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Original Article

Original Article

Predicting stress and depressive symptoms using high-resolution smartphone data and sleep behavior in Danish adults

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Abstract

Study Objectives: The early detection of mental disorders is crucial. Patterns of smartphone behavior have been suggested to predict mental disorders. The aim of this study was to develop and compare prediction models using a novel combination of smartphone and sleep behavior to predict early indicators of mental health problems, specifically high perceived stress and depressive symptoms.

Methods: The data material included two separate population samples nested within the *SmartSleep Study*. Prediction models were trained using information from 4522 Danish adults and tested in an independent test set comprising of 1885 adults. The prediction models utilized comprehensive information on subjective smartphone behavior, objective night-time smartphone behavior, and self-reported sleep behavior. Receiver operating characteristics area-under-the-curve (ROC AUC) values obtained in the test set were recorded as the performance metrics for each prediction model.

Results: Neither subjective nor objective smartphone behavior was found to add additional predictive information compared to basic sociodemographic factors when forecasting perceived stress or depressive symptoms. Instead, the best performance for predicting poor mental health was found in the sleep prediction model (AUC = 0.75, 95% CI: 0.72–0.78) for perceived stress and (AUC = 0.83, 95%CI: 0.80–0.85) for depressive symptoms, which included self-reported information on sleep quantity, sleep quality and the use of sleep medication.

Conclusions: Sleep behavior is an important predictor when forecasting mental health symptoms and it outperforms novel approaches using objective and subjective smartphone behavior.

Statement of Significance

The detection of early signs of mental disorders is crucial to prevent the progression of these disorders. Using data from two large population samples with similar information, we applied a novel combination of objective high-resolution smartphone tracking data and subjective information on smartphone and sleep behavior to predict perceived stress and depressive symptoms. The best predictive performance was found in a basic model including only survey information on sleep behavior and sociodemographic factors. This indicates that basic information on sleep behavior outperforms novel approaches using smartphone behavior when predicting poor mental health. Monitoring sleep problems may be of clinical relevance in order to prevent and reduce the onset and progression of mental disorders.

Key words: smartphone behavior; sleep; mental health; depressive symptoms; perceived stress; adults; prediction modeling

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Introduction

Poor mental health is an increasing global public health issue, and it constitutes a major contributor to the overall burden of disease [1,2]. It has been estimated that one in ten adults suffers from one or more mental disorders worldwide, with depressive and anxiety disorders being the most common [2,3]. Mental disorders also impose a high societal burden in terms of costs, lost productivity, morbidity, and mortality [4]. Thus, identifying early signs of poor mental health and forecasting the onset of mental disorders may help mitigate their burden.

A growing body of studies have tried to exploit the enormous digital data traces left behind from smartphone use and utilized high-resolution smartphone tracking data to predict poor mental health [4–13]. Previous studies using smartphone tracking data identified specific smartphone behavior patterns that predicted stress, low mental health, and depressive symptoms [4–6,8,10,11]. However, these studies were undertaken in small samples and mainly in selected populations such as college students.

We hypothesize that prediction models can be improved by specifically focusing on night-time smartphone behavior and by considering additional subjective information on smartphone behavior. Even though self-reported smartphone behavior may not capture actual smartphone use [14–16], subjective smartphone behavior may convey important information in addition to objective tracking data [17]. Indeed, information about appraisals of smartphone behavior has previously been linked to mental health problems independently of actual use [14,17].

Sleep problems are key symptoms of depression and other mental disorders [18,19] and previous studies have shown that sleep behavior is a well-established predictor when forecasting mental disorders [5,20–22]. Thus, using a novel combination of objective night-time smartphone behavior, subjective smartphone behavior, and sleep behavior may contribute to an early detection of mental health symptoms.

In this study, we combine objective night-time smartphone behavior, a subjective appraisal of smartphone behavior, and self-reported sleep to predict early signs of mental disorders based on two separate population samples with information on sociodemographic factors, smartphone, and sleep behavior from both survey and tracking data. We hypothesize that models predicting poor mental health can be improved by adding information on smartphone behavior in addition to sleep behavior and sociodemographic information.

