Personalized User Modelling for Sleep Insight

Dhruv Deepak Upadhyay
University of California, Irvine
Irvine, CA, USA
ddupadhy@uci.edu

Nitish Nag
University of California, Irvine
Irvine, CA, USA
nagn@uci.edu

Vaibhav Pandey
University of California, Irvine
Irvine, CA, USA
vaibhap1@uci.edu

Ramesh Jain
University of California, Irvine
Irvine, CA, USA
jain@ics.uci.edu

ABSTRACT

Sleep is critical to leading a healthy lifestyle. Each day, most people go to sleep without any idea about how their night's rest is going to be. For an activity that humans spend around a third of their life doing, there is a surprising amount of mystery around it. Despite current research, creating personalized sleep models in real-world settings has been challenging. Existing literature provides several connections between daily activities and sleep quality. Unfortunately, these insights do not generalize well in many individuals. Thus, it is essential to create a personalized sleep model. This research proposes a user centered sleep model that can identify causal relationships between daily activities and sleep quality and present the user with specific feedback about how their lifestyle affects their sleep. Our method uses N-of-1 experiments on longitudinal multimodal user data and event mining to generate understanding between lifestyle choices (exercise, eating, circadian rhythm) and their impact on sleep quality. Our experimental results identified and quantified relationships while extracting confounding variables through a causal framework.

CCS CONCEPTS

• **Human-centered computing**; • **Computing methodologies**
→ **Model development and analysis**;

KEYWORDS

sleep quality;event mining;hypothesis verification;N-of-1 experiments;n=1;health;healthy lifestyle;personalized health;precision health

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1 INTRODUCTION

From affecting mood and demeanor to chronic conditions such as cardiovascular disease and diabetes, sleep is an integral part of leading a healthy and happy life [3, 4]. The quality of sleep affects the health state of all individuals [12, 16]. Although individuals spend a third of their lives sleeping, there are still many questions surrounding sleep quality and how it affects human health. Clinically, sleep research is still developing and far from accessible to the average person.

People usually need to participate in a sleep study, such as Polysomnography, to get accurate insights about their sleep. This type of study requires an individual to spend a night in a sleep lab and also requires medical sensors and professionals to analyze an individual's sleep. While this is the gold standard for understanding sleep quality, it is too cumbersome for an average person to perform nightly. Additionally, since the study setting does not take place regularly, nor does it occur in a person's usual sleeping environment, the study cannot be used to analyze natural sleeping habits. Thus, individuals are left to reading sleep research to find studies that they can apply to themselves to improve their sleep quality.

While there is a rich literature dedicated to sleep, most of the studies focus on population-based results. Sleep is a very personal activity, and everyone has different requirements and reactions to sleep [26]. The lack of personalization in sleep literature leaves a person using a generalized tool instead of a more sophisticated personalized approach towards lifestyle modification [14]. For example, a person may know that exercising should help their sleep quality [8], however, that would not tell them exactly how much they should exercise to improve their sleep quality significantly, nor how varying exercise amount consequently changes its effect on sleep quality. We observe this phenomenon when analyzing the sleep of an athlete vs. a non-athlete. An athlete would most likely see little to no benefit from exercising 30 minutes a day, whereas the non-athlete might significantly improve their next night's sleep. These insights are required if we wish to start controlling our health with more precision by using cybernetic principles and health navigation [13, 15]. For a person to have a concrete way to improve their sleep quality, they need to establish a personalized sleep model.

Every day an individual generates a large number of multimodal data streams that centers around their daily activities [5, 17, 22]. This phenomenon creates a unique opportunity to address understanding and improving sleep quality from a computational perspective. We can harness all the IoT devices, wearables, and smart

devices an individual interacts with to create a multi-modal data set that captures different aspects of a person's sleep and lifestyle. The relevant data streams can be used to create a personalized cross-modal sleep model [16]. This estimation will be personalized based on user data and maintain adaptability through daily updates.

