Wearable and app-based resilience modelling in employees

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Exploring the possibilities to model psychological resilience using wearable-measured heart rate variability and sleep

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CHAPTER 1

General introduction

STRESS AND RESILIENCE

Stress is associated with an increased risk of numerous diseases, including several forms of cancer (1), musculoskeletal diseases (2), periodontal diseases (3), type 2 diabetes mellitus (4), stroke (5) and (recurring) cardiovascular disease (6,7). It also can be detrimental to mental well-being, for instance in the development of mental-disorders (8) and burn-out (9). Besides this impact on the health and quality of life (10) of individuals, stress also impacts the work situation and thus has major implications for their employers. For instance, a nationwide survey under Dutch workers showed that occupational stress was attributed to be the primary cause in 36.8% of all absenteeism from work in 2021 (11). The resulting financial burden of stress is estimated to mostly come from productivity loss (70-90%) and medical costs (10-30%) (12). Stress therefore has a major individual and societal impact, especially in employees of high risk professions such as police officers (13) and military personnel (14). Early recognition of emerging stress-related problems that is followed-up with personalized just-in-time feedback may help alleviate these burdens (15). Recent developments in wearable sensor technology have introduced new opportunities for this and have spearheaded academic studies on this topic (16,17), including this thesis.

Before hypothesizing how interventions that aim to limit the negative impact of stress may be able to do so, it is helpful to first understand how stress emerges and causes these problems. Stress is the outcome of a psychological process that is known as appraisal (18). When an individual is confronted with certain demands, the brain subconsciously assesses to what extent resources are available that may be used to cope with the situation. If sufficient resources are perceived to be available, the demand is appraised as a non-threatening challenge. When this is not the case, the demand is appraised as a threat, causing a stress response. In the context of this thesis, 'stress' therefore does not refer to the trigger, but to the stress response itself. This stress response prepares the body for action via metabolic changes that prioritize the flow of oxygen and glucose to skeletal muscle and brain cells (19). It also strengthens the functioning of the brain's emotional response center (the amygdala) while impairing the part of the brain that is responsible for decision making and social behavior (the prefrontal cortex) (20). Essentially, a tradeoff is made by sacrificing certain restorative functions and cognitive abilities to be able to more swiftly respond to environmental demands. Although this response is helpful in the context of traditional stressors that require an individual to fight or flight to survive (e.g., a wild animal), it not always is for modern stressors that require individuals to think clearly or communicate well (e.g., cognitive workload or stressful social interactions). These modern stressors tend to be more chronic in nature and thus remain present or keep reoccurring, keeping the body in an aroused state (21), as well as limiting the quality and quantity of the rest (including sleep) that is needed to recover and sustain balanced psychophysiological functioning (22,23). The stress response of our neurological and hormonal systems that originally evolved thousands of years ago is therefore not always optimal to cope with these modern stressors that have emerged during the last centuries or even decades (24,25). Eventually, this leads to a wear and tear on bodily systems (allostatic load) that is detrimental for long-term health and well-being (26). Maintaining resources and sufficient quality and quantity of rest to prevent buildup of allostatic load is therefore essential in remaining resilient when meeting new demands.

Resilience can be defined as the process of positively adapting to adverse events (27), and is achieved when an individual functions well despite facing adversity by having sufficient relevant resources and being able to utilize them (28). Since resources are used to battle stress, an initial loss of resources may increase one's vulnerability to upcoming stress, potentially leading to a loss spiral that negatively impacts resilience (29) – especially when combined with limited recovery opportunities or quality (22,23).

Therefore, continuous monitoring of relevant resources and the recovery process may be a way to identify changes in resilience in an early stage. This data can then be used to provide just-in-time feedback that may allow the individual to take action before more serious harm is done (15). One approach for this, is to inquire about resources and recovery by taking short questionnaires throughout the day on a smartphone, but this is likely to result in a response burden that is detrimental to adherence (30). Unobtrusive monitoring via wearable sensors therefore is more convenient than daily questionnaires from a user perspective, and also differentiates from it by collecting more objective data. The following sections describe why recent developments in wearable sensor technology introduce new opportunities to potentially do so via monitoring of resting Heart Rate Variability (HRV) and sleep, before summarizing the overarching aims and outline of this thesis.

WEARABLE SENSOR TECHNOLOGY

The emergence of wearable sensor technology, often referred to as 'wearables', provides promising opportunities to unobtrusively monitor behavior and physiological states. A well-known example of this is the pedometer, of which the *'manpo-kei'* (literally translated as *'ten thousand steps meter'*) originates as both the first consumer-available step counter (1965) and coincidental basis for the 10.000 steps daily goal (31). Since around 2009, when the first modern wearables were launched (e.g., the Fitbit Classic), the devices primarily used an accelerometer (and later also a gyroscope) to measure physical activity and sleep (32). Another innovation in these devices that seems trivial today is the inclusion of a memory and Bluetooth connection, allowing the devices to store and communicate historical data. This opened up a breadth of possibilities to gain *'self-knowledge through numbers'*, as the Quantified Self movement that flourished around that time adopted as a slogan (33). Self-tracking became popular, incentivizing further development of consumer-available tools.

The next important technological innovation in consumer-available wearables was the introduction of photoplethysmography (PPG) sensors around 2015 (e.g., the Fitbit Charge HR) (34). PPG sensors shine a green, red or infrared light at the skin and use a photodetector to measure how much light of specific wavelength was absorbed (35). Since corpuscles (e.g., red blood cells) in the blood differ in what wavelength (color) light they absorb (e.g., red blood cells particularly absorb green light), PPG sensors can for instance detect volumetric variations in blood circulation as a result of contractions of the heart, which can thus be used to estimate heart rate (36). Although heart rate remains the primary use case for PPG sensor application, the technique can now also be used to estimate other physiological parameters such as blood oxygen saturation, blood pressure and respiration (37). These developments continue to increase the diversity of human behaviors and physiological states that can conveniently be measured in a real-life setting. In the context of stress, where continuous and unobtrusive monitoring of psychophysiological resources and recovery is seen as a promising approach to model (changes in) resilience, particularly resting Heart Rate Variability (HRV) and sleep stand out as interesting parameters that can be measured using consumer-available wearables, for instance via the Oura ring (Figure 1) that was used in chapters 5 and 6 of this thesis (38–42).

Figure 1: The Oura ring, a wearable that can validly measure resting heart rate variability and total sleep time.

HEART RATE VARIABILITY

HRV is a measure for the variation in inter-beat-intervals between heartbeats. Therefore, having a high HRV (Figure 2, green line) means that the heart rate is constantly accelerating and decelerating, whereas a low HRV means that it is beating at a relatively stable pace (Figure 2, red line). The latter may initially sound positive, but having a low HRV has actually been associated with an increased risk of cardiac events (43), diabetes (44), stroke (45) and mortality (46,47). HRV is a reflection of the functioning of the Autonomous Nervous System (ANS), which the part of the nervous system that is responsible for regulating bodily processes such as blood pressure, breathing and digestion (48). During low-stress circumstances, the parasympathetic branch of the ANS that directs the body to "rest and digest" is particularly active and HRV is relatively high, whereas during high-stress circumstances the sympathetic branch of the ANS takes control in order to prepare the body to "fight-or-flight", during which HRV drops (49). Prolonged disruptions of the balanced functioning of both branches provides a burden on bodily systems via allostatic load, which can express itself as a low HRV (50).

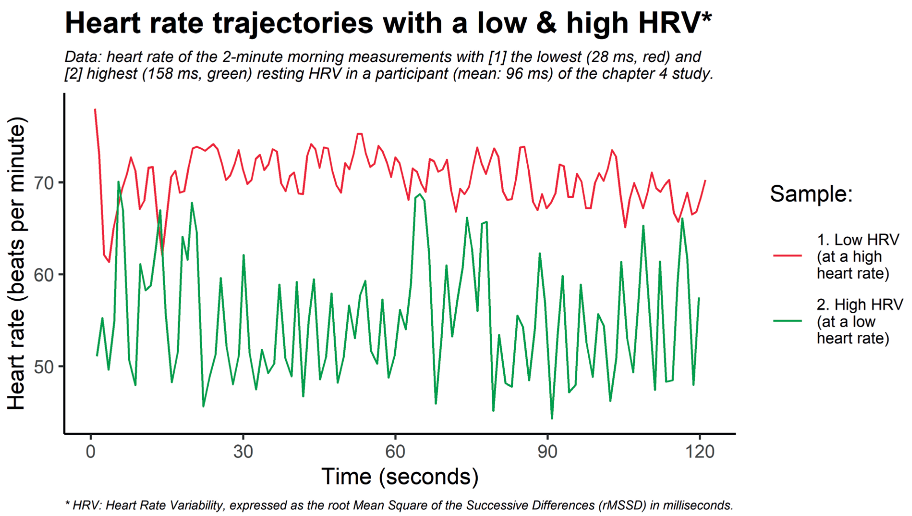

Figure 2: Examples of a low and high resting Heart Rate Variability (HRV).

During stress, HRV acutely declines (51), and can remain suppressed during sleep (52,53). In addition, having a low resting HRV has been associated with an increased sensitivity to perceive stress (54–56), as well as suboptimal emotion regulation (the ability to exert control over one's own emotional state) (57,58), cognitive inhibition (ability to tune out irrelevant stimuli) (59) and cognitive flexibility (ability to switch thinking about two concepts) (59). Neuroimaging studies showed that there is a relationship between HRV and the regions of the brain that are involved in the stress response (the amygdala and prefrontal cortex) (60). As a result, HRV is now widely seen a psychophysiological resource that is a reflection of the ability to flexibly adapt to changing environmental demands and regulate emotions (61), or even as an index of resilience (62,63).

Due to its association with resilience, monitoring trends in HRV may contribute to insights in individuals' resilience. To be able to draw conclusions based on HRV measurements, it is important that the datapoints are inter-comparable, which means that each measurement is taken in a relatively similar context. This is necessary because besides stress, HRV is influenced throughout the day by factors like body posture (64), exercise (65) and the intake of caffeine (66) or alcohol (67). Therefore, measuring HRV in a resting state that is minimally confounded by other factors (e.g., during sleep or upon awakening) is recommended (68).

The daily monitoring of resting HRV is still a novel and relatively under-explored topic in psychological research, but interesting lessons can be learned from the field of sports science, in which these techniques have been applied and studied for over a decade (69). In HRV guided training, athletes monitor their daily resting HRV and compare it to historical data in order to gain insight in the impact of training-, psychological- and lifestyle-stressors on their physiology and adjust the intensity of their training accordingly. HRV guided training was found to be more effective than predefined training for improving the body's peak oxygen uptake (VO_{2max}) (70), as well as for maintaining and improving resting HRV and lowering the likelihood of negative outcomes (71), proving its merit for optimizing performance while limiting unnecessary physiological burden. In these studies, psychological stress is regularly attributed to cause changes in resting HRV (72–74), which are sometimes even described to have a more distinct and lasting influence than the impact of intensive training itself (75). It is therefore possible that daily resting HRV monitoring holds promise for other contexts as well, such as for employees in demanding work environments.

SLEEP

Besides monitoring the physiological resting state over time, tracking the recovery process itself may also be a promising approach for estimating an individual's capacity for resilience. Sleep has an important role in the recovery from mental and physical demands (23). Adults are therefore recommended to sleep at least 7 hours per night on a regular basis in order to avoid adverse health outcomes (76). Although sleep is needed for the psychophysiological recovery from stress, stress itself can also negatively impact sleep (77–80). The complexity of the association between sleep and stress becomes even more apparent when learning that a lack of sleep also increases stress sensitivity (77–81). The association between stress and sleep is clearly bidirectional, but the adverse impact of sleep deprivation on perceived stress is more consistently reported and found to be stronger (80). Finally, sleep deprivation also negatively influences HRV on the subsequent workday (82), which is another sign that a lack of sleep can contribute to the draining of psychophysiological resources, as well as the buildup of allostatic load (22,23). “Getting a good night’s sleep” therefore truly is important to ensure that individuals have sufficiently recovered psychophysiological resources to contribute to their stress resilience.

AIM OF THIS THESIS

The *Wearable and app-based resilience Modelling in employees (WearMe)* study that is described in this thesis aims to model (changes in) resilience based on data that is derived from wearables and apps, particularly resting HRV and sleep. By doing so, it hopes to contribute valuable knowledge that may be used in the future development of automated interventions that use continuous and unobtrusive monitoring to generate personalized just-in-time feedback on employees’ resilience in order to mitigate or prevent the adverse impact of stress. To close off the general introduction of this thesis, the following outline will briefly address the gap in knowledge that each of the chapters will address and how each chapter aims to contribute to the overarching purpose of this thesis.

OUTLINE OF THE THESIS

Before diving into the specific rationales behind each of the chapters in this thesis, it may be supportive to first understand how these chapters complement each other regarding the broader aim of this thesis. In general, the current state of knowledge on this topic is mostly based on cross-sectional population studies in controlled environments. As a result, insight in the extent to which this knowledge also applies on a within-subject level in free-living conditions is limited. Therefore, there is a particular need for within-subject studies using wearables to collect continuous data in free-living conditions (63). Therefore, the studies that are presented in this thesis utilized three different within-subject methodologies to contribute to this body of knowledge.

Figure 3A visualizes the nested within-day analyses that were performed in the studies in chapters 2 and 4. In these studies, each participant collected data using a wearable and short daily questionnaire via an Ecological Momentary Assessment (EMA) smartphone app. These datapoints were then used to assess within-day associations (e.g., is nocturnal wearable data related to morning EMA questionnaire data) by analyzing them as one large pool of observations, while accounting for between-subject differences via multi-level modelling or within-subject standardization (83). In the (multiple) n-of-1 time series analysis that is described in Figure 3B and was applied in chapter 5, the data collection occurred in a similar fashion. The data analysis, however, differs in that it does not only assess within-day associations between both data sources, but investigates their relationship over a timespan of multiple days within each participant.

Finally, Figure 3C visualizes the nested longitudinal analysis that was used for the study in chapter 6. Similar to the aforementioned nested approach (Figure 3A), each participant contributes a certain number of observations to the pool of observations that are analyzed as a whole. However, in this case a time window of 5 weeks is analyzed instead of the within-day analysis that was discussed before. As such, these methodological approaches complement each other by investigating within-subject associations on multiple different timeframes in the chapters in this thesis, which will be briefly introduced in each of the following paragraphs.

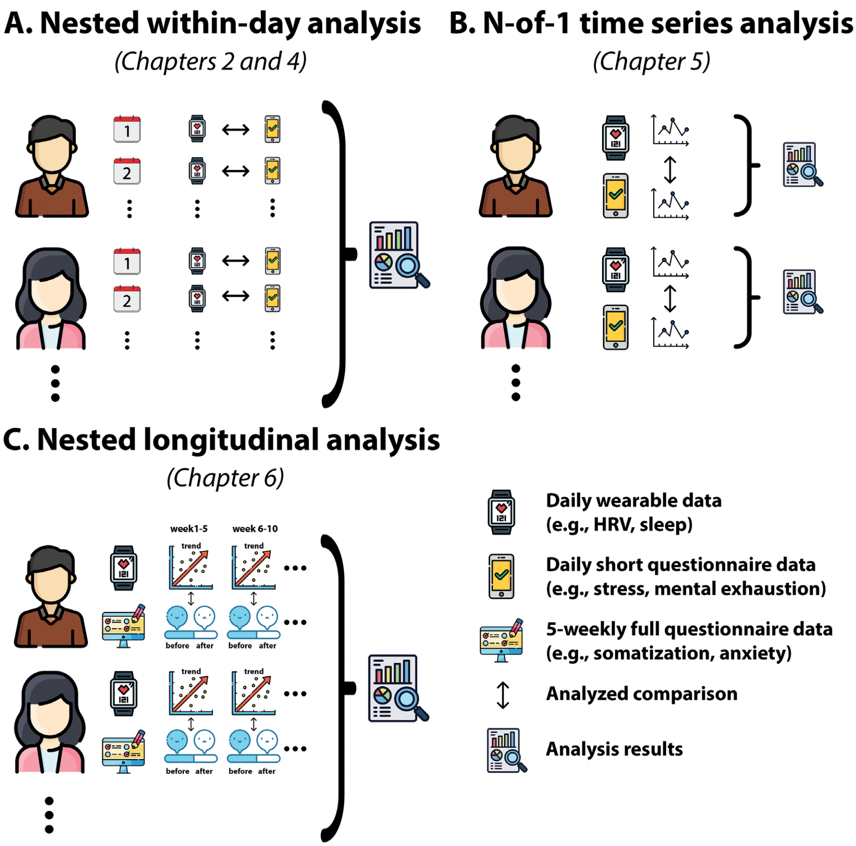

Figure 3: Visualization of the 3 within-subject research designs that were used for the studies in this thesis.

During stress appraisal, the brain subconsciously assesses the perceived availability of resources to cope with the situation (18), including the individual's perceived mental (84) and physical fitness (85). Resting HRV has been related to components of both mental (57,58,62,86) and physical fitness (87–92), but it is unknown to what extent it is associated with the subjectively perceived mental and physical fitness. Insight in the degree in which resting HRV is associated with perceived mental and physical fitness will improve our understanding of whether resting HRV should be seen as a proxy for the perceived fitness that is assessed during stress appraisal, or as an independent psychophysiological resource. Therefore, the study in chapter *2* explores to what extent wearable-measured HRV during sleep predicts perceived mental and physical fitness on the subsequent morning in military employees (n=63) in a nested within-subject design (Figure 3A).

Since most of the traditional research on resilience performed population studies that assess between-subject differences (63), existing resilience-related models and theories also tend to focus on relatively broad concepts and higher time-frame mechanisms. While such theories are essential for our current understanding of employee resilience (28), they do not necessarily explain how demands may or may not cause intra- or multi-day changes in resilience. In order to perform the wearable-based and within-subject research that is needed for the overarching purpose of this thesis, it is necessary to conceptualize this mechanism on a lower time. Chapter 3 therefore introduces a cyclical conceptual model for resilience that provides a basis for several short-term (intra- or multi-day) associations, as well as the study protocol for the first data collection of the WearMe study.

Chapter 4 describes the results of the study that was conceptualized in chapter 3. A nested within-subject design (Figure 3A) is utilized in a sample (n=26) of first-time interns that collected data during 15 weeks to test 4 hypotheses that are derived from the previously introduced conceptual model. Resting HRV upon awakening is hypothesized to have a buffering effect on the positive associations between daytime demands and stress (hypothesis 1), as well as between daytime stress and evening mental exhaustion (hypothesis 2). Furthermore, daytime stress is also expected to negatively influence sleep (hypothesis 3), whereas sleep is hypothesized to buffer against the expected negative association between evening mental exhaustion and subsequent-morning resting HRV (hypothesis 4). The combination of hypotheses 1, 2 and 4 creates a potential negative feedback loop, which aligns with the conservation of resources theory that states that an initial loss of resources may create a loss spiral, as resources are needed to adaptively cope with future demands (29). Insight in the degree in which these associations can indeed be observed in free-living conditions is important to improve our understanding of the role of resting HRV and sleep in how intra-day changes may potentially cascade into multi-day or multi-week trends, which are explored in the remaining chapters.

Stress can negatively impact resting HRV (52,53), whereas suppressed resting HRV has also been associated with increased stress sensitivity (54–56), suboptimal emotion regulation (57,58), as well as decreased cognitive inhibition and cognitive flexibility (59).

In a similar way, stress has been shown to have a negative bidirectional association with sleep (77–80,93). As these studies primarily focused on intra-day bidirectional effects, within-subject research assessing potential multi-day associations is lacking. Increased insight in the degree in which these associations can also be observed on a multi-day level in free-living conditions may improve the wearable-based resilience models that are targeted by this thesis. Therefore, the study in chapter 5 assesses to what extent wearable-measured sleep and nocturnal HRV can be predicted on a multi-day level by resilience-related diary outcomes and vice versa in a multiple n-of-1 time series analysis (Figure 3B) in 8 police officers that collected time series data during 15 to 55 weeks.

Longitudinal decreases in resting HRV can be associated with increased stress (94–97) and mental exhaustion (98–100). Having a relatively low resting HRV is also related to increased depression (101), anxiety (102) and somatization (103) at a population level. Furthermore, increasing fluctuations in the day-to-day resting HRV are associated with increased fatigue (104–106) and stress (72) in athletes, although these associations may be moderated by trends in the underlying resting HRV values (107). Although these studies show that trends in resting HRV and the daily fluctuations therein may be used to model longitudinal changes in mental health outcomes that would be relevant for the overarching purpose of this thesis, no studies to date have done so using granular wearable-based data. Therefore, the study in chapter 6 assesses if trends in daily resting HRV or the fluctuations therein are associated with 5-week changes in stress, somatization, depression and anxiety in a nested longitudinal design (Figure 3C) where 9 police officers collected 47 5-week observations.

Together, this thesis contributes to the existing body of knowledge on wearable-based resilience modelling by investigating relevant within-subject associations on multiple timeframes and in different occupational settings. By doing so, the studies in this thesis provide insights in the degree in which resting HRV and sleep may be useful in future wearable-based resilience interventions that hope to limit the negative consequences of stress. The results of these studies are described in the upcoming chapters (2 to 6), which were all reported as they were presented in the academic journals that they were published in. Finally, the general discussion in chapter 7 discusses the overarching findings regarding the overall aim of this thesis, some methodological considerations and finally reflect on potential future directions of research on wearable-based resilience modelling.

REFERENCES

1. Yang T, Qiao Y, Xiang S, Li W, Gan Y, Chen Y. Work stress and the risk of cancer: A meta-analysis of observational studies. International Journal of Cancer. 2019;144:2390–2400. doi: 10.1002/ijc.31955.

2. Buscemi V, Chang W-J, Liston MB, McAuley JH, Schabrun SM. The Role of Perceived Stress and Life Stressors in the Development of Chronic Musculoskeletal Pain Disorders: A Systematic Review. The Journal of Pain. 2019;20:1127–1139. doi: 10.1016/j.jpain.2019.02.008.

3. Decker A, Askar H, Tattan M, Taichman R, Wang H-L. The assessment of stress, depression, and inflammation as a collective risk factor for periodontal diseases: a systematic review. Clinical oral investigations. 2020;24:1–12.

4. Sui H, Sun N, Zhan L, Lu X, Chen T, Mao X. Association between Work-Related Stress and Risk for Type 2 Diabetes: A Systematic Review and Meta-Analysis of Prospective Cohort Studies. PLOS ONE. 2016;11:e0159978. doi: 10.1371/journal.pone.0159978.

5. Booth J, Connelly L, Lawrence M, Chalmers C, Joice S, Becker C, Dougall N. Evidence of perceived psychosocial stress as a risk factor for stroke in adults: a meta-analysis. BMC Neurology. 2015;15:233. doi: 10.1186/s12883-015-0456-4.

6. Magnavita N, Capitanelli I, Garbarino S, Pira E. Work-related stress as a cardiovascular risk factor in police officers: a systematic review of evidence. International Archives of Occupational and Environmental Health. 2018;91:377–389. doi: 10.1007/s00420-018-1290-y.

7. Li J, Zhang M, Loerbroks A, Angerer P, Siegrist J. Work stress and the risk of recurrent coronary heart disease events: A systematic review and meta-analysis. International Journal of Occupational Medicine and Environmental Health [Internet]. 2014; doi: 10.2478/s13382-014-0303-7.

8. van der Molen HF, Nieuwenhuijsen K, Frings-Dresen MHW, de Groene G. Work-related psychosocial risk factors for stress-related mental disorders: an updated systematic review and meta-analysis. BMJ Open. 2020;10:e034849. doi: 10.1136/bmjopen-2019-034849.

9. Chirico F. Job stress models for predicting burnout syndrome: a review. Annali dell'Istituto superiore di sanita. 2016;52:443–456.

10. Bhattacharya A, Ray T. Precarious work, job stress, and health-related quality of life. American Journal of Industrial Medicine. 2021;64:310–319. doi: 10.1002/ajim.23223.

11. van den Heuvel S, van Thor J, Ferandez Beiro L, van Dam L, Driven H. Nationale Enquete Arbeidsomstandigheden 2021 in vogelvlucht. 2022;

12. Hassard J, Teoh KRH, Visockaite G, Dewe P, Cox T. The cost of work-related stress to society: A systematic review. Journal of Occupational Health Psychology. 2018;23:1–17. doi: 10.1037/ocp0000069.

13. Collins PA, Gibbs ACC. Stress in police officers: a study of the origins, prevalence and severity of stress-related symptoms within a county police force. Occupational Medicine. 2003;53:256–264. doi: 10.1093/occmed/kqg061.

14. Holliday R, Borges LM, Stearns-Yoder KA, Hoffberg AS, Brenner LA, Monteith LL. Posttraumatic Stress Disorder, Suicidal Ideation, and Suicidal Self-Directed Violence Among U.S. Military Personnel and Veterans: A Systematic Review of the Literature From 2010 to 2018. Frontiers in Psychology [Internet]. 2020;11. doi: 10.3389/fpsyg.2020.01998.

15. Wang L, Miller LC. Just-in-the-Moment Adaptive Interventions (JITAI): A Meta-Analytical Review. Health Communication. 2020;35:1531–1544. doi: 10.1080/10410236.2019.1652388.

16. Owens AP. The Role of Heart Rate Variability in the Future of Remote Digital Biomarkers. Frontiers in Neuroscience [Internet]. 2020;14. doi: 10.3389/fnins.2020.582145.

17. Drury RL. Wearable biosensor systems and resilience: a perfect storm in health care? Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00853.

18. Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. Eur J Pers. 1987;1:141–169. doi: 10.1002/per.2410010304.

19. McCarty R. Chapter 4 - The Fight-or-Flight Response: A Cornerstone of Stress Research. In: Fink G, editor. Stress: Concepts, Cognition, Emotion, and Behavior [Internet]. San Diego: Academic Press; 2016. p. 33–37. Available from: https://www.sciencedirect.com/science/article/pii/B9780128009512000042.

20. Arnsten AFT. Stress signalling pathways that impair prefrontal cortex structure and function. Nature Reviews Neuroscience. 2009;10:410–422. doi: 10.1038/nrn2648.

21. McEwen BS. Stress, Adaptation, and Disease: Allostasis and Allostatic Load. Annals of the New York Academy of Sciences. 1998;840:33–44. doi: 10.1111/j.1749-6632.1998.tb09546.x.

22. McEwen BS. Sleep deprivation as a neurobiologic and physiologic stressor: allostasis and allostatic load. Metabolism. 2006;55:S20–S23. doi: 10.1016/j.metabol.2006.07.008.

23. McEwen BS, Karatsoreos IN. Sleep Deprivation and Circadian Disruption: Stress, Allostasis, and Allostatic Load. Sleep Medicine Clinics. 2015;10:1–10. doi: 10.1016/j.jsmc.2014.11.007.

24. Katsampouris E, Turner-Cobb JM, Barnett JC, Arnold RS. Can ancient and modern stressors be distinguished? A mixed-methods exploration of psychosocial characteristics and health symptoms in young and older adults. J Health Psychol. 2022;27:624–636. doi: 10.1177/1359105320965654.

25. Katsampouris E, Turner-Cobb JM, Arnold R, Barnett JC. Unconscious associations between stressor type and ability to cope: An experimental approach using ancient and modern sources of stress. British Journal of Health Psychology. 2022;27:1011–1025. doi: 10.1111/bjhp.12587.

26. Seeman TE, Singer BH, Rowe JW, Horwitz RI, McEwen BS. Price of Adaptation—Allostatic Load and Its Health Consequences: MacArthur Studies of Successful Aging. Archives of Internal Medicine. 1997;157:2259–2268. doi: 10.1001/archinte.1997.00440400111013.

27. Cosco TD, Kaushal A, Hardy R, Richards M, Kuh D, Stafford M. Operationalising resilience in longitudinal studies: a systematic review of methodological approaches. J Epidemiol Community Health. 2017;71:98. doi: 10.1136/jech-2015-206980.

28. Britt TW, Shen W, Sinclair RR, Grossman MR, Klieger DM. How Much Do We Really Know About Employee Resilience? Industrial and Organizational Psychology. 2016/07/04 ed. 2016;9:378–404. doi: 10.1017/iop.2015.107.

29. Hobfoll SE. The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. Applied Psychology. 2001;50:337–421. doi: 10.1111/1464-0597.00062.

30. Rolstad S, Adler J, Rydén A. Response Burden and Questionnaire Length: Is Shorter Better? A Review and Meta-analysis. Value in Health. 2011;14:1101–1108. doi: 10.1016/j.jval.2011.06.003.

31. Tudor-Locke C, Bassett DR. How Many Steps/Day Are Enough? Sports Medicine. 2004;34:1–8. doi: 10.2165/00007256-200434010-00001.

32. Leung W, Case L, Sung M-C, Jung J. A meta-analysis of Fitbit devices: same company, different models, different validity evidence. Journal of Medical Engineering & Technology. 2022;46:102–115. doi: 10.1080/03091902.2021.2006350.

33. Lupton D. The Quantified Self: A Sociology of Self-Tracking. Cambridge: Polity Press; 2016.

34. Stahl SE, An H-S, Dinkel DM, Noble JM, Lee J-M. How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough? BMJ Open Sp Ex Med. 2016;2:e000106. doi: 10.1136/bmjsem-2015-000106.

35. Allen J. Photoplethysmography and its application in clinical physiological measurement. Physiological Measurement. 2007;28:R1. doi: 10.1088/0967-3334/28/3/R01.

36. Castaneda D, Esparza A, Ghamari M, Soltanpur C, Nazeran H. A review on wearable photoplethysmography sensors and their potential future applications in health care. Int J Biosens Bioelectron. 2018;4:195–202. doi: 10.15406/ijbsbe.2018.04.00125. Cited: in: : PMID: 30906922.

37. Lee I, Park N, Lee H, Hwang C, Kim JH, Park S. Systematic Review on Human Skin-Compatible Wearable Photoplethysmography Sensors. Applied Sciences. 2021;11. doi: 10.3390/app11052313.

38. Stone JD, Ulman HK, Tran K, Thompson AG, Halter MD, Ramadan JH, Stephenson M, Finomore VS, Galster SM, Rezai AR, et al. Assessing the Accuracy of Popular Commercial Technologies That Measure Resting Heart Rate and Heart Rate Variability. Frontiers in Sports and Active Living [Internet]. 2021;3. doi: 10.3389/fspor.2021.585870.

39. Chee NIYN, Ghorbani S, Golkashani HA, Leong RLF, Ong JL, Chee MWL. Multi-Night Validation of a Sleep Tracking Ring in Adolescents Compared with a Research Actigraph and Polysomnography. Nat Sci Sleep. 2021;13:177–190. doi: 10.2147/NSS.S286070. Cited: in: : PMID: 33623459.

40. de Zambotti M, Rosas L, Colrain IM, Baker FC. The Sleep of the Ring: Comparison of the ŌURA Sleep Tracker Against Polysomnography. Behavioral Sleep Medicine. 2019;17:124–136. doi: 10.1080/15402002.2017.1300587.

41. Kinnunen H, Rantanen A, Kenttä T, Koskimäki H. Feasible assessment of recovery and cardiovascular health: accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG. Physiological Measurement. 2020;41:04NT01. doi: 10.1088/1361-6579/ab840a.

42. Cao R, Azimi I, Sarhaddi F, Niela-Vilen H, Axelin A, Liljeberg P, Rahmani AM. Accuracy Assessment of Oura Ring Nocturnal Heart Rate and Heart Rate Variability in Comparison With Electrocardiography in Time and Frequency Domains: Comprehensive Analysis. J Med Internet Res. 2022;24:e27487. doi: 10.2196/27487.

43. Tsuji H, Larson MG, Venditti FJ, Manders ES, Evans JC, Feldman CL, Levy D. Impact of Reduced Heart Rate Variability on Risk for Cardiac Events. Circulation. 1996;94:2850–2855. doi: 10.1161/01.CIR.94.11.2850.

44. Singh JP, Larson MG, O'Donnell CJ, Wilson PF, Tsuji H, Lloyd-Jones DM, Levy D. Association of hyperglycemia with reduced heart rate variability (The Framingham Heart Study). The American Journal of Cardiology. 2000;86:309–312. doi: 10.1016/S0002-9149(00)00920-6.

45. Ernst G, Watne LO, Frihagen F, Wyller TB, Dominik A, Rostrup M. Low Heart Rate Variability Predicts Stroke and Other Complications in the First Six Postoperative Months After a Hip Fracture Operation. Frontiers in Cardiovascular Medicine [Internet]. 2021;8. doi: 10.3389/fcvm.2021.640970.

46. Tsuji H, Venditti FJ, Manders ES, Evans JC, Larson MG, Feldman CL, Levy D. Reduced heart rate variability and mortality risk in an elderly cohort. The Framingham Heart Study. Circulation. 1994;90:878–883. doi: 10.1161/01.CIR.90.2.878.

47. Kleiger RE, Miller JP, Bigger JT, Moss AJ. Decreased heart rate variability and its association with increased mortality after acute myocardial infarction. The American Journal of Cardiology. 1987;59:256–262. doi: 10.1016/0002-9149(87)90795-8.

48. van Ravenswaaij-Arts CMA, Kollee LAA, Hopman JCW, Stoelinga GBA, van Geijn HP. Heart Rate Variability. Ann Intern Med. 1993;118:436–447. doi: 10.7326/0003-4819-118-6-199303150-00008.

49. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health [Internet]. 2017;5. doi: 10.3389/fpubh.2017.00258.

50. Thayer JF, Sternberg E. Beyond Heart Rate Variability. Annals of the New York Academy of Sciences. 2006;1088:361–372. doi: 10.1196/annals.1366.014.

51. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 2018;15:235–245. doi: 10.30773/pi.2017.08.17.

52. Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, Kupfer D, Thayer JF. Acute Stress Affects Heart Rate Variability During Sleep. Psychosomatic Medicine [Internet]. 2004;66. doi: 10.1097/01.PSY.0000106884.58744.09.

53. Hynynen E, Konttinen N, Kinnunen U, Kyröläinen H, Rusko H. The incidence of stress symptoms and heart rate variability during sleep and orthostatic test. European Journal of Applied Physiology. 2011;111:733–741. doi: 10.1007/s00421-010-1698-x.

54. Park G, Vasey MW, Van Bavel JJ, Thayer JF. When tonic cardiac vagal tone predicts changes in phasic vagal tone: The role of fear and perceptual load. Psychophysiology. 2014;51:419–426. doi: 10.1111/psyp.12186.

55. Park G, Thayer JF. From the heart to the mind: cardiac vagal tone modulates top-down and bottom-up visual perception and attention to emotional stimuli. Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00278.

56. Gaebler M, Daniels JK, Lamke J-P, Fydrich T, Walter H. Heart rate variability and its neural correlates during emotional face processing in social anxiety disorder. Biological Psychology. 2013;94:319–330. doi: 10.1016/j.biopsycho.2013.06.009.

57. Mather M, Thayer JF. How heart rate variability affects emotion regulation brain networks. Current Opinion in Behavioral Sciences. 2018;19:98–104. doi: 10.1016/j.cobeha.2017.12.017.

58. Holzman JB, Bridgett DJ. Heart rate variability indices as bio-markers of top-down self-regulatory mechanisms: A meta-analytic review. Neuroscience & Biobehavioral Reviews. 2017;74:233–255. doi: 10.1016/j.neubiorev.2016.12.032.

59. Magnon V, Vallet GT, Benson A, Mermillod M, Chausse P, Lacroix A, Bouillon-Minois J-B, Dutheil F. Does heart rate variability predict better executive functioning? A systematic review and meta-analysis. Cortex. 2022;155:218–236. doi: 10.1016/j.cortex.2022.07.008.

60. Thayer JF, Åhs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012;36:747–756. doi: 10.1016/j.neubiorev.2011.11.009.

61. Heiss S, Vaschillo B, Vaschillo EG, Timko CA, Hormes JM. Heart rate variability as a biobehavioral marker of diverse psychopathologies: A review and argument for an “ideal range.” Neuroscience & Biobehavioral Reviews. 2021;121:144–155. doi: 10.1016/j.neubiorev.2020.12.004.

62. An E, Nolty AAT, Amano SS, Rizzo AA, Buckwalter JG, Rensberger J. Heart Rate Variability as an Index of Resilience. Military Medicine. 2020;185:363–369. doi: 10.1093/milmed/usz325.

63. Perna G, Riva A, Defillo A, Sangiorgio E, Nobile M, Caldirola D. Heart rate variability: Can it serve as a marker of mental health resilience?: Special Section on "Translational and Neuroscience Studies in Affective Disorders" Section Editor, Maria Nobile MD, PhD. Journal of Affective Disorders. 2020;263:754–761. doi: 10.1016/j.jad.2019.10.017.

64. Buchheit M, Al Haddad H, Laursen PB, Ahmaidi S. Effect of body posture on postexercise parasympathetic reactivation in men. Experimental Physiology. 2009;94:795–804. doi: 10.1113/expphysiol.2009.048041.

65. Michael S, Graham KS, Davis GM. Cardiac Autonomic Responses during Exercise and Post-exercise Recovery Using Heart Rate Variability and Systolic Time Intervals—A Review. Frontiers in Physiology [Internet]. 2017;8. doi: 10.3389/fphys.2017.00301.

66. Koenig J, Jarczok MN, Kuhn W, Morsch K, Schäfer A, Hillecke TK, Thayer JF. Impact of Caffeine on Heart Rate Variability: A Systematic Review. Journal of Caffeine Research. 2013;3:22–37. doi: 10.1089/jcr.2013.0009.

67. Romanowicz M, Schmidt JE, Bostwick JM, Mrazek DA, Karpyak VM. Changes in Heart Rate Variability Associated With Acute Alcohol Consumption: Current Knowledge and Implications for Practice and Research. Alcohol: Clinical and Experimental Research. 2011;35:1092–1105. doi: 10.1111/j.1530-0277.2011.01442.x.

68. Malik M. Heart Rate Variability: Standards of Measurement, Physiological Interpretation, and Clinical Use: Task Force of The European Society of Cardiology and the North American Society for Pacing and Electrophysiology. Annals of Noninvasive Electrocardiology. 1996;1:151–181. doi: 10.1111/j.1542-474X.1996.tb00275.x.

69. Kiviniemi AM, Hautala AJ, Kinnunen H, Tulppo MP. Endurance training guided individually by daily heart rate variability measurements. European Journal of Applied Physiology. 2007;101:743–751. doi: 10.1007/s00421-007-0552-2.

70. Granero-Gallegos A, González-Quílez A, Plews D, Carrasco-Poyatos M. HRV-Based Training for Improving VO2max in Endurance Athletes. A Systematic Review with Meta-Analysis. International Journal of Environmental Research and Public Health. 2020;17. doi: 10.3390/ijerph17217999.

71. Manresa-Rocamora A, Sarabia JM, Javaloyes A, Flatt AA, Moya-Ramón M. Heart Rate Variability-Guided Training for Enhancing Cardiac-Vagal Modulation, Aerobic Fitness, and Endurance Performance: A Methodological Systematic Review with Meta-Analysis. International Journal of Environmental Research and Public Health. 2021;18. doi: 10.3390/ijerph181910299.

72. Flatt AA, Esco MR, Nakamura FY. Individual Heart Rate Variability Responses to Preseason Training in High Level Female Soccer Players. The Journal of Strength & Conditioning Research [Internet]. 2017;31. doi: 10.1519/JSC.0000000000001482.

73. Figueiredo DH, Figueiredo DH, Moreira A, Gonçalves HR, Stanganelli LCR. Effect of Overload and Tapering on Individual Heart Rate Variability, Stress Tolerance, and Intermittent Running Performance in Soccer Players During a Preseason. The Journal of Strength & Conditioning Research [Internet]. 2019;33. doi: 10.1519/JSC.0000000000003127.

74. Tian Y, He Z, Zhao J, Tao D, Xu K, Earnest CP, Mc Naughton LR. Heart Rate Variability Threshold Values for Early-Warning Nonfunctional Overreaching in Elite Female Wrestlers. The Journal of Strength & Conditioning Research [Internet]. 2013;27. doi: 10.1519/JSC.0b013e31826caef8.

75. Sanders D, Spindler DJ, Stanley J. The Multidisciplinary Physical Preparation of a Multiple Paralympic Medal-Winning Cyclist. International Journal of Sports Physiology and Performance. 2022;17:1316–1322. doi: 10.1123/ijspp.2022-0039.

76. Consensus Conference Panel, Watson Nathaniel F., Badr M. Safwan, Belenky Gregory, Bliwise Donald L., Buxton Orfeu M., Buysse Daniel, Dinges David F., Gangwisch James, Grandner Michael A., et al. Recommended Amount of Sleep for a Healthy Adult: A Joint Consensus Statement of the American Academy of Sleep Medicine and Sleep Research Society. Journal of Clinical Sleep Medicine. 11:591–592. doi: 10.5664/jcsm.4758.

77. Yap Y, Slavish DC, Taylor DJ, Bei B, Wiley JF. Bi-directional relations between stress and self-reported and actigraphy-assessed sleep: a daily intensive longitudinal study. Sleep. 2020;43:zsz250. doi: 10.1093/sleep/zsz250.

78. Narmandakh A, Oldehinkel AJ, Masselink M, de Jonge P, Roest AM. Affect, worry, and sleep: Between- and within-subject associations in a diary study. Journal of Affective Disorders Reports. 2021;4:100134. doi: 10.1016/j.jadr.2021.100134.

79. Sperry SH, Kwapil TR. Variability in Sleep Is Associated with Trait-Based and Daily Measures of Bipolar Spectrum Psychopathology. Behavioral Sleep Medicine. 2022;20:90–99. doi: 10.1080/15402002.2021.1890076.

80. Ekuni R, Souza BMN, Cogo-Moreira H, Lourenço FC, Pompeia S. Bidirectional longitudinal dynamics of self-reported total sleep time and perceived stress: Establishing potential causal relationships. Sleep Health. 2022;8:406–409. doi: 10.1016/j.sleh.2022.01.004.

81. Lee S, Crain TL, McHale SM, Almeida DM, Buxton OM. Daily antecedents and consequences of nightly sleep. Journal of Sleep Research. 2017;26:498–509. doi: 10.1111/jsr.12488.

82. Jackowska M, Dockray S, Endrighi R, Hendrickx H, Steptoe A. Sleep problems and heart rate variability over the working day. Journal of Sleep Research. 2012;21:434–440. doi: 10.1111/j.1365-2869.2012.00996.x.

83. Enders CK, Tofighi D. Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods. 2007;12:121–138. doi: 10.1037/1082-989X.12.2.121.

84. Robinson P, Oades L, Caputi P. Conceptualising and measuring mental fitness: A Delphi study. International Journal of Wellbeing. 2015;5:53–73. doi: 10.5502/ijw.v5i1.4.

85. Caspersen CJ, Powell KE, Christenson GM. Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. Public Health Rep. 1985;100:126–131. Cited: in: : PMID: 3920711.

86. Hourani LL, Davila MI, Morgan J, Meleth S, Ramirez D, Lewis G, Kizakevich PN, Eckhoff R, Morgan T, Strange L, et al. Mental health, stress, and resilience correlates of heart rate variability among military reservists, guardsmen, and first responders. Physiology & Behavior. 2020;214:112734. doi: 10.1016/j.physbeh.2019.112734.

87. Lima-Borges DS, Martinez PF, Vanderlei LCM, Barbosa FSS, Oliveira-Junior SA. Autonomic modulations of heart rate variability are associated with sports injury incidence in sprint swimmers. The Physician and Sportsmedicine. 2018;46:374–384. doi: 10.1080/00913847.2018.1450606.

88. Gisselman AS, Baxter GD, Wright A, Hegedus E, Tumilty S. Musculoskeletal overuse injuries and heart rate variability: Is there a link? Medical Hypotheses. 2016;87:1–7. doi: 10.1016/j.mehy.2015.12.003.

89. Souza HCD, Philbois SV, Veiga AC, Aguilar BA. Heart Rate Variability and Cardiovascular Fitness: What We Know so Far. Vasc Health Risk Manag. 2021;17:701–711. doi: 10.2147/VHRM.S279322. Cited: in: : PMID: 34803382.

90. Tomes C, Schram B, Orr R. Relationships Between Heart Rate Variability, Occupational Performance, and Fitness for Tactical Personnel: A Systematic Review. Frontiers in Public Health [Internet]. 2020;8. doi: 10.3389/fpubh.2020.583336.

91. Williams S, Booton T, Watson M, Rowland D, Altini M. Heart Rate Variability is a Moderating Factor in the Workload-Injury Relationship of Competitive CrossFit™ Athletes. J Sports Sci Med. 2017;16:443–449. Cited: in: : PMID: 29238242.

92. Forte G, Troisi G, Pazzaglia M, Pascalis VD, Casagrande M. Heart Rate Variability and Pain: A Systematic Review. Brain Sciences. 2022;12. doi: 10.3390/brainsci12020153.

93. Nollet M, Wisden W, Franks NP. Sleep deprivation and stress: a reciprocal relationship. Interface Focus. 2020;10:20190092. doi: 10.1098/rsfs.2019.0092.

94. Borchini R, Ferrario MM, Bertù L, Veronesi G, Bonzini M, Dorso M, Cesana G. Prolonged job strain reduces time-domain heart rate variability on both working and resting days among cardiovascular-susceptible nurses. International Journal of Occupational Medicine and Environmental Health [Internet]. 2014; doi: 10.2478/s13382-014-0289-1.

95. Borchini R, Veronesi G, Bonzini M, Gianfagna F, Dashi O, Ferrario MM. Heart Rate Variability Frequency Domain Alterations among Healthy Nurses Exposed to Prolonged Work Stress. International Journal of Environmental Research and Public Health. 2018;15. doi: 10.3390/ijerph15010113.

96. Föhr T, Tolvanen A, Myllymäki T, Järvelä-Reijonen E, Peuhkuri K, Rantala S, Kolehmainen M, Korpela R, Lappalainen R, Ermes M, et al. Physical activity, heart rate variability–based stress and recovery, and subjective stress during a 9-month study period. Scandinavian Journal of Medicine & Science in Sports. 2017;27:612–621. doi: 10.1111/sms.12683.

97. Wagner JA, Feinn R, Lampert R, Bermúdez-Millán A, Pérez-Escamilla R. Changes in negative affect and changes in heart rate variability among low-income latinos with type 2 diabetes in a randomized, controlled stress management trial. Journal of Psychosomatic Research. 2019;124:109774. doi: 10.1016/j.jpsychores.2019.109774.

98. Zhang M, Liu L, Shi Y, Yang Y, Yu X, Angerer P, Kristensen TS, Li J. Longitudinal associations of burnout with heart rate variability in patients following acute coronary syndrome: A one-year follow-up study. General Hospital Psychiatry. 2018;53:59–64. doi: 10.1016/j.genhosppsych.2018.05.008.

99. Wekenborg MK, Hill LK, Thayer JF, Penz M, Wittling RA, Kirschbaum C. The Longitudinal Association of Reduced Vagal Tone With Burnout. Psychosomatic Medicine [Internet]. 2019;81. doi: 10.1097/PSY.0000000000000750.

100. Shi Y, Jiang R, Zhu C, Zhang M, Cai H, Hu Z, Ye Y, Liu Y, Sun H, Ma Y, et al. High Job Burnout Predicts Low Heart Rate Variability in the Working Population after a First Episode of Acute Coronary Syndrome. International Journal of Environmental Research and Public Health. 2021;18. doi: 10.3390/ijerph18073431.

101. Kemp AH, Quintana DS, Gray MA, Felmingham KL, Brown K, Gatt JM. Impact of Depression and Antidepressant Treatment on Heart Rate Variability: A Review and Meta-Analysis. Biological Psychiatry. 2010;67:1067–1074. doi: 10.1016/j.biopsych.2009.12.012.

102. Chalmers JA, Quintana DS, Abbott MJ-A, Kemp AH. Anxiety Disorders are Associated with Reduced Heart Rate Variability: A Meta-Analysis. Frontiers in Psychiatry [Internet]. 2014;5. doi: 10.3389/fpsyt.2014.00080.

103. de Jonge P, Mangano D, Whooley MA. Differential Association of Cognitive and Somatic Depressive Symptoms With Heart Rate Variability in Patients With Stable Coronary Heart Disease: Findings From the Heart and Soul Study. Psychosomatic Medicine [Internet]. 2007;69. doi: 10.1097/PSY.0b013e31815743ca.

104. Perrotta AS, Koehle MS, White MD, Taunton JE, Warburton DER. Consecutive non-training days over a weekend for assessing cardiac parasympathetic variation in response to accumulated exercise stress. European Journal of Sport Science. 2020;20:1072–1082. doi: 10.1080/17461391.2019.1688397.

105. Flatt AA, Esco MR. Smartphone-Derived Heart-Rate Variability and Training Load in a Women's Soccer Team. International Journal of Sports Physiology and Performance. 2015;10:994–1000. doi: 10.1123/ijspp.2014-0556.

106. Schmitt L, Regnard J, Desmarets M, Mauny F, Mourot L, Fouillot J-P, Coulmy N, Millet G. Fatigue Shifts and Scatters Heart Rate Variability in Elite Endurance Athletes. PLOS ONE. 2013;8:e71588. doi: 10.1371/journal.pone.0071588.

107. Plews DJ, Laursen PB, Kilding AE, Buchheit M. Heart rate variability in elite triathletes, is variation in variability the key to effective training? A case comparison. European Journal of Applied Physiology. 2012;112:3729–3741. doi: 10.1007/s00421-012-2354-4.

CHAPTER 2

Does wearable-measured heart rate variability during sleep predict perceived morning mental and physical fitness?

