Towards Smartphone-Based Assessment of Burnout

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Abstract. In this paper, we present work in progress on VITAL-IN, a pervasive mobile application that aims to operationalize and assess multi-dimensional risk factors increasing a person's chance of developing the burnout syndrome. To date, there are no conclusive scientific results of what causes burnout, yet some factors are evident. We propose VITAL-IN application, enabling the analysis of distributed, variable order, sensor input and ecological momentary self-assessment towards "just-in-time" inference of an individual's behaviour and state, and future burnout risk prediction. Understanding the risk factors and the developmental trajectories leading to burnout could facilitate its early recognition and help to determine the most effective strategies and the most appropriate time for prevention and intervention efforts.

Keywords: Mobile computing, behaviour modelling, burnout prevention, personalized health, self-monitoring, wellbeing, context awareness.

1 Introduction

In many contemporary work environments, in western, as well as developing countries, sedentary workers are suffering from chronic stress due to intensive workload, poor social support and insufficient personal resources to deal with daily life challenges [1]. These conditions are known to elicit a state of distressful psychophysiological arousal that may lead to negative health consequences [2] and facilitate the onset of burnout, a syndrome with devastating influences on the individual's psychological and physical health, cognition, and behaviour [3], as well as negative impact on an organization's effectiveness. In contrast to many occupational diseases that have their origin in exposure to particular hazardous agents, burnout is a highly multifactorial and dynamic psychophysiological process. Early stage symptoms look like normal fatigue, while in the late stages they overlap with major psychiatric disorders, such as depression and neurasthenia [4]. To date, a precise description of etiologically involved factors for burnout is lacking [5] and there is an on-going debate concerning the symptoms which belong to the syndrome, the use of appropriate measurements and how to make a proper diagnosis [6].

Self-administered paper inventories (*i.e.*, [7–9]) are currently the most typical burnout assessment form. These rely mainly on subjective past symptoms, which are summarized by patients over some period of time and are assessed when they visit

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their doctors. Despite being widely accepted, self-report by recall has an intrinsic problem; due to biases, such as mood states, people are not be able to accurately recall past experience, particularly experiences that are frequent, mundane, and irregular [17]. Moreover, to assess progressive biological, psychological or behavioural processes, multiple assessments over relevant time periods are necessary, as opposed to cross-sectional or global reports [18]. To address these gaps, we turn towards ICT and particularly towards recent advances in mobile computing and sensor devices.

In this work-in-progress paper we present our approach to operationalize the major risk factors for the onset or prevalence of burnout in healthy sedentary workers to provide reliable assessment and prediction of risk exposure (*i.e.*, “now” vs. “future”), which permits early recognition and preventive intervention. We thoroughly examine known burnout risk factors in order to identify which of these can be operationalized via ICT-based tools and particularly quantified by leveraging unobtrusive sensors and Ecological Momentary Assessment (EMA) methods [10]. To increase awareness of how different aspects of lifestyle impact the risk of burnout exposure, we design VITAL-IN, an evidence-based personal smartphone application, to monitor and assess multi-dimensional events, subjective symptoms as well as physiological and behavioural variables in the natural daily work settings of the individual.

The rest of the paper is organized as follows. Section 2 gives a brief overview of the etiology of burnout (which is presented in further detail by Aydemir and Icelli in [11]) and describes our approach to operationalize and quantify risk exposure. In Section 3 we describe the design of the VITAL-IN application and propose a user-based evaluation in the field. Finally, concluding remarks are presented in Section 4.

2 Risk Factors’ Quantification for Burnout Assessment

There is an increasing availability of commercial and research-based unobtrusive personal sensing devices (*i.e.*, psychophysiological, bio-kinetic, ambient), either standalone or embedded in smartphones that can be used to track large quantities of sensory inputs in the user’s natural settings [12]. These devices allow observing physiological signals, as well as unreported aspects of an individual’s behaviour, interactions (*e.g.*, nonverbal actions) and context (*e.g.*, in a crowd) offering a complex picture of his/her status at a certain point in time. As an example, the Android Remote Sensing app (AIRS) [13], which gathers contextual factors such as location and noise levels and combines it with information on the user's social events and communication spikes to provide an overview of the user's day, aims to help stress and activity management before chronic disease develops. In addition to sensing devices, EMA, which permits to report symptoms, affect and behaviour close in time to experience, has been recently proposed by the personality/social psychology research as a reliable sampling method to assess stress-related diseases [14].

