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Table 1 to 8 are available in the Supplementary Files section.

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Abstract

The affective sciences have predominantly investigated affective states at wakefulness. This leaves a significant research gap since affective processes during sleep remain largely unexplored. This research gap is particularly important given that evidence suggests that sleep is one critical timespan for affective processing. To date however, methodological limitations challenge the assessment of affect during sleep. To overcome these challenges, we propose a novel, contactless approach for the automated assessment of nocturnal affect using infrared recordings of facial expressions (ASANA-IF). ASANA-IF consists of three components: (1) recordings of facial expressions during sleep with infrared cameras, (2) extracting affective states from these expressions using machine learning tools for objective emotion assessment (OpenFace, a validated tool based on deep neural networks), (3) aggregating these estimates within domains of emotion (e.g., anger, fear) with an algorithm developed for this purpose. To explore the feasibility and validity of ASANA-IF, we used this approach to assess nocturnal affective states in 4 participants over 21 nights from 3 perspectives. Here, we empirically tested the hypothesis that affective states during sleep (anxious, angry, sad and happy affect) would predict self-reports of respective affective states on the following day. Findings provide evidence for the feasibility of ASANA-IF. Moreover, they confirm the hypothesis that nocturnal affective states predict levels of respective affective states on the following day. Future research should further improve this new approach and use it to address research questions associated with assessing nocturnal affect in a feasible and valid way.

Keywords Affect · Emotion · Machine Learning · Nocturnal Assessment · Sleep

1 Introduction

Affect (i.e., an umbrella term for emotions and moods) is regulated within a 24-h circadian cycle (Stone et al. 2006; Sikka & Gross 2023), displaying significant variation across the sleep-wake continuum (Sikka & Gross 2023). Despite this variation, traditional affective science has largely focused on the investigation of affect at wakefulness, with comparatively limited attention to the investigation of affect during sleep (Sikka & Gross 2023).

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This gap in research is relevant since sleep is one critical timespan for emotional processing (Walker & van der Helm 2009). Sleep, in particular rapid eye movement (REM) sleep, supports the consolidation of affective memories (Walker & van der Helm 2009; Hu, Stylos-Allen, & Walker, 2006), the regulation of emotional reactivity (Walker & van der Helm 2009; Yoo, Gujar, et al. 2007), and the recalibration of limbic-prefrontal circuits for the restoration of emotional brain sensitivity the next-day (Goldstein & Walker 2014). The close link between sleep and affect is underscored by the fact that several affective disorders are associated with REM sleep alterations; the sleep stage assumed to be most strongly associated with emotional processes (Walker & van der Helm 2009; Rivera-García et al. 2019). For example, in major depressive disorder (MDD), these alterations include a shortened REM sleep onset latency (i.e., the time until entering the first REM episode) and an increased REM density (the density of rapid eye movements) (Pillai et al. 2011). Moreover, a high REM density has been found in individuals with a high genetic risk for affective disorders (Modell et al. 2005). Finally, depressed individuals have been shown to exhibit overactive limbic activity from waking to REM sleep in the midbrain reticular formation and in the anterior paralimbic cortex, which

