Sleep Quality Monitoring with Human Assisted Corrections

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Abstract: Quality of life and wellness are heavily affected by sleep health, especially for older people who choose to remain active in the workforce. Work ability and efficiency are correlated to sleep quality. Several non-automated sleep assessment tools have been used by professionals in the healthcare industry. These tools may rely on the user report of sleep quality perception. There also are objective tools that can diagnose sleep disorder only for a limited amount of time in a hospital setting due to increased cost and heavy being very unwieldy in a house setting. This paper aims to present the SmartWork project approach for human assisted automated sleep quality assessment. The suggested method emphasizes the triggering mechanisms based on behavioural and lifestyle routine to assist an automated system in correcting the results for personalized scoring for each user. This work aims to guide older people in adopting a healthier sleep habit to enhance their sleep quality and increase satisfaction.

1 INTRODUCTION

In modern workplaces, many people suffer from sleep problems and struggle for achieving good sleep quality (Åkerstedt et al., 2002). The sleep of poor quality impacts health and quality of life (Lucena et al., 2020). Besides, small reductions in sleep duration or increase in sleep interruptions can impact significantly, especially older adults. It is shown in literature that sleep problems can have serious implications, especially in the case of older people (ROEHRS et al., 1983)(Cohen-Zion et al., 2001), including feelings of tiredness, chronic pathologic exhaustion, sleep disorders and potentially contributing to other health conditions (e.g., depression). These pathologies create even more complications by affecting work efficiency, work ability and productivity (Nebes et al., 2009). Having a lower ability to work or succeed, in turn, disturbs a person's emotional state and creates stress and disappointment, that can burden sleep quality. As a result, it can create a negative feedback loop that degrades an individual's wellness, health and quality of life (Nebes et al., 2009), (Knudsen et al., 2007).

In the last decade, the assessment of sleep quality has attracted the interest of the research community. Such an interest stems from the need for medical professionals to reliably monitor and measure sleep quality. Sleep quality monitoring helps in the diagnosis of sleep disorders, chronic conditions and many times monitoring symptoms that cause bad sleep resulted from other conditions (e.g., cough at night due to poor management of chronic respiratory conditions) (Kocsis et al., 2015), (Khusial et al., 2019). There exists a number of self-reported sleep quality tools, one of them being the Pittsburgh Sleep Quality Index (PSQI) (Smyth, 1999). The PSQI is one of the most used self-report assessment tools, however, it is impacted by the subjective feelings of the individual. An unobtrusive approach to monitoring sleep is to use hand-worn devices that monitor sleep like smartwatches (GalaxyFit[1], AppleSmartwatch[2], FitBit[3]). In hospital settings, there are a number of methods of objective sleep assessment that are either already in use or are being developed actively. Nonetheless, these methods aren't utilized in practice due to the need for machinery and specialized personnel to operate it. One of the most crucial parameters, for the users, in selecting or even using any of said systems is unobtrusiveness and comfort (Nakamura et al., 2017). Especially for older people the ease of use is even more important.

This paper is part of work in the context of the Smartwork project (Kocsis et al., 2019), which aims

[1]https://www.samsung.com/uk/support/mobile-devices/how-to-monitor-my-sleep-on-the-galaxy-fit-e/
[2]https://www.apple.com/apple-watch-series-5/
[3]http://www.fitbit.com.

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to provide sustainability of work ability in the case of older office workers and gives them a better chance in competing for jobs through the improvement of their work performance and quality of life. In the literature, there is a well-documented relation between sleep quality and work ability (Eriksen et al., 2001)(Lian et al., 2015). It demonstrates the correlation between bad health and work ability reduction, failure to acquire and sustain a steady job, perform well in demanding or even mundane tasks and, in general, be satisfied with the productivity of one's self. In previous work, we presented an ongoing approach for continuous sleep quality assessment thar will be integrated in the Smartwork system. This system supports triggering mechanisms for behavioural and lifestyle interventions in order to guide older people adopt healthier sleep habits and increase their sleep quality and satisfaction. The aim of this paper is to enhance our previous approach (Konstantoulas et al., 2020) considering human assistance in correcting the system perception on how to score sleep quality personally tailored to each person.

2 METHODS AND EXPERIMENTAL SETUP

In this section, we will analyze in detail the systems and methodology for assessing the quality of users' sleep. In addition, in the context of the SmartWork system, we will discuss the purpose of sleep assessment and the proposed approach to this problem. Challenges arising from our approach and related solutions will also be presented.

2.1 Selection of Sleep Assessment Methods

In an attempt to identify the appropriate monitoring/assessment device to use, we researched the possibilities of small to large-scale setups with obtrusive and unobtrusive methods to qualify sleep patterns in data form.