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ABSTRACT

The emergence of wearable sensor technology may provide opportunities for automated measurement of psychophysiological markers of mental and physical fitness, which can be used for personalized feedback. This study explores to what extent within-subject changes in resting Heart Rate Variability (HRV) during sleep predict the perceived mental and physical fitness of military personnel on the subsequent morning. Participants wore a Garmin wrist-worn wearable and filled in a short morning questionnaire on their perceived mental and physical fitness during a period of up to 46 days. A custom-built smartphone app was used to directly retrieve heart rate and accelerometer data from the wearable, on which open-source algorithms for sleep detection and artefact filtering were applied. A sample of 571 complete observations in 63 participants were analyzed using linear mixed models. Resting HRV during sleep was a small predictor of perceived physical fitness (marginal R^2=.031), but not of mental fitness. The items on perceived mental and physical fitness were strongly correlated (r=.77). Based on the current findings, resting HRV during sleep appears to be more related to the physical component of perceived fitness than its mental component. Recommendations for future studies include improvements in the measurement of sleep and resting HRV, as well as further investigation of the potential impact of resting HRV as a buffer on stress-related outcomes.

Keywords: heart rate variability; sleep; resilience; ecological momentary assessment; wearables; military.

INTRODUCTION

Occupational stress can lead to physical (1,2) and mental (3) health problems, decrease quality of life (4) and imposes a financial burden on society via absenteeism and productivity loss (5). Early recognition of the potential development of stress-related problems can be useful for personalized just-in-time interventions that may help alleviate or prevent these personal and societal burdens of stress (6). Due to recent developments in wearable sensor technology, continuous and unobtrusive measurement of physiological and behavioral data that may be related to stress resilience, is becoming increasingly feasible (7,8). One of the challenges for current research on this topic is to explore and verify to what extent these novel sources of personal data can indeed be related to one's ability to resiliently cope with stress.

Before hypothesizing how wearable-measured data may be related to resilience, it is important to understand how stress itself emerges. Stress is the outcome of a psychological process that is known as appraisal (9). When a person is faced with demands, the brain subconsciously assesses the perceived availability of resources to cope with the situation. When sufficient resources appear to be available, the demand is appraised as a challenge. When this is not the case, the demand is appraised as a threat – causing a stress response. Therefore, the subjective assessment of the availability of resources is what determines the stress response. This can be measured as the perceived fitness, which is defined as "the modifiable capacity to utilize resources and skills to flexibly adapt to challenges or advantages" (10). Since appraisal is a psychological process, it is not the person's objective fitness-related characteristics that are directly assessed during appraisal, but the person's *perceived* fitness. For instance, an objectively fit but insecure person may experience stress when confronted with a minor challenge that the person should easily be able to handle. Unfortunately, it is currently not possible to directly measure mental states like perceived fitness in an automated and unobtrusive way. However, if relevant physiological or behavioral data from wearables can be linked to it, it may be possible to use these measures as a proxy for perceived fitness in future studies and applications.

One metric that may be related to perceived fitness is Heart Rate Variability (HRV). HRV is a measure for the variation in the inter-beat-intervals (IBIs) between heartbeats that functions as a proxy for autonomous nervous system functioning (11). Throughout the day, HRV is continuously influenced by factors such as stress (12) and emotions (13), body posture (14), exercise (15) and intake of caffeine (16) or alcohol (17). HRV measurements are therefore context-dependent and fluctuate throughout the day, but when measured in a similar resting state where confounders are minimized (e.g., during sleep or upon awakening), accurate measurement of resting HRV is possible, even with consumer-available wearables or the camera of a smartphone (18,19).

Resting HRV has been consistently linked to diverse aspects of mental functioning. For instance, prior studies found that on a between-subject level, resting HRV is positively associated with cognitive flexibility (20), affective flexibility (21), emotion regulation (22,23) and resilience (24). Two recent studies also found that on a within-subject level, resting HRV buffered the positive associations between stress and negative affect (25), as well as between stress and both demands and mental exhaustion (26). These findings indicate that having a high resting HRV generally reflects more optimal mental functioning and adaptability to environmental demands, which makes it a potential proxy for perceived fitness.

Besides being linked to these mental aspects that may be related to perceived fitness, resting HRV has shown to be associated with physical components of fitness as well. On a between-subject level, resting HRV is positively associated with cardiovascular fitness (27,28), and negatively associated with overuse injuries (29–31) and pain perception (32). Finally, resting HRV has also been linked to viral infections on a within-subject level (33). These associations are the basis for HRV guided training, in which daily resting HRV is being used in comparison to the personal baselines of athletes to determine their physiological recovery from prior physical or mental stress and adjust training plans when necessary (34,35). In this setting, the objective resting HRV data are often combined with subjective questionnaire data in order to get a more complete view of the athlete's current status. Since resting HRV has been linked to both mental and physical aspects of fitness, it is possible that its potential association with perceived fitness may also differ for the perceived mental and physical fitness.

Wearable-measured resting HRV has been linked to diverse aspects of mental and physical functioning. As such, it may also be linked to a person's overall perception of fitness. From the perspective of appraisal theory, this is relevant, since a person's overall perception of fitness can be considered a resource to deal with demands. When this resource is perceived to be lacking, the person may be more susceptible to experience demands as stressors, and develop more stress-related complaints as a results. Exploration of the degree in which within-subject differences in resting HRV are indeed associated with perceived fitness will benefit the current state of knowledge on how HRV relates to subjective mental and physical functioning. Furthermore, insights in this association may be useful for the development of tools that provide automated and personalized feedback on its users' readiness to handle demands and cope with stress. Such tools may be useful in intervention programs that aim to prevent stress-related problems. These insights are therefore particularly relevant for high-risk professions such as military personnel, in which resting HRV has already been related to objective fitness and occupational performance (28). Therefore, this study aims to explore to what extent wearable-measured resting HRV during sleep predicts the perceived mental and physical fitness of military personnel on the subsequent morning. We hypothesize that wearable-measured resting HRV during sleep predicts both the mental and physical aspects of perceived fitness on the subsequent morning.

METHODS

An observational study was performed based on within-subject nested daily observations. The study protocol was approved (case 2019-038) by the internal Research Ethics Committee of TNO (TC-nWMO) in the Netherlands. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement was used as a guideline for reporting (36).

Participants

A convenience sample of 73 employees of the Dutch military were recruited to participate and collect data for a period of up to 8 weeks. This group consisted of 43 marines in training and 30 staff members of the Dutch Defense Healthcare Organization. Both the recruitment and data collection of this study was performed in the summer of 2019 at peacetime, in the Netherlands. Recruitment was facilitated by the Dutch military, but participation occurred on a voluntary basis and participants were free to stop at any time without adverse consequences. All participants gave explicit consent for the use of their (health) data.

Data collection

Descriptive data such as the age, gender and function of the participants were not collected out of privacy and security concerns related to the sensitive profession of the participants. Out of privacy and security concerns related to the military context of this study, it was not deemed acceptable to store the participants' data on servers outside the jurisdiction of the Dutch government, which would have been the case during regular use of the Garmin wearables. As such, descriptive statistics could only be provided based on the daily measurements of the independent and dependent variables, and no subgroup analyses were performed.

Independent variable: heart rate variability during sleep

All participants wore a Garmin Tactix Charlie smartwatch which is described as a multisport GPS watch with additional tactical functionality (37). Therefore, a custom-built smartphone application was used that utilized the Garmin Health Standard Software Development Kit (SDK), which allows the application to collect data directly from the wearable device and process and store it on a self-hosted server (38). Using this approach, data on accelerometry and green-light photoplethysmography-based IBIs between heartbeats were available, based on which sleep episodes and the related resting HRV can be detected and calculated.

Sleep detection was performed based on an open-source algorithm that detects sleep based on wrist movements (39), with three adjustments. First, the parameter that describes how long the user must lie still before that period is classified as 'in bed' was lowered from 30 minutes to 10 minutes. This was done because pilot tests of the applied algorithm showed that the original algorithm sometimes classified a full night sleep as separate sleep episodes when a participant was awake at night, which can be prevented by lowering this threshold. The second adjustment was done with the same goal, by adding a parameter that allowed participants to have a period of up to 10 minutes of small movements during (restless) sleep, without being classified as awake and thus potentially splitting the sleep episode. Finally, an adjustment was made in how the start of the sleep episode was detected. Initially, the start of a sleep episode was estimated based on accelerometer data, as per the original algorithm. The start of the sleep episode was then adjusted to use the timestamp of the peak in the HRV during the first 30 minutes of that episode (based on the 90 second time window with the highest HRV) was then attributed as the actual start of the sleep episode. This was done because pilot tests showed that the original algorithm sometimes classified a period during which participants were lying still but not sleeping (e.g., reading on smartphone) as sleep, and prior research showed that HRV briefly peaks around the start of the sleep episode (40). Since this study compares the perceived mental and physical fitness of the participants during the morning to their resting physiology, the nocturnal HRV data was then related to the subsequent morning's Ecological Momentary Assessment (EMA) questionnaire during statistical analysis. Finally, the Total Sleep Time (TST; the total duration of the sleep episode spent asleep) in hours and Resting Heart Rate (RHR; the average heart rate during sleep) were included as control variables.

The HRV was then calculated for each sleep episode. Since motion artefacts are common in real-life wearable-based measurements and can influence the accuracy of the HRV estimation, an artefact detection algorithm that has been used in prior research was used (18). This method consists of two steps. First, intervals are removed when they differ more than 75% from the previous one. Second, outliers are removed by including only intervals that are within less than 25% of the first quartile and within more than 25% of the third quartile. Additionally, sleep episodes where valid IBIs were available for less than 64% of the duration of the sleep episodes were discarded. This was done because prior research has shown that the rMSSD can be validly determined without clinically significant change (a 5% change in mean absolute percent difference) when up to 36% of the IBIs are removed (41). This study also showed that frequency domain HRV parameters are much more impacted by missing data and thus less robust in this context than time domain parameters. Another study confirmed that of all time and frequency domain HRV measures, rMSSD is one of the two (alongside mean NN) most robust features (42). Therefore, the root Mean Square of the Successive Differences (rMSSD) in milliseconds was used as the primary HRV variable and calculated based on the valid IBIs of the respective sleep episodes[1]. This metric was then logarithmically transformed (lnrMSSD) to improve its distribution for statistical modelling, which is a common procedure in HRV research (43).

Dependent variables: perceived mental and physical fitness

Participants filled in a brief EMA questionnaire in the morning that included two items on their perceived mental and physical fitness, each of which scored on a 11-point Numeric Rating Scale (NRS) ranging from 0 to 10. Perceived physical fitness was assessed based on the item "I feel physically fit", whereas perceived mental fitness was inquired via the item "I feel mentally fit". These items were originally self-composed, but align well with items of the Acute Readiness Monitoring Scale (items 5 and 13) that has since then been validated for the use in military personnel (44). Finally, the participants already were used to distinguish between mental and physical fitness based on their professional training and functioning. For these participants, perceived physical fitness is about feeling physically ready to perform (e.g., strength, endurance, mobility), whereas perceived mental fitness is related to feeling mentally (e.g., cognitively and emotionally) ready to perform.

Data analyses

All data-management and analyses were performed in RStudio (45) and R (46). Descriptive statistics on the HRV, TST, as well as the perceived mental and physical fitness of the participants were calculated. Due to the difference in scales between HRV, TST and the EMA items, standardizing the data was necessary to optimize the comparability of the coefficients of the independent variables. Standardization based on the within-subject values was considered since the level 1 association between HRV and the EMA items is of primary interest (47), but standardization at the grand mean was finally preferred, as some participants collected a relatively low number of complete observations.

Two two-step hierarchical linear mixed-effects models for each of the EMA outcomes were created using the "lme4" package in R (48) to account for repeated measures within participants. All models were based on fixed effects (level 1 association between HRV and the EMA outcomes) and random slopes (the participants themselves were allowed to differ from each other in level 2). For each model, a control model was first created using only TST and RHR, followed by the full model that also included HRV. The marginal and conditional R^2 of each model were then computed, which respectively represent the proportion of the variance that can be explained solely by the fixed effects (HRV, TST and RHR) and by the combination of the fixed and random effects (the

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1 Upon request during peer-review, the Standard Deviation of the NN intervals (SDNN) time domain HRV metric was also calculated and analyzed as an alternative to the rMSSD. SDNN during sleep was not found to be significantly associated with morning mental and physical fitness. For transparency, the findings of these additional alternative analyses are available in Appendix 1.

participant). Differences in the marginal and conditional R^2 between the control and full models were also calculated to assess (changes in) the goodness-of-fit of the models.

During statistical analysis, relatively large differences were found in the marginal and conditional R^2 in each of the created models. To facilitate interpretation of these relatively large differences in the variance that was explained by the fixed and the combination of fixed random effects, three versions of the Coefficient of Variation (CV) of each variable were calculated to explore how the within-subject variance, the between-subject variance and the overall variance in the dataset compared to each other. The first version describes the average within-subject CV for each variable, and was determined by first calculating the within-subject CV based on the values of each participant (standard deviation divided by the mean) and then calculating the mean of those values. A CV of 0 was imputed for the (7) participants that had collected only one complete observation. The second version describes the between-subject CV for each variable, and was calculated by first determining the mean value for each participant and then calculating the CV of those values. The third version describes the overall CV for each variable, and consisted of the CV of the full dataset without accounting for within- or between-subject differences.

RESULTS

Of the 73 recruited participants, 63 collected at least one complete observation that included valid sleep, HRV and morning EMA data. The participation period per analyzed participant ranged from 1 to 57 days, with a median of 44 days. During these periods, the analyzed participants collected complete data on 1 to 46 days, with a median of 15 days. A total of 571 complete observations were analyzed. Due to training-related circumstances, the marines in training could temporarily not use their smartphones and thus collect data. The descriptive statistics for and intercorrelations between the independent (HRV, TST and RHR) and dependent (EMA) items of the analyzed dataset are presented in table 1. A strong ($r=.77$; $p<.001$) correlation between perceived mental and physical fitness was found.

Analysis 1: perceived physical fitness

A two-step hierarchical linear mixed model for perceived physical fitness was created (table 2). After controlling for TST and RHR, resting HRV during sleep was a statistically significant ($p=.005$) predictor of perceived physical fitness on the subsequent morning. Based on this finding, participants reported a higher perceived physical fitness on mornings after a sleep episode during which they also had a relatively high resting HRV. RHR significantly ($p=.03$) predicted perceived physical fitness in the control model (step 1), but not in the final model that also included HRV (step 2). Participants also tended ($p=.10$) to report a higher perceived physical fitness on mornings that followed a sleep episode with a relatively high TST. The explained variance of the fixed effects in the full model that included HRV (step 2) increased with 1.2% to a total of 3.1% in comparison to the control only model that was based on TST and RHR (step 1). The combination of the fixed and random effects explained 57.7% of the variance in the control model and 58.9% of the full model.

Table 1: Descriptive statistics for and intercorrelations between the daily measurements

Variable	Mean	(SD)	Correlation 1	2	3	4
1. TST (hours)	6.22	(1.90)	-			
2. RHR (beats per minute)	61.80	(8.88)	-.09 *	-		
3. lnrMSSD (milliseconds)	3.83	(0.40)	-.03	-.64 ***	-	
4. Perceived physical fitness (0-10)	7.84	(1.37)	.04	.03	.01	-
5. Perceived mental fitness (0-10)	8.11	(1.27)	.05	.10 *	-.08 .	.77 ***

*Note. N=63, n=571; *** p<.001, ** p<.01, * p<.05, . p<.1; TST: Total Sleep Time; RHR: Resting Heart Rate; lnrMSSD: logarithmically transformed root Mean Square of the Successive Differences, a measure for Heart Rate Variability (HRV).*

Table 2: Hierarchical linear mixed model for perceived physical fitness

Independent variable	Perceived physical fitness Step 1 β	Step 2 β
Intercept	-0.053	-0.087
TST	0.051	0.052 .
RHR	-0.101 *	-0.066
HRV		0.124 *
Marginal R^2	*0.013*	*0.031*
Δ Marginal R^2		*0.018*
Conditional R^2	*0.577*	*0.589*
Δ Conditional R^2		*0.012*

*Note. N=63, n=571; * p<.05, . p<.1; TST: Total Sleep Time; RHR: Resting Heart Rate; HRV: Heart Rate Variability.*

Analysis 2: perceived mental fitness

Another two-step hierarchical linear mixed model on perceived mental fitness was created (table 3). After controlling for TST and RHR, resting HRV during sleep was not a statistically significant predictor of perceived mental fitness on the subsequent morning. TST was positively associated with perceived mental fitness (p=.04), as participants reported a higher perceived mental fitness on mornings that followed a sleep episode with a relatively high TST. Only 0.4% of the variance could be explained by the fixed effects in the full model, whereas 63.4% of the variance was explained by the combination of the fixed and random effects.

Table 3: Hierarchical linear mixed model for perceived mental fitness

Independent variable	Perceived mental fitness	
	Step 1 β	Step 2 β
Intercept	-0.052	-0.059
TST	0.057 *	0.058 *
RHR	-0.009	-0.002
HRV		0.025
Marginal R^2	*0.004*	*0.004*
Δ Marginal R^2		*0.000*
Conditional R^2	*0.633*	*0.634*
Δ Conditional R^2		*0.001*

*Note. N=63, n=571; * p<.05; TST: Total Sleep Time; RHR: Resting Heart Rate; HRV: Heart Rate Variability.*

Within-subject, between-subject and overall coefficients of variation

The within-subject, between-subject and overall CV for each predictor and outcome variable are visualized in figure 1. Two relevant observations can be made based on this data. First, participants reported consistently high scores on perceived mental and physical fitness (mean: 7.84-8.11) with a limited tendency to also report low scores from time to time (SD: 1.27-1.37). A second observation is that for perceived mental and physical fitness and particularly resting HRV, a relatively low amount of within-subject variance was available in the data in comparison to the between-subject and overall variance. This combination of findings indicates that there was a relatively modest amount of within-subject variance available for both outcome measures as well as the central predictor, which may have contributed to the relatively low explained variance of the fixed effects (marginal R^2) in relation to the explained variance of the combination of the fixed and random effects (conditional R^2).

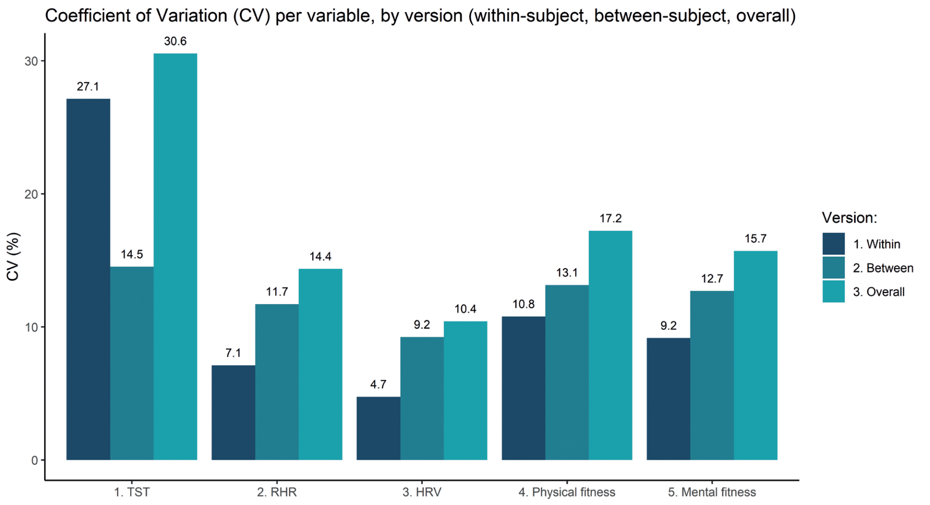

Figure 1: The Coefficient of Variation (CV) for the within-subject (left bar), between-subject (middle bar) and grand mean (right bar) version of each variable of the daily measurements.

DISCUSSION

This study aimed to explore to what extent wearable-measured resting Heart Rate Variability (HRV) during sleep predicts the perceived mental and physical fitness of military personnel on the subsequent morning. After controlling for Total Sleep Time (TST), resting HRV during sleep was a small but statistically significant predictor of perceived physical fitness, but not of perceived mental fitness. The current study yielded several insights that are relevant for future research on this topic. We will first provide a more in-depth interpretation of the findings and how they relate to prior research, then address strengths and limitations of this study, and finally provide recommendations for practice and future research.

Interpretation of the results

Wearable-measured resting HRV during sleep was a statistically significant positive predictor of perceived physical fitness on the subsequent morning. Although no prior studies utilizing a within-subject design to assess these relationships were identified, these results are in line with prior research that showed that between-subject differences in resting HRV are positively associated with cardiovascular fitness (27,28) and negatively associated with overuse injuries (29–31) and pain perception (32). However, resting HRV explained only a small portion of the variance in perceived physical fitness (3.1% after controlling for TST and RHR).

Unlike hypothesized, wearable-measured resting HRV during sleep did not predict perceived mental fitness on the subsequent morning. To our knowledge, no prior studies have assessed the direct association between within-subject differences in resting HRV during sleep and perceived mental fitness on the subsequent morning, but between-subject differences in resting HRV have been positively associated with emotion regulation (22,23) and resilience (24,49). However, within-subject differences in resting HRV were recently found to buffer against the associations between stress and negative affect (25), as well as between demands and stress or stress and mental exhaustion (26). It is therefore possible that despite not being directly associated to perceived mental fitness in the current study, resting HRV could play a relevant role as a (psycho)physiological resource during appraisal and/or emotion regulation regardless.

In the current study, perceived mental and physical fitness were assessed via two items in a short EMA questionnaire and therefore represent the participant's subjectively experienced mental and physical fitness rather than the underlying objective capacities. This, combined with the finding that the items on perceived mental and physical fitness were strongly correlated (r=.77), means that the found association between resting HRV and perceived physical fitness is reflective of a psychological state. Since psychological states can influence the perception of bodily sensations such as pain and vice versa (50), the potential influence of the items on perceived mental and physical fitness may be bidirectional. Although both items can therefore be seen as different components of the perceived overall fitness that is assessed as a psychophysiological resource during appraisal, the current results suggest that resting HRV during sleep may be more related to the physical component of perceived fitness rather than the perceived mental component.

The comparison of the CVs (figure 1) showed that there was a relatively low amount of within-subject variance in the two perceived fitness measures as well as the central predictor HRV in comparison to the between-subject and overall variance. Several possible explanations for this can be given. For instance, the participants collected data during a relatively short period (1-57 days: median 44 days). As a result, there were a relatively modest number of complete observations per participant that could be analyzed (1-46 observations: median 15 observations). Since a lack of relevant variance (e.g., floor or ceiling effects) can contribute to false negative conclusions (51), it is possible that this may have contributed to a potential underestimation of the strength of the associations and thus the low explained within-subject variance (marginal R^2).

Finally, the results showed that RHR had a negative correlation (r=-.64; table 1) with resting HRV and similar associations with mental and physical fitness. Neither RHR were related to mental fitness, but both RHR (table 3, step 1) and resting HRV (table 3, step 2) were linked to physical fitness. However, physical fitness was less strongly associated with RHR than with resting HRV, which was the only significant predictor in the full model where both were included. This observation aligns with that of a recent large-scale study which showed that RHR and resting HRV have similar associations to stress-related measures and concluded that resting HRV is a more sensitive but not specific marker of stress (52).

Strengths and limitations

A strength of this study is that it was based on data that was collected in a real-life setting, optimizing the generalizability of the findings. Furthermore, by utilizing an open-source sleep detection algorithm and a publicly available IBI artefact filtering method, the methods were transparent and reproducible. For instance, the used sleep detection algorithm and IBI artefact filtering method could in future research or applications be combined with hardware of another manufacturer.

Despite these advantages, a potential downside of using a novel open-source sleep detection algorithm is that it may be less accurate than algorithms of commercial wearable manufacturers that have more resources available for research and development. In the current study, the measurement of resting HRV during sleep directly depends on the respective sleep detection algorithm to ensure that the collected inter-beat-interval data is measured within the desired context. Potential inaccuracies in the sleep detection algorithm may therefore result in heart rate data of awake periods being included in the calculation of the resting HRV. Since motion artefacts are more likely to be present during awake periods, the accuracy of the HRV measurement may be indirectly affected by it. Potential inaccuracy in the detection of sleep and measurement of the related resting HRV may therefore have added error variance to the data, potentially leading to an underestimation of the strength of the associations that were tested. Another limitation of the current study was that a convenience sample was used where no data on the participants' age, gender, function or reasons for missing data or drop-outs could be logged due to privacy and security concerns related to the profession of this military personnel. Since this study primarily focused on short-term, within-subject associations, this limitation did not impact the accuracy or relevance of the current results. However, as a result, no subgroup analyses could be performed to assess potential differences in the investigated associations among participants of different ages, gender of function groups. This also impacts the generalizability of the current findings, as it limits potential extrapolation to similar populations.

Recommendations for practice

This study presented relatively modest findings on associations between sleep, resting HRV and perceived mental and physical fitness. Although the found associations where relatively modest, the insights gained from this exploration using novel methods can be used to guide future use in future research and practice and thus provide a relevant contribution to the broader purpose of this body of knowledge; to eventually provide individuals with relevant and timely feedback on their readiness to handle demands and cope with stress. This segment will therefore first reflect on how the current findings should be interpreted for practice, whereas the next segment will describe more detailed recommendations for future studies.

Wearable-measured resting HRV during sleep was positively associated with perceived physical fitness in the current study, but explained only a small portion of its variance (3.1% after controlling for TST and RHR). Resting HRV during sleep should therefore not be seen as a potential replacement of perceived physical fitness, but as a complement to it. Prior studies showed that utilizing resting HRV measurements to guide training-related decision making can lead to positive outcomes in comparison to predefined training (34,35). Therefore, resting HRV during sleep may be useful as a complement to the perceived physical fitness to guide decision-making on the physical readiness of the respective individual on the following day. Within this context, a resting HRV that is relatively high for the individual's own standards can be seen as a favorable sign of physical fitness, whereas a low resting HRV would reflect the opposite.

Based on the current results, resting HRV during sleep does not appear to be directly associated to the perceived mental fitness. However, recent studies showed that waking up with a relatively favorable (within-subject) resting HRV appears to buffer against the negative impact of demands and stress (25,26). It is therefore possible that resting HRV has no or a limited direct association to perceived mental fitness, but does function as a psychophysiological resource that allows the individual to flexibly adapt to challenges and thus as a component of the underlying mental fitness itself. Future research is needed to better understand the potential role of resting HRV in this process of resilience.

Recommendations for future studies

Several recommendations for future studies on improving the accuracy of the sleep and related resting HRV measures, as well as how to assess the potential role of resting HRV as a measure of (perceived) fitness. The capacity of wearable technology to detect sleep affects the accuracy of the resting HRV measurements that are automatically collected within those periods. Three potentially promising approaches to measure resting HRV in a daily-life setting using consumer wearables can be considered by future studies. First, contributing to the development of open-source sleep detection algorithms and using more recent and optimized iterations of them will result in optimally transparent and reproducible methods (53). Another approach for studies in which full custody of the collected data is required is to utilize the sleep algorithms of the used wearable devices itself and load the aggregated data of the full sleep episode directly from the wearable. For the present study, only accelerometer and inter-beat-interval data were available, but the latest versions of the Garmin Health SDK now also allow the extraction of the sleep data as classified by Garmin's sleep algorithm (38), of which the validity has been studied (54–56). Finally, studies in domains with more lenient data storage requirements can also consider using consumer-available wearables that have been directly validated to accurately measure the resting HRV during sleep, such as the Oura ring (19,57,58).

Besides optimizing the sleep and resting HRV measurement of wearables, future studies can consider taking a different approach in determining how HRV may be associated with (perceived) mental or physical fitness. Two recent studies showed that within-subject differences in resting HRV had a moderating effect on the associations between stress and negative affect (25), as well as on demands and stress and stress and mental exhaustion (26). This is consistent with the neurovisceral integration model, which considers (vagally mediated) resting HRV itself to be an index of relatively optimal nervous system functioning to support adaptability to environmental demands (59,60). Therefore, it is possible that wearable-measured resting HRV is not (strongly) correlated with perceived physical or mental fitness as was found in this study, but does directly act as a psychophysiological resource during the processes of appraisal or emotion regulation and thus as a relevant but perhaps subconscious component of mental fitness. Future studies are therefore recommended to further explore this potentially direct role of resting HRV as a psychophysiological resource on fitness or similar resilience-related outcomes on a within-subject level. Furthermore, the present study and discussed recent studies primarily assess within-day associations of resting HRV. Although this approach is important to better understand the short-term relationship of differences in resting HRV with these outcomes, studies assessing longitudinal relationships are also needed to explore the potential impact of within-subject trends in resting HRV on a larger timeframe.

Finally, future research could further explore the mechanisms that were proposed in this article. For instance, by assessing how perceived measures of mental and physical fitness relate to objective observations of fitness, as well as general health and functioning, and if it can be improved through training. Although the short EMA-questionnaires that were used in this study are likely preferable for longer and more intensive (daily) data collection, future studies with a different design could also consider using more detailed questionnaires, for instance (a subscale of) the recently introduced and validated Acute Readiness Monitoring Scale that also specifically differentiates between mental and physical readiness (44). Future studies in target populations with less privacy-related limitations should also include the analysis of whether the strength of these associations differs between individuals, for instance based on personal characteristics (e.g., age, gender, function-group).

REFERENCES

1. Kivimäki M, Kawachi I. Work Stress as a Risk Factor for Cardiovascular Disease. Current Cardiology Reports. 2015;17:74. doi: 10.1007/s11886-015-0630-8.

2. Yang T, Qiao Y, Xiang S, Li W, Gan Y, Chen Y. Work stress and the risk of cancer: A meta-analysis of observational studies. International Journal of Cancer. 2019;144:2390–2400. doi: 10.1002/ijc.31955.

3. Chirico F. Job stress models for predicting burnout syndrome: a review. Annali dell'Istituto superiore di sanita. 2016;52:443–456.

4. Bhattacharya A, Ray T. Precarious work, job stress, and health-related quality of life. American Journal of Industrial Medicine. 2021;64:310–319. doi: 10.1002/ajim.23223.

5. Hassard J, Teoh KRH, Visockaite G, Dewe P, Cox T. The cost of work-related stress to society: A systematic review. Journal of Occupational Health Psychology. 2018;23:1–17. doi: 10.1037/ocp0000069.

6. Wang L, Miller LC. Just-in-the-Moment Adaptive Interventions (JITAI): A Meta-Analytical Review. Health Communication. 2020;35:1531–1544. doi: 10.1080/10410236.2019.1652388.

7. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Modelling employee resilience using wearables and apps: a conceptual framework and research design. International Journal on Advances in Life Sciences. 2019;11:110–117.

8. Drury RL, Porges S, Thayer J, Ginsberg JP. Editorial: Heart Rate Variability, Health and Well-Being: A Systems Perspective. Frontiers in Public Health [Internet]. 2019;7. doi: 10.3389/fpubh.2019.00323.

9. Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. Eur J Pers. 1987;1:141–169. doi: 10.1002/per.2410010304.

10. Robinson P, Oades L, Caputi P. Conceptualising and measuring mental fitness: A Delphi study. International Journal of Wellbeing. 2015;5:53–73. doi: 10.5502/ijw.v5i1.4.

11. Thayer JF, Åhs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012;36:747–756. doi: 10.1016/j.neubiorev.2011.11.009.

12. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 2018;15:235–245. doi: 10.30773/pi.2017.08.17.

13. McCraty R, Atkinson M, Tiller WA, Rein G, Watkins AD. The effects of emotions on short-term power spectrum analysis of heart rate variability. The American Journal of Cardiology. 1995;76:1089–1093. doi: 10.1016/S0002-9149(99)80309-9.

14. Buchheit M, Al Haddad H, Laursen PB, Ahmaidi S. Effect of body posture on postexercise parasympathetic reactivation in men. Experimental Physiology. 2009;94:795–804. doi: 10.1113/expphysiol.2009.048041.

15. Michael S, Graham KS, Davis GM. Cardiac Autonomic Responses during Exercise and Post-exercise Recovery Using Heart Rate Variability and Systolic Time Intervals—A Review. Frontiers in Physiology [Internet]. 2017;8. doi: 10.3389/fphys.2017.00301.

16. Koenig J, Jarczok MN, Kuhn W, Morsch K, Schäfer A, Hillecke TK, Thayer JF. Impact of Caffeine on Heart Rate Variability: A Systematic Review. Journal of Caffeine Research. 2013;3:22–37. doi: 10.1089/jcr.2013.0009.

17. Romanowicz M, Schmidt JE, Bostwick JM, Mrazek DA, Karpyak VM. Changes in Heart Rate Variability Associated With Acute Alcohol Consumption: Current Knowledge and Implications for Practice and Research. Alcohol: Clinical and Experimental Research. 2011;35:1092–1105. doi: 10.1111/j.1530-0277.2011.01442.x.

18. Plews DJ, Scott B, Altini M, Wood M, Kilding AE, Laursen PB. Comparison of Heart-Rate-Variability Recording With Smartphone Photoplethysmography, Polar H7 Chest Strap, and Electrocardiography. International Journal of Sports Physiology and Performance. 2017;12:1324–1328. doi: 10.1123/ijspp.2016-0668.

19. Stone JD, Ulman HK, Tran K, Thompson AG, Halter MD, Ramadan JH, Stephenson M, Finomore VS, Galster SM, Rezai AR, et al. Assessing the Accuracy of Popular Commercial Technologies That Measure Resting Heart Rate and Heart Rate Variability. Frontiers in Sports and Active Living [Internet]. 2021;3. doi: 10.3389/fspor.2021.585870.

20. Colzato LS, Jongkees BJ, de Wit M, van der Molen MJW, Steenbergen L. Variable heart rate and a flexible mind: Higher resting-state heart rate variability predicts better task-switching. Cognitive, Affective, & Behavioral Neuroscience. 2018;18:730–738. doi: 10.3758/s13415-018-0600-x.

21. Grol M, De Raedt R. The link between resting heart rate variability and affective flexibility. Cognitive, Affective, & Behavioral Neuroscience. 2020;20:746–756. doi: 10.3758/s13415-020-00800-w.

22. Holzman JB, Bridgett DJ. Heart rate variability indices as bio-markers of top-down self-regulatory mechanisms: A meta-analytic review. Neuroscience & Biobehavioral Reviews. 2017;74:233–255. doi: 10.1016/j.neubiorev.2016.12.032.

23. Mather M, Thayer JF. How heart rate variability affects emotion regulation brain networks. Current Opinion in Behavioral Sciences. 2018;19:98–104. doi: 10.1016/j.cobeha.2017.12.017.

24. An E, Nolty AAT, Amano SS, Rizzo AA, Buckwalter JG, Rensberger J. Heart Rate Variability as an Index of Resilience. Military Medicine. 2020;185:363–369. doi: 10.1093/milmed/usz325.

25. da Estrela C, MacNeil S, Gouin J-P. Heart rate variability moderates the between- and within-person associations between daily stress and negative affect. International Journal of Psychophysiology. 2021;162:79–85. doi: 10.1016/j.ijpsycho.2021.02.001.

26. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Moderation of the stressor-strain process in interns by heart rate variability measured with a wearable and smartphone app: Within-subject design using continuous monitoring. JMIR cardio. 2021;5:e28731. doi: 10.2196/28731.

27. Souza HCD, Philbois SV, Veiga AC, Aguilar BA. Heart Rate Variability and Cardiovascular Fitness: What We Know so Far. Vasc Health Risk Manag. 2021;17:701–711. doi: 10.2147/VHRM.S279322. Cited: in: : PMID: 34803382.

28. Tomes C, Schram B, Orr R. Relationships Between Heart Rate Variability, Occupational Performance, and Fitness for Tactical Personnel: A Systematic Review. Frontiers in Public Health [Internet]. 2020;8. doi: 10.3389/fpubh.2020.583336.

29. Gisselman AS, Baxter GD, Wright A, Hegedus E, Tumilty S. Musculoskeletal overuse injuries and heart rate variability: Is there a link? Medical Hypotheses. 2016;87:1–7. doi: 10.1016/j.mehy.2015.12.003.

30. Lima-Borges DS, Martinez PF, Vanderlei LCM, Barbosa FSS, Oliveira-Junior SA. Autonomic modulations of heart rate variability are associated with sports injury incidence in sprint swimmers. The Physician and Sportsmedicine. 2018;46:374–384. doi: 10.1080/00913847.2018.1450606.

31. Williams S, Booton T, Watson M, Rowland D, Altini M. Heart Rate Variability is a Moderating Factor in the Workload-Injury Relationship of Competitive CrossFit™ Athletes. J Sports Sci Med. 2017;16:443–449. Cited: in: : PMID: 29238242.

32. Forte G, Troisi G, Pazzaglia M, Pascalis VD, Casagrande M. Heart Rate Variability and Pain: A Systematic Review. Brain Sciences. 2022;12. doi: 10.3390/brainsci12020153.

33. Conroy B, Silva I, Mehraei G, Damiano R, Gross B, Salvati E, Feng T, Schneider J, Olson N, Rizzo AG, et al. Real-time infection prediction with wearable physiological monitoring and AI to aid military workforce readiness during COVID-19. Scientific Reports. 2022;12:3797. doi: 10.1038/s41598-022-07764-6.

34. Düking P, Zinner C, Trabelsi K, Reed JL, Holmberg H-C, Kunz P, Sperlich B. Monitoring and adapting endurance training on the basis of heart rate variability monitored by wearable technologies: A systematic review with meta-analysis. Journal of Science and Medicine in Sport. 2021;24:1180–1192. doi: 10.1016/j.jsams.2021.04.012.

35. Manresa-Rocamora A, Sarabia JM, Javaloyes A, Flatt AA, Moya-Ramón M. Heart Rate Variability-Guided Training for Enhancing Cardiac-Vagal Modulation, Aerobic Fitness, and Endurance Performance: A Methodological Systematic Review with Meta-Analysis. International Journal of Environmental Research and Public Health. 2021;18. doi: 10.3390/ijerph181910299.

36. von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) Statement: Guidelines for Reporting Observational Studies. Ann Intern Med. 2007;147:573–577. doi: 10.7326/0003-4819-147-8-200710160-00010.

37. Garmin. Garmin tactix® Charlie | Tactical GPS Watch [Internet]. Garmin. [cited 2022 May 5]. Available from: https://www.garmin.com/en-US/p/623921.

38. Garmin. Overview | Health SDKs | Garmin Developers [Internet]. Garmin. [cited 2022 Apr 18]. Available from: https://developer.garmin.com/health-sdk/overview/.

39. van Hees VT, Sabia S, Anderson KN, Denton SJ, Oliver J, Catt M, Abell JG, Kivimäki M, Trenell MI, Singh-Manoux A. A Novel, Open Access Method to Assess Sleep Duration Using a Wrist-Worn Accelerometer. PLOS ONE. 2015;10:e0142533. doi: 10.1371/journal.pone.0142533.

40. Boudreau P, Yeh W-H, Dumont GA, Boivin DB. Circadian Variation of Heart Rate Variability Across Sleep Stages. Sleep. 2013;36:1919–1928. doi: 10.5665/sleep.3230.

41. Sheridan DC, Dehart R, Lin A, Sabbaj M, Baker SD. Heart Rate Variability Analysis: How Much Artifact Can We Remove? Psychiatry Investig. 2020;17:960–965. doi: 10.30773/pi.2020.0168. Cited: in: : PMID: 33017533.

42. Baek HJ, Shin J. Effect of Missing Inter-Beat Interval Data on Heart Rate Variability Analysis Using Wrist-Worn Wearables. Journal of Medical Systems. 2017;41:147. doi: 10.1007/s10916-017-0796-2.

43. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health [Internet]. 2017;5. doi: 10.3389/fpubh.2017.00258.

44. Keegan RJ, Flood A, Niyonsenga T, Welvaert M, Rattray B, Sarkar M, Melberzs L, Crone D. Development and Initial Validation of an Acute Readiness Monitoring Scale in Military Personnel. Frontiers in Psychology [Internet]. 2021;12. doi: 10.3389/fpsyg.2021.738609.

45. RStudio Team. Rstudio: Integrated Development Environment for R [Internet]. Boston, MA: RStudio, BPC; 2020. Available from: https://www.rstudio.com.

46. R Core Team. R: A Language and Environment for Statistical Computing [Internet]. Vienna, Austria: R Foundation for Statistical Computing; 2020. Available from: https://www.R-project.org/.

47. Enders CK, Tofighi D. Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods. 2007;12:121–138. doi: 10.1037/1082-989X.12.2.121.

48. Bates D, Mächler M, Bolker B, Walker S. Fitting linear mixed-effects models using lme4. arXiv preprint arXiv:14065823. 2014;

2

49. Hourani LL, Davila MI, Morgan J, Meleth S, Ramirez D, Lewis G, Kizakevich PN, Eckhoff R, Morgan T, Strange L, et al. Mental health, stress, and resilience correlates of heart rate variability among military reservists, guardsmen, and first responders. Physiology & Behavior. 2020;214:112734. doi: 10.1016/j.physbeh.2019.112734.

50. Loggia ML, Schweinhardt P, Villemure C, Bushnell MC. Effects of psychological state on pain perception in the dental environment. Journal of the Canadian Dental Association. 2008;74:651–656. Cited: in: : PMID: 18789200.

51. Šimkovic M, Träuble B. Robustness of statistical methods when measure is affected by ceiling and/or floor effect. PLOS ONE. 2019;14:e0220889. doi: 10.1371/journal.pone.0220889.

52. Altini M, Plews D. What Is behind Changes in Resting Heart Rate and Heart Rate Variability? A Large-Scale Analysis of Longitudinal Measurements Acquired in Free-Living. Sensors. 2021;21. doi: 10.3390/s21237932.

53. van Hees VT, Sabia S, Jones SE, Wood AR, Anderson KN, Kivimäki M, Frayling TM, Pack AI, Bucan M, Trenell MI, et al. Estimating sleep parameters using an accelerometer without sleep diary. Scientific Reports. 2018;8:12975. doi: 10.1038/s41598-018-31266-z.

54. Chinoy ED, Cuellar JA, Huwa KE, Jameson JT, Watson CH, Bessman SC, Hirsch DA, Cooper AD, Drummond SPA, Markwald RR. Performance of seven consumer sleep-tracking devices compared with polysomnography. Sleep. 2021;44:zsaa291. doi: 10.1093/sleep/zsaa291.

55. Mouritzen NJ, Larsen LH, Lauritzen MH, Kjær TW. Assessing the performance of a commercial multisensory sleep tracker. PLOS ONE. 2020;15:e0243214. doi: 10.1371/journal.pone.0243214.

56. Stone JD, Rentz LE, Forsey J, Ramadan J, Markwald RR, Finomore VS, Galster SM, Rezai A, Hagen JA. Evaluations of Commercial Sleep Technologies for Objective Monitoring During Routine Sleeping Conditions. Nat Sci Sleep. 2020;12:821–842. doi: 10.2147/NSS.S270705. Cited: in: : PMID: 33149712.

57. Cao R, Azimi I, Sarhaddi F, Niela-Vilen H, Axelin A, Liljeberg P, Rahmani AM. Accuracy Assessment of Oura Ring Nocturnal Heart Rate and Heart Rate Variability in Comparison With Electrocardiography in Time and Frequency Domains: Comprehensive Analysis. J Med Internet Res. 2022;24:e27487. doi: 10.2196/27487.

58. Kinnunen H, Rantanen A, Kenttä T, Koskimäki H. Feasible assessment of recovery and cardiovascular health: accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG. Physiological Measurement. 2020;41:04NT01. doi: 10.1088/1361-6579/ab840a.

59. Thayer JF, Hansen AL, Saus-Rose E, Johnsen BH. Heart Rate Variability, Prefrontal Neural Function, and Cognitive Performance: The Neurovisceral Integration Perspective on Self-regulation, Adaptation, and Health. Annals of Behavioral Medicine. 2009;37:141–153. doi: 10.1007/s12160-009-9101-z.

60. Thayer JF, Lane RD. A model of neurovisceral integration in emotion regulation and dysregulation. Journal of Affective Disorders. 2000;61:201–216. doi: 10.1016/S0165-0327(00)00338-4.

APPENDIX 1

Table 1: Hierarchical linear mixed model for perceived physical fitness

Independent variable	Perceived physical fitness	
	Step 1 β	Step 2 β
Intercept	-0.053	-0.070
TST	0.051	0.039
RHR	-0.101 *	-0.105 *
SDNN		0.066
Marginal R^2	*0.013*	*0.023*
Δ Marginal R^2		*0.019*
Conditional R^2	*0.577*	*0.580*
Δ Conditional R^2		*0.011*

*Note. N=63, n=571; * p<.05; TST: Total Sleep Time; RHR: Resting Heart Rate; SDNN: Standard Deviation of the NN intervals, a measure for Heart Rate Variability (HRV).*

Table 2: Hierarchical linear mixed model for perceived mental fitness

Independent variable	Perceived mental fitness	
	Step 1 β	Step 2 β
Intercept	-0.052	-0.061
TST	0.057 *	0.051 .
RHR	-0.009	-0.012
SDNN		0.035
Marginal R^2	*0.004*	*0.005*
Δ Marginal R^2		*0.001*
Conditional R^2	*0.633*	*0.632*
Δ Conditional R^2		*-0.001*

*Note. N=63, n=571; * p<.05, . p<.1; TST: Total Sleep Time; RHR: Resting Heart Rate; SDNN: Standard Deviation of the NN intervals, a measure for Heart Rate Variability (HRV).*

CHAPTER 3

Modelling employee resilience using wearables and apps: a conceptual framework and research design

A Herman de Vries, Wim Kamphuis, Hilbrand Oldenhuis, Cees van der Schans and Robbert Sanderman

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ABSTRACT

Occupational stress can cause health problems, productivity loss or absenteeism. Resilience interventions that help employees positively adapt to adversity can help prevent the negative consequences of occupational stress. 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 context, an automated resilience intervention that gives personalized, just-in-time feedback can be developed. This paper presents the conceptual framework and methods behind the WearMe project, which 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 operationalization of the concepts and the daily measurement cycle are described, including the use of wearable sensor technology (e.g., sleep tracking and heart rate variability measurements) and Ecological Momentary Assessment (mobile app). Analyses target the development of within-subject (n=1) and between-subjects models and include repeated measures correlation, multilevel modelling, time series analysis and Bayesian network statistics. Future work will focus on further developing these models and eventually explore the effectiveness of the envisioned personalized resilience system.

Keywords: occupational stress; personalized ehealth; sensors; wearables; virtual coaching.

INTRODUCTION

The *Wearables and app-based resilience Modelling in employees (WearMe)* project focuses on the mental resilience of employees with a stressful occupation (1). Occupational stress can cause health problems, such as musculoskeletal disease, cardiovascular disease, depression and burnout (2). Consequently, it can also lead to financial burdens due to treatment costs, productivity loss and absenteeism (3). The cumulative wear and tear on bodily systems caused by stress is particularly detrimental for health and well-being (4); 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 (5).

Resilience can be defined as the process of positively adapting to adverse events (6). It entails the use of individual (e.g., personality) and contextual (e.g., social support) resources to cope with adversity (7). By utilizing 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.

Companies and institutions may offer resilience interventions to their employees to promote their health and employability and prevent stress-related problems. These interventions often target a broad population which unfortunately disregards the variability between employees. More personalized approaches might monitor for early signs of stress-related outcomes, link these to causal factors in the employee's own context, and provide personalized advice to sustain relevant resources that may prevent the aforementioned loss spiral. Due to advances in sensor technology and smartphone applications, relatively unobtrusive self-monitoring of changes in resilience related outcomes is increasingly possible (8). While these advances open up the possibility of personalized monitoring in resilience interventions, models are needed to recognize intra-individual changes in these outcomes and relate these to causal factors and future consequences; this would allow for the opportunity to create automated resilience interventions that give personalized, just-in-time feedback, for employees to utilize in workplace applications.

In this paper, we present the conceptual framework and the study protocol of the ongoing WearMe project. After introducing the rationale behind the WearMe project in Section I, Section II describes a cyclical conceptual framework that is based on existing theories on stress and resilience. This framework represents the concepts and interrelations between concepts that we predict are necessary to model employee resilience. In Section III, we elaborate on how these concepts are operationalized in the WearMe Project, including the use of consumer-available wearables and an Ecological Momentary Assessment (EMA) app. Afterwards, we describe in Section IV the methods of the first WearMe study. Finally, Section V discusses possible directions for future work that can help develop predictive employee resilience models and personalized interventions.

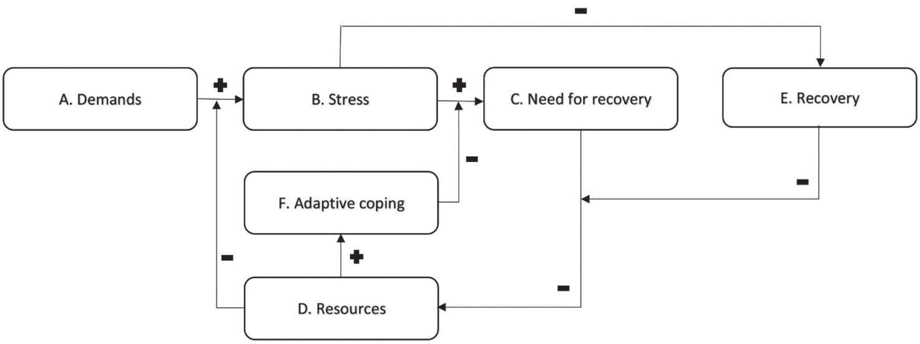

Figure 1: Conceptual framework for the WearMe study.

CONCEPTUAL FRAMEWORK

The conceptual framework of the WearMe project is presented in Figure 1. It illustrates our hypotheses on how the accumulation of the negative consequences of stress has a cyclical nature and how it can contribute to a loss spiral. This framework is based on the *Transactional Model of Stress and Coping* (9), the *Job Demands-Resources Model of Burnout* (10), the *Effort-Recovery Model* (11) and the *Conservation of Resources Theory* (5).

Stress accumulates when (job) *demands*, such as time pressure or physical workload, are appraised as threats due to inefficient available *resources* to *adaptively cope* with them (9). Afterwards, an individual's *need for recovery*, characterized by feelings of exhaustion and reduced vigor to undertake new activities, depends on the individual's ability to utilize the available resources to adaptively cope with the demands (9,10). A high need for recovery (i.e., little vigor to undertake activities), has a negative impact on an individual's resources to appraise and cope with new demands – unless there is sufficient *recovery* to alleviate this effect (11). Aside from causing a perceived need for recovery, stress can also decrease sleep quality (12) and psychological detachment (13), which are aspects of *recovery* (14).

