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BRIEF REPORT

Investigating the within-person relationships between activity levels and sleep duration using Fitbit data

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Abstract

The advancement of wearable technologies provides opportunities to continuously track individuals' daily activity levels and sleep patterns over extended periods of time. These data are useful in examining the reciprocal relationships between physical activity and sleep at the intrapersonal level. The purpose of this study is to test the bidirectional relationships between daily activity levels and sleep duration. The current study analyzed activity and sleep data collected from a Fitbit device as part of a 6 month employer-sponsored weight loss program. A total of 105 overweight/obese adults were included (92% female, 70% obese, and 44% Hispanic). Multilevel models were used to examine (a) whether daily active and sedentary minutes predicted that night's sleep duration and (b) whether sleep duration predicted active and sedentary minutes the following day. Potential extended effects were explored by using a 2 day average of the activity minutes/sleep duration as the predictor. No significant relationships between active minutes and sleep duration were found on a daily basis. However, having less sleep over two nights than one's usual level was associated with an increased likelihood of engaging in some physical activity the following day. There was a significant bidirectional negative association between sedentary minutes and sleep duration for both the daily and 2 day models. Data from wearable trackers, such as Fitbit, can be used to investigate the daily within-person relationship between activity levels and sleep duration. Future studies should investigate other sleep metrics that may be obtained from wearable trackers, as well as potential moderators and mediators of daily activity levels and sleep.

Keywords

Physical activity, Wearable technologies, Sleep tracker, Obesity, Free-living, Multilevel modeling

Implications

Practice: Commercially available wearable trackers, such as Fitbit, can be used to monitor daily activity levels and sleep over long periods of time.

Policy: Lifestyle programs that target overweight and obese adults should incorporate elements that aim to decrease sedentary behavior in addition to promote physical activity.

Research: Future research is needed to utilize newer generations of wearable trackers that can provide more comprehensive sleep metrics to better understand the reciprocal relationships between daily physical activity, sedentary behavior, and sleep quality.

INTRODUCTION

Regular physical activity is associated with various physical and mental health benefits and the primary and secondary prevention of several chronic medical conditions [1,2]. One of the many beneficial effects of physical activity is improved sleep, including total sleep time and sleep efficiency [3]. On the other hand, poor sleep may lead to lower physical activity [4]. The majority of previous studies have used self-reported questionnaires, sleep diaries, electroencephalogram (EEG), or polysomnography (PSG) as sleep assessment tools. While objective measurement tools, such as EEG and PSG, can provide accurate and detailed information about sleep, they are typically conducted in a lab-based setting, thus limiting the duration of monitoring period. Furthermore, these episodes might not reflect a person's usual sleep patterns. Self-reported cross-sectional questionnaires are useful in large cohort studies to compare subjective sleep characteristics between individuals or groups but are limited with respect to investigating within-person (WP) variation. Sleep diaries enable the investigation of WP daily sleep patterns but are burdensome for participants over long periods of time (e.g., over months) and are prone to recall and response biases.

There is an increasing interest in measuring sleep using wearable sensor devices, especially given the rapid acceleration of consumer-facing technology for sleep tracking [5,6]. Among these consumer-facing wearable devices, Fitbit is one of the most commonly used [7]. Fitbit trackers have high user acceptability over a sustained period of time (e.g., 5–7 months) [8], and research indicates that they can provide valid estimates for several sleep metrics [7,9,10]. In a recent meta-analysis, Fitbit devices correctly identified sleep episodes with accuracy values between 0.81 and 0.91 and sensitivity values between 0.87 and 0.99 when in reference to PSG (i.e., the "gold standard" [10]). The correlation of total sleep time was also high between Fitbit and PSG [9,11]. Furthermore, when compared with the research-grade sleep monitor (i.e., Actiwatch), Fitbit-measured total sleep time was statistically indistinguishable from the Actiwatch measure [12].

Fitbit devices are also useful for contributing to our understanding of physical activity patterns over time. They can continuously track activity levels and provide valid estimates of step counts, energy expenditure, and activity intensity [13,14]. Validation studies found similar accuracy of physical activity assessment between consumer monitors (e.g., Fitbit) and waist-worn research-grade accelerometer (i.e., ActiGraph) [15]. Evidence indicates that Fitbit's "active minutes" are comparable to accelerometry-measured moderate-to-vigorous physical activity assessed over a 7 day period [16]. It is also important to note that, in the study by Imboden and colleagues with 30 adults (aged 18–80 years old), all wearable monitoring devices (consumer facing and research grade) underestimated steps and active minutes when compared to direct observation in a laboratory setting [15]. Other studies have found that the wrist-worn Fitbit devices overestimated active minutes when compared to waist-worn ActiGraph under free-living conditions [17]. Nevertheless, this difference could be partly due to the placement area of the device. A person's wrist is likely to experience more movement in a day than the waist. Indeed, a study by Barrett and colleagues found that the waist-worn ActiGraph was unable to identify many self-reported activity bouts that the Fitbit device was able to capture [18]. Furthermore, Fitbit devices provide similar estimates for sedentary minutes when compared with ActiGraph [17]. Thus, consumer-facing activity monitors, such as Fitbit, could be a viable option to track daily activity and sedentary minutes in individuals' everyday life. Overall, consumer wearable devices, such as Fitbit, provide a great opportunity for behavioral researchers to collect both physical activity and sleep data over a long period of time and invite the exploration of daily relationships between physical activity and sleep at the intrapersonal level.