One of the most used self-reported questionnaires by medical professionals is the Pittsburgh Sleep Quality Index (PSQI) (Smyth, 1999), with a demonstrated long history compared to other sleep measurement systems (Smith and Wegener, 2003). It can differentiate poor from good sleep based on seven distinct categories: subjective sleep quality, sleep latency, sleep duration, habitual sleep efficiency, sleep disturbances, use of sleep medication, and daytime dysfunction over the last month. Nevertheless, the accuracy of any self-reported questionnaire is limited by the subjective perception of the reporter and does not qualify the sleep quality of the person objectively. This paved the way to objective sleep assessment, that many methods already provide. These methods include, on one hand, costly hospice systems that assess sleep disorders (e.g., polysomnography), and, on the other hand, less expensive in-home systems for unobtrusive monitoring, such as e-health applications (Corral et al., 2017). For any system, the use of unobtrusive affordable solutions is one of the main concern tied to any scalability concern (Nakamura et al., 2017). In the marketplace, there exists a number of wearable physiological monitoring devices such as smartwatches, that allow for monitoring of sleep-related physiological signals over many years in an unobtrusive and affordable manner.

Another method is Ear-ElectroEncephaloGraphy (EEG), that can even be used in a home setting (Nakamura et al., 2017). The performance of this method is assessed by comparing a manually scored hypnogram to a predicted label based on the in-ear sensor data. Ear-ElectroEncephaloGraphy (EEG) as a method is very precise and can predict sleep stages with high accuracy (Mporas et al., 2013), (Mporas et al., 2015), but as a disadvantage this method is unwieldy for personal use and obtrusive in a casual everyday setting. Another method is using radio signals to monitor insomnia and sleep at home. This method measures radio signals that bounce off of the user's body (Hsu et al., 2017). Finally, in the market, the acceptance of smartwatches and smartphones is increasing as they are less obtrusive, affordable and easy to use methods (GalaxyFit, FitBit).

For smart devices, especially, there is room for evolution. Though the smartwatch data collection methods are good enough, their companion back-end data analysis, calculations and estimations are not utilized to their best potential yet. These devices are accessible by everyone and can help in the development of a large scale health assistance system for sleep assessment and an integrated approach for matters that deter or promote sleep quality. For instance, in a specific user's life, bad sleep could be caused by poor nutrition leading to tiredness that flares up some other pathological condition. In this case, an integrated system with unobtrusive and easy to use smart devices can inform the user fora series of events that can prevent their health deterioration by switching out some poor nutrition options.

To our problem, in the scope of the SmartWork project (Kocsis et al., 2019), we combine a self-reported questionnaire with a quantitative objective method to calculate the relevant scores through a smartwatch. We aim to increase the accuracy of the objective method, give feedback to the user when their perception differentiates from reality, and render the user able to correct the underlying score when the objective system is misconfigured.

2.2 The SmartWork System

The SmartWork is a Worker-Centric AI system, in the context of the SmartWork project (Kocsis et al., 2019). Its purpose is to integrate unobtrusive sensing and modelling of the worker state considering a set of novel services for the support of the context and worker-aware adaptive work. The target groups of the SmartWork system comprise of the office workers, their employer and their carers. Motivated by the fact that the health, behaviour, cognitive and emotional status of the office worker is impacted, indirectly, by their sleep quality, the proposed approach will be implemented as a service of SmartWork.

2.2.1 An Overview of the Sleep Assessment System

Our past work in (Konstantoulas et al., 2020) introduced the design and implementation of the system that monitors and assesses sleep quality. Its design was based on a combination of an implementation of the PSQI self-reported questionnaire and an objective scoring system for daily sleep data gathered by a smartwatch. This system (see Figure 1) is part of a larger interconnected system (namely, SmartWork) that predicts or analyses data from multiple sources for a more holistic understanding of the user.

The system is fed with daily sleep data gathered from a smartwatch, commercially available and easy to use (FitBit). It is biometric data related to sleep, daily physical activity implied from steps and heart rate over the day and others. After data collection, a pre-processing step is applied using classical methods from data science to handle the potential uncertainty of the devices. Notice that missing values are imputed by a machine learning model but with unsatisfactory accuracy yet.

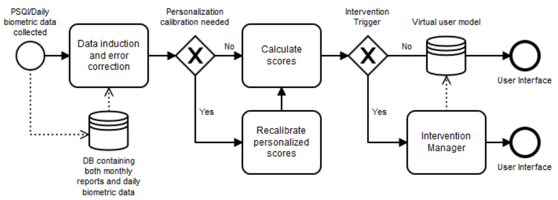

Figure 1: Asynchronous process design for sleep data collection.