This framework's cyclical nature is supported by the Conservation of Resources theory (5), which states that initial loss of resources increases one's vulnerability to stress. Since additional resources are necessary to battle stress, this may lead to a depletion of resources or a loss spiral.

OPERATIONALIZATION

Based on the conceptual framework described above, we developed a measurement cycle to operationalize concepts using consumer-available wearables and an EMA smartphone application. All concepts are measured daily except adaptive coping—due to its highly context-specific nature which makes it difficult to quantify. In this section, we will first briefly present our daily measurement cycle. Following this, we will describe each concept and its operationalization.

The presented conceptual framework is not bounded by a specific timeframe. However, since the WearMe study particularly aims to investigate day-to-day and multi-day trends, we operationalized the concepts in a daily measurement cycle (Figure 2). For the daily measures, the WearMe study protocol utilizes: (i) a wrist-worn tracker for unobtrusive, continuous measurements throughout the day and night, (ii) a Bluetooth chest strap and a smartphone application for a physiological measurement taken upon awakening and (iii) a smartphone application for EMA questionnaires taken upon awakening and before bedtime.

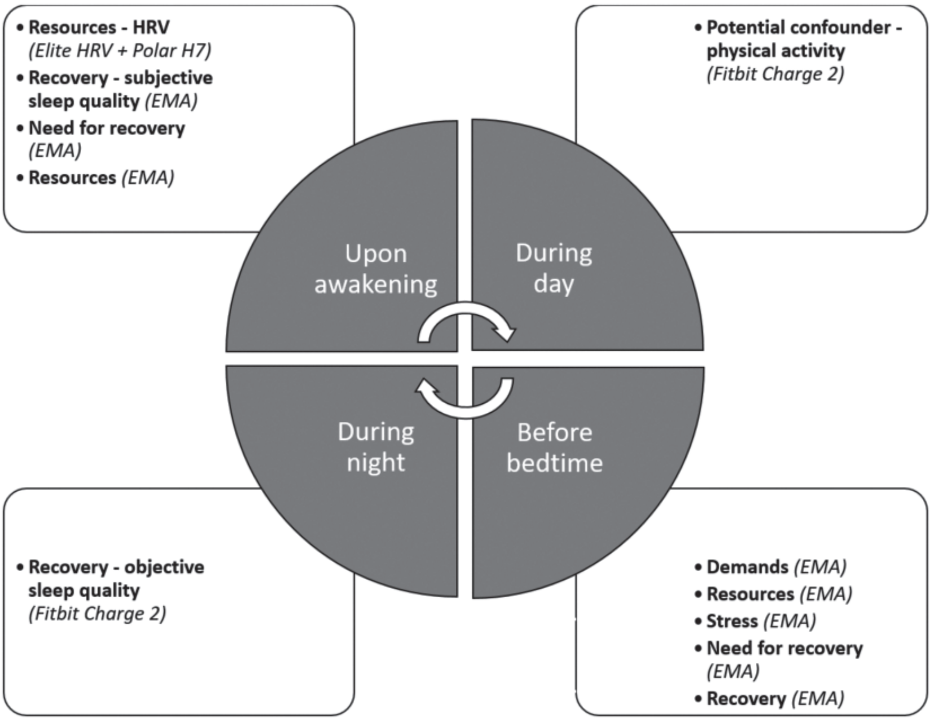

Figure 2: Measurement cycle of the WearMe study.

A. Demands

Demands refer to the physical, social or organizational aspects that require sustained physical or mental effort and are therefore associated with certain physiological costs (15). Participants' perceived daily demands are scored with the evening EMA questionnaire and is based on the self-composed diary question *"How demanding was your day?"*; this is scored on an 11-point Numeric Rating Scale (NRS) that ranges from 0 (*"Not at all"*) to 10 (*"Extremely"*).

B. Stress

Participants' perceived total daily stress is scored in the evening EMA questionnaire with a validated single-item scale (16): *"How much stress did you perceive today?"*. The question was rephrased to be applicable for daily use and the NRS that ranged from 1 (*"No stress"*) to 6 (*"Extreme stress"*) was adjusted to range from 0-10 for consistency.

C. Need for recovery

Need for recovery can be defined as a conscious emotional state and is connected with a temporal reluctance to continue with the present demands or to accept new demands; it is related to the depletion of resources following effort to meet certain demands (17). The concept is characterized by a combination of perceiving high fatigue, as well as low vigor to undertake new activities. Participants' perceived fatigue is questioned in both the morning and evening EMA questionnaires to allow the calculation of within-day changes, while mental exhaustion is only measured during the evening. For fatigue, a validated single-item scale (*"How fatigued do you currently feel?"*) is used (18). Item 3 of the Need For Recovery Scale is used to inquire mental exhaustion (19): *"I felt mentally exhausted as a result of my activities"*. All items are scored on an 11-point NRS ranging from 0 (*"Not at all"* for fatigue and *"Strongly disagree"* for exhaustion) to 10 (*"Extremely"* for fatigue and *"Strongly agree"* for exhaustion).

D. Resources

According to the Job Demands-Resources model, job resources refer to physical, psychological, social or organizational aspects of a job that: (i) are functional in achieving work goals, (ii) reduce job demands and the associated physiological and psychological costs and (iii) stimulate personal growth, learning and development (10). The resources in our conceptual framework can be seen as personal resources that enable an individual to better deal with stress. These resources include vigor, fitness, general self-efficacy (GSE), happiness, work engagement, and Heart Rate Variability (HRV). Items for vigor, fitness, general self-efficacy (GSE) and happiness are included in both the morning and evening EMA questionnaires, and are all scored on an 11-point NRS ranging from 0 (*"Not at all"*) to 10 (*"Extremely"*). Below, the measured resources are described in more detail.

Vigor can be characterized by high levels of energy and mental resilience, the willingness to invest effort in one's work and persistence even in the face of difficulties (20). Having high perceived vigor can therefore be seen as an individual resource during the appraisal of and coping with high demands. The item for vigor (measured in the morning and the evening) is based on an item of the vigor subscale of the Utrecht Work Engagement Scale (UWES) and rephrased for daily use in a neutral setting (*"Do you feel* *like undertaking activities?"*) (21). Additionally, one item from the dedication subscale of the UWES is only included in the evening EMA questionnaire (*"Today, my activities were full of meaning and purpose."*) (21).

Fitness is also an individual resource for the appraisal of and coping with high demands; it is scored with a self-composed item that is similarly phrased to the fatigue item: *"How fit do you currently feel?"*. The item on fitness is included due to its more physical characteristics in comparison to the other items.

GSE is the belief in one's competence to tackle novel tasks and cope with adversity in a broad range of stressful or challenging encounters (22). High GSE is associated with high optimism, self-regulation and self-esteem, and low depression and anxiety (22); it can therefore be seen as an individual resource that is addressed during the appraisal of a stressor. The EMA item for GSE is based on the item with the highest factor loading (item 6) of the Generalized Self-Efficacy Scale and is rephrased for daily use: *"Do you feel capable of solving problems today?"*. During the evening, *"today"* is replaced with *"tomorrow"*.

Happiness is a state of well-being and contentment, characterized by frequent positive affect, high life satisfaction and infrequent negative affect (23). Happiness has an inverse correlation with stress (24) and contributes to the psychological capital (resources) that may be key in better understanding the variation in perceived symptoms of stress (25). Positive emotions like happiness can also predict increases in (trait) resilience and life satisfaction (26). Participants' perceived happiness is scored using a validated single-item scale (*"Do you feel happy?"*) (27).

HRV refers to the variation in the inter-beat-intervals between heartbeats and is considered a proxy for autonomous nervous system functioning (28). While HRV mostly serves as a parameter that illustrates physiological changes during acute stress, the resting HRV can remain decreased during and after acute stress (29,30). In addition, having a lower resting HRV has been associated with increased sensitivity for stress (31), decreased emotion-regulation (32), decreased physical performance (33) and an increased risk of long-term physical or mental health problems (34). 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 for 2 minutes in a supine position using the Elite HRV smartphone application (35) and a Polar H7 chest strap (36). This aligns with existing standards that suggest a duration of 1-5 minutes under consistent circumstances with as little influence of circadian rhythms, meals, smoking, posture changes and significant mental or physical exertion (37,38). We chose not to apply guided breathing, as respiratory rate influences HRV (39,40), and we intend to measure the natural resting state of the participant. The exported inter-beat-interval data are analyzed using Kubios Premium software, version 3.1.0 (41). Our analyses will focus on a time-domain outcome called Root Mean Square of the Successive Differences (RMSSD).

E. Recovery

Recovery refers to the recuperation from potential load effects after the exposure to certain demands (11). The concept of recovery consists of two components that are known to limit the spillover of a perceived need for recovery from the previous day to the next day: (i) sleep and (ii) being able to psychologically detach from work during leisure time (42). Since stress is known to have a negative effect on sleep quality (12) and psychological detachment (13), deteriorated sleep and psychological detachment are also considered to be potential indicators for the accumulation of the negative consequences of stress. Sleep deprivation contributes to the accumulation of allostatic load (43,44), but also attenuates the relationship between negative affect experienced at work and negative affect in the next morning (42). Sleep is therefore an important component in the recovery from (work-related) stress and helps limit the potential loss of resources.

Detachment is measured with an item from the psychological detachment subscale of the Recovery Experience Questionnaire that had the highest average correlation to the other three included subscale questions (14): *"During my off-job time, I distanced myself from my work"*. Additionally, the perceived availability of time to recover throughout the day is measured based on an item used in a prior study (17): *"Today I had enough time to relax and recover from work"*. Both items are included in the evening EMA questionnaire and scored on an 11-point NRS ranging from 0 (*"Strongly disagree"*) to 10 (*"Strongly agree"*).

The Fitbit Charge 2 wrist-worn tracker is used to objectively measure the total sleep time and sleep efficiency (45). Additionally, the subjective sleep quality is measured in the morning EMA questionnaire with a validated single-item (46): *"How was the quality of your sleep?"* and is scored on an 11-point NRS ranging from 0 (*"Worst possible sleep"*) to 10 (*"Best possible sleep"*).

Other

In order to account for potentially confounding effects and explain relevant variance, two other variables are included in the daily measures: (i) alcohol intake and (ii) physical activity. Alcohol intake is associated with a lower resting HRV (47), but is sometimes also used as a strategy to cope with increased stress (48). Alcohol intake is therefore measured during the morning EMA questionnaire by asking for the number of alcoholic beverages that the participant consumed during the previous day. While the absolute amount of alcohol in different types of beverages may deviate, asking for the number of alcoholic beverages consumed is both convenient for daily inquiry and consistent with the widely used AUDIT-C questionnaire (49). Finally, physical activity (steps, sedentary minutes, minutes of moderate-to-vigorous physical activity) is measured throughout the day using the Fitbit Charge 2 (50). Physical activity levels are associated with decreased stress reactivity (51), a higher resting HRV (52) and improved sleep (53); therefore, physical is a potential confounder.

PRESENT STUDY

The first WearMe study aims to test the usability of the described measurement protocol, as well as to gather a first wave of data to be able to test the hypothesized relations in the conceptual model. Additionally, the development of both intra-individual and 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).

Population

For the first WearMe study, students who are starting their first full-time internship for Social Work and Applied Psychology are invited to participate. We anticipate this population to be at risk of experiencing stress due to the potentially stressful nature of these disciplines and the fact that these are the first full-time internships in the participants' curriculum. The students need to own an Android or iOS smartphone in order to participate. For recruitment, a message is placed on the school's digital learning environment and the students who are scheduled for their first internships receive an e-mail. Participation in the study is voluntary. In order to facilitate recruitment and optimize adherence during participation, participants who collect at least 80% valid data points are rewarded with a €25 gift voucher. Additionally, participants who collect enough data to create intra-individual models receive individual feedback. Since this first WearMe study is exploring a new topic, it was impossible to perform an accurate power calculation based on the considered data-analysis methods. Due to the availability of materials, a maximum of 15 participants can be simultaneously recruited. Therefore, the recruitment and data-collection processes are divided over two waves. The first recruitment wave started in September 2018, whereas the second waive started in September 2019.

Data collection

The total data collection period is 15 weeks, targeting a maximum of 105 full days of data per participant. The operationalization of the conceptual model and items included in the EMA questionnaires are described in the *Operationalization* section. The participants use a Polar H7 Bluetooth chest strap in combination with the Elite HRV smartphone application to measure their resting HRV upon awakening and used a Fitbit Charge 2 wrist-worn tracker to continuously measure their physical activity and sleep. In order to collect the subjective EMA questionnaire data, TNO's self-developed *"How am I?"* smartphone application is used. Participants are instructed to fill in their morning EMA questionnaire (7 items) after measuring their resting HRV and fill in their evening EMA questionnaire (12 items) before going to bed. The morning questionnaire is available between 06:00 and 15:00 and the evening questionnaire is available between 21:00 and 06:00 in order to offer participants a broad window to fill in the questionnaires (e.g., when potentially staying up late or sleeping in during weekends). Additionally, participants receive smartphone notifications as reminders at 06:00 for the morning questionnaires and at 21:00 for the evening questionnaires. Where available, validated Dutch versions of the questionnaires described in Section III are used. Items based on questionnaires that were only available in English were translated into Dutch. For validation of these items, backwards translation by a native English speaker was performed. No differences that significantly changed the meaning of the items were found during this process.

The daily measurements described in Section II consisted of concepts that can vary on a day-to-day basis. However, some of the concepts of the conceptual framework included aspects that are more trait-like (e.g., personality traits as potential resources or preferred coping strategies) or could be expected to vary over a longer timeframe (e.g., burnout, depression). Therefore, several full questionnaires are administered to benefit the development of population models using between-subject analyses: a questionnaire on personality traits (the Big Five Inventory; BFI) (54), coping strategies (the COPE-Easy) (55), burnout (the Oldenburg Burnout Inventory; OLBI) (56), work engagement (the Utrecht Work Engagement Scale; UWES) (20) and symptoms of somatization, distress, depression and anxiety (the Four-Dimensional Symptom Questionnaire; 4DSQ) (57). The questionnaires on burnout, work engagement and symptoms of somatization, distress, depression and anxiety are also administered after 5, 10 and 15 weeks. Finally, after 15 weeks, participants fill out a resources questionnaire to retrospectively assess the perceived personal and environmental resources throughout the internships, since participants are not able to accurately assess the environmental resources prior to or at the beginning of their internship. This resources questionnaire was inspired by resources questionnaires that were developed for other domain-specific work environments (58,59) and adjusted to better align with the participants' internship contexts. Additionally, the distributed questionnaires consisted of items that were derived from existing validated questionnaires such as the Life Orientation Test (60), the Connor Davidson Resilience Scale (61) and the Dispositional Resilience Scale (62). Figure 3 illustrates the timeline for the measurements in the first WearMe study.

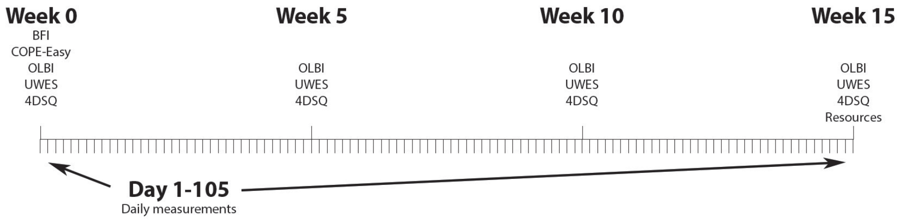

Figure 3: The WearMe study timeline.

Data analysis

Several approaches to data-analysis will be explored. First, the hypotheses formulated in the conceptual framework that were introduced in Section II will be tested using within-day relations and, if possible, on multi-day trends. The repeated measures correlation technique as described by Bakdash and Marusich (63) will be used to analyze the correlation between two variables while taking into account that data points are repeated measures within participants. Random intercept, fixed slopes multilevel modelling will be applied when two or more variables within a specific concept or potential confounders are included to predict the variance within a single dependent variable. Both methods allow the scores between participants to differ (random intercepts), but explore a fixed effect between the variables (fixed slopes). We anticipate that there will be insufficient data available to explore whether the effect between the included variables differ between participants (random slopes).

Second, we will explore the development of intra-individual (n=1) models for within-day and, if possible, multiday trends using the data of the participants with the highest adherence. Aside from the aforementioned techniques, the use of time series analysis techniques and Bayesian statistics will be considered for the multi-day trend analyses.

Finally, the data of the full questionnaires will be used to explore (i) if trends in relevant daily outcomes like sleep, resting HRV and the presence of resources and need for recovery can be predicted based on personality traits or preferred coping strategies measured at baseline, (ii) if these trends are also predictive for changes in burnout, work engagement and symptoms questionnaires and (iii) if there is an association between the daily measured state-related variables (e.g., individual resources and perceived stress) and the trait-variables measured at baseline (the personality traits and preferred coping strategies).

CONCLUSION AND FUTURE WORK

This article presented the conceptual framework for the WearMe project and a detailed description of the operationalization of these concepts in the first (ongoing) WearMe study. Data collected with a wrist-worn wearable tracker, a Bluetooth chest-strap and a smartphone EMA questionnaire app on a daily will be used to explore if the hypotheses that are presented in the conceptual framework are indeed supported.

When the results affirm that tracking sleep and resting HRV with the use of consumer wearables is feasible and can be useful in resilience modelling, the current models will 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 is validated, a more inductive approach to data-analysis may also 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 or limit the loss of relevant resources, which may help employees optimize their resilience.

Furthermore, it is likely that the development of within-subject models requires a long period of data collection. This means that in the envisioned automated resilience system, an individual will have to collect data for a relatively long period before receiving personalized feedback. The creation of a classification algorithm and the identification of subgroups with similar outcome trajectories using between-subject analyses of baseline and first-week data in a larger sample might allow for the development of a system that combines both methods (64). In such a system, participants could receive semi-personalized feedback early on based on their subgroup classification and receive fully personalized feedback when enough within-subject data are available. Such a method would be a compromise between deductive methods that test assumptions based on existing knowledge and inductive methods that allow specific intra-individual predictors to be included in even more personalized feedback.

REFERENCES

1. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Wearable and App-based Resilience Modelling in Employees (WearMe). Athens; 2019.

2. Colligan TW, Higgins EM. Workplace stress: Etiology and consequences. Journal of Workplace Behavioral Health. 2006;21:89–97. doi: 10.1300/J490v21n02_07.

3. Béjean S, Sultan-Taïeb H. Modelling the economic burden of diseases imputable to stress at work. The European Journal of Health Economics. 2005;6:16–23. doi: 10.1007/s10198-004-0251-4.

4. McEwen BS. Stress, Adaptation, and Disease: Allostasis and Allostatic Load. Annals of the New York Academy of Sciences. 1998;840:33–44. doi: 10.1111/j.1749-6632.1998.tb09546.x.

5. Hobfoll SE. The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. Applied Psychology. 2001;50:337–421. doi: 10.1111/1464-0597.00062.

6. Cosco TD, Kaushal A, Hardy R, Richards M, Kuh D, Stafford M. Operationalising resilience in longitudinal studies: a systematic review of methodological approaches. J Epidemiol Community Health. 2017;71:98. doi: 10.1136/jech-2015-206980.

7. Britt TW, Shen W, Sinclair RR, Grossman MR, Klieger DM. How Much Do We Really Know About Employee Resilience? Industrial and Organizational Psychology. 2016/07/04 ed. 2016;9:378–404. doi: 10.1017/iop.2015.107.

8. Drury RL. Wearable biosensor systems and resilience: a perfect storm in health care? Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00853.

9. Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. Eur J Pers. 1987;1:141–169. doi: 10.1002/per.2410010304.

10. Bakker AB, Demerouti E. The Job Demands-Resources model: state of the art. Journal of Managerial Psychology. 2007;22:309–328. doi: 10.1108/02683940710733115.

11. van Veldhoven MJPM. Need for recovery after work: An overview of construct, measurement and research [Internet]. Houdmont J, Leka S, editors. 3. Nottingham University Press; 2008. Available from: https://research.tilburguniversity.edu/en/publications/bbdeef64-c338-4d48-b93f-152afe2ac5ef.

12. Kim E-J, Dimsdale JE. The Effect of Psychosocial Stress on Sleep: A Review of Polysomnographic Evidence. Behavioral Sleep Medicine. 2007;5:256–278. doi: 10.1080/15402000701557383.

13. Sonnentag S, Kuttler I, Fritz C. Job stressors, emotional exhaustion, and need for recovery: A multi-source study on the benefits of psychological detachment. Journal of Vocational Behavior. 2010;76:355–365. doi: 10.1016/j.jvb.2009.06.005.

14. Sonnentag S, Fritz C. The Recovery Experience Questionnaire: Development and validation of a measure for assessing recuperation and unwinding from work. Journal of Occupational Health Psychology. 2007;12:204–221. doi: 10.1037/1076-8998.12.3.204.

15. Demerouti E, Bakker AB, Nachreiner F, Schaufeli WB. The job demands-resources model of burnout. Journal of Applied Psychology. 2001;86:499–512. doi: 10.1037/0021-9010.86.3.499.

16. Littman AJ, White E, Satia JA, Bowen DJ, Kristal AR. Reliability and validity of 2 single-item measures of psychosocial stress. Epidemiology. 2006;17:398–403. doi: 10.1097/01.ede.0000219721.89552.51. Cited: in: : PMID: 16641618.

17. Sonnentag S, Zijlstra FRH. Job characteristics and off-job activities as predictors of need for recovery, well-being, and fatigue. Journal of Applied Psychology. 2006;91:330–350. doi: 10.1037/0021-9010.91.2.330.

18. Van Hooff MLM, Geurts SAE, Kompier MAJ, Taris TW. “How Fatigued Do You Currently Feel?” Convergent and Discriminant Validity of a Single-Item Fatigue Measure. Journal of Occupational Health. 2007;49:224–234. doi: 10.1539/joh.49.224.

19. van Veldhoven M, Broersen S. Measurement quality and validity of the “need for recovery scale.” Occup Environ Med. 2003;60:i3. doi: 10.1136/oem.60.suppl_1.i3.

20. Schaufeli WB, Bakker AB, Salanova M. The Measurement of Work Engagement With a Short Questionnaire: A Cross-National Study. Educational and Psychological Measurement. 2006;66:701–716. doi: 10.1177/0013164405282471.

21. Schaufeli WB, Salanova M, González-romá V, Bakker AB. The Measurement of Engagement and Burnout: A Two Sample Confirmatory Factor Analytic Approach. Journal of Happiness Studies. 2002;3:71–92. doi: 10.1023/A:1015630930326.

22. Luszczynska A, Gutiérrez-Doña B, Schwarzer R. General self-efficacy in various domains of human functioning: Evidence from five countries. International Journal of Psychology. 2005;40:80–89. doi: 10.1080/00207590444000041.

23. Lyubomirsky S, Sheldon KM, Schkade D. Pursuing Happiness: The Architecture of Sustainable Change. Review of General Psychology. 2005;9:111–131. doi: 10.1037/1089-2680.9.2.111.

24. Schiffrin HH, Nelson SK. Stressed and Happy? Investigating the Relationship Between Happiness and Perceived Stress. Journal of Happiness Studies. 2010;11:33–39. doi: 10.1007/s10902-008-9104-7.

25. Avey JB, Luthans F, Jensen SM. Psychological capital: A positive resource for combating employee stress and turnover. Human Resource Management. 2009;48:677–693. doi: 10.1002/hrm.20294.

26. Cohn MA, Fredrickson BL, Brown SL, Mikels JA, Conway AM. Happiness unpacked: Positive emotions increase life satisfaction by building resilience. Emotion. 2009;9:361–368. doi: 10.1037/a0015952.

27. Abdel-Khalek AM. Measuring Happiness With a Single-Item Scale. Social Behavior and Personality: an international journal. 2006;34:139–150. doi: 10.2224/sbp.2006.34.2.139.

28. Thayer JF, Åhs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012;36:747–756. doi: 10.1016/j.neubiorev.2011.11.009.

29. Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, Kupfer D, Thayer JF. Acute Stress Affects Heart Rate Variability During Sleep. Psychosomatic Medicine [Internet]. 2004;66. doi: 10.1097/01.PSY.0000106884.58744.09.

30. Hynynen E, Konttinen N, Kinnunen U, Kyröläinen H, Rusko H. The incidence of stress symptoms and heart rate variability during sleep and orthostatic test. European Journal of Applied Physiology. 2011;111:733–741. doi: 10.1007/s00421-010-1698-x.

31. Park G, Van Bavel JJ, Vasey MW, Thayer JF. Cardiac vagal tone predicts inhibited attention to fearful faces. Emotion. 2012;12:1292–1302. doi: 10.1037/a0028528.

32. Williams DP, Cash C, Rankin C, Bernardi A, Koenig J, Thayer JF. Resting heart rate variability predicts self-reported difficulties in emotion regulation: a focus on different facets of emotion regulation. Frontiers in Psychology [Internet]. 2015;6. doi: 10.3389/fpsyg.2015.00261.

33. Jiménez Morgan S, Molina Mora JA. Effect of Heart Rate Variability Biofeedback on Sport Performance, a Systematic Review. Applied Psychophysiology and Biofeedback. 2017;42:235–245. doi: 10.1007/s10484-017-9364-2.

34. Liao D, Carnethon M, Evans GW, Cascio WE, Heiss G. Lower Heart Rate Variability Is Associated With the Development of Coronary Heart Disease in Individuals With Diabetes: The Atherosclerosis Risk in Communities (ARIC) Study. Diabetes. 2002;51:3524–3531. doi: 10.2337/diabetes.51.12.3524.

35. Perrotta AS, Jeklin AT, Hives BA, Meanwell LE, Warburton DER. Validity of the Elite HRV Smartphone Application for Examining Heart Rate Variability in a Field-Based Setting. The Journal of Strength & Conditioning Research [Internet]. 2017;31. doi: 10.1519/JSC.0000000000001841.

36. Plews DJ, Scott B, Altini M, Wood M, Kilding AE, Laursen PB. Comparison of Heart-Rate-Variability Recording With Smartphone Photoplethysmography, Polar H7 Chest Strap, and Electrocardiography. International Journal of Sports Physiology and Performance. 2017;12:1324–1328. doi: 10.1123/ijspp.2016-0668.

37. Quintana DS, Alvares GA, Heathers JAJ. Guidelines for Reporting Articles on Psychiatry and Heart rate variability (GRAPH): recommendations to advance research communication. Translational Psychiatry. 2016;6:e803–e803. doi: 10.1038/tp.2016.73.

38. Malik M. Heart Rate Variability: Standards of Measurement, Physiological Interpretation, and Clinical Use: Task Force of The European Society of Cardiology and the North American Society for Pacing and Electrophysiology. Annals of Noninvasive Electrocardiology. 1996;1:151–181. doi: 10.1111/j.1542-474X.1996.tb00275.x.

39. Denver JW, Reed SF, Porges SW. Methodological issues in the quantification of respiratory sinus arrhythmia. Biological Psychology. 2007;74:286–294. doi: 10.1016/j.biopsycho.2005.09.005.

40. Quintana DS, Heathers JAJ. Considerations in the assessment of heart rate variability in biobehavioral research. Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00805.

41. Tarvainen MP, Niskanen J-P, Lipponen JA, Ranta-aho PO, Karjalainen PA. Kubios HRV – Heart rate variability analysis software. Computer Methods and Programs in Biomedicine. 2014;113:210–220. doi: 10.1016/j.cmpb.2013.07.024.

42. Sonnentag S, Binnewies C. Daily affect spillover from work to home: Detachment from work and sleep as moderators. Journal of Vocational Behavior. 2013;83:198–208. doi: 10.1016/j.jvb.2013.03.008.

43. McEwen BS. Sleep deprivation as a neurobiologic and physiologic stressor: allostasis and allostatic load. Metabolism. 2006;55:S20–S23. doi: 10.1016/j.metabol.2006.07.008.

44. McEwen BS, Karatsoreos IN. Sleep Deprivation and Circadian Disruption: Stress, Allostasis, and Allostatic Load. Sleep Medicine Clinics. 2015;10:1–10. doi: 10.1016/j.jsmc.2014.11.007.

45. de Zambotti M, Goldstone A, Claudatos S, Colrain IM, Baker FC. A validation study of Fitbit Charge 2™ compared with polysomnography in adults. Chronobiology International. 2018;35:465–476. doi: 10.1080/07420528.2017.1413578.

46. Cappelleri JC, Bushmakin AG, McDermott AM, Sadosky AB, Petrie CD, Martin S. Psychometric properties of a single-item scale to assess sleep quality among individuals with fibromyalgia. Health and Quality of Life Outcomes. 2009;7:54. doi: 10.1186/1477-7525-7-54.

47. Quintana DS, Guastella AJ, McGregor IS, Hickie IB, Kemp AH. Moderate alcohol intake is related to increased heart rate variability in young adults: Implications for health and well-being. Psychophysiology. 2013;50:1202–1208. doi: 10.1111/psyp.12134.

48. Cooper ML, Russell M, George WH. Coping, expectancies, and alcohol abuse: A test of social learning formulations. Journal of Abnormal Psychology. 1988;97:218–230. doi: 10.1037/0021-843X.97.2.218.

49. Bush K, Kivlahan DR, McDonell MB, Fihn SD, Bradley KA, for the Ambulatory Care Quality Improvement Project (ACQUIP). The AUDIT Alcohol Consumption Questions (AUDIT-C): An Effective Brief Screening Test for Problem Drinking. Archives of Internal Medicine. 1998;158:1789–1795. doi: 10.1001/archinte.158.16.1789.

50. Figueroa IA, Lucio ND, Gamez Jr JL, Salazar VE, Funk MD. Validity of daily physical activity measurements of Fitbit Charge 2. International Journal of Exercise Science: Conference Proceedings [Internet]. 2018. p. 27. Available from: https://digitalcommons.wku.edu/ijesab/vol2/iss10/27.

51. Fox KR. The influence of physical activity on mental well-being. Public Health Nutrition. 2007/01/02 ed. 1999;2:411–418. doi: 10.1017/S1368980099000567.

52. Rennie KL, Hemingway H, Kumari M, Brunner E, Malik M, Marmot M. Effects of Moderate and Vigorous Physical Activity on Heart Rate Variability in a British Study of Civil Servants. American Journal of Epidemiology. 2003;158:135–143. doi: 10.1093/aje/kwg120.

53. Sherrill DL, Kotchou K, Quan SF. Association of Physical Activity and Human Sleep Disorders. Archives of Internal Medicine. 1998;158:1894–1898. doi: 10.1001/archinte.158.17.1894.

54. Denissen JJ, Geenen R, Van Aken MA, Gosling SD, Potter J. Development and validation of a Dutch translation of the Big Five Inventory (BFI). Journal of personality assessment. 2008;90:152–157.

55. Kleijn WChr, van Heck GL, van Waning A. Ervaringen met een Nederlandse bewerking van de COPE copingvragenlijst. De COPE-Easy. [Experiences with a Dutch adaptation of the COPE coping questionnaire: The COPE-Easy.]. Gedrag & Gezondheid: Tijdschrift voor Psychologie en Gezondheid. 2000;28:213–226.

56. Halbesleben JRB, Demerouti E. The construct validity of an alternative measure of burnout: Investigating the English translation of the Oldenburg Burnout Inventory. Work & Stress. 2005;19:208–220. doi: 10.1080/02678370500340728.

57. Terluin B, van Marwijk HW, Adèr HJ, de Vet HC, Penninx BW, Hermens ML, van Boeijen CA, van Balkom AJ, van der Klink JJ, Stalman WA. The Four-Dimensional Symptom Questionnaire (4DSQ): a validation study of a multidimensional self-report questionnaire to assess distress, depression, anxiety and somatization. BMC Psychiatry. 2006;6:34. doi: 10.1186/1471-244X-6-34.

58. Delahaij R, Binsch O, Kamphuis W. Weerbaarheidsmonitor voor de politie. Soesterberg, The Netherlands: TNO; 2012. Report No.: M10280. .

59. Delahaij R, Kamphuis W, Binsch O, Venrooij W. Ontwikkeling Militaire Resilience Monitor. Soesterberg, The Netherlands: TNO; 2015. Report No.: R11652..

60. Scheier MF, Carver CS, Bridges MW. Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): A reevaluation of the Life Orientation Test. Journal of Personality and Social Psychology. 1994;67:1063–1078. doi: 10.1037/0022-3514.67.6.1063.

61. Connor KM, Davidson JRT. Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). Depression and Anxiety. 2003;18:76–82. doi: 10.1002/da.10113.

62. Bartone PT, Ursano RJ, Wright KM, Ingraham LH. The Impact of a Military Air Disaster on The Health of Assistance Workers: A Prospective Study. The Journal of Nervous and Mental Disease. 1989;177:317–328.

63. Bakdash JZ, Marusich LR. Repeated Measures Correlation. Frontiers in Psychology [Internet]. 2017;8. doi: 10.3389/fpsyg.2017.00456.

64. Spanakis G, Weiss G, Boh B, Lemmens L, Roefs A. Machine learning techniques in eating behavior e-coaching. Personal and Ubiquitous Computing. 2017;21:645–659. doi: 10.1007/s00779-017-1022-4.

CHAPTER 4

Moderation of the stressor-strain process in interns by heart rate variability measured with a wearable and smartphone app: within-subject design using continuous monitoring

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ABSTRACT

Background: The emergence of smartphones and wearable sensor technologies enables easy and unobtrusive monitoring of physiological and psychological data related to an individual's resilience. Heart rate variability (HRV) is a promising biomarker for resilience based on between-subject population studies, but observational studies that apply a within-subject design and use wearable sensors in order to observe HRV in a naturalistic real-life context are needed.

Objective: This study aims to explore whether resting HRV and total sleep time (TST) are indicative and predictive of the within-day accumulation of the negative consequences of stress and mental exhaustion. The tested hypotheses are that demands are positively associated with stress and resting HRV buffers against this association, stress is positively associated with mental exhaustion and resting HRV buffers against this association, stress negatively impacts subsequent-night TST, and previous-evening mental exhaustion negatively impacts resting HRV, while previous-night TST buffers against this association.

Methods: In total, 26 interns used consumer-available wearables (Fitbit Charge 2 and Polar H7), a consumer-available smartphone app (Elite HRV), and an ecological momentary assessment smartphone app to collect resilience-related data on resting HRV, TST, and perceived demands, stress, and mental exhaustion on a daily basis for 15 weeks.

Results: Multiple linear regression analysis of within-subject standardized data collected on 2379 unique person-days showed that having a high resting HRV buffered against the positive association between demands and stress (hypothesis 1) and between stress and mental exhaustion (hypothesis 2). Stress did not affect TST (hypothesis 3). Finally, mental exhaustion negatively predicted resting HRV in the subsequent morning but TST did not buffer against this (hypothesis 4).

Conclusions: To our knowledge, this study provides first evidence that having a low within-subject resting HRV may be both indicative and predictive of the short-term accumulation of the negative effects of stress and mental exhaustion, potentially forming a negative feedback loop. If these findings can be replicated and expanded upon in future studies, they may contribute to the development of automated resilience interventions that monitor daily resting HRV and aim to provide users with an early warning signal when a negative feedback loop forms, to prevent the negative impact of stress on long-term health outcomes.

Keywords: stress; strain; burnout; resilience; heart rate variability; sleep; wearables; digital health; sensors; ecological momentary assessment; mobile phone.

INTRODUCTION

Background

Psychological stress is associated with increased risk of several forms of cancer (1), musculoskeletal diseases (2), periodontal diseases (3), type 2 diabetes mellitus (4), stroke (5), cardiovascular disease (6), and recurrent cardiovascular disease (7). In an occupational setting, psychosocial risk factors such as high job demands are estimated to increase the risk of stress-related diseases (e.g., burnout) by 60%-90% (8). Occupational stress can therefore cause absenteeism, organizational dysfunction, and decreased productivity, and it has a large economic burden (9).

Stress occurs when the brain subconsciously appraises a demand as threatening because of a lack of resources to cope with it (10). This threat appraisal that we refer to as stress is sometimes referred to as *distress*, whereas demands for which sufficient coping resources are available are appraised as a challenge or as *eustress*. Therefore, stress can be seen as a psychological state that is the result of a divergence between demands on an individual and the individual's perceived capacity to cope with them. Stress causes an imbalance in the body's biological equilibrium (homeostasis), which requires a neural, neuroendocrine, and neuroendocrine-immune adaptation to restore it (allostasis) (11,12). Although acute stress can have negative effects, it is particularly the cumulative wear and tear on bodily systems (allostatic load) caused by excessive stress or inefficient management of the systems that promote adaptation that is detrimental to long-term health and well-being (13). In addition, lifestyle-related factors such as obesity, sleep, and substance abuse can also contribute to allostatic load (14). Allostatic load is therefore considered a measure of the cumulative biological burden on health (15).

To complement this biological and neuroendocrinological perspective on the negative long-term health effects of stress and provide a framework for how short-term spillover effects of stress accumulate the need for a recovery concept be introduced (16). A need for recovery arises when an individual has problems using resources to adaptively cope with demands that induce stress (17). Need for recovery is a conscious emotional state that is related to the temporal depletion of resources following effort to meet demands and is characterized by feelings of mental exhaustion (18). As the availability of resources is assessed during appraisal and the use of resources may be needed during coping, the Conservation of Resources Theory states that an initial loss of resources can lead to a negative feedback loop that increases one's vulnerability to stress (19). Such a loss spiral may become even more distinct if stress negatively impacts the recovery process itself, for instance, by negatively impacting sleep quality (20) and psychological detachment (21). Resilience, which can be defined as the process of positively adapting to adverse events (22), is a term describing this process from a positive perspective. During a resilient process, the aforementioned loss spiral is prevented by using resources to adaptively cope with demands and stress to limit long-term strain and its related negative consequences on health and well-being from developing (23). Resilience is therefore an ongoing process that influences the extent to which adverse events that occur on a small timescale have an impact on mid- to long-term health outcomes.

Heart rate variability

A challenge for resilience research that focuses on resilience-related associations on timescales is that it requires continuous data collection, making it relatively labor-intensive for participants to do so. Over the past decade, the emergence of smartphones and wearable sensor technologies has enabled the easy and unobtrusive measurement of physiological and psychological data related to an individual's resilience (24). A promising example of such a metric is heart rate variability (HRV), which refers to the variation in inter-beat intervals of the heartbeats (25). HRV is a plausible, noninvasive, and easily applicable biomarker for resilience that may serve as a global index of an individual's flexibility and adaptability to stressors (26,27). HRV is negatively correlated with allostatic load, illustrating its use as an overall health risk indicator (28). Stress is also known to decrease HRV, particularly with reduced parasympathetic activation (29–31). Although an acute decline in HRV may be indicative of increased acute stress levels, HRV can remain lowered during rest and sleep after stress or mental exhaustion (32–35). Conversely, having a lower trait resting HRV has been linked to increased sensitivity to stress via appraisal when faced with demands (36) and to suboptimal emotion regulation that may result in mental exhaustion (37,38). Therefore, resting HRV can be seen as a physiological resource that is addressed during the appraisal of demands and coping with stress. Therefore, resting HRV can be hypothesized to have a buffering effect on the positive associations between demands and stress, as well as between stress and mental exhaustion. These two hypothesized buffering effects are depicted as circles 1 and 2 in Figure 1, which represent the conceptual model for this study and were based on a previous publication (39). The model is based on the Transactional Model of Stress and Coping (10), the Job Demands-Resources Model of Burnout (40), the Effort-Recovery Model (17), and the Conservation of Resources Theory (19). In short, it depicts that demands are appraised as stress when resources are low, that stress leads to mental exhaustion when resources to cope with the demands are lacking, and that mental exhaustion limits resources to deal with future demands, unless there are sufficient recovery opportunities. In this study, HRV is the resource of interest, whereas sleep, operationalized as total sleep time (TST), represents the model's recovery process.

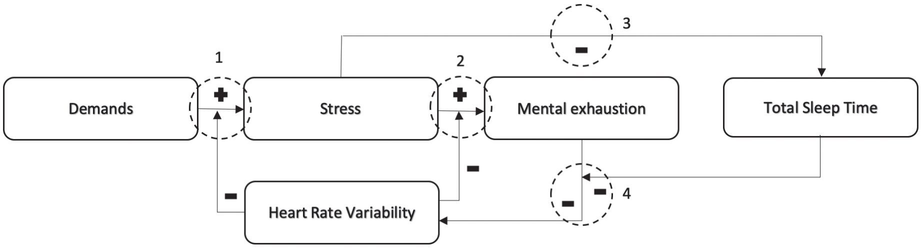

Figure 1: The conceptual model for this study and the four hypotheses that will be tested.

Sleep

Besides resting HRV, sleep is also a relevant potential indicator for the accumulation of the negative consequences of stress and predictor of spillover need for recovery. In the literature, stress has been consistently shown to decrease slow-wave sleep, rapid eye movement sleep, and sleep efficiency, as well as to increase the number of awakenings that may impact the overall sleep duration (20). Therefore, stress can be hypothesized to negatively affect the TST, which is the total time during a sleep episode in which one was not awake (Figure 1; hypothesis 3). In contrast, sleep has important homeostatic functions that are essential during recovery from both physiological and psychological strains (41). Sleep deprivation therefore has been linked to an increase in allostatic load (42) and has been linked to decreased HRV in some studies (43,44). As mental exhaustion may result in decreased resting HRV (34,35) and sleep is an essential aspect of the recovery process, TST can be hypothesized to buffer against the negative association between mental exhaustion and resting HRV (Figure 1; hypothesis 4).

AIMS OF THIS STUDY

HRV measurement is regularly used as a biofeedback tool in mobile health (mHealth) interventions that target acute stress relief (45–47) but may also be useful for interventions that aim to provide users with feedback on their resilience over a longer timeframe. A recent literature review confirmed that HRV has potential as a biomarker for resilience but suggested that more longitudinal studies are needed that use wearable sensors to observe HRV in a naturalistic context of real-life and associate it with resilience-related outcomes, as most of the evidence is based on cross-sectional population studies (27). Therefore, this study longitudinally assessed the aforementioned hypotheses in a free-living context using consumer-available wearable sensors. Exploring these will provide insight into the potential causal pathways of the within-day accumulation of the negative consequences of stress. Gained insights may therefore be beneficial to the future development of (automated) resilience interventions that target the prevention of stress-related health problems.

METHODS

The study protocol was approved by the ethical committee of the Hanze University of Applied Sciences Groningen (heac.2018.008) in the Netherlands.

Participants

Students in applied psychology, social work, and physiotherapy who were about to start their first full-time internship were invited to participate via a message on the school's digital learning environment and email. This population was anticipated to be at risk of experiencing stress because of the potentially stressful nature of these internships, as well as the fact that this was the first internship in the participants' curriculum. A maximum of 15 participants could be simultaneously recruited because of the availability of materials. The recruitment and data collection processes were therefore divided into two waves that started in September 2018 and September 2019, respectively. The students were sent an email with an information letter that described the goal of the study, a description of the measurement protocol, and management of the collected data; the email also stated that participation would be unrelated to their internship or educational progress, that participation would occur on a voluntary basis, and that they could stop at any time without negative consequences. Some of the researchers were employed by the university in which the students were enrolled but had no other associations with the invited students (e.g., via education). The participants provided written informed consent before participation. Participants who collected complete data on at least 84 days during the formal participation period were rewarded with a €25 (US $27.50) gift voucher to facilitate recruitment and optimize adherence during participation. This reward threshold represents an adherence of at least 80% over a data collection period of 15 weeks (105 days). The threshold was solely used as a cutoff point for the reward and not for statistical analyses.

Data collection

Participants were assisted in installing the required apps on their smartphones and were instructed on how to use the devices used for data collection. The data collection period started immediately after the measurement instructions, after which participants collected data for 15 weeks. Some participants completed additional daily measurements on a voluntary basis until their appointment was planned to return the used materials. At this appointment, an additional 20-minute conversation was held about how they experienced the daily measurements and to learn about potential improvements for future studies. During the study, anonymized user accounts were used for the applied consumer-available wearables in order to protect the participants' privacy on the companies' cloud servers, before being exported and deleted by the researchers after completing their participation.

Main variables

Resting HRV was measured daily using a consumer-available Polar H7 Bluetooth chest strap in combination with the Elite HRV app that is freely available in the iOS App Store and Google Play Store. The Polar H7 chest strap has been shown to accurately measure resting HRV when compared with an electrocardiogram (48). The Elite HRV app was chosen because it is easy to use for daily HRV measurements in a consumer setting and allows data export on an inter-beat interval level. Participants were instructed to perform a 2-minute HRV measurement in a supine position after awakening before getting out of bed. This is consistent with existing standards and recommendations that suggest a measurement duration of 1-5 minutes and consistent circumstances with as little influence as possible from circadian rhythms, meals, smoking, posture changes, and before significant mental or physical exertion (49,50). We considered sitting or standing resting HRV measurements to account for the possible presence of parasympathetic saturation in case we recruited an elite endurance athlete (51). However, we opted for supine measurements immediately after awakening in order to limit the potential influence of posture changes, physical activity, meals, and smoking as recommended by the aforementioned guidelines, as well as to ensure that all participants performed the measurement at a similar post-awakening time and in a similar context.

The wrist-worn Fitbit Charge 2 activity tracker was used to measure TST, which tends to slightly overestimate but for which has acceptable measurement accuracy in diverse populations (52–54). Participants were instructed to continuously wear the Fitbit during the day and night and charge it at least once every 5 days.

Before bedtime (available between 08 PM and 06 AM), participants completed a short ecological momentary assessment (EMA) questionnaire using an internally developed smartphone app to measure demands, stress, and mental exhaustion. The daily EMA questionnaire data were stored on premise. In the absence of a single item or full scale that was relevant for the study setting, demands were scored on the self-composed diary question, “How demanding was your day?” These demands represent the contextual circumstances that exerted pressure on the participant, whereas stress reflected the resulting threat appraisal that these evoked within the individual. Stress was scored on a validated single-item scale (55): “How much stress did you perceive today?” Mental exhaustion is an aspect of the need for recovery concept and was based on item 3 of the Need for Recovery Scale (56), which was chosen because it appropriately represents strain within the context of the used conceptual model (39): “I felt mentally exhausted as a result of my activities.” All three items were scored on a 11-point numeric rating scale ranging from 0 (not at all for demands and stress and strongly disagree for mental exhaustion) to 10 (extremely for demands and stress and strongly agree for mental exhaustion).

Control variables

Although the Fitbit Charge 2 was chosen for its accuracy in measuring TST, its data on moderate-to-vigorous physical activity (MVPA) and sedentary time were also used during analysis as potential confounders. MVPA is defined as the total amount of daily minutes where the participant was physically active at an intensity of 3 metabolic equivalents or more, where 1 metabolic equivalent represents the resting metabolism. In previous studies, MVPA was negatively associated with state anxiety (57), mental strain (58), and HRV recovery (59), as well as positively associated with TST (60). Similarly, sedentary time was positively associated with depression and anxiety (61) and negatively associated with TST (62) and HRV (63). Finally, Fitbit-measured TST was also used as a control variable in the analyses for stress and mental exhaustion because intraindividual variability in accelerometer-measured TST has been associated with increased stress (64).

In addition, alcohol consumption during the previous day was measured in a morning questionnaire (available between 6 AM and 3 PM) for use as a potential confounder. In previous literature, alcohol consumption has been negatively associated with wearable-measured TST (65) and reduced HRV (66). Alcohol consumption was scored as a numeric variable by asking for the number of alcoholic beverages consumed during the previous day. Although the absolute amount of alcohol in different types of beverages may deviate, asking for the number of alcoholic beverages consumed is both convenient for daily inquiry and consistent with the widely used AUDIT-C questionnaire (67).

Data analysis

All data management and analyses were performed in RStudio (68) and R (69).

Data management

For HRV data management, the RHRV package (70) was used. Inter-beat interval data of all daily observations were filtered for artifacts using the algorithm in the RHRV package. The respective algorithm is described fully in a complementary book written by the authors of the RHRV package (71). The algorithm is too comprehensive to be fully described here but is summarized by the authors to apply an adaptive threshold to reject beats whose inter-beat interval value differs from previous and following beats, and from a mobile mean more than a threshold value, as well as beats that are not within acceptable physiological values. Subsequently, the root mean square of the successive differences (RMSSD) was calculated for every observation by first calculating each successive difference between heartbeats in milliseconds, then squaring these values, averaging that result, and finally taking its square root (72). However, algorithmic artifact correction can only distinguish potential measurement errors on an inter-beat interval level and can result in abnormally high RMSSD values if there are too many measurement errors present. As this study was performed in free-living conditions, it was not possible to verify if participants performed the daily measurements exactly as instructed. Therefore, a second filtering method was applied to filter out HRV observations with extreme RMSSD values for that specific participant. To achieve this, within-subject RMSSD outliers of daily observations with a value that lies more than 1.5 IQR below the first quartile or 1.5 IQR above the third quartile for all available data of the respective participant were removed (73). Finally, the RMSSD values were logarithmically transformed to improve the distribution for parametric statistical modelling of resting HRV.

The TST data were filtered for episodes that started after filling in the evening EMA questionnaire and ended before the morning questionnaire was filled in to obtain the nighttime TST. When more than one TST episode was present between the evening and the subsequent morning EMA questionnaire, they were combined. No outliers were removed from the EMA data because no unfeasible values were identified.

Because of the different scales of the resting HRV, TST, and EMA data, centering and standardizing the data was necessary to prevent potential multicollinearity and allow comparability of the coefficients of the independent variables. As the level 1 association between the aforementioned main variables is the primary interest in this study, centering within subject is recommended as opposed to centering at the grand mean (74). Therefore, all data were centered and standardized within subjects by subtracting the subject's mean value over all daily observations from each value and dividing it by the subject's SD over all daily observations. The z-scores that were used during analysis therefore reflect the degree to which a daily observation differed from the individual's own mean. As the mean z-scores for each variable in each individual were zero, there was no between-subject variance left in the data. Therefore, multiple regression analysis was performed instead of the multi-level modelling that we originally planned to undertake, despite the observations being nested within subjects (Linear Mixed Modelling with fixed effects and random slopes using the within-subject standardized values resulted in the same outcomes and conclusions on all analyses but had a boundary [singular] fit and no differences in the within- and between-subject explained variance because there was no between-subject variance. As these multi-level models had no benefit, the results of our multiple regression analyses were presented in this study).

