



# Sleep and health: examining the relation of sleep to burnout and well-being using a consumer fitness tracker

Nina R. Grossi<sup>1</sup> · Bernad Batinic<sup>1</sup> · Sebastian Moharitsch<sup>1</sup>

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## Abstract

Sleep is an essential requirement for both physiological and psychological functioning and has an impact on various health parameters. The present study aimed to examine how quantity and quality of sleep predicts burnout and well-being by using both self-reported and objectively collected sleep data. The participants were 104 white-collar workers who wore a fitness tracker for 14 consecutive days and filled out a questionnaire about sleep, burnout, and well-being. The results showed that self-reported sleep quality predicts burnout and well-being, but neither did self-reported nor objective sleep duration. We concluded that although measuring sleep duration with a consumer fitness tracker still needs to be improved, it is a useful addition to self-reported sleep measures. The study did solidify results from previous self-reported measures and point out the prominent role of sleep quality rather than hours of sleep.

**Keywords** Sleep · Burnout · Well-being · Tracking · Fitness tracker · Objective data

## 1 Introduction

Sleep is one of the most important factors for various health indicators and crucial to meeting the challenges in daily life. Insufficient or disturbed sleep has an impact on physical, cognitive, and psychological parameters and can lead to serious health complications [1–3]. One of the most common problem that underlies disturbed sleep is insomnia. However, several other parameters require equal attention when examining the relation between sleep and health. These include the time it takes to fall asleep (sleep latency), the quantity and extension of awakenings during the night, the total hours of sleep, the regularity of the sleep schedule, as well as heart rate, blood pressure, and rhythm of sleep phases (rapid eye movement vs. deep sleep) [2]. The importance of the topic becomes clear as disturbed sleep was shown to

affect between 16.6% (Denmark) and 31% (Poland) of Europeans [4]. Furthermore, in a national survey in Australia, Adams et al. [5] found that self-reported, insufficient sleep affected 33–45% of a representative sample. The participants reported various sleep indicators as being responsible for insufficient sleep, ranging from difficulty falling asleep, to waking up too early and not being able to fall asleep again, to feeling unrefreshed upon waking. In another international longitudinal study with over 100,000 participants from 21 countries, Wang et al. [6] examined the relation between sleep and health. Their results showed that participants with insufficient sleep are more likely to die from cardiovascular diseases. These findings are in line with Itani et al. [7] who examined the relations between sleep and mortality and other notable health conditions. Their results showed that insufficient sleep is associated with diabetes mellitus, cardiovascular difficulties (e.g., hypertension or stroke), as well as obesity and mortality. Furthermore, insufficient sleep has been associated with difficulties concerning both mental concentration and daily functioning [2].

However, what remains less clear is whether the quality of sleep or the quantity (hours) of sleep is more suitable to explain the relation between sleep and health. For example, while Lee et al. [8] found that longer sleep duration is associated with better sleep quality and a shorter period of falling asleep, Zhang et al. [3] found that short sleep duration

✉ Nina R. Grossi  
nina.grossi@jku.at  
Bernad Batinic  
bernad.batinic@jku.at  
Sebastian Moharitsch  
sebastian.moharitsch@jku.at

<sup>1</sup> Department of Work, Organizational and Media Psychology, Johannes-Kepler University, Altenbergerstrasse 69, 4040 Linz, Austria

is associated with higher levels of anxiety, behavioral disorders, suicidality, tobacco smoking, as well as poor mental and physical health. Itani et al. [7] found that short sleep duration is associated with diabetes mellitus, cardiovascular difficulties, as well as with obesity and mortality. They found the association with mortality to be especially strong when the average sleep duration was shorter than 6 h per night. The authors reported no significant association between sleep duration and depression, however, this might be due to the fact that they only included one study on depression and sleep in their review. Most of the studies included in the review from Itani et al. [7] defined short sleep duration as an average of fewer than 6 or 7 h per night, whereas a normal sleep duration was 7 h or more per night.

In sum the literature presented above concludes that clearly sleep in general is crucial for our health. The goal of the present study is to examine this relation by taking a closer look on the role of sufficient sleep considering the two specific health parameters well-being and burnout. Furthermore, the study aims to clarify whether objective sleep data from a common fitness tracker is adequate to describe this relation and if research may even benefit from including it. We want to determine whether objective sleep measures are more accurate than self-reported data to display the relation of sleep, burnout and well-being. Furthermore, we want to take a closer look on the chances and challenges when including objective sleep data, especially with devices which are easily accessible for everyone on the consumer market.

### 1.1 Sleep, burnout and well-being

The impact of disturbed or non-restorative sleep on well-being is another dominant factor in the relation between sleep and health [9–11]. Findings in literature show that poor mental health is associated with a short duration of sleep [3]. Therefore, we hypothesize that a longer sleep duration improves well-being (Hypothesis 1). What is interesting is, that literature also indicates curvilinear effects of hours of sleep on well-being. Hamilton et al. [12] found that optimal sleep duration is associated with higher scores in psychological health, such as well-being, depression, and anxiety. They defined optimal sleep to be an average of 6 to 8.5 h of sleep per night, and non-optimal sleep to be fewer than 6 h or more than 8.5 h of sleep per night. Therefore, when testing Hypothesis 1, we will statistically control for curvilinear effects.

Furthermore, literature shows that disturbed or non-restorative sleep also influences one of the most prominent health issues in the last decade: burnout [1, 13, 14]. Metlaine et al. [14] found subjective sleep data (insomnia and non-restorative sleep) to be associated with a higher risk of burnout. Allen et al. [13] examined the relations among stress, burnout, and sleep. They found two major burnout indicators—exhaustion

and cynicism—are positively associated with shorter sleep duration [13]. Therefore, we assume that a shorter sleep duration will increase burnout symptoms (Hypothesis 2). When testing hypothesis 2, we will also statistically control for curvilinear effects because literature showed that both too few (< 6) and too many (> 8) hours of sleep on average per night might be associated with mortality [6]. Another study also found differences in the prevalence of burnout among groups of habitual sleep time in hours: Participants with fewer than 6 h as well as participants with more than 9 h of sleep per night showed a higher percentage of burnout than participants with 7 to 9 h of sleep [14].

