Development of an e-Coaching Framework to Promote Sleep Hygiene Using Machine Learning

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Abstract—Computational sciences have gradually allowed scientists to develop novel technological projects to promote a healthy way of life. Most efforts have focus in promoting healthy diets and physical activity. Sleeping is also a crucial activity for humans. Poor sleep quality has adverse effects on health and might lead to physical and mental deterioration. Many computer systems have been used to measure sleep quantity and quality; however, there are few efforts to guide users about aspects that can influence sleeping. Sleep hygiene is a concept that allows controlling sleep-related habits and promoting good sleep quality; unfortunately, modern lifestyles can cause people to adopt wrong habits without being aware of their impact on sleep quality. This work describes a framework developed to guide user's during the day in order to achieve good sleep quality during sleep time. A set of sleep hygiene factors (SHFs) intended to control hours before going to sleep was defined. The framework identifies personal SHFs using machine learning algorithms; furthermore, a new algorithm was designed to improve results. The framework also includes a mobile persuasive system to encourage users to control personal SHFs.

Keywords—Persuasive system, Machine learning, Mobile health, sleep

1 Introduction

Noncommunicable diseases (NCDs) are a global issue and have increased costs associated with health care. NCDs are a growing strain on health systems, especially since treatments are long-lasting. Consequently, many global regulations are put forward to treat and prevent NCDs, especially type II diabetes, obesity, cardiovascular diseases, and hypertension. These conditions can be prevented by considering factors for what is usually referred to as a healthy lifestyle, which can be maintained by following a healthy balanced diet and exercising regularly, for instance. In this sense, stress self-management and proper sleep are two other crucial factors for NCD prevention, yet they seem to be less often explored [1].

Recent works [2][3] have confirmed that sleep quality and quantity are important aspects for both healthy and sick people. Sleep quantity is the actual time during which the individual is asleep. Sleep quality, on the other hand, refers to the subjective indices of how sleep is experienced, including the feeling of being rested when waking up [4]. Sleep is a fundamental process for brain function and cognition [4], moreover, little and/or poor quality rest are linked to issues such as mental deterioration [6], cardiovascular diseases[7], depression [8], and other degenerative diseases[9]. Despite all the information that is spread on the importance of health care, the modern society is not always aware of the factors that contribute to the development of preventable, chronic diseases. On the other hand, computational sciences have gradually allowed scientists to develop novel technological projects and applications to promote a healthy way of life and diseases control [10][11]. For instance, some of these projects can monitor user eating habits and promote physical activity[12][13][14][15].

Concerning sleep quality assessment projects, they are less prominent, and those that have succeeded are usually viewed as invasive. We proposed a set of sleep hygiene factors (SHFs) intended to control hours before going to sleep. The system relies on machine learning algorithms to determine personal critical success factors for good sleep hygiene. Similarly, we employ computational persuasion to encourage users to control their personal SHFs.

2 State of The Art

The term coaching can be defined as a result-oriented process in which the coach facilitates the enhancement of life experiences and goal attainment in the personal or professional lives of normal, non-clinical clients [16]. The digitalization of traditional coaching systems and the use of information and communication technologies (ICTs) have given rise to a new concept, known as e-coaching, where coaches can be replaced by computer systems. Persuasive systems based on psychological theories can act as e-coaching systems to guide users to successfully perform a task and achieve a goal. Previous works have demonstrated that e-coaching systems have the power to encourage users to improve their self-management skills and change habits [17]. Some of the applications of current e-coaching systems include remote athlete coaching[18], eating behavior coaching [19] and pervasive coaching for young diabetes patients[20].