Statistical analysis

To test the four hypotheses described in the Introduction, four statistical analyses were performed. In the first analysis, stress was first modeled based on the control variables MVPA, sedentary time, and previous-day TST, after which the main variables demands, resting HRV, and the interaction effect of demands and resting HRV were added to create the full model. In the second analysis, a control variable model for mental exhaustion was first developed based on MVPA, sedentary time, and previous-night TST, after which a full model was created by adding the main effects of stress and resting HRV, as well as the interaction effect between stress and resting HRV. For analysis three, the control variable model for TST contains previous-day MVPA, sedentary time, and alcohol consumption, with previous-day stress being added to the full model. Finally, the fourth analysis first modeled resting HRV based on control variables previous-day MVPA, sedentary time, and alcohol consumption before adding the main effects of previous-evening mental exhaustion and previous-night TST, as well as the interaction effect between previous-evening mental exhaustion and previous-night TST. To compare the explained variance and statistical significance of the control variable and full models, the difference in the adjusted R-squared value and F statistic was calculated for all four analyses.

RESULTS

Overview

A total of 26 participants were recruited for this study. The participants were predominantly women (n=24). Most participants studied applied psychology (n=19), followed by social work (n=6) and physiotherapy (n=1). The participants were aged between 19.2 and 33.2 years (median 22.6). The participants collected TST data on 2129 days (per participant range 10-119; median 94), 1731 morning EMA questionnaires (range 5-109; median 74), 1653 evening EMA questionnaires (range 7-111; median 73), and HRV data on 1443 days (range 6-115; median 53). In total, for 1004 of the 2379 days (42.2%) on which a participant collected data, the participant collected complete data containing all required TST, HRV, and EMA data. The descriptive statistics for and intercorrelations between the main and control variables are presented in Table 1. Three participants did not complete the full (105 days) measurement period because they lost motivation for the daily measurements, and one participant stopped the daily measurements because of skin rash related to wearing the Fitbit. All three participants who did not complete the full measurement period contributed daily measurements and were thus still included in the analyses. During the exit conversations, several participants stated that they found it difficult to adhere to the HRV measurement, because the need to apply a moistened chest strap and lay still for 2 minutes after awakening while they wanted to continue with their day was inconvenient. Missing Fitbit data were primarily ascribed to forgetting to charge it, particularly when participants were away from home. Finally, participants mostly attributed missing EMA data to simply forget to act on the smartphone notification as they were busy at that time.

Table 1: Descriptive statistics and correlations for the main (1-5) and control (6-8) variables.

Variable	Mean (SD)	Correlation (p-value)						
		1	2	3	4	5	6	7
1. HRV	75.3 (49.9)	-						
2. TST	7.3 (1.4)	-.03 (.36)	-					
3. Demands	4.6 (2.4)	.06 (.03)	-.01 (.68)	-				
4. Stress	3.6 (2.4)	.06 (.03)	.02 (.42)	.53 (<.01)	-			
5. Mental exhaustion	3.6 (2.4)	<.01 (.89)	-.03 (.31)	.55 (<.01)	.64 (<.01)	-		
6. MVPA	33.9 (37.0)	-.05 (.10)	-.11 (<.01)	.04 (<.13)	-.05 (.06)	-.06 (.02)	-	
7. Sedentary time	687.2 (220.7)	-.13 (<.01)	-.48 (<.01)	-.07 (<.01)	.06 (.02)	.03 (.18)	-.24 (<.01)	-
8. Alcohol use	1.3 (2.8)	-.04 (.13)	-.28 (<.01)	-.21 (<.01)	-.10 (<.01)	-.06 (.03)	.10 (<.01)	.08 (<.01)

Note. N=26, n=1125-2276; HRV: Heart Rate Variability (in milliseconds); TST: Total Sleep Time (in hours); MVPA: Moderate-to-Vigorous Physical Activity (in minutes).

Analysis 1: stress

A two-step hierarchical multiple regression model explaining stress scores was developed (Table 2). After controlling for MVPA, sedentary time, and previous-night TST, demands were positively associated (P<.001) with stress. In addition, the interaction effect of demands and resting HRV significantly (P=.044) buffered against this positive association. This means that participants tended to report higher stress scores on days that they also considered to be more demanding, but this relationship was weaker on days where the participant woke up with a relatively high resting HRV. The positive association between demands and stress, as well as the buffering effect of resting HRV, confirms hypothesis one. Furthermore, the control variable MVPA was positively associated with stress (P=.044), which means that participants reported higher stress scores on days where they were more physically active. In the control variable model, TST was a negative predictor of stress (P=.03), but this effect was no longer significant in the full model. The control variable model of analysis explained 2.0% of the within-subject variance in the daily stress scores, whereas the full model had an explained variance of 21.7%, which is a significant increase from the control variable model.

Table 2: Hierarchical multiple regression model for stress (analysis 1).

Independent variable	Stress			
	Step 1		Step 2	
	β	p	β	p
Intercept	.05	.14	.00	.96
TST	-.09	.03	.00	.89
MVPA	.12	<.01	.06	.04
Sedentary time	.02	.75	.05	.29
Demands			.47	<.01
HRV			.01	.70
Demands * HRV			-.06	.04
Adjusted R^2	*.02*		*.22*	
F	*7.541*		*44.86*	
Δ Adjusted R^2			*.20*	
Δ F			*37.32*	

Note. N=26, n=953; TST: Total Sleep Time (in hours); MVPA: Moderate-to-Vigorous Physical Activity (in minutes); HRV: Heart Rate Variability (in milliseconds).

Analysis 2: mental exhaustion

A two-step hierarchical multiple regression model explaining mental exhaustion scores was developed (Table 3). After controlling for MVPA, sedentary time, and previous-night TST, stress was positively associated (P<.001) with mental exhaustion. In addition, the interaction effect of stress and resting HRV significantly (P=.029) buffered against this positive association. This means that participants tended to report higher mental exhaustion scores on days that they were also considered stressful, but this relationship was weaker on days where the participant woke up with a relatively high resting HRV. The positive association between stress and mental exhaustion, as well as the buffering effect of resting HRV confirm hypothesis two. In the control variable model, MVPA was also positively associated with mental exhaustion (P=.017), but this effect was no longer significant in the full model. The control variable model of analysis two explains 1.4% of the within-subject variance in the daily mental exhaustion scores, whereas the full model has an explained variance of 31.6%, which is a significant increase from the control variable model.

Table 3: Multiple regression model for mental exhaustion (analysis 2).

Independent variable	Mental exhaustion			
	Step 1		Step 2	
	β	p	β	p
Intercept	.05	.12	.02	.37
TST	-.06	.15	-.01	.68
MVPA	.09	.02	.02	.58
Sedentary time	.09	.09	.07	.09
Stress			.55	<.01
HRV			-.04	.15
Stress * HRV			-.06	.03
Adjusted R^2	*.01*		*.32*	
F	*5.42*		*74.17*	
Δ Adjusted R^2			*.30*	
Δ F			*68.75*	

Note. N=26, n=953; TST: Total Sleep Time (in hours); MVPA: Moderate-to-Vigorous Physical Activity (in minutes); HRV: Heart Rate Variability (in milliseconds).

Analysis 3: total sleep time

A two-step hierarchical multiple regression model explaining nighttime TST was developed (Table 4). After controlling for previous-day MVPA, sedentary time, and alcohol consumption, previous-day stress did not predict TST, unlike our expectation based on hypothesis 3. However, the control variables previous-day MVPA and alcohol consumption were negatively associated with TST, whereas sedentary time was positively associated with TST. This means that participants had a lower TST on days where they were relatively physically active, consumed alcohol, and had limited sedentary time. The control variable model of analysis three explains 3.8% of the within-subject variance in TST, whereas the full model has an explained variance of 4.6%, which is not a statistically significant increase from the control variable model.

Table 4: Multiple regression model for Total Sleep Time (analysis 3)

Independent variable	TST			
	Step 1		Step 2	
	β	p	β	p
Intercept	-.03	.32	-.03	.33
MVPA	-.07	.01	-.07	.01
Sedentary time	.08	<.01	.08	.01
Alcohol consumption	-.20	<.01	-.20	<.01
Stress			-.01	.64
Adjusted R^2	*.05*		*.05*	
F	*21.88*		*16.46*	
Δ Adjusted R^2			*.01*	
Δ F			*-5.42*	

Note. N=26, n=1285; MVPA: Moderate-to-Vigorous Physical Activity (in minutes).

Analysis 4: heart rate variability

A two-step hierarchical multiple regression model explaining resting HRV was developed (Table 5). After controlling for previous-day MVPA, sedentary time, and alcohol consumption, previous-evening mental exhaustion negatively predicted (P<.001) resting HRV, but previous-night TST did not buffer against this negative association. Therefore, these results partially support hypothesis four. Among the control variables, previous-day alcohol consumption negatively predicted resting HRV (P<.001). The control variable model explained 2.3% of the within-subject variance in resting HRV, whereas the full model had an explained variance of 3.6%, which was not a statistically significant increase from the control variable model.

Table 5: Multiple regression model for Heart Rate Variability (analysis 4)

Independent variable	HRV			
	Step 1		Step 2	
	β	p	β	p
Intercept	-0.00	.98	0.00	.96
MVPA	-0.06	.06	-0.05	.10
Sedentary time	0.02	.53	0.03	.40
Alcohol consumption	-0.18	<.01	-0.19	<.01
Mental exhaustion			-0.12	<.01
TST			0.02	.52
Mental exhaustion * TST			-0.00	.92
Adjusted R^2	*0.02*		*0.04*	
F	*8.42*		*6.96*	
Δ Adjusted R^2			*0.01*	
Δ F			*-1.46*	

Note. N=26, n=948; TST: Total Sleep Time (in hours); MVPA: Moderate-to-Vigorous Physical Activity (in minutes).

DISCUSSION

Principal findings

This study aimed to test the hypotheses that (i) demands are positively associated with stress and resting HRV buffers against this association, (ii) stress is positively associated with mental exhaustion and resting HRV buffers against this association, (iii) stress negatively impacts subsequent-night TST, and (iv) previous-evening mental exhaustion negatively impacts resting HRV, while previous-night TST buffers against this association. By assessing these associations based on longitudinal data that were collected using consumer-available wearables and smartphone apps in a free-living context, this study provides insight into the potential pathways of the within-day accumulation of the negative consequences of stress. The results of this study support hypotheses one and two and partially support hypothesis four.

Heart rate variability as an index of resilience

As hypothesized, having a high resting HRV buffered against the positive associations between demands and stress (hypothesis 1), as well as between stress and mental exhaustion (hypothesis 2). Similarly, mental exhaustion negatively predicted resting HRV, as expected (hypothesis 4). These findings suggest that waking up with a relatively high intraindividual resting HRV decreases an individual's sensitivity to stress when faced with demands, as well as the likelihood of being mentally exhausted during a stressful day. In addition, as the accumulation of mental exhaustion negatively impacts an individual's resting HRV, an increase in mental exhaustion negatively impacts this (psycho) physiological resource and thus potentially creates a negative feedback loop that can lead to a loss spiral. These results therefore confirm our hypothesis that a decline in resting HRV is indicative of the accumulation of the negative consequences of stress, as well as the continued accumulation of negative consequences of stress. Therefore, resting HRV can be seen as a biomarker for or an index of resilience, where a decline in resting HRV may signal that buildup of allostatic load is present and suggests that the individual's readiness to face new demands may at least be temporarily decreased.

As highlighted in a recent literature review, most studies to date investigating the role of HRV as an index for resilience have a cross-sectional nature and assess relationships at the between-subject level (27). To our knowledge, this study is the first to apply a nested longitudinal design and assess the potential of resting HRV as an index of resilience to stress on a within-subject level. Previous studies that investigated between-subject differences identified similar relationships between resting HRV and mental health outcomes. For instance, a recent study with school teachers concluded that 48-hour trait HRV buffered the effect of emotional demands on exhaustion (75). Another recent study cross-sectionally assessed a population of young female adults and found that having a high resting HRV buffered against the positive association between emotion regulation difficulties and depressive symptoms (76). Resting HRV has also been reported to buffer against the negative effects of chronic stress on sleep quality, which in turn is related to greater depressive symptoms (77). Finally, high stress-induced HRV was shown to buffer against the negative effect of hostility on cortisol sensitivity (78). Therefore, the within-subject findings of this study align with previous studies that also reported favorable between-subject effects of resting HRV on diverse mental health outcomes.

The role of sleep in the within-day stressor-strain process

Contrary to our hypothesis, stress did not negatively affect TST (hypothesis 3). The absence of a negative association between stress and TST conflicts with previous literature that consistently links experimental stress to decreased slow-wave sleep, rapid eye movement sleep, sleep efficiency, and increases in awakenings (20). A possible explanation for this could be the difference in context, as those studies examined the influence of experimental stress on polysomnographically measured sleep, whereas this study investigated daytime stressors and TST in a natural free-living context. Because of the increasing capabilities and performance of consumer wearables to measure sleep and the resulting rise in the use of consumer wearables in sleep research, future studies may increase insights into the potential relationship between daily stressors and TST in a natural free-living context (79).

TST also did not buffer against the negative association between mental exhaustion and resting HRV, as expected (hypothesis 4). This expectation was based on the rationale that sleep has important homeostatic functions that are essential during recovery from strain (41), and that sleep deprivation has been linked to an increase in allostatic load (42) and a decrease in HRV (43,44). As mental exhaustion was measured during the evening and resting HRV during the morning, we expected TST to potentially have a buffering effect, meaning that the negative impact of mental exhaustion on resting HRV would be smaller if the participant slept well that night. This buffering effect was not present in these findings, but TST was also not positively associated with resting HRV, as might be expected based on the aforementioned literature. A possible explanation for this could be that the relationship between sleep deprivation and HRV in previous literature seems to be particularly present in studies assessing a longer sleep deprivation period (80), which might suggest that the nuanced day-to-day differences in TST are too small to significantly impact the resting HRV. Future studies investigating the impact of TST on resting HRV or the recovery from strain in a natural free-living context in which such long periods of sleep deprivation are relatively uncommon, assessing the impact of multi-day trends in TST might help increase insight on this topic.

Notable effects of MVPA, sedentary time, and alcohol consumption

The effects of most of the control variables that were significantly associated with the outcomes of the four analyses were as expected, but some of the effects seem to conflict with previous literature. For instance, MVPA was negatively associated with TST, but a recent study found a positive association between MVPA and TST (60). Similarly, sedentary time was positively associated with TST in this study, whereas a negative association with TST was reported in another recent study assessing obese adults (62). A possible explanation can be found in the reported significant correlations between MVPA, sedentary time, and alcohol consumption (Table 1). This young student population spends part of their leisure time enjoying the local nightlife, in which dancing and alcohol consumption are common. It is therefore possible that this will have caused the low sedentary time, high MVPA, and alcohol consumption that were associated with low TST.

Strengths and limitations

The strengths of this study are its longitudinal design and large sample of nested observations, optimizing the within-subject variance. Moreover, the use of consumer-friendly wearable sensors and smartphone apps allowed for relatively unobtrusive monitoring in a free daily living context, optimizing the generalizability for similar settings. A limitation of this study was the need to apply relatively coarse algorithmic artifact correction and rule-based outlier filtering during HRV data management. Because of the choice to use a consumer-available sensor and app for long-term daily measurements in free-living conditions, electrogram-level data were unavailable, and it was impossible to verify if participants performed the measurements as instructed. As the applied algorithmic artifact removal method can only filter out inter-beat interval artifacts within an HRV measurement, it has no rules to decide whether an observation should be removed altogether, filtering out extreme within-subject RMSSD outliers was necessary. Furthermore, algorithm-based artifact correction was preferred over manually adjusting inter-beat interval artifacts to make the findings of this study applicable to the context of an automated resilience intervention that does not rely on human interference during data management. In addition, the use of single-item scales in the evening EMA questionnaire forms a limitation of comprehensiveness at which the concepts can be measured. Therefore, validated single-item scales or items with the most favorable psychometric properties in existing validated scales were used where available (39). As single-item scales have consistently been found to be valid measures for diverse concepts in comparison to full scales (81–84) and have become common good in EMA research, the applied EMA methods can still be considered appropriate. The participants also received some feedback on their sleep, physical activity, and HRV because of the use of the consumer-available Fitbit and Elite HRV apps, which might have influenced their behavior. Nevertheless, any such influence was not considered a problem because this study observes the natural relationship between several variables and does not reflect on the behaviors themselves. Finally, only 3.6% of the within-subject variance in resting HRV could be explained, and the buffering effect of resting HRV was relatively modest.

Generalizability

The HRV-related results can be generalized to young and employed female adults who track their resting HRV upon awakening. As 92% (24/26) of the participants were female and HRV can be related to menstrual cycle changes (85), further research on young males is necessary to improve the generalizability of these findings to young adults regardless of gender. As the resting HRV was measured upon awakening in this study, the influence of a phenomenon called the cortisol awakening response (CAR) might have played a role. Upon awakening, cortisol levels start to increase and peak approximately 30-45 minutes thereafter because of the CAR, where 1%-3.6% of its variance can be explained by psychosocial factors (86). Although the CAR is associated with post-awakening changes in HRV, these changes appear to be unrelated to perceived stress and measures of emotion regulation (87). Therefore, it is possible that measuring HRV during sleep could yield similar results. An advantage of measuring resting HRV during sleep is that participants would not need to apply a moistened chest strap and lay still in a supine position upon awakening to collect their resting HRV data. As multiple participants described that this procedure negatively impacted their adherence to the measurement protocol, unobtrusively measuring the resting HRV during sleep might improve adherence and thus increase statistical power. Future research is needed to confirm whether resting HRV during sleep can be used to yield similar results.

Implications

To our knowledge, this study is the first to report a significant within-subject buffering effect of resting HRV on the positive associations between demands and stress, as well as between stress and mental exhaustion and a negative association between mental exhaustion and resting HRV. Replication of these findings in future studies is needed. As the combined findings form a feedback loop, it is possible that multi-day trends in resting HRV could be linked to longitudinal mental health outcomes in future studies. Furthermore, exploring the use of time series analysis to create within-subject models in which multi-day trend data are used to assess the daily outcomes could potentially improve the accuracy of the presented models. Future studies are advised to use passive monitoring techniques that require little to no user attention whenever possible to improve participant adherence and optimize statistical power.

If the findings of this study can indeed be replicated and expanded upon, it would show that longitudinally monitoring resting HRV as a biomarker of or index for resilience may be useful in the context of prevention. In this context, a structural increase or decline in resting HRV could provide an early warning signal that a positive or negative feedback loop is formed. When used in a consumer wearable–based automated resilience intervention, these signals can be used to prompt user feedback. For instance, users could be rewarded when a positive feedback loop is recognized or suggested to perform cognitive behavioral therapy–based self-reflection exercises or relaxation techniques when a negative feedback loop occurs. Such an automated resilience intervention that unobtrusively monitors the user's resting HRV for the early recognition of (un)favorable feedback loops and generation of just-in-time feedback may therefore limit the buildup of allostatic load and improve long-term health outcomes.

REFERENCES

1. Yang T, Qiao Y, Xiang S, Li W, Gan Y, Chen Y. Work stress and the risk of cancer: A meta-analysis of observational studies. International Journal of Cancer. 2019;144:2390–2400. doi: 10.1002/ijc.31955.

2. Buscemi V, Chang W-J, Liston MB, McAuley JH, Schabrun SM. The Role of Perceived Stress and Life Stressors in the Development of Chronic Musculoskeletal Pain Disorders: A Systematic Review. The Journal of Pain. 2019;20:1127–1139. doi: 10.1016/j.jpain.2019.02.008.

3. Decker A, Askar H, Tattan M, Taichman R, Wang H-L. The assessment of stress, depression, and inflammation as a collective risk factor for periodontal diseases: a systematic review. Clinical Oral Investigations. 2020;24:1–12. doi: 10.1007/s00784-019-03089-3.

4. Sui H, Sun N, Zhan L, Lu X, Chen T, Mao X. Association between Work-Related Stress and Risk for Type 2 Diabetes: A Systematic Review and Meta-Analysis of Prospective Cohort Studies. PLOS ONE. 2016;11:e0159978. doi: 10.1371/journal.pone.0159978.

5. Booth J, Connelly L, Lawrence M, Chalmers C, Joice S, Becker C, Dougall N. Evidence of perceived psychosocial stress as a risk factor for stroke in adults: a meta-analysis. BMC Neurology. 2015;15:233. doi: 10.1186/s12883-015-0456-4.

6. Magnavita N, Capitanelli I, Garbarino S, Pira E. Work-related stress as a cardiovascular risk factor in police officers: a systematic review of evidence. International Archives of Occupational and Environmental Health. 2018;91:377–389. doi: 10.1007/s00420-018-1290-y.

7. Li J, Zhang M, Loerbroks A, Angerer P, Siegrist J. Work stress and the risk of recurrent coronary heart disease events: A systematic review and meta-analysis. International Journal of Occupational Medicine and Environmental Health [Internet]. 2014; doi: 10.2478/s13382-014-0303-7.

8. van der Molen HF, Nieuwenhuijsen K, Frings-Dresen MHW, de Groene G. Work-related psychosocial risk factors for stress-related mental disorders: an updated systematic review and meta-analysis. BMJ Open. 2020;10:e034849. doi: 10.1136/bmjopen-2019-034849.

9. Béjean S, Sultan-Taïeb H. Modelling the economic burden of diseases imputable to stress at work. The European Journal of Health Economics. 2005;6:16–23. doi: 10.1007/s10198-004-0251-4.

10. Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. Eur J Pers. 1987;1:141–169. doi: 10.1002/per.2410010304.

11. McEwen BS. Stress, Adaptation, and Disease: Allostasis and Allostatic Load. Annals of the New York Academy of Sciences. 1998;840:33–44. doi: 10.1111/j.1749-6632.1998.tb09546.x.

12. McEwen BS. Protective and damaging effects of stress mediators: central role of the brain. Dialogues in Clinical Neuroscience. 2006;8:367–381. doi: 10.31887/DCNS.2006.8.4/bmcewen.

13. Seeman TE, Singer BH, Rowe JW, Horwitz RI, McEwen BS. Price of Adaptation—Allostatic Load and Its Health Consequences: MacArthur Studies of Successful Aging. Archives of Internal Medicine. 1997;157:2259–2268. doi: 10.1001/archinte.1997.00440400111013.

14. Suvarna B, Suvarna A, Phillips R, Juster R-P, McDermott B, Sarnyai Z. Health risk behaviours and allostatic load: A systematic review. Neuroscience & Biobehavioral Reviews. 2020;108:694–711. doi: 10.1016/j.neubiorev.2019.12.020.

15. Seeman TE, McEwen BS, Rowe JW, Singer BH. Allostatic load as a marker of cumulative biological risk: MacArthur studies of successful aging. Proceedings of the National Academy of Sciences. 2001;98:4770–4775. doi: 10.1073/pnas.081072698.

16. Sluiter JK, de Croon EM, Meijman TF, Frings-Dresen MHW. Need for recovery from work related fatigue and its role in the development and prediction of subjective health complaints. Occup Environ Med. 2003;60:i62. doi: 10.1136/oem.60.suppl_1.i62.

17. van Veldhoven MJPM. Need for recovery after work: An overview of construct, measurement and research [Internet]. Houdmont J, Leka S, editors. 3. Nottingham University Press; 2008. Available from: https://research.tilburguniversity.edu/en/publications/bbdeef64-c338-4d48-b93f-152afe2ac5ef.

18. Sonnentag S, Zijlstra FRH. Job characteristics and off-job activities as predictors of need for recovery, well-being, and fatigue. Journal of Applied Psychology. 2006;91:330–350. doi: 10.1037/0021-9010.91.2.330.

19. Hobfoll SE. The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. Applied Psychology. 2001;50:337–421. doi: 10.1111/1464-0597.00062.

20. Kim E-J, Dimsdale JE. The Effect of Psychosocial Stress on Sleep: A Review of Polysomnographic Evidence. Behavioral Sleep Medicine. 2007;5:256–278. doi: 10.1080/15402000701557383.

21. Sonnentag S, Kuttler I, Fritz C. Job stressors, emotional exhaustion, and need for recovery: A multi-source study on the benefits of psychological detachment. Journal of Vocational Behavior. 2010;76:355–365. doi: 10.1016/j.jvb.2009.06.005.

22. Cosco TD, Kaushal A, Hardy R, Richards M, Kuh D, Stafford M. Operationalising resilience in longitudinal studies: a systematic review of methodological approaches. J Epidemiol Community Health. 2017;71:98. doi: 10.1136/jech-2015-206980.

23. Britt TW, Shen W, Sinclair RR, Grossman MR, Klieger DM. How Much Do We Really Know About Employee Resilience? Industrial and Organizational Psychology. 2016/07/04 ed. 2016;9:378–404. doi: 10.1017/iop.2015.107.

24. Drury RL. Wearable biosensor systems and resilience: a perfect storm in health care? Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00853.

25. Thayer JF, Åhs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012;36:747–756. doi: 10.1016/j.neubiorev.2011.11.009.

26. An E, Nolty AAT, Amano SS, Rizzo AA, Buckwalter JG, Rensberger J. Heart Rate Variability as an Index of Resilience. Military Medicine. 2020;185:363–369. doi: 10.1093/milmed/usz325.

27. Perna G, Riva A, Defillo A, Sangiorgio E, Nobile M, Caldirola D. Heart rate variability: Can it serve as a marker of mental health resilience?: Special Section on "Translational and Neuroscience Studies in Affective Disorders" Section Editor, Maria Nobile MD, PhD. Journal of Affective Disorders. 2020;263:754–761. doi: 10.1016/j.jad.2019.10.017.

28. Viljoen M, Claassen N. Allostatic load and heart rate variability as health risk indicators. Afr Health Sci. 2017;17:428–435. doi: 10.4314/ahs.v17i2.17. Cited: in: : PMID: 29062338.

29. Jarczok MN, Jarczok M, Mauss D, Koenig J, Li J, Herr RM, Thayer JF. Autonomic nervous system activity and workplace stressors—A systematic review. Neuroscience & Biobehavioral Reviews. 2013;37:1810–1823. doi: 10.1016/j.neubiorev.2013.07.004.

30. Järvelin-Pasanen S, Sinikallio S, Tarvainen MP. Heart rate variability and occupational stress—systematic review. Industrial Health. 2018;56:500–511. doi: 10.2486/indhealth.2017-0190.

31. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 2018;15:235–245. doi: 10.30773/pi.2017.08.17.

32. Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, Kupfer D, Thayer JF. Acute Stress Affects Heart Rate Variability During Sleep. Psychosomatic Medicine [Internet]. 2004;66. doi: 10.1097/01.PSY.0000106884.58744.09.

33. Hynynen E, Konttinen N, Kinnunen U, Kyröläinen H, Rusko H. The incidence of stress symptoms and heart rate variability during sleep and orthostatic test. European Journal of Applied Physiology. 2011;111:733–741. doi: 10.1007/s00421-010-1698-x.

34. Uusitalo A, Mets T, Martinmäki K, Mauno S, Kinnunen U, Rusko H. Heart rate variability related to effort at work. Applied Ergonomics. 2011;42:830–838. doi: 10.1016/j.apergo.2011.01.005.

35. van Amelsvoort LGPM, Schouten EG, Maan AC, Swenne CA, Kok FJ. Occupational determinants of heart rate variability. International Archives of Occupational and Environmental Health. 2000;73:255–262. doi: 10.1007/s004200050425.

36. Park G, Van Bavel JJ, Vasey MW, Thayer JF. Cardiac vagal tone predicts inhibited attention to fearful faces. Emotion. 2012;12:1292–1302. doi: 10.1037/a0028528.

37. Park G, Thayer JF. From the heart to the mind: cardiac vagal tone modulates top-down and bottom-up visual perception and attention to emotional stimuli. Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00278.

38. Williams DP, Cash C, Rankin C, Bernardi A, Koenig J, Thayer JF. Resting heart rate variability predicts self-reported difficulties in emotion regulation: a focus on different facets of emotion regulation. Frontiers in Psychology [Internet]. 2015;6. doi: 10.3389/fpsyg.2015.00261.

39. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Modelling employee resilience using wearables and apps: a conceptual framework and research design. International Journal on Advances in Life Sciences. 2019;11:110–117.

40. Bakker AB, Demerouti E. The Job Demands-Resources model: state of the art. Journal of Managerial Psychology. 2007;22:309–328. doi: 10.1108/02683940710733115.

41. McEwen BS. Sleep deprivation as a neurobiologic and physiologic stressor: allostasis and allostatic load. Metabolism. 2006;55:S20–S23. doi: 10.1016/j.metabol.2006.07.008.

42. McEwen BS, Karatsoreos IN. Sleep Deprivation and Circadian Disruption: Stress, Allostasis, and Allostatic Load. Sleep Medicine Clinics. 2015;10:1–10. doi: 10.1016/j.jsmc.2014.11.007.

43. Virtanen I, Kalleinen N, Urrila AS, Leppänen C, Polo-Kantola P. Cardiac autonomic changes after 40 hours of total sleep deprivation in women. Sleep Medicine. 2015;16:250–257. doi: 10.1016/j.sleep.2014.10.012.

44. Zhong X, Hilton HJ, Gates GJ, Jelic S, Stern Y, Bartels MN, DeMeersman RE, Basner RC. Increased sympathetic and decreased parasympathetic cardiovascular modulation in normal humans with acute sleep deprivation. Journal of Applied Physiology. 2005;98:2024–2032. doi: 10.1152/japplphysiol.00620.2004.

45. Kizakevich PN, Eckhoff RP, Lewis GF, Davila MI, Hourani LL, Watkins R, Weimer B, Wills T, Morgan JK, Morgan T, et al. Biofeedback-Assisted Resilience Training for Traumatic and Operational Stress: Preliminary Analysis of a Self-Delivered Digital Health Methodology. JMIR Mhealth Uhealth. 2019;7:e12590. doi: 10.2196/12590.

46. Chang I-C, Cheng W-C, Kung W-C. A Stress Relief App Intervention for Newly Employed Nursing Staff: Quasi-Experimental Design. JMIR Mhealth Uhealth. 2019;7:e15785. doi: 10.2196/15785.

47. Munster-Segev M, Fuerst O, Kaplan SA, Cahn A. Incorporation of a Stress Reducing Mobile App in the Care of Patients With Type 2 Diabetes: A Prospective Study. JMIR Mhealth Uhealth. 2017;5:e75. doi: 10.2196/mhealth.7408.

48. Plews DJ, Scott B, Altini M, Wood M, Kilding AE, Laursen PB. Comparison of Heart-Rate-Variability Recording With Smartphone Photoplethysmography, Polar H7 Chest Strap, and Electrocardiography. International Journal of Sports Physiology and Performance. 2017;12:1324–1328. doi: 10.1123/ijspp.2016-0668.

49. Malik M. Heart Rate Variability: Standards of Measurement, Physiological Interpretation, and Clinical Use: Task Force of The European Society of Cardiology and the North American Society for Pacing and Electrophysiology. Annals of Noninvasive Electrocardiology. 1996;1:151–181. doi: 10.1111/j.1542-474X.1996.tb00275.x.

50. Quintana DS, Heathers JAJ. Considerations in the assessment of heart rate variability in biobehavioral research. Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00805.

51. Plews DJ, Laursen PB, Buchheit M. Day-to-Day Heart-Rate Variability Recordings in World-Champion Rowers: Appreciating Unique Athlete Characteristics. International Journal of Sports Physiology and Performance. 2017;12:697–703. doi: 10.1123/ijspp.2016-0343.

52. de Zambotti M, Goldstone A, Claudatos S, Colrain IM, Baker FC. A validation study of Fitbit Charge 2™ compared with polysomnography in adults. Chronobiology International. 2018;35:465–476. doi: 10.1080/07420528.2017.1413578.

53. Liang Z, Chapa-Martell MA. Accuracy of Fitbit Wristbands in Measuring Sleep Stage Transitions and the Effect of User-Specific Factors. JMIR Mhealth Uhealth. 2019;7:e13384. doi: 10.2196/13384.

54. Tedesco S, Sica M, Ancillao A, Timmons S, Barton J, O'Flynn B. Validity Evaluation of the Fitbit Charge2 and the Garmin vivosmart HR+ in Free-Living Environments in an Older Adult Cohort. JMIR Mhealth Uhealth. 2019;7:e13084. doi: 10.2196/13084.

55. Littman AJ, White E, Satia JA, Bowen DJ, Kristal AR. Reliability and validity of 2 single-item measures of psychosocial stress. Epidemiology. 2006;17:398–403. doi: 10.1097/01.ede.0000219721.89552.51. Cited: in: : PMID: 16641618.

56. van Veldhoven M, Broersen S. Measurement quality and validity of the "need for recovery scale." Occup Environ Med. 2003;60:i3. doi: 10.1136/oem.60.suppl_1.i3.

57. Ensari I, Greenlee TA, Motl RW, Petruzzello SJ. Meta-analysis of acute exercise effects on state anxiety: An update of randomized controlled trials over the past 25 years. Depression and Anxiety. 2015;32:624–634. doi: 10.1002/da.22370.

58. Chatzitheodorou D, Kabitsis C, Malliou P, Mougios V. A Pilot Study of the Effects of High-Intensity Aerobic Exercise Versus Passive Interventions on Pain, Disability, Psychological Strain, and Serum Cortisol Concentrations in People With Chronic Low Back Pain. Physical Therapy. 2007;87:304–312. doi: 10.2522/ptj.20060080.

59. Michael S, Graham KS, Davis GM. Cardiac Autonomic Responses during Exercise and Post-exercise Recovery Using Heart Rate Variability and Systolic Time Intervals—A Review. Frontiers in Physiology [Internet]. 2017;8. doi: 10.3389/fphys.2017.00301.

60. Lee AJ, Lin W-H. The effects of physical activity on sleep quality. Medicine & Science in Sports & Exercise. 2002;34:S70. doi: 10.1097/00005768-200205001-00384.

61. Teychenne M, Stephens LD, Costigan SA, Olstad DL, Stubbs B, Turner AI. The association between sedentary behaviour and indicators of stress: a systematic review. BMC Public Health. 2019;19:1357. doi: 10.1186/s12889-019-7717-x.

62. Liao Y, Robertson MC, Winne A, Wu IHC, Le TA, Balachandran DD, Basen-Engquist KM. Investigating the within-person relationships between activity levels and sleep duration using Fitbit data. Translational Behavioral Medicine. 2021;11:619–624. doi: 10.1093/tbm/ibaa071.

63. Hallman DM, Sato T, Kristiansen J, Gupta N, Skotte J, Holtermann A. Prolonged Sitting is Associated with Attenuated Heart Rate Variability during Sleep in Blue-Collar Workers. International Journal of Environmental Research and Public Health. 2015;12:14811–14827. doi: 10.3390/ijerph121114811.

64. Veeramachaneni K, Slavish DC, Dietch JR, Kelly K, Taylor DJ. Intraindividual variability in sleep and perceived stress in young adults. Sleep Health. 2019;5:572–579. doi: 10.1016/j.sleh.2019.07.009.

65. Devenney LE, Coyle KB, Roth T, Verster JC. Sleep after Heavy Alcohol Consumption and Physical Activity Levels during Alcohol Hangover. Journal of Clinical Medicine. 2019;8. doi: 10.3390/jcm8050752.

66. Quintana DS, McGregor IS, Guastella AJ, Malhi GS, Kemp AH. A Meta-Analysis on the Impact of Alcohol Dependence on Short-Term Resting-State Heart Rate Variability: Implications for Cardiovascular Risk. Alcoholism: Clinical and Experimental Research. 2013;37:E23–E29. doi: 10.1111/j.1530-0277.2012.01913.x.

67. Bush K, Kivlahan DR, McDonell MB, Fihn SD, Bradley KA, for the Ambulatory Care Quality Improvement Project (ACQUIP). The AUDIT Alcohol Consumption Questions (AUDIT-C): An Effective Brief Screening Test for Problem Drinking. Archives of Internal Medicine. 1998;158:1789–1795. doi: 10.1001/archinte.158.16.1789.

68. RStudio Team. Rstudio: Integrated Development Environment for R [Internet]. Boston, MA: RStudio, BPC; 2021. Available from: https://www.rstudio.com.

69. The R project for statistical computing [Internet]. R Core Team; 2021 [cited 2021 Aug 17]. Available from: https://www.r-project.org.

70. RHRV: Heart Rate Variability Analysis of ECG Data [Internet]. CRAN - R Project; 2020 [cited 2021 Mar 1]. Available from: https://cran.r-project.org/web/packages/RHRV/.

71. Martínez CAG, Quintana AO, Vila XA, Touriño MJL, Rodríguez-Liñares L, Presedo JMR, Penín AJM. Heart rate variability analysis with the R package RHRV. Springer; 2017.

72. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health [Internet]. 2017;5. doi: 10.3389/fpubh.2017.00258.

73. Mowbray FI, Fox-Wasylyshyn SM, El-Masri MM. Univariate Outliers: A Conceptual Overview for the Nurse Researcher. Can J Nurs Res. 2019;51:31–37. doi: 10.1177/0844562118786647.

74. Enders CK, Tofighi D. Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods. 2007;12:121–138. doi: 10.1037/1082-989X.12.2.121.

75. Schmid RF, Thomas J. Teachers' ambulatory heart rate variability as an outcome and moderating variable in the job demands-resources model. Anxiety, Stress, & Coping. 2020;33:387–402. doi: 10.1080/10615806.2020.1746286.

76. Fantini-Hauwel C, Batselé E, Gois C, Noel X. Emotion Regulation Difficulties Are Not Always Associated With Negative Outcomes on Women: The Buffer Effect of HRV. Frontiers in Psychology [Internet]. 2020;11. doi: 10.3389/fpsyg.2020.00697.

77. da Estrela C, MacNeil S, Gouin J-P. Heart rate variability moderates the between- and within-person associations between daily stress and negative affect. International Journal of Psychophysiology. 2021;162:79–85. doi: 10.1016/j.ijpsycho.2021.02.001.

78. Murdock KW, LeRoy AS, Fagundes CP. Trait hostility and cortisol sensitivity following a stressor: The moderating role of stress-induced heart rate variability. Psychoneuroendocrinology. 2017;75:222–227. doi: 10.1016/j.psyneuen.2016.10.014.

79. de Zambotti M, Cellini N, Menghini L, Sarlo M, Baker FC. Sensors Capabilities, Performance, and Use of Consumer Sleep Technology. Sleep Medicine Clinics. 2020;15:1–30. doi: 10.1016/j.jsmc.2019.11.003.

80. Quintana DS, Elvsåshagen T, Zak N, Norbom LB, Pedersen PØ, Quraishi SH, Bjørnerud A, Malt UF, Groote IR, Kaufmann T, et al. Diurnal Variation and Twenty-Four Hour Sleep Deprivation Do Not Alter Supine Heart Rate Variability in Healthy Male Young Adults. PLOS ONE. 2017;12:e0170921. doi: 10.1371/journal.pone.0170921.

81. Wanous JP, Hudy MJ. Single-Item Reliability: A Replication and Extension. Organizational Research Methods. 2001;4:361–375. doi: 10.1177/109442810144003.

82. Bergkvist L, Rossiter JR. The Predictive Validity of Multiple-Item versus Single-Item Measures of the Same Constructs. Journal of Marketing Research. 2007;44:175–184. doi: 10.1509/jmkr.44.2.175.

83. Finkel EJ, Burnette JL, Scissors LE. Vengefully ever after: Destiny beliefs, state attachment anxiety, and forgiveness. Journal of Personality and Social Psychology. 2007;92:871–886. doi: 10.1037/0022-3514.92.5.871.

84. Spörrle M, Bekk M. Meta-Analytic Guidelines for Evaluating Single-Item Reliabilities of Personality Instruments. Assessment. 2014;21:272–285. doi: 10.1177/1073191113498267.

85. Schmalenberger KM, Eisenlohr-Moul TA, Jarczok MN, Eckstein M, Schneider E, Brenner IG, Duffy K, Schweizer S, Kiesner J, Thayer JF, et al. Menstrual Cycle Changes in Vagally-Mediated Heart Rate Variability Are Associated with Progesterone: Evidence from Two Within-Person Studies. Journal of Clinical Medicine. 2020;9. doi: 10.3390/jcm9030617.

86. Boggero IA, Hostinar CE, Haak EA, Murphy MLM, Segerstrom SC. Psychosocial functioning and the cortisol awakening response: Meta-analysis, P-curve analysis, and evaluation of the evidential value in existing studies. Biological Psychology. 2017;129:207–230. doi: 10.1016/j.biopsycho.2017.08.058.

87. Stalder T, Evans P, Hucklebridge F, Clow A. Associations between the cortisol awakening response and heart rate variability. Psychoneuroendocrinology. 2011;36:454–462. doi: 10.1016/j.psyneuen.2010.07.020.

CHAPTER 5

Wearable-measured sleep and resting heart rate variability as an outcome of and predictor for subjective stress measures: a multiple n-of-1 observational study

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ABSTRACT

The effects of stress may be alleviated when its impact or a decreased stress-resilience are detected early. This study explores whether wearable-measured sleep and resting HRV in police officers can be predicted by stress-related Ecological Momentary Assessment (EMA) measures in preceding days and predict stress-related EMA outcomes in subsequent days. Eight police officers used an Oura ring to collect daily Total Sleep Time (TST) and resting Heart Rate Variability (HRV) and an EMA app for measuring demands, stress, mental exhaustion, and vigor during 15–55 weeks. Vector Autoregression (VAR) models were created and complemented by Granger causation tests and Impulse Response Function visualizations. Demands negatively predicted TST and HRV in one participant. TST negatively predicted demands, stress, and mental exhaustion in two, three, and five participants, respectively, and positively predicted vigor in five participants. HRV negatively predicted demands in two participants, and stress and mental exhaustion in one participant. Changes in HRV lasted longer than those in TST. Bidirectional associations of TST and resting HRV with stress-related outcomes were observed at a weak-to-moderate strength, but not consistently across participants. TST and resting HRV are more consistent predictors of stress-resilience in upcoming days than indicators of stress-related measures in prior days.

Keywords: wearables, heart rate variability, sleep, stress, time series analysis, police, ecological momentary assessment, resilience.

INTRODUCTION

Stress is associated with an increased risk of numerous diseases (1–7) and mental disorders (8,9). Besides these adverse effects on individuals, it also imposes a large financial burden on society via absenteeism, healthcare costs, and productivity loss (10,11). Personalized just-in-time interventions may be able to prevent or alleviate some of these burdens (12). To do this, either the negative impact of stress or a decreased resilience to cope with stress should be detected early, preferably via unobtrusive monitoring. For instance, unobtrusive detection of the negative impact of stress (e.g., on sleep or physiological systems) in an early state may help increase awareness that current circumstances may be causing wear and tear on bodily systems (allostatic load) that may be contributing to health-related problems if sustained over time (13). Similarly, recognition of the potential depletion of resources that are needed for resiliently coping with challenges could be used to trigger feedback to take it easy that day and avoid overly challenging circumstances where possible. Recent developments in wearable sensor technology introduce promising opportunities for this type of unobtrusive monitoring (14,15).

When the first modern wearables came to market around 2009 (e.g., the Fitbit Classic), these devices initially became popular as pedometers or activity trackers but were already able to estimate sleep duration via accelerometry as well (16). Since then, consumer wearable-based sleep tracking has improved to a point where it is considered proficient for measuring the Total Sleep Time (TST), while the detection of sleep stages needs further work (17). Sleep deprivation is known to have a reciprocal relationship with stress, meaning that it is both caused and can be caused by stress (18). Longitudinal studies with repeated daily measures confirm this bidirectional association (19–21) but tend to rely on subjective TST measures (e.g., measured via questionnaires) and need verification using objective sleep measurements (22). Wearable-based research can therefore contribute to this body of knowledge and explore the potential of wearables to unobtrusively monitor for signs of the negative impact of stress or decreased resilience.

Besides behavioral outcomes such as physical activity and sleep, around 2015 (e.g., the Fitbit Charge HR) consumer wearables started measuring heart rate after photoplethysmography (PPG) sensors were included (23). Today, PPG sensors are also used to track physiological outcomes such as heart rate, blood oxygen saturation, blood pressure, and respiration (24). Perhaps the most important PPG-based innovation in the context of stress and resilience is the measurement of Heart Rate Variability (HRV), which can now be accurately measured using wearables or even camera-based smartphone apps in a resting state or during sleep (25). HRV is a measure of the variation in heartbeats and is a proxy for autonomous nervous system functioning (26). HRV acutely declines during stress (27) and afterward can remain suppressed during subsequent sleep (28,29). Consequently, individuals with a low resting HRV are more likely to interpret seemingly mild stimuli as significant stressors (30–32) and have suboptimal emotion regulation (33,34). Although these findings are based on population studies that investigated between-subject differences, the reciprocal nature of these findings illustrates that an initial decline in resting HRV could potentially cascade into subsequent days and thus have downstream effects.

A recent paper introduced a conceptual model in which the potential underlying mechanism for such a cascading effect of an initial decline in resting HRV was described (14). The model suggests that resting HRV buffers against the impact of demands on stress by making potentially stressful situations seem less stressful (30–32), as well as against the impact of stress on mental exhaustion via more optimal emotion regulation (33,34). Since this model also proposes that the need for recovery (e.g., increased mental exhaustion and/or decreased vigor) negatively influences resting HRV (28,29), a potential negative feedback loop is formed. This aligns with the conservation of resources theory, which states that since resources are needed to cope with demands, an initial loss of resources may result in a loss spiral (35). Finally, the model hypothesizes stress to both be negatively impacted by stress (18–21), as well as to buffer against the negative impact of an increased need for recovery on resting HRV due to its restorative properties (36,37). A study was then performed to test these hypotheses by utilizing wearables to measure TST and resting HRV, as well as an Ecological Momentary Assessment (EMA) smartphone app to measure subjective demands, stress, and mental exhaustion (38). The study confirmed that resting HRV is both negatively impacted by mental exhaustion and buffers against the negative associations between demands and stress, as well as stress and exhaustion. Day-to-day changes in resting HRV may therefore be both indicative of the negative impact of stress and predictive of stress-resilience, potentially even on a multiday level. Further exploration of these potential multi-day bidirectional associations will improve our understanding of the degree to which day-to-day changes in wearable-measured resting HRV can be interpreted as potentially stress-related and in which they should be expected to reflect a state of lowered resilience.

To summarize: wearable-measured sleep and resting HRV have both been bidirectionally associated with subjective stress-related outcomes, but within-subject research investigating the potential patterns in multi-day associations in a real-world context is lacking. Increased insight into the degree to which these relationships are consistently observed in individuals may help improve models for the early recognition of the negative impact of stress and of lowered resilience. Such insights could contribute to the development of automated resilience interventions that may help to prevent stress-related problems. These interventions are especially relevant for individuals working in safety-critical professions, such as police officers (39). Therefore, this study explores whether wearable-measured TST and resting HRV in police officers (1) can be predicted by stress-related EMA outcomes (demands, stress, mental exhaustion and vigor) in the preceding days, and (2) predict stress-related EMA outcomes in the subsequent days.

MATERIALS AND METHODS

Study design

An observational multiple n-of-1 study design was used (40), where individuals collected data on a daily basis, which were then individually assessed as independent time series. The results are therefore presented as a series (n = number of participants) of independent quantitative analyses on within-subject associations (e.g., a case series) based on samples with a high number of observations per participant (N = number of observations per participant) that can be relatively well-intercompared due to consistency in the applied methods. The current design is therefore optimized to provide a first exploration of possible multi-day associations at a within-subject level based on high-quality data, as is the aim of this study. Additionally, a rough estimate of the extent to which the respective associations may be found across individuals can be described in order to guide future studies. The current methods were based on a prior study that investigated nested within-day associations (14,38). Missing data are problematic for time-series analysis. To limit missing data, we made several adaptations to optimize the previously used research design. We included automatic resting HRV measurements, a shorter daily Ecological Momentary Assessment (EMA) questionnaire, and an improved reward for adhering to the measurement protocol (participants were allowed to keep the wearable if they collected at least 100 complete daily observations). Data were collected for two purposes: (1) comparing longitudinal (5-week) trends in daily resting HRV and fluctuations therein to full questionnaire outcomes for stress, somatization, anxiety, and depression, and (2) the assessment of potential bidirectional and/or multi-day associations of sleep and resting HRV with stress-related EMA outcomes. The results of the former are published elsewhere (41), whereas the results of the latter are presented in this paper. The study protocol was approved by the ethical committee of the Hanze University of Applied Sciences Groningen (heac.2020.012).

Participants

Police officers working in a large Dutch city and possessing an Android- or iOS-based smartphone were invited to participate by the human resources bureau of their office. Interested respondents received the study information via e-mail. Participation was voluntary. The data collection period lasted a minimum of 15 weeks but could be extended with a number of additional 5-week periods. Extending the data-collection period was optional. Since at least 20 but preferably 50 observations with limited missing data are needed for accurate time series analysis (42,43), this data collection period (105–140 days) was expected to be appropriate to collect sufficient data. To also minimize potential missing data participants could keep the wearable and received a personal feedback report after the study as a reward if they collected complete daily data for at least 100 days and completed all baseline and 5-weekly questionnaires. The recruitment period lasted until the maximum capacity of 10 participants was reached (i.e., it ran from June 2020 and July 2020). Before the start of their data collection, participants had a conversation with the first author during which the study requirements were explained, and participants gave their written informed consent. Due to COVID-19 restrictions, all contact with the participants occurred via teleconferencing and e-mail. After data collection, one participant was excluded because they were diagnosed with atrial fibrillation. This participant's data were excluded from the study, because this may have interfered with the accuracy of the HRV measurements. Another participant of whom only 56.3% of the daily observations were available was also excluded from the analysis. The remaining eight analyzed participants were predominantly male (n = 6), had an average age of 37.0 years (range: 29–51), and contributed at least 80% (range: 80.7–96.8%) of complete observations.

