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► **To cite this version:**

Luan Chen, Xujun Ma, Meenakshi Chatterjee, Juha M Kortelainen, Teemu Ahmaniemi, et al.. Fatigue and sleep assessment using digital sleep trackers: insights from a multi-device pilot study. 44th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Jul 2022, Glasgow, United Kingdom. pp.1133 - 1136, <10.1109/embc48229.2022.9870923>. <hal-05580200>

HAL Id: hal-05580200

<https://hal.science/hal-05580200v1>

Submitted on 3 Apr 2026

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Fatigue and Sleep Assessment using Digital Sleep Trackers: Insights from a Multi-Device Pilot Study

Luan Chen¹, Xujun Ma¹, Meenakshi Chatterjee^{*2}, Juha M. Kortelainen³, Teemu Ahmaniemi³, Walter Maetzler⁴, Pei Wang¹ and Daqing Zhang¹

Abstract—For the patient community with neurodegenerative disorders (NDD) and immune-mediated inflammatory diseases (IMID), fatigue and sleep disturbances stand out as two of the most common and disabling symptoms, which mightily impair patient’s quality of life. Traditional questionnaire-oriented approaches to reflect such symptoms suffer from recall bias and poor sensitivity to change. By virtue of multiple sensing modalities at home, IDEA-FAST project aims to identify novel digital endpoints of fatigue and sleep disturbances, that are objective, reliable and sensitive to change. This article presents and discusses results from a pilot study of IDEA-FAST to evaluate the feasibility of capturing sleep and fatigue measures from three sleep trackers. Data collected from 143 participants (age range: 21-82) across 6 disease groups and healthy cohort for a period of 9 months, were investigated using our proposed sensor analytical pipeline. The overall performance reveals that the median coverage rate of sleep trackers ranged from 48.3% to 76.9%. Furthermore, the digital measures obtained from each device, indicated a higher association with sleep related patient reported outcomes (PROs) than fatigue related ones, when taking all participants into account.

I. INTRODUCTION

With the aging of general population in modern societies, the prevalence of chronic diseases such as neurodegenerative disorders (NDD) and immune-mediated inflammatory diseases (IMID), is expected to rise dramatically in the coming decades, incurring a mounting societal and financial burdens in the healthcare domains [1], [2]. NDD is marked by the loss of neurons within the brain and/or spinal cord largely due to pathological cell aging, which involves two major contributing factors of oxidative stress and inflammation [3]. IMIDs are a group of autoimmune inflammatory disorders characterized by an alteration in cellular homeostasis. The etiology of such diseases is multifactorial including environmental factors, dietary habits, infectious agents as well as genetic predisposition [4]. The success of a therapeutic intervention in such disease groups will largely rely on its ability to improve the patients’ activities of daily living (ADL) and health-related quality of life (HRQoL) [5]. However, how to precisely evaluate ADL and HRQoL still remains challenging.

There is strong evidence that disabling fatigue and sleep disturbances are highly prevalent in individuals with NDD and IMID [6], [7]. Hence, an accurate depiction of such symptoms can be crucial to reflect and predict the impairment level of ADL and HRQoL. Traditional evaluations rely mainly on subjective reports, typically using standardized questionnaire-based patient reported outcomes (PROs). This approach is often prone to recall bias, reliability issues and poor sensitivity to change over time [8].

Recent advancement in digital technologies and wearable devices have fuelled the opportunity to capture digital correlates of ADL and HRQoL which are objective, reliable and more sensitive to change [9]–[11]. Building on these advancements, IDEA-FAST project utilizes multiple sensing modalities and technologies at home to identify digital endpoints of fatigue and sleep in the following six disease groups [12]: Parkinson’s disease (PD), Huntington’s disease (HD), rheumatoid arthritis (RA), systemic lupus erythematosus (SLE), primary Sjogren’s syndrome (PSS), inflammatory bowel disease (IBD).

In this paper, we present preliminary insights from a feasibility study (FS) conducted in preparation for a clinical observation study in the context of IDEA-FAST project. Here we focus on evaluating the promise of using sleep trackers in measuring fatigue by comparison with PROs utilizing a proposed analytical pipeline. Through extensive clinical studies in four European medical centers, the performance of data quality and associations with PROs has been discussed alongwith some derived clinically meaningful informations.

II. MATERIALS OVERVIEW

The IDEA-FAST FS was registered with the German Clinical Trial Registry (DRKS00021693) and conducted according to the principles of the Declaration of Helsinki (version of 2013). In this section we describe the experimental materials relevant to sleep measures collected in the study. As shown in Fig. 1, three main sleep devices (i.e., Dreem [13], ZKOne [14] and BedSensor [15]) are deployed in a home scenario to record nocturnal datasets separately.

