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# Affect during sleep: Exploring the capabilities of Artificial Intelligence in Sleep Research

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***Abstract*— Clinical research demonstrates the bidirectional associations between affect and sleep: Major depressive disorder is a prevalent clinical disorder, characterized by alterations in affect and sleep. Conversely, sleep disturbances emerge as prodromal manifestations preceding the onset of the disorder. Despite these close links, few studies investigated depressed daytime affect and its bidirectional associations with sad affect at the time of sleep. This lack of evidence can be attributed to methodological constraints, challenging the assessment of affect during sleep. To address this research gap, the present study introduces an innovative method utilizing Machine Learning and Infrared technology for the unobtrusive assessment of affect during sleep. The objectives of the present proof of concept were as follows: First, to introduce a novel approach for measuring affect during sleep. Second, to determine the bidirectional associations of depressed affect at daytime and sad affect during sleep in a healthy sample. Sad affect during sleep was measured using three infrared cameras with adaptive night vision, recording 63 videos during sleep. Daytime depressed affect was measured by survey, data analysis included general linear modeling (GLM). In line with the first objective, sad affect during sleep was extracted from video-based facial expressions using Artificial Intelligence software frameworks open DBM and open Face (AiCure). In line with the second objective, GLM analysis yielded that higher levels of depressed affect at daytime predicted higher levels of sad affect during sleep significantly. The inverse association was not significant. Conclusionally, we present an innovative method for the unobtrusive measurement of affect during sleep. This method may be particularly advantageous for the early detection of depressed mood states in subclinical populations and samples undergoing transient depressed mood states. Clinical and general implications are discussed.**

***Keywords—depression, sleep, Artificial Intelligence, deep neural networks, methodological innovations***

## I. INTRODUCTION

Clinical and neuroscientific evidence underscores the critical role of sleep in emotional brain processing [1]. Consistent with this, translational clinical research demonstrates a bidirectional relationship between sleep and affect. Major depressive disorder (MDD), a highly prevalent syndrome with adverse health consequences [2], is characterized by mood alterations and sleep disturbances [3]. Aligning with this, sleep alterations emerge as prodromal manifestations, preceding the onset of the disorder [4]. In addition, both MDD and insomnia show significant alterations in neurotransmitter systems that regulate both mood and sleep-wake cycles [5]. Drawing upon the maladaptive interaction between compromised sleep and affective disorders, the aim of this research is to further investigate affect during sleep.

Research has primarily focused on the impact of clinical depression on sleep architecture and sleep quality [6]. In contrast, the impact of transient negative affect on sleep (e. g., sadness) remains less understood in healthy individuals. Healthy individuals can experience day-to-day sadness and transient depressed affect due to stress [7], chronotypes (e. g., eveningness) [8], negative thinking patterns such as attributional styles [9], or a low future self-perception [8]. Aggregating previous findings from healthy individuals, sadness compromises the quality of sleep and influences the total sleep time (TST) [10]. Pre-sleep emotional states, in particular, seem to shape the affective experience during sleep, with studies linking negative pre-sleep depressed mood to the emotional tone of early rapid-eye-movement sleep (REM sleep) dreams [11]. Importantly, these findings align with the affective continuity framework, presuming that affective daytime occurrences translate to proximal sleep intervals (e. g., [12] [13]). Taken together, the available evidence suggests that day-to-day

sadness and depressed affect can persist into sleep. Accordingly, we hypothesize that higher levels of depressed affect prior to sleep predict higher levels of sad affect during sleep (H1).