Sleep duration, however, is not the only factor that has an impact on health:

Pilcher et al. [9] conducted a diary-study in which participants filled out a sleep-log for seven consecutive days to report their sleep duration and perceived quality of sleep. The results showed that quality of sleep is more strongly associated with health measures such as depression, anger or fatigue, than is quantity of sleep. Results of several studies show the importance of a good quality of sleep for well-being [9–11, 15]. Reciprocity marks the relation between well-being and sleep quality: When people sleep better, they report a higher well-being and, conversely, when people feel well, they report better sleep quality [15, 16]. Additionally, good quality of sleep not only improves well-being but also facilitates the finding of balance between work and life [17]. Furthermore, also Jean-Louis et al. [18] found that self-reported satisfaction as a measure of sleep quality had an impact on well-being. In line with the presented literature, we expect a better quality of sleep to be associated with more well-being (Hypothesis 3).

A recent study of Allen et al. [13] also point out the importance of quality of sleep by reporting an increased relation of stress and exhaustion when quality of sleep was poor. In detail, all three burnout indicators they examined – exhaustion, cynicism, and inefficacy – were shown to be positively associated with a lower quality of sleep [13]. Another study found that participants with high sleep quality had significantly lower burnout scores than participants with poor sleep quality [1]. Consequently, we expect a better sleep quality to be associated with lower burnout-scores (Hypothesis 4).

In sum, the literature indicates that both sleep quality and hours of sleep are important indicators for health parameters.

### 1.2 Subjective and objective data on sleep

Self-reported data often include difficulties and inaccuracies [19–22]. Study participants on the one hand tend to overestimate sleep latency and on the other hand to overestimate sleep duration [23]. Findings regarding sensitivity and specificity for smartphone applications to measure

sleep are similar. In a study Fino et al. [24] compared different smartphone apps to detect sleep and wake time with a polysomnography (PSG). The results indicate that most apps were correlated with the PSG for time spent in bed but not necessarily for time or quality of actual sleep (sleep efficacy). The authors, therefore, have recommended adding external sensors to measure physiological parameters, for example, heart rate or breathing, to improve the validity of sleep applications on smartphones. It is, thus, important to use multiple modalities when examining sleep and health. For example, it may not be enough to use a sleep tracking mat alone when trying to understand the interaction between sleep and well-being, but combining the mat with a device to measure vital parameters may be more useful [25]. The evidence reviewed here seems to suggest a pertinent role for both subjective and objective data when examining the relation between sleep and health. A common tool to collect objective data on sleep is a fitness tracker worn on the wrist [26]. For that reason, we also include objective sleep measures to test the hypotheses. Objective sleep measures provide the possibility to calculate the day-to-day variability of sleep duration [11]. A study from Lemola [11] used actigraphy to examine the relation of sleep and health. Results showed a significant association between sleep quality and well-being. When considering the fact that the regularity of the sleep schedule is an indicator for better sleep [2], the day-to-day variability of sleep duration could serve as an objective parameter of sleep quality. Furthermore, findings indicate an association between a longer sleep duration and a better quality of sleep [8]. We expect this to be true for the relation of both self-reported and objective measures of sleep duration and quality (Hypothesis 5). Based on this expectation and the other hypotheses we further propose an indirect effect of sleep duration on well-being through sleep quality (Hypothesis 6) and an indirect effect of sleep duration on burnout through sleep quality (Hypothesis 7).

## 2 Method

### 2.1 Participants

In total 104 (45.2% female) white-collar workers participated in the study. To provide anonymity we asked the age of participants in form of categories: < 25 years (0%), 25–29 years (7.7%), 30–34 years (5.8%), 35–39 years (13.5%), 40–44 years (5.8%), 45–49 years (10.6%), 50–54 years (18.3%), 55–59 years (21.1%), 60–64 years (10.6%) and no statement (6.7%). Participants worked at a certain department of a public institution in Austria. The majority of them worked fulltime:  $\leq 25$  h per week (10.6%), 26–45 h per week (8.7%) and  $\geq 36$  h per week (68.3%), no statement (12.5%). Work activity of participants included both in-house activities and

on-the-road activities, visiting customers. Regardless of activity, employees could easily take the fitness tracker (wrist band) with them all day.

### 2.2 Procedure

Participation was fully voluntary. As a benefit for taking part, each participant received individual feedback on their health parameters and some suggestions on how to improve their health at the end of the study. Participants needed to register for participation in advance in order to take part at the opening event of the study where they were informed about content and purpose of the study and gave consent. The field study was approved in terms of ethical compliance by the committee of the public institution's workers' council. At the opening event participants also received a fitness tracker, which they chose randomly. Overall, they could wear the fitness tracker for fourteen consecutive days, but because of work-related appointments some participants received their device one day later and/or returned it one day earlier. Therefore, in terms of data continuity, we excluded the first and the last two days of data collected and included ten days for further analyses, because this was the official time of data collection.

We used the XIAOMI “Mi Band 2” fitness tracker for several reasons. First, it had enough internal storage to save all data during the duration of data collection. We only synchronized the data when the participants returned their trackers. Second, the trackers had a long-lasting battery which kept the effort for participants to a minimum. They did not have to charge the device every other day, which was important for both participants' commitment and continuous collection of data. Finally, third, the trackers had an application programming interface that we used to pair the devices exclusively with our own application based on the open source app Gadgetbridge to ensure data security. When participants returned their fitness tracker, they received the link to an online questionnaire that included standard sociodemographic data (age, gender, educational level, marital status, working hours) as well as measures about sleep quality, sleep duration, burnout, and wellbeing. It also included other health parameters (e.g., physical activity) that are not part of the current research model. We then used the serial number of the fitness tracker as the identification code for each participant to match the objective sleep data with the data of the online survey.