2.2.2 User-perceived Sleep Quality

The user-perceived sleep quality is based on self-reported data derived by a questionnaire similar to the one in our previous work (Konstantoulas et al., 2020). The underlying process for sleep quality assessment is implemented in the SmartWork project using the PSQI sleep assessment tool. For each user, a general sleep quality score is acquired by the received answers on a number of qualitative and quantitative questions (Smyth, 1999) (Global PSQI score), with values between 0 and 21. The 0 value corresponds to no sleep problems at all, while values equal to 5 or higher concern a “poor” sleeper. This score is defined as the sum of 7 different scores (with values between 0 to 3) which are calculated by a unique formula. The PSQI survey implemented as part of the user profile initialization interface in SmartWork. The main components of the PSQI survey are as follows:

`PSQI_C1`: Subjective Sleep is based on PSQI question #9 which directly links the user’s answers to a score from 0 to 3.

`PSQI_C2`: Sleep Latency is based on questions #2 and #5a of PSQI. More specifically, Question #2 captures the time in minutes the user needs to fall asleep, while question #5a refers to how often the user was unable to fall asleep within 30 minutes of lying-in bed. The final score for this component is the average of the 2 questions.

`PSQI_C3`: Sleep Duration captures the upper perceived amounts of hours of sleep each night (`PSQI #4`).

`PSQI_C4`: Habitual Sleep Efficiency calculates the total hours in bed as the ratio of bedtime (`PSQI #1`) to wake time (`PSQI #3`), then total hours of sleep (`PSQI #4`) to calculate total rest time.

$$\frac{hours\ of\ sleep}{time\ in\ bed} 100\% \tag{1}$$

`PSQI_C5`: Sleep Disturbance denotes the number of sleep disturbances in a week level. The final score is derived by summing up the individual scores assigned to each of the questions from #5b to #55j.

`PSQI_C6`: Use of Sleep Medication represents the user’s assessment on how often they need medication to fall asleep.

`PSQI_C7`: Daytime Dysfunction. The user reports mid-day sleepiness (`PSQI #7`) and general enthusiasm about activities (`PSQI #8`). The score for this component is the average one acquired from PSQI questions #7 and #8.

In the following subsection, the automatic sleep scores estimation will be presented.

2.2.3 Automatic Sleep Scores Estimation

In this section, we present the automatic sleep score estimation made by an objective viewpoint. Knowing that objectivity may be not the best approach for wellness optimization of the user, in the next section we present the intervention-based feedback system for correcting the objective benchmark values (objective in the sense that these mark values are backed by usual healthy estimates of researchers in the literature) (Knudsen et al., 2007)(Smyth, 1999)(Hirshkowitz et al., 2015)(Åkerstedt et al., 2002).

During the lifetime of a person, sleep duration fluctuates and it is highly affected by their age. To implement the proper guidance or intervention systems towards enhancement of sleep quality, internationally established recommendations, such as the Sleep Duration Recommendations established by the National Sleep Foundation (Hirshkowitz et al., 2015), are considered. In particular, in the case of SmartWork target users (office workers aged between 50 and 65 years old), the expected normal sleep duration is between 7 to 9 hours. Note that, 6 or 10 hours are also as acceptable. Exploiting the smartwatch device, the sleep stages are identified and used to estimate, on a daily level, the total and actual hours of sleep, respectively. Also, the amount and duration of sleep interruptions are recorded. Then, relevant scores are assigned to the collected data, in a similar way as the one adopted by the user self-reported sleep quality using the PSQI tool. The automatic sleep quality components are the following:

Auto_C3: Daily Sleep Duration uses the recommended sleep duration by medical professionals (Åkerstedt et al., 2002) as a ground truth. According to the age group a user belongs to and the recommended sleep duration, minutes deviation (md) is calculated. The formula for scoring is the same as in the calculation of PSQI_C3.

$$if\ \mathtt{md} \leq 120\ then\ score = \frac{\mathtt{md}}{60}$$
$$if\ \mathtt{md} > 120\ then\ score = 2 + \frac{\mathtt{md} - 120}{360}$$
$$if\ score > 3\ then\ score = 3$$

Auto_C4: Habitual Sleep Efficiency (Auto_C4) is defined by pr as percentile rest over time in bed. Its formula is based on the PSQI_C4 formula with minimal changes to account for user misconceptions.

$$if\ \mathtt{pr} > 90\%\ then\ score = 0$$
$$if\ \mathtt{pr} \geq 60\%\ and\ \mathtt{pr} \leq 90\%\ then\ score = 3 - \frac{\mathtt{pr} - 60}{10}$$
$$if\ \mathtt{pr} < 60\%\ then\ score = 3$$

Auto_C5a: Daily Sleep Interruptions (Auto_#5b) are calculated in minutes using the data collected by the smartwatch. We define as sim the duration of sleep interruptions in minutes, overnight, during the rest time. Its formula is based on matching subject data to the score they reported that month (PSQI #5b) and may change with a larger data sample and could be unique to each user.