In addition to the proposed continuity of affect during sleep [11][12][13], the unique neurobiology of sleep offers an ideal milieu to redress the emotional charge of affective experiences [1]. According to Reference [1], sleep removes the affective blanket of emotions, facilitating their processing [1]. Empirical support for this framework is provided by Reference [14], reporting significant reductions in negative affect levels from pre- to post-sleep. In alignment, Reference [15] exposed participants to negative stimuli in a sleep and no-sleep condition, measuring affective arousal markers (e.g., skin conductance response, corrugator supercilii). Participants in the sleep condition exhibited significantly lower somatic affective responses compared to those in the no-sleep condition [15]. While these findings suggest that sleep serves an emotional regulatory function, state-of-the-art studies exclusively compared pre- and post-sleep affect levels as indicators of emotional processing. However, according to Reference [1], it is the emotions reactivated *during* sleep that are processed; suggesting that comparing pre- and post-sleep levels may offer limited insight into the processing of affect during sleep. Drawing upon this, we hypothesize that (re)experiencing sad affect during sleep leads to lower levels of depressed affect after sleep. Specifically, we hypothesize that higher levels of sad affect during sleep predict lower levels of depressed affect in the morning (H2).

The available evidence offers a general insight into how sad and depressed mood states may impact sleep-related affect and next-day affect. However, due to methodological constraints, these theoretical foundations could not be empirically investigated so far. Consequently, limited research has been conducted on the bidirectional links between daytime affect and affect during sleep. Specifically, regarding affect during sleep, the available evidence relies dominantly on retrospective self-reports [16], contact-based approaches such as facial electromyography (EMG) [17] and paradigms deploying instrumental awakenings during sleep [18]. While self-reports rely on introspection, contact-based measures can interfere with sleep quality, underscoring the need for innovative research approaches.

Recent advances in Artificial Intelligence (AI) and Machine Learning (ML) in health research have led to an emerging interest regarding the monitoring of sleep-related processes with unobtrusive measurements [19]. These measurements offer several methodological advances since they are noninvasive, economic and achieve high levels of accuracy [19]. During wake state, AI studies successfully extracted affect levels from facial activity using video-based sensors and deep neural networks [20]. Reference [20] demonstrate a pre-trained three-layer deep convolutional network (DCNN), achieving recognition accuracies of 90.7% for sadness and 100% for happiness. Reference [21] developed a three-layer classification system for depression detection using Active Appearance Models (AAM), Support Vector Machines (SVM), and optimal feedforward neural networks. The proposed architecture allowed to discriminate between depressed and non-depressed individuals with an accuracy of 93% [21]. While the aforementioned work achieved high accuracy levels, video-based ML approaches for detecting facial affect are limited to wake state exclusively. A noninvasive extraction of affect from facial activity during sleep was not possible up to date, since the accuracy of video-based systems relies on daylight [22]. In the field of ML applications during sleep, research has mainly focused on sleep stage classification, sleep posture recognition, sleep disorders detection, and vital signs monitoring [19]. Reference [23] present a contact-based ML approach measuring arousal during sleep. The extraction of arousal rates from Electroencephalogram (EEG) Wavelets during sleep achieved a sensitivity of 82.68% [23]. While these advances demonstrate the potential of ML in sleep research, no unobtrusive ML approach extracted affect levels from facial activity during sleep so far.

To address this research gap, we introduce an innovative, method to assess affect during sleep using infrared technology and deep neural networks (DNN). To attain this goal, we employed the AI software frameworks Open DBM [24] and OpenFace [25] for the analysis of infrared video recordings during sleep. Open DBM [24] is a digital biomarker analysis software framework that integrates OpenFace [25], a proficient AI tool that utilizes DNNs for the analysis of facial activity. Traditional DNN models dominantly operate on extensive labeled data, pre-processing and validation against ground truth datasets [26]. By contrast, Open Face is trained on large facial expression datasets [25, 27], allowing the automatic assessment of facial activity (e. g., affect indices). Consequently, our approach offers a pre-trained, open-source, non-invasive affect measurement without extensive training efforts. This positions our work as a practical tool for detecting affect during sleep, especially in clinical health settings, where it may help prevent the progression of depressed affect into more severe conditions, such as major depressive disorder (MDD) [2].

In the present research, we conducted a proof-of-concept trial in a healthy sample to provide valuable insights into affect at daytime and sleep. Summarized, this proof-of-concept trial aimed to address two key research gaps: 1) introducing an innovative measure of (sad) affect during sleep and 2) advancing the understanding of the overnight continuity and processing of depressed affect.

