The Relationship Between Diagnosed Burnout and Sleep Measured by Activity Trackers: Four Longitudinal Case Studies

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Abstract. Employee burnout is an increasing global problem. Some countries, such as The Netherlands, diagnose and treat burnout as a medical condition. While deficient sleep has been implicated as the primary risk factor for burnout, the longest current sleep measurement of burnout individuals is 4 weeks; and no studies have measured sleep throughout the burnout process (i.e.: pre-burnout, burnout diagnosis, recovery time, and returning to work). During a 7 month longitudinal study on wearable technology use, 4 participants were diagnosed with (pre)burnout by their company doctor using the Maslach's Burnout Inventory (MBI). Our study captured the participants' sleep data including: sleep quality, number of awakenings, sleep duration, time awake, and amount of light sleep during the burnout and recovery process. One participant experienced a burnout diagnosis, recovery at home, and returning to work within the 7 months providing the first look at sleep trends during the entire burnout process. Our results show that the burnout participants experienced decreased sleep quality (n = 2), sleep duration (n = 2), and light sleep (n = 3). In contrast, a sample of 3 non-burnout participants sleep remained stable on all measures except for time awake for one participant. The results of this study answer past calls for longer analysis of sleep's influence on burnout and highlight the vast opportunity to extend burnout research using the millions of active devices currently in use.

Keywords: eHealth · Wearable technology · Sleep quality · Quantified self · Digital health · Self-tracking

1 Introduction

The identification of burnout as an increasing global problem has significant implications for individuals, organizations, and healthcare systems [1–4]. Few countries diagnose and treat burnout as a medical disorder. In The Netherlands the number of individuals medically diagnosed with burnout per year has increased from 11% in 2007

L. Mucchi et al. (Eds.): BODYNETS 2019, LNICST 297, pp. 315–331, 2019.
https://doi.org/10.1007/978-3-030-34833-5_24

to 14% in 2014 [5] and employees reporting mental exhaustion increased from 13% in 2015 to 16% in 2017 [6]. Burnout is a slow progressive loss of energy and enthusiasm, resulting from chronic stress [7]. It contributes to a general decline in health [8], including depression, anxiety, and sleep impairment [9–11]. Poor sleep, too little sleep, or regular deviation from 7 to 9 h of sleep can negatively affect health and put individuals at risk for burnout [9, 12–16]. While sleep problems are an indicator of burnout they are also a symptom of burnout. So insufficient sleep can lead to burnout and burnout can lead to insufficient sleep. One reason for sleep's impact on burnout may be sleep's restorative role in facilitating appropriate emotional reactivity and prominence discrimination; individuals are more sensitive to stressful stimuli without proper sleep [17], and more vulnerable to misinterpretation or overreaction [18]. One study found that individuals with burnout reported subjectively less cognitive recovery after a night of sleep compared to healthy individuals [19]. The suggested correlation between sleep and burnout along with the gradual progression and regression of burnout highlights the value of longitudinal measurement of sleep quality and duration. The current popularity of wearable technology and self-tracking trends enable a unique opportunity to gather deeper understanding of the relationships between sleep and burnout over the long term and on a large scale. The aim of the current study is to explore how sleep quality, including number of awakening's during sleep, sleep duration, time awake, and amount of light sleep fluctuate over time for individuals in a (pre)burnout state.

To obtain deeper understanding of the ways in which sleep is impaired in individuals with burnout, it is important to understand the accuracy and flexibility of different sleep measurement tools. Polysomnography (PSG), a multi-parameter test analyzing changes during sleep, is considered the most accurate in reporting different sleeping phases [20, 21]. However, polysomnography involves studying patients in an artificial sleep environment (i.e.: laboratory) [22], which is impractical, invasive and expensive for longitudinal studies. A less intrusive process of measuring sleep is via actigraphy, which measures rest/activity cycles through the person's movement (i.e.: accelerometry) [23]. Actigraphy trackers are worn on the body and are usually small, cordless, easy to wear, require no lifestyle changes, and consequently are suitable for longitudinal research [21, 24, 25]. One study compared five different actigraphy activity trackers with (PSG): Basis Health Tracker, Misfit Shine, Fitbit Flex, Withings Pulse O2, and Actiwatch Spectrum [20]. The activity trackers gave valid measures of total sleeping time. Time asleep, total time in bed, and total time asleep differed from PSG in all activity trackers except for Actiwatch. Light sleep was consistently underestimated for all activity trackers. Deep sleep was overestimation by 4 out of 5 activity trackers. No differences between PSG and Basis were found. While some actigraphy sleep parameters are not validated, wake time and sleep duration can be accurately measure [20, 21] and have an overall agreement rating of 87.3% to Polysomnography [21]. The relatively high agreement rating to PSG as well as the unobtrusive functionality and affordability suggest that use of actigraphy activity trackers was suitable for this longitudinal study of sleep measurement for some sleep measures.

Previous research on sleep's implications on burnout using activity trackers has been limited to short intervals [26–28], the longest lasting for 4 weeks [27, 28]. This shorter research has identified the need for longitudinal analysis to verify findings [26, 28]. In a 5 night actigraphy study researchers found that sleep duration was not related to burnout symptoms in shift workers [26]. During a 4 week actigraphy study, more sleep was predictive of fewer reported burnout symptoms [28]. Another 4 week actigraphy study revealed that faculty members had higher burnout rates, less total sleep, and more rapid sleep onset compared to residents [27]. During a one week actigraphy study chronic stress in adolescents was shown to positively relate to nocturnal awakenings, lower sleep efficiency and subjective lower sleep quality [29]. Additionally, researchers found a negative relationship between sleep duration and burnout [27, 28] and people with chronic stress report lower sleep quality and more nocturnal awakenings [29]. In long term sleep studies using sleep journals, burnout participants experienced a slow deterioration in sleep [9, 12–16] while sleep trends remained stable in non-burnout individuals, [30, 31]. In summary, decreasing sleep trends have been related to increased burnouts while stable sleep has been consistent with non-burnout individuals; and while sleep journal studies suggest long-term trends of decreasing sleep in burnout individuals, sleep trackers have only measured a 4 week period. This research extends past research from 4 weeks to 7 months and gives insight into the different stages of burnout (pre-burnout, diagnosed, and recovery).