### 2.3 Measures

#### 2.3.1 Self-reported Sleep Quality

To assess self-reported sleep quality (SSQ), we used the German version of the Jenkins Sleep Quality Index [27]. The index consists of four items that ask about the most

common parameters for sleep quality, for example, trouble falling asleep or not feeling refreshed after a sufficient time of sleep. Items were originally rated on a 6-point scale, expressing how often the condition appeared in the last month. We changed the instructions from “in the last month” to “in the last 14 days.” To fit the design of the current study, the answering scale was adapted from: “not at all”, “1 to 3 days”, “4 to 7 days”, “8 to 14 days”, “15 to 21 days” and “22 to 31 days” to: 1 “to a very large extent”, 2 “to a large extent”, 3 “somewhat”, 4 “to a small extent” and 5 “to a very small extent.” Originally, high sleep quality was demonstrated with a low score, but for statistical analyses, items were revised so that a high sleep quality was demonstrated with a high score. Observed reliability within this sample was Cronbach’s  $\alpha$  (alpha) = 0.81.

### 2.3.2 Self-reported Sleep Duration (SSD)

To assess SSD, we used the single item for sleep duration from the Pittsburgh Sleep Quality Index: “How many hours of actual sleep do you get at night? (This may be different than the number of hours you spend in bed)” [28]. To fit the study design, we adapted the instructions slightly from “... do you get at night” to “... did you on average get at night in the last 14 days.” Participants responded with the average hours of sleep, for example, 6.5 h or 7 h.

### 2.3.3 Objective Sleep Duration (OSD)

To record OSD, we used the Xiaomi “Mi Band 2” tracker and extracted the data with our own application based on the open source app, Gadgetbridge. With this software we were able to extract the raw data to a database and divided it into the columns: id, mac-address, timestamp in 60 s steps, raw intensity, heart rate, and raw kind. The first two columns (id and mac-address) were necessary for unique identification of data set with person; raw intensity and raw kind were indicators for specific activities like sitting, running, or sleeping. After some investigation at the official github wiki and the relevant reddit forum, we identified the raw kind codes for sleep as 105, 106, 112, 121, 122, 123, 124 for the latest version of Gadgetbridge, numbered 0.24.2. We verified the codes using a small test study with 8 participants, who recorded their sleeping time every night by hand as well. We identified the relevant raw data (according to the raw kind codes) and calculated sum scores of sleeping hours per night and person. We used the sum scores to build an individual mean of hours of sleep for each person. We examined the accuracy of the Mi Band 2 in measuring sleep duration in a diary-study with 45 participants, ages ranging from 18 to 59 years (manuscript in preparation). Participants wore the fitness tracker on 10 consecutive days and filled out a daily sleep protocol. The protocol involved questions on the times

of going to bed and waking up, sleep quality, and concrete hours of sleep. The results of multilevel analyses show a significant relation between objective and self-reported hours of sleep. Thus, the Mi Band 2 is, at least to some extent, suitable for measuring objective sleep duration (manuscript in preparation).

### 2.3.4 Objective Sleep Quality (OSQ)

The regularity of the sleep schedule is an indicator for better sleep [2]. Therefore, we used the day-to-day variability of sleep duration as indicator for objective sleep quality. We calculated the day-to-day variability based on the objective hours of sleep from the Mi Band 2. We divided the individual variance of sleep duration with the individual mean of sleep duration and multiplied it with 100 as suggested by Lemola et al. [11]. This procedure results in the coefficient of variance. A higher coefficient indicates a higher variability of sleep duration from day-to-day whereas a smaller coefficient indicates a lower variability [29].

### 2.3.5 Burnout

To measure personal burnout, we used the German version of the Copenhagen Burnout Inventory (CBI) [30]. The authors refer to personal burnout in the following way “*Personal burnout is the degree of physical and psychological fatigue and exhaustion experienced by the person*”, p. 197 [30]. The CBI consists of 6 items that ask about physical and psychological fatigue and exhaustion, for example, “*How often are you emotionally exhausted*” or “*How often are you physically exhausted*.” Participants can choose 100% “always”, 75% “often”, 50% “sometimes”, 25% “seldom” and 0% “never/almost never” to answer the items. In order to make it easier to interpret the burnout score, we transformed answer options to a 5-point scale for statistical analysis (100% “always” = 5, 75% “often” = 4, 50% “sometimes” = 3, 25% “seldom” = 2 and 0% “never/almost never” = 1). Cronbach’s  $\alpha$  (alpha) was 0.89, indicating adequate internal consistency.

### 2.3.6 Well-being

We assessed well-being with the WHO-5 Well-Being Index [31]. The five items can be answered on a 6-point scale ranging from 0 “at no time” to 5 “at all times.” The questionnaire contains items about general well-being, for example, “*I have felt calm and relaxed*” or “*My daily life has been filled with things that interest me*.” To fit the design of the current study, we adapted the instruction slightly from “*Please respond to each item by marking one box per row regarding how you felt in the last two weeks*” to “*Please respond to each item by marking one box per row regarding how you*

felt in the last ten days.” Internal consistency using Cronbach’s  $\alpha$  (alpha) was 0.85.

### 3 Results

#### 3.1 Descriptive statistics and correlations

For data analysis and management, we used SPSS 26.0. Table 1 contains descriptive statistics, sample sizes, correlations and p-values of study variables. Sleep quality showed the expected association with health parameters: a better quality of sleep was linked to lower burnout scores and more well-being. There was also a low but significant association with self-reported hours of sleep, indicating that longer sleep duration is related to better sleep quality. In this sample we found no significant correlation between self-reported and objective sleep duration. As expected, we found burnout and well-being to be negatively associated, indicating that participants who felt better also experienced fewer burnout symptoms.