Figure 1: User Centered Semantic Rings with a focus on sleep. These rings show the most relevant factors that contribute to an individuals sleep state.

Figure 1 shows a depiction of user centered semantically meaningful rings. Data from multi-modal and multimedia informs us of the status of each of the rings regarding their sleep model. This figure shows the most relevant factors that affect the next night's sleep quality. The closer the ring is to the person at the center the more relevant the factors are to the next night of sleep and the more effect the next night of sleep has on those factors. Physical and Mental Health significantly affect the next night of sleep and the quality of last night's sleep greatly affect the health for the next day. The rings present in the figure give us a gateway to approach sleep health state estimation computationally. Our study uses parts of rings 2 and 3 (starting from the center) to estimate and predict the sleep health state of an individual via a personalized model based on multi-modal lifestyle data-streams. In order to create this model we predict causal relationships through confounder analysis. Contrary to most literature on sleep, our study approaches the issue of improving sleep quality on an individual basis in order to give the most relevant and helpful information to the user based on their health state estimation.

By combining existing knowledge about sleep research with an event mining engine, we can create a personalized sleep model

to understand the relationships between daily activities and sleep. With a personalized sleep model, sleep health can be brought to a new era, one in which each person is empowered by their model to shape the quality of their next night's rest actively. Our research proposes a new computational approach to sleep research that can introduce a much needed personal touch to the field.

2 RELATED WORKS

Sleep monitoring and data collection for quality assessments is a growing area of research. This is true in both clinical-grade research applications and consumer-grade applications and products.

2.1 Clinical Tools to Understand Sleep Quality

The current gold standard for understanding sleep quality is a study known as Polysomnography. This study requires a person to be present in a sleep lab. It is primarily used to diagnose sleep disorders. The test records various metrics such as brain waves, oxygen levels in the blood, heart rate, breathing, and eye and leg movements [9, 24]. This type of study requires a sleep expert and multiple medical sensors. The study's accuracy comes at the cost of needing too many resources and equipment to be performed every night reliably.

Another popular measurement technique used to measure sleep quality is known as Actigraphy [1]. Actigraphy measures sleep quality via a wearable device (e.g., a watch). Throughout a sleep event, the wearable device measures movement via an onboard accelerometer. Actigraphy is a much more accessible form of measuring sleep quality as it only requires the user to remember to wear the device. Its simplicity comes at the cost of accuracy, as it can only infer sleep quality via movement measurements. For our study, we used a combination of actigraphy and ambient sound to record the night's sleep events.

2.2 Other Sleep Monitoring and Prediction Applications

Previous systems have used smartphone mic data in conjunction with machine learning to classify and predict sleep quality [11]. While this study did achieve personalization to a given user, it also does not create a complete sleep profile. Our study hopes to utilize more than smartphone mic data to create an explainable model of sleep. Other studies have attempted to utilize actigraphy graphs and Deep Learning to predict sleep quality, as well [21]. There are even studies that attempt to forgo the idea of tracking sleep and use factor graph models based on daily activity to predict sleep quality with 78% accuracy [2].

Several sleep applications such as, Sleep Cycle, Sleep Score, and Sleep Genius use audio from the phone mic to record and report sleep quality. These applications may try to incorporate recommendations for improving sleep quality, but many times, the application does not reveal their intuition behind the quality calculation nor does it perform in-depth reviews about how the user can improve their sleep. These applications are also missing a holistic approach to creating their sleep model as they often only have access to steps taken throughout the day and the last night's sleep to make their recommendations. Our study incorporates multiple lifestyle factors that go beyond the scope of steps taken throughout the

day to provide more insightful feedback about sleep. By creating a multimodal dataset that takes advantage of the data mentioned in previous studies and more, we can construct a more comprehensive sleep model that can take in multiple significant lifestyle activities into account. This model can then be used in many research problems, including sleep applications, and recommender systems.