Based on these past research studies an expectation could be that sleep quality and sleep duration as measured with activity trackers would also deteriorate over time for our participants as (pre)burnout becomes more severe. Furthermore, number of awakenings per night might occur more frequently over time as (pre)burnout becomes more severe. Discovering distinctive patterns in the burnout participants would provide ground for analyzing whether this difference is also found in a larger sample that is more representative of the general population. The quantified self movement could enable a large study since this way of looking at health, wellbeing and adaptability fits very well with the current trends that involve monitoring daily activities, including sleep and movement. Data for a large study could become available through eHealth and digital health tools, which are increasingly being used for both personal and medical practice. The present study could provide the incentive and motivation for systematically analyzing sleep data in relation to burn-out, which could lead to identification of early burnout indicators. Finally, these indicators could then guide tool-based interventions designed for prevention and treatment of the different stages of burnout.

2 Methodology

In this study we used sleep data captured during a longitudinal study of wearable technology use (n = 41). Multiple sleep parameters (sleep quality, sleep duration, light sleep, awake time, and frequency of awakenings) were capturing through the activity tracker's actigraphy, which measured movement via the accelerometer in the device. This data was collected over seven months in 41 employees of a consultancy company in the Netherlands. While consultancy covers a wide array of industries it is considered a high stress occupation with a elevated burnout rate in many countries [32] thus making it a representative sample given the aims of this study. Of the 41 participants, 4 individuals were diagnosed with (pre)burnout during the longitudinal study, which gave us the opportunity to look closely at their sleep parameters.

2.1 Participants

Before the start of the data collection, the participants were asked to read and sign an informed consent regarding the use of their biological data for scientific analysis and publication. At the end of the research, it was discovered that 4 individuals were medically diagnosed with (pre)burnout during the 7 months study using the Maslach's Burnout Inventory (MBI) by their company doctor. A second consent form was therefore drafted and signed by the 4 participants to address the highly personal nature of the data in line with General Data Protection Regulation (GDPR) guidelines [33]. This form addressed the use of their sleep data for analysis and scientific publication while keeping their personal details private. The participants were between the ages of 31 and 40, two female and two male. Any further personal details are kept private as agreed upon by the second consent agreement. The initial and additional consent were approved by the ethics committee of the faculty of Behavioral Management and Social Sciences at the University of Twente.

2.2 Measurements

2.2.1 Sleep

In this study, several parameters of sleep were measured with actigraphy including: light sleep, sleep duration, awake time and frequency of awakenings. These measurements were combined within the Jawbone tool to give an overall sleep value called sleep quality. The activity trackers that were used were the Jawbone UP move [34] wristbands (see Fig. 1). Participants had to install an application of the activity tracker and a secondary application [35] on their smartphone prior to the research study to collect the sleep data securely. Data was collected via the Jawbone UP move application and forwarded to the secondary application for collecting, storing and visualizing the data in a structured and secure system.

Sleep quality has been quantified through different measures involving sleep quality and sleep duration [36]. In this case, light sleep, sleep duration, and nocturnal awakenings were measured in hours and minutes through tracking movements of participants while they were sleeping with the help of an accelerometer [23]. Sleep quality

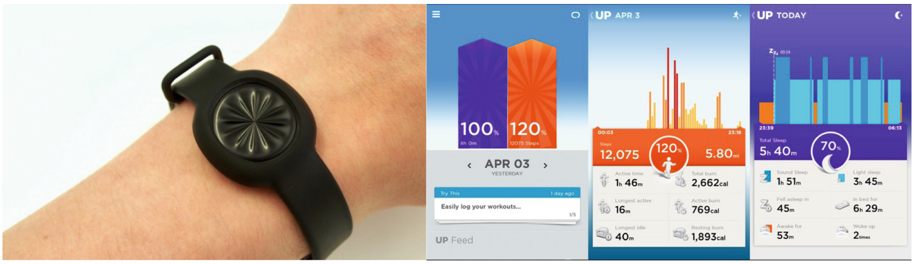

Fig. 1. Jawbone UP move wristband and app

was calculated based on combination of the different sleep measures: light sleep, sleep duration, nocturnal awakenings and was measured in hours and minutes. Light sleep, the REM stage before deep sleep [37], was categorized through smaller unique movement during sleep. Sleep duration was established from the start time of being asleep until the end time. To determine beginning and end of being asleep or awake, participants had to press a button before going to sleep and when they awoke. Manual input of sleep and awake time can help decrease false sleep measures (i.e.: lying still watching TV) and thus can improve the validity of the sleep measurement [20]. Frequency of awakenings were established through nighttime movement consistent with wakefulness.

2.2.2 (pre)Burnout Diagnosis

Burnout is not an official disorder in most countries and does not appear in the Diagnostic and Statistical Manual of Mental Disorders (DSM-V), a tool used by medical practitioners to diagnose mental conditions [38]. However, in the Netherlands, burnout is diagnosed by either a doctor or psychologist who instruct the burned out individual to leave work and rest at home for a period of weeks or months. The Maslach's Burnout Inventory (MBI) is the most commonly used screening tool to detect burnout [39]. The MBI has 22 questions that are used to detect burnout symptoms and severity of symptoms [40]. The MBI includes three different multi-item instruments: depersonalization (5 items), emotional fatigue (9 items), and personal accomplishment (8 items). A sample item from the depersonalization scale is 'I feel burned out from my work'. An example item from the emotional fatigue scale is 'I feel emotionally drained from my work'. An example item from the personal fulfillment scale is 'working with people all day is really a strain for me.' Each item was filled out by the participant on a 7-point Likert scale with 1 indicating never and 7 indicating every day. Each multi-item scale was calculated and placed in categories of high (Emotional exhaustion $\geq$ 27, Depersonalization $\geq$ 14, Personal accomplishment 0–30), moderate (Emotional exhaustion 17–26, Depersonalization 9–13, Personal accomplishment 31–36), and low (Emotional exhaustion 0–16, Depersonalization 0–8, Personal accomplishment $\geq$ 37) to indicate the severity of burnout for each scale with cut-off scores for certain diagnoses (i.e.: pre burnout or burnout). Personal accomplishment is scored in the opposite direction from emotional exhaustion and depersonalization. The doctor used the MBI's scores in conjunction with information taken from sessions with the employees, combined with professional judgment to decide the severity and state of the burnout symptoms [41]. The specific dates of pre-burnout and burnout diagnosis were noted for the 4 participants.