#### 3.2 Regression analyses

Overall, we conducted two hierarchical regression analyses to test the hypotheses 1 to 4 and two multiple linear regression analyses to test the hypothesis 5. Literature indicated curvilinear effects of sleep duration on well-being and burnout [6, 12, 14]. Therefore, we included quadratic terms as control variables in the first step of both hierarchical regression analyses. In the second step of hierarchical analyses we included measures of sleep duration and in the third step we added measures of sleep quality as predictors to determine the incremental amount of variance explained. With the first hierarchical regression analysis we examined if hours of sleep and sleep quality added to prediction of well-being (Hypotheses 1 and 3). For the first step, the quadratic terms of self-reported and objective sleep duration were added as control variables and results indicate that there are no curvilinear effects ( $R^2 = 0.034, p = 0.269$ ). In the second step

the predictor variables objective and self-reported sleep duration were included. The results still showed a model not to be statistically significant ( $\Delta R^2 = 0.045, p = 0.643$ ). For the third step, we added the predictor variables self-reported and objective sleep quality to the analysis. The results showed a significant change in the  $R^2$  value, suggesting that the addition of sleep quality explained 41.6% of the variation in well-being ( $F(2, 73) = 23.23, p < 0.001$ ). The beta coefficients show, that only self-reported sleep quality significantly added to prediction of well-being ( $B = 0.629, SE = 0.093, p < 0.001$ ), whereas objective sleep quality did not ( $B = -0.003, SE = 0.002, p = 0.082$ ). We repeated the procedure for the outcome variable burnout (Hypotheses 2 and 4). The results of the first two models indicated, that there are no curvilinear effects of sleep duration on burnout ( $R^2 = 0.013, p = 0.600$ ) and that sleep duration did not statistically add to prediction of burnout ( $\Delta R^2 = 0.016, p = 0.898$ ). After adding the third block of predictors (self-reported and objective sleep quality) the analysis revealed a significant change in the  $R^2$  value ( $\Delta R^2 = 0.235, p < 0.001$ ). Therefore, the results indicate that the addition of sleep quality explained 23.5% of variance in burnout ( $F(1, 73) = 10.479, p < 0.001$ ). The beta coefficients show, that only self-reported sleep quality significantly added to prediction of burnout ( $B = -0.418, SE = 0.091, p < 0.001$ ), whereas objective sleep quality did not ( $B = -0.001, SE = 0.002, p = 0.724$ ). In sum, the results of the analyses did not support the hypotheses 1 and 2 but did partly support the hypotheses 3 and 4. Table 2 contains the details of the two hierarchical regression analysis.

To test the assumption that a longer sleep duration leads to more sleep quality we conducted two multiple linear regression analyses (Hypothesis 5). In the first analysis self-reported and objective sleep duration served as predictors for self-reported sleep quality and in the second analysis for objective sleep quality. Overall, the results show, that the predictors could significantly explain variance in self-reported sleep quality ( $R^2 = 0.087, p = 0.030$ ) but not in objective sleep quality ( $R^2 = 0.001, p = 0.970$ ). The beta coefficients considering the outcome variable self-reported

**Table 1** Descriptive statistics and correlations of study variables

Variable	<i>M</i>	<i>SD</i>	<i>n</i>	(1)	(2)	(3)	(4)	(5)	(6)
(1) SSD	6.63	0.87	89	-					
(2) OSD	7.78	0.78	92	0.11	-				
(3) SSQ	3.30	0.93	99	0.24*	-0.09	-			
(4) OSQ	32.23	43.61	92	0.00	-0.08	0.08	-		
(5) Well-being	4.06	0.91	99	0.04	-0.13	0.57**	-0.09	-	
(6) Burnout	2.14	0.93	89	-0.04	0.12	-0.49**	-0.01	0.78**	-

SSD self-reported sleep duration, OSD objective sleep duration, SSQ self-reported sleep quality, OSQ objective sleep quality

\*  $p < .05$ ; \*\*  $p < .001$

**Table 2** Summary of hierarchical regression analyses for variables predicting well-being and burnout

Variable	Model 1				Model 2				Model 3			
	<i>B</i>	<i>SE (B)</i>	$\beta$	<i>p</i>	<i>B</i>	<i>SE (B)</i>	$\beta$	<i>p</i>	<i>B</i>	<i>SE (B)</i>	$\beta$	<i>p</i>
Well-being												
Quadratic Term SSD	0.009	0.009	0.106	0.35	0.09	0.109	1.122	0.412	0.144	0.087	1.979	0.103
Quadratic Term OSD	-0.013	0.009	-0.162	0.155	0.024	0.115	0.307	0.836	0.177	0.094	2.277	0.063
SSD					-1.066	1.415	-1.023	0.454	-1.964	1.131	-1.886	0.087
OSD					-0.564	1.757	-0.472	0.749	-2.817	1.433	-2.36	0.053
SSQ									0.629	0.093	0.66	<0.001**
OSQ									-0.003	0.002	-0.159	0.082
<i>R</i> <sup>2</sup>	0.034				0.045				0.416**			
Burnout												
Quadratic Term SSD	-0.006	0.008	-0.086	0.455	-0.028	0.095	-0.408	0.769	-0.067	0.085	-0.978	0.433
Quadratic Term OSD	0.006	0.008	0.087	0.448	-0.025	0.1	-0.376	0.802	-0.12	0.092	-1.807	0.194
SSD					0.291	1.228	0.327	0.813	0.934	1.107	1.049	0.401
OSD					0.474	1.525	0.465	0.757	1.868	1.402	1.983	0.187
SSQ									-0.418	0.091	-0.513	<0.001**
OSQ									0.001	0.002	0.037	0.724
<i>R</i> <sup>2</sup>	0.013				0.016				0.235**			

SSD self-reported sleep duration, OSD objective sleep duration, SSQ self-reported sleep quality, OSQ objective sleep quality

\*  $p < .05$ ; \*\*  $p < .001$

sleep quality show, that only self-reported sleep duration significantly added to the prediction ( $B=0.309$ ,  $SE=0.282$ ,  $p=0.012$ ) whereas objective sleep duration did not ( $B=-0.151$ ,  $SE=0.137$ ,  $p=0.275$ ). Therefore, the results partly support hypothesis 5. Table 3 contains the details of the multiple linear regression analyses.