As regards sleep quality, most e-coaching systems currently aim at measuring sleep quality rather than assessing sleep-related activities performed before going to bed. In [21] BuddyClock is proposed as a mobile alarm clock application that allows users in a social network to automatically share information about their sleeping habits. On the other hand, Win-Win Asleep (WWaS) [21]is a persuasive application for insomnia treatment. WWaS works with user therapists, who determine the set of personal activities that WWaS users must perform to alleviate insomnia. In a similar context, ShutEye [22] was developed as mobile application that works as a wallpaper. ShutEye promotes healthy sleep hygiene, as it addresses factors such as caffeine consumption, napping, physical activity, alcohol consumption, nicotine consumption, and relaxation. Finally, SleepCare Coach [24] is a system that promotes personalized self-help therapy to treat insomnia. If compared with the aforementioned works, our framework can determine, from the beginning, which SHFs are critical to each user. To this end, we implement an inference model that relies on machine learning algorithms (MLAs). Once the personal critical SHFs are determined, we use a mobile persuasive system (MPS) to encourage users to improve sleep hygiene behaviors and thus increase the quality of their sleep.

3 Framework Design and Implementation

Fig. 1 below illustrates the overall functional design of our e-coaching system which is formed by two major components: A machine learning (ML) model used to both identify user critical SHFs and predict the expected sleep quality (SQ) and a mobile persuasive system (MPS) that sends users persuasive notifications but also receives user's feedback, which is then sent to the ML model to improve the system's predictions. A remote database is used as a link between the ML model and the MPS.

The e-coaching framework was implemented following four stages:

1. Identify initial SHFs from a study population
2. Design and implement the ML model to determine user critical SHFs
3. Design and implement the MPS to send notifications to the users regarding good SH habits
4. Implement a mechanism of interaction between the ML model and the MPS

This interaction allows the ecosystem to improve its parameters, and if necessary, send feedback to the ML model until a perfect alignment is achieved between what the model predicts and what the user perceives as good sleep quality.

The following paragraphs thoroughly discuss each stage.

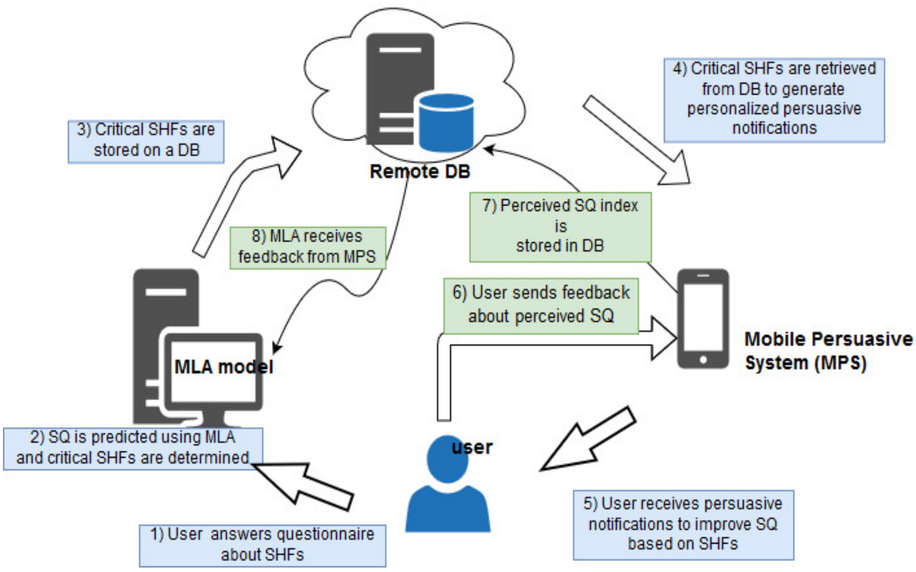

Fig. 1. Overall functionality of the sleep hygiene e-coaching framework

3.1 Initial SHFs identification

Sleep hygiene can be defined as “the set of lifestyle behaviors and environmental conditions that facilitate sleep and improve sleep quality”[25]. Initially, the concept was developed to encompass a series of recommendations for treating insomnia[26]; however, multiple works explore in detail sleep hygiene improvement suggestions. In this context, the American Academy of Sleep [27] lists the following factors as SH inhibitors:

1. Inappropriate sleep schedules
2. Tobacco and caffeine products that interfere with sleep
3. Mentally stimulating activities performed close to bedtime
4. Sleep-incompatible activities performed in bed or in the bedroom
5. Unsuitable relaxing environments (e.g. uncomfortable mattress or temperature)

Similarly, [21] claims that the four elements have an impact on sleep: Homeostatic sleep drive, circadian factors, effects of drugs and sleep environment.