$$if\ \mathtt{sim} < 20\ then\ score = 0$$
$$if\ \mathtt{sim} \geq 20\ and\ \mathtt{sim} < 60\ then\ score = \frac{\mathtt{sim} - 20}{40}$$
$$if\ \mathtt{sim} \geq 60\ then\ score = 1 + \frac{\mathtt{sim} - 60}{60}$$
$$if\ score > 3\ then\ score = 3$$

Auto_C5b: Daily Sleep Interruptions. (Auto_#5b discrete) As for the absolute number of sleep interruptions using the data collected by the smartwatch, si captures the absolute number of sleep interruptions during time rest overnight. Its formula is based on matching user-perception of sleep interruptions to results automatically calculated based on their FitBit data (as Auto_C5a).

$$if\ \mathtt{si} < 10\ then\ score = 0$$
$$if\ \mathtt{si} \geq 10\ and\ \mathtt{sim} < 20\ then\ score = \frac{\mathtt{sim} - 10}{10}$$
$$if\ \mathtt{si} \geq 20\ then\ score = 1 + \frac{\mathtt{si} - 20}{20}$$
$$if\ score > 3\ then\ score = 3$$

Auto_C7: Daytime Dysfunction. (Auto_C7). We define mds as the minutes of mid-day sleep events. These events are classified as mid-day sleep if their duration is small enough and that are not categorized as actual secondary actual sleep in a day. The formula is based on aligning the daily data of users with the self-reports of users for question #7 (PSQI #7).

$$if\ \mathtt{mds} < 5\ then\ score = \frac{\mathtt{mds}}{5}$$
$$if\ \mathtt{mds} > 5\ and\ \mathtt{mds} \leq 30\ then\ score = \frac{\mathtt{mds} - 5}{25}$$
$$if\ \mathtt{mds} > 30\ then\ score = 2 + \frac{\mathtt{mds} - 30}{30}$$
$$if\ score > 3\ then\ score = 3$$

Auto_C8: Daily Bedtime has no clear analogous score in the PSQI, thus, we use the answers of question #1 (PSQI #1) for a "usual" time of reference. Concerning the bedtime, bd represents the deviation in minutes from the usual bedtime. The usual bedtime of a user is a composite mean of the last 5 days of sleeping whose contribution is smaller as we move away from "today".

$$if\ \texttt{bd} \leq 240\ then\ score = \frac{\texttt{bd}}{120}$$
$$if\ \texttt{bd} > 240\ then\ score = 2 + \frac{\texttt{bd} - 240}{480}$$
$$if\ score > 3\ then\ score = 3$$

Auto_C1: Daily Overall Sleep Quality is calculated as the average score of Auto_C3, Auto_C4, Auto_C5, Auto_C7 and Auto_C8. Notice that this component is compared to the user's self-reported subjective sleep quality component of the PSQI (PSQI_C1) and not the Global PSQI score.

Automatically Calculated Monthly Scores are derived as mean values of the daily scores.

In the next subsection, we will present the contribution of the current study which is founded in Sections 2.2.2 and 2.2.3. In particular, the proposed approach aims to correct the automatically calculated sleep quality scoring taking into account the user perception.

2.2.4 Human Assisted Corrections

An intervention is triggered for a specific event, such as a suddenly worse or better sleep quality than usual. In this intervention, the user is asked if the scoring was corrected or informed that they could see a doctor based on the data. Also, the user can decide to bypass the data and claim that the triggered intervention was false. Focusing on the latter case, the correction system has been implemented for exceptions in the calculation of sleep quality scores. The system corrects scoring methods based on the user's feedback in the moment of the intervention based on their answers in the PSQI questionnaire each month. The main components of the human assisted approach are the following:

Corr_C3: Corrected Daily Sleep Duration. We define ard as the adjusted recommended sleep duration, rd as the recommended sleep duration, md as minutes deviation from adjusted recommended sleep duration and msd as the median sleep duration which is calculated as the median of the last 30 days of sleep and *relu*, which is a function that sets as 0 any negative values. The subtraction of PSQIC3 from AutoC3 is divided by 10 to normalize the multiplication of this modifier with the modified recommendation for sleep, this is a number we reached after experimentation. For the corrected score the recommended sleep duration is adjusted as follows.

$$\texttt{ard} = \texttt{rd} + (\texttt{rd} - \texttt{msd}) \cdot \frac{relu(\texttt{AutoC3} - \texttt{PSQIC3})}{10}$$

$$\texttt{md} = |\texttt{sleep duration} - \texttt{ard}|$$
$$if\ \texttt{md} \leq 120\ then\ score = \frac{\texttt{md}}{60}$$
$$if\ \texttt{md} > 120\ then\ score = 2 + \frac{\texttt{md} - 120}{360}$$
$$if\ score > 3\ then\ score = 3$$