### 3.3 Mediation analysis

The hypotheses 1 to 5 provided the stage for two mediation hypotheses: On the one hand we proposed an effect of sleep duration and sleep quality on well-being and burnout. On the other hand we assumed that a longer sleep duration leads to more sleep quality. Therefore, we further proposed indirect effects of sleep duration on well-being and burnout through sleep quality (Hypotheses 6 and 7). Overall to test the hypotheses 6 and 7 we conducted two mediation analyses. The analyses were performed using Hayes' PROCESS macro [32] in SPSS version 26. The PROCESS macro [32] can estimate mediation models with more than one independent variable by including the additional variable as covariate [33]. The only difference is that the model has to be executed again for each additional independent variable as X variable and the remaining variables as covariates, to determine the indirect effects for all X variables [33]. Therefore, in the first mediation model on the outcome variable well-being we included self-reported sleep duration as predictor, whereas the objective sleep duration was added as covariate. To statistically control for curvilinear effects we also included the quadratic terms of subjective and objective sleep duration in the mediation analyses as control variables. Then we repeated the analysis by taking objective sleep duration as the X variable and the self-reported sleep duration as covariate to determine the indirect effects of objective sleep duration on well-being. The results of the total effect of sleep duration on well-being, excluding the mediators and the direct effect, including the mediators were

already estimated by the regression analyses for the hypotheses 1 to 4. To determine whether sleep quality mediated the effect of sleep duration on well-being we considered the indirect effects of mediation analyses. The results indicate, that neither self-reported nor objective sleep quality significantly mediated the effect of sleep duration on well-being (Table 4). To examine if sleep quality mediated the effect of sleep duration on burnout we repeated the whole procedure but replaced well-being as outcome variable with burnout. The total effect and the direct effect were already estimated by the regression analyses for the hypotheses 1 to 4. The results of the mediation analyses showed, that the indirect effects were not significant, indicating that neither self-reported nor objective sleep quality mediated the effect of sleep duration on burnout (Table 4).

## 4 Discussion

The present study was designed to determine the effect of sleep quality and duration on burnout and well-being. Additionally, to increase knowledge about the benefit of using objective sleep data, we used a fitness tracker to collect data on the objective hours and quality of sleep. We assumed that a longer sleep duration and a higher quality of sleep would enhance well-being and reduce burnout (Hypotheses 1 to 4). Furthermore, we expected the sleep duration to predict sleep quality (Hypotheses 5). These expectations further lead to the assumption that sleep quality might mediate the effect sleep duration had on well-being (Hypothesis 6) and burnout (Hypothesis 7).

The correlation of study variables showed the expected positive relation between better sleep quality and well-being and a reduced burnout-score. Furthermore, we found a small but significant correlation between sleep duration and quality. Participants reporting a higher quality of sleep also reported more hours of sleep, although this relation was

**Table 3** Results of multiple linear regression analyses on the prediction of sleep quality through sleep duration

Outcome variable	Predictors	<i>B</i>	<i>SE B</i>	$\beta$	<i>t</i>	<i>p</i>
SSQ	Intercept	2.367	1.267		1.868	0.066
	SSD	0.309	0.12	0.282	2.578	0.012*
	OSD	-0.151	0.137	-0.12	-1.099	0.275
						$R^2 = .063, p = .03$
OSQ	Intercept	42.76	61.071		0.7	0.486
	SSD	0.201	5.811	0.004	0.035	0.973
	OSD	-1.64	6.617	-0.028	-0.248	0.805
						$R^2 = .001, p = .97$

SSD self-reported sleep duration, OSD objective sleep duration, SSQ self-reported sleep quality, OSQ objective sleep quality

\*  $p < .05$ ; \*\*  $p < .001$

**Table 4** Summary of indirect effects of mediation analyses of sleep quality mediating the effect of sleep duration on well-being and burnout

Indirect Effects	<i>B</i>	<i>SE</i>	95% <i>CI</i>
Well-being			
SSD → SSQ → Well-being	0.996	0.9522	[-1.1872, 2.5494]
SSD → OSQ → Well-being	-0.0689	0.2368	[-0.6578, 0.3277]
SSD → SSQ → OSQ → Well-Being	-0.0286	0.0709	[-0.1821, 0.1102]
OSD → SSQ → Well-being	2.0307	1.5696	[-2.2977, 4.7154]
OSD → OSQ → Well-being	0.2806	0.4439	[-0.4880, 1.2787]
OSD → SSQ → OSQ → Well-Being	-0.0582	0.1326	[-0.3246, .2435]
Burnout			
SSD → SSQ → Burnout	-0.662	0.6344	[-1.6973, 0.8339]
SSD → OSQ → Burnout	0.0135	0.143	[-0.2470, 0.3239]
SSD → SSQ → OSQ → Burnout	0.0056	0.0371	[-0.0863, 0.0589]
OSD → SSQ → Burnout	-1.3498	1.0471	[-3.1342, 1.3499]
OSD → OSQ → Burnout	-0.0551	0.332	[-1.0871, 0.3472]
OSD → SSQ → OSQ → Burnout	0.0114	0.0771	[-0.1821, 0.1178]

*SSD* self-reported sleep duration, *OSD* objective sleep duration, *SSQ* self-reported sleep quality, *OSQ* objective sleep quality, *CI* confidence interval

only true for self-report and not objective sleep measures. Against our expectation, we did not find a significant correlation between self-reported and objective hours of sleep. This might be related to the fact that people tend to overestimate sleep latency and overestimate sleep duration which, in turn, is an indication of bias in self-reported sleep data [23].

Consistent with our assumption, the results of the hierarchical regression analyses showed that sleep quality significantly added to prediction of both burnout and well-being. Overall, self-reported sleep quality explained 41.6% of the variance in well-being and 23.5% of the variance in burnout. When sleep quality was better participants reported more well-being and showed lower burnout scores. However, the day-to-day variability of sleep duration as parameter for objective sleep quality did not significantly add to the prediction of the outcome variables. Although the regularity of the sleep schedule is an indicator for better sleep [2] it might be useful for future research to include multiple objective parameters on sleep quality and not only the day-to-day variability of sleep duration. Against our expectation, neither subjective nor objective hours of sleep significantly predicted well-being or burnout in the hierarchical regression analyses. Regarding the mean sleep duration per night (Table 1), we came to results similar to those reported by Zhang et al. [3] and Adams et al. [5], which implies that hours of sleep within our sample were in a normal range. One reason that sleep duration did not predict burnout and well-being might be that participants themselves reported fewer hours of sleep on average than the fitness tracker did. This inconsistency can be explained in part by previous studies that have shown how most trackers underrated quality of sleep whereas they overrated hours of sleep [34]. Some previous findings in the literature also suggest that both too

little and too much sleep were associated with less well-being and higher burnout scores [6, 12, 14]. To investigate whether a curvilinear relation of variables was the reason self-reported and objective sleep duration did not significantly predict well-being and burnout, we included quadratic terms in the hierarchical regression analyses. Nevertheless, results of the analyses indicated that there were no curvilinear effects in this sample.

