eMoodie

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PREDICTING SLEEP DIFFICULTIES IN EARLY ADOLESCENCE: An ML Analysis Of EMA Data Coupled With Passive Smartphone Sensing Using eMoodie App

BACKGROUND

» There has been a recent, **global rise in indicators of maladaptive sleep patterns** – such as shorter sleep duration and sleep-onset difficulties – in youth (Gradisar et al., 2011).

» The developmental trajectory of emotional problems from late childhood through adolescence confirms sleep disturbance contributes to anxiety and depression, though bidirectional causality is also observed (Wang, Isensee, et al. 2016). Concurrent **generational rises in symptoms of depression and anxiety in youth** (Twenge et al., 2018) **are at least partially mediated by the increased prevalence in sleep disturbances** in young people (Sivertsen et al., 2015).

» It is important to develop accurate, scalable means for detection of sleep disturbance in this key transitional period of early adolescence. It is possible **to capitalize on the ubiquity of smartphones and their data collection capacities** (Miller, 2012) as a means of developing precise, cost-effective ways, to **facilitate early screening, and preventative or treatment focused interventions for sleep disturbances** in childhood and adolescence (Mohr, Zhang, & Shueller, 2017).

CURRENT STUDY & ANALYSIS

» **Aim:** This study is the first (to our knowledge) to report on using **ML analyses to evaluate ecological momentary assessment (EMA) data coupled with smartphone sensing for assessing sleep disturbance in a pediatric sample**.

» **Sample:** Participants were recruited from three high schools **(N =265)** in Edinburgh, Scotland. Eligibility was based on age **(11-13 years)** and access to a smartphone during the study period.

» **App:** The study used a smartphone application we developed called "eMoodie".

» **Analysis:** The current analysis is based on a **balanced binary classification task** whereby EMA and accelerometry data is combined to predict whether children **met the clinical threshold for sleep disturbance based on the well-validated screening measure Pittsburg Sleep Quality Index** (PSQI; Buysse et al., 1989). The predictions of Support Vector Machine (SVM) and Random Forest (RF) algorithms were compared. For each prediction, the metrics that were used in experiments were: precision, recall, f1-score, ROC-curve and AUC-ROC score.

EMOODIE

» **"eMoodie" is a developmentally-informed, EMA app specifically designed for research with children and adolescents.**

» It is a cross-platform app deployed on both Android and iOS (Apple) devices. It was created as a **research tool for the express purpose of studying mental health**, digital technology use, socialization patterns, and other health factors (e.g., physical activity and sleep) in developmental populations.

» eMoodie **incorporates gamification features** such as the use of pictures in question and answer formats to convey the meaning of difficult concepts, and a points feedback system to help engage young participants and improve compliance

» The app unobtrusively **collects sensing data** from the device it is installed too, including indices of activity and smartphone usage data

REFERENCES

DATA SET

Information for Datasets for Each Prediction

	Samples	Positive Class [a]	Negative Class [b]	% of Negative	Size of EMA data	Size of Sensor data
Prediction Task (Sleep Problem)						
	254	112	142	56%	(254,92)	(254,10)

[a] Do not have sleep difficulties scores above threshold on PSQI.

[b] Have sleep difficulties scores above threshold on PSQI.

RESULTS

» The overall sleep problem prediction results are shown in the following table. **Precision, recall and F-1 scores were calculated based on the average of 10-fold cross validation**.

» Feature selection was based on Recursive Feature Elimination combined with RF (i.e., RFE-RF; Guyon et al., 2002). A subset of the **best performing EMA questions (n = 15)** were selected from the entire EMA survey.