2.3 Understanding the Effect of Lifestyle Activities on Sleep Quality

Current literature has made many attempts to identify daily activities that affect a person's sleep quality. Studies have shown that sleep and exercise are related, and higher physical activity levels can lead to better sleep latency [7, 8, 27]. A systematic review has also shown that dietary patterns and the types of food eaten throughout the day lead to better sleep quality and duration [23]. The environment (temperature and humidity) is also important to our sleep duration and quality [25]. From these studies and many more, it is clear that choices made throughout the day affect the quality of the next night's sleep.

Literature shows that certain daily activities affect sleep quality, but it also makes these conclusions with controlled environments set in place. The controlled environments eliminate possible confounding variables, which helps show relationships between daily activities and sleep quality for the general population. This control fails to take into account the complexity of daily life, in which confounding variables cannot be controlled. Our model uses an event mining approach with user based multimedia data to help us perform N-of-1 experiments to identify causal relationships between daytime activities and sleep quality.

3 EVENT MINING

Our main goal is to model the relationships between sleep and daily activities computationally. We utilize an analytic technique known as event mining [6, 19]. Event mining, combined with causal inference principles, allows us to run N-of-1 experiments [10] using a person's data streams. In this work, we attempt to use event mining to find patterns in a user's longitudinal sleep and lifestyle data. This approach can help us describe relationships between daily activities and create an explainable model of a person's sleep. Event mining will utilize different events that affect the user's health [20],

and produce rules for us in the form of $Event_i \xrightarrow{C} Event_o$, where $Event_i$ defines the input event, $Event_o$ is the outcome event, and C represents the confounding variables and the temporal conditions that may affect the relationship between $Event_i$ and $Event_o$. For our experiments, input events will be various daily activities, such as exercise, feeding times, and temperature. The output events will be the various sleep quality measures (latency, efficiency, awakenings, and awake minutes). An example of a specific relationship would be

$$ExerciseMins \xrightarrow{StartTemp} Latency$$

Hypothesis verification is the process of verifying trends under different scenarios. These patterns can be defined by scientific literature or human intuition. Once we have defined our relations between input and output variables, we attempt to identify the confounding variables that significantly affect the relationship. After

finding confounding variables, we can perform a technique called contextual matching. This step will find data points that account for similar cases of the confounding variable. From there, we can verify the validity of the relationship and measure the impact of an input event on the corresponding output event.

3.1 Hypothesis Verification and Confounder significance

All experiments utilize the power of Welch's t-tests and a p-value of 0.05 as an indicator of statistical significance. We find the input event's average effect on the output variable by conditioning over all other confounding variables. By averaging out the effects, we can identify how variations in the input event affect sleep quality.

We establish the first category of each input event as the baseline category. For example, if we look at Table 2, the baseline event for Starting Temperature would be cold. This is an arbitrary selection, but it serves as an important part of the experiment. We use the remaining input variables and treat them as confounding variables. We find the conditional distribution of a sleep quality measure while conditioning on the confounding variable. We compare the distributions corresponding to each category of the input variable to that of the baseline category. At this point, we would perform t-tests between the baseline distribution and distributions for the other categories of the input event to see if, under the condition of C , variations in the input event significantly affect the distribution of sleep quality. If the two distributions are found to be significantly different, the difference between the means is considered to be the effect of the input event. An example would perform a t-test between the distribution of Awake Minutes created by being awake GT 17 hours, when the previous night had poor awakening minutes vs. being awake LT 15 Hours, when the previous night had poor awakening minutes as well. This experiment is performed for other combinations of confounding variable C , and all of the significant differences are used to find the average difference that variations in the input event have on the output sleep quality measure. This method is used to create a personalized sleep model as it can inform the user how their daily activities affect their sleep quality.