Methods

Study samples

We used data from the *SmartSleep Study*, which includes two separate population samples with similar information on sociodemographic factors, smartphone, and sleep behavior from both survey and tracking data. For model training, we used data from the *Population Sample*, in which 85 000 randomly selected Danish adults aged between 18–50 years (mean 34.4 (SD: 9.6)) were invited to participate in the *SmartSleep Study* between July and October 2020 via a secure digital postbox. Participants were asked to download and install the *SmartSleep* app (GitHub repository: https://github.com/smartsleepku) on their smartphone (either iOS or Android). The app was specifically developed for this research project. The app continuously tracked all screen activations during self-reported sleep hours. Each night, participants specified their sleep onset and offset times from which sleep hours were calculated. If the sleep onset or offset times specified in the evening had changed during the specific night, the participants were asked to correct sleep onset and offset times in the morning. The participants were asked to have the app running in the background for up to 14 nights (median: 3 nights (Interquartile range (IQR)1–6)) and once complete a survey, which was embedded in the app. The survey collected detailed information on sociodemographic factors, smartphone behavior, sleep patterns, mental health, and well-being. Up to two reminders were sent to nonresponders. In total, 4522 adults tracked their night-time smartphone behavior and filled out the survey (5% response rate) (Supplementary Figure S1)

To assess the performance of the prediction models, we used independent data. The *Citizen Science Sample* included 1885 Danish adults aged >15 years who were invited to participate in the study between February and July 2020 (15% response rate) (Supplementary Figure S1). The participants were similarly asked to download and install the *SmartSleep* app and have the app running in the background for up to 14 nights (median: 5 nights (IQR: 2–11)) and fill in a survey once. The *Citizen Science Sample* is part of a citizen science arm of the *SmartSleep Study* where 25 135 adults in 2018 participated in a shorter version of the survey carried out for one week in collaboration with the Danish Broadcasting Corporation. In total, 12 348 adults consented to be further contacted. Details about this study population have been described previously [23].

The present study was approved by the Danish Data Protection Agency through the joint notification of The Faculty of Health and Medical Sciences at The University of Copenhagen (approval no. 514-0288/19-3000).

Analytical framework

Mental health prediction models. We hypothesize that models predicting poor mental health can be improved by adding information on smartphone behavior in addition to sleep behavior and sociodemographic information. To test this hypothesis, we have organized the features into five prediction models based on the complexity of information (Table 1). In the sociodemographic model, we only include sociodemographic features of age, sex, and educational level as a basic model for comparison. Then follows three models in which we in addition to the basic sociodemographic features include a) objective night-time smartphone behavior, b) subjective smartphone behavior and c) self-reported sleep measures to test the individual predictive value of each of these three dimensions. Finally, we combine the previous four models into the smartphone and sleep model in which we include all features used in the previous models.

Data cleaning and missing data imputation

Missing survey data and missing summary measures of tracking data were imputed using the *missForest* R package [24], which is an algorithm utilizing random forest to impute missing data in the data matrix based on observed data points. We assumed a missing-at-random (MAR) missingness pattern for the utilized variables [25]. The two study samples were imputed within a

Table 1. Overview of features in the five prediction models

Features	Prediction models: Sociodemographic model	Objective night-time smartphone behavior model	Subjective smartphone behavior model	Sleep model	Combined model
Sociodemographic factors	X	X	X	X	X
Objective night-time smartphone behavior		X			X
Subjective smartphone behavior			X		X
Sleep behavior				X	X

multiple imputation framework; ten imputed data sets of both study samples were imputed, and all downstream analyses were undertaken in each of the ten imputed data sets.

In total, 188 variables were included in the two data sets before multiple imputations. Before multiple imputations, data in both samples were preprocessed by removing variables with zero or near-zero variance (n = 30) using the *caret* R package [26]. After multiple imputations, the self-reported duration of night-time smartphone use per night and the self-reported number of night-time smartphone activations per night were removed due to a high correlation (Spearman's rho > 0.8) with other features.