Data-collection

Baseline questionnaires

Immediately after consent was provided, participants were asked to fill in a baseline questionnaire. The baseline questionnaire included two items on gender and birthdate, as well as full questionnaires on personality traits (the Big Five Inventory; BFI) (44), symptoms of distress, somatization, depression, and anxiety (the Four-Dimensional Symptom Questionnaire; 4DSQ) (45), burnout (the Oldenburg Burnout Inventory; OLBI) (46) and work engagement (the Utrecht Work Engagement Scale; UWES) (47). The outcomes of the baseline questionnaires and the mean values of the daily wearable and EMA outcomes were summarized per participant and on aggregate and used to describe the current sample for generalization purposes and as background information on the characteristics of the participants (Table 1). The age and gender of the individual participants were not described out of privacy considerations.

Table 1: Participant characteristics

	Participant							
Baseline questionnaires	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Extraversion (1-5)	2.8	3.3	3.3	2.5	3.8	4.4	3.8	4.1
Agreeableness (1-5)	3.3	3.9	3.8	3.6	3.4	3.8	3.9	3.8
Conscientiousness (1-5)	3.9	3.8	3.3	3.3	3.8	3.0	3.8	4.0
Neuroticism (1-5)	2.1	2.5	2.4	2.4	2.5	2.3	2.9	2.4
Openness (1-5)	4.1	2.8	3.7	3.6	3.4	3.8	2.5	3.4
Distress	Low	Moderate	Low	Low	Low	Low	Moderate	Low
Depression	Low	Low	Low	Low	Low	Low	Low	Low
Anxiety	Low	Low	Low	Low	Low	Low	Low	Low
Somatization	Low	Low	Low	Low	Low	Low	Low	Low
Exhaustion (1-4)	3.0	2.5	3.3	2.5	3.0	2.6	2.6	2.6
Disengagement (1-4)	2.4	2.6	3.3	2.9	2.9	2.3	2.4	3.8
Work engagement (1-7)	5.4	4.6	5.3	4.5	5.2	5.1	4.2	5.9
Daily measurements								
Total observations	147	125	386	150	285	143	147	140
% complete observations	81.6	94.4	88.3	80.7	96.8	93.0	95.9	80.7
TST (hours)	7.0 (1.5)	6.5 (0.8)	7.4 (1.5)	5.5 (1.3)	6.7 (1.3)	7.6 (1.5)	7.4 (1.3)	6.5 (1.2)
HRV (rMSSD in milliseconds)	51.3 (15.6)	43.8 (5.1)	54.8 (15.9)	72.8 (9.8)	47.4 (15.2)	29.6 (4.3)	39.6 (6.9)	26.8 (5.1)
Demands (0-10)	4.4 (3.0)	4.7 (2.0)	3.2 (1.6)	5.1 (2.7)	4.1 (1.2)	2.4 (1.9)	4.3 (2.7)	3.4 (2.2)
Stress (0-10)	3.9 (2.7)	3.5 (1.9)	2.6 (1.8)	3.3 (2.0)	1.5 (0.9)	1.6 (1.8)	1.3 (1.9)	2.8 (1.6)
Mental exhaustion (0-10)	2.8 (2.7)	4.8 (2.0)	3.7 (1.7)	4.2 (2.4)	2.1 (1.0)	1.4 (1.9)	2.6 (2.9)	3.3 (2.1)
Vigor (0-10)	5.3 (2.8)	5.6 (1.4)	5.8 (2.1)	5.0 (2.1)	4.9 (1.1)	6.0 (1.7)	5.5 (2.5)	7.4 (0.8)
MVPA (minutes)	54.2 (33.4)	49.3 (24.2)	45.4 (35.6)	28.0 (26.5)	49.7 (28.7)	33.4 (30.3)	25.7 (19.2)	18.5 (14.2)
Alcohol use (units)	0.4 (0.8)	0.5 (0.9)	0.4 (0.7)	0.1 (0.6)	0.5 (0.9)	0.1 (0.4)	0.9 (1.3)	0.1 (0.5)

Note. For the baseline questionnaires, the observed values are reported. For the daily measurements, mean and standard deviation are reported. TST: Total Sleep Time; HRV: Heart Rate Variability; rMSSD: root Mean Square of the Successive Differences; MVPA: Moderate-to-Vigorous Physical Activity

Wearable-based variables

The Oura ring (generation 2, Oura Ring, Oulu, Finland) was used to measure TST and resting HRV during sleep. The Oura ring is a consumer wearable that measures sleep, physical activity, temperature, heart rate, and HRV. The consumer-available ring contains 2 infrared Light-Emitting Diode (LED) sensors, 2 Negative Temperature Coefficient (NTC) thermistor sensors, a tri-axial accelerometer, and a gyroscope. Although the algorithms that are used by the Oura ring to classify sleep and HRV based on the outputs of these sensors are proprietary, the ring (generation 2) has been confirmed to provide valid measurements of TST (48,49) and HRV (25,50,51) in independent research. Participants used a ring-size kit to determine their correct ring size to optimize fit for both user comfort and measurement accuracy and were allowed to choose a ring color of their preference. To preserve privacy, anonymized Oura accounts were created by using e-mail addresses on a custom domain to create accounts without the participants' names. The Oura-reported TST was used, which represents the total Duration of the Sleep Episode (DSE) minus the Sleep Onset Latency (SOL) and Wake-time After Sleep Onset (WASO). Similarly, the Oura-reported HRV was used, which represents the root Mean Square of the Successive Differences (rMSSD) in the inter-beat-intervals. This metric was then logarithmically transformed (lnrMSSD) to improve its distribution for statistical modelling, which is a common procedure in HRV research (52). Finally, the Moderate-to-Vigorous Physical Activity (MVPA) was used as a control variable during analysis (53).

Ecological Momentary Assessment-based variables

Every day at 7 PM, participants received a notification that a new EMA questionnaire was available on their smartphone app. Participants were instructed to complete the EMA before they went to bed. Since participants regularly worked night shifts, the EMA was available until 3 PM on the next day while participants received a reminder at noon to fill in their previous-day questionnaire if they had not finished it already. The EMA items were based on items used in a similar study (14,38). The EMA measured: demands (*"How demanding was your day?"*), stress (*"How much stress did you perceive today?"*), mental exhaustion (*"I felt mentally exhausted as a result of my activities"*), vigor (*"Do you feel like undertaking activities?"*), and alcohol intake (*"I consumed … alcoholic beverages today"*). The demands, stress, and vigor items were scored on an 11-point Numeric Rating Scale (NRS), ranging from 0 (*"Not at all"*) to 10 (*"Extremely"*). Mental exhaustion was scored on an 11-point NRS ranging from 0 (*"Strongly disagree"*) to 10 (*"Strongly agree"*). The item for stress was based on a validated single-item scale (54), the item for mental exhaustion on an item of the Need For Recovery Scale (55), the item for vigor on an item of the Utrecht Work Engagement Scale (47), whereas the item for demands was self-composed in a similar style as the item for stress. The number of alcoholic beverages participants consumed during the passing day was included for use as a control variable during analysis and based on the AUDIT-C questionnaire (56), since alcohol consumption is known to impact resting HRV (57).

Data-analysis

All analyses were performed in RStudio version 2022.7.1.554 (58) using R version 4.2.1 (59). The 'zoo' package was used for linear interpolation of missing data (60), the 'vars' package was used for Vector Auto-Regression (VAR) modelling, Granger causation testing, and Impulse Response Function (IRF) calculation (61). Finally, 'ggplot2' was used to visualize the IRFs (62).

Data preparation

First, descriptive statistics on the number of observations, the percentage of complete observations, and the wearable- and EMA-variables were calculated based on the full set of collected data. Since VAR analyses do not allow for missing data, missing data were imputed via linear interpolation. Rows, where data were missing at the beginning or end of the time series, were removed, as these could not be imputed. All values were standardized (by first subtracting the within-subject mean from each daily value and then dividing it by the within-subject standard deviation) to optimize the inter-comparability of beta-coefficients and prevent multicollinearity. Finally, two versions of the vectors with the four core EMA variables (demands, stress, mental exhaustion, and vigor), two core wearable variables (TST and resting HRV), and two control variables (MVPA and alcohol consumption) were constructed to answer both research questions. The vector for the first analysis contained rows with values for the passing night's TST and nocturnal HRV, combined with the EMA items of the subsequent evening so that the lagged values of the EMA items (the values on the previous row that represent the EMA of the previous day) could be interpreted as predictors for TST and HRV (the values on the current row that represent the values for the passing night). For analysis 2, the TST and HRV data were shifted to the previous day, so that the lagged values of the TST and HRV (the values on the previous row, representing the passing night) could be interpreted as predictors for the EMA items (the values on the current row, representing the current day).

Vector Auto-Regressive modelling

To assess the stationarity of the time series as a prerequisite to performing VAR analysis, the Phillips-Perron (PP) unit root test was used on all variables (63). All-time series were stationary (PP $p < 0.05$). Next, the number of lags (i.e., number of preceding days included as predictor values) to include in the VAR model was determined. This was completed via the 'VARselect' function, which calculates models up to 7 lags (i.e., one full week's worth of lags). The most optimal lag order is based on four information criteria corresponding to the different models (i.e., Akaike Information Criterion (AIC), Hannan-Quinn (HQ) criterion, Schwarz Criterion (SC), and Final Prediction Error (FPE) criterion). The mode of these four information criteria was selected as the most optimal lag order used in the VAR model. In the case of a tie, the most conservative estimate was chosen. Assumptions were tested on the residuals of the VAR model. The residuals were assessed for autocorrelation via an asymptotic multivariate Portmanteau Test (PT)

(64), for heterogeneity via an ARCH-LM test (65), and for normality via a Jarque-Bera (JB) test (66).

Granger causation testing

To increase confidence in the predictive value of core EMA variables that were found to be statistically significant predictors of wearable variables (or vice versa) in the full VAR models, Granger causation tests were applied (67). Granger causation tests assess if the inclusion of a predictor significantly improves a VAR. To isolate the direct relationships between these associations of interest from interrelations with the other variables in the vector, the Granger causation tests were applied to vectors with only the core predictor and outcome variables. Therefore, significant Granger causation tests showed that the predictor variable itself explains meaningful variance in the outcome variable and is not just significant in the VAR due to interrelations with other variables in the vector.

Impulse Response Function visualization

An IRF is the reaction of a dynamic system in response to an external change (68). IRF visualizations of relevant predictors on the outcomes can illustrate how the outcome varies on subsequent days after being faced with an increase in a predictor variable. The IRF of predictors that were both statistically significant in the full VAR model and in the additional Granger causation test were visualized. The IRF visualizations consisted of an overlay of participants where the respective association was observed. The IRFs with the same predictor were grouped in a grid in order to cluster visualizations of the multi-day impact of a predictor on all relevant outcomes (including bootstrapped 95% confidence interval (CI) based on 1000 runs).

RESULTS

Participant characteristics

The eight participants, who were 29.4 to 51.1 years old (median = 36.8) and predominantly male (75%), collected 125 to 386 observations per person (median = 147) of which 80.7 to 96.8% (median = 90.7%) contained complete data on the EMA outcomes, as well as daytime and nighttime wearable outcomes. The average TST ranged from 5.5 to 7.6 h (median = 6.8), during which they had an average resting HRV (rMSSD) of 26.8 to 72.8 milliseconds (median = 45.6). The participants were moderate-to-vigorously physically active for 18.5 to 54.4 min per day (median = 39.4). The median reported daily scores on the stress-related outcomes was in the lower half of the scale (0–10) for demands (median = 4.2, range = 2.4–5.1), stress (median = 2.7, range = 1.3–3.9) and mental exhaustion (median = 3.0, range = 1.4–4.8). The mean reported daily scores on vigor were in the upper half of the scale (median = 5.6, range = 4.9–7.4). On average, the participants consumed between 0.1 and 0.9 (median = 0.4) alcoholic beverages per day. An overview of all participant characteristics is presented in Table 1.

Analysis 1: Predicting TST & HRV by EMA

All analyzed time series were found to be stationary (PP unit root test $p < 0.05$). The AIC, HQ, SC, and FPE information criteria that were used to determine the lag order for the VAR models unanimously suggested an optimal lag order of 1 in all participants, with exception of participant 7, where 2 out of 4 information criteria suggested a lag order of 2. Since the conservative option was chosen in case of a tie (§2.4.2), VAR models with 1 lag were created for all participants. No heterogeneity (ARCH-LM test $p > 0.05$) was found in the residuals of any model. The residuals also contained no autocorrelation (PT $p > 0.05$) in most participants, except for participant 5. This autocorrelation could not be resolved (e.g., by adding additional lags to the model), and suggests that an unobserved but relevant factor was not included in the model, which therefore may be useful but not complete. Finally, none of the residuals of any model were found to be normally distributed (JB-test $p < 0.05$). This was likely attributable to the distribution of some of the EMA items, which were occasionally skewed or even bimodal. Since simulation studies showed that non-normally distributed residuals are not problematic in analyses with a sample of at least 100 observations (69), this was not considered to be a problem for the interpretation of these results.

The results of the VAR models on TST are presented in Table 2. Demands was a statistically significant ($p < 0.05$) negative predictor of TST for three participants (4, 5, 7). For participant 5 this finding was confirmed by a statistically significant Granger causation test. Mental exhaustion was a significant positive predictor of TST in participant 4, but this was not confirmed in Granger causation testing and therefore interpreted as a potentially spurious relationship. Stress and vigor were not statistically significant predictors of TST in any model. The explained variance in the TST of the participant (5) in which demands was a significant predictor that was confirmed by a significant Granger causation test was 9%.

Table 2: Vector autoregression models for Total Sleep Time (TST) per participant (1-8)

Independent variable	**TST**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	β	**β**	**β**	**β**	**β**	**β**	**β**	**β**
Constant	0.00	0.03	-0.01	-0.00	0.01	-0.02	0.02	0.00
TST (lag 1)	0.08	0.06	-0.02	0.21 **	0.04	-0.10	-0.08	-0.05
HRV (lag 1)	0.07	0.01	-0.07	0.10	-0.10 .	0.04	-0.12	-0.08
MVPA (lag 1)	0.02	-0.09	0.05	0.18 *	0.04	-0.02	0.07	0.07
Alcohol intake (lag 1)	0.17 .	0.08	0.09 .	0.02	0.08	0.04	0.08	0.01
<u>Demands (lag 1)</u>	0.24 .	-0.02	0.05	-0.40 **	<u>-0.39</u> ***	0.01	-0.21 *	0.02
Stress (lag 1)	-0.16	-0.13	-0.12 .	0.03	0.08	-0.07	-0.00	-0.12
Mental exhaustion (lag 1)	0.24 .	0.14	0.02	0.32 *	0.01	-0.14	0.10	-0.07
Vigor (lag 1)	-0.01	-0.06	-0.10 .	-0.10	0.10	0.16 .	-0.07	0.02
N	*142*	*123*	*385*	*148*	*283*	*141*	*146*	*138*
Adjusted R^2	*0.03*	*-0.04*	*0.02*	*0.11*	*0.09*	*0.03*	*0.01*	*-0.03*
F-statistic	*1.49*	*0.48*	*1.76* .	*3.26* **	*4.53* ***	*1.47*	*1.19*	*0.54*

*Note. *** p<.001, ** p<.01, * p<.05, . p<.1; Underlined: both the beta-coefficient and Granger causation test p<.05; TST: Total Sleep Time; HRV: Heart Rate Variability; MVPA: Moderate-to-Vigorous Physical Activity.*

Table 3: Vector autoregression models for Heart Rate Variability (HRV) per participant (1-8)

Independent variable	**HRV**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	β	**β**	**β**	**β**	**β**	**β**	**β**	**β**
Constant	-0.01	0.02	-0.01	0.03	-0.01	-0.01	0.00	0.03
TST (lag 1)	0.04	0.00	-0.02	-0.03	-0.04	0.01	0.11	0.10
HRV (lag 1)	0.74 ***	0.06	0.40 ***	0.25 **	0.59 ***	0.30 ***	0.32 ***	0.36 ***
<u>MVPA (lag 1)</u>	0.03	0.03	<u>-0.18</u> ***	0.10	<u>-0.11</u> *	0.04	-0.14	-0.12
<u>Alcohol intake (lag 1)</u>	<u>-0.12</u> *	0.06	<u>-0.19</u> ***	-0.11	<u>-0.18</u> ***	-0.10	-0.07	0.03
<u>Demands (lag 1)</u>	-0.01	0.01	<u>-0.16</u> *	-0.20	0.01	0.16	-0.01	-0.08
Stress (lag 1)	0.05	0.03	-0.01	-0.22 .	-0.04	-0.23	0.04	-0.05
Mental exhaustion (lag 1)	0.05	-0.08	0.04	0.33 *	0.07	0.09	-0.07	-0.07
Vigor (lag 1)	0.05	-0.12	-0.02	0.15	-0.04	0.02	-0.06	0.06
N	*142*	*123*	*385*	*148*	*283*	*141*	*146*	*138*
Adjusted R^2	*0.59*	*-0.05*	*0.22*	*0.12*	*0.40*	*0.07*	*0.12*	*0.17*
F-statistic	*26.61* ***	*0.34*	*14.20* ***	*3.46* **	*24.15* ***	*2.41* *	*3.40* **	*4.51* ***

*Note. *** p<.001, ** p<.01, * p<.05, . p<.1; Underlined: both the beta-coefficient and Granger causation test p<.05; TST: Total Sleep Time; HRV: Heart Rate Variability; MVPA: Moderate-to-Vigorous Physical Activity.*

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The results of the VAR models on HRV are presented in Table 3. Demands was a significant negative predictor of HRV in participant 3, which was also confirmed via Granger causation testing. Mental exhaustion was a significant positive predictor of HRV in participant 4, but it was in Granger causation testing and therefore interpreted as a potentially spurious relationship. Stress and vigor were not statistically significant predictors of HRV in any model. The explained variance in the HRV of the participant (3) in which demands was a significant predictor that was confirmed by a significant Granger causation test was 22%.

To support the interpretation of the temporal associations where both the beta coefficient and Granger causation tests were significant, IRF visualizations for the impact of an increase in demands on (A) TST and (B) HRV are displayed in Figure 1. In both outcomes, an increase in demands results in a sudden drop in the outcome variable, which then gradually recovers in subsequent days. However, the recovery of HRV takes longer (0 enters the 95% CI on the sixth day) than that of TST (0 enters the 95% CI on the third day). This difference can be attributed to the highly significant autoregression component in HRV ($p < 0.001$), which is not observed in TST. This means that resting HRV values are relatively likely to be similar to the previous day (e.g., if yesterday's resting HRV value was relatively low, today's value is likely to be relatively low again), whereas TST values have little to no association to the value of the previous day. The impact of demands, therefore, appears to be more long-lasting on HRV than on TST—at least in these participants.

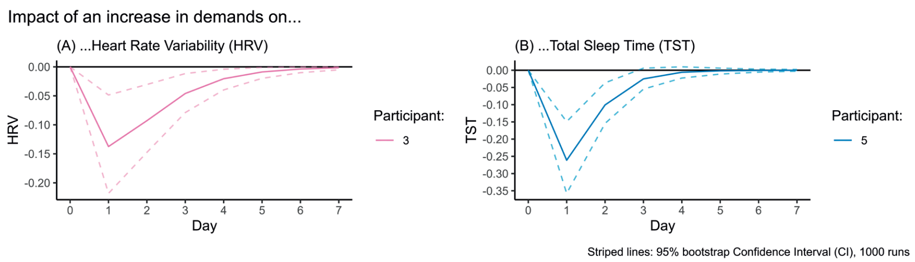

Figure 1: Visualization of the Impulse Response Function (IRF) of the impact of an increase in demands on the (A) Total Sleep Time (TST) and (B) resting Heart Rate Variability (HRV) during the subsequent week.

Analysis 2 Predicting EMA by TST & HRV

The outcomes of the pre- and post-model diagnostic tests of analysis 2 were similar to those of analysis 1. The only difference in the pre- and post-model diagnostic tests of analysis 1 is that in analysis 2, participant 7 had just 1 out of 4 information criteria suggesting an optimal lag order of 2 instead of 2 out of 4. Therefore, VAR models with 1 lag were again created for all participants.

The results of the VAR models on demands are presented in Table 4. TST was a statistically significant negative predictor of demands in two participants (1, 2), which was confirmed with the Granger causation test in both cases. HRV was a significant negative predictor of demands in two participants (7, 8), also confirmed via Granger causation tests. The explained variance in the demands of these participants was 16% and 23%, respectively.

Table 5 contains the results of the VAR models on stress. TST was a significant negative predictor of stress in three participants (1, 2, 7), all confirmed via the Granger causation test. HRV was a significant negative predictor of stress in one participant (8), again confirmed via Granger causation tests. The explained variance in the stress of these participants ranged from 2% to 23%.

Table 4: Vector autoregression models for demands per participant (1-8)

Independent variable	**Demands**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	β	**β**	**β**	**β**	**β**	**β**	**β**	**β**
Constant	-0.00	0.01	-0.01	0.03	0.00	-0.01	0.02	0.02
Demands (lag 1)	0.03	0.17	0.21 **	0.49 ***	0.34 ***	-0.09	0.21 *	0.31 **
Stress (lag 1)	0.25 *	-0.05	-0.06	-0.02	-0.17 *	0.17	-0.10	-0.06
Mental exhaustion (lag 1)	0.03	-0.03	0.08	0.06	0.08	0.18	0.05	0.13
Vigor (lag 1)	0.06	0.04	0.02	-0.06	0.15 *	0.03	-0.05	-0.04
MVPA (lag 1)	0.09	-0.06	0.08	0.00	0.12 *	0.06	0.01	0.19 *
Alcohol intake (lag 1)	-0.13 .	-0.07	-0.04	-0.10	-0.04	0.00	-0.24 **	-0.12
TST (lag 1)	-0.37 ***	-0.42 ***	-0.09 .	-0.06	0.00	-0.12	-0.11	0.08
HRV (lag 1)	0.06	0.14	-0.02	0.03	-0.07	0.11	-0.21 **	-0.18 *
N	*142*	*123*	*385*	*148*	*283*	*141*	*146*	*138*
Adjusted R^2	*0.24*	*0.15*	*0.04*	*0.28*	*0.14*	*0.05*	*0.16*	*0.23*
F-statistic	*6.50* ***	*3.63* **	*3.23* **	*8.18* ***	*6.72* ***	*1.94* .	*4.41* ***	6.01 ***

*Note. *** p<.001, ** p<.01, * p<.05, . p<.1; Underlined: both the beta-coefficient and Granger causation test p<.05; MVPA: Moderate-to-Vigorous Physical Activity; HRV: Heart Rate Variability; TST: Total Sleep Time.*

Table 5: Vector autoregression models for stress per participant (1-8)

Independent variable	Stress							
	1	2	3	4	5	6	7	8
	β	β	β	β	β	β	β	β
Constant	-0.00	-0.00	-0.01	0.03	-0.00	0.01	-0.01	0.03
Demands (lag 1)	-0.03	0.01	-0.06	0.04	-0.02	-0.04	0.01	-0.10
Stress (lag 1)	0.32 *	0.06	0.22 **	0.49 ***	0.19 *	0.13	0.18 .	0.30 **
Mental exhaustion (lag 1)	0.02	0.06	0.05	0.01	0.07	0.14	-0.01	-0.10
Vigor (lag 1)	0.11	-0.03	-0.05	-0.00	0.11 .	0.06	0.01	0.00
MVPA (lag 1)	0.04	0.03	0.07	-0.07	0.09	0.01	-0.02	0.15 .
Alcohol intake (lag 1)	-0.18 *	-0.13	-0.08	-0.09	-0.02	-0.00	-0.01	-0.04
TST (lag 1)	-0.19 *	-0.49 ***	-0.04	0.01	-0.01	-0.05	-0.19 *	0.05
HRV (lag 1)	-0.12	0.08	0.03	-0.00	-0.02	0.08	0.06	-0.29 **
N	*142*	*123*	*385*	*148*	*283*	*141*	*146*	*138*
Adjusted R^2	*0.18*	*0.23*	*0.04*	*0.23*	*0.05*	*0.01*	*0.02*	*0.12*
F-statistic	*4.88* ***	5.44 ***	*3.17* **	*6.56* ***	*2.80* **	*1.09*	*1.39*	*3.32* **

*Note. *** p<.001, ** p<.01, * p<.05, . p<.1; Underlined: both the beta-coefficient and Granger causation test p<.05; MVPA: Moderate-to-Vigorous Physical Activity; HRV: Heart Rate Variability; TST: Total Sleep Time.*

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The results of the VAR models on mental exhaustion are presented in Table 6. TST was a significant negative predictor of mental exhaustion in five participants (1, 2, 3, 5, 7), all confirmed via Granger causation tests. HRV was a significant negative predictor of mental exhaustion in one participant (8), again confirmed via Granger causation testing. The explained variance in the mental exhaustion of these participants ranged from 3% to 36%.

Finally, the results of the VAR models on vigor are presented in Table 7. TST was a significant positive predictor of vigor in five participants (1, 3, 4, 5, 7), all confirmed via Granger causation tests. HRV did not predict vigor in any participant. The explained variance in the vigor of these participants ranged from 8% to 34%.

IRF visualizations for the impact of an increase in TST on each of the four EMA outcomes (A–D) are displayed in Figure 2. In all outcomes, an increase in TST resulted in a sudden decline (or incline in the case of vigor) that recovered (0 enters the 95% CI) in the subsequent 1 or 2 days. The IRF visualizations for the impact of an increase in HRV on the four EMA outcomes (Figure 3A–C) is similar for demands (1–2 days), although recovery from the impact on stress (2–3 days) and mental exhaustion (2–3 days) appears to take a bit longer. It appears that in these participants, the impact of changes in HRV is more long-lasting than for changes in TST.

Table 6: Vector autoregression models for mental exhaustion per participant (1-8)

Independent variable	Mental exhaustion							
	1	2	3	4	5	6	7	8
	β	β	β	β	β	β	β	β
Constant	-0.00	0.01	-0.01	0.02	-0.00	0.00	0.01	0.03
Demands (lag 1)	0.08	0.05	0.13 .	0.25 *	-0.03	-0.14	0.05	0.17
Stress (lag 1)	-0.07	-0.18	-0.17 *	0.17 .	0.02	0.22	0.08	0.02
Mental exhaustion (lag 1)	0.23 .	0.27 *	0.13 .	0.17	0.30 ***	0.04	0.16	0.01
Vigor (lag 1)	0.03	-0.07	-0.04	-0.14	0.00	-0.11	0.05	-0.05
MVPA (lag 1)	0.04	-0.06	0.01	-0.07	-0.05	0.08	-0.07	0.11
Alcohol intake (lag 1)	-0.17 .	-0.10	-0.02	-0.05	0.11 .	-0.05	-0.14 .	-0.09
TST (lag 1)	-0.17 *	-0.41 ***	-0.12 *	-0.05	-0.25 ***	-0.11	-0.17 *	0.02
HRV (lag 1)	0.10	0.16 .	-0.06	0.02	-0.00	0.04	-0.12	-0.22 *
N	*142*	*123*	*385*	*148*	*283*	*141*	*146*	*138*
Adjusted R^2	*0.07*	*0.17*	*0.03*	*0.36*	*0.15*	*0.02*	*0.08*	*0.08*
F-statistic	*2.37* *	4.05 ***	*2.68* **	*11.15* ***	*7.04* ***	*1.44*	*2.61* *	*2.47* *

*Note. *** p<.001, ** p<.01, * p<.05, . p<.1; Underlined: both the beta-coefficient and Granger causation test p<.05; MVPA: Moderate-to-Vigorous Physical Activity; HRV: Heart Rate Variability; TST: Total Sleep Time.*

Table 7: Vector autoregression models for vigor per participant (1-8)

Independent variable	**Vigor**							
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
	b	**b**	**b**	**b**	**b**	**b**	**b**	**b**
Constant	0.06	-0.00	-0.01	0.00	-0.00	-0.00	-0.01	0.02
Demands (lag 1)	-0.24 *	-0.10	-0.04	-0.16	-0.05	0.02	-0.09	0.07
Stress (lag 1)	0.32 **	-0.12	0.14 *	-0.03	0.09	0.04	-0.07	0.11
Mental exhaustion (lag 1)	-0.06	-0.16	0.04	0.01	-0.03	-0.14	0.02	-0.13
Vigor (lag 1)	0.37 ***	0.19 *	0.31 ***	0.48 ***	0.18 **	0.19 *	0.22 **	0.22 *
MVPA (lag 1)	-0.02	-0.04	0.02	0.05	0.06	0.05	0.10	0.13
Alcohol intake (lag 1)	0.11	-0.06	0.02	0.10	-0.04	0.12	0.10	-0.04
TST (lag 1)	0.27 ***	0.11	0.12 *	0.17 *	0.41 ***	0.13	0.49 ***	-0.17 .
HRV (lag 1)	0.06	-0.01	-0.01	-0.07	0.10 .	0.11	0.04	0.06
N	*142*	*123*	*385*	*148*	*283*	*141*	*146*	*138*
Adjusted R^2	*0.27*	*0.11*	*0.08*	*0.34*	*0.20*	*0.08*	*0.34*	*0.05*
F-statistic	*7.45* ***	*2.93* **	*5.23* ***	*10.60* ***	*9.62* ***	*2.44*	*10.39* ***	*1.81* .

*Note. *** p<.001, ** p<.01, * p<.05, . p<.1; Underlined: both the beta-coefficient and Granger causation test p<.05; MVPA: Moderate-to-Vigorous Physical Activity; HRV: Heart Rate Variability; TST: Total Sleep Time.*

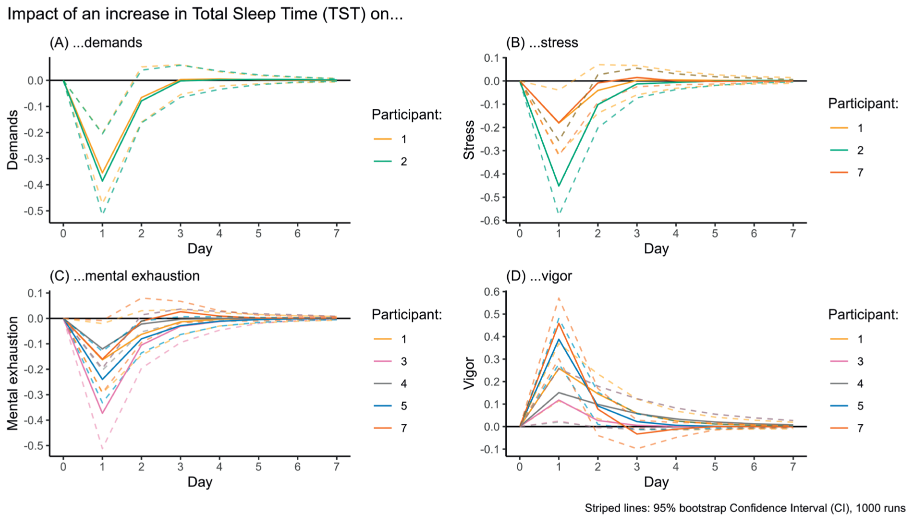

Figure 2: Visualization of the Impulse Response Function (IRF) of the impact of an increase in Total Sleep Time (TST) on the subsequent week's (A) demands, (B) stress, (C) mental exhaustion and (D) vigor.

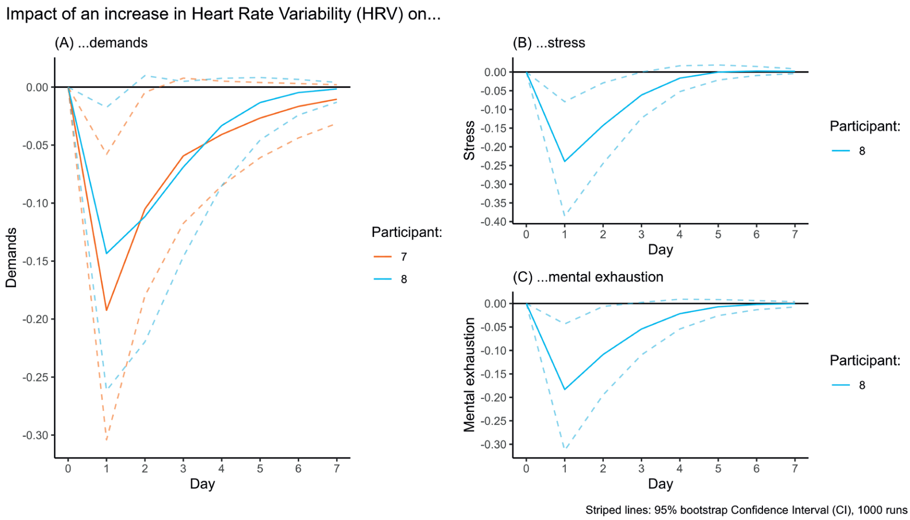

Figure 3: Visualization of the Impulse Response Function (IRF) of the impact of an increase in resting Heart Rate Variability (HRV) on the subsequent week's (A) demands, (B) stress and (C) mental exhaustion.

DISCUSSION

This study aimed to explore to what degree wearable-measured sleep and resting HRV in police officers (1) can be predicted by stress-related EMA outcomes in the preceding days, and (2) predict stress-related EMA outcomes in the subsequent days. After performing a time series analysis on eight participants, the results showed that associations in both directions of modest strength were observed and that TST and resting HRV were more consistent predictors for the next day's perceived demands, stress, mental exhaustion, and vigor than the other way around. Demands was a negative predictor of TST of one participant, and for resting HRV in another. Mental exhaustion predicted both resting HRV and TST in the same participant. Especially, TST seemed a strong predictor of stress-related EMA outcomes. TST negatively predicted demands in two participants, stress in three participants, mental exhaustion in five participants, and positively predicted vigor in five participants. Resting HRV negatively predicted demands in two participants, and both stress and mental exhaustion in one participant.

This study led to three key findings that will first be reflected upon, followed by a discussion of the strengths and limitations of the study, and finally a summary of the main conclusions and recommendations for future research.

Associations between TST, HRV and EMA outcomes are not consistently observed

Although TST was a negative predictor of mental exhaustion and a positive predictor of vigor in the majority (62.5%) of the participants, no association between a wearable- and an EMA-based item was consistently observed in all participants. No convincing explanations for the prevalence of these associations were identified after inspection of differences in the participant characteristics (Table 1).

The number of participants in this study (n = 8) was too low to meaningfully assess to what extent between-subject differences in participant characteristics could predict the prevalence of these associations. Future studies with a larger sample size are recommended to explore if the occurrence or strength of these associations may be explained by participant characteristics, for instance via multilevel VAR (70). If these differences can be explained in future studies, they may be used to further personalize wearable-based models for stress-resilience.

It is also possible that the strength of these associations does not (only) depend on differences between individuals, but (also) on differences within individuals or in their environment. However, it may be difficult to determine beforehand what these influencing factors may be. It is possible to first explore if the strength of these relationships changes over time, for example via time-varying VAR models (71). Detecting such changes over time is particularly feasible in datasets with a larger number of observations and/or more granular data. If these associations do change over time, it is possible that they may be actually relevant for all participants, but only under certain circumstances. Depending on the outcomes of such studies, it could provide new insights into the internal or external factors that determine when these associations are observed.

The impact of changes in HRV appears to be more abiding than that of changes in TST

The IRF visualizations in Figure 1 demonstrated that a demand-induced decline of resting HRV appears to have a longer recovery time (5–6 days) than a demand-induced decline of TST (2–3 days). Similarly, the impact of a change in resting HRV on stress-related EMA outcomes (Figure 3) appears to also be more long-lasting (1–3 days) than that of a change in TST (1 day) (Figure 2). This was attributed to the significant autoregression component that was observed in resting HRV, but not in TST. The strong autoregression component in the resting HRV model means that resting HRV values are relatively likely to be similar to those of the previous day(s). Therefore, a demand-induced decline in resting HRV (analysis 1) may take several days to recover from. Similarly, the impact of a decline in resting HRV on demands, stress, mental exhaustion, and vigor is likely to spill over into subsequent days, as it means that resting HRV is likely to remain suppressed for another few days.

This observation may be explained by the fundamentally different nature of the concepts resting HRV and TST. Resting HRV is a quantification of a physiological state that is continuously striving to maintain stability (homeostasis) despite disruptive challenges (allostasis) (13). The recovery from a stressor that has a physiological impact (allostatic load) could take longer depending on the intensity and frequency of the stressor, as well as the quality and quantity of the subsequent recovery (36,37). As such, a large decline in resting HRV can logically be expected to take some time as well. TST, on the other hand, is a quantification of the recovery process itself. Stress can negatively influence TST on the following night (18–21) and can therefore also impact TST on subsequent nights in the case of a recurring or sustained stressor. However, when this is not the case, it is also possible that the individual compensates for the previous sleep loss via recovery sleep (72), which would mean that TST on a subsequent night is no longer suppressed but actually increased. From this perspective, TST values can be expected to be more volatile than changes in resting HRV and thus have a weaker autoregression component. However, it is possible that changes in TST do have a longer-lasting impact on relevant underlying (psycho)physiological states such as vigor, which was observed to consistently have a significant autoregression component (Table 4).

The seemingly more abiding impact of a change in resting HRV on the resting HRV of the subsequent days may also be influenced by the development of a negative feedback loop. A previous study showed that evening mental exhaustion negatively impacted subsequent resting HRV and that resting HRV itself buffered against the positive association between demands and stress, as well as between stress and mental exhaustion

(38). This aligns with the Conservation of Resources Theory, which describes that an initial loss of resources could lead to a negative feedback loop. This means that fewer resources are available to handle upcoming challenges, which leads to lower resilience (35). However, in the current study, no bidirectional association between a stress-related EMA item and resting HRV was observed within a single participant. Future studies with a larger sample are needed to increase insight into the multi-day impact of stress-related changes in resting HRV.

TST and HRV are more consistent predictors of stress-related outcomes than vice versa

These findings indicate that wearable-measured TST and HRV seemed better predictors of stress-related EMA outcomes than the other way around. EMA-based predictions of TST and resting HRV were only observed in two participants, who had relatively large samples of observations (N = 385 and N = 283) compared to the median (N = 144). Additionally, these relationships were not consistently observed in both participants. These differences cannot merely be explained by statistical power. Nevertheless, these models explained a modest amount of variance in TST (9%) and resting HRV (22%) in some participants. It is possible that these relationships are relatively small in nature and can only be observed in larger samples.

The finding that TST is a more consistent predictor of stress-related outcomes than that it can be predicted by stress-related outcomes aligns with prior research (22). For instance, a lower TST has consistently been shown to predict increased stress (19–21,73). Conversely, in the same studies, the opposite is regularly associated with smaller effect sizes (19–21), but in another study, TST was not associated with stress-related outcomes (73).

Similar scientific findings on the combination of both the predictive power and predictability of resting HRV in the context of stress-related outcomes are limited. However, the current findings do align with prior research, which has shown that stress-related outcomes negatively affect resting HRV (27,28,38) and that a relatively lower resting HRV than an individual's normal resting HRV can negatively impact stress-related outcomes on the following day (38,74).

One of the implications of this finding is that a decrease in wearable-measured TST or resting HRV does not necessarily point toward the occurrence of stress-related outcomes. Although the observed decrease in TST or resting HRV might have been caused by subsequent high demands or stress, this outcome may have been confounded by other factors. In situations where sudden extreme demands or stress occur, this might in some cases directly cause a decreased TST or resting HRV. However, in these circumstances, the wearable-user is likely already aware of the impact of such events. In such instances, the wearable-user less likely needs objective feedback to confirm this short-term effect.

Based on these findings, wearable-measured TST and resting HRV are not necessarily usable as a direct indication of the negative impact of stress but hold more promise to function as potential predictors to estimate one's resilience. For instance, these insights could be implemented in resilience interventions in the form of a readiness score that gives the user feedback on his or her expected readiness to handle mental and physical challenges that day (75). Ideally, these factors will be expanded upon in future research (e.g., by also assessing behavioral outcomes such as smartphone usage, geolocation, or patterns in communication) that also explore different modelling approaches (e.g., machine learning) in order to improve the performance of these models.

Strengths and limitations of the current study

This study applied a novel research design and recruited a motivated number of participants that resulted in a series (n = 8) of sizable datasets (N = 125–386) with mostly (80.7–96.8%) complete observations. By utilizing a consumer-available wearable that is validated for both TST and resting HRV measurements to collect observational data in a real-life environment, the generalizability of the findings to practical settings is relatively good. However, three limitations of the current study should also be considered during the interpretation of the presented results.

First, the multiple n-of-1 study design with a small number of participants (n) but a large number of observations per participant (N) was optimized as a first exploration of the potential existence of the hypothesized multi-day associations at a within-subject level based on high-quality data but limits the generalizability of the current findings to a broader target population. Therefore, future research with a larger number of participants is needed to increase confidence that the found associations are indeed relevant for larger groups of people. Future research is also needed to better understand why the identified relationships are prevalent in some cases, but not in others. For instance, it is possible that studies with a larger number of observations per participant can unveil to what extent associations with a smaller strength can be observed in other participants, and to what extent the strength of these associations may change over time (e.g., via time-varying VAR).

Second, the included healthy participants and data collection during the COVID-19 lockdown might have affected the participants' perceptions of demanding and stressful situations. Their daily practice may not have been very demanding, which may have resulted in relatively low variance in the data. This aligns with the findings of a study on 2567 European police officers, which reported decreased strain during the pandemic (76). The analyzed participants all scored relatively well on the mental well-being questionnaires (Table 1). Another article that was based on data from this same study population showed that some participants reported moderately elevated stress and somatization throughout the study period, but that there were no clinically relevant signs of anxiety and depression (41). Future studies with a more mentally challenged sample need to verify the current findings for more challenging conditions.

Finally, some of the statistical assumptions of the created VAR models were technically violated. Most notably, none of the VAR models had normally distributed residuals, which was likely the result of sometimes skewed or bimodally distributed EMA items. Since simulation studies have shown that this assumption is particularly relevant when relatively small samples are assessed but not problematic when a sample of at least 100 observations is analyzed (70), this was not considered to be a problem for the interpretation of the results. The VAR model of participant 5 was also found to have autocorrelated residuals, which could not be resolved (e.g., by adding additional lags). Although this does not necessarily limit the interpretability of the model and related findings, it does show that the model is incomplete, and at least one unobserved but relevant factor was not included in the present study.

CONCLUSIONS AND RECOMMENDATIONS

This multiple n-of-1 study showed that in relatively healthy police officers, demands were occasionally observed to be a negative predictor of wearable-measured TST and resting HRV. TST and resting HRV were more regularly observed to be negative predictors of demands, stress, or mental exhaustion, whereas TST also positively predicted vigor in several participants. The presented results illustrate that caution is needed when interpreting changes in TST and resting HRV to be potentially stress-related and that TST and resting HRV are more likely to be useful as predictors of stress-resilience (e.g., expressed as a readiness score).

However, since the identified associations were not consistently observed amongst participants, further research is necessary to better understand the underlying mechanism. For instance, future studies with a larger sample of participants, which is also needed to improve the generalizability of the current findings, could consider assessing if these between-subject differences could be explained by participant characteristics (e.g., via multilevel VAR). Another direction could be to explore if the strength of these associations' changes over time in samples with a larger number or more granular data (e.g., via time-varying VAR). Finally, future studies should explore if predictive models with a higher explained variance can be achieved by including additional data sources (e.g., smartphone usage, geolocation, or patterns in communication) or utilizing more inductive methods (e.g., machine learning approaches).

REFERENCES

1. Booth J, Connelly L, Lawrence M, Chalmers C, Joice S, Becker C, Dougall N. Evidence of perceived psychosocial stress as a risk factor for stroke in adults: a meta-analysis. BMC Neurology. 2015;15:233. doi: 10.1186/s12883-015-0456-4.

2. Buscemi V, Chang W-J, Liston MB, McAuley JH, Schabrun SM. The Role of Perceived Stress and Life Stressors in the Development of Chronic Musculoskeletal Pain Disorders: A Systematic Review. The Journal of Pain. 2019;20:1127–1139. doi: 10.1016/j.jpain.2019.02.008.

3. Decker A, Askar H, Tattan M, Taichman R, Wang H-L. The assessment of stress, depression, and inflammation as a collective risk factor for periodontal diseases: a systematic review. Clinical Oral Investigations. 2020;24:1–12. doi: 10.1007/s00784-019-03089-3.

4. Li J, Zhang M, Loerbroks A, Angerer P, Siegrist J. Work stress and the risk of recurrent coronary heart disease events: A systematic review and meta-analysis. International Journal of Occupational Medicine and Environmental Health [Internet]. 2014; doi: 10.2478/s13382-014-0303-7.

5. Magnavita N, Capitanelli I, Garbarino S, Pira E. Work-related stress as a cardiovascular risk factor in police officers: a systematic review of evidence. International Archives of Occupational and Environmental Health. 2018;91:377–389. doi: 10.1007/s00420-018-1290-y.

6. Sui H, Sun N, Zhan L, Lu X, Chen T, Mao X. Association between Work-Related Stress and Risk for Type 2 Diabetes: A Systematic Review and Meta-Analysis of Prospective Cohort Studies. PLOS ONE. 2016;11:e0159978. doi: 10.1371/journal.pone.0159978.

7. Yang T, Qiao Y, Xiang S, Li W, Gan Y, Chen Y. Work stress and the risk of cancer: A meta-analysis of observational studies. International Journal of Cancer. 2019;144:2390–2400. doi: 10.1002/ijc.31955.

8. van der Molen HF, Nieuwenhuijsen K, Frings-Dresen MHW, de Groene G. Work-related psychosocial risk factors for stress-related mental disorders: an updated systematic review and meta-analysis. BMJ Open. 2020;10:e034849. doi: 10.1136/bmjopen-2019-034849.

9. Chirico F. Job stress models for predicting burnout syndrome: a review. Annali dell'Istituto superiore di sanita. 2016;52:443–456.

10. Hassard J, Teoh KRH, Visockaite G, Dewe P, Cox T. The cost of work-related stress to society: A systematic review. Journal of Occupational Health Psychology. 2018;23:1–17. doi: 10.1037/ocp0000069.

11. Béjean S, Sultan-Taïeb H. Modelling the economic burden of diseases imputable to stress at work. The European Journal of Health Economics. 2005;6:16–23. doi: 10.1007/s10198-004-0251-4.

12. Wang L, Miller LC. Just-in-the-Moment Adaptive Interventions (JITAI): A Meta-Analytical Review. Health Communication. 2020;35:1531–1544. doi: 10.1080/10410236.2019.1652388.

13. McEwen BS. Stress, Adaptation, and Disease: Allostasis and Allostatic Load. Annals of the New York Academy of Sciences. 1998;840:33–44. doi: 10.1111/j.1749-6632.1998.tb09546.x.

14. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Modelling employee resilience using wearables and apps: a conceptual framework and research design. International Journal on Advances in Life Sciences. 2019;11:110–117.

15. Drury RL. Wearable biosensor systems and resilience: a perfect storm in health care? Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00853.

16. Leung W, Case L, Sung M-C, Jung J. A meta-analysis of Fitbit devices: same company, different models, different validity evidence. Journal of Medical Engineering & Technology. 2022;46:102–115. doi: 10.1080/03091902.2021.2006350.

17. de Zambotti M, Cellini N, Menghini L, Sarlo M, Baker FC. Sensors Capabilities, Performance, and Use of Consumer Sleep Technology. Sleep Medicine Clinics. 2020;15:1–30. doi: 10.1016/j.jsmc.2019.11.003.

18. Nollet M, Wisden W, Franks NP. Sleep deprivation and stress: a reciprocal relationship. Interface Focus. 2020;10:20190092. doi: 10.1098/rsfs.2019.0092.

19. Narmandakh A, Oldehinkel AJ, Masselink M, de Jonge P, Roest AM. Affect, worry, and sleep: Between- and within-subject associations in a diary study. Journal of Affective Disorders Reports. 2021;4:100134. doi: 10.1016/j.jadr.2021.100134.

20. Sperry SH, Kwapil TR. Variability in Sleep Is Associated with Trait-Based and Daily Measures of Bipolar Spectrum Psychopathology. Behavioral Sleep Medicine. 2022;20:90–99. doi: 10.1080/15402002.2021.1890076.

21. Yap Y, Slavish DC, Taylor DJ, Bei B, Wiley JF. Bi-directional relations between stress and self-reported and actigraphy-assessed sleep: a daily intensive longitudinal study. Sleep. 2020;43:zsz250. doi: 10.1093/sleep/zsz250.

22. Ekuni R, Souza BMN, Cogo-Moreira H, Lourenço FC, Pompeia S. Bidirectional longitudinal dynamics of self-reported total sleep time and perceived stress: Establishing potential causal relationships. Sleep Health. 2022;8:406–409. doi: 10.1016/j.sleh.2022.01.004.

23. Stahl SE, An H-S, Dinkel DM, Noble JM, Lee J-M. How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough? BMJ Open Sp Ex Med. 2016;2:e000106. doi: 10.1136/bmjsem-2015-000106.

24. Lee I, Park N, Lee H, Hwang C, Kim JH, Park S. Systematic Review on Human Skin-Compatible Wearable Photoplethysmography Sensors. Applied Sciences. 2021;11. doi: 10.3390/app11052313.

25. Stone JD, Ulman HK, Tran K, Thompson AG, Halter MD, Ramadan JH, Stephenson M, Finomore VS, Galster SM, Rezai AR, et al. Assessing the Accuracy of Popular Commercial Technologies That Measure Resting Heart Rate and Heart Rate Variability. Frontiers in Sports and Active Living [Internet]. 2021;3. doi: 10.3389/fspor.2021.585870.

26. Thayer JF, Åhs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012;36:747–756. doi: 10.1016/j.neubiorev.2011.11.009.

27. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 2018;15:235–245. doi: 10.30773/pi.2017.08.17.

28. Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, Kupfer D, Thayer JF. Acute Stress Affects Heart Rate Variability During Sleep. Psychosomatic Medicine [Internet]. 2004;66. doi: 10.1097/01.PSY.0000106884.58744.09.