Table 1: Overall Sleep Problem Prediction Results for 10-fold Cross Validation

Sleep Problem Prediction Results for 10-fold Cross Validation								
Survey Data Without Feature Selection								
		SVM			RF			
Sleep Problem	Class	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score	Support
No	0	0.68	0.63	0.64	0.68	0.55	0.60	9
Yes	1	0.73	0.76	0.74	0.68	0.77	0.72	11
Average*		0.71	0.70	0.70	0.68	0.67	0.67	20
AUC-ROC Score		0.78±0.13			0.73±0.12			
Survey Data With Feature Selection								
		SVM			RF			
Sleep Problem	Class	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score	Support
No	0	0.71	0.74	0.70	0.69	0.61	0.63	9
Yes	1	0.79	0.73	0.75	0.72	0.77	0.73	11
Average		0.75	0.73	0.73	0.71	0.70	0.69	20
Increased Avg**		0.04	0.03	0.03	0.03	0.03	0.02	
AUC-ROC Score		0.83 ± 0.09			0.80 ± 0.09			
Increased AUC score		0.05			0.07			
Selected Survey Data and Sensor Data								
		SVM			RF			
Sleep Problem	Class	Precision	Recall	F-1 Score	Precision	Recall	F-1 Score	Support
No	0	0.95	0.75	0.83	0.99	0.97	0.98	9
Yes	1	0.84	0.97	0.89	0.98	1.00	0.99	11
Average		0.90	0.87	0.86	0.98	0.99	0.99	20
Increased Avg		0.11	0.09	0.08	0.21	0.23	0.22	
AUC-ROC Score		0.83 ± 0.09			0.80 ± 0.09			
Increased AUC score		0.05			0.07			

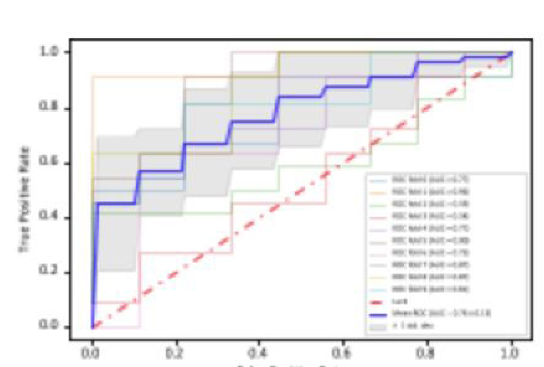
* Average is the weighted average sum of each score.

** Increased scores are calculated based on the scores of the previous step.

» The best performing classifiers combined sensor data with survey data. This implies that sensor data is useful when inferring the presence of a potential sleep problem from self-reported data. Overall, SVMs and Random Forests performed at a similar level of accuracy.

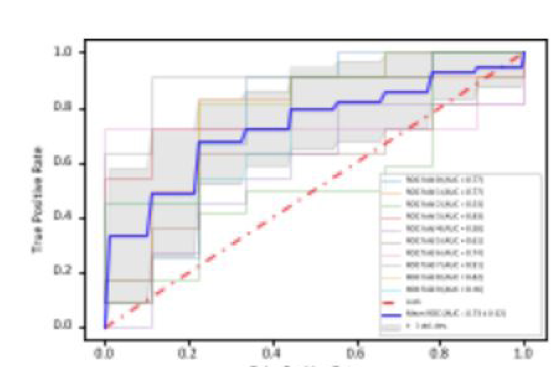
Figure 1. The comparison of the ROC curves given by SVM and RF based on survey data without selecting questions.

Receiver operating characteristic example



(a) ROC curves of 10-fold cross validation based on SVM model.

Receiver operating characteristic example



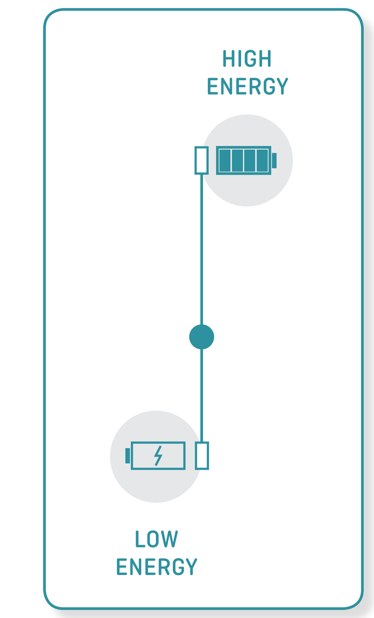
(b) ROC curves of 10-fold cross validation based on RF model.