A. Patient Reported Outcomes

The patient reported outcomes from this study were collected by using the VTT stress monitor application (SMA) [16], which prompts mainly fatigue and sleep related questionnaire up to four times a day at predefined times: 9:00 (morning), 13:00 (early afternoon), 17:00 (late afternoon) and 21:00 (evening).

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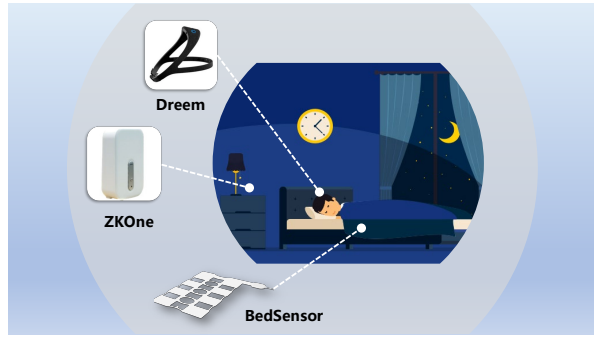


Fig. 1. An illustrative example of home study scenario for sleep sensing

B. Main Sleep Trackers

BedSensor is a force-sensitive porous electret film manufactured by eLive Ecosystems Ltd., Finland [17]. The sensor foil is placed under the mattress, and it measures heart rate, breathing rate and movements. Data is stored with USB-connected microcomputer which also calculates the overnight sleep analysis on site and enables showing the results with touch screen. BedSensor recording was able to run without any user interaction over several weeks, and data was collected from the device by the study site with external USB-flash drive.

ZKOne uses an ultra-wideband (UWB) radar signal to monitor and record the nocturnal respiratory rate, heart rate and body movement passively and unobtrusively. It can sense body movement up to three meters from the device and can detect a range of sleep conditions, such as sleep apnea and staging. The device should be placed next to a bed at waist height. The data is mainly transferred through Wi-Fi to an online data management system.

Dreem is a wireless headband worn during sleep that records physiological data in real time. During measurement, the raw data is transferred via WiFi to Dreem's remote servers for processing. Afterwards, the aggregated metrics can be downloaded to a dedicated mobile device (e.g., smart phone and tablet) via Bluetooth.

III. ANALYTICAL PIPELINE DESIGN

This section describes the holistic structure of our proposed data analytical pipeline. As can be observed in Fig. 2, it is composed of data pre-processing, data quality assessment, performance association between device data and PROs.

A. Data Pre-processing

For three sleep sensors, the analysis algorithms are either built into their hardware or executed in a remote server. After recording the participant's activities during sleep, some basic physiological measures (e.g., heartbeat rate, respiration rate) and sleep-related assessment results (e.g., sleep duration, hypnogram, and sleep quality) are stored in ".json" files (for ZKOne and Dreem) and ".csv" files (for BedSensor).

Specifically, since ZKOne only analyses nocturnally recorded data from 4 p.m. to the next day's 10 a.m., while

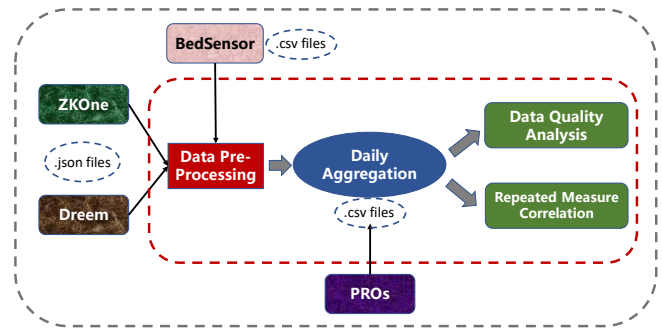


Fig. 2. The overall architecture of the proposed analytical pipeline

both BedSensor and Dreem cover the data recordings for up to 24 hours, it is necessary that invalid non-nocturnal datasets should be first discarded and then all selected parameters across three devices should also be unified in terms of both time stamps and units. After such pre-processing, all processed aggregated data including PROs are stored in files with ".csv" extension for further analysis.

B. Data Quality Assessment

Data quality evaluation comprises outlier assessment and coverage analysis of the sleep data. Since these devices use their built-in or cloud server-based algorithms to process the data at the first stage, only sleep recordings with long enough duration can successfully generate sleep report whereas insufficient recordings with poor quality would return empty aggregative data. Therefore, in our quality analysis, for nocturnal sleep durations shorter than two hours, they are considered as outliers. After removing outliers for each device, the number of valid aggregative recordings represents the number of effective sleep nights. Based on IDEA-FAST internal database which includes the information of subjects' intended testing days, the actual data coverage rate for each subject can be analysed by calculating the proportion of effective nights over the expected testing period.