has been suggested as susceptibility towards negative affect during sleep (Nofzinger et al. 2000). Despite evidence for the importance of affective processes during sleep for mental health, however, there are hardly any studies investigating specific affective states during sleep, nor studies on antecedents and consequences of such states. As a result, affective processes during sleep and their implications for depression and other mental health conditions remain poorly understood. This significant gap in empirical research on affect during sleep can be explained by methodological challenges inherent to assessing affect during sleep. These challenges include the following: First, conclusions on affect during sleep are primarily based on participants' subjective reports of dream experiences (Sikka & Gross 2023), which are inherently vulnerable to inter- and intraindividual variability (Elce et al. 2025). Second, standard contact-based methods such as Polysomnography (PSG), including facial Electromyography (EMG), provide high temporal resolution data but are constrained by low ecological validity and high participant burden (Patterson et al. 2023). In particular, electrode placement can disrupt natural sleep patterns, potentially confounding the affective experience during sleep. Finally, novel approaches utilizing wearable devices for objective physiological measures can unobtrusively capture autonomic activity, such as cardiac autonomic indices during sleep (De Zambotti et al. 2024), but fail to accurately capture the valence of emotions during sleep. Therefore, they cannot validly differentiate between emotions such as fear and anger during sleep. To overcome these limitations, significant promise emerges from recent advances in contactless optical assessments and machine learning technology. The latter had been shown to be able to accurately assess emotions from information contained in facial expressions (Khan 2022). So far, these algorithms have not yet been used to assess nocturnal emotion from video-based technology, since optical approaches requires sufficient illumination (Cai et al. 2022) and can, hence, not be used to measure nocturnal affect. However, recent developments in infrared and radar technology provide the possibility to capture optical data in the dark, which can then be analyzed using automated detection software. However, so far, the feasibility and validity of this approach has not been investigated systematically. To bridge this gap, the present research aims to introduce a novel, contactless approach for the *Automated Assessment of Nocturnal Affect Using Infrared Recordings of Facial Expressions* (ASANA-IF). ASANA-IF combines the following components: (1) infrared recordings of facial expressions during sleep, (2) the extraction of quantitative estimates of affective states from these expressions using machine learning tools developed for the automated assessment of emotion (OpenFace, Baltrušaitis et al. 2016), and (3) the aggregation of these estimates within distinct domains of affect (e.g., anxiety, anger, sadness) with an algorithm developed for this purpose. Moreover, we will present findings from a study exploring the feasibility and the validity of ASANA-IF. To evaluate the latter, we used ASANA-IF to test the hypothesis that affective states during sleep can predict respective affective states on the following day. Based on existing literature, two distinct directions of the association between nocturnal affect and daytime affect can be presumed: The affective continuity hypothesis states that daytime affect is mirrored in affect during sleep (Schredl & Hofmann 2003; Sikka & Gross 2023). Consequently, affect during sleep may positively predict next-day affect. By contrast, Walker & van der Helm (2009) propose that affect is reactivated and regulated during sleep in healthy individuals. Consequently, experiencing affect during sleep may lead to affective processing, resulting in negative prospective associations between affect during sleep and next-day affect. Given that both sleep quality and total sleep time significantly impact next-day affect (Bouwmans et al. 2017; Barber et al. 2023), there is a need to control for these two factors when exploring which of the two theories can be empirically confirmed using the present paradigm.

2 Method

2.1 Design and Procedures

The study design consisted of a one-arm, longitudinal ambulatory study, participants received no intervention or manipulation. Before initiating the study, a system of three infrared night-vision cameras (Imou Life Rex 3D IPC-A26LP) was installed in each participant's dormitory room for facial infrared video recording during sleep. The infrared cameras were positioned as follows: one on each side of the bed (left and right) and one centrally placed above the head. All devices were adjusted to maintain a distance of 30 cm from the participant's face, with the lateral cameras additionally adjusted to ensure optimal angular alignment. Participants then received a test run demonstrating the experimental procedure, including instructions for the video recordings. For completing the associated digital surveys, a file was distributed containing survey access links, guidelines for pre-sleep video recordings, and a personalized log sheet for video recordings and survey responses. To minimize potential confounding due to the "first-night effect" (Agnew et al. 1966) and to support the participants' habituation to the experimental setup, a test night was conducted following the experimental setup. After the feedback from the test night was implemented, the formal data collection phase was initiated. On the first day of the study, participants completed baseline self-reports measuring stress, emotion regulation, depressivity and sleep quality. Additionally, sociodemographic information was completed. On the following 21 days, participants completed the daytime

affect survey three times daily: in the morning, at midday, and in the evening. Each daytime affect survey included 20 items assessing state affect and stress. These items were developed by the authors to evaluate daytime affect and sleep-related affect. This was the prerequisite to determine the prospective associations between sleep affect collected overnight and next-day affective states. The morning version of the daytime affect survey included additional items addressing sleep-related factors from the previous night, including the sleep quality and questions regarding sleep hygiene behaviors, medication use, and the presence of pain in the last night. Completion of each daytime affect survey took approximately 15 minutes. In parallel, for 21 consecutive nights, participants initiated the infrared video recordings immediately before sleep and stopped them upon awakening the following morning. All datasets were recorded in a time of 84 days and nights (4 x 21).