That said, this work proposes the concept of sleep hygiene factors (SHFs) as all the events and actions that have an impact on night sleep. We conducted both a cross-sectional study and a prospective study to identify the SHFs for our study population. The goal was to determine whether some SHFs could be predominant among the entire study population. Similarly, the gathered data were used to determine which ML techniques could best predict sleep quality from SHFs. The study population comprised healthy 20-to-70-year-old adults who do not suffer from any sleep disorder and wish to improve their life quality in terms of sleep hygiene.

The cross-sectional study was conducted in Mexico among college students and professionals, including college professors, from six states of Mexico. Namely, two surveys were administered: the Pittsburgh Sleep Quality Index (PSQI) [28] and Mastin’s Sleep Hygiene Index (SHI) [29]. In the end, we collected 338 surveys containing information on SHFs and SQ in general. Table 1 below lists the 21 SHFs that we identified as relevant among the participants.

Considering that 21 SHF is a large number of factors, we tried to identify a smaller set of SHFs with a major influence on sleep behaviors among the study population. To do this we applied six ML algorithms to the data to select the SHFs that affect most the study population. These algorithms are Random Forest [30], LASSO [28], Relief [31], Best First Search, Chi-Square, and Information Gain [32][33]. Every algorithm was executed multiple times, and we performed a consistency test to discard those that showed different results from the rest (i.e. Relief and Best First Search). Then, we performed a variable selection process and identified three factors as determinants of good sleep quality: sleep time (SHF2), stress (SHF12), and night-time worries (SHF20). We also conducted a prospective study to determine whether these factors could be generalized to the entire population. For 30 days, we conducted continuous tests on three volunteers who provided information on their SH-related habits. Similarly, the participants used a sleep monitoring device (Beddit Sleep Monitor), which aimed at determining sleep quality from a quantitative perspective, considering six parameters: sleep onset latency (SOL), total sleep time, number of awakenings per night, number of movements, heart rate, and respiratory rate. Beddit measures sleep quality on a 0-100 scale, with 75 as the cutoff value to determine good or bad sleep quality. The gathered data were extrapolated using binomial distribution, where the SQ values were imputed using the k-nearest-neighbors (KNN) algorithm. Then, the validity of the results was tested and confirmed by the coefficient of determination (R^2). We trained three linear regression models using the data gathered from the three volunteers (denoted VF1, VF2, and VM), whose age ranged from 25 to 40 years. The three models took into account only the three critical SHFs, namely SH2, SH12, and SH20.

Table 1. Sleep Hygiene Factors (SHFs)

Feature	SHF	Feature	SHF
SH1	Naps	SH11	Activity before sleep
SH2	Sleep time	SH12	Stress before sleep
SH3	Wake up times	SH13	Uses of bed
SH4	Exercise at night	SH14	Uncomfortable bed
SH5	Exercise in the morning	SH15	Light
SH6	Exercise in the afternoon	SH16	Noise
SH7	Time in bed	SH17	Cold
SH8	Tobacco consumption	SH18	Heat
SH9	Alcohol consumption	SH19	Intellectual activity before sleep
SH10	Caffeine consumption	SH20	Night-time worries
		SH21	Dinner

The results indicated that it was impossible to construct prediction models based on these three factors only. In fact, for two participants, the model predicted less than 50% of the data's variance, whereas good results were only observed in the third volunteer (R2 = 0.79).