Statistical analysis

Statistical analyses were conducted using R software version 4.1.1.

Firstly, characteristics of the *Population Sample* and the *Citizen Science Sample* were pooled across the ten imputed data sets. Two sets of prediction models, one for high perceived stress and one for depressive symptoms as outcomes were developed using three different algorithms: logistic regression (GLM), artificial neural network (ANN), and random forest (RF). Prediction models were trained in the *Population Sample* using a 5-fold cross-validation [27]. Default parameters of the nnet() and randomForest() functions were used. Two hyper-parameters were used for the ANN algorithm: the number of units in the hidden layer (3; 6; 9) and the regularization parameter decay (0; 0.1; 0.0001). One hyper-parameter was used for the RF algorithm: the number of variables in each split (2, 4, 6, and 8). Model performance was assessed using the area under the receiver operating characteristics curve (ROC AUC) metric during both training and testing [28]. For GLM, the best performing model from the cross-validation was subsequently tested in the *Citizen Science Sample* (independent test set). For ANN and RF, the best performing hyper-parameters were used to re-train a model using the entire *Population Sample* and the resulting models were subsequently tested on the *Citizen Science Sample*. ROC AUC values across the ten imputed data sets of the *Citizen Science Sample* were pooled using Rubin's Rules [29] and recorded as the final performance metrics.

Measures

Supplementary Table S1 shows an overview of the features included in the prediction models and details are briefly outlined below.

Sociodemographic factors. We used self-reported information on the age, sex (female; male), and the highest educational level (long-cycle higher education; medium-cycle higher education; short-cycle higher education; technical vocational education, upper secondary education; primary school; other)

Objective night-time smartphone behavior. High-resolution data from the *SmartSleep* app included more than two million data points from more than 27 000 nights (5.5 nights on average per participant). We objectively recorded whether participants had any smartphone activations between the self-reported sleep onset and offset times. Only nights with more than 5% of smartphone activity during sleep hours were considered. *The frequency of nights with smartphone activity* was then calculated as the percentage of nights with activity in relation to all fully tracked nights. Furthermore, we determined the average percentage of the duration of smartphone activity in relation to self-reported sleep hours (*average duration of smartphone activity*).

Subjective smartphone behavior. The survey included comprehensive information on the participants' self-reported smartphone behavior including frequency of daytime smartphone use, frequency of social media use, problematic smartphone use (a seven-item subscale of the Problematic Mobile Phone Use Questionnaire (PMPU-SV) [30] where each item is rated on a four-point Likert scale from 1 "strongly disagree" to 4 "strongly agree"), frequency of smartphone use immediately before falling asleep, frequency of smartphone use during sleep hours and whether the participants feel disturbed by the smartphone during sleep hours. Moreover, we obtained self-reported information on the duration of night-time smartphone use per night, the number of smartphone activations per night, and the timing of smartphone use during sleep hours.

Sleep behavior. Participants' sleep duration on weekdays was calculated based on self-reported sleep onset and offset times on weekdays. Additionally, we surveyed sleep quality assessed using a Danish translation of a validated short version of the Karolinska Sleep Questionnaire (KSQ) [31]. The KSQ includes four items, and each item is rated on a 5-point Likert scale from 1 "never" to 5 "every night or almost every night". The frequency of sleep medication use was assessed by asking how often during the past month they have taken medicine (prescribed or over the counter) to help them sleep with response options ranging from "never" to "3 or more times a week".

High perceived stress. Perceived stress was measured using a Danish consensus translation of the Perceived Stress Scale (PSS-10), which is a psychological instrument measuring the degree to which individuals believe their life has been unpredictable, uncontrollable, and overloaded during the previous month [32,33]. PSS-10 consists of 10 items each rated on a five-point

Likert scale from 0 “never” to 4 “very often”. The PSS-10 score thus ranges between 0 and 40 where higher scores indicate higher levels of perceived stress. To identify individuals with high perceived stress, the PSS-10 was dichotomized. As there is no predefined cut-off for PSS-10, individuals with high perceived stress were defined as the highest quintile (20% of the total sample) of the participants in the *Population Sample,* which corresponded to a cut-off of 19. The same cut-off of 19 was subsequently used in the *Citizen Science Sample*.