2.2 Participants

$N = 252$ infrared videos and $N = 252$ surveys were provided by 4 healthy participants (1 male, 3 female). The participants were recruited through advertisements at the Friedrich-Alexander-University Erlangen-Nuremberg. Eligibility was verified based on the following inclusion criteria: (1) an age of at least 18 years, (2) German skills of ≥ C1, (3) informed consent and (4) an agreement on providing video recordings over 21 nights. Exclusion criteria included: (1) meeting the criteria of ≥1 psychiatric disorder assessed by clinical psychologists with the Screening Version of the Structural Clinical Interview based on DSM-V (SCID-V-Screening) (American Psychiatric Association 2013) at the University Outpatient Clinic for Psychological Psychotherapy of the Friedrich-Alexander-University Erlangen-Nuremberg. Further exclusion criteria included (2) a sleep onset latency of > 20 minutes, (3) a sleep duration of < 6 hours, (4) symptoms of primary insomnia in the Regensburg Insomnia Scale (RIS) (Crönlein et al. 2013) (cut-off score = 13), (5) facial paralysis and (6) non-organic and organic sleep disorders.

2.3 Compliance with Ethical Standards

Transparent information regarding the studys' variables, procedure, data analysis and data management was provided as part of the informed consent that was obtained from the participants. Equally, prior to participating in the study, informed consent was obtained from the participants to publish their data. The study was conducted in accordance with ethical standards as defined by the World Medical Associations' Declaration of Helsinki (World Medical Association 2013). Ethical approval for the study was granted by the Ethics committee of the medical faculty of the Friedrich-Alexander-University Erlangen-Nuremberg on the 07.01.2024 (24-11-B).

2.4 Measures

2.4.1 Sleep Affect: Development of ASANA-IF

The primary analysis tools included the open-source software framework OpenFace (Baltrušaitis et al. 2016), a validated software framework operating on deep neural networks for facial behavior analysis, including facial landmark detection, head pose estimation, facial action unit recognition and eye-gaze estimation (Baltrušaitis et al. 2016). While OpenFace has been applied in several studies on affect and emotions at wakefulness (e.g., Kosch et al. 2020), we firstly used it for the analysis of infrared videos, enabling the unobtrusive, automatic assessment of sleep affect. Each video was sampled at a rate of 25 Hz. To restrict the analysis to facial activity, the processing pipeline "facial" was applied within OpenFace. As illustrated in Figure 1 (see supplementary material), all infrared video recordings of the participants (average total recording time: 7:18 hours per night) were analyzed framewise to extract the presence and duration of facial expressions associated with affective states during sleep. In the first step, infrared frames were cropped to isolate relevant facial regions ("crop"), reducing noise in the data. In the second step, deep neural networks transformed these frames into three-dimensional facial landmarks, comprised of x, y, and z spatial coordinates, representing all distinct areas of the face ("3 D landmarks"). In a third step, facial muscular movements were quantified by calculating the Euclidean distance between successive facial landmarks, allowing for the detection of facial micro-expressions ("Euclidian distance"). For instance, movements like lifting a mouth corner change the Euclidean distance between successive facial landmarks. In a fourth step, Action Units (AUs) were extracted using a deep learning algorithm based on these Euclidian distance changes. AUs are discrete facial muscle movements, categorized in the Facial Action Coding System (FACS; Ekman & Friesen 1978). The FACS is a standardized taxonomy that objectively categorizes facial muscle activity as distinct AUs. Affect detection during sleep was based on the core AU patterns associated with specific emotions in the FACS manual (Ekman et al. 2002). Sad affect is defined as the concurrent activation of AU 1 (inner brow raiser), AU 4 (brow lowerer), and AU 15 (lip corner depressor). Happy affect is defined as the concurrent activation of AU 6 (cheek raiser) and AU 12 (lip corner puller). Anger is defined as the concurrent activation of AUs 4 (brow lowerer), AU 5 (upper lid raiser), AU 7 (lid tightener), and AU 23 (lip tightener), while anxiety is defined as the concurrent activation of AU 1 (inner brow raiser), AU 2 (outer brow raiser), AU 4 (brow lowerer), AU 5 (upper lid raiser), AU 7 (lid tightener), AU 20 (lip stretcher), AU 26 (jaw drop). To ensure a rigor analytic approach, we exclusively classified the concurrent activation of all specified AUs exclusively for a given affective