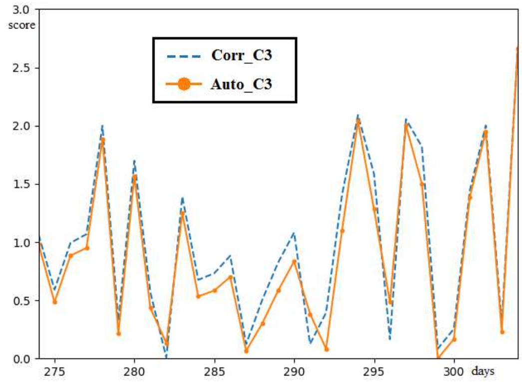

Figure 2: Sleep duration score automatically calculated (Auto_C3) and user-assisted correction (Corr_C3) over 31 days.

Corr_C4: Habitual Sleep Efficiency. We define hm as the high mark of scoring and lm as the low mark, as in Auto_C4 we define pr as percentile rest over time in bed, and all relevant calculations are done the same way, except scoring is calculated as follows.

$$\texttt{hm} = 90 + 3 * (\texttt{PSQIC4} - \texttt{AutoC4})$$
$$\texttt{lm} = 60 + 12 * (\texttt{PSQIC4} - \texttt{AutoC4})$$
$$if\ \texttt{pr} > \texttt{hm}\%\ then\ score = 0$$
$$if\ \texttt{pr} \geq \texttt{lm}\%\ and\ \texttt{pr} \leq \texttt{hm}\%\ then\ score = 3 - \frac{\texttt{pr} - \texttt{lm}}{\frac{\texttt{hm} - \texttt{lm}}{3}}$$
$$if\ score > 3\ then\ score = 3$$

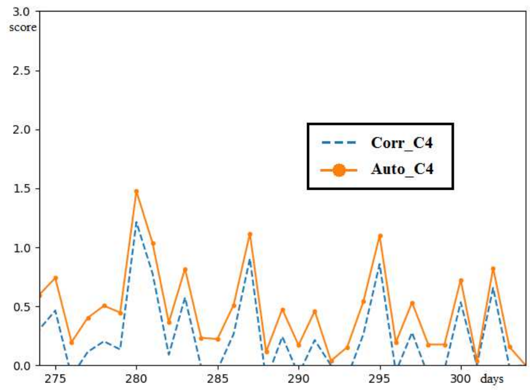

Figure 3: Habitual sleep efficiency score automatically calculated (Auto_C4) and user-assisted correction (Corr_C4) over 31 days.

`Corr_C5a`: Daily Sleep Interruptions. (minutes) We define hm as the high mark of scoring and lm as the low mark, as in `Auto_C5a` we define sim as minutes of sleep interruptions over nighttime rest.

$$\mathtt{hm} = 40 + 6 * (\mathtt{AutoC5a\_last\_month} - \mathtt{PSQI\#4})$$

$$\mathtt{lm} = 20 + 6 * (\mathtt{AutoC5a\_last\_month} - \mathtt{PSQI\#4})$$

$$if\ \mathtt{sim} < \mathtt{lm}\ then\ score = 0$$

$$if\ \mathtt{sim} \geq \mathtt{lm}\ and\ \mathtt{sim} < \mathtt{hm}\ then\ score = \frac{\mathtt{sim} - \mathtt{lm}}{\mathtt{lm}}$$

$$if\ \mathtt{sim} \geq \mathtt{hm}\ then\ score = 1 + \frac{\mathtt{sim} - (\mathtt{hm} + \mathtt{lm})}{\mathtt{hm} + \mathtt{lm}}$$

$$if\ score > 3\ then\ score = 3$$

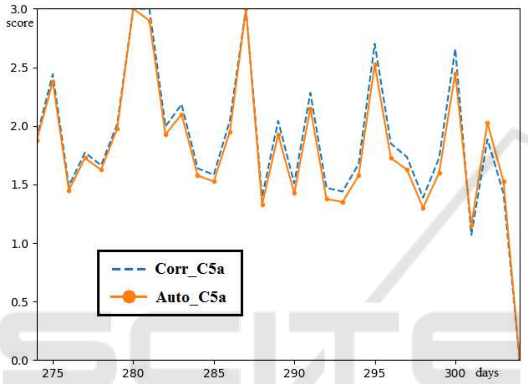

Figure 4: Daily sleep interruptions in minutes score automatically calculated (`Auto_C5a`) and user-assisted correction(`Corr_C5b`) over 31 days.

