Sleep Quality Evaluation in Rich Information Data

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***Abstract*—Sleep is a vital component of human physical and mental health, but also a necessary condition for well-being and a better quality of life. In the work environment, sleep has an impact on employee productivity, workability, mental health and performance. This research work aims to combine applied methods of the GATEKEEPER and SmartWork projects on measuring sleep quality to the dataset provided by the Tesserae project and investigate the possibility of critical advice being given to office workers when their sleep health deteriorates.**

***Index Terms*—Sleep Quality Monitoring, PSQI, Human Assisted Automation, Wearable Devices**

I. Introduction

Sleep health can affect the quality of life of modern people. In addition, it can have an impact on work, stress levels and overall human health. Employees and, more specifically, office workers can suffer from sleep problems and trying to achieve good sleep health can affect their daily lives and mental health [1]. Sleep problems cause chronic pathological exhaustion, chronic sleep disorders and, in some cases, can even lead to depression [2]. Finally, the quality of sleep is associated with the occurrence of serious diseases such as heart disease [3], [4], hypertension [5], [6] and high cholesterol [7], [8] as well as affecting blood glucose [9], [10].

In recent years, the domain of sleep health assessment has expanded with the advent of smartwatches and other electronic health devices that monitor and document sleep stages, breaks, duration and more. Due to the radical improvement in the field of sleep monitoring, the sleep assessment aspect is of great interest to the research community. Through rapidly automated accurate sleep health assessments, medical professionals can have more reliable, faster, and easier access to their patients' sleep health data. A mechanical sleep health assessment can also help diagnose sleep disorders, chronic conditions, and other sleep disorders (e.g. nocturnal symptoms that interfere with sleep) [11].

Sleep quality is measured by the Pittsburgh Sleep Quality Index (PSQI). More specifically, PSQI is the tool of preference, and its reliability and accuracy are the standards for sleep quality assessment research. Although the PSQI is the best tool for its purpose, it is still affected by patients' subjective feelings and views, as it is a self-reported tool for sleep health. That could be improved by the objectivity of the monitoring devices, whose data have been filtered through a digital version of PSQI [12].

In patients with long-term or short-term hospital care, if there is a need for sleep monitoring, the patient should be examined, or a physician should conduct daily interviews and record the patient's health. Hospitals could save a lot of time and money if these problems are solved with automated systems. There are already automated systems in hospital facilities, but their operation is associated with specialized staff and huge cumbersome machines that can not be applied simultaneously to many patients. That means that the equipment is not utilized, and the maintenance costs remain high. Patients prefer discreet, smart and comfortable ways to monitor their health [13].

A way of monitoring, evaluating and analyzing sleep health through a smart device is presented and thoroughly implemented in the GATEKEEPER [1] and SmartWork[2] projects. There are recent works on monitoring the quality of sleep. In [14], the authors compare manual and automatic scoring of sleep monitoring data from portable polygraphy. In [11], it is reviewed the advances in wearable sensors, miniaturized electronics, and system packaging for home sleep monitoring. Finally, in [15] the monitoring of sleep quality with human-assisted corrections is done.

In the present work, we aim to use the aforementioned methods in order to evaluate the sleep quality of the participants in the Tesserae dataset[3]. Our method divides sleep into distinct categories of sleep health, namely, sleep duration, sleep efficiency, sleep latency and sleep interruptions, which are components of overall sleep health and can be causes of reduced sleep quality. As a complementary metric, we measure the dysfunction during the day, which is a symptom of a bad night's sleep.

The rest of the paper is organized as follows. In Section II, we describe the dataset and its features. Besides, in Section III, an analysis of the methodology followed is made. In addition, in Section IV, we discuss the acquired research results. Finally, conclusions and future directions are outlined in Section V.

II. Dataset and Description

The present work was based on data from the Tesserae project. The dataset consists of a study of 757 users belonging to cognitively demanding professions (information technologies and others) and was run for a period of 1 year. The measurements are in all cases being taken from smartwatches and then converted to a time series, from which the different

[1] www.gatekeeper-project.eu
[2] www.smartworkproject.eu
[3] https://tesserae.nd.edu/

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metrics are calculated. Depending on the smartwatch some metrics might be taken as is. More specifically, the dataset is comprised of multiple consecutive 24-hour measurements of sleep. Sleep is graded in stages, and each differentiation in the stage is branded, and so we can discern different metrics from them and from the heart rate (HR) of the subject. These metrics are sleep latency, sleep duration, sleep efficiency, sleep disturbance, daytime dysfunction and overall sleep. The dataset that our method was developed on is a set of 17 users that were being measured for a period of 6 months to 2 years depending on their own choice. The Tesserae project includes data measuring heart rate, physical activity, sleep, social context, and other aspects through smartwatches, a phone agent, beacons, and social media.