## II. METHODS

### A. Transparency

In agreement with the World Medical Association Declaration of Helsinki (2013) [28], all parts of the study were conducted following ethical standards. In alignment, the informed consent (IC) that was administered to the participant included the following criteria: Transparent information about the study procedure, the assessment of variables, data analysis and data management. IC was given prior to the experimental start on 07.01.2024.

### B. Inclusion and exclusion Criteria

General inclusion criteria included an agreement on providing video recordings of oneself during sleep for a period of 21 nights and German language skills at a level of C1 minimum. General exclusion criteria were defined as the following: Fulfilling the clinical criteria of severe depressive

symptoms as defined by the german version of the General Depression Scale [29] [30] (cut-off score = 17), and/or symptoms of primary insomnia as defined by the Regensburg Insomnia Scale (RIS) [31] (cut-off score = 13), a sleep onset latency of > 20 minutes, a sleep duration of < 6 hours and an age of < 18 years. Inclusion and exclusion criteria were determined using a screening questionnaire in advance of the study participation.

### C. Participant and Design

Data analysis included the aggregation of $N = 63$ videos and $N = 63$ daytime questionnaires of one healthy participant (male, aged = 21 years, academic student). Data was recorded in an ambulatory setting over a time span of 21 days and nights (x 3 infrared camera angles). To assess baseline sample characteristics, a baseline survey determining depression and stress levels, emotional regulatory skills and sleep parameters was administered to the participant. The study design was a one-arm, longitudinal study without intervention or manipulation.

### D. Procedure

The infrared camera setups were installed after the participant provided written consent to study participation and data management. The participant then received a file containing all links to the questionnaires for the assessment of daytime affect. To assess affect during sleep, the technical set-up comprised three infrared cameras equipped with night vision technology (iMOU Life Rex 3D IPC-A26LP). The first infrared camera was installed at the left-hand side of the ambulatory bed, the second infrared camera at the right-hand side of the bed and the third infrared camera central above the bed. The three cameras were adjusted for optimal angle, with additional height adjustments made to the left and right cameras. Subsequently, the principal investigator (PI) instructed the participant on the procedures of the video recordings and the completion of the daytime questionnaires (each morning, midday and evening at the same times). Following the installation, a test night was conducted to ensure that any participant feedback was implemented in advance of the study start. After this feedback was revised, the study was initiated.

### E. Measures: Depressed affect at daytime

Depressed affect was assessed with the daytime questionnaire comprising 15 state items assessing depressed affect, positive affect and stress. These questions were implemented in our previous study [32] to operationalize exact correlates of affect and stress during sleep. Depressed affect was measured by the intervention survey item “To what extent do you feel depressed right now?”, which was answered on a 10-point Likert Scale (0 = “not at all”– 10 = “very high”). In addition to the 15 standard items, every morning daytime questionnaire contained five items examining 1) the sleep quality in the previous night, 2) pain levels during the previous night, 3) dream content, 4) the use of sleep medication and 5) one sleep hygiene factor. The midday and evening daytime questionnaire solely consisted of the 15 state items [32].

### F. Measures: Sad affect during sleep

The following method is in alignment with our previous study [32]. Open-Source code is available via https://github.com/AiCure/open_dbm and https://github.com/TadasBaltrusaitis/OpenFace.

All facial expressions of the sleeping participant’s infrared recordings were filtered and analyzed (mean duration 8:20 hours per night). Primary analysis software included artificial intelligence software frameworks open DBM and open Face [24, 25]. As described in the first section, Open DBM is a software framework for the analysis of digital biomarkers that includes Open Face, a software tool for facial recognition that utilizes deep neural networks [24, 25]. Each video was sampled at a rate of 25 Hz, the open DBM analysis group 'facial' was applied to limit deep learning algorithms to facial activity. For the extraction of affect during sleep, all video frames were converted into facial landmarks, represented three-dimensionally by x-, y-, and z-vectors. In a first step, the infrared video frames (input images) were converted into relevant sections (crop) to restrict the analysis to the sections of facial expressions. In a second step, deep neural networks were utilized for the representation of facial expressions as three-dimensional landmarks, with separate landmarks representing each area of the face (representation). In a third step, changes in facial expressions were quantified analyzing the Euclidean distance between each facial landmark and the subsequent facial landmark. Movements in a particular region of the face, like a raised corner of the mouth, alter the Euclidean distance [24, 25].

