Wearable and App-based Resilience Modelling in Employees (WearMe)

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Abstract – **Occupational stress can cause all kinds of health problems. Resilience interventions that help employees deal with and adapt to adverse events can prevent these negative consequences. Due to advances in sensor technology and smartphone applications, relatively unobtrusive self-monitoring of resilience-related outcomes is possible. With models that can recognize intra-individual changes in these outcomes and relate them to causal factors within the employee's own context, an automated resilience intervention that gives personalized, just-in-time feedback (e.g., a virtual coach) can be developed. This 'Work in Progress' paper presents the study protocol for the Wearables and app-based resilience Modelling in employees (WearMe) project that aims to develop such models. A cyclical conceptual framework based on existing theories of stress and resilience is presented, as the basis for the WearMe project. The included concepts are operationalized and measured using sleep tracking (Fitbit Charge 2), heart rate variability measurements (Elite HRV + Polar H7) and Ecological Momentary Assessment (mobile app), administered in the morning (7 questions) and evening (12 questions). Analyses will target the development of both within-subject (n=1) models, as well as between-subjects models. If successful, future work will focus on further developing these models and eventually exploring the effectiveness of the envisioned personalized resilience system.**

Keywords – Occupational Stress; Personalized eHealth; Sensors; Wearables; Virtual Coaching

I. INTRODUCTION

Occupational stress can cause health problems, such as musculoskeletal disease, cardiovascular disease, depression and burnout [1], but also has financial consequences due to treatment costs, productivity loss and absenteeism [2]. Especially the cumulative wear and tear on bodily systems caused by stress or inefficient management of mechanisms that promote adaptation is detrimental for health and well-being [3]. This so-called 'allostatic load' increases the brain's sensitivity to appraise stimuli as threats and reduces resources to cope, which can result in a loss spiral.

There are all kinds of ways people cope with stress. The process of positively adapting to adverse events is also known as resilience [4]. In order to demonstrate positive adaptation (e.g., maintaining job performance and health), both individual (e.g., personality) and contextual (e.g., social support) resources can be used to cope with adversity [5]. By using these resources, resilient individuals are able to recover from the negative impact of stress relatively quickly and thus decrease their risk of negative long-term consequences.

Resilience interventions are often offered to a broad population. However, those that target employees with a higher risk of experiencing stress tend to have better long-term effects [6]. An even more personalized approach could be to monitor for early signs of the consequences of stress, relate these to causal factors in the employee's context, and provide personalized advice to better cope with the stressor. Due to advances in sensor technology and smartphone applications, relatively unobtrusive self-monitoring of changes in resilience related outcomes is possible [7]. What is needed are models that can recognize intra-individual changes in these outcomes and relate these to causal factors and future consequences. With such models, one can potentially create an automated resilience intervention that gives personalized, just-in-time feedback, for instance in a virtual coaching application.

In this 'Work in Progress' paper, we present the study protocol of the ongoing Wearables and app-based resilience Modelling in employees (WearMe) project. After introducing the WearMe project in Section I, a cyclical conceptual framework that is based on existing theories on stress and resilience is described in Section II. In Section III, we elaborate on how these concepts are operationalized in the first WearMe study. This includes the use of consumer-available wearables and an Ecological Momentary Assessment (EMA) app. In Section IV, some possible approaches for future work are described in our overarching goal to develop predictive models of employee resilience that can be used in personalized interventions such as virtual coaching applications.

II. CONCEPTUAL FRAMEWORK

The conceptual framework presented in Figure 1 has a cyclical nature and is based on several existing theories on stress and resilience.

When (job) *demands* such as time pressure or physical workload are interpreted as threats because the available *resources* to *adaptively cope* with the demands are perceived to be insufficient, it results in stress [8]. Depending on whether the person can utilize the available resources to adaptively cope with the demands, the short-term accumulated *stress* determines the individual's perceived *need for recovery* afterwards, which is