The current study presents a secondary data analysis from a 6 month employer-sponsored weight loss program in which participants wore a Fitbit as part of the program. The goal of the paper is to demonstrate how data from wearable trackers, such as Fitbit, can be used to investigate the bidirectional relationships between daily activity levels and sleep. To do that, we tested (a) whether daily active and sedentary minutes predicted that night's sleep duration and (b) whether sleep duration predicted active and sedentary minutes the following day. We also explore the potential extended effects of daily activity on sleep and sleep on daily activity by examining (a) whether the average of 2 days' daily active and sedentary minutes predicted the second night's sleep duration and (b) whether the average of two prior nights' sleep duration predicted active and sedentary minutes the following day.

METHODS

Study sample

This study used data from Vibrant Lives Plus, a 6 month employer-sponsored lifestyle weight loss program. Vibrant Lives Plus is a part of Pasadena Vibrant Community, an initiative that unites individuals, schools, workplaces, and other key stakeholders to make positive, long-lasting changes in people's lives. Participants were overweight or obese employees of a school district in the Houston, TX, area. Vibrant Lives Plus was comprised of 16 lessons that participants received by email or mail over the course of 26 weeks. Program content focused on increasing moderate-to-vigorous intensity aerobic activity, eating smaller portions, and consuming a healthy diet. Participants also received 5–10 text messages per week that provided brief reminders about the lesson content. All text messages were sent out and received by all participants. As part of the program, participants received a Fitbit Flex 2 (Fitbit Inc., San Francisco, CA). Participants completed questionnaires at baseline and end of the program.

Measures

Participants' Fitbit data were synced with the Fitbit server and processed by Fitabase (Small Steps Labs, San Diego, CA). Day-level and minute-level data were downloaded from Fitabase. Proprietary Fitbit algorithms estimated daily total step counts, "Very active minutes," "Fairly active minutes," and "Lightly active minutes," as well as "Minutes asleep" for each sleep episode and "Total minutes asleep" within a day.

Consistent with standard protocols for ActiGraph wear time and prior research using Fitbit, greater than 60 consecutive minutes of 0 steps, with 2 min tolerance (i.e., for 2 min with nonzero counts during nonwear intervals), was deemed nonwear [19,20]. A valid day was determined as having at least 10 hr valid wear. The active minutes variable was the sum of the "very active" and "fairly active" minutes. The sedentary minutes variable was computed by subtracting the active and light activity minutes from the total valid wear time.

Valid sleep data were defined as having nonnap sleep duration >3 hr. We defined nap as a sleep episode with a start time between 8 am to 5 pm. Sleep duration was computed by subtracting total nap minutes from "total minutes asleep."

Statistical analysis

Multilevel modeling was used to account for multiple observations for each participant. The WP effect represents the deviation from one's own mean at any given day, and the between-person (BP) effect represents individual's mean deviation from the grand mean [21]. To test whether daily active and sedentary minutes predict that night's sleep duration, multilevel linear regression was conducted with sleep duration as the outcome and the active/sedentary minutes from the same day as the predictor (Model 1). To test whether sleep duration predicts active and sedentary minutes the following day, the daily active/sedentary minutes was used as the outcome, and sleep duration from the previous night was used as the predictor (Model 2). The daily active minutes variable was not normally distributed and contained many zeros. Thus, a two-piece modeling approach was used [22]. The Piece 1 model was a multilevel logistic regression model predicting the probability of engaging in some physical activity (i.e., nonzero active minutes) versus no physical activity (i.e., zero active minutes). The Piece 2 model was a multilevel linear regression model predicting the log-transformed nonzero active minutes. To explore the extended effects of sleep and daily activity, we used the average of active/sedentary minutes from the same day and the prior day as the predictor in Model 1 and the average of the two previous nights' sleep duration as the predictor in Model 2. All models controlled for weekend versus weekdays. SAS (version 9.4) was used for multilevel linear regression models and Mplus (version 7.11) was used for two-piece models.