state as affect during sleep. Partial activation of AUs was not rated sufficient for extracting affective states. Further, only consecutive frames were classified as affective states. This distinction was relevant in order to isolate affective states that are longer-lasting from muscle twitching that can occur during REM sleep.

2.4.2 Daytime Affect

Daytime affect was assessed using a daytime questionnaire containing 15 state items on negative and positive affect. Sad affect was measured with the daytime affect survey item "To what extent do you feel sad right now?", angry affect "To what extent do you feel angry right now?", anxious affect "To what extent do you feel anxious right now?", happy affect "To what extent do you feel happy right now?", all answered on a 10-point Likert Scale (1 = not at all – 10 = very high). The midday and evening daytime questionnaire comprised the 15 state items exclusively.

2.4.3 Potential Confounds

In addition to the 15 state items, every morning questionnaire comprised 5 additional items on potential confounds: sleep quality, pain, sleep medication, dreams and one sleep hygiene factor. Self-perceived sleep quality was assessed with the item "How would you rate your sleep quality in the previous night?" (1 = very low - 10 = very high), self-perceived pain with the item "How would you rate your pain levels in the previous night?" (1 = very low - 10 = very high), the use of sleep medication with the item "Did you use any sleep medication in the previous night?" (Yes/No), the presence of dreams with the item "Do you remember one or more dream(s) in the previous night? (Yes/No) and sleep hygiene with the item "Did you sleep alone last night?" (Yes/No).

2.4.4 Secondary Outcomes: Stress, emotion regulation, depressive symptoms, sleep quality

General stress levels were measured using the German version of the Perceived Stress Scale (PSS; Klein et al. 2016). A shortened 10-item version with a five-point Likert scale (1 = never - 5 = very often) was used to assess the extent to which individuals perceived their daily demands and stressors as uncontrollable and overwhelming. Emotion-specific self-perceived competencies and general emotional well-being were assessed with the SEK-ES questionnaire (Ebert, Christ & Berking 2014). The instrument is divided into two parts: Part A covers emotions and moods in general, while Part B focuses on specific emotional situations. All items were rated on a five-point Likert scale (ranging from 1 = not at all - 5 = completely). Depressive symptoms experienced during the past week were assessed using the Allgemeine Depressions Skala (ADS; Hautzinger & Bailer 1993). The ADS consists of 20 items rated on a four-point Likert scale (0 = rarely - 3 = most of the time). Sleep quality from the previous month was assessed using the German version of the Pittsburgh Sleep Quality Index (PSQI) (Backhaus et al. 2002). The 18 items assess the frequency of sleep disturbances, subjective sleep quality, usual sleep times, sleep onset latency and duration, use of sleep medication and daytime sleepiness. Each item was rated on a scale from 0 - 3 (meaning), with a total score ranging from 0 to 21, with higher scores indicating poorer sleep quality.

2.4.5 Feasibility

To assess the technical feasibility, we determined whether affect can be reliably extracted during sleep (operationalized as obtaining complete, analyzable data for all targeted parameters across participants and nights), and whether the technical setup functions robustly, including reliable infrared video recordings, uninterrupted data acquisition and the absence of hardware or software failures. To determine the feasibility of the approach rated by participants, we implemented two survey measures following best practice recommendations by Orsmond and Cohn (2015). These survey measures captured dimensions such as patient burden and acceptability of the study procedures. Based on these recommendations, one survey was administered one time a week during the trial (after 1, 2 and 3 weeks), and one survey after the trial on the day following the end of the trial. Table 1 (see supplementary material) depicts the feasibility surveys.

