Identifying Common Sleep Disorders via a Digital Survey using Machine Learning Prediction Models

M. Cohen-Zion[1,2], LV. Pham[3], M. Sowho[3], F. Sgambati[3], T. Klopfer[3], I. Hawks[3], T. Etzioni[4,5], L. Glasner[2,6], A. Gal[7], E. Druckman[8], G. Pillar[4,5], AR. Schwartz[3]

[1]The Academic College of Tel Aviv-Jaffa, Tel Aviv, [2]dayzz Live Well, Ltd, Herzeliya, Israel, [3]Johns Hopkins University School of Medicine, Baltimore, United States, [4]Carmel Medical Center, [5]Technion School of Medicine, Haifa, [6]Sheba Medical Center, Ramat Gan, [7]The Open University, Raanana, [8]Druckman Research and Statistics, Rishon Lezion, Israel

JOHNS HOPKINS UNIVERSITY

TECHNION Israel Institute of Technology

Introduction

- Over their lifetime, most adults experience transient sleep disturbances, a significant proportion of which become chronic.
- Inadequate access to medical care and proper screening have resulted in most sleep disorders remaining undiagnosed or untreated, increasing the public health burden from these sleep conditions and their sequelae.
- This study addressed this critical unmet need by developing a well-validated, time-efficient, scalable approach to identify sleep disorders in the public-at-large.

Main aim

To develop and validate an abbreviated, 30-item, Digital Sleep Questionnaire (DSQ) to identify common sleep disturbances, including insomnia, delayed sleep phase syndrome (DSPS), insufficient sleep syndrome (ISS), and suspected obstructive sleep apnea (OSA), compared to gold-standard physician diagnosis.

Protocol

The DSQ survey was administered online to 3,799 community volunteers (ages 20-65), of which 2,114 were eligible and consented to participate in the study.

Of those, a sample of 247 (149F; 39.9±12.4 years; 192 Caucasians; BMI=29.7±7.3) were interviewed by expert sleep physicians at the Johns Hopkins Sleep Disorder Center.

Participants were diagnosed with ≤2 sleep disorders.

Completed online DSQ
n=3,799

→ **Excluded** (n=805)
Age: n=85
Sleep aids: n-166
Pregnant/breast feeding: n=41
Night shift work: n=143
Sleep disorder(s): n=370

Eligible
n=2,994

→ **Did not consent**
n=880

Consented
n=2,114

Invited for an interview
n=2,114

→ **No show**
n=5

Physician diagnosis
n=247

Diagnosis	1	2
Insomnia	60	25
OSA/snoring	67	38
DSPS	53	31
ISS	43	43
No diagnosis	17	92
Other diagnosis	7	21

References

Altevogt, B. M., & Colten, H. R. (Eds.). (2006). Sleep disorders and sleep deprivation: an unmet public health problem.

Kim, M.-H., Banerjee, S., Park, S. M., & Pathak, J. (2016). Improving risk prediction for depression via Elastic Net regression. AMIA Annual Symposium Proceedings.

Sidey-Gibbons, J. A. M., & Sidey-Gibbons, C. J. (2019). Machine learning in medicine: a practical introduction. BMC Medical Research Methodology, 19(1), 64.

Data analysis

Entire dataset

24/7 participants completed DSQ and Physician interview

Suspected OSA	Insomnia	Delayed Sleep Phase	Insufficient Sleep Syndrome

Generating >20,000 features based on the 18 Likert-scale items of the DSQ

Workflow for each diagnosis

Feature engineering

- **Test of Variance** At least 5% frequency for both 0 & 1
- ↓ **Test of Covariance** At least 5% difference between features
- ↓ **Test for "Lift"** At least 10% contribution to the prediction model

→ **Model fitting**

- **ElasticNet Model algorithm** ↓ Overfitting & multicollinearity ↑ Generalizability
- ↓ **5 x 5-fold cross validation** The model is evaluated using prediction accuracy
- ↓ **Hyper-parameters selection:** Lambda & Alpha - Regularization parameters that optimize the results

→ **Threshold setting**

- **Optimal threshold is set** using 200 bootstrap samples to train each model
- ↓ **Clinical estimated threshold:** Sensitivity > 80% Specificity > 60%

A Machine Learning (ML) approach was employed to develop, optimize and validate predictive models. This process consisted of three steps (below). Each step included a validation phase to verify that outcomes were likely to be generalizable, and free from common threats to validity such as overfitting and inadequate power.

1 **Feature Engineering:** The DSQ questionnaire responses provided raw data, which were recombined into more than 20,000 "features" containing detailed information from participants' responses. To reduce risks to statistical power and multicollinearity, we performed 3 tests (test of variance, test of co-variance, and test Lift) on each feature and discarded those that failed any of the tests. We built four datasets of features, one for each prediction model. Each model contained between ~300 to ~1100 features (with some features appearing in several models).

2 **Model fitting:** To build predictive models, we used an "ElasticNet" approach. The ElasticNet algorithms incorporated two "regularization mechanisms" (Lasso and Ridge), whose purpose was to reduce the risks of overfitting and multicollinearity, thereby increasing generalizability of the models. Prediction accuracy with ElasticNet models was accomplished with a 5-fold cross validation approach. Our ElasticNet models depended on two "hyper-parameters," alpha and lambda, that governed how strongly the two regularization mechanisms influenced the resulting model. We repeated the cross-validation process many times with different values of lambda and alpha, and compared the cross-validation average error before selecting those parameters yielding the greatest accuracy for the model.

3 **Threshold setting:** The ElasticNet models produced probability estimates for the desired diagnostic outcome. which enabled us to compute each model's specificity and sensitivity, and the area under the receiver operating curve (AUC). In order to choose an optimal threshold, we used 200 bootstrap samples, trained our model on each sample, and generated probability predictions on cases that were left out.