`Corr_C5b`: Daily Sleep Interruptions. (Discrete) We define `hm` as the high mark of scoring and `lm` as the low mark, as in `Auto_C5b` we define `si` as the number of sleep interruptions over nighttime rest.

$$\mathtt{hm} = 20 + 3 * (\mathtt{AutoC5a\_last\_month} - \mathtt{PSQI\#4})$$

$$\mathtt{lm} = 10 + 3 * (\mathtt{AutoC5a\_last\_month} - \mathtt{PSQI\#4})$$

$$if\ \mathtt{si} < \mathtt{lm}\ then\ score = 0$$

$$if\ \mathtt{si} \geq \mathtt{lm}\ and\ \mathtt{si} < \mathtt{hm}\ then\ score = \frac{\mathtt{si} - \mathtt{lm}}{\mathtt{lm}}$$

$$if\ \mathtt{sim} \geq \mathtt{hm}\ then\ score = 1 + \frac{\mathtt{si} - (\mathtt{hm} + \mathtt{lm})}{\mathtt{hm} + \mathtt{lm}}$$

$$if\ score > 3\ then\ score = 3$$

`Corr_C8`: Daily Bedtime. For bedtime correction, we adjust the scale by which we measure usual bedtime. We use a weighted median of the last k sleep nights to calculate usual sleep time. We define `ust` as usual sleep time, `st` as sleep time since 00:00 that day and `bd` as bedtime distance in minutes from usual sleep time(`ust`) for that day.

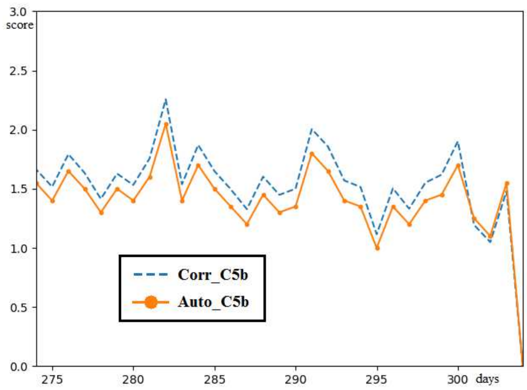

Figure 5: Number of daily sleep interruptions score automatically calculated (`Auto_C5b`) and user-assisted correction (`Corr_C5b`) over 31 days.

$$\mathtt{ust} = \sum \frac{\alpha_i \cdot \mathtt{st}}{N \cdot \frac{N+1}{2}}$$

$$if\ \mathtt{bd} \leq 240\ then\ score = \frac{\mathtt{bd}}{120}$$

$$if\ \mathtt{bd} > 240\ then\ score = 2 + \frac{\mathtt{bd} - 240}{480}$$

$$if\ score > 3\ then\ score = 3$$

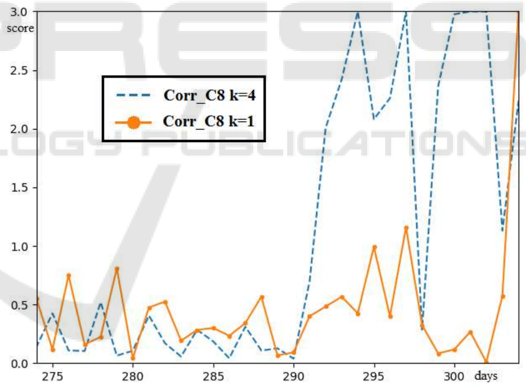

Figure 6: Corrected bedtime score (`Corr_C8`) over 31 days, for $k = 1$ (number of consecutive previous days attributed for median bedtime used for calculation) and $k = 4$.

`Corr_C1`: Daily Overall Sleep Quality. As total score is calculated as the median of other scores, total score for the user assisted corrections is plainly the median of the individual scores on each of these categories.

2.2.5 Test Data Set

The test data derived from a volunteer group of office workers in the age group of 40-55 and, specifically, in this work in 50-65 group. Due to the dynamic nature of the system, good results are expected in all age

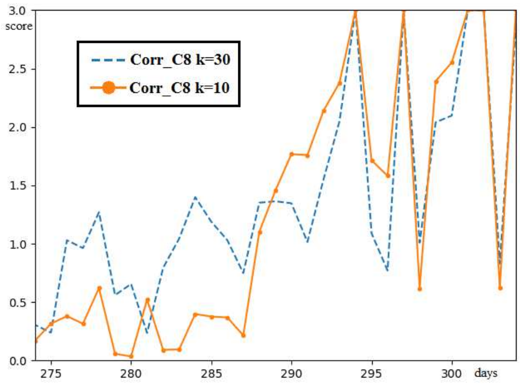

Figure 7: Corrected bedtime score (`Corr_C8`) over 31 days, for $k = 10$ (number of consecutive previous days attributed for median bedtime used for calculation) and $k = 30$.