Depressive symptoms. Depressive symptoms were measured by the Major Depression Inventory (MDI) [34], which consists of 12 items, each item rated on a six-point Likert Scale from 0 “at no time” to 5 “all the time”. For item pairs 8 and 9 and 11 and 12, only the highest score was used to calculate the total MDI score. The resulting ten item scores were summed up ranging from 0 to 50 where higher scores indicate more depressive symptoms. To identify individuals with depressive symptoms, the MDI scale was dichotomized, and depressive symptoms were defined as a score of 21 or above as suggested in previous studies [35].

Results

Characteristics of the two samples

Table 2 shows the characteristics of the *Population Sample* and the *Citizen Science Sample.*

When comparing the distributions of age, sex, and educational level in both samples with the general adult Danish population, both samples had a larger proportion of women, middle-aged individuals (31–50 years), and individuals with a higher educational level (Supplementary Table S2).

Performance of prediction models

The ROC AUC values for the training set (the *Population Sample*) are shown in Supplementary Table S3. Table 3 shows the ROC AUC values and 95% confidence intervals (CI) for each of the five models predicting high perceived stress and depressive symptoms in the test set (the *Citizen Science Sample)* using the GLM, ANN, and RF algorithms. As shown in Table 3, there were only minor differences across the three different algorithms and the results presented below are based on the GLM model, which showed the best performance.

The basic sociodemographic model demonstrated a ROC AUC value of 0.63 (95% CI: 0.59–0.66) for predicting high perceived stress and 0.66 (95% CI: 0.62–0.70) for predicting depressive symptoms. Neither information on objective night-time smartphone behavior nor subjective smartphone behavior increased the performance of the models. The sleep model achieved a ROC AUC value of 0.75 (95% CI: 0.72–0.78) for predicting high perceived stress and 0.83 (95% CI: 0.80–0.85) for predicting depressive symptoms. The combined model with information on sociodemographic factors, objective and subjective smartphone behavior and sleep (ROC AUC = 0.74, 95% CI = 0.72–0.77 for high perceived stress and ROC AUC = 0.81, 95% CI = 0.78–0.84 for depressive symptoms) did not perform better than the sleep model.

ROC AUC values in the training set and the test set were relatively similar and the predictive performance was only slightly higher in the training set than in the test set.

Figures 1 and 2 show the ROC curves for the five prediction models for predicting high perceived stress and depressive symptoms, respectively.

Conclusion/Discussion

We hypothesized that smartphone behavior could help predict early signs of mental health problems. We tested this hypothesis in two large independent data sets using both objectively and subjectively measured smartphone behavior, in comparison to a well-established approach relying on self-reported information on sleep behavior. Contrary to our hypothesis, we found that the best predictive performance was achieved using self-reported information on sleep. This seems to indicate that the seven basic questions on sleep quantity, sleep quality and the use of sleep medication can outperform novel approaches using smartphone behavior in predicting and identifying individuals suffering from high perceived stress and depressive symptoms. As shown in the literature, poor sleep behavior is strongly related to mental disorders [22,36,37]. Our findings confirm that individuals’ sleep behavior may carry important clinical information and help forecast the onset of mental health symptoms.