29. Hynynen E, Konttinen N, Kinnunen U, Kyröläinen H, Rusko H. The incidence of stress symptoms and heart rate variability during sleep and orthostatic test. European Journal of Applied Physiology. 2011;111:733–741. doi: 10.1007/s00421-010-1698-x.

30. Park G, Vasey MW, Van Bavel JJ, Thayer JF. When tonic cardiac vagal tone predicts changes in phasic vagal tone: The role of fear and perceptual load. Psychophysiology. 2014;51:419–426. doi: 10.1111/psyp.12186.

31. Park G, Thayer JF. From the heart to the mind: cardiac vagal tone modulates top-down and bottom-up visual perception and attention to emotional stimuli. Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00278.

32. Gaebler M, Daniels JK, Lamke J-P, Fydrich T, Walter H. Heart rate variability and its neural correlates during emotional face processing in social anxiety disorder. Biological Psychology. 2013;94:319–330. doi: 10.1016/j.biopsycho.2013.06.009.

33. Mather M, Thayer JF. How heart rate variability affects emotion regulation brain networks. Current Opinion in Behavioral Sciences. 2018;19:98–104. doi: 10.1016/j.cobeha.2017.12.017.

34. Holzman JB, Bridgett DJ. Heart rate variability indices as bio-markers of top-down self-regulatory mechanisms: A meta-analytic review. Neuroscience & Biobehavioral Reviews. 2017;74:233–255. doi: 10.1016/j.neubiorev.2016.12.032.

35. Hobfoll SE. The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. Applied Psychology. 2001;50:337–421. doi: 10.1111/1464-0597.00062.

36. McEwen BS, Karatsoreos IN. Sleep Deprivation and Circadian Disruption: Stress, Allostasis, and Allostatic Load. Sleep Medicine Clinics. 2015;10:1–10. doi: 10.1016/j.jsmc.2014.11.007.

37. McEwen BS. Sleep deprivation as a neurobiologic and physiologic stressor: allostasis and allostatic load. Metabolism. 2006;55:S20–S23. doi: 10.1016/j.metabol.2006.07.008.

38. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Moderation of the stressor-strain process in interns by heart rate variability measured with a wearable and smartphone app: Within-subject design using continuous monitoring. JMIR cardio. 2021;5:e28731. doi: 10.2196/28731.

39. Collins PA, Gibbs ACC. Stress in police officers: a study of the origins, prevalence and severity of stress-related symptoms within a county police force. Occupational Medicine. 2003;53:256–264. doi: 10.1093/occmed/kqg061.

40. De Groot MD Mark; Martin-Sanchez, Fernando J; Wolf, Gary. Single Subject (N-of-1) Research Design, Data Processing, and Personal Science. Methods Inf Med. 2018;56:416–418. doi: 10.3414/ME17-03-0001.

41. de Vries H, Kamphuis W, van der Schans C, Sanderman R, Oldenhuis H. Trends in Daily Heart Rate Variability Fluctuations Are Associated with Longitudinal Changes in Stress and Somatisation in Police Officers. Healthcare. 2022;10:144. doi: 10.3390/healthcare10010144.

42. Jebb AT, Tay L, Wang W, Huang Q. Time series analysis for psychological research: examining and forecasting change. Frontiers in Psychology [Internet]. 2015;6. doi: 10.3389/fpsyg.2015.00727.

43. Warner RM. Spectral analysis of time-series data. Guilford Press; 1998.

44. Denissen JJA, Geenen R, van Aken MAG, Gosling SD, Potter J. Development and Validation of a Dutch Translation of the Big Five Inventory (BFI). Journal of Personality Assessment. 2008;90:152–157. doi: 10.1080/00223890701845229.

45. Terluin B, van Marwijk HW, Adèr HJ, de Vet HC, Penninx BW, Hermens ML, van Boeijen CA, van Balkom AJ, van der Klink JJ, Stalman WA. The Four-Dimensional Symptom Questionnaire (4DSQ): a validation study of a multidimensional self-report questionnaire to assess distress, depression, anxiety and somatization. BMC Psychiatry. 2006;6:34. doi: 10.1186/1471-244X-6-34.

46. Halbesleben JRB, Demerouti E. The construct validity of an alternative measure of burnout: Investigating the English translation of the Oldenburg Burnout Inventory. Work & Stress. 2005;19:208–220. doi: 10.1080/02678370500340728.

47. Schaufeli WB, Bakker AB, Salanova M. The Measurement of Work Engagement With a Short Questionnaire: A Cross-National Study. Educational and Psychological Measurement. 2006;66:701–716. doi: 10.1177/0013164405282471.

48. de Zambotti M, Rosas L, Colrain IM, Baker FC. The Sleep of the Ring: Comparison of the ŌURA Sleep Tracker Against Polysomnography. Behavioral Sleep Medicine. 2019;17:124–136. doi: 10.1080/15402002.2017.1300587.

49. Chee NIYN, Ghorbani S, Golkashani HA, Leong RLF, Ong JL, Chee MWL. Multi-Night Validation of a Sleep Tracking Ring in Adolescents Compared with a Research Actigraph and Polysomnography. Nat Sci Sleep. 2021;13:177–190. doi: 10.2147/NSS.S286070. Cited: in: : PMID: 33623459.

50. Kinnunen H, Rantanen A, Kenttä T, Koskimäki H. Feasible assessment of recovery and cardiovascular health: accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG. Physiological Measurement. 2020;41:04NT01. doi: 10.1088/1361-6579/ab840a.

51. Cao R, Azimi I, Sarhaddi F, Niela-Vilen H, Axelin A, Liljeberg P, Rahmani AM. Accuracy Assessment of Oura Ring Nocturnal Heart Rate and Heart Rate Variability in Comparison With Electrocardiography in Time and Frequency Domains: Comprehensive Analysis. J Med Internet Res. 2022;24:e27487. doi: 10.2196/27487.

52. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health [Internet]. 2017;5. doi: 10.3389/fpubh.2017.00258.

53. Henriksen A, Svartdal F, Grimsgaard S, Hartvigsen G, Hopstock LA. Polar Vantage and Oura Physical Activity and Sleep Trackers: Validation and Comparison Study. JMIR Formative Research. 2022;6:e27248.

54. Littman AJ, White E, Satia JA, Bowen DJ, Kristal AR. Reliability and validity of 2 single-item measures of psychosocial stress. Epidemiology. 2006;17:398–403. doi: 10.1097/01.ede.0000219721.89552.51. Cited: in: : PMID: 16641618.

55. van Veldhoven M, Broersen S. Measurement quality and validity of the “need for recovery scale.” Occup Environ Med. 2003;60:i3. doi: 10.1136/oem.60.suppl_1.i3.

56. Bush K, Kivlahan DR, McDonell MB, Fihn SD, Bradley KA, for the Ambulatory Care Quality Improvement Project (ACQUIP). The AUDIT Alcohol Consumption Questions (AUDIT-C): An Effective Brief Screening Test for Problem Drinking. Archives of Internal Medicine. 1998;158:1789–1795. doi: 10.1001/archinte.158.16.1789.

57. Romanowicz M, Schmidt JE, Bostwick JM, Mrazek DA, Karpyak VM. Changes in Heart Rate Variability Associated With Acute Alcohol Consumption: Current Knowledge and Implications for Practice and Research. Alcohol: Clinical and Experimental Research. 2011;35:1092–1105. doi: 10.1111/j.1530-0277.2011.01442.x.

58. RStudio Team. RStudio: Integrated Development Environment for R [Internet]. Boston, MA: RStudio, BPC; 2022. Available from: https://www.rstudio.com.

59. R Core Team. R: A Language and Environment for Statistical Computing [Internet]. Vienna, Austria: R Foundation for Statistical Computing; 2022. Available from: https://www.R-project.org/.

60. Zeileis A, Grothendieck G. zoo: S3 Infrastructure for Regular and Irregular Time Series. Journal of Statistical Software. 2005;14:1–27. doi: 10.18637/jss.v014.i06.

61. Pfaff B. VAR, SVAR and SVEC Models: Implementation Within R Package vars. J Stat Soft. 2008;27:1–32. doi: 10.18637/jss.v027.i04.

62. Wickham H. ggplot2: Elegant Graphics for Data Analysis [Internet]. Springer-Verlag New York; 2016. Available from: https://ggplot2.tidyverse.org.

63. Phillips PC, Perron P. Testing for a unit root in time series regression. Biometrika. 1988;75:335–346. doi: 10.1093/biomet/75.2.335.

64. Hosking JRM. The Multivariate Portmanteau Statistic. Journal of the American Statistical Association. 1980;75:602–608. doi: 10.1080/01621459.1980.10477520.

65. Engle RF. Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. Econometrica. 1982;50:987–1007. doi: 10.2307/1912773.

66. Jarque CM, Bera AK. A Test for Normality of Observations and Regression Residuals. International Statistical Review / Revue Internationale de Statistique. 1987;55:163–172. doi: 10.2307/1403192.

67. Granger CWJ. Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica. 1969;37:424–438. doi: 10.2307/1912791.

68. Lütkepohl H. Impulse response function. In: Durlauf SN, Blume LE, editors. Macroeconometrics and Time Series Analysis [Internet]. London: Palgrave Macmillan UK; 2010. p. 145–150. Available from: https://doi.org/10.1057/9780230280830_16.

69. Lumley T, Diehr P, Emerson S, Chen L. The Importance of the Normality Assumption in Large Public Health Data Sets. Annu Rev Public Health. 2002;23:151–169. doi: 10.1146/annurev.publhealth.23.100901.140546.

70. Epskamp S, Deserno MK, Bringmann LF. mlVAR: Multi-Level Vector Autoregression [Internet]. 2021. Available from: https://CRAN.R-project.org/package=mlVAR.

71. Haslbeck JMB, Bringmann LF, Waldorp LJ. A Tutorial on Estimating Time-Varying Vector Autoregressive Models. Multivariate Behavioral Research. 2021;56:120–149. doi: 10.1080/00273171.2020.1743630.

72. Carskadon MA, Acebo C, Seifer R. Extended nights, sleep loss, and recovery sleep in adolescents. Arch Ital Biol. 2001;139:301–312. doi: 10.4449/aib.v139i3.505. Cited: in: : PMID: 11330207.

73. Lee S, Crain TL, McHale SM, Almeida DM, Buxton OM. Daily antecedents and consequences of nightly sleep. Journal of Sleep Research. 2017;26:498–509. doi: 10.1111/jsr.12488.

74. da Estrela C, MacNeil S, Gouin J-P. Heart rate variability moderates the between- and within-person associations between daily stress and negative affect. International Journal of Psychophysiology. 2021;162:79–85. doi: 10.1016/j.ijpsycho.2021.02.001.

75. B. Carper, D. McGowan, S. Miller, J. Nelson, L. Palombi, L. Romeo, K. Spigelman, A. Doryab. Modelling Biological Rhythms to Predict Mental and Physical Readiness. 2020 Systems and Information Engineering Design Symposium (SIEDS). 2020. p. 1–6.

76. Frenkel MO, Giessing L, Egger-Lampl S, Hutter V, Oudejans RRD, Kleygrewe L, Jaspaert E, Plessner H. The impact of the COVID-19 pandemic on European police officers: Stress, demands, and coping resources. Journal of Criminal Justice. 2021;72:101756. doi: 10.1016/j.jcrimjus.2020.101756.

CHAPTER 6

Trends in daily heart rate variability fluctuations are associated with longitudinal changes in stress and somatization in police officers

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ABSTRACT

The emergence of wearable sensors that allow for unobtrusive monitoring of physiological and behavioral patterns introduces new opportunities to study the impact of stress in a real-world context. This study explores to what extent within-subject trends in daily Heart Rate Variability (HRV) and daily HRV fluctuations are associated with longitudinal changes in stress, depression, anxiety, and somatization. Nine Dutch police officers collected daily nocturnal HRV data using an Oura ring during 15–55 weeks. Participants filled in the Four-Dimensional Symptoms Questionnaire every 5 weeks. A sample of 47 five-week observations was collected and analyzed using multiple regression. After controlling for trends in total sleep time, moderate-to-vigorous physical activity and alcohol use, an increasing trend in the seven-day rolling standard deviation of the HRV (HRVsd) was associated with increases in stress and somatization over 5 weeks. Furthermore, an increasing HRV trend buffered against the association between HRVsd trend and somatization change, undoing this association when it was combined with increasing HRV. Depression and anxiety could not be related to trends in HRV or HRVsd, which was related to observed floor effects. These results show that monitoring trends in daily HRV via wearables holds promise for automated stress monitoring and providing personalized feedback.

Keywords: stress; somatization; heart rate variability; longitudinal; wearables; ecological momentary assessment

INTRODUCTION

Stress can be defined as a relationship between the person and the environment that is appraised by the person as taxing or exceeding one's resources and endangering one's well-being (1). Stress disturbs the body's biological equilibrium (homeostasis), requiring a neural, neuroendocrine and neuroendocrine-immune adaptation to restore it (allostasis) (2). Acute stress has a function to trigger a behavioral response to cope with the demand, but chronic stress leads to cumulative wear and tear on bodily systems (allostatic load), which is detrimental to long-term health and well-being (3). Policing is a good example of a physically and psychologically demanding job that can cause stress (4). In police officers, chronic stress is associated with neuro-endocrine changes (5) and an increased risk of physical (6), mental illness (7), and absenteeism (8).

The emergence of wearable sensors that allow for unobtrusive monitoring of physiological and behavioral patterns introduces new opportunities to study the impact of stress in a real-world context (9). In particular, Heart Rate Variability (HRV), which can be measured using wearable sensors, is promising as a biomarker for resilience to stress (10). If trends in daily HRV observations can be related to mental health outcomes, it enables possibilities for early recognition of the impact of stress and personalized stress counselling based on objective feedback. This study, therefore, explores to what extent daily HRV trends are related to longitudinal changes in several mental health outcomes in police officers. Below, we provide a detailed description of HRV and how its daily fluctuations may be a relevant proxy for homeostatic disturbances, and then we describe this study's hypotheses.

Heart Rate Variability (HRV)

HRV is a measure for the variation in inter-beat-intervals that reflects autonomic nervous system functioning and is negatively correlated to allostatic load (11). HRV declines during stress (12) and can remain suppressed during subsequent rest and sleep (13). Originally, HRV was measured using electrocardiography (ECG), but in recent years, wearable sensor technologies increasingly started using photoplethysmography (PPG). Unlike ECG, which is based on the electrocardiographic signal that is related to the contraction of the heart muscle, PPG quantifies HRV by assessing the blood flow in peripheric arteries to assess heart rate. Due to this subtle difference, PPG-based HRV is sometimes referred to as "Pulse Rate Variability" (14), but it has been shown to estimate HRV and mental states, such as stress and anxiety (15,16).

HRV can be seen as a resource that enables cognitive and emotional regulation (17) and is physiologically depleted when dealing with demands (18). Since HRV is associated with stress-buffering effects (19,20), its depletion may indicate a decline in resilience to cope with new demands and thus lead to unfavorable outcomes if a trend develops.

This aligns with the conservation of resources theory, which suggests that an initial loss of resources can create a negative feedback loop that results in a loss spiral (21).

Longitudinal studies showed that a decline in HRV can be related to increased stress (22–25) or emotional exhaustion (26–28). HRV-related emotional exhaustion is often interpreted in the context of burnout but can overlap with depression (29), suggesting that changes in HRV may also be related to other mental health outcomes. Although longitudinal evidence for relationships between HRV and other mental health and well-being outcomes is limited, population studies have shown that HRV is indeed not just negatively associated with stress (30) but also with anxiety (31), depression (32), and somatic symptoms (33). The overlap in the associations between these diverse mental health and well-being outcomes with HRV is the result of their similar negative impact on autonomic nervous system functioning (decreased vagal tone), of which HRV is a reflection (34). Since changes in HRV are therefore not a direct proxy for any specific mental state, using a broad approach when investigating the relationship between structural changes in HRV and diverse mental health and well-being outcomes is warranted.

Since most of the existing evidence is based on cross-sectional population studies, recent reviews on HRV literature call for future studies with a longitudinal and within-subject focus (30,35). Traditional longitudinal studies assess HRV by taking one- or multiday samples across a period of weeks, months or years, but wearables can unobtrusively collect HRV data on a daily basis. An academic study of this more granular HRV data may help in obtaining a better understanding of relationships between HRV and other variables in a naturalistic setting. These more granular data allow us to look at trends in daily HRV but also open up the possibility to assess the degree to which the daily HRV fluctuates over time.

Daily HRV fluctuations

Since HRV reflects autonomic nervous system functioning, daily HRV fluctuations can be seen as a proxy for the homeostatic disturbances that form an allostatic burden. The autonomic nervous system continually strives to restore homeostasis. As such, it is possible that homeostatic disturbances exist while the average level of physiological functioning itself (e.g., the mean HRV) remains relatively constant. In this scenario, the allostatic process that continuously restores homeostasis is successful, but the pressure on the system as a whole may still be indicative of underlying problems.

Research on associations between daily HRV fluctuations and stress is still nascent in occupational settings, but interesting parallels to sports science can be drawn. For instance, increases in daily HRV fluctuations have consistently been associated with increased fatigue in athletes (36–38) but were also attributed to increased stress in a study describing a notable case of a female soccer player (39). Another study found that soccer players that had a decreased HRV and increased daily HRV fluctuations after a high-load week had a decreased stress tolerance (40), suggesting that these homeostatic disturbances may also impact the individuals' resilience to cope with upcoming demands. Therefore, changes in daily HRV fluctuations may be an interesting precursor to identify the development of more structural changes in stress.

As a result, trends and fluctuations in daily HRV may not only be directly related to changes in mental health outcomes, but trends in the underlying daily HRV itself may also moderate that association. An example of this was presented in a case study under elite triathletes. In the study, a decrease in daily HRV fluctuations, which is usually seen as a sign of positive adaptation, preceded poor performance and subsequent illness when the downtrend in daily fluctuations was combined with a downtrend in the daily HRV itself (41). The decrease in daily HRV fluctuations was not a sign of positive adaptation in this case but may actually have been indicative of a lack of autonomous nervous system reactivity to the challenges at hand since the underlying daily HRV was also trending down. Conversely, it is also possible that an uptrend in the daily HRV may buffer against the unfavorable effect of uptrends in daily HRV fluctuations on relevant outcomes. In that scenario, an uptrend in the daily HRV fluctuations would indicate that the individual's homeostasis is increasingly being challenged, but the uptrend in the daily HRV itself shows that the underlying physiological system itself is actually responding resiliently.

Aim of the study

Existing literature showed that a longitudinal decrease in HRV is positively associated with increased stress and that having a lower HRV is related to increased depression, anxiety and somatization at a population level. There are also indications that increases in daily HRV fluctuations are related to unfavorable outcomes and that an increasing daily HRV trend could have a buffering effect. Therefore, this study aims to explore to what extent within-subject trends in daily HRV and daily HRV fluctuations are related to changes in stress, depression, anxiety, and somatization in police officers in a large Dutch city. By applying a longitudinal design that utilizes continuous daily measurements in a real-world context, this study provides a unique contribution to the existing body of knowledge. We hypothesize that increasing trends in daily HRV fluctuations and decreasing trends in daily HRV are associated with increased (i) stress, (ii) depression, (iii) anxiety, and (iv) somatization, as well as that increasing trends in daily HRV buffer against the positive association between trends in daily HRV fluctuations and these outcomes.

MATERIALS AND METHODS

The study protocol was approved by the ethical committee of the Hanze University of Applied Sciences Groningen (heac.2020.012).

Participants

Police officers that worked in a large Dutch city and possessed a smartphone running on Android or iOS were invited to participate. The officers received an information letter via e-mail that informed them about the study. Participants were asked to collect data for 15 weeks, with an option to extend this to 20 weeks to reach a reward threshold, but participated voluntarily and were free to stop at any time. Participants that collected complete daily data on at least 100 days (>71–95% adherence based on a period of 15–20 weeks) and completed all longitudinal questionnaires were allowed to keep the wearable and received a feedback report after the study. Recruitment started in June 2020 and was completed in July 2020 after reaching the capacity of 10 participants, which was related to the availability of materials. Participants gave their informed consent prior to participation and had a conversation with the first author before and after their data collection period. Due to policies related to the COVID-19 pandemic, which was ongoing during data collection, these conversations were held via a teleconferencing tool. One participant was excluded from analysis due to diagnosed atrial fibrillation. The remaining 9 participants were predominantly male (77.8%) and had mean age of 35.8 years (25.8–51.1).

Data collection

Data collection started after the participants received their wearable and was planned to run for 15 to 20 weeks. Some participants voluntarily extended this period. During data collection, participants collected daily wearable data and a daily Ecological Momentary Assessment (EMA) question and filled in a longitudinal questionnaire every 5 weeks. Participants, therefore, collected multiple nested five-week observations. All participants reached the reward threshold. One participant collected data for 15 weeks, five for 25 weeks, whereas three participants proceeded to collect data for 25, 40, and 55 weeks. As a result, change scores and trends in the corresponding daily measurements were calculated for a sample of 47 five-week observations that were analyzed.

Stress, anxiety, depression and somatization

The Dutch version of the Four-Dimensional Symptom Questionnaire (4DSQ) was used to measure stress, anxiety, depression, and somatization every 5 weeks (42). The 4DSQ consists of 50 items, of which 16 concerning stress, 12 on anxiety, 5 on depression, and 16 on somatization. All items inquire about the occurrence of symptoms over the previous week and are scored on a 5-point Likert scale ('no', 'sometimes', 'regularly', 'often', or 'very often or constantly'). Responses are scored as 0 ('no'), 1 ('sometimes'), or 2 ('regularly', 'often', or 'very often') and summarized to create the overall scores on each scale. Each scale has cut-off points for moderately or severely elevated levels for clinical use, but these were not used for data analysis in this study. Five-week change scores were calculated by subtracting the scores of the 4DSQ scales from the scores on the subsequent measurement, resulting in 4 variables in which a higher score indicates an increase in the measured concept: stress increase, anxiety increase, depression increase, and somatization increase.

Daily HRV & daily HRV fluctuations

Daily HRV was measured with an Oura ring during sleep. The Oura ring is a consumer-available wearable with the size of a wedding ring, has a battery life of 4–7 days and measures sleep, physical activity, temperature, heart rate, and HRV. In this study, a second-generation Oura ring was used, which uses infrared light to measure HRV via PPG. The Oura ring uses a built-in artefact identification algorithm that is described in more detail elsewhere (43). In short, the algorithm in the ring labels each inter-beat-interval (IBI) as normal or abnormal by calculating its deviation from the median of the nearest surrounding IBIs. The night is then subdivided into 5-min segments for which the HRV is calculated. Finally, the average HRV of all 5-min segments that have sufficient valid measurements is then calculated to obtain the HRV for the full night. A validation study under 49 healthy individuals aged 15–72 years showed that the Oura ring's HRV measure explained 98.0% of the variance (r2 = 0.980) in the gold standard ECG-based HRV measurement (43). Another study under 5 healthy young adults that generated 23 trials found that the Oura ring had the second-lowest mean absolute percent error of the 7 investigated consumer-available wearables and reported a 0.91 correlation coefficient with ECG measurements (44). Participants in this study selected a ring type and color of their preference with an optimal fit for both user comfort and measurement accuracy. To preserve privacy, anonymized Oura accounts were created. The HRV metric reported by the Oura ring is the Root Mean Square of the Successive Differences (RMSSD), which is a time-domain metric for vagally mediated HRV and is expressed in milliseconds (45). To improve the distribution for statistical modelling, the RMSSD was logarithmically transformed (lnrMSSD), which is a common procedure (46).

Daily HRV fluctuations were operationalized by calculating the 7-day rolling standard deviation (HRVsd) when HRV observations on at least three out of the seven prior days were available (47). Other studies on daily HRV fluctuations have applied a seven-day moving window to account for weekly influences and calculate a coefficient of variation (37,41). Using the coefficient of variation is helpful if between-subject comparison of HRV fluctuations is targeted, as HRV can differ vastly between individuals (48). That approach does not apply to this study, which analyses within-subject trends in daily HRV and fluctuations therein. Since this study explores moderating effects between those two trends, using a coefficient of variation means that a small portion of the variation of the daily HRV trend is included in the daily HRV fluctuations metric, increasing the likelihood of a type II error occurring and making it less ideal than using a seven day rolling standard deviation within the aims of this study.

To determine trends in daily HRV, HRVsd, and control variables, a linear regression model was used to examine the rate of change as a function of time (41). To do so,

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measurements between longitudinal questionnaires were first filtered into subsets with the daily observations between two questionnaires. Linear regression models were then created by regressing each of the variables on time (the dates). A positive beta-coefficient, therefore, represents an uptrend over the respective period, whereas a negative beta-coefficient represents a downtrend.

Control variables

To account for confounders, control variables for Total Sleep Time (TST), Moderate-to-Vigorous Physical Activity (MVPA), and alcohol use were included. TST, which is the total duration of the main sleep episode that the user is asleep, was measured using the Oura ring (49). The Oura ring also measured MVPA, which is the number of minutes of physical activity at an intensity of at least 3 times the metabolic equivalent (MET) of the resting state. Alcohol use was measured with a daily EMA question that was available from 19:00 to 15:00 the next day to accommodate for night shifts. The item inquired about the number of consumed alcoholic beverages that day and was based on the AUDIT-C questionnaire (50). Data for the EMA question were collected using an in-house developed smartphone application and stored on-premise. As with HRV and HRVsd, trend scores were determined via linear regression models, where a positive beta-coefficient represents an uptrend, and a negative beta-coefficient represents a downtrend on the measure within the respective five-week period.

Data analysis

Data management and analyses were performed in RStudio (51) and R (52). Values for the changes on the longitudinal questionnaires and trends in the daily observations were standardized at the grand mean (subtracting the mean value of all observations from each value and then dividing it by the standard deviation of all observations). This procedure was applied to prevent scaling issues during statistical testing and optimize the comparability of the beta-coefficients of the final models (53). Each five-week data collection period represented one observation for which the change scores on the longitudinal questionnaire are compared to the trends in the daily measurements. For instance, if all 10 participants completed 4 data collection periods, that would result in a total sample of 40 observations available for analysis.

A three-step hierarchical modelling approach was used. The outcomes were first modelled based on the control variables for trends in TST, MVPA, and alcohol use, after which the main variables for trends in HRV and HRVsd were added in step two. In the third and final step, the interaction effect between trends in HRV and HRVsd was added to create the full model. Initially, Linear Mixed Modelling with fixed effects and random slopes was performed to account for repeated measurements within participants. However, analyses experienced singular bound problems due to a lack of between-subject variance, which is a sign that the fitted models may be too complex and more parsimonious models should be considered (54,55). We, therefore, chose to apply more parsimonious multiple regression analyses instead, which yielded the same results and conclusions that were drawn based on the initial multi-level modelling approach.

RESULTS

The data of this sample of 47 five-week observations included a total of 57 longitudinal questionnaires. Daily data were available on 1734 unique person-days, of which 1648 (94.3%) included HRV data and 1458 (89.0%) included EMA data. Based on interviews and manual inspection of missing data, missing HRV data were attributed to drained ring batteries, accidentally not wearing the ring, or could not be explained. Missing EMA questionnaire data were primarily attributed to forgetting to fill it in before going to bed. Two participants (22.2%) had moderately elevated stress on the 4DSQ at baseline, whereas the remaining seven (77.8%) did not have elevated stress at baseline. No participants (0%) had elevated depression, anxiety, or somatization levels at baseline. The intercorrelations between the changes in the longitudinal questionnaires and trends in the wearable and control variables are described in Table 1.

Table 1: Intercorrelations between the wearable (1-2), longitudinal (3-6) and control (7-9) variables.

Variable	Correlation							
	1	2	3	4	5	6	7	8
1. HRV uptrend	-							
2. HRVsd uptrend	-.04	-						
3. Stress increase	-.09	.43 **	-					
4. Anxiety increase	-.00	-.04	.24	-				
5. Depression increase	.06	-.03	.31 *	.15	-			
6. Somatization increase	-.03	.42 **	.56 ***	-.03	.09	-		
7. TST uptrend	.01	-.01	.11	-.22	.10	.09	-	
8. MVPA uptrend	-.13	.09	-.21	-.05	.12	-.17	-.28 .	-
9. Alcohol use uptrend	-.12	-.21	-.06	.28 .	.03	-.19	-.47 ***	.14

*Note. N=47; *** p<0.001, ** p<0.01, * p<0.05, . p<0.1; HRV: Heart Rate Variability; HRVsd: 7 day rolling standard deviation of the HRV; TST: Total Sleep Time; MVPA: Moderate-to-Vigorous Physical Activity.*

A three-step hierarchical multiple regression model for five-week stress changes was formed (Table 2). After controlling for trends in TST, MVPA, and alcohol use, uptrends in daily HRVsd were associated (p = 0.004) with increased stress, whereas daily HRVsd downtrends were associated with decreased stress (Figure 1). Trends in the daily HRV itself were unrelated to stress and did not buffer against the positive association between trends in daily HRVsd and stress increases. Hypothesis 1 is therefore partially

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confirmed. The full model explains 18.5% of the variance in five-week stress changes and provides a marginally significant improvement ($p = 0.08$) over the control model but is not significantly different from the main effects model ($p = 0.96$).

Table 2. Hierarchical multiple regression model for five-week stress increase

Independent variable	Stress increase					
	Step 1		Step 2		Step 3	
	β		β		β	
Intercept	−0.019		−0.024		−0.029	
TST uptrend	0.048		0.075		0.056	
MVPA uptrend	−0.209		−0.275	.	−0.276	.
Alcohol use uptrend	−0.005		0.100		0.092	
HRV uptrend			−0.098		−0.089	
HRVsd uptrend			0.590	**	0.542	**
HRV uptrend * HRVsd uptrend					−0.224	
R^2	*0.047*		*0.267*		*0.291*	
Adjusted R^2	*−0.019*		*0.177*		*0.185*	
F	*0.711*		*2.984*	*	*2.737*	*
ΔR^2			*0.220*		*0.024*	
ΔF			*2.273*	.	*−0.247*	

*Note. N = 47; ** p < 0.01, * p < 0.05, p < 0.1; HRV: Heart Rate Variability; HRVsd: Heart Rate Variability, 7-day rolling standard deviation; TST: Total Sleep Time; MVPA: Moderate-to-Vigorous Physical Activity.*

Another three-step hierarchical multiple regression model was formed for a five-week somatization change (Table 3). After controlling for trends in TST, MVPA, and alcohol use, uptrends in daily HRVsd were positively associated ($p = 0.01$) with somatization increase, whereas downtrends in daily HRVsd were associated with a decrease in somatization. Trends in daily HRV itself were not associated with changes in somatization, but uptrends in daily HRV moderated ($p = 0.04$) the association between daily HRVsd uptrends and somatization increase. The interaction plot in Figure 2 shows that uptrends in daily HRVsd are associated with somatization increase when the daily HRV trends down, but not when it trends up. Therefore, uptrends in daily HRV buffer against the positive association between uptrends in daily HRV fluctuations and somatization increase, as expected. Hypothesis 4 is therefore partially confirmed. The full model explains 21.3% of the variance in the five-week somatization change and provides a marginally significant improvement ($p = 0.07$) over the control model but not over the main effects model ($p = 0.76$).

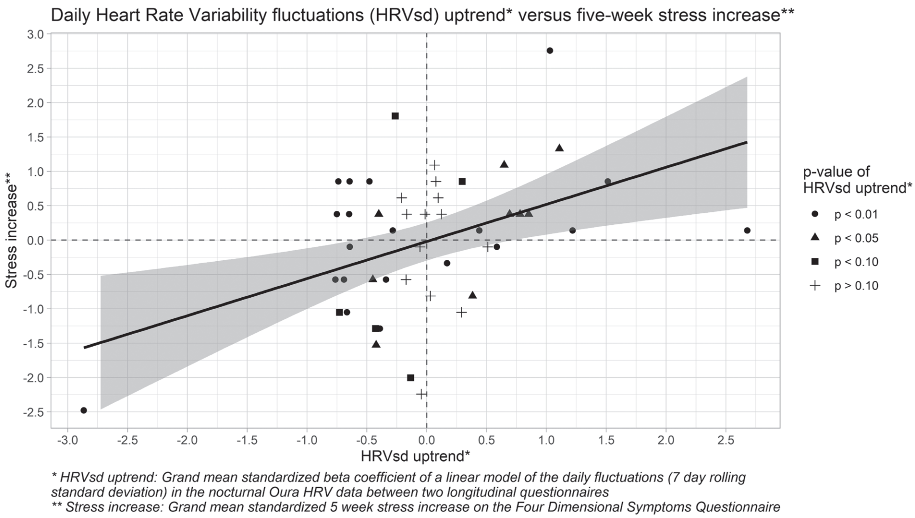


Figure 1: Scatter plot for the five-week uptrends in the 7 day rolling mean of the Heart Rate Variability (HRV_{sd}) versus five-week stress increases on the Four-Dimensional Symptom Questionnaire (4DSQ). The grey area represents the 95% confidence interval for the values that are estimated by the linear model (the black line).

Table 3. Hierarchical multiple regression model for five-week somatization increase.

Independent variable	Somatization Increase				
	Step 1	Step 2		Step 3	
	β	β		β	
Intercept	0.003	−0.002		−0.012	
TST uptrend	−0.051	−0.024		−0.058	
MVPA uptrend	−0.169	−0.224		−0.226	
Alcohol use uptrend	−0.191	−0.091		−0.107	
HRV uptrend		−0.054		−0.038	
HRVsd uptrend		0.530	**	0.443	*
HRV uptrend * HRVsd uptrend				−0.407	*
R^2	*0.061*	*0.234*		*0.315*	
Adjusted R^2	*−0.004*	*0.141*		*0.213*	
F	*0.931*	*2.508*	*	*3.069*	*
ΔR^2		*0.173*		*0.081*	
ΔF		*1.577*		*0.561*	

*Note. N = 47; * p < 0.05, p < 0.1; HRV: Heart Rate Variability; HRVsd: Heart Rate Variability, 7-day rolling standard deviation; TST: Total Sleep Time; MVPA: Moderate-to-Vigorous Physical Activity.*

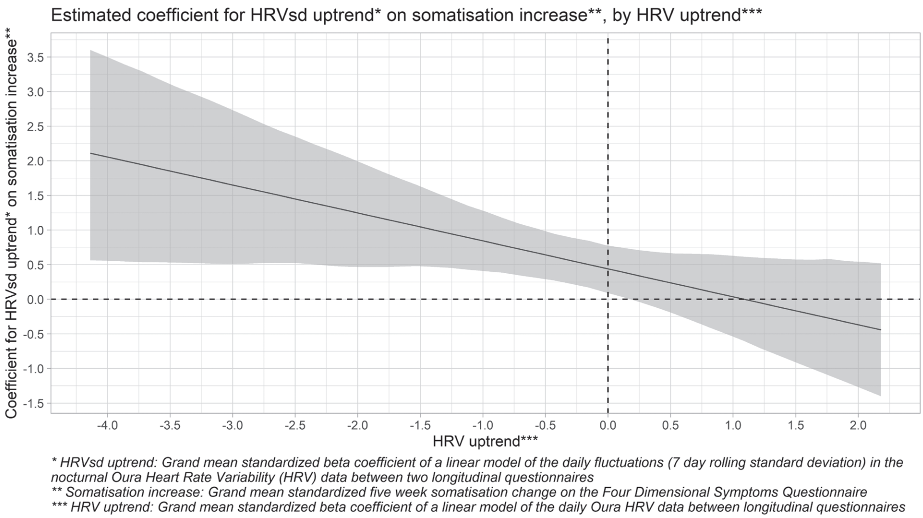


Figure 2: Estimated coefficient for the association between the five-week uptrend in the 7-day rolling standard deviation of the Heart Rate Variability (HRVsd) and five-week somatization increase by the five-week HRV uptrend. The grey area represents the 95% confidence interval for the values that are estimated by the linear model (the black line)

For depression (Hypothesis 2) and anxiety (Hypothesis 3), no models could be formed. This was related to floor effects on both scales. On the 56 questionnaires, 52 (92.9%) were scored zero on depression and 49 (87.5%) on anxiety. None reached cut-off points for elevated levels, illustrating a complete absence of clinically relevant symptoms.

DISCUSSION

This study hypothesized that increasing trends in daily HRV fluctuations and decreasing trends in daily HRV are associated with five-week increases in (i) stress, (ii) depression, (iii) anxiety, and (iv) somatization, and that increasing trends in daily HRV buffer against the positive association between the uptrends in daily HRV fluctuations and increases in these outcomes. The results of this study showed that uptrends in daily HRV fluctuations were indeed associated with increased stress and somatization, and uptrends in daily HRV buffered against the positive association between uptrends in daily HRV fluctuations and somatization increase (Hypotheses 1 and 4). Uptrends in daily HRV were not directly associated with changes in any of the outcomes, and changes in depression and anxiety could not be linked to trends in daily HRV nor daily HRV fluctuations (Hypotheses 2 and 3) due to floor effects. Hypotheses 1 and 4 are therefore partially confirmed, whereas Hypotheses 2 and 3 are unconfirmed.

Associations between daily HRV fluctuations, stress and somatization

When the day-to-day variation in the daily HRV trended up, participants were more likely to report increased stress on the next five-weekly questionnaire. Since HRV reflects the functioning of the autonomic nervous system (56), which continuously strives to restore homeostasis when faced with stress (2), the relationship between increased stress and homeostatic disturbances is intuitive. Although the existing body of knowledge on this topic is limited, this result aligns with that of two prior studies that related an uptrend in daily HRV fluctuations to stress increase in soccer players (39,40). To our knowledge, this study is the first to explore associations between trends in daily HRV and fluctuations therein to longitudinal mental health outcomes in an occupational setting. The reported results, therefore, contribute valuable new insights that measuring HRV on a daily basis using a consumer-available wearable may be a feasible and effective approach for the unobtrusive and early recognition of changes in stress in occupational settings.

This study also linked uptrends in daily HRV fluctuations to increased somatization scores, whereas daily HRV uptrends were buffered against this. The interaction plot in Figure 2 showed that the association between uptrends in daily HRV fluctuations and increases in somatization is only significant when combined with a downtrend in daily HRV but not when daily HRV is increasing. To our knowledge, this specific association has not been addressed in prior literature. There is some overlap with a prior study that reported an association of increased daily HRV fluctuations and decreased daily HRV with muscle soreness in swimmers during overload training (57). However, in our study, somatization increase was not related to uptrends in MVPA (Table 3) but was significantly correlated ($r = 0.56$; Table 1) to stress increase, underlining a possible difference in the underlying mechanisms between training- and stress-induced somatic symptoms.

Floor effects in depression and anxiety

No associations of trends in daily HRV and daily HRV fluctuations with five-week changes in depression and anxiety were found. Since 92.9% of all depression scores and 87.5% of all anxiety scores were zero and the cut-off points for elevated levels on these scales were not reached on any observation, there was a complete absence of clinically relevant symptoms on these dimensions. Since the presence of floor effects means that there may be insufficient variance within the respective sample to find a statistically significant effect even if there could be one in the full population (type II error) (58), this absence of proof should not be interpreted as a proof of the absence of this association. Based on population studies that related HRV to depression (32) and anxiety (31), this hypothesis warrants further investigation in future studies under populations that experience more clinically relevant symptoms or that use more sensitive measurement instruments.

Strengths and limitations

This study used a consumer-available wearable that is known to produce valid daily HRV data (43,44) to measure HRV on 94.3% of all 1734 person-days on which data were reported. The trends in daily HRV that are analyzed in this paper are therefore based on more granular data than longitudinal studies that apply a pretest-posttest design and are likely a good reflection of the true daily HRV trends over the full five-week periods. Another strength of this study is that data were collected within a naturalistic setting, optimizing the generalizability of the reported findings to real-world applications. By applying a novel design to assess the relationship between daily HRV observations that are measured with a consumer-available wearable and longitudinal mental health outcomes, this study takes important steps in a nascent but promising research field.

A sample of 47 five-week observations was analyzed, based on data collected by nine Dutch police officers. Not all participants contributed equally in the number of collected five-week observations. Although there are no indications that using nested observations within this sample or the unequal contribution of observations were problematic, replication of these findings in a larger sample of participants collecting an equal number of observations would be beneficial for the external validity. Similarly, future studies that analyses a larger number of observations may consider applying cross-validation methods. For example, studies could use the observations of a subset of participants to predict the outcomes in the remainder of the participants.

Finally, data collection occurred during the COVID-19 pandemic. A study under 2567 European police officers reported decreased strain during the pandemic, where the risk of infection and deficient communication were the main stressors (59). Another study found that COVID-19 lockdowns lead to increased HRV in 20% and decreased HRV in 80% of the French general population (60). Thus, it is possible that the unique context of this period influenced the observed daily HRV values and mental health outcomes. However, since this study does not assess these actual outcomes but observes to what extent trends between them are interrelated, this context is unlikely to have directly influenced this study's findings.

Implications

The results showed that uptrends in daily HRV fluctuations were related to five-week increases in stress and somatization and that uptrends in daily HRV buffer against the association between uptrends in daily HRV fluctuations and somatization increase. If these findings are replicated in future studies, they show that tracking daily HRV using a consumer-available wearable holds promise for early recognition of the impact of stress and for personalized feedback based on objective data in stress management interventions. Companies that are developing these wearable devices or related systems can then consider including metrics for daily HRV fluctuations (e.g., the 7-day rolling standard deviation or coefficient of variation) and estimate periodic trends in the daily

HRV and daily HRV fluctuations. The presence of a statistically significant trend in the daily HRV fluctuations could then be used to trigger personalized in-app feedback, notifying the user that a trend was witnessed that may be stress-related. Such a trigger could, for instance, nudge the user to reflect on the current situation, consider coaching or offer other interventions aiming to limit the negative impact of stress.

REFERENCES

1. Lazarus RS, Folkman S. Stress, appraisal, and coping. Springer publishing company; 1984.

2. McEwen BS. Stress, Adaptation, and Disease: Allostasis and Allostatic Load. Annals of the New York Academy of Sciences. 1998;840:33–44. doi: 10.1111/j.1749-6632.1998.tb09546.x.

3. Sun J, Wang S, Zhang J-Q, Li W. Assessing the cumulative effects of stress: The association between job stress and allostatic load in a large sample of Chinese employees. Work & Stress. 2007;21:333–347. doi: 10.1080/02678370701742748.

4. Collins PA, Gibbs ACC. Stress in police officers: a study of the origins, prevalence and severity of stress-related symptoms within a county police force. Occupational Medicine. 2003;53:256–264. doi: 10.1093/occmed/kqg061.

5. Violanti JM, Fekedulegn D, Andrew ME, Hartley TA, Charles LE, Miller DB, Burchfiel CM. The impact of perceived intensity and frequency of police work occupational stressors on the cortisol awakening response (CAR): Findings from the BCOPS study. Psychoneuroendocrinology. 2017;75:124–131. doi: 10.1016/j.psyneuen.2016.10.017.

6. Magnavita N, Capitanelli I, Garbarino S, Pira E. Work-related stress as a cardiovascular risk factor in police officers: a systematic review of evidence. International Archives of Occupational and Environmental Health. 2018;91:377–389. doi: 10.1007/s00420-018-1290-y.

7. Garbarino S, Cuomo G, Chiorri C, Magnavita N. Association of work-related stress with mental health problems in a special police force unit. BMJ Open. 2013;3:e002791. doi: 10.1136/bmjopen-2013-002791.

8. Magnavita N, Garbarino S. Is Absence Related to Work Stress? A Repeated Cross-Sectional Study on a Special Police Force. American Journal of Industrial Medicine. 2013;56:765–775. doi: 10.1002/ajim.22155.

9. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Modelling employee resilience using wearables and apps: a conceptual framework and research design. International Journal on Advances in Life Sciences. 2019;11:110–117.

10. Owens AP. The Role of Heart Rate Variability in the Future of Remote Digital Biomarkers. Frontiers in Neuroscience [Internet]. 2020;14. doi: 10.3389/fnins.2020.582145.

11. Thayer JF, Sternberg E. Beyond Heart Rate Variability. Annals of the New York Academy of Sciences. 2006;1088:361–372. doi: 10.1196/annals.1366.014.

12. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 2018;15:235–245. doi: 10.30773/pi.2017.08.17.

13. Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, Kupfer D, Thayer JF. Acute Stress Affects Heart Rate Variability During Sleep. Psychosomatic Medicine [Internet]. 2004;66. doi: 10.1097/01.PSY.0000106884.58744.09.

14. Yuda E, Shibata M, Ogata Y, Ueda N, Yambe T, Yoshizawa M, Hayano J. Pulse rate variability: a new biomarker, not a surrogate for heart rate variability. Journal of Physiological Anthropology. 2020;39:21. doi: 10.1186/s40101-020-00233-x.

15. Perpetuini D, Chiarelli AM, Cardone D, Filippini C, Rinella S, Massimino S, Bianco F, Bucciarelli V, Vinciguerra V, Fallica P, et al. Prediction of state anxiety by machine learning applied to photoplethysmography data. Liuzza MT, editor. PeerJ. 2021;9:e10448. doi: 10.7717/peerj.10448.

16. K. Awasthi, P. Nanda, K. V. Suma. Performance analysis of Machine Learning techniques for classification of stress levels using PPG signals. 2020 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT). 2020. p. 1–6.

17. Martens A, Greenberg J, Allen JJB. Self-Esteem and Autonomic Physiology: Parallels Between Self-Esteem and Cardiac Vagal Tone as Buffers of Threat. Pers Soc Psychol Rev. 2008;12:370–389. doi: 10.1177/1088868308323224.

18. Baethge A, Junker NM, Rigotti T. Does work engagement physiologically deplete? Results from a daily diary study. Work & Stress. 2021;35:283–300. doi: 10.1080/02678373.2020.1857466.

19. Schmid RF, Thomas J. Teachers' ambulatory heart rate variability as an outcome and moderating variable in the job demands-resources model. Anxiety, Stress, & Coping. 2020;33:387–402. doi: 10.1080/10615806.2020.1746286.

20. de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Moderation of the stressor-strain process in interns by heart rate variability measured with a wearable and smartphone app: Within-subject design using continuous monitoring. JMIR cardio. 2021;5:e28731. doi: 10.2196/28731.

21. Hobfoll SE. The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. Applied Psychology. 2001;50:337–421. doi: 10.1111/1464-0597.00062.

22. Borchini R, Ferrario MM, Bertù L, Veronesi G, Bonzini M, Dorso M, Cesana G. Prolonged job strain reduces time-domain heart rate variability on both working and resting days among cardiovascular-susceptible nurses. International Journal of Occupational Medicine and Environmental Health [Internet]. 2014; doi: 10.2478/s13382-014-0289-1.

23. Borchini R, Veronesi G, Bonzini M, Gianfagna F, Dashi O, Ferrario MM. Heart Rate Variability Frequency Domain Alterations among Healthy Nurses Exposed to Prolonged Work Stress. International Journal of Environmental Research and Public Health. 2018;15. doi: 10.3390/ijerph15010113.

24. Wagner JA, Feinn R, Lampert R, Bermúdez-Millán A, Pérez-Escamilla R. Changes in negative affect and changes in heart rate variability among low-income latinos with type 2 diabetes in a randomized, controlled stress management trial. Journal of Psychosomatic Research. 2019;124:109774. doi: 10.1016/j.jpsychores.2019.109774.

6

25. Föhr T, Tolvanen A, Myllymäki T, Järvelä-Reijonen E, Peuhkuri K, Rantala S, Kolehmainen M, Korpela R, Lappalainen R, Ermes M, et al. Physical activity, heart rate variability–based stress and recovery, and subjective stress during a 9-month study period. Scandinavian Journal of Medicine & Science in Sports. 2017;27:612–621. doi: 10.1111/sms.12683.

26. Zhang M, Liu L, Shi Y, Yang Y, Yu X, Angerer P, Kristensen TS, Li J. Longitudinal associations of burnout with heart rate variability in patients following acute coronary syndrome: A one-year follow-up study. General Hospital Psychiatry. 2018;53:59–64. doi: 10.1016/j.genhosppsych.2018.05.008.

27. Wekenborg MK, Hill LK, Thayer JF, Penz M, Wittling RA, Kirschbaum C. The Longitudinal Association of Reduced Vagal Tone With Burnout. Psychosomatic Medicine [Internet]. 2019;81. doi: 10.1097/PSY.0000000000000750.

28. Shi Y, Jiang R, Zhu C, Zhang M, Cai H, Hu Z, Ye Y, Liu Y, Sun H, Ma Y, et al. High Job Burnout Predicts Low Heart Rate Variability in the Working Population after a First Episode of Acute Coronary Syndrome. International Journal of Environmental Research and Public Health. 2021;18. doi: 10.3390/ijerph18073431.

29. Kanthak MK, Stalder T, Hill LK, Thayer JF, Penz M, Kirschbaum C. Autonomic dysregulation in burnout and depression: evidence for the central role of exhaustion. Scandinavian Journal of Work, Environment & Health. 2017;475–484. doi: 10.5271/sjweh.3647.

30. Järvelin-Pasanen S, Sinikallio S, Tarvainen MP. Heart rate variability and occupational stress—systematic review. Industrial Health. 2018;56:500–511. doi: 10.2486/indhealth.2017-0190.

31. Chalmers JA, Quintana DS, Abbott MJ-A, Kemp AH. Anxiety Disorders are Associated with Reduced Heart Rate Variability: A Meta-Analysis. Frontiers in Psychiatry [Internet]. 2014;5. doi: 10.3389/fpsyt.2014.00080.

32. Kemp AH, Quintana DS, Gray MA, Felmingham KL, Brown K, Gatt JM. Impact of Depression and Antidepressant Treatment on Heart Rate Variability: A Review and Meta-Analysis. Biological Psychiatry. 2010;67:1067–1074. doi: 10.1016/j.biopsych.2009.12.012.

33. de Jonge P, Mangano D, Whooley MA. Differential Association of Cognitive and Somatic Depressive Symptoms With Heart Rate Variability in Patients With Stable Coronary Heart Disease: Findings From the Heart and Soul Study. Psychosomatic Medicine [Internet]. 2007;69. doi: 10.1097/PSY.0b013e31815743ca.