2.3 Procedure

At the start of the data collection, one of the researchers helped participants to install the activity tracker's application on their phone and set up the device. The Jawbone app took the participants through a virtual tour of how to use the functionality of the activity tracker and jawbone app. Sleep analytics and feedback were available on their mobile application as well as some notifications of irregular behavior (i.e.: a shorter or longer period of total sleep often popped up as a notification to alert the participant of a change from the individual's norm). Sleep data was presented each day and trends were represented with multiples days, weeks, or months. The Jawbone application suggested a nightly overall sleep period (including light and deep sleep) of 8 h in total. Most of the individuals reported following this goal, and some adjusted their devices in an effort to strive for a different goal. The participants were asked to behave naturally and engage in their normal daily activities. Wearing the wristband was voluntary and the participants could stop wearing the wristband at any time. One of the researchers was present each week at the company so that participants could ask questions about their wristband or mobile application or discuss any problems related to the devices (i.e.: needing a new battery for the device, trouble with the mobile application, or customizing the functionality/notifications). Data was collected for the 41 participants over 7 months. Multiple sleep measurements were captured each night (sleep quality, sleep duration, light sleep, time awake and frequency of awakenings). The multiple data points were then used for single subject time series measurement and correlation.

2.4 Data Analysis

For execution of the data analysis, the software package *Statistical Package of the Social Sciences* was used [42]. A time series analysis: single subject approach was used to analyze the relationships of the sleep variables to themselves, other sleep variables, and to time in days within a single case study [43]. This approach allowed us to discover the within-person variability of a particular case study. We chose two methods for our time series analysis. To analyze frequency of awakenings, a method was specifically developed for analyzing trends in longitudinal single case studies [44]. With this seven step method we calculated the direction of trends and stability of data points for number of awakenings.

Following this 7 step process [44], the total number of awakenings for every two weeks was calculated using SPSS for the participants. During the first 2 steps, the number of conditions and sessions are determined. During step 3, the mean, median, range and stability envelope are calculated. The median value $\times$ 0.25 gives the range of the stability envelope. In step 4 the median of the first half and second half of the sessions are calculated as well as the first value of available data and last value. During step 5, the mid-dates and the mid-rates are calculated to estimate the trend. After creating a visualization of the trend, trend stability is determined by looking at the percent of data points that fall within the stability envelope (step 6). At least 80 percent need to fall within the stability envelope to conclude that the trend is stable. In the last step, three questions are answered: (1) the direction of the trend (accelerating or decelerating) (2) the stability of the trend (either stable or not stable) (3) the number of paths within the trend (singular or multiple) [44].

Pearson correlations were calculated, to analyze the correlation between time in days and: sleep quality, sleep duration, light sleep, awakenings, and awake time in burnout participants. Most of the time series analysis includes all 7 months of available data for each case study. Participant 1 (pre burnout) and participant 2 (full burnout) remained in the same burnout state throughout the study. Participant 4 (pre burnout) only changed states in the last 2 weeks of the study. However, participant 3 experienced multiple states within the burnout process (pre burnout, diagnosis and recovery at home, returning to work part time, and returning to work almost full time). This participant's data was separated to look for differences in awakening during these different stages of burnout.

3 Results

Data were collected for each participant, manually sorted in SPSS, and missing values were noted. Values of 0 for sleep duration, sleep quality, and light sleep were interpreted as missing values and indicated accordingly. Participant 3 frequently napped during the day. The naps could be a confounder and could create a bias in the measurement. Therefore, the nap-data was excluded. Not all participants recorded their sleep every night during the duration or the data collection, which led to some missing data (see Table 2). When data points within a 2 week period did not reach the stability criterion of 80% or more, that time period was excluded.

3.1 Descriptive Statistics

For the burnout participants, means and standard deviations for sleep quality, sleep duration, light sleep, awake time and awakenings were calculated (see Table 1). Total period of measurements with available and missing data-points are presented in Table 2. All burnout participants were individually analyzed using a time series analysis: single subject approach [43] and discussed in the following paragraphs.

Table 1. Means and (Standard Deviations) for sleep quality, sleep duration in hours, light sleep in hours, awake time during sleep in hours, number of awakenings during sleep

Participant number	Sleep quality	Sleep duration	Light sleep	Awake time	Awakenings	(pre) burnout
1	80,4 (17,4)	7,1 (1,7)	3,5 (1,1)	0,3 (0,2)	0,4 (0,6)	Yes
2	77,0 (19,5)	8,5 (1,8)	3,8 (1,3)	0,6 (0,5)	0,8 (1,2)	Yes
3	70,8 (39,0)	7,1 (3,7)	3,7 (2,27)	0,5 (0,5)	1,1 (1,1)	Yes
4	73,1 (26,5)	7,5 (2,1)	2,4 (2,0)	0,6 (0,6)	1,2 (1,4)	Yes

Table 2. Total number of nights of sleep captured: available data-points and missing data-points, measured in nights

Participant number	Total period	Available data-points	Missing data-points
1	108	74	34
2	134	100	34
3	235	310	1
4	77	31	46

3.2 Participant 1: Pre Burnout Diagnosis Throughout 7 Months - Continued Working Full Time

Participant 1 was diagnoses as pre burnout before the start of the research study and remained in that state throughout the 7 month study. However, the individual did not leave work and continued to work full time. The results are consistent with what we would expect from someone developing burnout: sleep quality, light sleep, and sleep duration decreased, while frequency of awakening increased during the 7 months. This individual ranged from waking up 0-3 times per night during the 7 months. Time in days was significantly negatively correlated to: sleep quality r (74) = −0.263, p = 0.02, light sleep r(74) = −0.292, p = 0.01, and sleep duration r(74) = −0.288, p = 0.01. In short, as number of days increased, sleep quality, light sleep, and sleep duration decreased. No significant correlation between time awake and time in days was found (see Fig. 2). The evaluation of level change in frequency of awakenings showed an accelerating trend (see Fig. 2). However, in week 9–13 more than 20% of data was missing so these weeks were excluded. The percentage of data points within the stability envelope is 100%, which is within the stability criterion of 80%. Therefore, we conclude that a stable trend was found.