Table 2. Pooled characteristics of individuals in the *Population Sample* and the *Citizen Science Sample*

	Population Sample N = 4522	*Citizen Science Sample* N = 1885
Age, mean (SD)	36.6 (10.2)	44.4 (14.5)
Female, %	65	64
Educational level,%		
Long-cycle higher education	25	33
Medium-cycle higher education	28	32
Short-cycle higher education	8	9
Technical vocational education	18	13
Upper secondary school	13	8
Primary school	6	3
Other	2	2
Smartphone dependency, mean (SD)	17.5 (3.8)	17.5 (3.9)
Nights with at least 5% screen activity, mean % (SD)[a]	43.5 (35.4)	38.5 (34.6)
Hours of sleep duration, mean (SD)	7.8 (0.94)	7.8 (0.96)
High perceived stress, %	20	19
Depressive symptoms, %	12	10

[a]Mean percentage of nights with at least 5% screen activity in relation to all tracked nights for each participant

Table 3. Pooled ROC AUC[a] values and 95% confidence intervals for predicting high perceived stress and depressive symptoms in the *Citizen Science Sample* of 1885 Danish adults

	High perceived stress			Depressive symptoms		
	GLM[b]	ANN[c]	RF[d]	GLM[b]	ANN[c]	RF[d]
	ROC AUC (95%CI)	ROC AUC (95%CI)	ROC AUC (95%CI)	ROC AUC (95%CI)	ROC AUC (95%CI)	ROC AUC (95%CI)
Sociodemographic model	0.63 (0.59–0.66)	0.63 (0.59–0.66)	0.52 (0.49–0.56)	0.66 (0.62–0.70)	0.65 (0.60–0.69)	0.50 (0.46–0.54)
Objective night-time smartphone behavior model	0.63 (0.60–0.67)	0.64 (0.60–0.67)	0.61 (0.57–0.65)	0.67 (0.64–0.72)	0.67 (0.62–0.72)	0.63 (0.58–0.67)
Subjective smartphone behavior model	0.65 (0.62–0.69)	0.63 (0.59–0.68)	0.64 (0.61–0.68)	0.68 (0.64–0.73)	0.66 (0.60–0.71)	0.67 (0.62–0.71)
Sleep model	0.75 (0.72–0.78)	0.74 (0.70–0.77)	0.71 (0.68–0.74)	0.83 (0.80–0.85)	0.78 (0.66–0.89)	0.78 (0.75–0.81)
Sleep and smartphone behavior model	0.74 (0.72–0.77)	0.72 (0.67–0.77)	0.73 (0.70–0.76)	(0.78–0.84)	0.77 (0.72–0.82)	0.79 (0.76–0.82)

[a]ROC AUC: Area under the receiver operating characteristic curve,
[b]GLM: logistic regression models,
[c]ANN: artificial neural network algorithm,
[d]RF: random forest algorithm