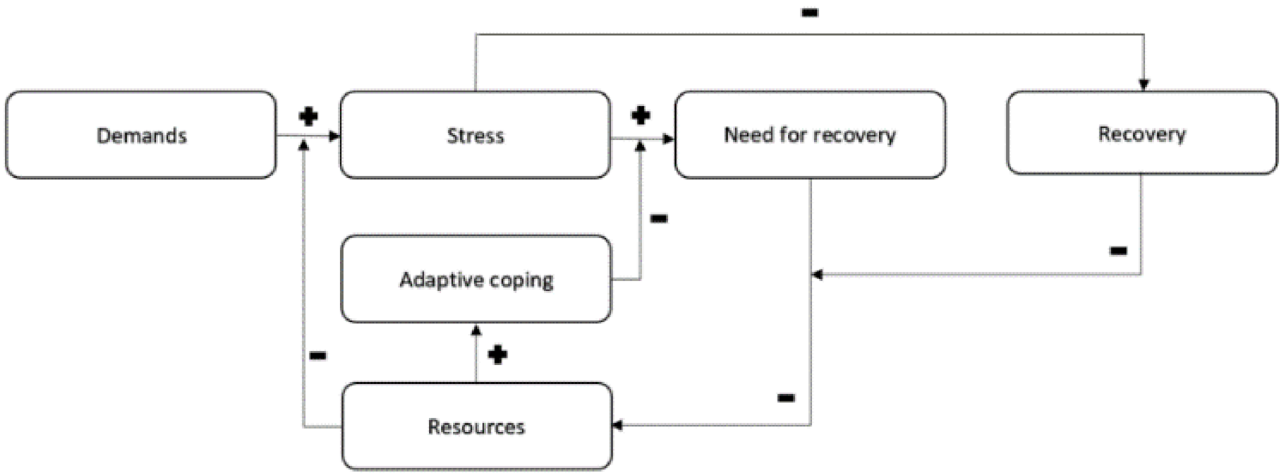

Figure 1. Conceptual framework for the WearMe study.

characterized by feelings of exhaustion and having less vigour to undertake new activities [9], [10]. The need for recovery therefore has a negative impact on the individual resources to appraise and cope with new demands – unless there is sufficient *recovery* present to alleviate this effect [9]. Besides causing a perceived need for recovery, stress also decreases sleep quality [11] and psychological detachment [12], which are aspects of recovery [13].

The cyclical nature of the conceptual framework is also supported by the Conservation of Resources theory [14] that states that resource loss leads to stress and that initial loss of resources may cause a loss spiral because resources are also used to prevent resource loss.

III. MEASUREMENT CYCLE

Based on the conceptual framework, a measurement cycle was developed that suggests how the described concepts may be operationalized using consumer-available wearables and EMA smartphone application to monitor for early signs of the consequences of stress. With exception of adaptive coping, which was not included because it is highly context-specific and thus difficult to quantify, all concepts are measured daily (Figure 2).

Although the *resources* that are needed to cope with demands are context-specific as well, several individual psychological and physiological resources were identified that are be relevant in a broad spectrum of situations, that may change on a day-to-day basis, and that can be measured using consumer-available wearables and apps. The first resource, Heart Rate Variability (HRV), is a measure for the variability in the intervals between two heartbeats and is considered to be a proxy for autonomous nervous system functioning [15]. While HRV is mostly known as a parameter that illustrates physiological changes during acute stress, the resting HRV can remain decreased during and afterwards acute stress [15] [16]. In contrast, having a lowered resting HRV has been associated with an increased sensitivity for stress [18], decreased emotion-regulation [19], a decrease in physical performance [20] and an increased risk of long-term physical or mental health problems [21]. In the WearMe study, resting HRV is therefore considered to be a potential indicator for the accumulation of stress, as well as an individual resource used in the appraisal of and coping with upcoming demands. Participants measure their resting HRV in the morning after waking up and before getting out of bed during 2 minutes in a supine position using the Elite HRV smartphone application [22] and a Polar H7 chest strap [23].

Besides HRV, perceived happiness, work engagement (vigour and dedication) and generalized self-efficacy are individual *resources* that are measured in a short EMA questionnaire in the morning and evening. Similarly, perceived *demands*, *stress* and *need for recovery* during the day are measured during the evening EMA questionnaire in a smartphone application.