3.2 Designing and implementing the Machine Learning (ML) model

Since it was impossible to determine a generalized set of critical SHFs and not all the 21 SHFs affect in a similar way to everybody, we designed a model to determine personalized critical SHFs for each user. To do this we tested three ML algorithms to find the one that could best identify personal critical SHFs, and thus predict sleep quality with an R value equal to or higher than 90%. These algorithms are well-known for their efficiency in feature selection and are XGBOOST, LASSO, and Random Forest (RF). We set as input data all the 21 SHFs. Then, we compared the data collected on the three participants with those obtained from the Beddit Sleep Monitor device. The goal was to determine which critical SHFs could best predict the SQ measured by the Beddit device. The results are summarized in Table 2 below. As can be observed, none of the algorithms meet the initial criteria (R2 > 90). Moreover, none of the three algorithms provide mechanisms for segmenting the SHF list in case the differences among the weights were small. To solve these two issues, we propose a new algorithm, named "fsXLR" (feature selection based on XGBOOST, LASSO and RF). with the following capabilities: The resulting algorithm is introduced in Fig. 2. The ML model requires continuous alignment with users. The alignment cycle depends on user feedback to increase the system's prediction accuracy in terms of both sleep quality and personal critical SHFs. The cycle initiates when the "fsXLR" algorithm receives the 21 SHFs as input data and makes an initial prediction.

Table 2. Comparison of prediction accuracy among MLAs

	Random Forest		LASSO		XGBOOST	
	SHF	R^2	***SHF***	R^2	***SHF***	R^2
VF1	1,4,10	85%	13,1,6,20,10,17,7,11,12	79%	7,6,20,1,10	76%
VF2	21,5,6,20,2	81%	1,5,3,14,18,21,6,15,2	70%	1,14,5,9,7	83%
VM	18,21,20,2,13,4,15,5	60%	2,3,18,13,12,7, 20,6	29%	12,3,21,5, 20,10	70%

Then, as found in our tests, a 10-week period of user feedback must follow to determine the set of critical SHFs of each user. The system thus discards the least relevant factors and determines the expected sleep quality, which ranges from 0 to 100. In this sense, user feedback is essential to adapt the SHFs thru the weeks. User feedback is received through the MPS and a database, which works as the interaction mechanism.

3.3 Designing and implementing the Mobile Persuasive System (MPS)

As mentioned before, once personal SHFs are determined by the ML model they are stored on a database. The MPS retrieves them and sends persuasive notifications to the user during the day in order to control SHFs. It is also used to retrieve feedback from the user and send it to the ML model to adjust SHFs if required.

Algorithm fsXLR

```
procedure fsXLR(workDS,try,ve,....)
    cardnonzero  <-- AllFSCardGreat1(workDS)
#Selects variables with cardinality greater than 1
    listofselfeat  <--
SelFmultAlgFS(workDS[cardnonzero],list_of_alg)
#Returns a list of all selected SHF
    ordfeatbyweight <--
OrderFS(listofselfeat,selecttype)
    bestfeatsearch <--
BruteForceFS(workDS,ordfeatbyweight,FBmode,R2)
# Returns a list of set of features searched using Best-Search
    if replace then
        lstofnonsel <--!(cardnonzero in
bestfeatsearch)
    else
        lstofnonsel <--!(cardnonzero in
order featbyweight)
    endif
     if (ve < R²) and (try <= maxoftries)
and length (cardnonzero) > 2
     then
        dfSelFeat <--
fsXLR(workDS[lstofnonsel],try+1,ve,....)
     else
         return bestfeatsearch
    end if
end procedure
```

Fig. 2. The "fsXLR" algorithm

MPS design: To design and implement the MPS, we adopted the methodology proposed by [34] that discuss and address stages such as persuasive system design and interactive system design. We relied on this methodology to design our system. with the following capabilities:

1. Show users the sleep quality reached daily
2. Show users the set of SHFs that adversely affect the quality of their sleep
3. Send users persuasive notifications regarding good SH practices, however, two conditions must be followed:
   (a) Notifications must be sent only to address the factors that had an adverse effect on the quality of the user's sleep the previous night
   (b) Notifications must be sent only when user feedback on the notification's usefulness has been positive
4. Record user feedback regarding the usefulness of the notifications
5. Record user-perceived sleep quality to provide feedback to the ML model
6. Implement persuasion strategies to inform of and encourage users to
7. follow good SH practices

The system takes advantage of user intrinsic motivation and does not need external motivators to encourage them to improve sleep hygiene[35]. One of the basic tasks of the MPS is to inform users on good SH practices, which is achieved thanks to notifications and messages sent by the system.

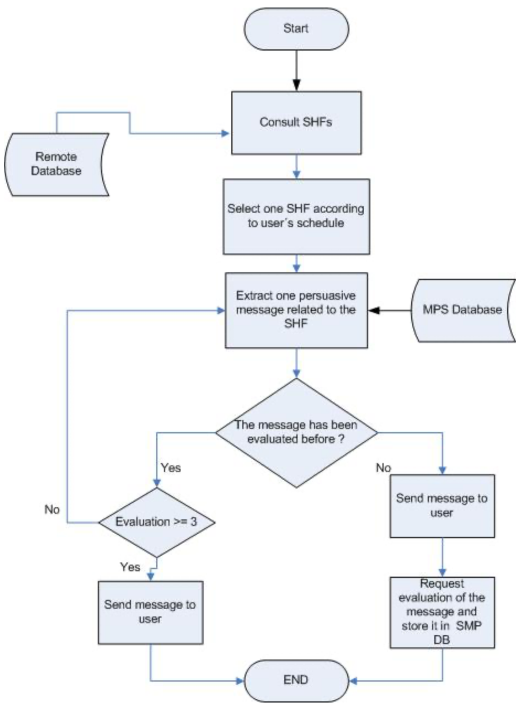

Fig. 3. Feedback diagram of the MPS

Table 3 lists some examples of these notifications and messages. In order to guarantee user's persuasion acceptance, they can provide the system internal feedback to inform on how useful a given notification/message is. Namely, after sending a persuasive notification for the first time, the MPS asks the user to rank its usefulness using a 1 to 5 scale. Then, both the persuasive message and its rating are directly stored in the system's local database. This information is used to select future notifications as depicted in Fig. 3.

Table 3. Examples of messages and persuasive notifications issued by the MPS

Factor	Example of persuasive notification	SHF
SHF1	It is better not to sleep now.	Napping
SHF 2	Sleeping time notification Video message on the benefits of having a sleep routine.	Sleep time
SHF 4	Suggestion to avoid physical exercise two hours before going to bed.	Exercise at night
SHF 5	Night reminder to avoid doing physical exercise the following morning.	Exercise in the morning
SHF 6	Morning reminder to not do physical exercise in the afternoon.	Exercise in the afternoon
SHF 8	Informative message on the adverse effects of tobacco on good night sleep.	Tobacco
SHF 9	Informative message on the adverse effects of alcohol on good night sleep. Notification to avoid drinking alcohol within four hours before going to sleep.	Alcohol
SHF 12	Suggestion to not bring work home. Do 20 min. of yoga before going to sleep.	Stress before sleep
SHF 13	Suggestion to not bring work to bed. Suggestion to avoid watching TV in bed before going to sleep.	Uses of bed
SHF 15	Notification one hour before going to bed to control room lighting.	Light
SHF 16	Notification to turn the TV off. Suggest wearing earplugs to sleep if the room is too noisy.	Noise
SHF 17	Regulate room temperature if it is too cold. Suggest wearing thermal clothing if the room is too cold.	Cold
SHF 18	Notification to regulate the bedroom's temperature one hour before going to bed.	Heat
SHF 19	Suggestion to go for a short walk within one hour before going to sleep. Video message on relaxing activities to do before bedtime.	Intellectual activity before sleep
SHF 20	Suggestion to write down pending work before going to bed. It will be waiting right there the following day.	Night-time worries

MPS implementation: An Android application was developed following the agile methodology presented in [32]. The MPS consists of four main sections: Sleep Diary, Plan, Progress, and Rewards.