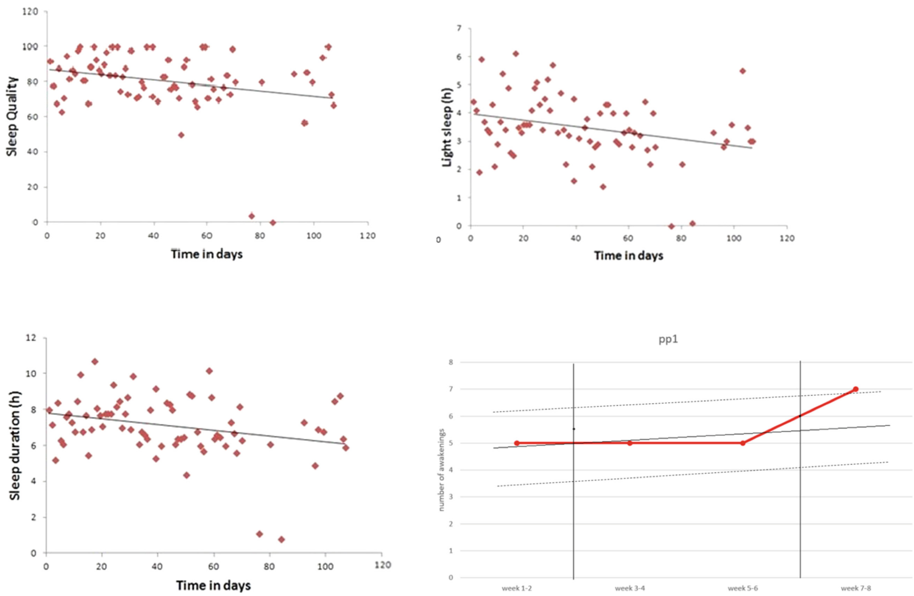

Fig. 2. Sleep quality, light sleep and sleep duration verses time in days. Frequency of awakenings, horizontal accelerating line is the trend line & dotted lines the stability envelope midrates are indicated by the horizontal black lines.

3.3 Participant 2: Burnout Diagnosis- Recovering at Home Throughout Most of Study

Participant 2 was diagnosed as burned out during the beginning of the study and went home to recover, staying there throughout the remainder of the study and remained diagnosed as burned out at the end of the study. This individual's data is consistent with literature stating burnout individuals experience decreased sleep quality. However, their frequency of awakening also went down during their recovering time except for the last weeks (week 11 & 12). This individual had the highest number of awakenings in a single night, ranging from 0–8 awakenings per night. The variables time in days and the variable sleep quality were significantly negatively correlated, $r(100) = -0.207$, $p = 0.04$. When time in days increased, sleep quality deteriorated. No significant correlations between time in days and: light sleep, sleep duration or time awake were found (see Fig. 3). Frequency of awakenings analysis shows a decelerating trend (see Fig. 3). However, The percentage of data points within the stability envelope is below the stability criterion of 80% (66,66%) therefore, no stable trend was found.

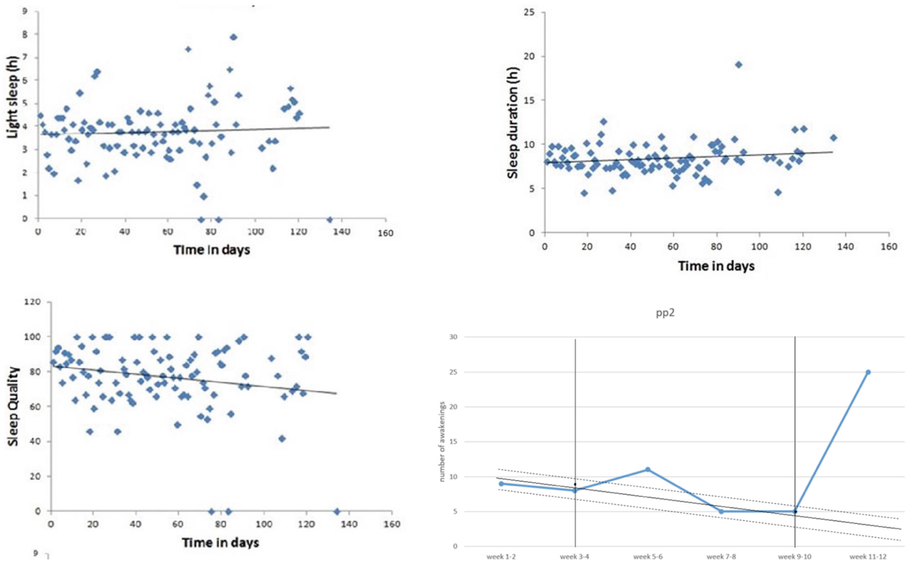

Fig. 3. Sleep quality, light sleep and sleep duration verses time in days. Frequency of awakenings calculated over every two weeks. The horizontal decelerating line is the trend line and dotted lines indicate the stability envelope. (Week 13–16 data was <80% and therefore excluded)

3.4 Participant 3: Pre Burnout, Burnout Diagnosis, Recovery at Home, Return to Work Part Time, Return to Work Almost Full Time

Participant 3 gave us the most comprehensive look at the full spectrum of burnout. This individual experienced pre burnout from day 0–33, full burnout diagnosis recovering at home day 34–107, returned to work part time day 107–216, and returning almost full time to work day 217+. Overall, this participant experienced decreased sleep duration and light sleep and had the second most number of awakenings in a night ranging from 0–6 awakenings per night. No significant correlation was found for time in days: and sleep quality or time awake for the entire period of the study. Time in days and sleep duration, r (234) = −0.192, $p < 0.01$ and light sleep were significantly negatively correlated, r (234) = −0.140, $p = 0.03$. In short, as time passed, amount of light sleep and overall sleep decreased (see Fig. 4).

The data from different burnout states (i.e.: burnout diagnosis/sick leave and recovery from burnout/returning to work) allowed us to separate the different burnout states conducting 3 different analyses for frequency of awakenings. Analysis was conducted over the data (1) in general (including the entire 7 months), (2) within-condition (time recovering at home and returning to work), (3) between-condition analyses (between recovery time at home and returning to work) [44] (see Fig. 5). The frequency of awakenings over the entire time (*general analysis*) indicated a decelerating trend. However, The percentage of data points within the stability envelope was below the stability criterion of 80% (53,33%). Therefore, no distinguishable stable trend was found for the data over the entire time span. Results of the *within-condition analysis* indicated that awakenings were decelerating during burnout and the period returning to work. Data was stable during burnout state (condition A), (100% data within stability envelope), and, returning to work (condition B) (87.5% data within stability envelope). A decelerating stable trend was observed in both conditions. Results of the *between-condition analysis* show no significant difference between conditions, both trends were decelerating.