C. Association with PROs

The association study between sleep sensors and PROs was conducted for different patient cohorts, which comprises HD, IBD, PD, PSS, RA, SLE and healthy control. The repeated measures correlation (RMC) was conducted to quantify the associations between PROs and the features extracted from each sleep device [18]. This study was first carried out for all participant groups. In the sequel, the same analytical methodology was applied to the respective patient cohort. Since SMA do not directly report the patient's actual sleep duration, which serves as an important parameter for sleep analysis, it should be first derived by using other relevant SMA features, i.e., time to wake up, time to go bed and fall asleep time.

After the calculation of repeated measure correlation, only the r values (correlation coefficients) with p value less than 0.05 are regarded as statistically significant results, which are saved and visualized in the correlation heat maps.

IV. RESULTS

In this section, we display the analytical results which consists of data quality comparisons, association with PROs for all participants and also for all disease cohorts. As the clinical study is still ongoing, it is worth noting that the datasets involved in this work take up around 88% of the FS data. Further analyses will be followed when FS is complete.

A. Data Quality Analysis

After aforementioned data pre-processing, we then map the datasets from all sleep trackers with that from PROs and summarize the cohort-based subject number and its corresponding testing days as expressed in Table I.

TABLE I
PARTICIPANT SUMMARY (AFTER MAPPING WITH PROS)

Cohort	Healthy	HD	IBD	PD	PSS	RA	SLE	Total
Subjects No.	28	5	10	14	14	13	11	95
Testing Days	565	94	208	245	337	261	246	1956

Based on the above summary, Fig. 3 explicitly illustrates the coverage distributions for three sleep sensors in this feasibility study. As can be observed, BedSensor is able to perform the best with most participants achieving over 80% coverage rates.

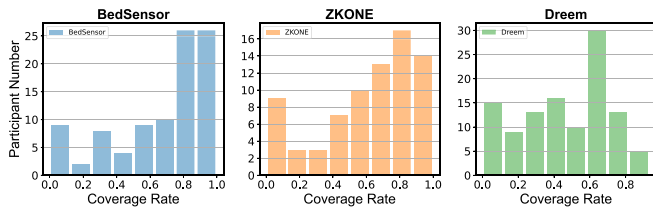


Fig. 3. The coverage histograms for all three sleep trackers

Furthermore, Table II shows a more detailed data quality assessment for three candidate sensors. Given the valid number of participants, BedSensor outperforms the others with the highest median coverage rate of 76.9%. When it comes to outlier rate comparison, ZKOne stands out with zero outlier for 76 subjects.

TABLE II
DATA QUALITY SUMMARY

Device	ZKOne	BedSensor	Dreem
Number of participants	76	94	111
Med. coverage rate	69.0%	76.9%	48.3%
Outlier rate	0%	1.26%	1.67%

B. Association with PROs: All Participants

Recall that repeated measures correlation was exploited to quantify the association between PROs and the features extracted from each device. In this study, a total of 17 derived PRO features were utilized to associate with 23, 32 and 15 features from BedSensor, ZKOne and Dreem, respectively. Among these large amount of resultant associations, we

TABLE III
ASSOCIATION SUMMARY FOR ALL PARTICIPANTS

device	PRO class	$ r $ range	top association (PRO/device)
BedSensor	fatigue	[0.07, 0.11]	Mental Fatigue / RR
	sleep	[0.07, 0.37]	Sleep Time / Sleep_RECs
ZKOne	fatigue	[0.09, 0.15]	Mental Fatigue_M / REM
	sleep	[0.09, 0.30]	Sleep Time / Sleep_RECs
Dreem	fatigue	[0.14, 0.18]	Physical Fatigue_M / RR
	sleep	[0.13, 0.52]	Fall Asleep / FallAsleep

TABLE IV
SMA-BEDSENSOR COHORT EFFECT SUMMARY

cohort	r value	subjects/days	top association (PRO/device)
PSS	0.230	11/191	Physical Fatigue_E / RR_std
SLE	0.352	8/98	Mental Fatigue_M / HR
RA	-0.233	10/145	Sleepiness_E / Sleep_RECs
HD	-0.676	3/19	Mental Fatigue_E / HR_std
PD	0.373	11/95	Mental Fatigue / RR

highlight the statistically significant observations ($p < 0.05$) and summarize them in the following tables.