RESULTS

Descriptive statistics

A total of 117 overweight and obese employees enrolled in the Vibrant Lives Plus program in late 2017. One hundred and thirteen participants completed the baseline survey and 97 participants completed the follow-up survey at the end of the program. A total of 112 participants had valid Fitbit data. Of the 112 participants, 105 had valid sleep data. Thus, the analytical sample included 105 participants (92% female, 70% obese, and 44% Hispanic). Their mean age at baseline was 43.6 years old (ranged from 23 to 68). On average, these people had valid physical activity data for 103 ± 44 days (ranged from 2 to 175, median = 114) and valid sleep data for 76 ± 47 days (ranged from 1 to 168, median = 84). Participants wore the Fitbit device for an average of 20.2 hr each day (ranged from 13.0 to 22.8). Participants on average spent 20 min (*SD* = 14.8) in physical activity and 505 min (*SD* = 40.2) in sedentary behavior per day. The average sleep duration was 390 min (*SD* = 80.6). The intraclass correlation coefficient (ICC) for active minutes was .244, for sedentary minutes was .159, and for sleep duration was .330. A waterfall plot was included in the Supplementary File to help with visualizing the intraindividual and interindividual pattern for each of these variables.

Association between daily activity levels and subsequent sleep duration

Results (see Table 1) showed no significant WP association between active minutes and sleep duration in the daily model or in the 2 day model. A negative WP association was found between sedentary minutes and sleep duration of that night (WP $\beta = -0.113$, standard error [*SE*] = 0.011, $p < .001$), suggesting that more minutes spent sedentary than one's average level was associated with less sleep that night. This negative WP association was also found in the 2 day model (WP $\beta = -0.077$, *SE* = 0.015, $p < .001$).

Association between sleep duration and subsequent daily activity levels

As shown in Table 2, no significant WP association was found between sleep duration and subsequent active minutes in the daily model. In the 2 day model, a negative WP association was found between the average of two nights' sleep duration and the likelihood of engaging in some physical activity versus no physical activity the following day (WP $\beta = -0.002$, *SE* = 0.001, $p = .02$), suggesting that

Table 1 | Association between activity minutes and subsequent night sleep duration (in minutes)

	Daily model[a]		Two day model[b]	
	Beta estimate (*SE*)	*p*	Beta estimate (*SE*)	*p*
Active minutes				
WP effect	0.057 (0.035)	.11	0.036 (0.048)	.45
BP effect	0.247 (0.355)	.49	0.153 (0.357)	.67
Sedentary minutes				
WP effect	−0.113 (0.011)	<.001	−0.077 (0.015)	<.001
BP effect	−0.222 (0.129)	.09	−0.200 (0.130)	.12

All models controlled for weekend versus weekday.

BP between person; *SE* standard error; *WP* within person.

[a] Total active/sedentary minutes of the same day as the predictor.

[b] Average active/sedentary minutes of the same day and the prior day as the predictor.

Table 2| Association between night sleep duration (in minutes) and subsequent activity minutes

	Daily model[a]				Two day model[b]			
Active minutes								
	Piece 1 model		Piece 2 model		Piece 1 model		Piece 2 model	
	Beta estimate (*SE*)	*p*	Beta estimate (*SE*)	*p*	Beta estimate (*SE*)	*p*	Beta estimate (*SE*)	*p*
WP effect	0.000 (0.000)	.21	0.000 (0.000)	.36	−0.002 (0.001)	.02	0.000 (0.000)	.39
BP effect	0.002 (0.002)	.37	0.000 (0.001)	.66	0.002 (0.002)	.50	0.000 (0.001)	.94
Sedentary minutes								
	Beta estimate (SE)		*p*		Beta estimate (SE)		*p*	
WP effect	−0.218 (0.013)		<.001		−0.296 (0.019)		<.001	
BP effect	−0.114 (0.077)		.15		−0.198 (0.081)		.02	

Piece 1 model: some versus 0 active minutes. Piece 2 model: log-transformed active minutes. All models controlled for weekend versus weekday.

BP between person; *SE* standard error; *WP* within person.

[a] Sleep duration of the prior night as the predictor.

[b] Average sleep duration of two prior nights as the predictor.

less sleep in two nights was associated with increased likelihood of engaging in some physical activity the following day. The two nights' sleep duration was not associated with the amount of active minutes the following day. A negative WP association was also found between sleep duration and sedentary minutes the following day at the WP level (WP $\beta = -0.218$, $SE = 0.013$, $p < .001$), suggesting that less sleep than one's average level was associated with more minutes spent in sedentary the following day. This negative WP association was also found in the 2 day model (WP $\beta = -0296$, $SE = 0.019$, $p < .001$).