In the last step of the analysis, Action Units were extracted by applying a deep learning algorithm that calculated the Euclidean distance between each facial landmark and the subsequent facial landmark. Action Units are defined as facial activity movements, i. e., anatomical facial muscle contractions (FMCs) [33]. The Facial Action Coding System (FACS) [33], is an objective, reliable categorization system of facial activity as Action Units (AUs) [34]. As defined by the manual of the FACS [35], the core pattern of sad affect is the concurrent activity of the AUs 1 + 4 + 15. These AUs include the activity of the AU 1 (Frontalis muscle), the AU 4 (Depressor Supercilli/Corrugator Supercilii muscle) and the AU 15 (Depressor anguli oris muscle/Lip Corner Depressor) [35]. Consequently, we applied the concurrent activity of this AU core pattern for the extraction of sad affect in the deep learning algorithm by open Face [24, 25]. Simultaneously, we applied hard criteria for the extraction of AUs; only the concurrent activity of the AUs 1 + 4 + 15 was scored as sad affect during sleep. An average of 1.34 hours of concurrent Action Units classified as sad affect ($SD$ = 0.08 minutes) was measured in every night of sleep.

## III. DATA ANALYSIS & RESULTS

### A. Descriptive Results

Table I yields the descriptive results of depressed daytime affect and sad affect levels during sleep.

TABLE I. DESCRIPTIVE RESULTS

| Variables | *Mean* | *SD* |
|---|---|---|
| **Daytime affect** | | |
| Depressed Affect Morning (0-10) | 3.35 | 1.70 |
| Depressed Affect Mid-day (0-10) | 2.77 | 1.90 |
| Depressed Affect Evening (0-10) | 2.61 | 2.19 |
| **Affect during sleep** | | |
| Total recording time (hours) | 8.20 | 1.00 |
| Sad Affect during sleep (hours/minutes) | 1.34 | 0.08 |
| Sad Affect during sleep (minutes) | 94.00 | 8.00 |
| Sad Affect during sleep (%) | 18.00 | 7.00 |
| Sad Affect during sleep (Duration in seconds) | 11.15 | 13.50 |

*Note*. All values represent mean values, *SD* = Standard Deviation, % means percentage of all facial expressions during sleep.

### B. Statistical Analysis

Hypothesis testing included general linear modeling (GLM) using R version 4.2.3 and jamovi version 2.5 [36] [37]. All predictors were mean centered, the data indicated a Gaussian distribution, indicating normal distribution of the residuals. Based on a pre-analysis we ran, total recording time was no significant predictor of sad affect during sleep ($p > .05$). Consequently, we ruled out total recording time as covariate in the main models.

Using the spicy.stats package and the sf() function in Python [38], we calculated the $p$ value of the $\chi^2$-statistic as function (1).

$$p\_value\_df\_1 = stats.chi2.sf(chi\_square\_value, df\_1) \quad (1)$$

The call for hypothesis 1 (higher levels of depressed affect prior to sleep predict higher levels sad affect during sleep (H1)) was built on the function (2). The call for hypothesis 2 (higher levels of sad affect during sleep predict lower levels of depressed affect in the morning (H2)) was built on function (3).

$$glm(SadAffect\_Sleep \sim 1 + DepressedAffect\_preSleep) \quad (2)$$

$$glm(DepressedAffect\_Morning \sim 1 + SadAffect\_Sleep) \quad (3)$$

### C. Statistical Results

The loglikelihood ratio tests for Hypothesis 1 indicated a $\chi^2$ of 4.87 with a degree of freedom of df = 1. Based on the significant $p$ value of 0.027 we calculated using function (1), we rejected the null hypothesis, concluding that the predictor depressive affect prior to sleep has a statistically significant effect on the predictor sad affect during sleep. The model summary for function (2) confirms our first hypothesis: Higher levels of depressed affect prior to sleep were significantly predicting higher levels of sad affect during sleep, $R^2 = 20.4$, $B = 7.00$, $t = 2.20$, $p = 0.040$.