2.5 Data Analysis

To test our hypothesis, we predicted next-day affect (t = next-day affect) by sleep affect of the previous night (t-1 = sleep affect), controlling for sleep quality (t-1) and total recording time of the previous night (t-1). Statistical analysis included general linear modeling (GLM) using R version 4.2.3 (R Core Team, 2023), lme4 package (Bates et al. 2015) and jamovi version 2.5 (The jamovi project 2024), GAMLj package (Galluci 2019) to examine prospective associations between sleep affect and next-day affect. Because predictors were measured on different scales, all predictors were z-standardized (mean-centered and divided by their standard deviation) before analysis. This allowed the interpretation of regression coefficients as the change in the outcome per one standard deviation increase in the predictor, thereby allowing direct comparison of effect sizes. The data indicated a Gaussian distribution, indicating a normal distribution of the residuals. All analyses included sleep quality and total recording time as time-varying covariates entered simultaneously in all models. To account for the time series structure of the data, predictors were lagged such that sleep-related variables from day t-1 were used to predict affect on day t. In addition, a fixed effect of time

(day 1-21) was included to account for time-dependent effects (e.g., time trends) across the 21-day assessment.

All models were based on the following formula (1):

(1) $\text{Next-DayAffect}_{t} = \beta_0 + \beta_1 \cdot \text{SleepAffect}_{t-1} + \beta_2 \cdot \text{TRT}_{t-1} + \beta_3 \cdot \text{time}_t + \beta_4 \cdot \text{SleepQuality}_{t-1} + \varepsilon_t$

Where variables and coefficients were defined as the following:

Next-DayAffect_t: Mean Affect of day t (t)

SleepAffect_{t-1}: Mean consecutive frames of Sleep Affect from the previous night (t-1)

TRT_{t-1}: Mean total recording time from the previous night (t-1)

time_t: Time variable (t-1)

SleepQuality_t = Mean Sleep Quality from the previous night (t-1)

β_0: Intercept (baseline level of SleepAffect)

β_1 to β_4: Coefficients representing the effect of each predictor

ε_t: Error term at t, assumed to be normally distributed

3 Results

3.1 Sociodemographic Characteristics of the Participants

Table 2 (see supplementary material) summarizes the sociodemographic characteristics of the participants.

3.2. Feasibility

All video recordings and questionnaires were successfully captured across all weeks, with no camera failures or technical errors reported. Minor procedural issues were limited to a single participant demonstrating one delayed video recording in week 1, which was due to this participant falling asleep while reading, awakening again and then initiating the video recordings. No such issues were observed in subsequent weeks. Data for the analysis of affect during sleep was successfully obtained for all targeted parameters. In sum, the reliable infrared video recording, the uninterrupted data acquisition and the absence of hardware or software failures indicate that ASANA-IF is technically robust. Feasibility rated by participants was consistently high. All participants reported that the questionnaires and instructions for the video recordings were understandable across all weeks of the trial. The study procedures were regarded as feasible, with all participants indicating that they had sufficient time and capacity to complete both the questionnaires and recordings. Similarly, study participation was described as compatible with daily routines by all participants. Study acceptability was consistently rated as high: All participants rated the study as acceptable and stated that they would recommend participation to others. The effort required was perceived as minimal, particularly for individuals comfortable with video-recorded sleep. Further, participants expressed appreciation for the opportunity to contribute to sleep research. Time demands were generally evaluated positively, with questionnaires described as quick and easy to complete. Sleep continuity was slightly affected in one participant, though the changes (slightly decreased sleep continuity) were described as minor and not burdensome, and did, reportedly, not impair the participant's feeling of being well-rested. The participant attributed the slightly decreased sleep continuity to an increased awareness towards sleep rather than to the technology used in the study. Perceived participant burden was rated as low, with ratings ranging from 1 to 3 out of 10 (mean = 2.33/10). Reported burden primarily related to the necessity of remaining at the location where their sleep was recorded. Suggestions for improvement included the use of shorter encryption codes for identifiers and automatic study day settings. In their overall ratings, all participants expressed satisfaction with the study procedures and outcomes, valuing the opportunity to contribute to sleep research. Thus, findings indicate that ASANA-IF is sufficiently accepted by participants.