34. Beauchaine T. Vagal tone, development, and Gray's motivational theory: Toward an integrated model of autonomic nervous system functioning in psychopathology. Development and Psychopathology. 2001/05/16 ed. 2001;13:183–214. doi: 10.1017/S0954579401002012.

35. Smith TW, Deits-Lebehn C, Williams PG, Baucom BRW, Uchino BN. Toward a social psychophysiology of vagally mediated heart rate variability: Concepts and methods in self-regulation, emotion, and interpersonal processes. Social and Personality Psychology Compass. 2020;14:e12516. doi: 10.1111/spc3.12516.

36. Perrotta AS, Koehle MS, White MD, Taunton JE, Warburton DER. Consecutive non-training days over a weekend for assessing cardiac parasympathetic variation in response to accumulated exercise stress. European Journal of Sport Science. 2020;20:1072–1082. doi: 10.1080/17461391.2019.1688397.

37. Flatt AA, Esco MR. Smartphone-Derived Heart-Rate Variability and Training Load in a Women's Soccer Team. International Journal of Sports Physiology and Performance. 2015;10:994–1000. doi: 10.1123/ijspp.2014-0556.

38. Schmitt L, Regnard J, Desmarets M, Mauny F, Mourot L, Fouillot J-P, Coulmy N, Millet G. Fatigue Shifts and Scatters Heart Rate Variability in Elite Endurance Athletes. PLOS ONE. 2013;8:e71588. doi: 10.1371/journal.pone.0071588.

39. Flatt AA, Esco MR, Nakamura FY. Individual Heart Rate Variability Responses to Preseason Training in High Level Female Soccer Players. The Journal of Strength & Conditioning Research [Internet]. 2017;31. doi: 10.1519/JSC.0000000000001482.

40. Figueiredo DH, Figueiredo DH, Moreira A, Gonçalves HR, Stanganelli LCR. Effect of Overload and Tapering on Individual Heart Rate Variability, Stress Tolerance, and Intermittent Running Performance in Soccer Players During a Preseason. The Journal of Strength & Conditioning Research [Internet]. 2019;33. doi: 10.1519/JSC.0000000000003127.

41. Plews DJ, Laursen PB, Kilding AE, Buchheit M. Heart rate variability in elite triathletes, is variation in variability the key to effective training? A case comparison. European Journal of Applied Physiology. 2012;112:3729–3741. doi: 10.1007/s00421-012-2354-4.

42. Terluin B, van Marwijk HW, Adèr HJ, de Vet HC, Penninx BW, Hermens ML, van Boeijen CA, van Balkom AJ, van der Klink JJ, Stalman WA. The Four-Dimensional Symptom Questionnaire (4DSQ): a validation study of a multidimensional self-report questionnaire to assess distress, depression, anxiety and somatization. BMC Psychiatry. 2006;6:34. doi: 10.1186/1471-244X-6-34.

43. Kinnunen H, Rantanen A, Kenttä T, Koskimäki H. Feasible assessment of recovery and cardiovascular health: accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG. Physiological Measurement. 2020;41:04NT01. doi: 10.1088/1361-6579/ab840a.

44. Stone JD, Ulman HK, Tran K, Thompson AG, Halter MD, Ramadan JH, Stephenson M, Finomore VS, Galster SM, Rezai AR, et al. Assessing the Accuracy of Popular Commercial Technologies That Measure Resting Heart Rate and Heart Rate Variability. Frontiers in Sports and Active Living [Internet]. 2021;3. doi: 10.3389/fspor.2021.585870.

45. Pham T, Lau ZJ, Chen SHA, Makowski D. Heart Rate Variability in Psychology: A Review of HRV Indices and an Analysis Tutorial. Sensors. 2021;21. doi: 10.3390/s21123998.

46. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health [Internet]. 2017;5. doi: 10.3389/fpubh.2017.00258.

47. Plews DJ, Laursen PB, Meur YL, Hausswirth C, Kilding AE, Buchheit M. Monitoring Training With Heart-Rate Variability: How Much Compliance Is Needed for Valid Assessment? International Journal of Sports Physiology and Performance. 2014;9:783–790. doi: 10.1123/ijspp.2013-0455.

48. Tegegne BS, Man T, van Roon AM, Snieder H, Riese H. Reference values of heart rate variability from 10-second resting electrocardiograms: the Lifelines Cohort Study. European Journal of Preventive Cardiology. 2020;27:2191–2194. doi: 10.1177/2047487319872567.

49. de Zambotti M, Rosas L, Colrain IM, Baker FC. The Sleep of the Ring: Comparison of the ŌURA Sleep Tracker Against Polysomnography. Behavioral Sleep Medicine. 2019;17:124–136. doi: 10.1080/15402002.2017.1300587.

50. Utility C, Properties P. AUDIT-C Questionnaire. Intern Med. 2003;163:2–3.

51. RStudio Team. RStudio: Integrated Development Environment for R [Internet]. Boston, MA: RStudio, BPC; 2022. Available from: https://www.rstudio.com.

52. R Core Team. R: A Language and Environment for Statistical Computing [Internet]. Vienna, Austria: R Foundation for Statistical Computing; 2022. Available from: https://www.R-project.org/.

53. Enders CK, Tofighi D. Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. Psychological Methods. 2007;12:121–138. doi: 10.1037/1082-989X.12.2.121.

54. Bates D, Kliegl R, Vasishth S, Baayen H. Parsimonious mixed models. arXiv preprint arXiv:150604967 [Internet]. 2015; doi: 10.48550/arXiv.1506.04967.

55. Matuschek H, Kliegl R, Vasishth S, Baayen H, Bates D. Balancing Type I error and power in linear mixed models. Journal of Memory and Language. 2017;94:305–315. doi: 10.1016/j.jml.2017.01.001.

56. Thayer JF, Åhs F, Fredrikson M, Sollers JJ, Wager TD. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews. 2012;36:747–756. doi: 10.1016/j.neubiorev.2011.11.009.

57. Flatt AA, Hornikel B, Esco MR. Heart rate variability and psychometric responses to overload and tapering in collegiate sprint-swimmers. Journal of Science and Medicine in Sport. 2017;20:606–610. doi: 10.1016/j.jsams.2016.10.017.

58. Šimkovic M, Träuble B. Robustness of statistical methods when measure is affected by ceiling and/or floor effect. PLOS ONE. 2019;14:e0220889. doi: 10.1371/journal.pone.0220889.

59. Frenkel MO, Giessing L, Egger-Lampl S, Hutter V, Oudejans RRD, Kleygrewe L, Jaspaert E, Plessner H. The impact of the COVID-19 pandemic on European police officers: Stress, demands, and coping resources. Journal of Criminal Justice. 2021;72:101756. doi: 10.1016/j.jcrimjus.2020.101756.

60. Bourdillon N, Jeanneret F, Nilchian M, Albertoni P, Ha P, Millet GP. Sleep Deprivation Deteriorates Heart Rate Variability and Photoplethysmography. Frontiers in Neuroscience [Internet]. 2021;15. doi: 10.3389/fnins.2021.642548.

CHAPTER 7

General discussion

General discussion

The aim of the *Wearable and app-based resilience Modelling in employees (WearMe)* study was to improve the current state of knowledge on how (changes in) resilience can be modelled based on data that is derived from wearables and apps. Models on the extent to which wearable-based data can be used to recognize the negative impact of stress in an early stage, or predict when the individual is more vulnerable to stress, may benefit the future development of automated resilience interventions. Such interventions could use continuous and unobtrusive monitoring to generate personalized just-in-time feedback on a person's resilience, allowing the individual to be more frugal with the available resources or better prepare for upcoming demands in order to mitigate the adverse impact of stress. This approach is for instance relevant for individuals in high-risk professions that are regularly faced with highly demanding circumstances (e.g., police officers or military personnel), but can also be utilized in other sectors that cope with increased stress and related absenteeism (e.g., education, healthcare) and thus benefit a broad audience.

The chapters in this thesis describe several studies that contributed to this goal. This final chapter will first provide an overview of the main findings of these studies and discuss their relevance for the overarching purpose of this thesis in the context of the broader scientific literature on the topic. Subsequently, several methodological considerations with regard to these studies are discussed (e.g., differences between and iterative improvements in the study design of these studies). Finally, a reflection on the future directions of research on wearable-based resilience modelling is presented, before closing off by briefly summarizing the overarching conclusions that can be drawn.

Main findings and discussion

The chapters of this thesis explored associations of wearable-measured sleep and resting Heart Rate Variability (HRV) with subjective resilience-related outcomes based on several different methodologies and on intra-day, multi-day and multi-week timeframes. For each of the main outcomes, the findings of the respective timeframes are therefore complementary to each other. To provide a compelling overview, the main findings of these studies are therefore grouped per main outcome in the following sections by discussing (i) resting HRV as an index for resilience (chapters 2 to 5), (ii) stable daily resting HRV values during periods of adversity as a demonstration of resilience (chapter 6), and (iii) sleep as a predictor of resilience-related outcomes (chapters 3 to 5).

Resting HRV as an index for resilience

Chapter 1 introduced resting HRV as a psychophysiological resource that is a reflection of the ability to flexibly adapt to changing environmental demands and regulate emotions (1). Based on population studies that investigate between-subject differences, having a high resting HRV is generally found to be positive for resilience, which is why it is sometimes referred to as an index for resilience (2,3). For instance, a high resting HRV is associated with a lower sensitivity to perceive stress (4–6) and more optimal emotion regulation (ability to exert control over one's own emotional state) (7,8). Resting HRV has also been found to be positively associated with cognitive inhibition (ability to tune out irrelevant stimuli) and cognitive flexibility (ability to switch thinking about two concepts) (9). Since the majority of the current knowledge on the role of resting HRV in resilience is based on cross-sectional population studies that assess between-subject differences, longitudinal within-subject studies to measure resting HRV in a naturalistic context of real-life were needed (3). Chapters 2 to 5 utilized several different approaches to explore whether within-subject differences in resting HRV may indeed be reflective of changes in resilience. This section will briefly describe the main findings of each of these chapters and then provide an overarching discussion of them in the final paragraph.

The first study of this thesis, which is described in chapter 2, aimed to investigate to what extent resting HRV during sleep is associated with perceived mental and physical fitness on the subsequent morning. After following a group of 63 employees of the Dutch military for a period of up to 46 days using a wrist-worn wearable (Garmin Tactix Charlie) and daily Ecological Momentary Assessment (EMA) questionnaires on a smartphone app, resting HRV during sleep was found to have a small (2.4% explained variance) but significant positive association with perceived physical fitness, but not with perceived mental fitness. Based on this finding, resting HRV should not be interpreted as a direct proxy for perceived mental or physical fitness, but rather as a relatively independent psychophysiological resource. Therefore, resting HRV appears to be more complementary than substitutive for subjective measures of perceived resources that are subconsciously assessed during stress appraisal.

Chapter 3 introduced a conceptual model for the (intra-day) process of resilience by combining insights of existing theories (the *Transactional Model of Stress and Coping* (10), *Job Demands-Resources Model of Burnout* (11), *Effort-Recovery Model* (12) and *Conservation of Resources Theory* (13)) into a cyclical model. In this model, resting HRV was positioned as a psychophysiological resource that is utilized during the appraisal of demands and emotion regulation with regard to stress, and gets drained after mental exhaustion. Based on population studies, having a high resting HRV was expected to result in lower stress in demanding circumstances (more favorable appraisal) (4–6), as well as to lower the impact of stress on mental exhaustion (more favorable emotion regulation) (7,8). Mental exhaustion was also expected to lower resting HRV (14–16), which would thus form a potential negative feedback loop where an initial loss of resources lowers the individual's resources to cope with upcoming demands and thus results in decreased resilience (13).

The study in chapter 4 tested these intra-day hypotheses in a group of 26 first-time interns that collected data during 15 weeks. This time, resting HRV was measured using a validated Bluetooth chest strap (Polar H7) (17) and smartphone app (Elite HRV) (18) in a supine position during 2 minutes upon awakening whereas the subjective items were again inquired via a short evening EMA questionnaire on a smartphone app. The results showed that, as expected, resting HRV buffered against the positive association between demands and stress (22% explained variance), as well as between stress and mental exhaustion (32% explained variance). This means that when participants woke up with a relatively high resting HRV, they were less likely to report a highly demanding day as stressful, and less likely to feel mentally exhausted after a stressful day. Since evening mental exhaustion also negatively predicted resting HRV on the subsequent morning (4% explained variance), the cyclical nature of the conceptual model in chapter 3 was confirmed. This finding aligns with the Conservation of Resources Theory, which states that an initial loss of resources increases one's vulnerability to upcoming stress, potentially leading to a loss spiral that negatively impacts resilience (13). Although this study itself exclusively assessed intra-day associations, these findings provided valuable insights in the mechanism of how changes in resting HRV could potentially have a cascading effect on subsequent days.

Building on chapters 3 and 4, the study in chapter 5 investigated to what extent resting HRV can also be predicted by and is predictive of subjective resilience-related outcomes on a multi-day level. Data of 8 police officers that were followed for 15-55 weeks were analyzed using in a multiple n-of-1 observational study. Participants continuously wore a smart ring (Oura ring, generation 2) that was validated for both sleep (19,20) and resting HRV (18,21,22) and filled in a short EMA questionnaire on their smartphone at the end of each day. Resting HRV could only be predicted based on prior-day demands in 1 participant, and was also predictive of demands (n=2), stress (n=1) and mental exhaustion (n=1) on subsequent days in some participants. Although the applied vector autoregression models could only be based on data of the preceding day (1 lag), impulse response functions revealed that the impact of a change in resting HRV could take multiple days to fade out due to the strong autoregression that was consistently observed for resting HRV itself. These results showed that resting HRV was a better predictor of subjective resilience-related outcomes than vice versa, and were only observed in a select number of participants.

Several overarching conclusions can be drawn from this. Taken together, these results confirm the potential of wearable-measured resting HRV as an index for resilience, but also show that the daily resting HRV values are by themselves insufficient to meaningfully guide resilience-related decision-making. The findings of chapters 2 to 5 also generally align with those of similar studies. For instance, a recent study found that within-subject differences in resting HRV buffered against the spillover of stress on negative affect (23), which is comparable to the buffering effects of resting HRV that were described in chapter 2. Another recent large-scale study found that mixed-effects generalized linear models could only explain an average of 1% of the variance in daytime stress based on wearable-measured HRV data and EMA questionnaires (24). The authors concluded that although HRV is clearly associated with perceived stress in laboratory settings, the strength of those associations diminishes in real-life settings. Although this association between daytime HRV and stress is even more likely to be confounded by factors like body posture (25), exercise (26) and the intake of caffeine (27) or alcohol (28), the overarching conclusion regarding the modest strength of these associations may also apply to the findings of chapters 2-5.

Stable daily resting HRV values as a demonstration of resilience

The studies in chapters 2 to 5 assessed HRV as an index for resilience ("higher is better"), but it is also possible to look at stability in daily resting HRV values during periods of adversity as a demonstration of resilience ("stable is better", chapter 6). This method originates from sports science, where researchers observed that athletes whose resting HRV values are stable on a day-to-day basis despite undergoing intensive training tend to respond better to training (29,30) and have a higher aerobic fitness (31–33). Seen through this lens, stable daily resting HRV values despite challenging circumstances are interpreted as a sign of positive adaptation, whereas increasing day-to-day fluctuations represent homeostatic disruptions that may result in cumulative wear and tear on bodily systems (allostatic load) (34,35). Increasing fluctuations in the daily resting HRV have also been linked to increased stress (36) and fatigue (37–39) in athletes, but were not yet explored in occupational settings. Despite being unexplored in this setting, the approach aligns with the Integrative Model of Resilience for Employees, which considers positive adaptation by maintaining optimal functioning despite adversity to be a demonstration of resilience (40).

The study that is described in chapter 6 utilized this approach to assess whether trends in the daily resting HRV and the fluctuations therein are associated with changes in stress, somatization, anxiety and depression in police officers. Nine police officers wore an Oura ring during 15-55 weeks and filled in a 5-weekly questionnaire on stress, somatization, anxiety and depression. The results showed that increasing trends in daily resting HRV fluctuations were associated with 5-week increases in stress and somatization. Trends in the daily resting HRV measurements themselves were not directly related to these outcomes, but increasing trends in resting HRV did buffer against the positive association between the daily resting HRV fluctuations and somatization. This means that increasing daily resting HRV fluctuations were only associated with somatization when the underlying daily resting HRV measurements themselves were trending down or neutral, but not when the daily measurements were increasing. After publication of the results described in chapter 6, a similar study in a healthy general population was published, and found that individuals with relatively high or more stable daily resting HRV measurements have more favorable health and lifestyle markers, including lower perceived stress (41). These results therefore show that besides having a relatively high resting HRV, having a relatively stable resting HRV on a day-to-day basis despite challenging circumstances or adversity can be seen as a sign of positive adaptation (e.g., the demands did not disrupt the balanced functioning of the autonomous nervous system), and thus as a demonstration of resilience (40).

Sleep as a predictor of resilience related outcomes

The third and final main outcome that was assessed as a potential predictor of resilience in this thesis (chapters 3 to 5) is Total Sleep Time (TST), which is the duration of the sleep episode without the sleep onset latency and waketime after sleep onset. In the conceptual model in chapter 3, TST was introduced as one of the variables reflecting the process of recovery. Based on prior research that showed that stress can negatively impact the recovery process by negatively impacting psychological detachment (42) and sleep (43), increased prior-day stress was expected to predict lower TST (hypothesis 1). Subsequently, TST was expected to moderate the hypothesized negative association between evening mental exhaustion and subsequent morning resting HRV (hypothesis 2) based on the Effort-Recovery Model (12). Neither hypothesis was confirmed in the study in chapter 4. Other studies have also observed stress to be an inconsistent predictor of TST (44).

The study in chapter 5, which analyzed n-of-1 data of 8 police officers via vector autoregression, also did not find stress, mental exhaustion and vigor to be significant predictors of TST in any participant, although increased demands did predict lower TST in 1 participant. On the other hand, increased TST did predict lower demands (n=2), stress (n=3) and mental exhaustion (n=5) on the subsequent day, as well as increased vigor (n=5) in multiple participants. TST therefore appears to be a stronger and/or more consistent predictor of resilience-related outcomes than an outcome variable that is impacted by them, which aligns with findings of prior studies (44–47). Impulse response functions showed that the impact of changes in TST only lasted for about 1 day, illustrating that these associations are of a short-term nature.

Methodological considerations

Although the studies described in chapters 2 to 6 use similar approaches to collect within-subject data on sleep and resting HRV, subtle nuances between these studies can be observed. This section will address several methodological considerations that were made in these studies and how in some cases follow-up studies iterated on prior data collections.

Sample size

Due to limitations in the available materials, budget and time, a choice had to be made between achieving (i) a sample with a larger number of participants (N) and lower number of observations per participant (n) via multiple data-collection waves, or (ii) a sample where a small number of individuals (N) are followed over a longer time span and thus a larger number of observations per participant (n). Exploring temporal within-subject associations between wearable-data and subjective outcomes was important for the overarching purpose of the WearMe study to contribute to systems that provide personalized risk-signaling and support. Therefore, a choice was made to prioritize a larger number of observations per participant over the total number of participants for the studies in chapters 3 to 6. This allowed us to contribute valuable insights based on longitudinal wearable data that was collected in a naturalistic real-world context which are needed for the current body of knowledge (3). As a resulting limitation of the described trade-off, the studies in this thesis were not equipped to draw conclusions on between-subject differences, for instance, concerning why certain associations were observed in some participants but not in others. The study in chapter 2 did have a larger number of participants (N=63) with a lower number of observations per participant (median n=15, maximum n=46) to accommodate the testing of intra-day, within-subject associations, but complementary between-subject models could not be formed due to privacy-related limitations (e.g., data on personal characteristics could not be collected).

Recruitment of healthy individuals in high-risk professions

The goal of the WearMe study was to develop models that may benefit the early detection of resilience-related problems. Therefore, all studies recruited samples with healthy adults, optimizing their generalizability for this preventive context. Due to the observational nature of these studies, it was unknown to what extent the participants would actually experience stress- and resilience-related problems. Since the presence of variance in the analyzed data is a pre-requisite for the development of relevant statistical models, participants were recruited in populations (military personnel, first-time interns and police officers) that were expected to be at risk for experiencing stress. However, chapter 2 showed that the military participants felt mentally (M=8.11, SD=1.27) and physically (M=7.84, SD=1.37) fit throughout the study, while only modest within-subject variation (CV=4.7%) in resting HRV was observed as well. Similarly, the police officers in chapters 5 and 6 reported moderate stress and somatization but had a total absence of symptoms of anxiety and depression. These participants attributed this to unusually quiet and predictable work environments due to lockdowns during the COVID-19 pandemic, which other European police officers also described (48). The resulting floor effects may have led to an underestimation of the strength of the reported associations (49). Therefore, it is unknown to what extent these findings also apply to individuals that are experiencing more extreme problems. Insight in the extent in which that is the case would benefit generalizability of the current findings, and thus allow for a potentially more diverse target group of future wearable-based resilience interventions that aim to prevent stress-related problems in employees.

Optimizing adherence

As described in the previous section, achieving a sample with sufficient observations per participant was necessary to create within-subject models. Besides collecting data over a sufficiently long period, ensuring completeness of the collected data is (at least) equally important. Therefore, the study protocol (chapter 3) for the study in chapter

4 described that participants would receive a gift voucher and individual feedback if they collected complete data for at least 80% of their full participation period. Although some participants did very well, just 42.2% (1,004 out of 2,379) of the total daily observations contained complete data of the participants' resting HRV, sleep and the morning and evening EMA questionnaires. Of these four measurements, the completeness for resting HRV data was the lowest (60.7%). The relatively low availability of resting HRV data was attributed to the protocol that asked participants to lie still and perform a 2-minute HRV measurement upon awakening, and even caused dropouts. While the data availability was sufficient to test the hypothesized within-subject nested, intra-day associations, it limited the possibilities to also assess temporal associations via time series analysis.

In preparation of the data-collection for the follow-up studies in chapters 5 and 6, three adaptations were made to the study protocol in order to improve adherence. First, the manual morning resting HRV measurement was replaced with an automatic nocturnal measurement via a wearable (Oura ring generation 2) that was validated for both sleep (19,20) and resting HRV (18,21,22). This reduced the number of measurement devices and allowed for a more passive data-collection. Second, the participants ordered a ring of their preferred size, shape and color, and were allowed to keep it if they collected complete data on at least 100 days (>71-95% of their expected participation period of 15 to 20 weeks), improving the reward threshold. Finally, the morning and evening EMA questionnaires were combined into a single evening EMA questionnaire and limited to 7 items. As a result, it was possible to send participants that forgot to fill in their evening questionnaire a reminder to do so on the next morning, which was particularly relevant for the police officers that also worked night shifts. The combination of these adjustments resulted in significantly more complete observations in the studies in chapters 5 (89.5%) and 5 (94.3% for sleep and resting HRV and 89.0% for EMA), allowing us to report on multi-day and -week associations.

Morning or nocturnal resting HRV measurements

The previous paragraphs described that in an iterative process, automated nocturnal HRV measurement was preferred over manual morning measurements. Although this adjustment was beneficial for adherence and made it possible to explore hypotheses that might not have been testable without it, there can be circumstances in which morning measurements may be preferrable. For instance, an older study (2011) found that between-subject differences in self-reported stress were related to a morning orthostatic (a protocol that includes a standing measurement) resting HRV measurement, but not nocturnal HRV (50). A possible explanation for this is the occurrence of parasympathetic saturation, which is a situation in which parasympathetic activity is high but not reflected well in HRV (51–53). Parasympathetic saturation is particularly observed in highly trained individuals (54), but may also occur in heart patients or healthy individuals with a low resting heart rate (53). It has been suggested that adding orthostatic stress and increase heart rate by measuring resting HRV upon awakening in a sitting (55) or standing (56) position, may help prevent parasympathetic saturation. However, parasympathetic saturation is not always eliminated by measuring resting HRV in an upright position (57) and standing measurements can vastly reduce compliance (52). To summarize, sitting or standing measurements upon awakening appear to be more ideal resting HRV measurements in individuals that are highly trained or have an otherwise very low resting heart rate and are motivated to adhere to a strict measurement protocol, but for the broader general public, the convenience of unobtrusive HRV measurements during sleep are more likely to result in usable data. All things considered, for future wearable-based resilience interventions that aim to reach a relatively broad audience, unobtrusive nocturnal HRV measurements are therefore likely the best option.

Inter-beat-interval data processing

For accurate wearable-based HRV measurements, it is important to apply appropriate data processing methods, as photoplethysmography measurements are susceptible to motion artefacts (58). Motion artefacts particularly influence frequency domain HRV parameters, whereas time domain parameters are more robust (58,59). As a result, both wearable-based HRV research and wearable manufacturers have converged to using the root Mean Square of the Successive Differences (rMSSD), which reflects parasympathetic nervous system activity, as a primary HRV metric (60). The studies in this thesis have utilized several different methods for measuring resting HRV data. These can largely be grouped into (i) custom resting HRV calculation based on self-collected and -processed inter-beat-interval data, and (ii) HRV measurements derived from wearables using proprietary but validated algorithms.

Due to privacy-related considerations, the data of the study in chapter 2 was not allowed to be stored on external servers. As a practical implication, it was necessary to directly derive and process heart rate and accelerometer data from the wearable. An open-source algorithm was used to detect sleep (61), of which the inter-beat-intervals were also analyzed using a publicly available artefact correction method (17). Using a validated wearable was preferred for the study in chapters 3 and 4 but unavailable at that time. Electrocardiography-based measurements using a validated Polar H7 chest strap (17) were found to be best alternative with regard to the validity and feasibility of the measurements. The resulting inter-beat-intervals were processed using an algorithm in a publicly available R-package (62), after which it was necessary to also remove within-subject outliers with values with extreme values (>1.5 interquartile range above the first quartile or below the third quartile) to clean the data. The follow-up study in chapters 5 and 6 used the Oura ring (2nd generation), which was by then validated for both TST (19,20) and resting HRV (18,21,22). Since the accuracy of nocturnal HRV measurements indirectly depends on the accuracy of sleep detection (e.g., to limit motion artefacts during an awake state), using a wearable that is validated for both 2-stage (sleep/wake) sleep detection and HRV measurement itself is important.

Future directions of wearable-based resilience modelling

This thesis provided a first exploration of the potential of wearable sensor technology for modelling stress resilience. Although valuable insights were gained, future research is needed to confirm and expand on the presented findings. This section discusses recommendations and potential directions for future research regarding the improvement of current within-subject models, the potential expansion towards between-subject models and the eventual development of personalized feedback and applications.

Recommendations for studies based on the current findings

This thesis introduced novel insights on within-subject associations of wearable-based sleep and resting HRV measurements with resilience-related outcomes that need to be confirmed. Three practical methodological recommendations for similar research efforts can be made. First, future studies are recommended to use a wearable that can validly and automatically measure sleep and nocturnal resting HRV. In sub-populations that have a very low resting heart rate (e.g., highly trained individuals or patients that use heart rate suppressing medication) and are motivated to adhere to a strict measurement protocol, morning resting HRV measurements in a sitting or standing position may be more expressive. Second, studies that are processing inter-beat-intervals themselves are recommended to consider the methods that were used in chapter 2 (a well-described method in prior research (52)) over those used in chapter 4 (the combination of a publicly-available R package (62) and removing within-subject outliers), as the former do not rely on measurements outside of the HRV measurement that is being processed. Finally, adherence may be improved by minimizing the number of measurement devices and -moments and appropriately rewarding participants for adhering to the measurement protocol.

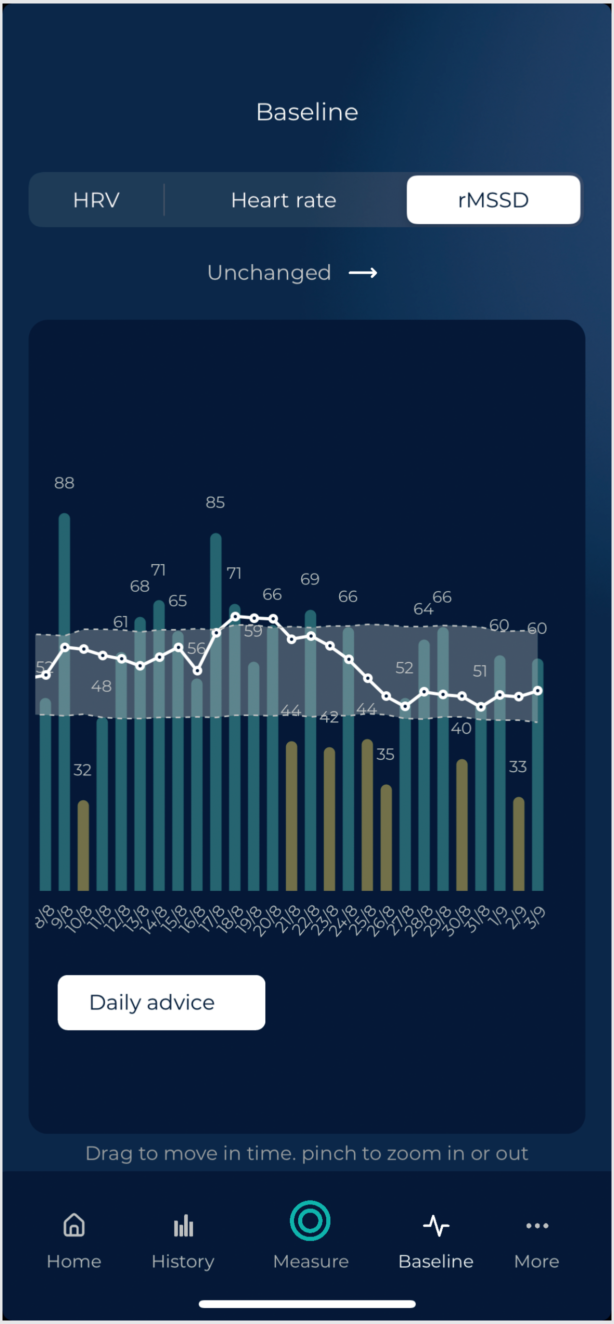
Besides confirmation and further exploration of the current results, two recommendations on different design and statistical approaches can be made. First, future studies with a large number observations per individual are encouraged to explore to what extent the strength of the associations between wearable-based metrics and subjective resilience-related outcomes changes over time, for instance via Time-Varying Vector-Auto-Regression (TV-VAR) analysis (63). Such insights may improve our understanding of why the associations in chapter 5 were not consistently observed, as well as potentially benefit personalization in future interventions. Second, future studies with a large number of participants are recommended to investigate if between-subject differences in the strength of the associations between wearable-based metrics and subjective resilience-related outcomes can be explained by participant characteristics, for instance via Multi-Level Vector-Auto-Regression (ML-VAR) (64). Such models may be able to distinguish differences in resilience between individuals based on stable characteristics (e.g., gender, age, personality traits), before any of the continuous within-subject data (e.g., resting HRV or sleep) is collected. Since a certain amount of this continuous data needs to be collected to form within-subject models, future interventions would benefit from between-subject models that can provide semi-personalized feedback while the system is still gathering the within-subject data that is needed to provide fully personalized feedback (65).

Finally, it may be interesting for future studies to explore similarities in and differences between the type of field studies in this thesis and studies in laboratory conditions. Similarities between both types of research provides confluence that strengthens confidence in existing theories, whereas differences could inspire the development and testing of new theories.

Interpretation of daily resting HRV measurements

This thesis investigated resting HRV as an index for resilience ("higher is better", chapters 2 to 5) and trends in the day-to-day fluctuations therein as a demonstration of resilience ("stable is better", chapter 6). A third approach is to assess how (un)usual daily resting HRV measurements are in comparison to intra-individual norms ("normal is better"), where values that deviate (e.g., 0.5 or 1 standard deviation) from a longer-term (e.g., 4 to 8 weeks) rolling within-subject mean are labelled as abnormal disruptions of the balanced functioning of the autonomous nervous system that may signal increased physiological stress and/or insufficient recovery from previous mental or physical demands (66–68). This approach is currently unexplored in psychological resilience research but common in HRV guided training (69). An interesting and promising application of such an approach is described in Box 1.

Box 1: Using personalized norm zones to detect abnormal HRV values



An example of an HRV guided training application that uses the "normal is better" approach is HRV4training Pro (70), a smartphone app that provides personalized training recommendations based on a combination of resting HRV and subjective inputs on perceived sleep, fatigue, soreness, stress and more. The app displays a personal norm zone (the translucent white band) that is based on historical measurements (1 standard deviation around the rolling 60-day mean), a rolling weekly mean (white line) and each of the daily measurements (colored bars) that are color-coded by the daily advice on whether to "proceed as planned" (green), "limit intensity today" (yellow) or "take it easy today" (red, not displayed here). The displayed data are of the author of this thesis and contain values of a relatively care-free summer holiday but with unusually high training volume (dates up to 20-8) and the return home with lower training volume but relatively long workdays in order to finish this thesis, illustrating the relative impact of mental demands on resting HRV in comparison to physical demands. The daily resting HRV measurements with values below the norm zone triggered recommendations to limit intensity on those days, and here particularly occurred during the period with relatively low training load but high mental workload. In this example, the measurements with values above the norm zone were not flagged because they were combined with positive subjective inputs, but can also trigger a warning when the subjective inputs are less favorable. From this perspective, resting HRV values that deviate from the personal norm reflect an imbalance in the autonomous nervous system, where extremely low values represent abnormally high sympathetic activity and extremely high values represent abnormally high parasympathetic activity. This approach has been applied in numerous athletic studies for over a decade (66–68), in which extreme deviations in daily resting HRV are for instance associated with suboptimal athletic performance on that day (71). The applicability of this specific "normal is better" approach for stress resilience modelling and/or providing feedback is currently unexplored.

Promising developments in wearable sensors and related technologies

The studies that are described in this thesis reported modest associations between resting HRV, TST and subjective resilience-related outcomes. It may be possible to increase the explained variance by including additional relevant metrics to these models. When it comes to wearables, several potentially interesting developments may introduce new opportunities for this on a short-term basis. Current consumer-available wearables are generally considered to be valid for sleep-wake detection but not for 5-stage sleep stage measurement (72), but vastly improved algorithms have recently been announced (73). Since the impact of emotions on sleep can differ per sleep stage (74), more accurate wearable-based sleep stage detection could contribute to a more detailed understanding of associations between sleep and resilience. Another current development is the addition of continuous electrodermal activity (EDA) sensors in consumer-available wearables (e.g., in the Fitbit Sense 2 that was announced in August 2022). EDA sensors assess (changes in) the electrical conductivity of the skin and can, particularly when combined with other metrics such as HRV, contribute to automatic stress detection (75). Although the accuracy of these sensors needs to be verified first, the prospect of unobtrusively quantifying an individual's daily (emotional) burden is conceptually interesting for resilience modelling.

In more fundamental research, several other promising developments may also eventually trickle down towards consumer-available wearable systems. One example of this is the noninvasive detection of the stress hormone cortisol via wearable-based sweat analysis (76). By triangulating the current autonomic nervous system-based metrics (e.g., HRV) with endocrine system-based metrics like this, it may be possible to better distinguish when an aroused state also has hormonal impacts that may impact health and well-being. Similarly, wearable-based solutions for noninvasive continuous glucose monitoring are currently being investigated (77). Since changes in blood glucose levels influence cognitive performance (78), wearable-based continuous glucose monitoring may also be relevant for stress resilience modelling. Finally, recent explorations of electrogastrography (EGG) provide intriguing prospects. EGG measures gut activity and has been used to estimate affect (79). Since current wearable-based metrics for stress recognition (e.g., HRV) are particularly good at detecting arousal, adding sensors that can also estimate emotional valence would allow more nuanced distinguishment of emotional stages as proposed by the circumplex model of affect (80), sometimes also referred to as the Valence-Arousal model.

Several recent studies showed that affect can be also predicted by complementing wearable data (e.g., sleep, physical activity, heart rate, HRV) with smartphone use and/or geolocation data (81–84). Although the specific metrics that were used differed between these studies, the machine learning models in these studies all achieved a similar an Area Under the Curve (AUC) of the receiver operating characteristic of up to 0.81-0.82 (81,83,84). This also highlights the potential of machine learning to generate well-performing models. The studies in this thesis utilized a deductive approach to formally test hypotheses that were driven by fundamental reasoning and prior studies. As our understanding of these associations improves and research efforts gradually move towards implementation in Just-In-Time Adaptive Interventions (JITAI) that aim to have a real-world impact (85), inductive machine learning approaches may be more beneficial to optimize model performance. Improved model performance would mean that the envisioned resilience interventions are able to provide more accurate personalized feedback. As such, they would be more equipped to contribute to the prevention of the stress-related problems that are currently posing a major burden on society (86).

To conclude

This thesis explored to what extent subjective resilience-related outcomes can be modelled based on data that is derived from wearables and apps. The chapters in this thesis showed that (i) waking up with a relatively high resting HRV compared to one's own norm is positive in the context of resilience, (ii) having relatively stable daily resting HRV values during periods of adversity can be seen as a demonstration of resilience, and (iii) subjective resilience-related outcomes tend to be more favorable after nights with a relatively high TST. However, the explained variance in these models was modest and some of the observed associations were not consistently observed in all cases. Future studies that investigate potential changes of the strength of these associations in specific conditions or between individuals are therefore needed. Furthermore, complementing the current models by adding additional variables (e.g., EDA, smartphone use, geolocation, etc.) and using more inductive approaches (e.g., machine learning) can be considered to generate high-performing models for resilience. If successful, such models can be implemented in automated interventions that provide personalized and just-in-time feedback on resilience based on unobtrusive monitoring via wearables and apps.

REFERENCES

1. Heiss S, Vaschillo B, Vaschillo EG, Timko CA, Hormes JM. Heart rate variability as a biobehavioral marker of diverse psychopathologies: A review and argument for an “ideal range.” Neuroscience & Biobehavioral Reviews. 2021;121:144–155. doi: 10.1016/j.neubiorev.2020.12.004.

2. An E, Nolty AAT, Amano SS, Rizzo AA, Buckwalter JG, Rensberger J. Heart Rate Variability as an Index of Resilience. Military Medicine. 2020;185:363–369. doi: 10.1093/milmed/usz325.

3. Perna G, Riva A, Defillo A, Sangiorgio E, Nobile M, Caldirola D. Heart rate variability: Can it serve as a marker of mental health resilience?: Special Section on “Translational and Neuroscience Studies in Affective Disorders” Section Editor, Maria Nobile MD, PhD. Journal of Affective Disorders. 2020;263:754–761. doi: 10.1016/j.jad.2019.10.017.

4. Park G, Vasey MW, Van Bavel JJ, Thayer JF. When tonic cardiac vagal tone predicts changes in phasic vagal tone: The role of fear and perceptual load. Psychophysiology. 2014;51:419–426. doi: 10.1111/psyp.12186.

5. Park G, Thayer JF. From the heart to the mind: cardiac vagal tone modulates top-down and bottom-up visual perception and attention to emotional stimuli. Frontiers in Psychology [Internet]. 2014;5. doi: 10.3389/fpsyg.2014.00278.

6. Gaebler M, Daniels JK, Lamke J-P, Fydrich T, Walter H. Heart rate variability and its neural correlates during emotional face processing in social anxiety disorder. Biological Psychology. 2013;94:319–330. doi: 10.1016/j.biopsycho.2013.06.009.

7. Mather M, Thayer JF. How heart rate variability affects emotion regulation brain networks. Current Opinion in Behavioral Sciences. 2018;19:98–104. doi: 10.1016/j.cobeha.2017.12.017.

8. Holzman JB, Bridgett DJ. Heart rate variability indices as bio-markers of top-down self-regulatory mechanisms: A meta-analytic review. Neuroscience & Biobehavioral Reviews. 2017;74:233–255. doi: 10.1016/j.neubiorev.2016.12.032.

9. Magnon V, Vallet GT, Benson A, Mermillod M, Chausse P, Lacroix A, Bouillon-Minois J-B, Dutheil F. Does heart rate variability predict better executive functioning? A systematic review and meta-analysis. Cortex. 2022;155:218–236. doi: 10.1016/j.cortex.2022.07.008.

10. Lazarus RS, Folkman S. Transactional theory and research on emotions and coping. Eur J Pers. 1987;1:141–169. doi: 10.1002/per.2410010304.

11. Bakker AB, Demerouti E. The Job Demands-Resources model: state of the art. Journal of Managerial Psychology. 2007;22:309–328. doi: 10.1108/02683940710733115.

12. van Veldhoven MJPM. Need for recovery after work: An overview of construct, measurement and research [Internet]. Houdmont J, Leka S, editors. 3. Nottingham University Press; 2008. Available from: https://research.tilburguniversity.edu/en/publications/bbdeef64-c338-4d48-b93f-152afe2ac5ef.

13. Hobfoll SE. The Influence of Culture, Community, and the Nested-Self in the Stress Process: Advancing Conservation of Resources Theory. Applied Psychology. 2001;50:337–421. doi: 10.1111/1464-0597.00062.

14. Kim H-G, Cheon E-J, Bai D-S, Lee YH, Koo B-H. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Psychiatry Investig. 2018;15:235–245. doi: 10.30773/pi.2017.08.17.

15. Hall M, Vasko R, Buysse D, Ombao H, Chen Q, Cashmere JD, Kupfer D, Thayer JF. Acute Stress Affects Heart Rate Variability During Sleep. Psychosomatic Medicine [Internet]. 2004;66. doi: 10.1097/01.PSY.0000106884.58744.09.

16. Thayer JF, Sternberg E. Beyond Heart Rate Variability. Annals of the New York Academy of Sciences. 2006;1088:361–372. doi: 10.1196/annals.1366.014.

17. Plews DJ, Scott B, Altini M, Wood M, Kilding AE, Laursen PB. Comparison of Heart-Rate-Variability Recording With Smartphone Photoplethysmography, Polar H7 Chest Strap, and Electrocardiography. International Journal of Sports Physiology and Performance. 2017;12:1324–1328. doi: 10.1123/ijspp.2016-0668.

18. Stone JD, Ulman HK, Tran K, Thompson AG, Halter MD, Ramadan JH, Stephenson M, Finomore VS, Galster SM, Rezai AR, et al. Assessing the Accuracy of Popular Commercial Technologies That Measure Resting Heart Rate and Heart Rate Variability. Frontiers in Sports and Active Living [Internet]. 2021;3. doi: 10.3389/fspor.2021.585870.

19. de Zambotti M, Rosas L, Colrain IM, Baker FC. The Sleep of the Ring: Comparison of the ŌURA Sleep Tracker Against Polysomnography. Behavioral Sleep Medicine. 2019;17:124–136. doi: 10.1080/15402002.2017.1300587.

20. Chee NIYN, Ghorbani S, Golkashani HA, Leong RLF, Ong JL, Chee MWL. Multi-Night Validation of a Sleep Tracking Ring in Adolescents Compared with a Research Actigraph and Polysomnography. Nat Sci Sleep. 2021;13:177–190. doi: 10.2147/NSS.S286070. Cited: in: : PMID: 33623459.

21. Kinnunen H, Rantanen A, Kenttä T, Koskimäki H. Feasible assessment of recovery and cardiovascular health: accuracy of nocturnal HR and HRV assessed via ring PPG in comparison to medical grade ECG. Physiological Measurement. 2020;41:04NT01. doi: 10.1088/1361-6579/ab840a.

22. Cao R, Azimi I, Sarhaddi F, Niela-Vilen H, Axelin A, Liljeberg P, Rahmani AM. Accuracy Assessment of Oura Ring Nocturnal Heart Rate and Heart Rate Variability in Comparison With Electrocardiography in Time and Frequency Domains: Comprehensive Analysis. J Med Internet Res. 2022;24:e27487. doi: 10.2196/27487.

23. da Estrela C, MacNeil S, Gouin J-P. Heart rate variability moderates the between- and within-person associations between daily stress and negative affect. International Journal of Psychophysiology. 2021;162:79–85. doi: 10.1016/j.ijpsycho.2021.02.001.

24. Martinez GJ, Grover T, Mattingly SM, Mark G, D'Mello S, Aledavood T, Akbar F, Robles-Granda P, Striegel A. Alignment Between Heart Rate Variability From Fitness Trackers and Perceived Stress: Perspectives From a Large-Scale In Situ Longitudinal Study of Information Workers. JMIR Hum Factors. 2022;9:e33754. doi: 10.2196/33754.

25. Buchheit M, Al Haddad H, Laursen PB, Ahmaidi S. Effect of body posture on postexercise parasympathetic reactivation in men. Experimental Physiology. 2009;94:795–804. doi: 10.1113/expphysiol.2009.048041.

26. Michael S, Graham KS, Davis GM. Cardiac Autonomic Responses during Exercise and Post-exercise Recovery Using Heart Rate Variability and Systolic Time Intervals—A Review. Frontiers in Physiology [Internet]. 2017;8. doi: 10.3389/fphys.2017.00301.

27. Koenig J, Jarczok MN, Kuhn W, Morsch K, Schäfer A, Hillecke TK, Thayer JF. Impact of Caffeine on Heart Rate Variability: A Systematic Review. Journal of Caffeine Research. 2013;3:22–37. doi: 10.1089/jcr.2013.0009.

28. Romanowicz M, Schmidt JE, Bostwick JM, Mrazek DA, Karpyak VM. Changes in Heart Rate Variability Associated With Acute Alcohol Consumption: Current Knowledge and Implications for Practice and Research. Alcohol: Clinical and Experimental Research. 2011;35:1092–1105. doi: 10.1111/j.1530-0277.2011.01442.x.

29. Flatt AA, Esco MR. Evaluating Individual Training Adaptation With Smartphone-Derived Heart Rate Variability in a Collegiate Female Soccer Team. The Journal of Strength & Conditioning Research. 2016;30:378–385. doi: 10.1519/JSC.0000000000001095.

30. Flatt AA, Howells D. Effects of varying training load on heart rate variability and running performance among an Olympic rugby sevens team. Journal of Science and Medicine in Sport. 2019;22:222–226. doi: 10.1016/j.jsams.2018.07.014.

31. Boullosa DA, Abreu L, Nakamura FY, Muñoz VE, Domínguez E, Leicht AS. Cardiac Autonomic Adaptations in Elite Spanish Soccer Players During Preseason. International Journal of Sports Physiology and Performance. 2013;8:400–409. doi: 10.1123/ijspp.8.4.400.

32. González-Fimbres RA, Hernández-Cruz G, Flatt AA. Ultrashort Versus Criterion Heart Rate Variability Among International-Level Girls' Field Hockey Players. International Journal of Sports Physiology and Performance. 2021;16:985–992. doi: 10.1123/ijspp.2020-0362.

33. Flatt AA, Esco MR, Nakamura FY, Plews DJ. Interpreting daily heart rate variability changes in collegiate female soccer players. J Sports Med Phys Fitness. 2017;57:907–915. doi: 10.23736/S0022-4707.16.06322-2. Cited: in: : PMID: 26997322.

34. McEwen BS. Stress, Adaptation, and Disease: Allostasis and Allostatic Load. Annals of the New York Academy of Sciences. 1998;840:33–44. doi: 10.1111/j.1749-6632.1998.tb09546.x.

35. Seeman TE, Singer BH, Rowe JW, Horwitz RI, McEwen BS. Price of Adaptation—Allostatic Load and Its Health Consequences: MacArthur Studies of Successful Aging. Archives of Internal Medicine. 1997;157:2259–2268. doi: 10.1001/archinte.1997.00440400111013.

36. Flatt AA, Esco MR, Nakamura FY. Individual Heart Rate Variability Responses to Preseason Training in High Level Female Soccer Players. The Journal of Strength & Conditioning Research [Internet]. 2017;31. doi: 10.1519/JSC.0000000000001482.

37. Perrotta AS, Koehle MS, White MD, Taunton JE, Warburton DER. Consecutive non-training days over a weekend for assessing cardiac parasympathetic variation in response to accumulated exercise stress. European Journal of Sport Science. 2020;20:1072–1082. doi: 10.1080/17461391.2019.1688397.

38. Flatt AA, Esco MR. Smartphone-Derived Heart-Rate Variability and Training Load in a Women's Soccer Team. International Journal of Sports Physiology and Performance. 2015;10:994–1000. doi: 10.1123/ijspp.2014-0556.

39. Schmitt L, Regnard J, Desmarets M, Mauny F, Mourot L, Fouillot J-P, Coulmy N, Millet G. Fatigue Shifts and Scatters Heart Rate Variability in Elite Endurance Athletes. PLOS ONE. 2013;8:e71588. doi: 10.1371/journal.pone.0071588.

40. Britt TW, Shen W, Sinclair RR, Grossman MR, Klieger DM. How Much Do We Really Know About Employee Resilience? Industrial and Organizational Psychology. 2016/07/04 ed. 2016;9:378–404. doi: 10.1017/iop.2015.107.

41. Grosicki GJ, Culver MN, McMillan NK, Cross BL, Montoye AHK, Riemann BL, Flatt AA. Self-recorded heart rate variability profiles are associated with health and lifestyle markers in young adults. Clin Auton Res. 2022; doi: 10.1007/s10286-022-00884-z. Cited: in: : PMID: 35999422.

42. Sonnentag S, Kuttler I, Fritz C. Job stressors, emotional exhaustion, and need for recovery: A multi-source study on the benefits of psychological detachment. Journal of Vocational Behavior. 2010;76:355–365. doi: 10.1016/j.jvb.2009.06.005.

43. Kim E-J, Dimsdale JE. The Effect of Psychosocial Stress on Sleep: A Review of Polysomnographic Evidence. Behavioral Sleep Medicine. 2007;5:256–278. doi: 10.1080/15402000701557383.

44. Ekuni R, Souza BMN, Cogo-Moreira H, Lourenço FC, Pompeia S. Bidirectional longitudinal dynamics of self-reported total sleep time and perceived stress: Establishing potential causal relationships. Sleep Health. 2022;8:406–409. doi: 10.1016/j.sleh.2022.01.004.

45. Narmandakh A, Oldehinkel AJ, Masselink M, de Jonge P, Roest AM. Affect, worry, and sleep: Between- and within-subject associations in a diary study. Journal of Affective Disorders Reports. 2021;4:100134. doi: 10.1016/j.jadr.2021.100134.