We expected sleep duration to have an effect on sleep quality and therefore, we conducted two multiple linear regression analysis to test the hypothesis. The results partly supported our assumption: Self-reported sleep duration explained 6.3% of the variance of self-reported sleep quality, whereas no significant prediction was found for objective sleep duration and quality. We computed the day-to-day variability of sleep duration as parameter of objective sleep quality as we aligned it to findings in the literature, that the regularity of the sleep schedule is an indicator for better sleep [2]. Nevertheless, we are unsure if the day-to-day variability of sleep duration is the best fit for an objective parameter of sleep quality. Maybe research would also benefit from using multiple parameters for objective sleep quality rather than relying on one parameter.

To test the assumption that sleep quality mediated the effect of sleep duration on burnout and well-being we conducted mediation analyses. We included quadratic terms of sleep duration to control for curvilinear effects but no effect was found. Against our expectations, the results did not show a significant mediating effect, neither for self-reported nor objective sleep quality. An explanation might be that we did not ask participants on a daily basis about their sleeping behavior, but only retrospectively. The challenge of retrospective data is that it can be inaccurate because people

tend to forget, not remember properly, or answer in accordance with social desirability [23, 35, 36]. Thus, it becomes clear that further research on sleep duration should use a diary-study design in order to get continuous subjective data instead of asking retrospectively. Unfortunately, a diary-design was beyond the constraints of this study because of the collaboration with a public institution we had to keep effort for participants at a minimum. Furthermore, collecting sleep data with a fitness tracker is challenging and validity can be a struggle. Adams et al. [5] found that 44% of people in their sample spent time on the internet and 52% watched TV before going to bed. Since people are most likely to do these activities whilst laying on the couch or in bed, the physiological parameters (movement and heartrate) that the fitness tracker uses to calculate whether a person is sleeping or not decrease. When a person does not move and has a low heart rate over some time, the fitness tracker is likely to track this period as “sleep” even if the person is just in a state of reduced activity. This might result in an inaccurate real-time sleep duration. In a recent study by Mendelsohn et al. [37], participants wore a fitness tracker over fourteen consecutive days to learn more about the associations among work hours, physical activity, sleep, well-being and burnout. The average sleep duration per night was rather low, at 5.90 h, whereas the average daily physical activity was even higher than the WHO recommendation of 8,000 steps per day. While around 60% of the participants had high burnout scores, they also found no significant association with sleep duration [37].

Although consumer wearable technology has become more popular to measure sleep, results on the validity of the devices are inconsistent, especially when the samples include people with disturbed sleep or short sleep duration. When using a fitness tracker to learn more about sleep behavior, we need to rely on the algorithm that processes the data to generate the feedback. Although some algorithms are open source, most of them are proprietary to the manufacturer [34]. This circumstance leads to a classical black-box problem: A device collects data to generate feedback about a certain behavior, but the exact steps on how the data are processed are not available. This is also true when working with raw data because an algorithm is used to transform behavior into numbers before further analysis by the researcher. In their review about the validity of fitness trackers to measure sleep parameters, Kolla et al. [34] described seven studies where the accuracy of different fitness trackers was compared to reliable tools such as actigraphy and PSG. The authors concluded that some fitness trackers were able to display sleep parameters with some accuracy, but there was still a large discrepancy compared to actigraphy and PSG. They state that fitness trackers “*tend to have reasonable sensitivity in detecting sleep but have poor specificity i.e. they are unable*

*to accurately detect wake*”, p. 505 [34]. When Lemola et al. [11] assessed both objective and subjective duration of sleep, they also found no significant relation between sleep duration and psychological well-being. However, they found that sleep quality partially mediates the relation between higher day-to-day variability in sleep duration and lower scores of well-being.

In summary, there were several limitations of the study. First, we could not use a diary-study design to collect continuous self-reported data on quality and quantity of sleep, because we had to keep effort for participants at a minimum. Nevertheless, a diary-design in the future would be useful to better understand the complex relation between sleep and health. This might also be the reason that self-reported sleep duration is not associated with objective sleep duration in our study. Second the sample size for statistical analysis was rather small because we could only include participants who fully completed the questionnaire and who continuously wore the fitness tracker. Because sample size was small and all participants worked at the same department, results may lack representativity.

While acknowledging the limitations of the present study, the equal distribution of male and female participants is a strength because men usually engage more in studies using fitness trackers, which could lead to gender bias in the results [26]. For future research, it might also be useful to include interpersonal differences in detecting sleep patterns with wearable devices. As existing studies have shown, in some cases sleep duration is crucial for understanding the interaction of sleep and health, while in others, the quality of sleep in terms of awakening during the night is more important [38]. In a technical meeting the World Health Organization (WHO) has also stated that “*Self-reported sleep can also be used as an indicator: it is considered the least reliable objectively but perceived as the most important by the individual*”, p. 2 [2].

In a nutshell, the results of our study support the importance of adequate sleep for health—it decreases the risk of burnout and increases well-being. Although measuring sleep data with consumer fitness trackers still lacks validity, it does solidify results from self-reported measures when used concurrently. To enhance the understanding of the complex relationships between sleep and health, exploiting the potential of fitness trackers in measuring sleep data can be an important avenue for future research.

**Authors' contributions** All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Nina Raffaella Grossi, Bernad Batinic and Sebastian Moharitsch. The first draft of the manuscript was written by Nina Raffaella Grossi and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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**Data availability** There is no online data set associated with the paper.