The concept of *recovery* consists of two components that are known to limit the spill over of a perceived need for recovery during the next day; sleep and being able to psychologically detach from work during leisure time [24]. Therefore, psychological detachment is measured in the evening EMA questionnaire, while the morning EMA questionnaire includes an item on the perceived sleep quality. Furthermore, sleep onset latency, the number of awakenings, wake time after sleep onset, total sleep time and sleep efficiency are also objectively measured using the

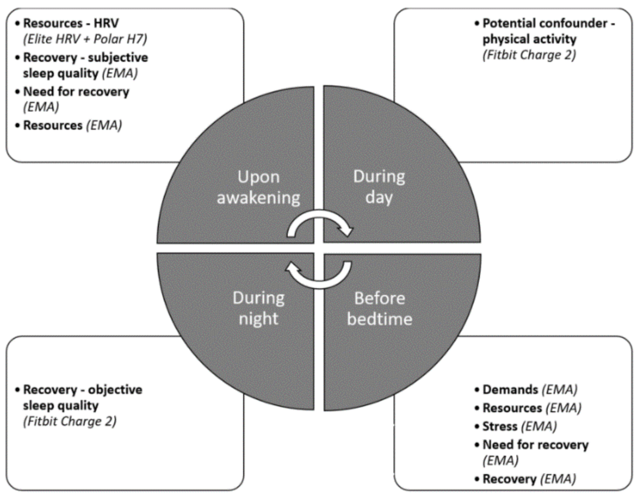

Figure 2. Measurement cycle of the WearMe study.

Fitbit Charge 2 wrist-worn tracker [25]. Since stress is also known to have a negative effect on sleep quality [11] and psychological detachment [12], it is also considered to be a potential indicator for the accumulation of stress.

Finally, alcohol intake [26] and physical activity [27] were measured due to potential confounding effects on sleep and/or HRV. Alcohol intake during the previous evening was measured in the morning EMA questionnaire and physical activity (steps, sedentary minutes, minutes of moderate-to-vigorous physical activity) was measured throughout the day using the Fitbit Charge 2.

III. PRESENT STUDY

The first WearMe study aims to explore the feasibility of the described measurement cycle to monitor for early signs of the accumulation of stress and to relate these to other factors based on the hypotheses described in the conceptual framework. Additionally, the development of population models will be explored. The study protocol was approved by the ethical committee of the Hanze University of Applied Sciences Groningen (heac.2018.008).

A. Population

For this ongoing 15-week study, twelve students in Applied Psychology (n=5) and Social Work (n=7) that are on their first full-time internship, are at least 18 years old and own an Android or iOS smartphone were recruited. Due to the potentially stressful nature of the context of these internships, as well as this being the participants' first full-time internship in their curriculum, we anticipate this population to be at risk of experiencing stress.

B. Data collection

Besides the daily measurements that were described in section two, several questionnaires are being administered to benefit the development of population models using between-subject analyses. Therefore, questionnaires on personality traits [28], coping strategies [29], burnout [30], work engagement [31] and symptoms of somatisation, distress, depression and anxiety [32] were administered at study onset. The questionnaires on burnout, work engagement and symptoms of somatization, distress, depression and anxiety will also be administered after 5, 10 and 15 weeks. Finally, participants will fill out a resources questionnaire to retrospectively assess the perceived personal and environmental resources throughout the internships after 15 weeks.

C. Data analysis

Data analyses will target the development of within-subject (n=1) models to predict changes in individual physiological and psychological resources (resting HRV, vigour, happiness, generalized self-efficacy) and recovery (sleep, psychological detachment) based on the hypotheses described in the conceptual framework. Furthermore, the development of population models will be explored. While no specific data-analysis techniques are pre-defined, both the use of traditional statistical analysis techniques and machine learning will be explored.

IV. CONCLUSION

If the results affirm that tracking sleep and resting HRV using consumer wearables is feasible and may be useful in resilience modelling, the current models could be expanded. Future studies will therefore focus on the development of predictive models that allow early detection of stress-related symptoms. In addition, expanding the current model by using additional consumer-available wearables or apps that can unobtrusively collect potentially relevant data (e.g., GPS location, calendar events) may be explored. When our conceptual framework that illustrates hypotheses based on deductive reasoning shows to be valid, a more inductive approach to data-analysis may be explored (e.g., using machine learning) to increase the explained variance of the individual models. If successful, these models can be implemented in applications that create personalized feedback on how to cope with demands.

Furthermore, it is possible that within-subject models can be formed but require a long period of data collection. If subgroups with similar outcome trajectories can be identified using between-subject analyses of baseline and first-week data in a larger sample in order to create a classification algorithm, it might be possible to develop a system that combines both methods [33]. In such a system, participants would first receive semi-personalized feedback based on their subgroup classification and start receiving fully personalized feedback when enough within-subject data are available.

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