This result demonstrates that a one-unit increase in depressed affect prior to sleep (on a scale from 0-10) was associated with an increase of 7 minutes in sad affect during sleep. Effect size (*Beta* = 0.45) was medium.

For hypothesis 2, the loglikelihood ratio tests indicated a $\chi^2$ of 1.41 with a degree of freedom of df = 1. Based on the nonsignificant $p$ value of 0.235 we calculated using function (1), this result favors the null hypothesis, concluding that the predictor sad affect during sleep has no statistically significant effect on the predictor depressive affect in the morning. These results map with the summary for function (3) in Table 3.

Table 2 yields the model summary for hypothesis 1, Table 3 yields the model summary for hypothesis 2.

TABLE II. PARAMTER ESTIMATES (HYPOTHESIS I)

| Predictors | | | | 95% (*B*) CI | | | |
|---|---|---|---|---|---|---|---|
| | ***B*** | ***SE*** | ***Beta*** | ***Lower*** | ***Upper*** | ***t*** | ***p*** |
| Intercept | 75.80 | 10.73 | 0.00 | 53.35 | 98.30 | 7.07 | <.001 |
| DA_pre Sleep | 7.00 | 3.16 | 0.45 | 0.35 | 13.60 | 2.20 | 0.040 |

TABLE III. PARAMTER ESTIMATES (HYPOTHESIS II)

| Predictors | | | | 95% (*B*) CI | | | |
|---|---|---|---|---|---|---|---|
| | ***B*** | ***SE*** | ***Beta*** | ***Lower*** | ***Upper*** | ***t*** | ***p*** |
| Intercept | 2.45 | 1.01 | 0.00 | 0.34 | 4.56 | 2.43 | 0.025 |
| SA_Sleep | 0.72 | 0.61 | 0.26 | -0.55 | 1.99 | 1.19 | 0.249 |

*Note*. DA_preSleep = Depressed Affect prior to sleep, SA_Sleep = Sad Affect during Sleep, *B* = unstandardized regression coefficient, *SE* = Standard Error, *Beta* = standardized regression coefficient, CI = Confidence Interval, *t* = t-value, *p* = significance level at $p < .05$.

## IV. DISCUSSION

This proof-of-concept research had a double aim: First, to provide a novel measure of affect during sleep and second, to assess the bidirectional associations of depressed daytime affect and sad affect during sleep. In line with the first objective, extracting sad affect from facial expressions was feasible using artificial intelligence software frameworks based on deep neural networks. Extracted affect was in alignment with evidence-based measures of sad affect (FACS) [33], demonstrating preliminary evidence for the validity and feasibility of the novel method. Congruent with our first hypothesis, levels of depressed affect prior to sleep were predictive of sad facial expressions during sleep. Sad facial expressions during sleep, on the other hand, were unrelated to next-day-affect. Clinical and general implications are discussed in the following.

### A. Innovations of the approach

To the best of our knowledge, this is the first study to investigate affect during sleep unobtrusively. The present method utilizes infrared technology connected with the application of deep neural networks, which offers several methodological advantages: The unobtrusive measure circumvents methodological challenges arising from previous methods, as it provides a noninvasive, economic measure that abstains from instrumental awakenings and retrospective measurements. In addition, prior studies on affect during sleep

used facial EMG to assess mood states during sleep [17] [39]. By contrast, these studies did not correlate facial EMG activity during sleep with daytime affect [17] [39]. Since translational clinical evidence underscores the bidirectional associations of affect and sleep [4], we aimed to address this research gap in the present study. Further, as opposed to previous ML approaches [40], we used a pre-trained, economic and accessible open-source AI framework. Consequently, the method appears suitable for clinicians, health practitioners and biomedical engineering applications.