III. Methodology

In the Tesserae project dataset, sleep is measured by smart devices. Sleep can be categorized into 4 stages, awake, light sleep, deep sleep and REM sleep. We extract each sleep metric (e.g. sleep duration) from a time series of sleep stages provided by the dataset for each night. In this way, a time series of sleep stages can be meaningfully divided into useful metrics similar to the ones used by the PSQI. The adopted methodology is based on our previous work [15] [16] and calculates the following metrics as a way of assessing and scoring sleep health. In previous work, questionnaires were used to develop and calibrate the model to accurately assess an individual's sleep scores based on the PSQI responses for that month. When applying the sleep assessment system to the Tesserae project dataset, we do not use their questionnaires as a calibration method but as an accuracy, metric to distinguish whether our method is applicable to other more generalized datasets.

The sleep assessment method consists of the following metrics, paired with the PSQI questionnaire responses. These metrics have been analytically described in [16]. In the following, it is presented a brief definition, while Tables I-III show the conditions and the related scoring. Note that scores greater than 3 are assigned to 3.

C3 Daily sleep duration: The age of the subject changes the suggested duration of sleep. This metric is based on a PSQI metric (PSQI C3) targeting the same health indicator. We define `md` as minutes deviation from the suggested sleep duration.

C4 Habitual sleep efficiency: Is calculated as the time sleeping divided by the time lying in bed. This metric is based on a PSQI metric (PSQI C4) targeting the same health indicator. We define `pr` as percentile rest over a night's sleep.

C5a Daily sleep interruptions: The duration in minutes of interrupted in a night's sleep. This metric is based on a PSQI metric (PSQI #5b) targeting the same health indicator. We define `sim` as the duration of sleep interruption that occurred in a night's sleep.

C5b Daily sleep interruptions: The absolute number of interruptions in a night's sleep. This metric is based on a PSQI metric (PSQI #5b discrete) targeting the same health indicator.

TABLE I
Scores for percentile rest and suggested sleep deviation in minutes

C4 Habitual sleep efficiency		C3 Daily sleep duration	
Conditions	**score**	**Conditions**	**score**
$pr > 90\%$	0	$md \leq 120$	$\frac{md}{60}$
$60\% \leq pr \leq 90\%$	$\frac{3-pr}{60}$	$md > 120$	$2 - \frac{md-120}{360}$
$pr < 60\%$	3		

TABLE II
Scores for sleep interruption in minutes and number of discrete events

C5 Daily sleep interruptions			
a:Minutes		**b:Absolute number**	
Conditions	**score**	**Conditions**	**score**
$sim < 20$	0	$si < 10$	0
$20 \leq sim \leq 60$	$\frac{sim-20}{40}$	$10 \leq si < 20$	$\frac{si-10}{10}$
$sim > 60$	$1 + \frac{sim-60}{60}$	$si \geq 20$	$1 + \frac{sim-20}{20}$

We define `si` as the number of discrete interruptions over a night's sleep.

C7 Daytime dysfunction: The number of daytime sleep events. These include small sleepiness events like doing chores, driving etc. but do not include actual secondary sleep like midday napping. This metric is based on a PSQI metric (PSQI #7) targeting the same health indicator. The variable `mds` is defined as minutes of midday sleep events.

C8 Sleep latency: The time difference between the start of different nights of sleep. This metric is based on a PSQI metric (PSQI #1) targeting the same health indicator. We define `bd` as a deviation in minutes from usual bedtime, while usual bedtime is calculated through a complex dynamic system, but can be summarized in some cases as the mean of bedtime between the x previous days.

IV. Results

For assessing sleep, as per the PSQIndex, scores range from 0 to 3, with 0 being the best and 3 being the worst. In the PSQIndex 0 is designated "Very good sleep", 1 is "Fairly good sleep", 2 is "Fairly bad sleep", and 3 is "Very bad sleep". In the Figures that follow, we sample the results of one subject's sleep evaluation, during 30 days of sleep, with scores ranging from 0 to 3 for every day's-night's sleep.