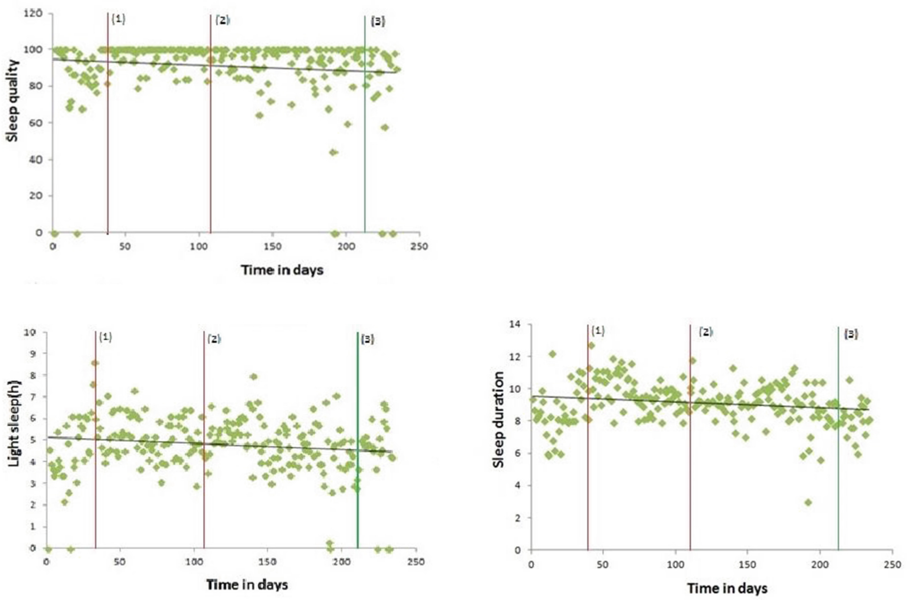

Fig. 4. Sleep duration, Light sleep, & Sleep quality verses time in days. Frequency of awakenings calculated over every two weeks. Line (1) indicates burnout diagnosis, line (2) indicates part time return to work and line (3) indicates almost full time at work.

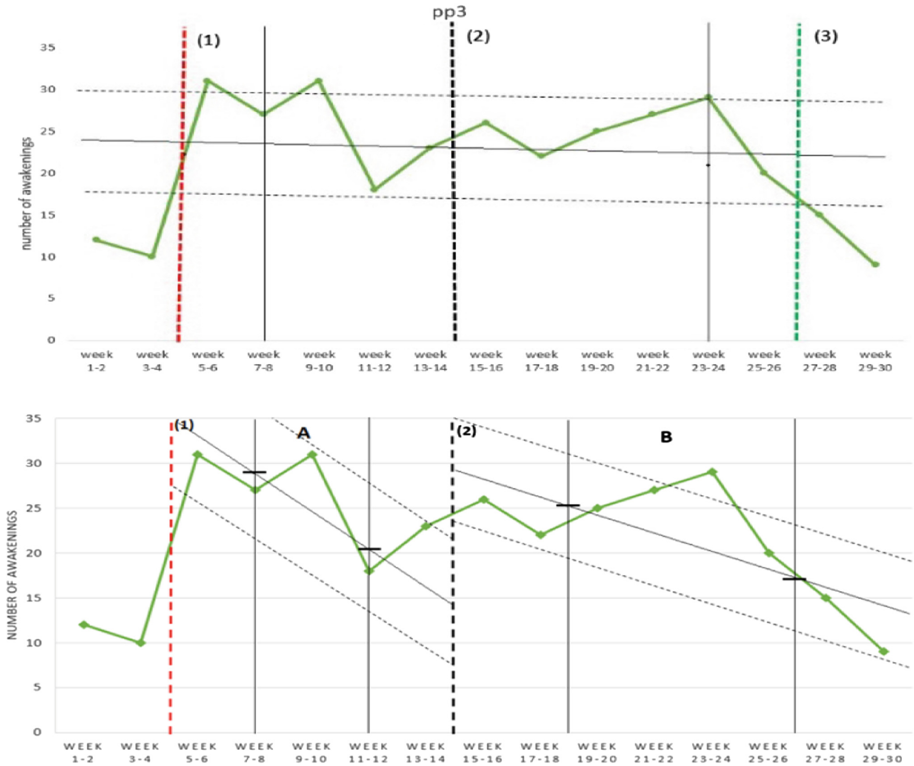

Fig. 5. Time awake verses time in weeks. Line (1) indicates burnout diagnosis, line (2) indicates part time return to work and line. The decelerating horizontal lines display the trend lines and dotted lines indicate the stability envelopes. A = burnout phase & B = returning to work for within-and between-condition analysis

3.5 Participant 4: Pre Burnout Diagnosis Day 74 - Worked Full Time Until Diagnosis

Non-burnout Participants

Three participants of the study without burnout, participant 5, 6 and 7, were randomly selected for comparison. With 1 exception the sleep measures of these participants remained stable for the duration of the study. For participant 7, a significant correlation was found for time in days and time awake, r (104) = −0.242, p = 0.01. When time in days progressed, the time awake decreased (See Fig. 6). No other significant correlations were found for the three participants for time in days and sleep quality, sleep duration, light sleep, or awake time (See Fig. 7). Participant 5 and 7 had missing data during some of the 2 - weeks periods of the study which rose above 20%. Therefore, the stability could not be calculated for the entire period. Participant 6 showed an accelerating trend. The percentage of data points within the stability envelope is 100%. This is above the stability criterion of 80% which means that the data is stable. Therefore, a distinguishable stable trend was found. Figure 7 shows participant 8's