The following paragraphs thoroughly describe the content of the sections.

1. **Sleep diary**: The goal is to allow users to consult daily sleep hygiene records saved by the ML model with respect to user SHFs. Furthermore, users can provide feedback to the inference model on how they perceive the quality of their sleep. This information is sent to the remote database.

2. **Plan:** The aim of the Plan section is to allow users to select the activities that best fit their routine and choose the most suitable time to perform them.
3. **Progress**: This section supports is divided into four subsections: SH pyramid, positions chart, weekly SH, and weekly assessment. The system needs to measure user SH progress in some way, and to this end, it relies on the weekly assessment subsection. On the other hand, the SH pyramid initially displays all the stages in gray, yet as users improve SH, the stages will be colored until reaching the top. Fig. 4 displays the progress section.
4. **Rewards**: This section displays a series of gray-colored blocked badges that can be unlocked as users improve their weekly SH assessment scores. In other words, depending on how well users perform every week, they can unlock a badge each time, and the badge thus changes its color. Fig. 5 illustrates this section of the MPS.

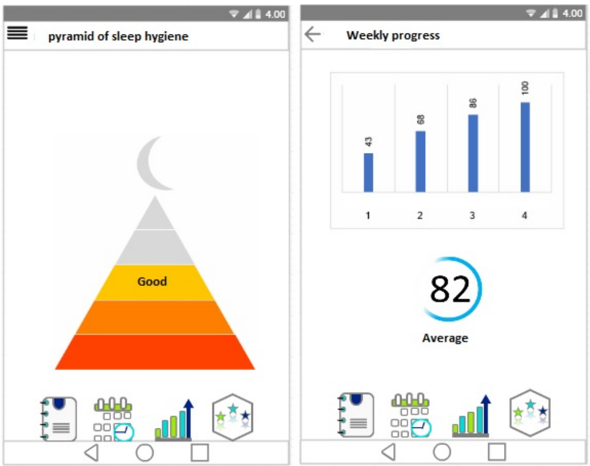

Fig. 4. Progress section of the MPS

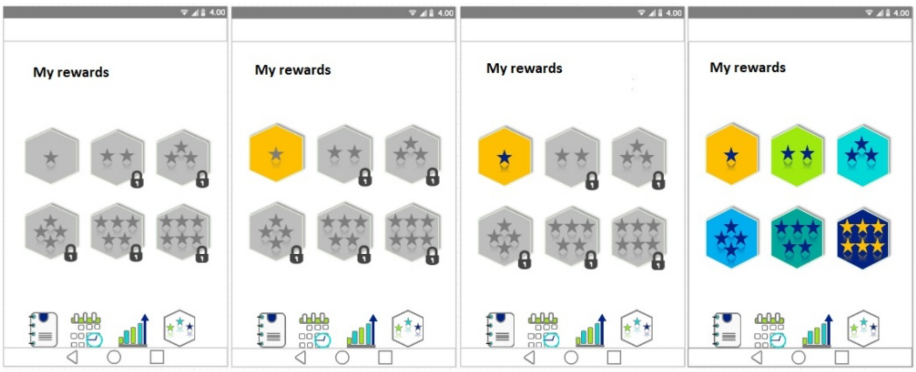

Fig. 5. Rewards section of the MPS

4 Framework Evaluation

The e-coaching framework was assessed by following two stages in order to properly identify its important aspects. First, we assessed the efficacy of the ML model, and then, we evaluated the system's acceptance and usability. The following paragraphs thoroughly discuss these stages.