Input Sources and Data Quantification. Our work is based on a comprehensive review of the literature on risk factors that are consistently related to and may accelerate the development of burnout. Table 1 summarizes the factors considered by VITAL-IN and presents how we propose to operationalize these by leveraging o ff-the-shelf unobtrusive sensors, smartphone applications and computerized EMA.

Table 1. Factors, input sources for its quantification and data sampling rates.

Factor	Source(s) to Quantify the Factor	Sampling Rate
Job Settings [11]		
Work overload	Virtual sensors Work hours / week, Contract type	Continuous, Static
Lack of control Insufficient reward Conflicting values Job insecurity Absence of fairness	Quality of working life - Self-assessment scales	Time-contingent
Working Conditions [11]		
Human-Computer Interaction	Virtual sensors	Continuous
Involvement with People	Outgoing/incoming phone calls/SMS	Signal-contingent
	EMA self-assessment, Sociometer	Signal-contingent
Daylight/Artificial illumination	Ambient light sensor	Time-contingent
Shift work	Digitalized shift calendar	Time-contingent
Ambient noise	Microphone-based noise quantification	Continuous
	EMA self-assessment	
Overcrowding	Bluetooth devices in vicinity	Continuous
	EMA self-assessment	Signal-contingent
Physical and Spatial Context		
Location information	Smartphone (GPS, WLAN, Cell info)	Continuous
Distance travelled	Smartphone (GPS)	Signal-contingent
Posture	Bio-kinetic sensor	Continuous
Activity / Intensity level	Bio-kinetic sensor	Signal-contingent
Neurobiological Features [11]		
Genetic factors	Genetic tests	Static
Biomarkers	Micro-biometrics	
Socio-demographic Features [11]		
Age Gender Marital / Education status Occupation type Personality traits	Structured questionnaires	Static
Psychophysiological Context		
Heart rate (HR) / Var (HRV) Arousal Current mood	Ambulatory electrocardiogram Skin conductance level EMA self-assessment	Continuous / Event-contingent

VITAL-IN readings are repeated multiple times over a day/week. Following the principles of Ambulatory Assessment [15] the data sampling can be continuous (*e.g.*, in the case of physiological assessment), event-contingent (*e.g.*, initiated by the individual or automatically by change of physiological signals detected by monitoring device), signal-contingent (*e.g.*, initiated by a signal given to the person at random times), time-contingent (*e.g.*, initiated on specified time intervals: hourly, daily, weekly, monthly), as well as combinations of these. Wherever possible, passively monitored context information is additionally acquired to support and verify the self-assessment scores. For example, for a social interaction assessed as anxious and stressful, additional objective measures could be skin conductance level as an indicator of arousal or affective information transmitted through speech. Pitch appears to be an index of arousal, while prosody [16] and non-linguistic vocalizations (e.g., laughs, cries) can be used to decode affective signals such as stress, boredom, and excitement. Zeng et al. [17] present a survey on audio-based affect recognition systems.

Environmental Risk Factors for Burnout. The environmental risk factors are influences external to the individual. Although these factors (enumerated in Table 1) are not necessarily negative, they become job stressors when they require a physical and/or psychological effort, either cognitive or emotional, that produces negative effects [18].

Job Settings comprise mostly of subjective measures (*i.e.*, insufficient reward, job insecurity) which can be assessed by standardized scales related to the quality of working life [19]. Objective variables such as the number of hours worked per week or the contract type give information about the work overload. Additional indirect information can be collected using virtual sensors instrumented on the user's smartphone (*i.e.*, total interaction time, number of sessions) [20] or workstation (*i.e.*, keyword-based filtering of keystrokes, applications used).