3.3 Descriptive Statistics of Next-day Affect and Sleep Affect

Table 3 (see supplementary material) summarizes the descriptive statistics of sleep quality and sleep affect, Table 4 (see supplementary material) the descriptive statistics of next-day affect. At daytime, participants generally reported high levels of happiness and positive affect (both means around 6.00), while negative emotions such as anger, anxiety and depressivity were relatively low (means ranging from 1.70 - 1.89). Sad affect and overall negative affect were moderate but still notably lower than positive affect, attributable to the healthy sample. Narrow confidence intervals indicate stable estimates, highlighting a clear dominance of positive affective states over negative affective states in daytime questionnaires. At night, sleep quality was moderate-to-high (mean = 6.01). Sad affect had the highest mean of consecutive frames, where these facial expressions were present (mean of 6,201 frames). By contrast, other negative affects (anxious, angry) were lower on average. Yet, the wide dispersion displayed by all sleep affects highlights strong individual differences in nocturnal emotional experiences.

3.4 Prediction of Next-Day Affect

1) **Prediction of sad affect.** Predicting mean sad affect the next day, the overall model was statistically significant, $R = .613$, $R^2 = .375$, $F(3, 77) = 11.0$, $p < .001$, indicating that approximately 38% of the variance in mean sad affect the next day could be explained by the predictors. Table 5 (see

supplementary material) yields the regression coefficients. Mean sad sleep affect (β = -.243, p = .014), sleep quality (β = -.307, p = .002) and total recording time (β = .504, p < .001) were significant predictors of mean sad affect the next day.

2) **Prediction of anxiety.** Predicting mean anxiety the next day, the overall model was not statistically significant, R = .329, R^2 = .108, $F(3, 77)$ = 2.21, p = .076. Table 6 (see supplementary material) yields the regression coefficients. Total recording time (β = .289, p = .012) was a significant predictor of mean anxiety the next day. Mean anxious sleep affect (β = .104, p = .364) and sleep quality (β = .148, p = .189) and time (β = -.033, p = .772) were no significant predictors.
3) **Prediction of happiness.** Predicting mean happiness the next day, the overall model was statistically significant, R = .502, R^2 = .252, $F(3, 77)$ = 7.74, p < .001, indicating that approximately 25% of the variance in mean happy affect the next day could be explained by the predictors. Table 7 (see supplementary material) yields the regression coefficients. Mean happiness during sleep (β = .290, p = .006) and total recording time were significant predictors (β = - .370, p < .001). Sleep quality (β = .085, p = .410) and time (β = - .157, p = .127) were no significant predictors of mean happiness the next day.
4) **Prediction of anger.** Predicting mean anger the next day, the overall model was statistically significant, R = .518, R^2 = .268, $F(3, 77)$ = 6.69, p < .001, indicating that approximately 27% of the variance in mean anger the next day could be explained by the predictors. Table 8 (see supplementary material) yields the regression coefficients. Mean angry sleep affect (β = -.140, p = .170) and time (β = .061, p = .550) were no significant predictors of anger the next day. Sleep quality (β = -.289, p = .006) and total recording time (β = .440, p <.001) were significant predictors of mean anger the next day.