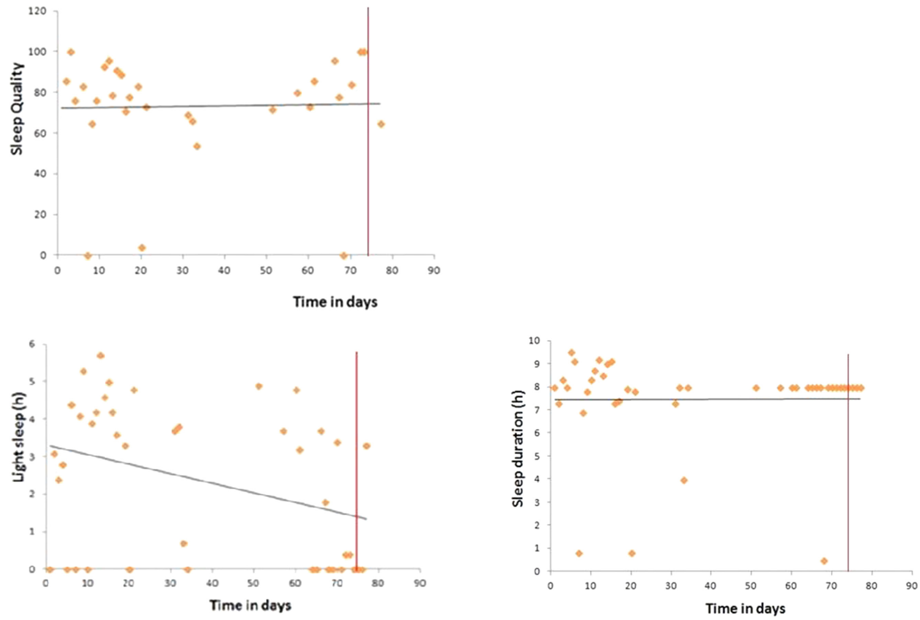

Fig. 6. Sleep quality, light sleep and sleep duration. The red line indicates diagnosis of pre-burnout. (Color figure online)

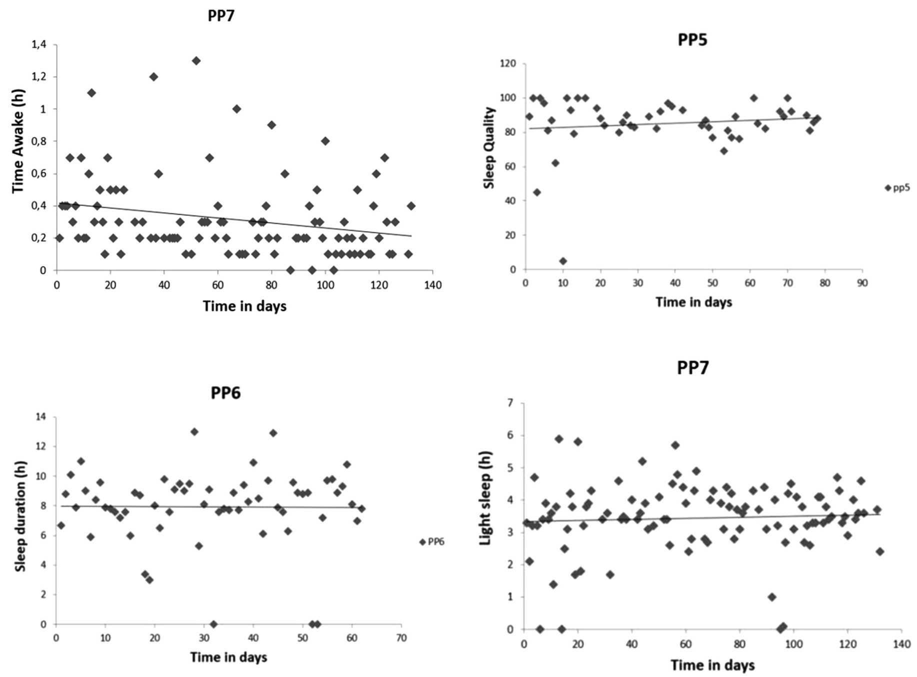

Fig. 7. Time awake over time in days for participant 7, Sleep quality participants 5, sleep duration participant 6 & light sleep participant 7.

decelerating trend in time awake and time in days. It also shows the three separate sleep measures: sleep quality sleep duration and light sleep for the separate participants. Since sleep measures were found to be stable for the 3 non-burnout participants, this figure shows the 3 measures and 3 participants to show the trend across all measures and participants (See Fig. 7).

4 Discussion and Conclusions

In this study we looked at the relationship between sleep and burnout in four longitudinal burnout case studies. Our findings suggest three main outcomes. First, we found a progressive decrease in sleep quality (Participant 1 & 2), sleep duration (Participant 1 & 3), and light sleep (Participant 1, 3, & 4) over the 7 month period. This is consistent with past short term studies on burnout [15, 27, 28]. Burnout is a gradual and progressive decrease in energy, so the decrease in sleep quality and sleep duration would also be expected to progress slowly if the burnout remains stable [7]. We found a possible correlation between light sleep and sleep duration (Participant 1 & 3). It seems logical that when total sleep duration decreases, the amount of sleep of all sleep phases gets shorter, including light sleep [37]. Participant 4, our pre-burnout participant, deviates from this pattern: light sleep decreased over time, but sleep duration did not. For participant 4, it must be noted that considerable data is missing and therefore conclusions are less reliable. Moreover, only data before the pre-burnout state of this participant was available. We are therefore reticent when interpreting the light sleep data of the participants, since some research has concluded that activity trackers are not accurate when measuring some sleep phases including light sleep [20].

Second, we found a decreasing trend in number of awakenings during the burnout state (on sick leave) and after returning to work for participant 3. Participant 3 experienced multiple burnout states including: pre burnout, burnout diagnosis recovering at home, returning to work part time, and returning to work almost full time. The decline in awakenings could be an indication that Participant 3 was recuperating during their time recovering at home. This could also explain why participant 3 did not experience decreased sleep quality during the study.

Third, no changes in sleep parameters were found for healthy participants, except for participant 7 who decreased in time awake during the night and displayed an upward trend for number of awakenings as time progressed. Unchanging sleep patterns are consistent with sleep research on non-burnout participant in both sleep diary studies and laboratory experiments [30, 31]. They found that sleep parameters remain stable for months or even years. The stability of sleep for the healthy participants supports the idea that the trends we found in burnout participants are associated to the burnout process.