Conclusions

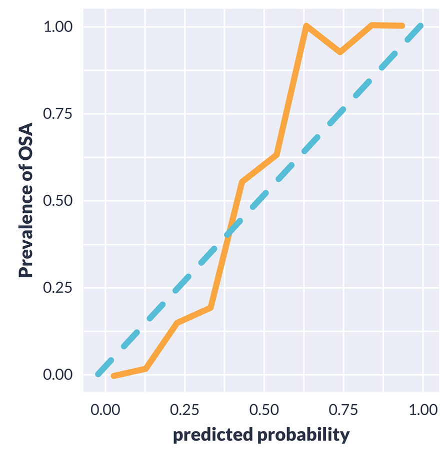
- The brief online DSQ is a feasible, engaging and efficient way to screen for common sleep disorders in a large population, with a high degree of accuracy relative to sleep expert physician diagnoses.
- A Machine Learning approach can generate and optimize prediction models for highly prevalent sleep disorders with good generalizability. The methods and results of which are easily reproducible.
- A digital platform provided an efficient means for canvassing a large population, the vast majority of whom self-identified with sleep-related complaints and had never sought medical attention to address these issues.
- If implemented, the DSQ has the potential for detecting sleep disturbances as an initial step in designating people for additional assessments and specific therapeutic strategies.

Results

Model performance by diagnosis:

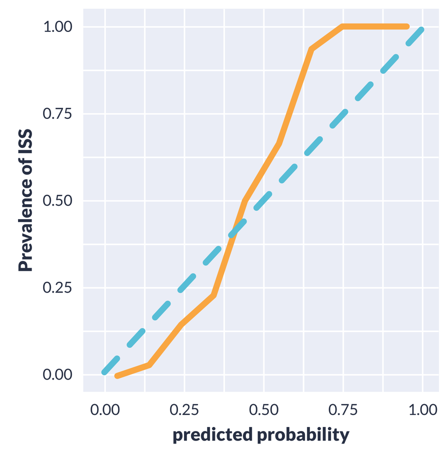
The predictiveness plots show the actual average prevalence of each diagnosis in the cohort plotted against the model's estimate of the probability for this outcome. Probability bins on X-axis represent the probability of the prediction from the ElasticNet model (i.e., the predicted prevalence of the sleep disorder displayed as a percentile, (e.g., 1.00 = 100%). The Y-axis is the actual average outcomes in the study population.

Type: Actual Expected



Sleep Apnea Model OSA

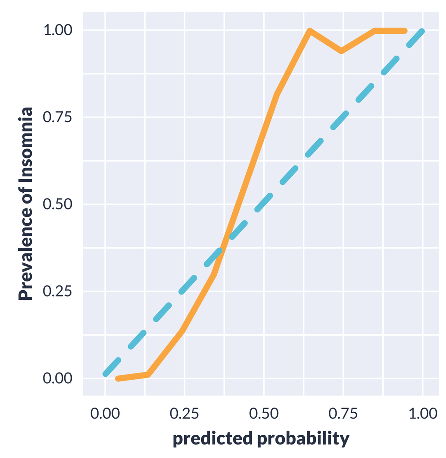
The model for the diagnosis of suspected OSA started with building 1110 features, of which 289 were chosen by the ElasticNet algorithm. Snoring was the most important factor, contributing to 198 fine-grained predictive features. In addition, ease of waking up on weekday mornings contributed to 23 features, followed by early morning awakenings and likelihood of falling asleep in a passive/ comfortable state.



Insufficient Sleep Syndrome Model ISS

For this model, 294 features were initially identified, of which 96 were incorporated by the ElasticNet algorithm.

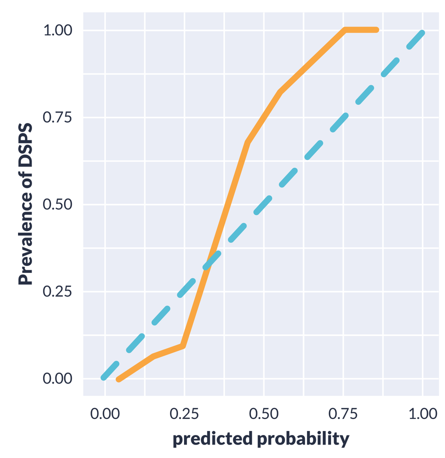
Predictive factors encompassed a high likelihood of dozing in a passive and uncomfortable position, early morning awakenings, nocturnal awakenings, feeling unrefreshed in the morning, along with difficulty awakening on weekday mornings.



Insomnia Model

The model for the diagnosis of Insomnia started with 1119 features, of which 280 were chosen by the ElasticNet algorithm.

The model incorporates three main factors, early morning awakenings, nocturnal awakenings and snoring, which contribute similarly to predicting this diagnosis.



Delayed Sleep Phase Syndrome Model DSPS

This model started with 1123 features, of which only 21 where chosen by the ElasticNet algorithm. These features captured circadian fluctuations in alertness, difficulty in performing complex tasks, depressed mood and delayed weekend bedtimes.

Performance parameters of prediction models per diagnosis

Parameter	OSA	Insomnia	DSPS	ISS
Sensitivity	83.4%	80.3%	80.5%	82.3%
Specificity	66.5%	69.4%	62.9%	63.6%
Accuracy	73.2%	72.9%	67.9%	69.6%
AUC	0.85	0.83	0.80	0.82

The ElasticNet models for each diagnosis showed high sensitivity, acceptable specificity, high AUC and good accuracy.

The research was supported by **dayZz Live Well, Ltd.**

dayZz Live well. sleep well

GET IT ON Google Play

Download on the App Store

Registration code: **RESZZZ**