**Code availability** The basis of the application code we used is the open source app Gadgetbridge for Android. It can be accessed via Google Play Store. The final code including the modifications we made cannot be accessed in terms of copyright.

## Declarations

**Ethics approval** As participation in the study was both voluntary and anonymous, approval by the official ethic committee was not necessary. Nevertheless approval was obtained from the committee of the public institutions workers' council. The procedures used in the study adhere to the tenets of the Declaration of Helsinki and the legal requirements of the country (Austria, Europe).

**Consent to participate** Informed consent was obtained from all individual participants included in the study.

**Consent for publication** Not applicable because all data were collected and processed anonymously. At the opening event of the study participants took their individual device out of a box full of fitness trackers. The serial number of the tracker was written in the case of the device. Participants were asked to report their number in the online survey to match survey data with data from the tracker. Therefore only the participant knew his or her serial number. No one else (including the research team and other participants) knew which serial number belonged to the participant.

**Conflicts of interest/Competing interests (include appropriate disclosures)** The authors declare that there are no competing interests or conflicts of interest.

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## References

- Gao X, Ma KL, Wang H, Lei LJ, Wang T. Association of sleep quality with job burnout among Chinese coal mine staff: a propensity score weighting analysis. *Sci Rep*. 2019;9(8737):1–9. <https://doi.org/10.1038/s41598-019-45329-2>.
- World Health Organization. WHO technical meeting on sleep and health. World Health Organization Regional Office for Europe and the European Centre for Environment and Health Bonn Office. 2004. [https://www.ilo.org/wcmsp5/groups/public/---ed\\_protect/---protrav/---safework/documents/publication/wcms\\_118388.pdf](https://www.ilo.org/wcmsp5/groups/public/---ed_protect/---protrav/---safework/documents/publication/wcms_118388.pdf). Accessed 5 Oct 2021.
- Zhang J, Paksarian D, Lamers F, Hickie IB, He J, Merikangas KR. Sleep patterns and mental health correlates in US adolescents. *J Pediatr*. 2016;182(1):137–43. <https://doi.org/10.1016/j.jpeds.2016.11.007>.
- van de Straat V, Bracke P. How well does Europe sleep? A cross-national study of sleep problems in European older adults. *Int J Public Health*. 2015;60(6):643–50. <https://doi.org/10.1007/s00038-015-0682-y>.
- Adams RJ, Appleton SL, Taylor AW, Gill WK, Lang C, McEvoy RD, Antic NA. Sleep health of Australian adults in 2016: results of the 2016 Sleep Health Foundation national survey. *Sleep Health*. 2016;3(1):35–42. <https://doi.org/10.1016/j.sleh.2016.11.005>.
- Wang C, Bangdiwala SI, Rangarajan S, Lear SA, AlHabib KF, Mohan V, Teo K, Poirier P, Tse LA, Liu Z, Rosengren A, Kumar R, Lopez-Jaramillo P, Yusuf S, Monsef N, Krishnapillai V, Ismail N, Seron P, Dans AL, Kruger L, ... Yusuf S. Association of estimated sleep duration and naps with mortality and cardiovascular events: a study of 116 632 people from 21 countries. *Eur Heart J*. 2019;40(20):1620–9. <https://doi.org/10.1093/eurheartj/ehy695>.
- Itani O, Jike M, Watanebe N, Kaneita Y. Short sleep duration and health outcomes: a systematic review, meta-analysis, and meta regression. *Sleep Med*. 2017;32:246–56. <https://doi.org/10.1016/j.sleep.2016.08.006>.
- Lee S, Buxton OM, Andel R, Almeida DM. Bidirectional associations of sleep with cognitive interference in employees' work days. *Sleep Health*. 2019;5(3):298–308. <https://doi.org/10.1016/j.sleh.2019.01.007>.
- Pilcher JJ, Ginter DR, Sadowsky B. Sleep quality versus sleep quantity: Relationships between sleep and measures of health, well-being and sleepiness in college students. *J Psychosom Res*. 1997;42(6):583–96. [https://doi.org/10.1016/S0022-3999\(97\)00004-4](https://doi.org/10.1016/S0022-3999(97)00004-4).
- Steptoe A, O'Donnell K, Marmot M, Wardle J. Positive affect, psychological well-being, and good sleep. *J Psychosom Res*. 2008;64(4):409–15. <https://doi.org/10.1016/j.jpsychores.2007.11.008>.
- Lemola S, Ledermann T, Friedmann EM. Variability of sleep duration is related to subjective sleep quality and subjective well-being: an actigraphy study. *PLoS ONE*. 2013;8(8):1–9. <https://doi.org/10.1371/journal.pone.0071292>.
- Hamilton NA, Nelson CA, Stevens N, Kitzman H. Sleep and psychological well-being. *Soc Indic Res*. 2007;82(1):147–63. <https://doi.org/10.1007/s11205-006-9030-1>.
- Allen HK, Barrall AL, Vincent KB, Arria AM. Stress and burnout among graduate students: moderation by sleep duration and quality [Special Issue]. *Int J Behav Med*. 2020;1–8. <https://doi.org/10.1007/s12529-020-09867-8>.
- Metlaine A, Sauvet F, Gomez-Merino D, Elbaz M, Delafosse JY, Leger D, Chennaoui M. Association between insomnia symptoms, job strain and burnout syndrome: a cross-sectional survey of 1300 financial workers. *BMJ Open*. 2017;7(1):1–10. <https://doi.org/10.1136/bmjopen-2016-012816>.
- Gothe NP, Ehlers DK, Salerno EA, Fanning J, Kramer AF, McAuley E. Physical Activity, Sleep and Quality of Life in Older Adults: Influence of Physical, Mental and Social Well-being. *Behav Sleep Med*. 2019;18(6):1–12. <https://doi.org/10.1080/15402002.2019.1690493>.
- Howell AJ, Digdon NL, Buro K, Sheptycki AR. Relations among mindfulness, well-being, and sleep. *Personality Individ Differ*. 2008;45(8):773–7. <https://doi.org/10.1016/j.paid.2008.08.005>.
- Honda A, Iwasaki Y, Honda S. The Mediating Role of Sleep Quality on Well-Being Among Japanese Working Family Caregivers. *Home Health Care Manag Pract*. 2017;29(3):139–47. <https://doi.org/10.1177/1084822317692320>.