The second experimental method finds the confounding variables that affect the relationship between input and output events significantly. A personalized sleep model should inform a user about which activities can most harm or benefit the relationship that they are trying to target. These tests attempt to tackle that issue. For this type of experiment, we compare the aggregate distribution of an input variable category (i.e., no conditioning on confounding variables) to the distribution created between the same input variable category and a certain conditioned variable category. An example in Figure 3, would be to compare the distribution of being awake GT 17 hours (greater than 17 hours) to the distribution when it is conditioned on the previous night having good Awake Minutes. If the distributions are significantly different, we know if a confounding variable is indeed important to consider as a part of the personal sleep model.

With these experimental methods we leverage our user centered multimodal data set to set up our sleep model. This shows how our model uses confounder analysis to create a personalized model that can help individuals take control over their sleep.

Figure 2: Rule based personal model for predicting sleep outcomes. We divide the occurrences of the outcome events into smaller subsets based on the values of co-occurring contextual factors. This minimizes the variance in the outcome due to the confounding variables within each subset. Subsets that exhibit significantly different distribution for different values of input events are converted to rules and added to the model.

4 EXPERIMENTS

This section will explore our data and apply it to create a model that can give users personalized feedback about their sleep quality. Figure 2 shows the basic outline of the process we will go through to perform our experiments.

4.1 Data Set

We used the latest review on sleep quality to identify the most important factors relating to sleep quality including Sleep Latency (the time it takes to fall asleep), Number of Awakenings Greater than 5 Minutes, Sleep Efficiency (ratio of asleep minutes to minutes in bed), and the Number of Minutes Awake throughout the night [18]. These four measures flesh out many factors of a night's sleep that experts believe are essential to attaining high sleep quality. Our model uses these four factors to reason about sleep quality. The review also identified thresholds for sleep quality measures to define further what it means to get a good night's sleep (Table 1).

The multimodal data set we used was made by temporally merging multiple data sources to understand better the connection between input and output events with regards to sleep quality. These input events are all based on sleep research.

To perform a holistic review of a person's daily activities and their effects on their sleep, we recorded the following pieces of data over multiple years. Daily data were gathered from four primary sources: Sleep Cycle, Apple Health Kit, Strava, and Environmental

Table 1: Sleep Quality Measure and Event Thresholds

Variable	Classification Ranges	Event Name
Sleep Latency	[0, 15]	Good
	(15, 30]	Average
	(30, ∞)	Poor
Awake Minutes	[0, 20]	Good
	(20, ∞)	Poor
Awakenings >5 mins	[0, 1]	Good
	(1, ∞)	Poor
Sleep Efficiency	[0.85, 1.00]	Good
	[0, 0.85)	Poor

Sensors. The devices used to create these data sets include the user's Garmin Fenix 5 Smart Watch, their smartphone, and an IoT sensor. Sleep Cycle was primarily used to keep track of sleep events. Apple Health Kit was used to help compile sleep quality measures recorded by the Garmin Smart Watch, daily step counts, and floors climbed. The actigraphy measures of the smartwatch were combined with the sound recordings of Sleep Cycle to create sleep quality measures. Strava was used to keep track of exercise events. Environmental Sensors were used to track feeding times (phone camera metadata), temperature and humidity, and the start of sleep events (IoT Sensor).

Table 2: Lifestyle Factors and Event Thresholds

Variables	Classifications Ranges	Event Name
Exercise Minutes Per Day	[0]	None
	(0, 50]	Poor
	(50, 150]	Average
	(150, ∞)	Good
Exercise Minutes Per Week	[0, 150]	Poor
	(150, 300]	Average
	(300, ∞)	Good
Interval Between Eating and Sleeping	[0]	Missing
	(0, 180]	Poor
	(180, ∞)	Good
Minutes Awake Between Sleep Events	[0, 900]	LT 15 Hours
	(900, 1020]	Btwn 15-17 Hours
	(1020, ∞)	GT 17 Hours
Starting Temperature	[0, 60]	Cold
	(60, 67]	Comfortable
	(67, ∞)	Warm
Starting Humidity	[0, 30]	Low
	(30, 50]	Ideal
	(50, 100]	High

All of these data sources were then temporally matched to record lifestyle events that took place throughout the day accurately.