Fourth, this study gave an initial indication that activity trackers may be an efficient and viable tool for measuring certain sleep parameters for longitudinal case studies. Past studies have highlighted the validity of certain measurements captured by activity trackers [20, 21]. While no studies could be found specifically on the Jawbone up move's (which was used in the present study) sleep validity and reliability. Other studies have shown that Jawbone wristbands such as the Jawbone up overestimates sleep when compared to PSG [45, 46]. Total sleep time was overestimated by 10 min ($p < 0.001$), sleep efficiency was overestimated by 1.9% ($p < 0.001$), and sleep onset latency was overestimated by 1.3 min ($p = 0.33$), and wake time after sleep onset was overestimated by 10.6 min ($p < .001$). The affordability, mobility, and popularity of activity trackers makes them an attractive option for large longitudinal studies. Data for a large study could become available through eHealth and digital health tools, which are increasingly being used for both personal and medical practice. Gathering more data could lead to identification of early burnout indicators as well as gained understanding of the different stages of burnout such as pre-burnout, diagnosed burnout, and partial/full recovery. This information could then guide tool-based interventions designed for prevention in the early stages of burnout as well as burnout and post burnout treatment. While the opportunity for measurement and treatment is substantial, careful steps must be taken to protect the privacy of individuals, especially in work settings. In this case extra consent was requested by the researchers and presented to the ethics committee for approval. This approach can be a good example for other researchers who want to further understanding in this area while protecting their participants wishes and privacy. While participants reported the wristbands were comfortable during sleep, the feedback of sleep information to the individual is equally important [47]. For instance, an individual may become anxious after seeing they slept badly which in turn might affect their sleep the following night [48]. eHealth interventions are especially interesting to countries that do not have a structure in place to recover from burnout. This study was done in The Netherlands where burnout is diagnosed, and individuals leave work to recover over weeks or months. In most countries this diagnosis and support does not exist. Burnout prevention could radically reduce the number of employees working during a state of burnout. This insight could also be used by technology developers to enhance certain features of lifelogging tools as well as eHealth interventions to empower those using sleep trackers to avoid or fight burnout.

This study did experience some limitations. First, the sample size is limited ($n = 4$) given that this data was captured serendipitously during another study. Research with more cases is advised. Including a burnout measurement tool within an eHealth tool or active tracker's mobile application could produce a larger longitudinal sample. Second, the missing data points for the participants could affect the validity of the findings. In future studies we recommend selecting wearable technology which does not require actions from the participants (in this case pressing a button before going to sleep and upon waking up). This could greatly decrease the number of missing data points captured for sleep. However, it should be noted that the current accuracy of automated sleep detection for activity trackers has shown false positives (e.g. sleep state can be falsely identified if a person is very still) [20]. Hopefully, future evolutions of these products decrease this problem. Third, the accuracy of actigraphy sleep measurements is not absolutely known. As discussed earlier in the paper there are many benefits of using wearable technology (actigraphy) to measure longitudinal sleep trends. However, the flexibility of the device decreases some of the precision used in other measurement tools. Also, the tools themselves differ in their measurement between brand. Further research on validity of the specific measurement of actigraphy tools can shed light on which measurements and which brands are best used in future studies.

References

1. Consiglio, C., Borgogni, L., Alessandri, G., Schaufeli, W.B.: Does self-efficacy matter for burnout and sickness absenteeism? The mediating role of demands and resources at the individual and team levels. Work Stress **27**(1), 22–42 (2013)
2. Ahola, K., et al.: Occupational burnout and medically certified sickness absence: A population-based study of Finnish employees. J. Psychosom. Res. **64**(2), 185–193 (2008)
3. Taris, T.W.: Is there a relationship between burnout and objective performance? A critical review of 16 studies. Work Stress **20**(4), 316–334 (2006)
4. Schaufeli, W.B., Bakker, A.B., Van Rhenen, W.: How changes in job demands and resources predict burnout, work engagement, and sickness absenteeism. J. Organ. Behav. **30** (7), 893–917 (2009)
5. Burn-out: de rol van werk en zorg: Central Bureau of Statistics (2013). https://www.cbs.nl/nl-nl/achtergrond/2013/04/burn-out-de-rol-van-werk-en-zorg. Accessed 14 Jun 2018
6. Meer psychische vermoeidheid ervaren door werkL Statistics, Central of Bureau (2018). https://www.cbs.nl/nl-nl/nieuws/2018/46/meer-psychische-vermoeidheid-ervaren-door-werk . Accessed 07 Apr 2019
7. Leiter, C., Maslach, M. P.: Areas of Worklife Survey Manual. Wolfville: Centre for Organizational Research and Development, Acadia University
8. Kim, H., Ji, J., Kao, D.: Burnout and physical health among social workers: a three-year longitudinal study. Soc. Work **56**(3), 258–268 (2011)
9. Ekstedt, M., Söderström, M., Akerstedt, T., Nilsson, J., Søndergaard, H.-P., Aleksander, P.: Disturbed sleep and fatigue in occupational burnout. Scand. J. Work Environ. Health **32**(2), 121–131 (2006)
10. Toker, S., Biron, M.: Job burnout and depression: unraveling their temporal relationship and considering the role of physical activity. J. Appl. Psychol. **97**(3), 699–710 (2012)
11. Peterson, U., Demerouti, E., Bergström, G., Samuelsson, M., Åsberg, M., Nygren, Å.: Burnout and physical and mental health among Swedish healthcare workers. J. Adv. Nurs. **62**(1), 84–95 (2008)
12. Harrison, Y., Horne, J.A.: One night of sleep loss impairs innovative thinking and flexible decision making. Organ. Behav. Hum. Decis. Process. **78**(2), 128–145 (1999)
13. Maislin, G., Dinges, D.F., Van Dongen, H.P.A., Mullington, J.M.: The cumulative cost of additional wakefulness: dose-response effects on neurobehavioral functions and sleep physiology from chronic sleep restriction and total sleep deprivation. Sleep **26**(2), 117–126 (2003)
14. Hirshkowitz, M., et al.: National sleep foundation's sleep time duration recommendations: methodology and results summary. Sleep Heal. **1**(1), 40–43 (2015)
15. Söderström, M., Jeding, K., Ekstedt, M., Perski, A., Åkerstedt, T.: Insufficient sleep predicts clinical burnout. J. Occup. Health Psychol. **17**(2), 175–183 (2012)
16. Nilsson, J.P., et al.: Less effective executive functioning after one night's sleep deprivation. J. Sleep Res. **14**(1), 1–6 (2005)
17. Vandekerckhove, M., Cluydts, R.: The emotional brain and sleep: an intimate relationship. Sleep Med. Rev. **14**(4), 219–226 (2010)
18. Geurts, S.A.E., Sonnentag, S.: Recovery as an explanatory mechanism in the relation between acute stress reactions and chronic health impairment. Scand. J. Work Environ. Health **32**(6), 482–492 (2006)
19. Sonnenschein, M., Sorbi, M.J., van Doornen, L.J.P., Schaufeli, W.B., Maas, C.J.M.: Evidence that impaired sleep recovery may complicate burnout improvement independently of depressive mood. J. Psychosom. Res. **62**(4), 487–494 (2007)