The score in one category is important on its own, but also in conjunction with other categories important conclusions or suggestions can be made. Bellow, we demonstrate a subject's

TABLE III
Scores for midday sleep events in minutes and deviation from usual bedtime

C7 Daytime dysfunction		C8 Sleep latency	
Conditions	**score**	**Conditions**	**score**
$mds < 5$	$\frac{mds}{5}$	$bd \leq 240$	$\frac{bd}{240}$
$5 \leq mds \leq 30$	$\frac{mds-5}{25}$	$bd > 240$	$2 + \frac{bd-240}{480}$
$mds > 30$	$2 + \frac{md-30}{30}$		

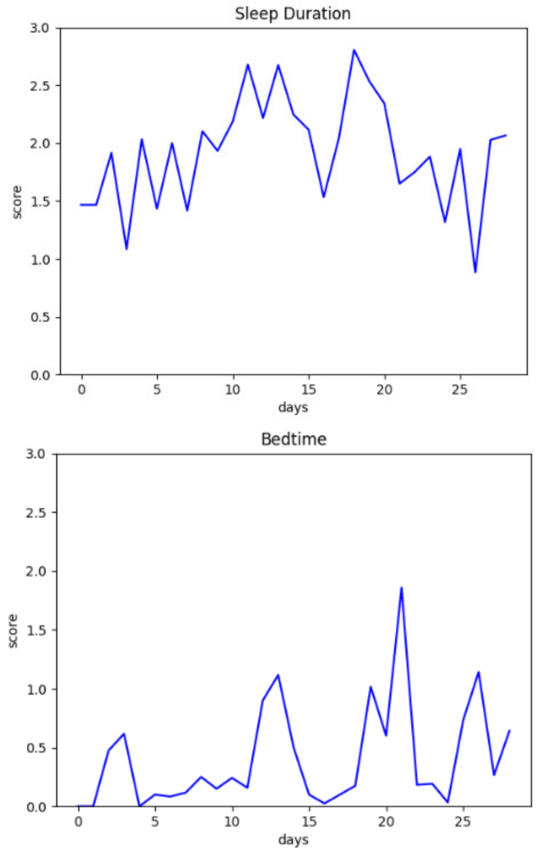

Fig. 1. Sleep duration and bedtime score of a subject for 30 days of monitoring

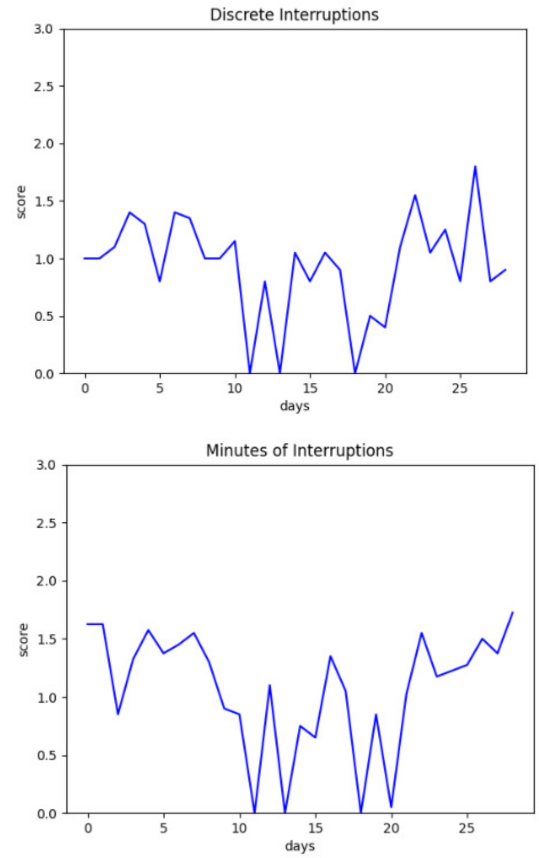

Fig. 2. Discrete number of interruptions score and minutes of interruptions score of a subject for 30 days of monitoring

scores for a month worth of measuring and possible conclusions or suggestions that can be drawn or given.