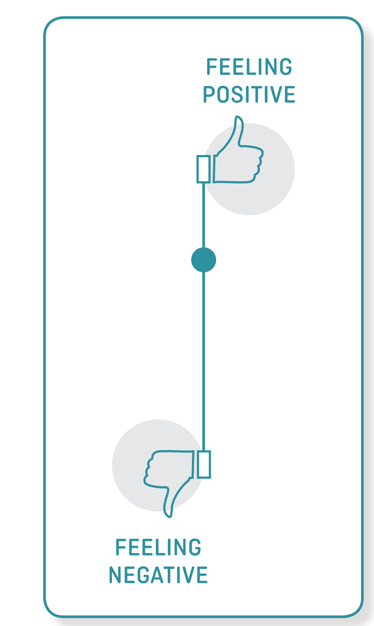
CONCLUSIONS

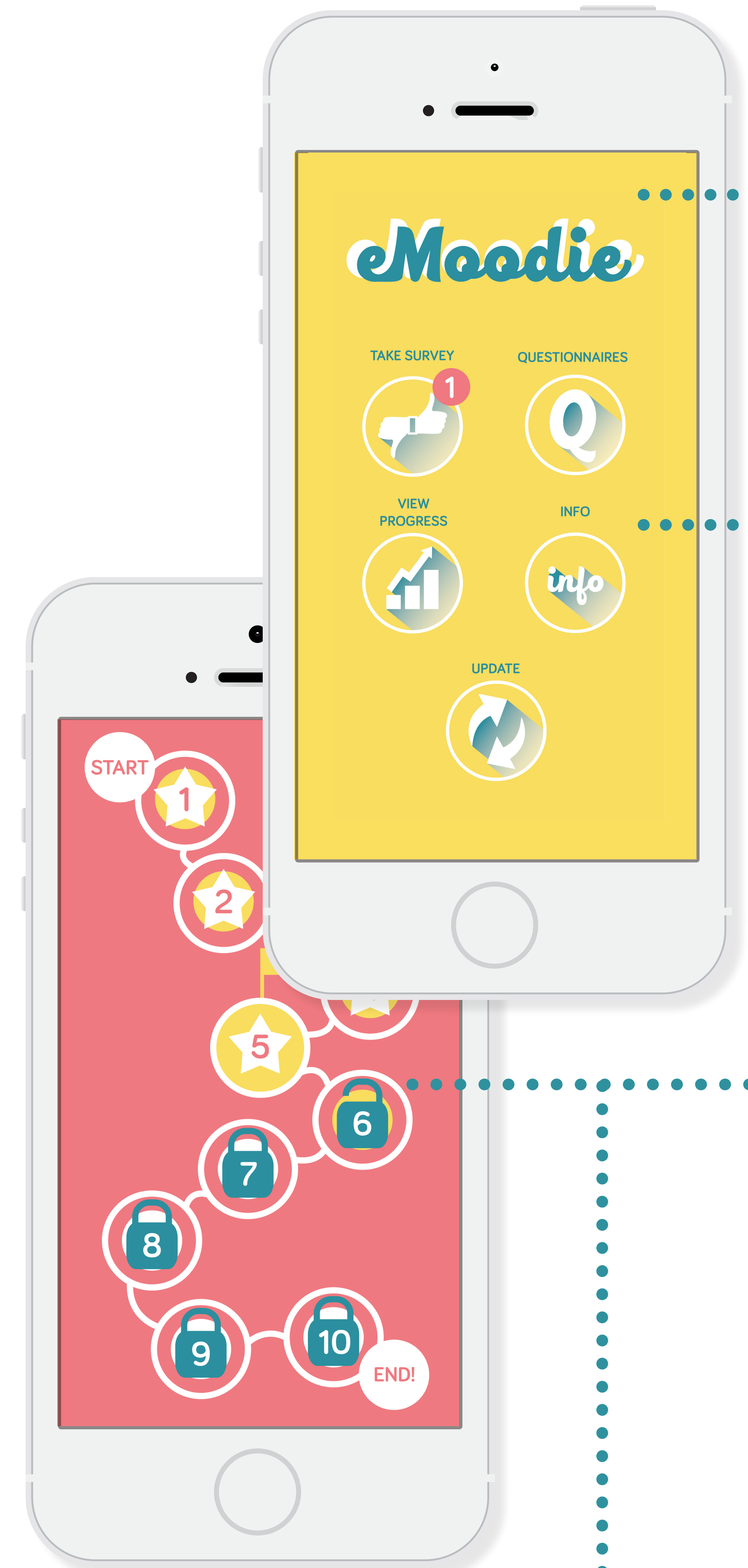
» The results of the current analysis **confirm the feasibility** and promise of combining the explanatory power of EMA and passive sensing data, paired with ML analytic techniques (cf. Dwyer, Falkai, & Koutsouleris, 2018) to **predict sleep disturbance in young people**.