20. Mantua, J., Gravel, N., Spencer, M.R.: Reliability of sleep measures from four personal health monitoring devices compared to research-based actigraphy and polysomnography. Sensors **16**(5), 646 (2016)
21. Kosmadopoulos, A., Sargent, C., Darwent, D., Zhou, X., Roach, G.D.: Alternatives to polysomnography (PSG): a validation of wrist actigraphy and a partial-PSG system. Behav. Res. Methods **46**(4), 1032–1041 (2014)
22. Van de Water, A.T.M., Holmes, A., Hurley, D.A.: Objective measurements of sleep for non-laboratory settings as alternatives to polysomnography – a systematic review. J. Sleep Res. **20**(1pt2), 183–200 (2011)
23. Berry, M.H., Wagner, R.B.: Sleep Medicine Pearls. Elsevier Health Sciences, Amsterdam (2014)
24. Nelson, E.C., Verhagen, T., Noordzij, M.L.: Health empowerment through activity trackers: an empirical smart wristband study. Comput. Hum. Behav. **62**, 364–374 (2016)
25. Nelson, E.C., Verhagen, T., Vollenbroek Hutten, M.M.R., Noordzij, M.L.: Is wearable technology becoming part of us? Developing and validating a measurement scale for wearable technology embodiment. JMIR mHealth uHealth **7**, e12771 (2019)
26. Tzischinsky, O., Zohar, D., Epstein, R., Chillag, N., Lavie, P.: Daily and yearly burnout Symptoms in Israeli shift work residents. J. Hum. Ergol. (Tokyo) **30**(1–2), 357–362 (2001)
27. Tan, M.Y., Low, J.M., See, K.C., Aw, M.M.: Comparison of sleep, fatigue and burnout in Post-Graduate Year 1 (PGY1) residents and faculty members – a prospective cohort study. Asia Pac. Sch. **2**(2), 1–7 (2018)
28. Shea, J.A., et al.: Impact of protected sleep period for internal medicine interns on overnight call on depression, burnout, and empathy. J. Grad. Med. Educ. **6**(2), 256–263 (2014)
29. Astill, R.G., Verhoeven, D., Vijzelaar, R.L., Van Someren, E.J.W.: Chronic stress undermines the compensatory sleep efficiency increase in response to sleep restriction in adolescents. J. Sleep Res. **22**(4), 373–379 (2013)
30. Hoch, C.C., et al.: Longitudinal changes in diary- and laboratory-based sleep measures in healthy ‘old old’ and ‘young old’ subjects: a three-year follow-up. Sleep **20**(3), 192–202 (1997)
31. Gaines, J., et al.: Short- and long-term sleep stability in insomniacs and healthy controls. Sleep **38**(11), 1727–1734 (2015)
32. O’Kelly, F., et al.: Rates of self-reported ‘burnout’ and causative factors amongst urologists in Ireland and the UK: a comparative cross-sectional study. BJU Int. **117**(2), 363–372 (2016)
33. European Union General Data Protection Regulation: EU GDPR.ORG. https://www.eugdpr.org. Accessed 25 Mar 2018
34. Broughall, N.: Jawbone UP Move review. techradar (2014). https://www.techradar.com/reviews/gadgets/jawbone-up-move-1277383/review
35. Sense Labs: https://www.sense-labs.com/
36. Pirrera, S., De Valck, E., Cluydts, R.: Nocturnal road traffic noise: a review on its assessment and consequences on sleep and health. Environ. Int. **36**(5), 492–498 (2010)
37. Maquet, P., et al.: Brain imaging on passing to sleep. In: The Physiologic Nature of Sleep, pp. 123–137 (2005)
38. American Psychiatric Association: Diagnostic and statistical manual of mental disorders (DSM-5®). American Psychiatric Publishing (2013)
39. Walter, J.M., Van Lunen, B.L., Walker, S.E., Ismaeli, Z.C., Oñate, J.A.: An assessment of burnout in undergraduate athletic training education program directors. J. Athl. Train. **44**(2), 190–196 (2009)
40. Schaufeli, W.B.: Maslach Burnout Inventory-General Survey (MBIGS). In: Maslach Burnout Inventory Manual (1996)

41. Van Rood, Y., van Ravesteijn, H., de Roos, C., Spinhoven, P., Speckens, A.: Protocollaire behandelingen voor volwassenen met psychische klachten. Deel 2. In [Manualized treatments for adults with psychological disorders, part 2], pp. 15–47 (2010)
42. Arbuckle, J.L.: IBM® SPSS® Amos™ 23 User's Guide (2014)
43. Mehl, C.T.S., Matthias, R.: Handbook of Research Methods for Studying Daily Life. Guilford Press, New York (2011)
44. Lane, J.D., Gast, D.L.: Visual analysis in single case experimental design studies: brief review and guidelines. Neuropsychol. Rehabil. **24**(3–4), 445–463 (2014)
45. Evenson, K.R., Goto, M.M., Furberg, R.D.: Systematic review of the validity and reliability of consumer-wearable activity trackers. Int. J. Behav. Nutr. Phys. Act. **12**(1), 159 (2015)
46. de Zambotti, M., Baker, F.C., Colrain, I.M.: Validation of sleep-tracking technology compared with polysomnography in adolescents. Sleep **38**(9), 1461–1468 (2015)
47. Gorman, G.E.: What's missing in the digital world? Access, digital literacy and digital citizenship. Online Inf. Rev. **39**(2) (2015). https://doi.org/10.1108/OIR-02-2015-0053
48. Hsiao, K.-L.: Compulsive mobile application usage and technostress: the role of personality traits. Online Inf. Rev. **41**(2), 272–295 (2017)