Additionally, some preprocessing was done on the data to ensure that the data set consisted of consecutive days in terms of sleep recordings. This ensures that we would be able to accurately gather information about the daily activities that would then directly affect the next night's sleep. After all preprocessing we were left with approximately 800 days of data.

To make the data easier to work with in terms of an event mining framework, we set up classification ranges for our important data points. The classifications in Table 1 and Table 2 are both used to transform our data from a continuous to discrete format.

For the experiments, there are ten input/confounding events that can be used: Previous Night's Sleep Quality Measures (4 categories), Exercise Minutes in the Day, Exercise Minutes Per Week, Interval Between Eating and Sleeping, Minutes Awake Between Sleep Events, Starting Temperature, and Starting Humidity. The possible output events are sleep quality measures (Table 1). For the experiments performed in this study, we used every combination of the input, output, and confounding variables to determine the average effect each input event has on the respective sleep quality measures. This produced the results that can be seen in Figure 4.

If we carried out the first experimental method from the previous section, we would find that, on average, staying awake for 15 to 17 hours when compared to the baseline, staying awake greater than 17 hours would increase the minutes awake during a sleep event by 18 minutes. Similarly, when we compare the baseline event of staying awake greater than 17 hours to staying awake for less than 15 hours, we can see that, on average, the minutes awake during the sleep event will increase by 15 minutes. Both test conditions show that, compared to the baseline, staying awake less than 17

hours seems to detract from sleep quality, we can say that staying awake greater than 17 hours seems to improve sleep quality.

The results of all these experiments can be inspected in Figure 4. One interesting observation to note is that if we hold E_{event_i} the same and attempt to analyze its average effect on output events, we can see that an average temperature (60-67 F°) seems to improve every sleep quality measure except for sleep latency. This is a profound observation as it shows that not all quality measures are correlated with each other and that an improvement in one does not necessarily equate to an improvement in all other sleep quality measures. Another example of this phenomenon can be seen in the number of Awakenings greater than 5 minutes for the previous night. Compared to the baseline of waking up more than once for greater than 5 minutes, getting a good sleep quality measure seems to improve only 3 out of the four sleep quality measures for the next night. Once again, sleep latency deteriorates, while all other sleep quality measures get improved.

Another interesting metric that should be noted is that exercise improves sleep latency the most. On average, we can tell that exercising a lot will reduce sleep latency by 10.5 minutes, and a small workout will help reduce sleep latency by an average of 8 minutes. This model can now give evidence-backed feedback to its user about how daily activities affect their sleep quality and even predict how much specific lifestyle changes will transform their sleep quality.

The next set of experiments we carried out used the second experimental method. An example t-test would be one that compares the distribution between being awake GT 17 Hours and Awake Minutes to the distribution made by being awake GT 17 Hours and Awake Minutes when conditioned on having Good Awake Minutes the Previous Night. A simplified summary of these experiments is presented in Figure 5. This image is simplified such that it only displays the p-value of the most significant t-test that was performed when exploring how the input variable's relation between its respective sleep quality measure for all categories. While the personalized sleep model itself would keep track of all of the significant relationships found, this figure provides a fast way to see the most important confounding factors that affect the relationship between specific input and output variables.

These experiments provide useful insights into how daily activities can affect the relation between input events and output events such as sleep latency. From Figure 5, we can see interesting trends that the minutes awake throughout the day is a very significant confounding factor with regards to sleep latency. This confounding factor seems to affect almost every relationship significantly. We can also tell that the starting temperature is a crucial factor in every sleep quality measure. The previous night's awakening minutes also seems to affect the relationship between for all sleep quality measures except for sleep latency. Another unexpected result is that exercise performed throughout the day is a lot less significant to affecting sleep quality relationships than expected. Its effects are not as strong as other confounding factors, such as time spent awake.