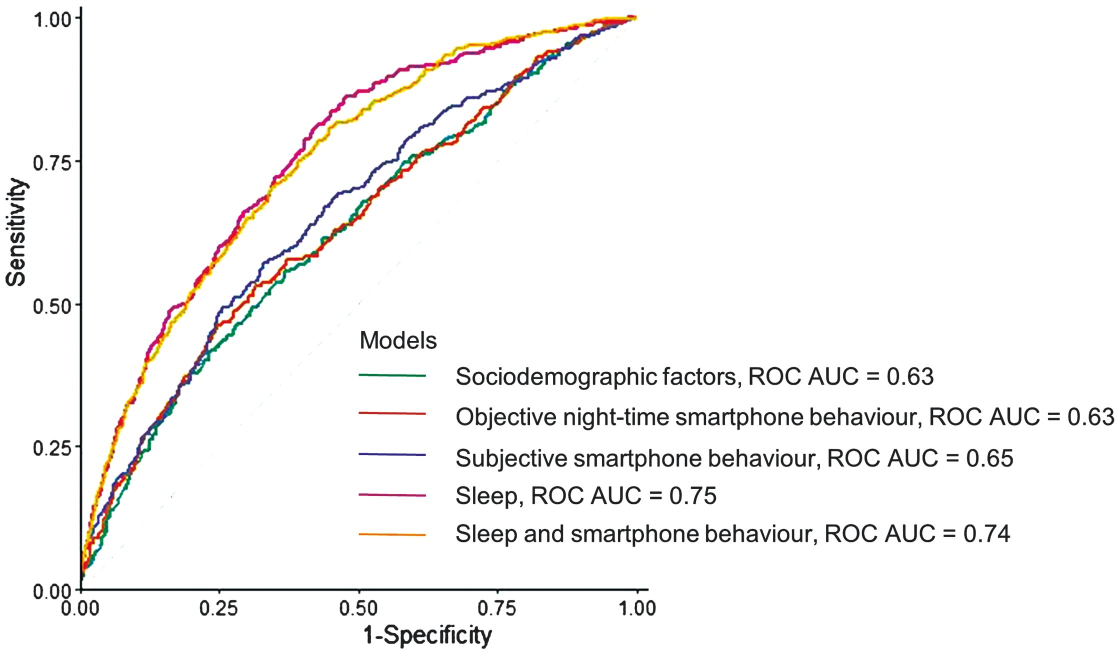

Figure 1. Receiver operating characteristics (ROC) curves for the five prediction models predicting high perceived stress. The ROC curves are based on prediction models from one imputed dataset. ROC AUC: Area under the receiver operating characteristics curve.

Furthermore, screening the general population for sleep problems may be a valuable tool for early identification and prevention of mental health symptoms.

Contrary to previous studies [4–6,8–10], findings in the present study indicate that objective and subjective smartphone behavior does not add more information than basic sociodemographic factors when forecasting poor mental health. A recent study identified clusters of mobile phone use, showing that frequent and prolonged night-time smartphone use was associated with poor mental well-being, but prolonged daytime smartphone use was not [7]. However, this previous study did not include information on sleep patterns. Similarly, no previous studies have developed prediction models using information on both sleep and smartphone behavior to predict poor mental health [4–6,8,10].

Strengths, limitations, and future directions

The main strength of this study is that we considered two large population samples. We hence had the unique opportunity to train the prediction models in a large sample of 4522 adults using a 5-fold cross-validation and then, test the models in an independent sample, which may improve the applicability and generalizability of the prediction models. Moreover, we used multiple imputations to reduce bias introduced by