Table III lists the overall association summary of three sleep trackers for all participants, where PRO label ending with “_M” and “_E” indicates the morning and evening. RR and REM represent respiration rate and rapid eye movement duration, respectively. In order to concisely display the results, PRO features are first selected and classified into fatigue and sleep related groups. The range of absolute values of correlation coefficients is expressed in the sequel, followed by the corresponding top association descriptions. Specifically, fatigue related PROs present generally low correlations with all sleep trackers. It is also notable that the derived PRO sleep time for all participants has the highest correlation (positive r value of 0.37) with the recorded sleep time (Sleep_RECs) from BedSensor. This demonstrates the BedSensor’s good capability of sleep time detection. In addition, Dreem exhibits the most significant association ($r = 0.52$) with PRO for the “fall asleep time” feature.

C. Association with PROs: Cohort Effects

Table IV presents some association observations between SMA and BedSensor specifically in individual disease cohorts. As can be noticed, for cohort HD, SMA’s evening mental fatigue index has a good negative correlation ($r = -0.676$) with BedSensor’s heart rate (HR) variation (std as standard deviation). Given its relatively small sample size, this certainly needs to be confirmed in a larger population in the future clinical observation study.

Table V also lists some important observations between SMA and ZKOne among different cohorts. For cohort RA, the morning physical fatigue questionnaire shows a good

TABLE V
SMA-ZKONE COHORT EFFECT SUMMARY

cohort	r value	subjects/days	top association (PRO/device)
PSS	\	2/34	Not applicable for RMC
SLE	0.516	3/37	Physical Fatigue / SleepScore
IBD	-0.205	10/136	Physical Fatigue / WakeCounts
RA	-0.641	4/34	Physical Fatigue_M / SleepScore
HD	-0.542	3/19	Mental Fatigue_E / Turnover
PD	0.427	8/38	Physical Fatigue_E / AHI

TABLE VI
SMA-DREEM COHORT EFFECT SUMMARY

cohort	r value	subjects/days	top association (PRO/device)
PSS	-0.328	11/67	Physical Fatigue_M / FallAsleep
SLE	-0.410	8/49	Mental Fatigue / Turnover
IBD	-0.584	6/40	Sleepiness_E / SleepScore
RA	0.631	8/35	Mental Fatigue / N2Duration
HD	-0.900	3/7	Mental Fatigue_E / N3Duration
PD	-0.584	7/25	Sleepiness_E / N1Duration

negative correlation (-0.641) with ZKOne’s sleep score, indicating that bad sleep quality could increase the patient’s fatigue level in the morning. The same phenomenon also applies for the cohort SLE. For cohort HD, the evening mental fatigue level is quite well associated with patient’s turnover times during sleep, which might suggest that the patient suffers certain level of sleep disturbance due to mental fatigue. For cohort PD, this group reveals that their evening physical fatigue level has a modest effect (with a positive correlation of 0.427) on the nocturnal apnea hypopnea index (AHI). It is also notable that for cohort IBD, a high level of daily physical fatigue could lead to less awake times (WakeCounts) during the night.

Table VI presents associations between SMA and Dreem. For cohort HD, the patient reported evening mental fatigue has an excellent negative correlation (-0.9) with Dreem’s N3 period duration. It can be interpreted that when the mental fatigue level increases, patients are prone to experiencing less time of deep sleep and thus resulting in a poor sleep quality. The similar situation can be also observed in RA cohort. For cohorts like IBD and PD, the sleepiness level indicator stands out as the most prominent feature to affect the sleep quality, both of which have the negative correlation values of -0.58. For PSS group, a certain level of association can be observed between the physical fatigue in the morning and fall asleep time of previous night.

V. CONCLUSIONS

In this article, we presented preliminary insights from an analysis of data collected as part of a feasibility study, to evaluate the potential of measuring fatigue and sleep

from three sleep trackers in seven different cohorts. An extensive analytical pipeline was developed that preprocessed the questionnaire and device signals, estimated nocturnal digital measures from devices, performed quality assessment of those measures, and finally investigated association with PROs to establish clinical meaningfulness of the measures. In light of its high coverage rate and association with a number of fatigue and sleep PROs, BedSensor exhibited the highest potential for deployment in the future larger clinical studies.

ACKNOWLEDGMENT

This work was supported by IDEA-FAST project, which has received funding from the Innovative Medicines Initiative 2 Joint Undertaking (JU) under grant agreement No 853981. The JU receives support from the European Union’s Horizon 2020 research and innovation programme EFPIA and associated partners.

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