With these insights, we can then develop a personalized sleep model that ingests multimodal data streams to help users navigate their sleep quality by controlling their daily activities. Since the

Figure 3: This figure shows the Baseline Distribution of Minutes Between Sleep Events and Awake Minutes (left) and then shows how the distribution changes when it is conditioned on each of the categories of Prev Night Awake Mins (right).

Average Effect of Input Events on Output Events

Figure 4: Average Effects that each input event has on the output event when compared to each input event's base category. If a metric is 0 then no significant relations were found. In the image GT stands for Greater Than.

system is built to include any new data dynamically, it can adapt to any lifestyle changes that the user makes.

5 CONCLUSION

Throughout this paper, we have shown the need for and created a user centered sleep model that utilizes multi-modal data event mining to provide useful feedback about the relationships between lifestyle events and sleep quality. With enough data, this model gives people increased control over their sleeping habits in a way that has not been previously possible. This model can identify various relationships between lifestyle choices and sleep quality and the possible variables that could strengthen or weaken those relationships.

Using our data and our event mining approach, we were able to identify various factors and how they affect the quality of sleep. For

example, one such finding showed that exercising more than 150 minutes on a day that a person has had a good previous night's sleep can, on average, decrease the next night's sleep latency by about 10.5 minutes. Further analysis shows that the starting temperature for the sleep event can significantly strengthen the relationship between exercise and sleep, whereas having a poor sleep the night before can detract from the beneficial effects of exercising. While these findings may not generalize well to the population, they do not have to. The power of the model comes from the fact that it is unique to the person. That being said, the model can utilize another person's data just as easily. Given another person's data set, the model can perform similar analyses and find different insights into how their daily activities affect their sleep quality.

A recommender system can harness the power of the model and its insights to give users daily advice about their next night of sleep.

Figure 5: This figure identifies the confounding variables (rows) that affect the relationship between various input events (columns) and sleep quality measures. The larger the square depicted the more significant the relationship that was found. Sleep Latency Relationships are depicted in Green, Sleep Efficiency Relationships are depicted in Gold, Awake Minutes Relationships are depicted in Pink, Awakenings GT 5 Minute Relationships are depicted in Purple.

For example, with the data presented, if a user wants to maximize their sleep efficiency, a recommender system could analyze the sleep model created and give the user a recommendation about controlling the humidity of their sleep environment to increase sleep efficiency. The system would also have the power to create secondary and tertiary recommendations based on the sleep model and what the user could change about their daily lifestyle. This model offers a clear cut way to not only help a user via a recommendation system but also to present the user with a clean visual that can summarize the effect of their daily activities on their sleep quality measures.

6 FUTURE DIRECTIONS

Although this model incorporates many useful data sources and provides insights about them, it is also a proof of concept. The input events were based on variables that literature had already identified to be important to sleep quality. While we were able to introduce further levels of complexity to the model to provide more insights than the literature does, there are also many more input events that we would need to include to create a comprehensive sleep model. The most significant missing piece from our current model is an input event that deals with mental components such as stress and anxiety as we illustrate in Figure 1. Literature has found that anxiety levels do indeed affect sleep quality [4]. Intuitively, it makes sense that heightened anxiety would lead to difficulty falling asleep and could even cause more awakenings during a sleep event. Additionally, while it is possible to analyze this data and present results, a lot more work would need to be done before a user could plug in various data sources and subsequently get a succinct presentation about how their lifestyle affects their sleep quality. We hope to incorporate even more input events to extend to personal events, emotions, caloric intake, and heart rate. With these inputs, we would hopefully be able to find more insights and even identify certain lifestyle factors that affect sleep quality that has not been considered by the literature yet. That being said, the model is built around a plug and play framework, so incorporation of these and any other future features are feasible.

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