4 Discussion

4.1 General Discussion

Sleep is one critical timespan for affective (re)processing and the modulation of affective neural circuits (Walker and van der Helm 2009). Despite evidence for the importance of affective processes during sleep, however, there are few studies quantifying affective states during sleep, nor studies aiming to identify antecedents and consequences of nocturnal affective states. This significant research gap can be explained by methodological constraints challenging the systematic and objective assessment of nocturnal affect. To overcome these challenges, we have proposed a novel approach for the contact-free investigation of affect during sleep. Unlike traditional methods used in sleep research (Saleem et al. 2020), ASANA-IF extracts indicators of affect during sleep without electrode placement; instrumental awakenings (Rivera-García et al. 2019) or retrospective dream reports (Yu 2007). This offers novel insights within the field of affective sleep science, which may be particularly advantageous for research on affective disorders and sleep-dependent emotional processing. Further, previous research has dominantly investigated the impact of sleep quality (Bouwmans et al. 2017) and sleep architecture (e.g., changes in slow wave sleep; Finan et al. 2015) on affect at wakefulness. The present work extends the state of research by demonstrating that affective states during sleep in fact predict affective states the next day, even when controlling for sleep quality and total recorded sleeping time. As opposed to existing methods like retrospective dream reports, ASANA-IF offers major strengths through the high temporal resolution and the objective assessment of affect during sleep. Retrospective self-reports may provide an incomprehensive representation of affect during sleep as they are limited by low temporal resolution (Sikka and Gross 2023) and a susceptibility to inter- and intraindividual variability (Elce et al. 2025). By overcoming these methodological constraints, the present method has the potential to reduce discrepancies between objective sleep measurements and subjective sleep reports (e.g., Hughes et al. 2018). Compared to gold-standard PSG requiring multiple electrode placement and paradigms using instrumental awakenings, ASANA-IF is contact-free, enabling the economic assessment of affective states in ecologically valid sleep settings. The absence of contact-based sleep interferences can represent a particularly strong advantage for research in clinical populations, preventing high levels of patient burden. Thereby, the current method goes beyond previous research, where dream affect inferred from instrumental awakenings was predicted by neural signatures (i.e., the EEG frontal alpha asymmetry) (Sikka et al. 2019). Utilizing ASANA-IF, we found that higher levels of sad affect during sleep predicted lower levels of corresponding affect the next day, suggesting affective regulation during sleep. This result aligns with one core function of sleep, suggesting that sleep "resets" the affective brain reactivity the next-day by maintaining the functional integrity of limbic and prefrontal neural circuits overnight (Walker and van der Helm 2009). To our knowledge however, this is the first study to directly link objective affective states during sleep with post-sleep affective levels, rather than only comparing pre- and post-sleep affective levels (e.g., Atunes-Alves and De Konick 2012). Building on this novel link, experiencing sad affect during sleep may serve an adaptive function by supporting emotional coping, for instance by promoting disengagement from unattainable goals, habituation towards sadness or disengagement from sadness- evoking stimuli at wakefulness. The investigation of depression and sadness-related affective processes during sleep may further deliver important insights into clinical disorders: The current state of research allows to determine the impact of sleep parameters (e.g., sleep duration, sleep quality and REM continuity) on affect at wakefulness. The present approach extends this framework by examining the affective processes unfolding within sleep itself. Thereby, ASANA-IF can deliver important insights into the vicious cycle of depression and sleep: For instance, a high REM density may be maladaptive if accompanied by negative affect during sleep, but potentially adaptive when coupled with positive affect. In depression, a