4.1 Efficacy assessment of the ML model

To evaluate the model's efficacy, we measured the percentage of explained data variance. To this end, we used as input data the SHFs identified by the "fsXLR" algorithm. The goal at this point was to determine how well the model could predict user sleep quality when it monitors the SHFs for a considerable period of time. To determine the length of this time period, we calculated the number of records that are necessary for the model to make accurate calculations. The resulting number thus indicated the number of weeks that the system needs to achieve a full alignment with its users in a real-case scenario.

We used the "fsXLR" algorithm to determine the set of critical SHFs for each volunteer (i.e. VF1, VF2 y VM, see section 3.1). Each volunteer's dataset comprised records on 208 weeks of monitoring their sleeping-related habits. Note that the algorithm was applied to the datasets in combination with one more algorithm (i.e. LASSO, RForest, and XGBOOST) at a time, and using the merge/expand options (FsXLR-ME and FxSLR-EX). The efficiency of the predictions was assessed by training the models through Elastic-Net ($\alpha = 0.3$). The FS algorithm "fsXLR" increases the cost of processing time but guarantees sets of factors that explain the variability of data in high percentages (> 90%). Table 4 summarizes the obtained results.

Table 4. Accuracy of Algorithm" fsXLR" when identifying personal critical SHFs

Algorithm	VF1	VF2	VM
	R^2	R^2	R^2
fsXLR-EX*	96%	93%	95%
fsXLR-ME*	95%	96%	90%
***min Of Features:3, max Of Features:7, max Of Tries:2,FB Mode: Backward, replace:F**			

By comparing the results of Table 2 (see section 3.2) from those listed above in Table 4, we found that combining Algorithm "fsXLR" with any of the three other algorithms provides better results. It is thus concluded that Algorithm "fsXLR" successfully reaches its goal, which is to help select personal critical SHFs that can predict at least 90% of the data's variance. On the other hand, the system's alignment cycle was assessed after training the model using extrapolated data from each volunteer. The first model was generated using 10-week sleep monitoring data. After every iteration, we added one record to represent one week of monitoring, until we reached a coefficient of determination value equal to or higher than 0.9.

Finally, we conducted an evaluation to determine to what extent the SHFs selected by the algorithm matched those considered by the volunteers as critical for improving their personal sleep hygiene. Initially, the three volunteers answered a survey, which we developed and named SHF_Q. The survey comprised four sections: demographic data, the Pittsburgh Sleep Quality Index (PSQI) form, an edited version of the Sleep Hygiene Index (SHI) form, and a SHFs ranking section. This last section demanded the volunteers to rank the 21 SHFs according to their perception in terms of each factor's impact on sleep quality. Additionally, the three volunteers used a sleep monitoring device (Beddit) to measure the quality of their sleep, and scores higher than 75 were used as indicators of good sleep quality. Then, the volunteers were asked to personally rate the quality of their sleep on a scale from 1 to 100, according to their perception. At the end of the study, the volunteer-perception-based results (i.e. SQ_VP and SHF_VP) were compared with those predicted by the model (SHF-model) and by the Beddit device (SQ_Beddit). Such results are summarized in Table 5.

Table 5. Comparative chart of volunteer-perception-based results with model-based results and Beddit-based results

	SQ_VP	SQ_Beddit	SHF_VP	SHF-model
VF1	Good	73	12,21,20	6,7,20
VF2	Good	80	12,13,16	1,5,14
VM	Good	82	2,7,12	3,12

As can be observed, the volunteer's perceptions are not consistent enough with the algorithm's predictions. According to the survey's results, the first participant claimed not being aware of sleeping few hours; moreover, she/he did not consider SH6 and SH7 as sources of sleep quality deterioration. Overall, the volunteers could notice that they were little aware of the factors that adversely affect sleep hygiene, yet this situation can be addressed by using an e-coaching system for sleep hygiene improvement that relies on an MPS.