In Figure 1, we see the sleep duration score of the subject. As shown in the figure, the score ranges mostly from 1 to 3, with a mean of about 2. That is a fairly bad to very bad score for this subcategory of sleep, and if this were a live study a suggestion to contact a health professional or try to remedy the problem themselves would have been made to the subject. Specifically, for this case, the subject sleeps a significant amount fewer hours than suggested for their age group, which probably causes other health issues as well.

Moreover, in Figure 1, we also see the sleep latency score of the subject or simply the bedtime score. This score is calculated based on the difference in sleep start time between the consecutive night of sleep. It is observed that the score ranges from 0 to 1.5, with the mean being about 0.5. That would be classified as very good sleep in this subcategory, and it is caused by the subject having a disciplined bedtime schedule, sleeping similar hours every night with no hectic changes in bedtime.

Figure 2 consists of the sleep interruptions scores, measured in both minutes of interruption and a discrete number of interruptions. This score is calculated based on waking up at night, disrupting the night's sleep which may cause bad rest and feelings of tiredness or even chronic exhaustion. As shown in the Figures, the score ranges from 0 to 1.5, with the mean being 1. It can also be observed that though differing on some days, on most days the number and minutes of interruptions are similar. That can be caused by restlessness in sleep, and even though the scores are good in the context of interruptions only, if taken in conjunction with sleep duration we may conclude that the bad sleep duration score could be caused by the few interruptions in sleep. In case there was a real-time interaction with a healthcare professional during the study, the subject would be advised to inform him/her of both of those metrics.

Figure 3 illustrates the sleep efficiency and overall sleep scores, respectively. Sleep efficiency is a score based on how much of the time spent in bed, is actually affected by sleep, and not just laying. As shown in the figure, sleep efficiency scores range from 0 to 0.5, with a mean close to 0. That is classified as very good sleep efficiency, indicating that the subject sleeps most of the time spent in bed. Overall sleep is a metric derived as the mean of all previous scores and is compared to the PSQIndex score of the general subjective feeling the subject has of his/her sleep health. As shown in the figure, the overall sleep score ranges from a little below 1 to a little above 1, with a mean close to 1. It is classified as fairly good sleep, and no suggestions for sleep improvements would be made, except for the fact that in this subject's case,

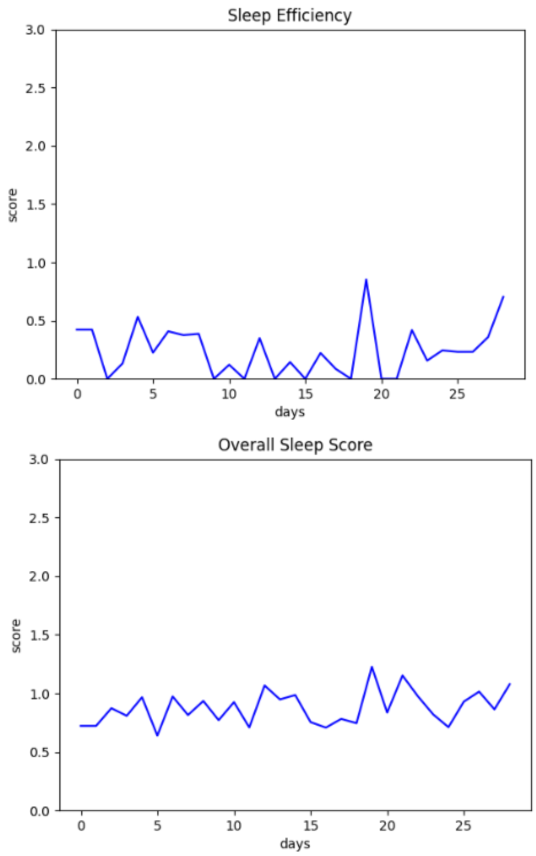

Fig. 3. Sleep efficiency score and overall sleep score of a subject for 30 days of monitoring

sleep duration score is fairly bad to very bad.

V. Conclusions

Concluding, our method can be used accurately to assess sleep in even more general data from different smart devices. The value of our system remains despite the specific context it was developed and has general usage beyond its original scope.

In future work, we aim to use more paired data from the Tesserae project, like daily physical activity, social media data and social context data, to inform our system of the type of day a subject had before any anomalies in sleep. In this way, we can try to predict possible sleep health abnormalities by sampling data of a subject's day and informing them of what they are doing that can cause or is causing said bad sleep.

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