46. Yap Y, Slavish DC, Taylor DJ, Bei B, Wiley JF. Bi-directional relations between stress and self-reported and actigraphy-assessed sleep: a daily intensive longitudinal study. Sleep. 2020;43:zsz250. doi: 10.1093/sleep/zsz250.

7

47. Lee S, Crain TL, McHale SM, Almeida DM, Buxton OM. Daily antecedents and consequences of nightly sleep. Journal of Sleep Research. 2017;26:498–509. doi: 10.1111/jsr.12488.

48. Frenkel MO, Giessing L, Egger-Lampl S, Hutter V, Oudejans RRD, Kleygrewe L, Jaspaert E, Plessner H. The impact of the COVID-19 pandemic on European police officers: Stress, demands, and coping resources. Journal of Criminal Justice. 2021;72:101756. doi: 10.1016/j.jcrimjus.2020.101756.

49. Šimkovic M, Träuble B. Robustness of statistical methods when measure is affected by ceiling and/or floor effect. PLOS ONE. 2019;14:e0220889. doi: 10.1371/journal.pone.0220889.

50. Hynynen E, Konttinen N, Kinnunen U, Kyröläinen H, Rusko H. The incidence of stress symptoms and heart rate variability during sleep and orthostatic test. European Journal of Applied Physiology. 2011;111:733–741. doi: 10.1007/s00421-010-1698-x.

51. Goldberger JJ, Challapalli S, Tung R, Parker MA, Kadish AH. Relationship of Heart Rate Variability to Parasympathetic Effect. Circulation. 2001;103:1977–1983. doi: 10.1161/01.CIR.103.15.1977.

52. Plews DJ, Laursen PB, Buchheit M. Day-to-Day Heart-Rate Variability Recordings in World-Champion Rowers: Appreciating Unique Athlete Characteristics. International Journal of Sports Physiology and Performance. 2017;12:697–703. doi: 10.1123/ijspp.2016-0343.

53. Kiviniemi AM, Hautala AJ, Seppänen T, Mäkikallio TH, Huikuri HV, Tulppo MP. Saturation of high-frequency oscillations of R-R intervals in healthy subjects and patients after acute myocardial infarction during ambulatory conditions. American Journal of Physiology-Heart and Circulatory Physiology. 2004;287:H1921–H1927. doi: 10.1152/ajpheart.00433.2004.

54. Buchheit M, Simon C, Piquard F, Ehrhart J, Brandenberger G. Effects of increased training load on vagal-related indexes of heart rate variability: a novel sleep approach. American Journal of Physiology-Heart and Circulatory Physiology. 2004;287:H2813–H2818. doi: 10.1152/ajpheart.00490.2004.

55. Stanley J, Peake JM, Buchheit M. Cardiac Parasympathetic Reactivation Following Exercise: Implications for Training Prescription. Sports Medicine. 2013;43:1259–1277. doi: 10.1007/s40279-013-0083-4.

56. Mourot L, Bouhaddi M, Perrey S, Rouillon J-D, Regnard J. Quantitative Poincaré plot analysis of heart rate variability: effect of endurance training. European Journal of Applied Physiology. 2004;91:79–87. doi: 10.1007/s00421-003-0917-0.

57. Kiviniemi AM, Hautala AJ, Kinnunen H, Tulppo MP. Endurance training guided individually by daily heart rate variability measurements. European Journal of Applied Physiology. 2007;101:743–751. doi: 10.1007/s00421-007-0552-2.

58. Baek HJ, Shin J. Effect of Missing Inter-Beat Interval Data on Heart Rate Variability Analysis Using Wrist-Worn Wearables. Journal of Medical Systems. 2017;41:147. doi: 10.1007/s10916-017-0796-2.

59. Sheridan DC, Dehart R, Lin A, Sabbaj M, Baker SD. Heart Rate Variability Analysis: How Much Artifact Can We Remove? Psychiatry Investig. 2020;17:960–965. doi: 10.30773/pi.2020.0168. Cited: in: : PMID: 33017533.

60. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Frontiers in Public Health [Internet]. 2017;5. doi: 10.3389/fpubh.2017.00258.

61. van Hees VT, Sabia S, Anderson KN, Denton SJ, Oliver J, Catt M, Abell JG, Kivimäki M, Trenell MI, Singh-Manoux A. A Novel, Open Access Method to Assess Sleep Duration Using a Wrist-Worn Accelerometer. PLOS ONE. 2015;10:e0142533. doi: 10.1371/journal.pone.0142533.

62. Martínez CAG, Quintana AO, Vila XA, Touriño MJL, Rodríguez-Liñares L, Presedo JMR, Penín AJM. Heart rate variability analysis with the R package RHRV. Springer; 2017.

63. Haslbeck JMB, Bringmann LF, Waldorp LJ. A Tutorial on Estimating Time-Varying Vector Autoregressive Models. Multivariate Behavioral Research. 2021;56:120–149. doi: 10.1080/00273171.2020.1743630.

64. Epskamp S, Deserno MK, Bringmann LF. mlVAR: Multi-Level Vector Autoregression [Internet]. 2021. Available from: https://CRAN.R-project.org/package=mlVAR.

65. Spanakis G, Weiss G, Boh B, Lemmens L, Roefs A. Machine learning techniques in eating behavior e-coaching. Personal and Ubiquitous Computing. 2017;21:645–659. doi: 10.1007/s00779-017-1022-4.

66. Kiviniemi AM, Hautala AJ, Kinnunen H, Nissilä J, Virtanen P, Karjalainen J, Tulppo MP. Daily exercise prescription on the basis of HR variability among men and women. Med Sci Sports Exerc. 2010;42:1355–1363. doi: 10.1249/mss.0b013e3181cd5f39.

67. Vesterinen V, Nummela A, Heikura I, Laine T, Hynynen E, Botella J, Häkkinen K. Individual Endurance Training Prescription with Heart Rate Variability. Med Sci Sports Exerc. 2016;48:1347–1354. doi: 10.1249/MSS.0000000000000910. Cited: in: : PMID: 26909534.

68. Plews DJ, Laursen PB, Stanley J, Kilding AE, Buchheit M. Training Adaptation and Heart Rate Variability in Elite Endurance Athletes: Opening the Door to Effective Monitoring. Sports Medicine. 2013;43:773–781. doi: 10.1007/s40279-013-0071-8.

69. Lundstrom CJF Nicholas A; Biltz, George. Practices and Applications of Heart Rate Variability Monitoring in Endurance Athletes. Int J Sports Med. 2022;44:9–19. doi: 10.1055/a-1864-9726.

70. Altini M. HRV4Training [Internet]. HRV4Training. [cited 2022 Oct 2]. Available from: https://www.hrv4training.com/.

71. DeBlauw J, Crawford D, Stein J, Lewis A, Heinrich K. Association of Heart Rate Variability and Simulated Cycling Time Trial Performance. J Sci Cycling. 2021;10:25–33. doi: 10.28985/1221.jsc.09.

72. de Zambotti M, Cellini N, Menghini L, Sarlo M, Baker FC. Sensors Capabilities, Performance, and Use of Consumer Sleep Technology. Sleep Medicine Clinics. 2020;15:1–30. doi: 10.1016/j.jsmc.2019.11.003.

73. Altini M, Kinnunen H. The Promise of Sleep: A Multi-Sensor Approach for Accurate Sleep Stage Detection Using the Oura Ring. Sensors. 2021;21. doi: 10.3390/s21134302.

74. Fairholme CP, Manber R. Chapter 3 - Sleep, Emotions, and Emotion Regulation: An Overview. In: Babson KA, Feldner MT, editors. Sleep and Affect [Internet]. San Diego: Academic Press; 2015. p. 45–61. Available from: https://www.sciencedirect.com/science/article/pii/B9780124171886000037.

75. Alberdi A, Aztiria A, Basarab A. Towards an automatic early stress recognition system for office environments based on multimodal measurements: A review. Journal of Biomedical Informatics. 2016;59:49–75. doi: 10.1016/j.jbi.2015.11.007.

76. Wang B, Zhao C, Wang Z, Yang K-A, Cheng X, Liu W, Yu W, Lin S, Zhao Y, Cheung KM, et al. Wearable aptamer-field-effect transistor sensing system for noninvasive cortisol monitoring. Science Advances. 2022;8:eabk0967. doi: 10.1126/sciadv.abk0967.

77. Zafar H, Channa A, Jeoti V, Stojanović GM. Comprehensive Review on Wearable Sweat-Glucose Sensors for Continuous Glucose Monitoring. Sensors. 2022;22:638. doi: 10.3390/s22020638.

78. Feldman J, Barshi I. The effects of blood glucose levels on cognitive performance: A review of the literature. NASA Technical Reports Server. 2007;

79. Vujic A, Tong S, Picard R, Maes P. Going with our Guts: Potentials of Wearable Electrogastrography (EGG) for Affect Detection. Proceedings of the 2020 International Conference on Multimodal Interaction [Internet]. New York, NY, USA: Association for Computing Machinery; 2020 [cited 2022 Aug 25]. p. 260–268. Available from: https://doi.org/10.1145/3382507.3418882.

80. Posner J, Russell JA, Peterson BS. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and Psychopathology. 2005/11/01 ed. 2005;17:715–734. doi: 10.1017/S0954579405050340.

81. Jafarlou S, Lai J, Mousavi Z, Labbaf S, Jain R, Dutt N, Borelli J, Rahmani A. Objective Prediction of Tomorrow's Affect Using Multi-Modal Physiological Data and Personal Chronicles: A Study of Monitoring College Student Well-being in 2020. arXiv preprint arXiv:220111230. 2022;

82. Moshe I, Terhorst Y, Opoku Asare K, Sander LB, Ferreira D, Baumeister H, Mohr DC, Pulkki-Råback L. Predicting Symptoms of Depression and Anxiety Using Smartphone and Wearable Data. Frontiers in Psychiatry [Internet]. 2021;12. doi: 10.3389/fpsyt.2021.625247.

83. Opoku Asare K, Moshe I, Terhorst Y, Vega J, Hosio S, Baumeister H, Pulkki-Råback L, Ferreira D. Mood ratings and digital biomarkers from smartphone and wearable data differentiates and predicts depression status: A longitudinal data analysis. Pervasive and Mobile Computing. 2022;83:101621. doi: 10.1016/j.pmcj.2022.101621.

84. Sükei E, Norbury A, Perez-Rodriguez MM, Olmos PM, Artés A. Predicting Emotional States Using Behavioral Markers Derived From Passively Sensed Data: Data-Driven Machine Learning Approach. JMIR Mhealth Uhealth. 2021;9:e24465. doi: 10.2196/24465.

85. Wang L, Miller LC. Just-in-the-Moment Adaptive Interventions (JITAI): A Meta-Analytical Review. Health Communication. 2020;35:1531–1544. doi: 10.1080/10410236.2019.1652388.

86. Hassard J, Teoh KRH, Visockaite G, Dewe P, Cox T. The cost of work-related stress to society: A systematic review. Journal of Occupational Health Psychology. 2018;23:1–17. doi: 10.1037/ocp0000069.

APPENDICES

SUMMARY

Introduction

As soon as a human being is exposed to demanding conditions, the brain subconsciously determines whether there are sufficient resources available to deal with the situation (for example: adequate physical and mental fitness). If there are, the brain interprets the situation as a challenge. If there are not, the brain interprets it as a threat. The latter evokes a state of tension that is also referred to as 'stress'. Stress prepares the body for 'fight or flight'. This is highly useful when facing traditional threats, such as predators, but is often less useful for modern threats, such as deadlines and social interactions. Stress suppresses the prefrontal cortex, which is the part of the brain that is responsible for decision-making and social behavior. It also suppresses the amygdala, which is the brain's emotional alarm center. Stress feels annoying and can be inconvenient, but when it persists for a long time, it can also contribute to the development of physical and mental health problems, reduced productivity, and absenteeism. Early recognition of stress-related problems or of reduced resilience (the capacity to adaptively cope with stress) can therefore serve as a timely warning to change something, and can even support to prevention.

Recent developments in wearable sensor technology, also known as wearables, offer promising opportunities for such early detection of problematic stress. Wearables initially became popular for tracking exercise, but are now also able to measure sleep and bodily signals such as heart rate variability (HRV). HRV is a measure for the amount of variation between heartbeats and reflects good functioning of the autonomic nervous system. For example, HRV declines after exposure to stress, exercise, alcohol, and illness so that the sympathetic part of the nervous system (that is active in the 'fight-or-flight' state) is activated at the expense of the parasympathetic 'rest-and-digestion' part. Having a high resting HRV is related to reduced stress sensitivity and to improved ability to control one's emotional state (emotion regulation), to ignore irrelevant stimuli (cognitive inhibition), and to think about different things (cognitive flexibility). Like sleep, which also positively contributes to stress-resilience and can be hindered/negatively impacted by stress, resting HRV may be useful for prediction of resilience and for timely recognition of the negative impact of stress. It therefore also has potential as a cue for timely feedback in automated resilience interventions.

Previous research on relationships between resting HRV and sleep with stress-related outcomes often looked at differences between individuals (for example: how does my resting HRV compare to that of others, and what does that mean?). This is useful for understanding how HRV and sleep relate to stress and resilience and for making statements about groups of people. However, these insights cannot be automatically translated into the context of personalized feedback, which focuses on differences within individuals (how does my current resting HRV today compare to that on other

days, and what does that mean for me?). Therefore, it is not possible to perform risk signaling based on *between-subject* models, but rather only on *within-subject* models. The studies in the Wearable and app-based resilience Modelling in employees (WearMe) study therefore used wearables and smartphone applications to collect daily data on resting HRV, sleep, and stress- and resilience-related outcomes in a natural context. Based on this data, statistical models were developed that may be used in future resilience interventions to provide timely personalized feedback. This summary briefly describes the main findings of each chapter and concludes with some overarching conclusions and points for discussion.

The first paragraph of this summary showed that the availability of perceived resources such as fitness determines whether the brain judges a demanding situation as challenging or threatening (for example: a very fit person may experience stress if they think they are not fit enough for a certain situation). In previous research, resting HRV has been related to various aspects of mental and physical functioning. However, it is still unclear to what extent it is also associated with *perceived* mental and physical fitness. Improved insight into this connection may help to better understand how resting HRV may affect stress and resilience. **Chapter 2** therefore explores to what extent resting HRV during sleep is predictive of perceived mental and physical fitness the following morning. A group of 63 marines in training and employees of the Health Organization of the Dutch Defense collected data for several weeks or up to a maximum of 57 days via a wrist-worn wearable (Garmin Tactix Charlie) and an app with short, daily questionnaires. The results showed that resting HRV during sleep had no demonstrable relationship with mental fitness, but a weak relationship with physical fitness (only 2.4% of the difference in physical fitness within individuals could be explained by it). Resting HRV thus appears to be somewhat more clearly related to perceived physical fitness than to perceived mental fitness, but should be seen as a largely independent psychophysiological resource in the context of stress and resilience.

In **chapter 3,** a conceptual model is introduced for how resting HRV and sleep relate to demands, stress, and mental exhaustion (Figure 1). Based on previous research, the model hypothesizes that resting HRV is a psychophysiological resource that has a protective effect on the influence of exercise on stress, as well as on the influence of stress on mental exhaustion. In addition, mental exhaustion is expected to lead to decreased resting HRV, and thus to a possible vicious cycle due to the protective influence of resting HRV on the impact of demands and stress. Stress is also expected to negatively impact the sleep that is needed to recover and thus limit any negative impact of mental exhaustion on resting HRV. The model is based on existing, more transcending models and theories, and it supplements these by describing short-term relationships (within a day) which can be tested, for example, using consumer wearables and smartphone applications.

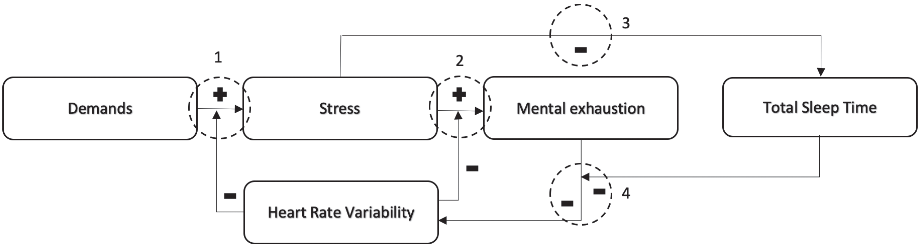


Figure 1: The conceptual model for the WearMe study.

Chapter 4 then describes a study in which the hypotheses from the conceptual model are tested among students of applied psychology, social work, and physiotherapy who are starting their first internship. The 26 participants wore a Fitbit Charge 2 over a period of 15 weeks to monitor (among other things) Total Sleep Time (TST). They also measured their resting HRV in the morning immediately after waking up while still lying in bed with a Polar H7 chest strap and an application (Elite HRV). In addition, they completed a short questionnaire in the morning and evening with items about (but not limited to) the perceived demands, stress, mental exhaustion, and alcohol use. The results confirmed the hypotheses that if participants woke up with a relatively high resting HRV, they reported less stress on demanding days and less mental exhaustion on stressful days. They also had a lower resting HRV after days when they felt more mentally exhausted. However, stress did not predict lower TST, and TST did not affect the relationship between mental exhaustion and resting HRV. This combination of findings showed that having a relatively high resting HRV indeed has a buffering effect against the consequences of strain and stress, and that through? mental exhaustion can have a negative influence on the resting HRV itself. These findings brought new insights into these short-term relationships. Further research will have to show whether the hypothesized vicious cycle is also present at a multi-day level.

The relationships between resting HRV, sleep, and stress-related outcomes on a multi-day level were then tested in the study presented in **chapter 5**. In order to perform the required time-series analyses, it was necessary to reduce the amount of missing data (e.g., missing wearable measurements and questionnaires) encountered in the previous study (chapter 4). This was achieved by using a wearable that automatically measures both sleep and resting HRV during sleep (the Oura ring), by only administering a shortened evening questionnaire of 7 items, and by incentivizing participants by rewarding them for adhering to the data collection procedures; they could keep the wearable and receive a personal report if they provided sufficient data. Based on analysis of the data of a group of 8 police officers who collected data for 15 to 55 weeks, resting HRV and sleep could each in only 1 participant be partly explained by perceived demands on the previous days. Waking up with a relatively low resting HRV or a lack of sleep therefore appears to offer limited-to-no retrospective reflection of stress-related measures experienced in the previous days. Prospectively, however, both low waking HRV and lack of sleep more clearly related to stress-related measures in multiple participants when looking forward to subsequent days. Waking up with a relatively high resting HRV predicted decreased demands in 2 participants and decreased stress in 1 participant on subsequent days. Furthermore, long TST predicted decreased demands in 2, stress in 3 and mental exhaustion in 5 participants. Finally, a long TST predicted increased vitality in 5 participants. The relationships found were weak to moderate (2-34% of the variance in the outcomes could be explained) and usually faded after 1 day for TST, although they tended to persist for multiple days according to the model for resting HRV. Based on these findings, resting HRV and sleep seem to be more suitable as predictors of stress-related outcomes in subsequent days than as indicators of them in preceding days.

The study in **chapter 6** used wearable data from the same agents as before, supplemented with data from a 5-weekly surveyed questionnaire on stress, somatization, anxiety, and depression (the 4-Dimensional Symptom Questionnaire, 4DSQ). While the study in chapter 4 looked at relationships *within a day* and the study in chapter 5 looked at *multi-day* relationships, the study in chapter 6 tested whether there are also relationships between trends in resting HRV and mental well-being *at a 5-week level*. In addition to trends in the resting HRV itself (i.e., is resting HRV increasing, decreasing, or staying the same over the period?), trends in the amount of fluctuations in the resting HRV from day to day (are the daily resting HRV values comparable each day, or will they increasingly or decreasingly vary?) were found?. The results show that an increasing trend in the amount of fluctuations in daily resting HRV was associated with an increase in both stress and somatization. In other words, a disturbance of the balanced daily functioning of the autonomous nervous system may be associated with increased stress or physical complaints that may coincide with it. In the case of somatization, the relationship was only present if there was a decreasing or constant trend in the resting HRV itself, but not if the resting HRV rose. No relationships were found for anxiety and depression, which could be explained by an absence of clinically relevant problems, resulting in floor effects. The relationships found were of weak to moderate strength (18.5 and 21.3% of the variance in stress and somatization could be explained). These results showed that having relatively stable resting HRV values can be seen as positive in the context of stress and resilience. Furthermore, monitoring trends in resting HRV and sleep may contribute to recognizing the potential emergence of stress-related problems and thus to initiating feedback via automated resilient interventions.

CONCLUSIONS AND FUTURE DEVELOPMENTS

The goal of the *WearMe* study was to contribute to the development of resilience interventions through the development of statistical models based on data from wearable sensors and smartphone apps. The studies in this thesis show that monitoring resting

HRV and sleep can play a role in this endeavor. Waking up with a relatively high resting HRV or after a night with a relatively long TST compared to one's personal norm usually indicates relatively favorable resilience. It also appears that having a relatively stable resting HRV over the past 5 weeks may be a signal of limited stress or somatization. The results described can in principle be used to initiate timely feedback in automated resilience interventions. However, the relationships found were weak to moderate, and not consistently present in all participants. The current models should therefore be supplemented for optimal application in initiating meaningful feedback at the right time.

The studies in this thesis explored the application of HRV as a short-term indicator of resilience ("higher is better") and as a demonstration of resilience over time ("stable is better"). Future research may consider investigating whether deviations from one's personal norm are a better short-term indicator of resilience ("normal is better"). This approach has been used in sports science to show that even extremely elevated resting HRV values can be unfavorable in the context of recovery and performance, but has not yet been explored in the context of stress and resilience.

The study in chapter 5 showed that relationships between resting HRV, sleep, and stress-related outcomes were not consistently present across all participants That said, when they were observed in participants, they were similar. To better understand why these relationships are not present in all individuals or situations, future research may explore two additional approaches. First, a research with a larger number of participants could consider also testing whether the strength of the tested relationships can be explained by differences between participants (for example, personal characteristics Second, studies with a larger number of measurements per participant may explore whether the relationships also vary within participants over time.

Finally, the current models could be expanded with wearable-based measures that become available in consumer wearables in the future and that have been related to stress-related outcomes in previous research. Examples include the application of skin conductance, non-invasive glucose monitoring, and the monitoring of gastrointestinal activity. Another promising direction is the use of smartphone data (such as smartphone or app use and GPS data), which recent studies show is also related to (changes in) mental well-being. By using different data sources and inductive data analysis techniques (e.g., machine learning), it may be possible to improve the models introduced in this thesis to identify appropriate triggers for the delivery of timely and meaningful feedback as a resilience intervention.

SAMENVATTING (SUMMARY IN DUTCH)

Inleiding

Zodra een mens wordt blootgesteld aan veeleisende omstandigheden, bepaalt het brein onbewust of er voldoende hulpbronnen beschikbaar zijn om met de situatie om te gaan (bijvoorbeeld: fysieke en mentale fitheid). Als dat het geval is, dan zal het brein dat vertalen naar een gevoel van uitdaging, en als dat niet het geval is als een bedreiging. Dit laatste roept een toestand van spanning op die ook wel 'stress' wordt genoemd. Stress bereidt het lichaam voor om te vechten of vluchten. Dit is bij traditionele bedreigingen (bijvoorbeeld: een roofdier) erg nuttig, maar bij moderne bedreigingen (bijvoorbeeld: een deadline of sociale interactie) vaak juist niet. Stress zorgt er namelijk voor dat de prefrontale cortex, het deel van het brein dat verantwoordelijk is voor besluitvorming en sociaal gedrag, wordt onderdrukt. Daarnaast neemt de amygdala, de emotionele alarmcentrale van het brein, de controle over bij stress. Stress voelt vervelend en is dus soms onhandig, maar kan als het langdurig aanhoudt ook bijdragen aan het ontstaan van fysieke en mentale gezondheidsproblemen of leiden tot verminderde productiviteit en werk-gerelateerd verzuim. Het vroegtijdig herkennen van stress-gerelateerde problemen of een verminderde veerkracht (het vermogen om adaptief met stress om te gaan) kan daarom gebruikt worden voor tijdige waarschuwingen en/of adviezen om iets te veranderen, en zo mogelijk bijdragen aan preventie.

Recente ontwikkelingen in draagbare sensor technologie, ook wel 'wearables' genoemd, bieden daarvoor veelbelovende kansen. Wearables werden aanvankelijk vooral populair om lichaamsbeweging bij te houden, maar zijn tegenwoordig ook in staat om slaap en lichamelijke signalen zoals hartritmevariabiliteit (HRV) te meten. HRV is een maat voor de hoeveelheid variatie tussen hartslagen, en zegt iets over de werking van het autonome zenuwstelsel. De HRV daalt bijvoorbeeld door stress, inspanning, alcohol gebruik of ziekte, waardoor het sympathische deel van het zenuwstelsel, dat actief is in de 'vechten-of-vluchten' toestand, geactiveerd wordt ten koste van het parasympatische 'rusten-en-verteren' gedeelte. Het hebben van een hoge rust HRV is te relateren aan een verlaagde stress-gevoeligheid en een verbeterd vermogen om de eigen emotionele staat te controleren (emotie regulatie), irrelevante prikkels te negeren (cognitieve inhibitie) en na te denken over verschillende dingen (cognitieve flexibiliteit). Net als slaap, dat ook negatief beïnvloed kan worden door stress en positief bijdraagt aan stressbestendigheid, is rust HRV mogelijk bruikbaar om enerzijds de impact van stress tijdig te herkennen als anderzijds om veerkracht te voorspellen – en dus als potentiële trigger voor tijdige feedback in geautomatiseerde veerkracht interventies.

Eerder onderzoek naar relaties tussen HRV en slaap met stress-gerelateerde uitkomsten keek veelal naar verschillen *tussen* personen (bijvoorbeeld: hoe verhoudt mijn rust HRV zich tot die van anderen, en wat zegt dat?). Dit is nuttig om beter te begrijpen hoe HRV en slaap zich tot stress en veerkracht verhouden of uitspraken te doen over groepen mensen. Deze inzichten vallen echter niet automatisch te vertalen naar de context van gepersonaliseerde feedback, waarbij juist gekeken wordt naar verschillen *binnen* personen (hoe verhoudt mijn rust HRV vandaag zich tot die op andere dagen, en wat zegt dat?). Op basis van modellen die zich richten op verschillen *tussen* personen is daarom niet persé bruikbaar om risicosignalering te doen op individueel niveau, wat bij modellen die dat doen *binnen* personen wel kan. De studies in de *Wearable and app-based resilience Modelling in employees (WearMe)* studie gebruiken daarom wearables en smartphone applicaties om dagelijks gegevens te verzamelen over rust HRV, slaap en stress- en veerkracht-gerelateerde uitkomsten in een natuurlijke context. Op basis daarvan worden statistische modellen ontwikkeld die mogelijk gebruikt kunnen worden in toekomstige veerkracht interventies die tijdig gepersonaliseerde feedback geven. In deze samenvatting worden de belangrijkste bevindingen van ieder hoofdstuk kort beschreven, waarna afgesloten wordt met enkele overstijgende conclusies en discussiepunten.

Uit de eerste paragraaf van deze bleek dat de beschikbaarheid van *ervaren* hulpbronnen zoals fitheid bepaalt of het brein een veeleisende situatie beoordeelt als uitdagend of bedreigend (bijvoorbeeld: een zeer fit persoon kan stress ervaren als diegene denkt niet fit genoeg te zijn voor een bepaalde situatie). Rust HRV is in eerder onderzoek gerelateerd aan diverse aspecten van mentaal en fysiek functioneren, maar het is nog onduidelijk in welke mate het samenhangt met *ervaren* mentale en fysieke fitheid. Verbeterd inzicht in of dat het geval is kan mogelijk helpen om beter te begrijpen hoe rust HRV invloed heeft op stress en veerkracht. **Hoofdstuk 2** verkent daarom in welke mate rust HRV tijdens de slaap voorspellend is voor de ervaren mentale en fysieke fitheid de volgende ochtend. Een groep van 63 medewerkers van Defensie (mariniers in opleiding en werknemers van de Defensie Gezondheidszorg Organisatie van de Nederlandse Defensie) verzamelde gedurende enkele weken tot maximaal 57 dagen gegevens via een pols-gedragen wearable (Garmin Tactix Charlie) en een app voor korte dagelijkse vragenlijsten. Uit de resultaten bleek dat rust HRV tijdens de slaap geen aantoonbare relatie heeft met mentale fitheid, maar wel een zwakke relatie met fysieke fitheid (slechts 2.4% van de verschillen in fysieke fitheid binnen personen kon erdoor worden verklaard). Rust HRV lijkt dus iets duidelijker gerelateerd aan de ervaren fysieke fitheid dan aan de ervaren mentale fitheid, maar lijkt vooral gezien te moeten worden als een grotendeels onafhankelijke psychofysiologische hulpbron in de context van stress en veerkracht.

In **hoofdstuk 3** wordt een volgende stap gedaan door een conceptueel model te introduceren voor hoe rust HRV en slaap zich verhouden tot belasting, stress en mentale uitputting (Figuur 1). Het model stelt op basis van eerder onderzoek dat rust HRV een psychofysiologische hulpbron is die een beschermend effect heeft op de invloed van belasting op stress, evenals op de invloed van stress op mentale uitputting. Daarnaast wordt verwacht dat mentale uitputting leidt tot een verlaagde rust HRV, en dus tot een

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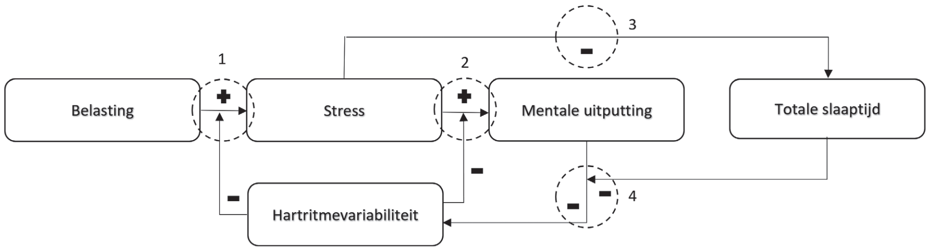
mogelijke vicieuze cirkel vanwege de beschermende invloed van rust HRV op de impact van belasting en stress. Ook wordt verwacht dat stress een negatieve invloed heeft op de slaap die nodig is om te herstellen en zo de eventuele negatieve impact van mentale uitputting op rust HRV te beperken. Het model is gebaseerd op bestaande, meer overstijgende modellen en theorieën en vult deze aan door juist kortdurende relaties (binnen een dag) te beschrijven, die bijvoorbeeld getoetst kunnen worden met behulp van consumenten wearables en smartphone applicaties.



Figuur 1: Het conceptuele model voor de WearMe studie.

Hoofdstuk 4 beschrijft vervolgens een studie waarbij de hypothesen uit het conceptuele model getoetst worden onder studenten Toegepaste Psychologie, Maatschappelijk Werk en Fysiotherapie die voor het eerst op stage gaan. De 26 deelnemers droegen gedurende een periode van 15 weken een Fitbit Charge 2 om met name de Totale Slaap Tijd (TST) te monitoren, en maten 's ochtends direct na ontwaken liggend in bed hun rust HRV met een Polar H7 borstband en een app (Elite HRV). Daarnaast vulden ze 's ochtends en 's avonds een korte vragenlijst in met items over onder meer de ervaren belasting, stress, mentale uitputting en alcohol gebruik. De resultaten bevestigden de hypothesen dat als deelnemers wakker werden met een voor hun doen hoge rust HRV zij minder stress rapporteerden op veeleisende dagen, en minder mentale uitputting rapporteren op stressvolle dagen. Ook hadden zij een lagere rust HRV na dagen dat zij zich meer mentaal uitgeput voelden. Stress voorspelde echter geen lagere TST, en TST had geen invloed op de relatie tussen mentale uitputting en rust HRV. De combinatie aan bevindingen toonde aan dat het hebben van een relatief hoge rust HRV inderdaad een beschermend effect lijkt te hebben tegen de gevolgen van belasting en stress. Deze gevolgen kunnen vervolgens via mentale uitputting een negatieve invloed op de rust HRV zelf hebben. Deze bevindingen brachten nieuwe inzichten in deze korte termijn relaties. Verder onderzoek zal moeten uitwijzen of de eventuele vicieuze cirkel ook op meer-dagen niveau aanwezig is.

De relaties tussen rust HRV, slaap en de stress-gerelateerde uitkomsten op meer-dagen niveau werden vervolgens getest in de studie uit **hoofdstuk 5**. Om de daarvoor benodigde tijdreeks analyses uit te kunnen voeren was het nodig om de hoeveelheid missende gegevens (bijvoorbeeld niet uitgevoerde metingen of vragenlijsten) te verminderen ten opzichte van de vorige studie uit hoofdstuk 4. Dit werd bereikt door een Oura ring te gebruiken die zowel slaap als de rust HRV tijdens de slaap automatisch kan meten, alleen nog een verkorte avondvragenlijst van 7 items af te nemen en deelnemers te prikkelen door ze te belonen voor trouwe deelname – deelnemers mochten de wearable houden en kregen een persoonlijk rapport als ze voldoende gegevens aanleverden. Op basis van een groep van 8 politieagenten die gedurende 15 tot 55 weken gegevens verzamelden, was te zien dat rust HRV en slaap ieder bij 1 deelnemer deels verklaard konden worden door ervaren belasting op de voorgaande dagen. Wakker worden met een relatief lage rust HRV of een gebrek aan slaap lijkt daarom *terugkijkend* slechts een beperkte of geen weerspiegeling te zijn van stress-gerelateerde uitkomsten in de voorgaande dagen. *Vooruitkijkend* kunnen ze daar echter duidelijker mee in verband gebracht worden. Wakker worden met een relatief hoge HRV in rust voorspelde namelijk een verminderde belasting bij 2 en stress bij 1 deelnemer in de daaropvolgende dagen. Bovendien voorspelde lange TST verminderde belasting bij 2, verminderde stress bij 3 en verminderde mentale uitputting bij 5 deelnemers. Ten slotte voorspelde een lange TST verhoogde vitaliteit bij 5 deelnemers. De gevonden relaties waren zwak tot matig (2-34% van de variatie in de uitkomsten kon verklaard worden) en doofden voor TST doorgaans na 1 dag al uit, hoewel ze volgens het model voor rust HRV geneigd waren om enkele dagen aan te houden. Op basis van de deze bevindingen lijken rust HRV en slaap meer geschikt als voorspellers voor stress-gerelateerde uitkomsten in de daarop volgende dagen dan als uiting van stress in de voorgaande dagen.

De studie in **hoofdstuk 6** gebruikte de wearable gegevens van dezelfde agenten als hiervoor, aangevuld met gegevens van een 5-wekelijks afgenomen vragenlijst over stress, somatisatie, angst en depressie (de 4-Dimensionale Klachten Lijst, 4DKL). Daar waar de studie uit hoofdstuk 4 keek naar relaties *binnen een dag* en de studie uit hoofdstuk 5 keek naar relaties *over enkele dagen*, toetste de studie uit hoofdstuk 6 of ook *op 5-wekelijks niveau* relaties bestaan tussen trends in rust HRV en het mentale welzijn. Naast trends in de rust HRV zelf (neemt de rust HRV toe, af, of blijft deze gelijk gedurende de periode?) werd nu ook gekeken naar trends in de hoeveelheid fluctuaties in de rust HRV van dag tot dag (zijn de dagelijkse rust HRV waarden iedere dag vergelijkbaar, of gaan ze steeds meer of minder variëren?). Uit de resultaten bleek dat een stijgende trend in de hoeveelheid fluctuaties in de dagelijkse rust HRV voorspellend was voor een toename in zowel stress als somatisatie. Anders gezegd: een eventueel toegenomen verstoring van de balans in het dagelijks functioneren van het autonome zenuwstelsel hangt mogelijk samen met toegenomen stress of lichamelijke klachten die daar mee te maken kunnen hebben. In het geval van somatisatie was die relatie alleen aanwezig als er sprake was van een dalende of gelijkblijvende trend in de rust HRV zelf, maar niet als de rust HRV steeg. Voor angst en depressie werden geen relaties gevonden, wat verklaard kon worden door een afwezigheid van klinisch relevante symptomen daarin wat zorgde voor vloer effecten. De gevonden relaties waren zwak tot matig (18.5 en 21.3% van de variantie in stress en somatisatie werd verklaard). Deze resultaten lieten zien dat het hebben van relatief stabiele dagelijkse rust HRV waarden gezien kan worden als positief in de context van stress en veerkracht, en het monitoren op trends in deze waarden een bijdrage kan leveren aan het herkennen van het mogelijk ontstaan van stress-gerelateerde problemen en dus aan het initiëren van tijdige feedback in geautomatiseerde veerkracht interventies.

CONCLUSIES EN TOEKOMSTIGE ONTWIKKELINGEN

Het doel van de *WearMe* studie was om bij te dragen aan de ontwikkeling van veerkracht interventies via de ontwikkeling van statistische modellen op basis van gegevens van wearable sensoren en smartphone apps. De studies in dit proefschrift laten zien dat het monitoren van rust HRV en slaap daar een rol in kunnen spelen. Het wakker worden met een hoge rust HRV of na een nacht met een relatief lange TST vergeleken met de persoonlijke norm kan doorgaans gezien worden als indicatie van relatief gunstige veerkracht. Ook blijkt dat het hebben van een relatief stabiele rust HRV tijdens de afgelopen 5 weken mogelijk een signaal van beperkt aanwezige stress of somatisatie. De beschreven resultaten kunnen in principe gebruikt worden om tijdige feedback te initiëren in geautomatiseerde veerkracht interventies. De gevonden relaties waren echter zwak tot matig, en niet consistent aanwezig in alle deelnemers. De huidige modellen dienen daarom eerst aangevuld te worden voor optimale toepassing bij het initiëren van betekenisvolle feedback op het juiste moment.

De studies in dit proefschrift verkende de toepassing van HRV als korte-termijn indicator voor veerkracht (“hoger is beter”) en als demonstratie van veerkracht over de tijd (“stabiel is beter”). Toekomstig onderzoek kan overwegen om daarnaast te onderzoeken of afwijkingen van de persoonlijke norm een betere korte-termijn indicator zijn voor veerkracht (“normaal is beter”). Die benadering is in de sportwetenschap gebruikt om aan te tonen dat ook extreem verhoogde rust HRV waarden ongunstig kunnen zijn in de context van herstel en presteren, maar is nog niet verkend in de context van stress en veerkracht.

De studie in hoofdstuk 5 liet zien dat relaties tussen rust HRV, slaap en de stress-gerelateerde uitkomsten niet consistent in alle deelnemers aanwezig waren – hoewel die wel vergelijkbaar waren *als* ze geobserveerd werden. Om beter te begrijpen waarom deze relaties niet in alle personen of in alle situaties aanwezig zijn, kan toekomstig onderzoek twee aanvullende benaderingen verkennen. Ten eerste kan onderzoek met een groter aantal deelnemers overwegen om ook te toetsen of de kracht van de getoetste relaties verklaard kan worden door verschillen *tussen* deelnemers (bijvoorbeeld: persoonlijke eigenschappen). Daarnaast is het mogelijk om te verkennen of de relaties mogelijk ook binnen deelnemers variëren over de tijd, waarvoor studies met een groter aantal metingen per deelnemer nodig zijn.

Ten slotte kunnen de huidige modellen mogelijk uitgebreid worden met wearable-gebaseerde metingen die in de toekomst mogelijk beschikbaar komen in consumenten-wearables en in eerder onderzoek gerelateerd zijn aan stress-gerelateerde uitkomsten. Voorbeelden hiervan zijn de toepassing van huidgeleiding, non-invasieve glucose monitoring en het monitoren van maag-darm activiteit. Een andere veelbelovende richting is het gebruik van smartphone data zoals smartphone of app gebruik en GPS gegevens, wat in recente studies ook gerelateerd is aan (veranderingen in) het mentale welzijn. Door gebruik te maken van verschillende gegevensbronnen en inductieve technieken voor gegevensanalyse (bijvoorbeeld: machine learning) is het wellicht mogelijk om de in dit proefschrift geïntroduceerde modellen te verbeteren, om zo te komen tot passende triggers voor tijdige en betekenisvolle feedback.

ABOUT THE AUTHOR

Herman de Vries was born on November 3rd, 1983, in Assen, The Netherlands. After finishing the pre-university education (VWO) with a Nature and Technique profile in 2003, he completed a propaedeutic year in Human Movement Sciences at the University of Groningen in 2004 and a Bachelor in Physiotherapy at the Hanze University of Applied Sciences in 2008. Between 2008 and 2017 he worked as a primary care physiotherapist at Paramedics in Assen, specialized in the treatment of patients with cardiopulmonary, vascular and metabolic diseases, as well as the use of biofeedback, wearables and eHealth tools. In 2016, he graduated with honors at the Master Clinical Health Sciences at Utrecht University, won the Talma Eykman thesis award and published four papers based on wearables- and eHealth-related studies. After subsequently working as a Physiotherapy lecturer at Saxion for one year, he started as a PhD candidate on the *Wearable and app-based resilience Modelling in employees (WearMe)* study at the Hanze University Groningen, TNO, University Medical Center Groningen in 2017, for which he also received a Best Paper Award in 2019 at eTELEMED congress in Athens. Since 2021, Herman works as a Research Scientist at TNO in the Unit Defense Safety & Security, Department of Human Behaviour & Training, on projects that investigate how employees in high-risk professions (e.g., police officers or military personnel) can be supported in optimizing their resilience and health using wearables and apps.

OVER DE AUTEUR

Herman de Vries is geboren op 3 november 1983 in Assen, Nederland. Na afronding van het Voorbereidend Wetenschappelijk Onderwijs (VWO) met een profiel in Natuur en Techniek in 2003 behaalde hij propedeuse Bewegingswetenschappen aan de Rijksuniversiteit Groningen in 2004 en de Bachelor Fysiotherapie aan de Hanzehogeschool Groningen in 2008. Tussen 2008 en 2017 werkte hij als eerstelijns fysiotherapeut bij Paramedics in Assen met een specialisatie in de behandeling van mensen met cardiopulmonale, vasculaire en metabole aandoeningen, evenals gebruik van biofeedback, wearables en eHealth tools. In 2016 studeerde hij cum laude af bij de Master Klinisch Gezondheidswetenschappen aan de Universiteit Utrecht, won de Talma Eykman scriptieprijs en publiceerde vier artikelen naar aanleiding van wearable- en eHealth-gerelateerde studies. Na vervolgens een jaar gewerkt te hebben als docent fysiotherapie bij Saxion begon hij in 2017 als promovendus aan de *Wearable and app-based resilience Modelling in employees (WearMe)* studie aan de Hanzehogeschool Groningen, TNO, Universitair Medisch Centrum Groningen, waarvoor hij in 2019 tevens een Best Paper Award ontving tijdens het eTELEMED congres in Athene. Sinds 2021 werkt Herman als onderzoeker bij TNO bij de Unit Defense Safety & Security, afdeling Human Behaviour & Training, aan projecten die onderzoeken hoe hoog-risico personeel (bijvoorbeeld politie en defensie) ondersteund kan worden in het optimaliseren van hun veerkracht en gezondheid met behulp van wearables en apps.

PHD PORTFOLIO

Name PhD Student: Herman de Vries
UMCG research institute: SHARE
Graduate School: GSMS
ECTS* required: 15

PhD period: Sept 2017 – Sept 2022
Promotors: Prof. Robbert Sanderman, Prof. Cees van der Schans
Copromotors: Dr. Hilbrand Oldenhuis, Dr. Wim Kamphuis

	Year	ECTS*
GSMS courses		
Ethics of Research and Scientific Integrity for Researchers	2018	2.50
Managing Your PhD	2018	2.00
Research Data Management Awareness	2018	0.00
Mixed Models for Clustered Data	2019	2.00
Applied Longitudinal Data Analysis: Modelling Change Over Time	2019	2.00
Introduction Into R	2019	1.40
Measuring Concepts in Quantitative Research	2019	0.00
		9.90
External courses		
Introduction In Work & Occupational Psychology (Open University)	2018	5.00
Practical Time Series Analysis (Coursera; State University of New York)	2019	0.90
Bayesian Statistics: From Concept to Data-Analysis (Coursera; University of California)	2019	0.80
Data Science Path (Codecademy)	2019	12.50
Learn the Command Line (Codecademy)	2020	0.35
Analyze Data with R (Codecademy)	2020	2.85
		22.40
Presenting data, awards and invited lectures outside institute (max 6 ECTS)		
Guest lecture on wearable-based resilience modelling, at IT Academy in Groningen	2018	0.50
Workshop on measuring recovery using wearables, at KNGF congress in Den Bosch	2018	0.50
Oral presentation on WearMe study at the eTELEMED conference, in Athens	2019	0.50
Best Paper Award at the eTELEMED conference, in Athens	2019	0.50
Oral presentation on study results at Health By Technology conference, in Groningen	2019	0.50
Guest lecture on ethics during WearMe study, at De Haagse Hogeschool in The Hague	2020	0.50
Session chair and oral presentation at Health By Technology conference, in Groningen	2022	0.50
		3.50

Supervised reviewing of manuscripts (max 3 ECTS)		
3 supervised peer-reviews for the Journal of Medical Internet Research (JMIR)	2019	1.50
		1.50
Attending annual PhD Day (max 1 ECTS)		
PhD Day 2018	2018	1.00
PhD Day 2019	2019	1.00
		1.00
Teaching / student supervision (max 2 ECTS)		
Lectures	2019	1.75
Thesis supervision	2020	2.25
		2.00
Total		**40.3**

** ECTS: European Credit Transfer System. 1 ECTS = 28 hours invested.*

PUBLICATIONS & OTHER OUTPUT

Publications in this thesis

de Vries H, Oldenhuis H, van der Schans C, Sanderman R, Kamphuis W. Does Wearable-Measured Heart Rate Variability During Sleep Predict Perceived Morning Mental and Physical Fitness? Applied Psychophysiology and Biofeedback [Internet]. 2023; doi: 10.1007/s10484-022-09578-8.

de Vries HJ, Pennings HJM, van der Schans CP, Sanderman R, Oldenhuis HKE, Kamphuis W. Wearable-Measured Sleep and Resting Heart Rate Variability as an Outcome of and Predictor for Subjective Stress Measures: A Multiple N-of-1 Observational Study. Sensors. 2023;23:332. doi: 10.3390/s23010332.

de Vries H, Kamphuis W, van der Schans C, Sanderman R, Oldenhuis H. Trends in Daily Heart Rate Variability Fluctuations Are Associated with Longitudinal Changes in Stress and Somatisation in Police Officers. Healthcare. 2022;10:144. doi: 10.3390/healthcare10010144.

de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Moderation of the stressor-strain process in interns by heart rate variability measured with a wearable and smartphone app: Within-subject design using continuous monitoring. JMIR cardio. 2021;5:e28731. doi: 10.2196/28731.

de Vries H, Kamphuis W, Oldenhuis H, van der Schans C, Sanderman R. Modelling employee resilience using wearables and apps: a conceptual framework and research design. International Journal on Advances in Life Sciences. 2019;11:110–117.

Publications outside this thesis

Kloek CJJ, Bossen D, de Vries HJ, de Bakker DH, Veenhof C, Dekker J. Physiotherapists' experiences with a blended osteoarthritis intervention: a mixed methods study. Physiotherapy Theory and Practice. 2020;36:572–579. doi: 10.1080/09593985.2018.1489926.

de Vries HJ, Kloek CJ, de Bakker DH, Dekker J, Bossen D, Veenhof C. Determinants of adherence to the online component of a blended intervention for patients with hip and/or knee osteoarthritis: a mixed methods study embedded in the e-exercise trial. Telemedicine and e-Health. 2017;23:1002–1010. doi: 10.1089/tmj.2016.0264.

de Vries HJ, Kooiman TJM, van Ittersum MW, van Brussel M, de Groot M. Do activity monitors increase physical activity in adults with overweight or obesity? A systematic review and meta-analysis. Obesity. 2016;24:2078–2091. doi: 10.1002/oby.21619.

Publications in vocational journals

de Vries H, Kloek C, Bossen D, Veenhof C. Waarom wordt e-health (niet) gebruikt?: fysiotherapeutisch gebruik van een blended e-health-interventie. FysioPraxis. 2016;3:35–37.

Conference contributions

de Vries, H, Kamphuis, W, van der Schans, C, & Sanderman, R, Oldenhuis, H. Trends in Daily Heart Rate Variability Fluctuations Are Associated With Longitudinal Changes in Stress and Somatisation in Police Officers. Presented at Supporting Health By Technology XI; Groningen, The Netherlands; 2022 May 12.

de Vries, H, Oldenhuis, H, Kamphuis, W, van der Schans, C, & Sanderman, R. Investigating Resilience Patterns Based on Within-Subject changes in Sleep and Resting Heart Rate Variability. Presented at Supporting Health By Technology IX; Groningen, The Netherlands; 2019 May 17.

de Vries, H, Kamphuis, W, Oldenhuis, H, van der Schans, C, & Sanderman, R. Wearable and App-based Resilience Modelling in Employees (WearMe). Presented at eHealth, Telemedicine, and Social Medicine (eTELEMED) XI; Athens, Greece; 2019 Feb 26.

Media appearances

Veronica Inside. Radio interview on wearable sensor technology. 2019 Feb 20.

Algemeen Dagblad (AD), Eindhovens Dagblad, Gelderlander, Tubantia, Brabants Dagblad, PCZ, Stentor, BN De Stem, Dagblad van het Noorden, Leeuwarder Courant. Meten is weten (of toch niet?): Gezondheidsapps zijn nuttig, maar geen wondermiddel. Published in print. 2019 Feb 20.

Libelle Gezond. Zelf doktertje spelen? De do's en don'ts. Published in print. 2017 Feb.

SmartHealth. Ga je daadwerkelijk meer bewegen door een activity tracker? 2016 Oct 13. Available from: http://www.smarthealth.nl/2016/10/13/ga-je-daadwerkelijk-meer-bewegen-door-een-activity-tracker/

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