DISCUSSION

The current study used Fitbit data from a 6 month weight loss program to test the bidirectional daily associations between activity levels and sleep duration at the intrapersonal level. Results showed no significant relationships between active minutes and sleep duration on a daily basis. However, having less sleep over two nights than one's usual level was associated with an increased likelihood of engaging in some physical activity the following day. Further, we found a significant negative association between sedentary minutes and sleep duration for both directions in the daily and 2 day models.

Previous studies that examined the temporal relationship between daily physical activity and sleep found a negative association for both directions in children [23]. And, in older women (mean age 73 years old), more physical activity was associated with less sleep time at night [24]. Our finding of a negative association between the average of two nights' sleep and the likelihood of engaging in some physical activity the following day is in accord with this previous research. The lack of a significant relationship in the daily models may be indicative of a differing dynamic in the present study's target population and/or partly a function of the considerably longer time period investigated in the present study. It is likely that we are able to capture more habitual physical activity sleep data than previous studies given that this study took place over the course of 6 months rather than 1 week.

Physical activity may have an impact on other sleep measures that were not tested in this study. For example, previous studies found a positive temporal relationship between physical activity and subjective sleep quality rating [25,26]. The current study only used sleep duration since this variable has a strong correlation with PSG for this specific Fitbit model (Fitbit Flex) [9,11]. Future studies could use models with heart rate sensors, which provide estimates of sleep architecture (i.e., sleep staging). For example, newer generation sleep-staging Fitbit models have shown promising sensitivity and accuracy in detecting sleep-wake states and sleep stage composition compared to PSG [10,27]. Since PSG has its limitations in extending to real-life monitoring, it would be interesting for future studies to use wearable sleep trackers with heart rate monitoring or other mechanisms (e.g., mobile EEG headband [28]) to capture sleep architecture.

In the current study, we found a negative association between sedentary minutes and sleep for both direction and in the daily and 2 day models. Although prolonged sedentary behavior has been found to be associated with an increased risk of insomnia and sleep disturbance [29], there is limited evidence of associations between objectively measured sedentary time and self-reported sleep duration at the interpersonal level in adults [30]. This study is among one of the few that tested the intrapersonal association between sedentary time and sleep duration. It is possible that less sleep time simply implies more sedentary time as a result of more time spent awake. Alternatively, it may be that when individuals were not getting their usual sleep at night, they tended to feel less energetic the following day and as a result spent more time in sedentary pursuits. Future studies could also further investigate some potential moderators and mediators (e.g., stress and eating behaviors) for the reciprocal relationship between sedentary time and sleep. For example, short sleep duration and poor sleep quality are associated with excess food intake [31] and may induce stress that leads to more emotional eating [32]. These behaviors could interact and adversely influence health outcomes in overweight and obese individuals.

Despite the advantages of using Fitbit data to examine the bidirectional intrapersonal relationships between daily activity levels and sleep duration over a 6 month period, this study had several limitations. First, the study findings might be limited by participants' device wear/nonwear patterns. As part of the weight loss program, our participants received text message reminders about wearing/syncing the Fitbit device. Nevertheless, overnight wearing was not emphasized. Therefore, some participants might not be consistently wearing the Fitbit while sleeping. Second, our results might be limited by the specific characteristics of the study sample (e.g., overweight/obese, mostly female, and employees of a local school district). Further, the current study only captured daily activity levels and sleep duration and evaluated the bidirectional relationships between the two. Various "third" variables may have been present and influenced the relationship between physical activity and sleep. We need to be particularly mindful of potential unmeasured mediators given that we are analyzing observational data from free-living settings versus well-controlled laboratory-based studies. A number of other factors may have impacted both daily activity levels and sleep. For example, daily stress, mood, or pain/discomfort could directly impact the reciprocal relationships under investigation. We encourage future studies to consider ways to capture these potential moderators and mediators when studying the daily relationship between physical activity and sleep in free-living settings, such as via experience sampling or electronic momentary assessment [33].

The current study demonstrated how data from wearable trackers, such as Fitbit, can be used to investigate the daily intrapersonal relationship between activity levels and sleep duration over an extended period. Overall, this study shows a promising direction for the use of consumer-facing wearable devices in behavior research to capture and investigate dynamic health-related behaviors and their immediate predictors/consequences in a person's daily lives.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Translational Behavioral Medicine* online.

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Compliance with Ethical Standards

Conflicts of Interest: All authors declare that they have no conflicts of interest.

Authors' Contributions: Y.L. conceived the research questions. T.A.L. contributed to the acquisition of data. Y.L. and M.C.R. developed the methodology. Y.L. analyzed the data. K.B.E., I.H.C.W. and D.D.B. contributed to the interpretation of data. Y.L. and A.W. drafted the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Ethical Approval: All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards. This article does not contain any studies with animals performed by any of the authors.

Informed Consent: Informed consent was obtained from all individual participants included in the study.

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