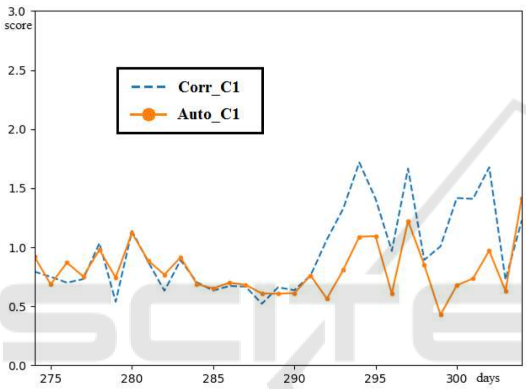

Figure 8: Total sleep quality score automatically calculated (`Auto_C1`) and user-assisted correction (`Corr_C1`) over 31 days.

groups as it is mainly based on perception and information of the user on their own health status. Data is being actively collected in the SmartWork project for participants in our pilots. The results will be demonstrated in the next section and concern a user with 2 years data who slept regularly with the smartwatch on and have completed the PSQI questionnaire for these years. According to the profile of this user, it is an office worker, female, aged 46-50, diagnosed with high cholesterol, mild asthma and allergic rhinitis.

3 RESULTS

Fig. 9 shows the automatically calculated objective score, compared to that calculated after the user input that corrects the values. As it is shown, the overall score for the sleep quality remains mainly the same, although, in what follows, it is observed that the individual corrections in scores vary.

Fig. 10 illustrates the monthly aggregate of sleep

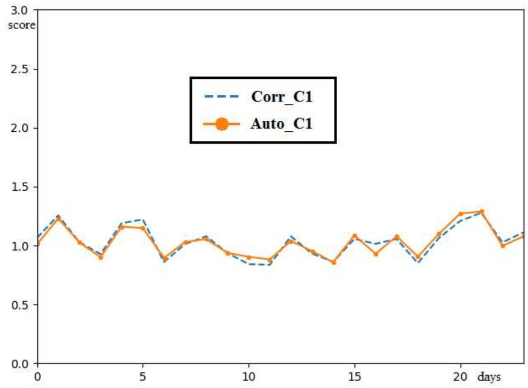

Figure 9: Total sleep quality score automatically calculated(`Auto_C1`) and user-assisted correction(`Corr_C1`) over 24 months.

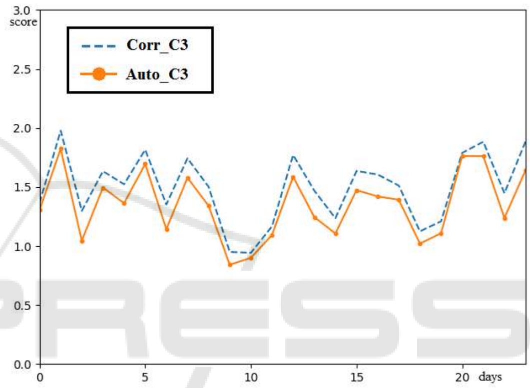

Figure 10: Sleep duration score automatically calculated(`Auto_C3`) and user-assisted correction(`Corr_C3`) over 24 months.

duration daily score calculations over a period of two years. In the figure we can see that the user assisted corrected score is worse than the previous objectively calculated one, as the user reports worse sleep than is objectively calculated.

Fig. 11 depicts the habitual sleep efficiency score calculations over a period of two years. We can see in the figure that the correction scores better than the non-corrected one, the reason is the user reports very good sleep efficiency even though the objective data calculate it worse, we can assume either that the smartwatch is miscalculating interruptions or sleep times, or that the user is satisfied with their sleep efficiency regardless of the objective qualification of their sleep efficiency.

Figs. 12 and 13 show sleep interruption score aggregates over a period of two years for automatically calculated and corrected values. For months the user reports more interruptions and months that user reports less interruptions we can see the corrected calculations vary based on that.

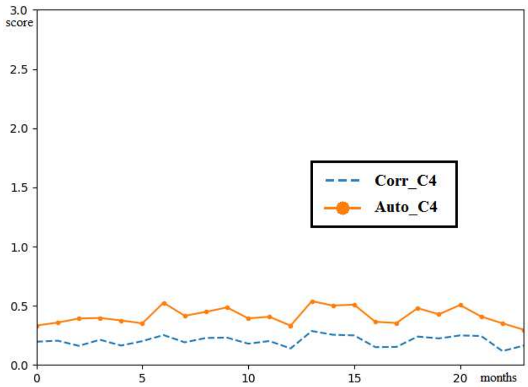

Figure 11: Habitual sleep efficiency score automatically calculated(`Auto_C4`) and user-assisted correction(`Corr_C4`) over 24 months.