Working Conditions, including the physical settings of the organizations have the potential to directly or indirectly affect the health of the individuals [11]. Artificial and inadequate illumination, one of the major problems in work settings, can be quantified using a smartphone ambient light sensor. Noise, a source of stress for workers in overcrowded environments can be measured by a number of commercial and research applications which turn smartphones into mobile noise level sensors (*e.g.*, NoiseTube [21]). Professionals of interpersonally demanding jobs tend to have less satisfaction with their work and experience burnout. Information about the user's social interaction can be inferred from sound/voice analysis (direct interaction), as well as PC instrumentation (*i.e.*, emails, chat programs) and smartphone call and messaging history (*i.e.*, total number and duration of calls, number of SMS, number of different contacts) for an indirect interaction. Research by Pentland using a device he termed the "Sociometer" [22] has shown the potential of using wearable sensors to track, analyse and even predict behaviour in social situations (via advanced sound/voice analysis).

Physical and spatial context, including factors such as bad posture and lack of exercise have serious health implications and impact on work performance. Bio-kinetic sensors deliver real-time feedback about body posture (*e.g.*, lumoBACK [23]) and the intensity of physical activities (*e.g.*, FitBit [24], accelerometer bracelet). The approximate distance travelled by an individual (*i.e.*, by foot or bike) can also be estimated from smartphone location data.

Individual Risk Factors for Burnout. Current literature indicates the possibility that stressful aspects of the work environment are more important burnout predictors than personality [3]. Nevertheless, knowledge of the individual characteristics implicated in the etiology of burnout is of considerable importance [11].

Neurobiological features. There are some predispositions and risk for burnout, with which we are born. Recent advances in micro-biometric (*i.e.*, UBIOME [25]) and genetic tests (*i.e.*, 23andme [26]) which report genetic health conditions and traits can contribute to the study for genetic predisposition to burnout.

Socio-demographic features may influence the risk of burnout. The syndrome is more prevalent in younger age groups and is experienced differently by men and women [11]. Questionnaires encompassing demographic and work-related information and measures of personality (*i.e.*, Big Five) are used to collect data.

Psychophysiological parameters such as skin conductance, blood pressure, heart rate (HR) and heart rate variability (HRV) have been statistically correlated as biomarkers for work stress. Smartphone applications with diagnostic capabilities are currently available and can be leveraged for long-term unobtrusive monitoring of psychophysiological parameters. Commercial examples include Tinké [27] a cardiorespiratory health and stress monitor for iOS devices or the Vital Signs Camera from Philips [28] that performs contactless HR and breathing rate measurements using a smartphone.

3 Application Design and Evaluation Plan

Given the above approach to operationalize burnout risk factors, we introduce the overall design of VITAL-IN, a field-configurable smartphone application for real-time monitoring and data acquisition, analysis and state assessment deployed over long-range wireless networks. Key aspects we consider for the design include the accuracy and reliability of data collection, maximizing battery energy efficiency and minimizing the monetary cost (*i.e.*, data uploading should only occur if cheap networking is available). VITAL-IN relies on a limited number of wearable sensors; both because of the amount of additional processing they require, as well as to prevent a cumbersome solution which might cause discomfort and stress, and alteration of the user's natural behaviour.

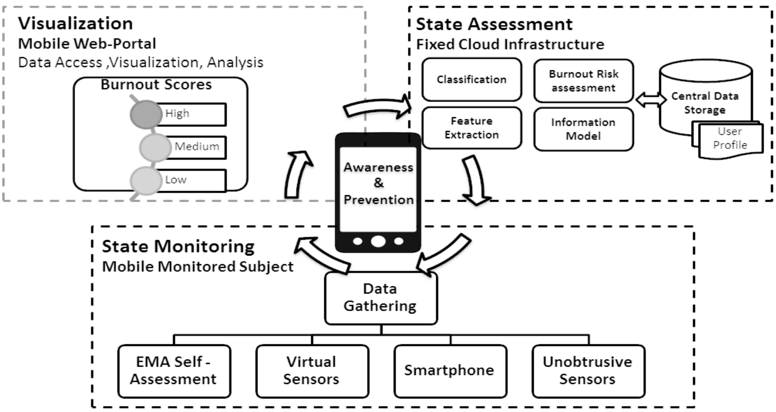

Fig. 1. VITAL-IN platform design and information flow

Figure 1 illustrates the preliminary conceptual design of the complete VITAL-IN solution. The monitored person is equipped with a commercial smartphone (usually carried in the pocket throughout the day) [29], which is used for collecting, interpreting, visualizing as well as remotely exchanging information, and small, cheap, minimally intrusive sensors located on-body or in-clothes or personal accessories, i.e., in the vicinity of the body and moving around with the person, thus enabling continuous ambulatory monitoring of his/her state and that of the environment (*i.e.*, workplace) [30].

