic heart failure results of the united kingdom heart failure evaluation and assessment of risk trial (uk-heart)," *Circulation*, vol. 98, no. 15, pp. 1510–1516, 1998.

24 Torres, J. M. M., Ghosh, A., Stepanov, E. A., and Riccardi, G., "Heal-t: an efficient ppg-based heart-rate and ibi estimation method during physical exercise," in *Signal Processing Conference (EUSIPCO), 2016 24th European*. IEEE, 2016, pp. 1438–1442.

25 Gulian, E., Glendon, A., Matthews, G., Davies, D., and Debney, L., "The stress of driving: A diary study," *Work & Stress*, vol. 4, no. 1, pp. 7–16, 1990.

26 Singer, J. E., Lundberg, U., and Frankenhaeuser, M., *Stress on the train: A study of urban commuting*. Psychological Laboratories, University of Stockholm, 1974.

27 White, S. M. and Rotton, J., "Type of commute, behavioral aftereffects, and cardiovascular activity a field experiment," *Environment and Behavior*, vol. 30, no. 6, pp. 763–780, 1998.

28 Ghosh, A. and Riccardi, G., "Recognizing human activities from smartphone sensor signals," in *Proceedings of the ACM International Conference on Multimedia*. ACM, 2014, pp. 865–868.