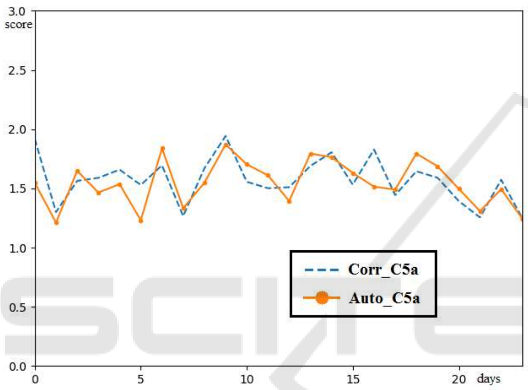

Figure 12: Daily sleep interruptions in minutes score automatically calculated(`Auto_C5a`) and user-assisted correction(`Corr_C5b`) over 24 months.

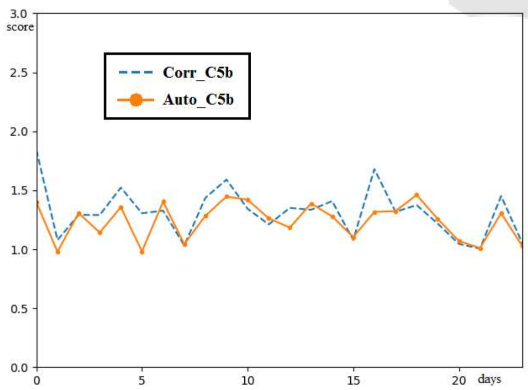

Figure 13: Number of daily sleep interruptions score automatically calculated(`Auto_C5b`) and user-assisted correction(`Corr_C5b`) over 24 months.

Figs. 14 and 15 display bedtime score aggregates over a period of two years for automatically calculated and corrected values. The correction for these scores is calculated based on the usual sleep time of

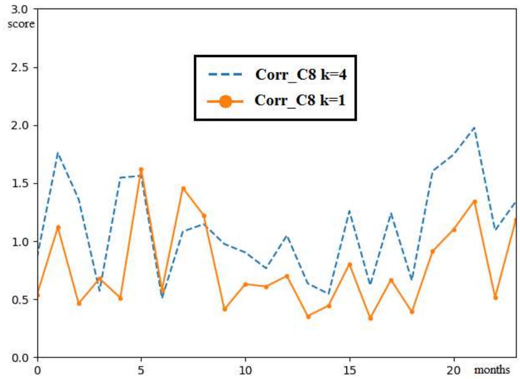

Figure 14: Daily corrected bedtime score (`Corr_C8`) over 24 months, for $k = 1$ (number of consecutive previous days attributed for median bedtime used for calculation) and $k = 4$.

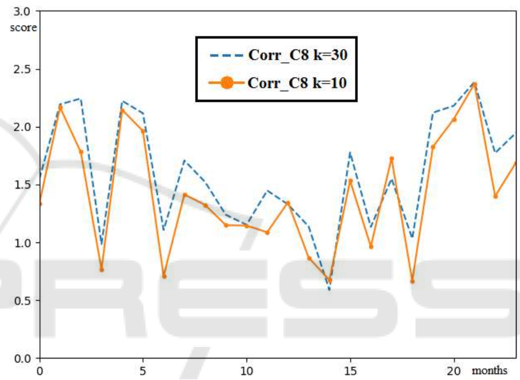

Figure 15: Daily corrected bedtime score (`Corr_C8`) over 24 months, for $k = 10$ (number of consecutive previous days attributed for median bedtime used for calculation) and $k = 30$.

the k previous days. From this, we can see that for $k = 1$ (versus $k = 4$) the user scores better, and as k increases the user's scores become worse, indicating that the user has a very unstable sleep schedule, with little sleep difference from one day to the other. But, compared to all the previous days, the user sleep schedule moves a lot.

4 DISCUSSION AND CONCLUSIONS

An advantage of this approach is that, due to its integration into the SmartWork system, it can get metadata from different datasets, such as dietary preferences or galvanic skin response from a smart mouse, that can help in creating a more comprehensive and holistic system that factors in minor data entries, such as the user of their daily routine and prior circumstances, that would be very laborious to factor in a health professional. A limitation of this work concerns scalability due to the fact that many people dislike wearing watches during their sleep, or just dislike being monitored.

As a future work, our goal is to finalize the integration and interconnectivity of different datasets to assist each other. A system that can predict poor or bad sleep quality at a specific night based on the user activities that morning or evening it can warn the user about the habits/activities that contributed to that prediction (e.g., knowing a specific dietary preference and eating habits of the user that causes bad sleep).

In conclusion, the correction system shows value, as it can be used by the user more actively and effectively to personalize their sleep monitoring with better resolution than in our previous work.

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