### B. *Evening affect predicting affect during sleep*

In line with our first hypothesis, higher levels of depressed affect prior to sleep predicted higher levels of sad affect during sleep (H1). This finding aligns with the key tenet of the affective continuity framework [12] [13], presuming that daytime affect translates to proximal sleep intervals. In contrast to previous findings, however, the present result extends the construct of affective continuity to the state of objective affect. In comparison, previous research has predominantly focused on subjective dream reports as affect indices (e. g., [41]). In addition, some studies have reported null findings between evening affect and subsequent dream mood [42]. As the absence of temporal proximity may account for these mixed findings, the present measure emerges as one promising alternative for studying sleep-related affect, providing a temporally close link between evening affect and affect during sleep. Hence, these results may aid in the investigation of the sleep-wake continuum of affect. In addition, replicating the result in a larger sample would also support the hypothesis that affective negativity during sleep can be related to pathological constructs with decreased positivity at wake state [43] since negative affect prior to sleep and negative affect during sleep were substantially related.

The continuity of depressed affect to sleep suggests that the emotional activity prior to sleep impacts the affective experience during sleep. Different factors may account for the association we found. Depression is associated with substantial alterations in REM sleep as compared to healthy controls; including a more rapid entrance in REM sleep after sleep onset (i. e. the REM onset latency) and a higher REM density [44]. This sleep stage is associated with more vivid dreaming [45] and a heightened emotional activity [46]. In line with this, Reference [47] conclude that REM alterations promote more intense negative dreams [48] and cognitive distortions [49] in depressed individuals. Aggregating these results and the result we obtained, depressed mood states prior to sleep may increase negative emotional experiences during sleep via an alteration of sleep architecture, thereby promoting sad affect during sleep. Notably, the results we obtained refer to depressed mood levels in a healthy sample. Yet, pre-sleep emotion induction can alter REM sleep parameters [50] and REM alterations are found in people without depression who undergo transient stress [51]. Conclusionally, our results confirm the predicted affective continuity, whereas more research is necessary to draw conclusions on the mechanisms conveying associations between depressivity and sad affect during sleep.

### C. *Affect during sleep and next-day affect*

In contrast to our second prediction, higher levels of sad affect during sleep did not significantly predict lower levels of depressed affect in the morning (H2). Instead, our results favored the null hypothesis; affect levels during sleep were unrelated to morning affect levels. The absence of predictive power of sad facial expressions during sleep on next-day affect suggests that affect during sleep does not necessarily translate into affective states upon awakening. If these results can be replicated in a larger sample, one possible explanation is that sleep's function may primarily serve to regulate or attenuate the emotional charge of affective stimuli, promoting a decoupling of affect during sleep and next-day affect. Another explanation is that moderating factors, such as the quality of sleep, influence the association between affect during sleep and next-day affect. The processing of emotional stimuli may depend on the level of sleep being unimpaired by the emotional experience during sleep. Aligning with this, in a review, Reference [52] emphasize the relevance of adequate sleep quality to convey adaptive emotional processing during sleep. These results highlight the principal role of good sleep in promoting emotional processing, simultaneously allowing recovery through sleep.

## V. ETHICAL CONSIDERATIONS

The use of Machine Learning for the measurement of sensitive data involving personal or biometric information, requires to be carefully revised. Ethical considerations must be thoroughly integrated into such applications. In the present study, we employed a two-step approach to ensure data privacy and ethical integrity. In the first step, all data was made accessible to the participant, located on their personal device for revision. In the second step, the data was analyzed using the ML approach we developed. Whereas converting facial expression data into digital format enhances the protection of personal information, all stages of data analysis had to adhere strict data management protocols. While ethical considerations have to be integrated in ML research, we consider the monitoring of health indicators during sleep as crucial for the development of early prevention tools, complementing existing sleep assessments.

## VI.CONCLUSION AND FUTURE WORK

In the present work, we provide preliminary evidence for a novel, unobtrusive measurement of affect during sleep. Monitoring noninvasive markers of depressed affect during sleep may depict one relevant future preventive tool for subclinical assessments, supporting the detection of early signs of depressed states. Using ambulatory, nonobtrusive and accessible tools can pave the road for preventing the escalation of sadness into more severe clinical conditions such as clinical depression. Simultaneously, the present method may be validated in clinical follow-up evaluations. Conclusionally, further validating this marker of affective experience during sleep in clinical populations has the potential to advance affective sleep science.

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