State monitoring occurs continuously without requiring the attention of the individual. Input is collected in different formats and it is filtered and uploaded on a trusted server in a cloud infrastructure, which supports data storage and analysis. Theoretically, analysis can be deployed on the smartphone, however to facilitate separation of functionalities and system scalability it is common practice to deploy a separate processing node [30]. A rule-based system and various knowledge bases (related to the mentioned context dimensions) are used for data processing and extraction of semantic labels (*e.g.*, loud ambient noise, crowded). Information that something unusual happened at a certain time (*e.g.*, elevated heart rate) coupled with context information (*e.g.*, people present, activity information) should enable the user to deduct own conclusions and become more aware of the impact of their actions on their risk exposure. Semantic information is further processed to assess the burnout scores of the user on a given long timescale. Appropriate cut-off points will be established to allow classifying between various levels of risk exposure. Individual's behaviour is expected to unfold, as well as change over time, thus static predefined models that map inputs to trend predictions are of limited use in this case; models and useful features in the data should be learned over time. Users have access to a web portal to access the acquired data, visualize it (*i.e.*, current and historical burnout scores) and possibly perform further analysis. For sake of simplicity, in this paper we focus on operationalizing and monitoring constructs for assessment and we do not consider nor discuss the feedback/intervention functionality of the system.

Evaluation in the Field. In this section we discuss our plans for establishing a relevant and valid evaluation in order to demonstrate the feasibility of VITAL-IN for monitoring multi-dimensional burnout risk exposure in a reliable, privacy-conscious and unobtrusive manner. For that, we initially plan experiments designed to deal with issues introduced by data collection and inaccuracies when monitoring user context, activities and psychophysiological parameters. We will validate the monitoring accuracy of our application by comparing the results with gold-standard methods and with similar smartphone sensing experiments conducted with large numbers of subjects. For monitoring parameters such as social interaction, we may randomly select days during the week and require the subjects to keep a detailed log of their social interactions at work. From such an experiment we can conclude if VITAL-INN underestimates or overestimates a person's involvement with people.

The precision of the burnout assessment scores is critically important to the overall performance and user acceptance of the application, thus we will perform a series of experiments to assess the consistency of the scoring and classification models against the gold standard methods used nowadays for burnout assessment. The most predominant measure is the Maslach Burnout Inventory [7], a self-administered questionnaire designed to assess burnout as a continuous variable, ranging from low to moderate to high degree. In the long term, to evaluate the potential of VITAL-IN to deliver significant benefits to users, we propose a longitudinal study where healthy adult office-workers leading a sedentary lifestyle in the Geneva area in Switzerland will use the system, by means of smartphones and wearable sensors, in their natural daily work environments for a period up to one year. Trials will be carried out in collaboration with medical practitioners from the mental health and epidemiology centres of the University Hospital of Geneva aiming at the detection of patterns in behaviour, which could precede the appearance of even sub-clinical physical or mental discomforts associated with burnout.

4 Conclusive Remarks

In this work-in-progress paper we proposed a smartphone-based instrument and application called VITAL-IN to assess the individual's environmental situation and individual characteristics possibly leading to increased burnout risk. Our primary aim is to exploit existing empirical knowledge on risk factors and developmental trajectories that lead to burnout and investigate how to operationalize these in a minimally obtrusive way, using off-the-shelf smartphones, applications and sensors. VITAL-IN detects stressors momentarily as they occur, by sensing an individual's environmental and psychophysiological status, in correlation with subjective self-assessments captured by computerized EMA. In collaboration with medical practitioners, we plan to conduct a large-scale user study to better understand how people with different lifestyles can benefit from this application helping them determine the most appropriate and effective strategies for prevention and behaviour-change based intervention. VITAL-IN will support users in self-awareness and self-understanding of their current actions and behaviours, by paying immediate attention to any of the warning signals associated to burnout.

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