» Deleterious sleep problems often moderate the development of other common mental health problems in **adolescence – a 'window of vulnerability'** for the development of psychopathology (Nelson et al., 2005).

» **Smartphone-based sleep monitoring**, coupled with passive sensing, provides an **unobtrusive, cost-effective and scalable means** (Abdullah et al., 2014) to implement the next generation of mHealth interventions directly at sleep disturbance.







RESEARCHERS CAN CONFIGURE QUESTION SETS, GRAPHICAL AIDS,STUDY PARAMETERS

ECOLOGICAL MOMENTARY ASSESSMENT SURVEYS AND ELECTRONIC QUESTIONNAIRES

QUESTION SAMPLES

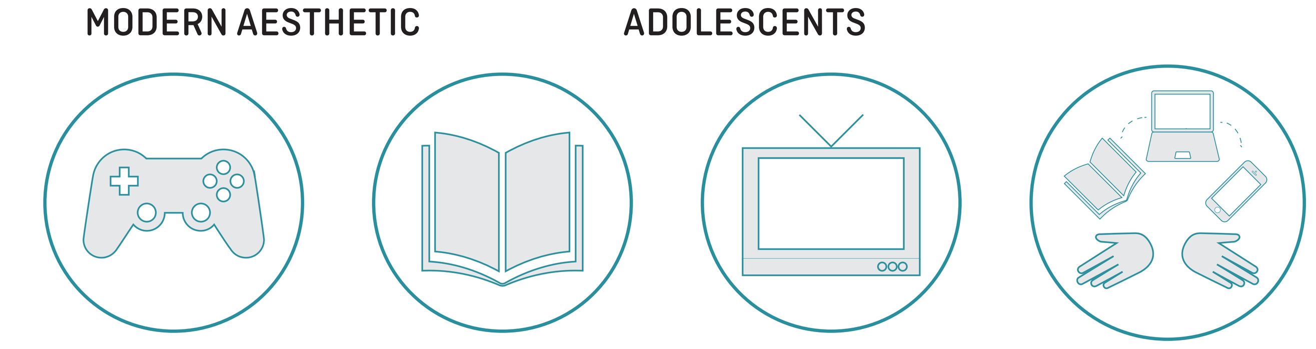
SENSORS

ADDITIONAL USAGE STATISTICS AND DATA COLLECTION

E.G., ACCELEROMETER & PHONE USE STATISTICS

CHILD-FRIENDLY UI AND GRAPHICS MODERN AESTHETIC

APPEALING TO OLDER CHILDREN AND ADOLESCENTS



THE FLEXIBILITY OF THIS APPLICATION TO COLLECT DIFFERENT TYPES OF EXPLICIT, REAL-TIME DATA IN CONJUNCTION WITH ECOLOGICALLY VALID EMA DATA WILL CONTRIBUTE TO ADVANCING THE EXPLANATORY POWER OF EXISTING ECOLOGICAL MOMENTARY ASSESSMENT METHODOLOGIES USED IN MENTAL HEALTH RESEARCH.

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