18. Jean-Louis G, Kripke DF, Ancoli-Israel S. Sleep and quality of well-being. *Sleep*. 2000;23(8):1115–1121. <https://doi.org/10.1093/sleep/23.8.1k>
19. Ainsworth BE, Montoye HJ, Leon AS. Methods of assessing physical activity during leisure and work. In: Bouchard C, Shephard RJ, Stephens T, editors. *Physical activity, fitness, and health: International proceedings and consensus statement*. Champaign, IL: Human Kinetics; 1994. p. 146–59. <https://doi.org/10.1249/00005768-199401000-00024>.
20. Gonyea RM. Self-reported data in institutional research: review and recommendations. *New Dir Inst Res*. 2005;2005(127):73–89. <https://doi.org/10.1002/ir.156>.
21. Razavi T. Self-report measures: An overview of concerns and limitations of questionnaire use in occupational stress research (Discussion Papers in Accounting and Management Science, 01–175). University of Southampton. 2001. <https://eprints.soton.ac.uk/35712/1/01-175.pdf>. Accessed 5 Oct 2021.
22. Sallis JF, Saelens BE. Assessment of physical activity by self-report: status, limitations, and future directions. *Res Q Exerc Sport*. 2000;71(2):1–14. <https://doi.org/10.1080/02701367.2000.11082780>.
23. Harvey AG, Tang NKY. (Mis)perception of sleep in insomnia: A puzzle and a resolution. *Psychol Bull*. 2012;138(1):77–101. <https://doi.org/10.1037/a0025730>.
24. Fino E, Plazzi G, Filardi M, Marzocchi M, Pizza F, Vandi S, Mazzetti M. (Not so) Smart sleep tracking through the phone: Findings from a polysomnography study testing the reliability of four sleep applications. *J Sleep Res*. 2019;29(1):1–9. <https://doi.org/10.1111/jsr.12935>.
25. Sadek I, Demarasse A, Mokhtari M. Internet of things for sleep tracking: wearables vs. nonwearables. *Heal Technol*. 2020;10(1):333–340. <https://doi.org/10.1007/s12553-019-00318-3>
26. Robbins R, Seixa A, Masters LW, Chanko N, Diaby F, Vieira D, Jean-Louis G. Sleep tracking: a systematic review of the research using commercially available technology. *Current Sleep Medicine Reports*. 2019;5(3):156–63. <https://doi.org/10.1007/s40675-019-00150-1>.
27. Jenkins CD, Stanton BA, Niemcryk SJ, Rose RM. A scale for the estimation of sleep problems in clinical research. *J Clin Epidemiol*. 1988;41(4):313–21. [https://doi.org/10.1016/0895-4356\(88\)90138-2](https://doi.org/10.1016/0895-4356(88)90138-2).
28. Buysse DJ, Monk TH, Berman SR, Kupfer DJ. The Pittsburgh Sleep Quality Index: A new instrument for psychiatric practice and research. *Psychiatry Res*. 1989;28(2):193–213. [https://doi.org/10.1016/0165-1781\(89\)90047-4](https://doi.org/10.1016/0165-1781(89)90047-4).
29. Rowe M, McCrae C, Campbell J, Horne C, Tiegs T, Lehman B, Cheng J. Actigraphy in older adults: comparison of means and variability of three different aggregates of measurement. *Behav Sleep Med*. 2008;6(2):127–45. <https://doi.org/10.1080/15402000801952872>.
30. Kristensen TS, Borritz M, Villiadsen E, Christensen KB. The Copenhagen Burnout Inventory: A new tool for the assessment of burnout. *Work Stress*. 2005;19(3):192–207. <https://doi.org/10.1080/02678370500297720>.
31. World Health Organization. WHO-5 well-being index. 1998. [https://www.psykiatri-regionh.dk/who-5/Documents/WHO5\\_German.pdf](https://www.psykiatri-regionh.dk/who-5/Documents/WHO5_German.pdf). Accessed 5 Oct 2021.
32. Hayes AF. *Introduction to Mediation, Moderation, and Conditional Process Analysis* (2nd ed.). Guilford Press. 2017. <https://www.guilford.com/books/Introduction-to-Mediation-Moderation-and-Conditional-Process-Analysis/Andrew-Hayes/9781462534654/print>. Accessed 5 Oct 2021.
33. Hayes AF. *Introduction to Mediation, Moderation, and Conditional Process Analysis* (2nd ed.). The Guilford Press. 2018.
34. Kolla BP, Mansukhani S, Mansukhani MP. Consumer sleep tracking devices: a review of mechanisms, validity and utility. *Expert Rev Med Devices*. 2016;13(5):497–506. <https://doi.org/10.1586/17434440.2016.1171708>.
35. Krumpal I. Determinants of social desirability bias in sensitive surveys: a literature review. *Qual Quant*. 2013;47(4):2025–47. <https://doi.org/10.1007/s11135-011-9640-9>.
36. Raphae K. Recall Bias: A Proposal for Assessment and Control. *Int J Epidemiol*. 1987;16(2):167–70. <https://doi.org/10.1093/ije/16.2.167>.
37. Mendelsohn M, Despot I, Gooderham P, Singhal A, Redekop GJ, Toyota BD. Impact of work hours and sleep on well-being and burnout for physicians-in-training: the Resident Activity Tracker Evaluation Study. *Med Educ*. 2019;53(3):306–15. <https://doi.org/10.1111/medu.13757>.
38. Liang Z, Chapa-Martell MA, Ploderer B. Inter-Individual Differences in Sleep Quality: Insights from Mining Wearable Sleep-Tracking Data (Report No. 54). Information Processing Society of Japan Technical Report 2017;82(54):1–6. <https://eprints.qut.edu.au/104727/>. Accessed 5 Oct 2021.

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