4.2 Usability and user acceptance assessment

The goal of the second part of the assessment was to measure MPS, usability, acceptance and persuasion impact. To this end, 15 participants from 20 to 60 years of age were asked to individually assess the MPS. Namely seven female participants and eight male participants who answered the four-section SHF_Q survey. The gathered data were used to populate the MPS's Sleep Diary section and also fed the predictive model. Then, the participants engaged in a two-week coaching session using the system. As regards the Plan section, the participants were asked to plan their schedule of activities and eventually consult the activity summaries. Then, in the Progress section, the participants answered the weekly SH assessments and later consulted the SH pyramid and their weekly SH scores. In the end, to record their perception on the system's usability and provide feedback, the 15 users responded to the System Usability Scale (SUS) [36]. Fig. 6 depicts the overall usability scores in each category.

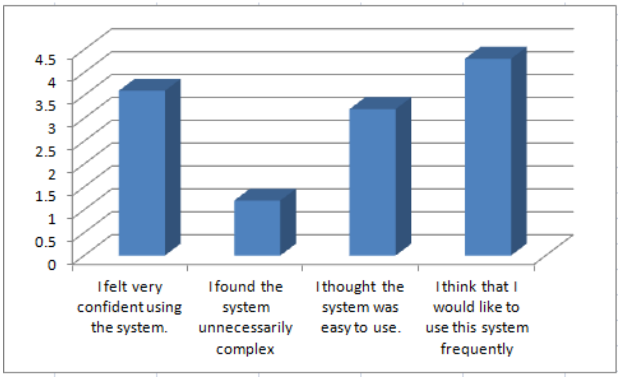

Fig. 6. Usability assessment of the MPS

The usability assessment also revealed that the system's usability score was lower among the 50-year-old participants, which might be due to their personal experience with technology. However, we also found that, to some participants, the system's icons were initially difficult to understand.

A personal interview with each user was conducted to evaluate the system's ability to help users improve SH-related habits. Only four participants claim to have modified their SH-related habits and thus improved the quality of their sleep. Such results imply that longer tests must be conducted to determine the system's effectiveness in the long term. Finally, as regards the usefulness of the persuasive notifications and messages, the survey results reveal that they can make users more aware of the impact of SHFs on sleep quality and can help users prioritize those factors that are crucial.

5 Conclusion

This work discusses the design, implementation, and assessment of an e-coaching framework that promotes good sleep hygiene and thus good sleep quality. The first section of this work involved defining the term sleep hygiene factors (SHFs). The e-coaching system relies on two main components: an inference model of critical SHFs and a mobile persuasive system (MPS). The two components share information through a remote database. Also, the inference model is based on machine learning algorithms (MLAs), and its goal is to determine which SHFs are critical for a particular user. To implement the model, we developed an MLA that adopts some characteristics of three similar algorithms. Initially, we sought to generalize SHFs to an entire and well-defined sample, yet our results revealed that it was impossible, as each person is different. Consequently, we concluded that there is not a specific set of SHFs that could accurately predict the quality of sleep of an entire study population. On the other hand, our model managed to make accurate predictions after 20 to 46 weeks of previous observations. In this sense, the model follows and alignment cycle in which user feedback is crucial. The results revealed that it is possible to identify personal critical SHFs with an explained variance higher than 90%. As regards the MPS, it was developed by adopting a methodology special for this type of systems, whose characteristics are user-based. Then, the MPS was implemented following an agile methodology. The MPS relies on user intrinsic motivation. The usability assessment results revealed good user acceptance of the system. Similarly, we found that the system allows users to better understand the role of SHFs on sleep hygiene and thus sleep quality. Finally, as regards the system's ability to help users improve SH-related habits, our results revealed that users manage to modify short-term SH-related habits, yet lengthier tests must be conducted to determine the system's effectiveness in the long term.

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