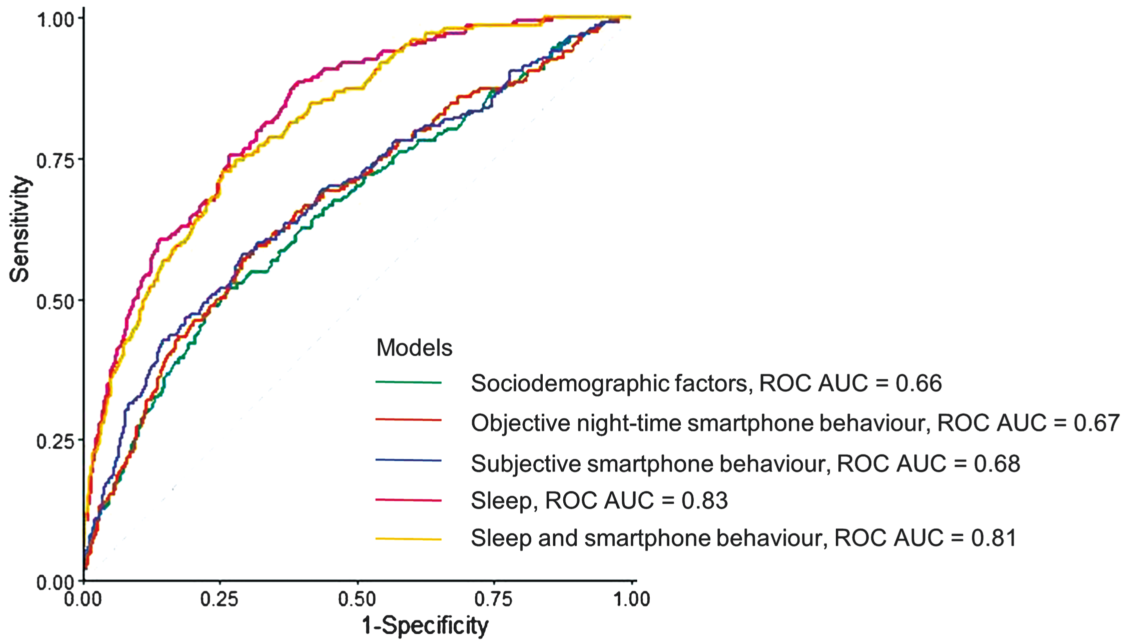

Figure 2. Receiver operating characteristics (ROC) curves the five prediction models predicting depressive symptoms. The ROC curves are based on prediction models from one imputed dataset. ROC AUC: Area under the receiver operating characteristics curve.

missingness. Finally, the use of validated scales limited the risk of measurement errors.

Despite the remarkable number of participants, we registered a relatively low response rate in both samples, probably due to the demanding task of downloading an app on participants' private phones and track their smartphone behavior for up to 14 nights to participate in the study. Indeed, most participants tracked their night-time smartphone use for fewer nights (*Population Sample*: median 3 nights (IQR: 1–6) and *The Citizen Science Sample*: median 5 nights (IQR: 2–11). Consequently, this may have lowered the reliability of the objective night-time smartphone use measures as participants may have tracked their night-time smartphone use on selected nights e.g., nights where they did not use their smartphone. If so, we may have underestimated the frequency of nights with smartphone activity in our study. Recent studies also struggle with low response rates and self-selected samples when using high-resolution smartphone tracking data [38–40]. As a consequence, the study populations in the present study are self-selected and not representative of the Danish adult population as there are larger proportions of women, middle-aged individuals, and individuals with a higher educational level in both population samples compared to the adult population in Denmark. Furthermore, it is likely that individuals with high perceived stress or depressive symptoms may be less likely to participate. While this may affect the generalizability of our results, it is reassuring to find very robust patterns across the training and test data samples.

In our sleep prediction model, we used self-reported validated information on sleep behavior. We showed that simple questions on sleep behavior are relatively good predictors when forecasting mental health symptoms. Identifying sleep problems as a symptom of poor mental health at an early stage may be of high clinical importance to prevent and reduce the onset and progression of mental disorders. Furthermore, sleep behavior may also be important for the individual's resilience level, which has shown to be important when coping with e.g., the COVID-19 pandemic [41,42]. Recent research has shown that smartphone tracking data and wearable devices offer great potential in the assessment of sleep behavior as they may overcome the challenges from self-reported sleep behavior [43]. Future studies may benefit from using high-resolution smartphone tracking data and wearable devices to measure sleep behavior. Furthermore, as poor sleep and poor mental health are highly intertwined, exploring to what extent measures of sleep behavior and poor mental health investigate the same underlying feature is a challenging task. Thus, we suggest future investigation on whether changes in sleep patterns may help us predict early signs of mental disorders using longitudinal studies.

In the present study, we use summary measures of objective night-time smartphone use and these may not capture the time-varying smartphone activity during the sleep hours over a two-week period. This may partly explain why night-time smartphone behavior did not predict poor mental health in the present study. Thus, we suggest caution in interpreting our findings and we emphasize that future studies will benefit from using temporal trajectories of night-time smartphone use or smartphone accelerometer data to explore whether smartphone behavior can predict early signs of poor mental health.

In conclusion, self-reported sleep behavior was found to outperform novel approaches using both subjective and objective smartphone behavior in predicting poor mental health in Danish adults. Monitoring sleep problems may be of clinical relevance to prevent and reduce the onset and progression of mental disorders.

Supplementary material

Supplementary material is available at *SLEEP* online.

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Disclosure Statement

ASD's contribution to the paper was confined to her previous position as Assistant Professor at University of Copenhagen, and not her current position at Lundbeck A/S.

Data Availability Statement

The data underlying this article cannot be shared publicly due to the privacy of individuals that participated in the study. The data will be shared on reasonable request to principal investigator of the SmartSleep project Professor Naja Hulvej Rod (nahuro@sund.ku.dk).

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