heightened limbic activity during sleep could reflect either a general susceptibility towards high affect during sleep, or a specific bias towards negative affect (as proposed by Nofzinger et al. 2000). Further, the present paradigm may help clarifying if nocturnal affect contributes to the maintenance of depression over and above sleep quality. Measuring the valence of affective states during sleep could thereby support differentiating potential processes and deepen the understanding of affective dysregulation in clinical conditions. By contrast, fear and anger levels during sleep did not significantly predict fear and anger levels the next day. These null findings contrast with previous research, suggesting that fear processing in dreams can facilitate more adaptive responses to negative stimuli during wakefulness, similar to fear extinction (Sikka et al. 2022; Scarpelli et al. 2019). The obtained results highlight the relevance of assessing valence and arousal simultaneously, as the relationship of these dimensions appears to be complex in the context of sleep. For instance, high-arousal affect such as anger may require conscious cognitive processing during wakefulness in order to be processed adequately. The null findings may therefore suggest that not all affective states experiences during sleep are processed simultaneously, and that some degree of priorization occurred. Alternatively, this result could reflect that anger and fear had been diminished after sleep, leading to an absence of a measurable impact on next-day mood. Ultimately, higher levels of positive affect during sleep significantly predicted higher levels of positive next-day affect. This result aligns with the affective continuity hypothesis, suggesting that pre- and post-sleep affect levels correspond with affect during sleep (i.e., dream affect; Schredl and Hofmann 2003). Importantly, previous work has supported this hypothesis with retrospective dream reports, by contrast, the present result delivers evidence using a novel marker of affect during sleep. If supported by a greater sample, the result may align with previous findings demonstrating a reward bias during sleep, where rewarding stimuli (compared to non-rewarding stimuli) are preferentially replayed and consolidated during sleep (Sterpenich et al. 2021). Strikingly, the observed affective processing of both negative and positive affect (diminishing negative affect while enhancing positive affect) could suggest a functional role of nocturnal affect in supporting emotional resilience in healthy people. If confirmed in a larger sample, these findings would suggest that the pathway of sleep-based affective processing depends upon both affective valence and arousal, rather than reflecting a general regulation or continuity mechanism. Of note, these inferences cannot be made until confirmed in a larger cohort. Taken together, the present findings align with previous research emphasizing the close relationship between emotion and sleep (Goldstein & Walker 2014; Vandekerckhove & Cluydts 2010). While the current results suggest adaptive emotional regulation of depression-related affect in a sample of healthy people, maladaptive emotional regulation and generation following low quality sleep contributes to the development of mood disorders (Palmer and Alfano 2017). Consequently, the present method may be especially beneficial in clinical populations, where sleep-dependent affective processing is presumably disturbed (Walker and van der Helm 2009). The findings support the view that sleep is not a passive process; but an active phase for the processing of different affective states, impacted distinctively by both affect and arousal. Ultimately, the results support the relevance of assessing affective states during sleep and their impact on next-day affect, since controlling for sleep quality and total sleep time suggest that affect has a significant impact on next-day affect that cannot be explained by restorative benefits of sleep.

4.2 Limitations

Limitations of the study include the small sample size. Despite generating 252 datapoints that ensured sufficient statistical power for longitudinal analysis, it is of note that the sample was comprised of only four individuals. Thus, the external validity of the study is limited. In addition, the sample may not be fully representative, as participation in such a study is likely to attract a subset of individuals who may differ systematically from the broader population (e.g., individuals less prone to anxiety). Furthermore, we did not assess sleep stages. Therefore, it remains unclear if affective processes indeed occurred during REM sleep, as suggested by previous research (Rivera-García et al. 2019). Additionally, we did not assess further objective indicators of affective states, such as EMG, EKG, accelerometry, or self-reports on perceived affect. Thus, it remains unclear how these indicators of affective states would relate to those assessed by ASANA-IF and to what extent a multi-source assessment of affective states can assess such states in a more valid way than a one-source assessment.

4.3 Future Work

Future studies should work to replicate present findings with a larger sample size and include other indicators of nocturnal affective states. With this technology, such research might aim to answer the following research questions:

1) Depression and affect regulation: Does nocturnal affect contribute to the maintenance of depression over and above sleep quality?
2) Adaptive functions of negative affect: Is nocturnal sadness adaptive by helping individuals disengage from unattainable goals?
3) Role of positive affect: To what extent does nocturnal positive affect support the restoration of mental and somatic energy?
4) Dynamic interplay of affective states: Does a sequence of negative nocturnal affect (sadness or fear) followed by positive nocturnal affect reflect successful disengagement or habituation?
5) Intervention possibilities: Can adaptive nocturnal affect be fostered through interventions applied prior to or during sleep, such as cognitive-behavioral techniques, relaxation exercises, or targeted memory reactivation (TMR)?

By addressing these concrete questions, future research could clarify how nocturnal affect contributes to emotional functioning and emotional dysregulation with the help of the present method.

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4.5 Statements and Declarations

The authors hereby disclose financial or non-financial interests that are directly or indirectly related to the work submitted for publication. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

4.6 Code Availability

The source code used in this study is available from the corresponding author upon reasonable request.

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Figures

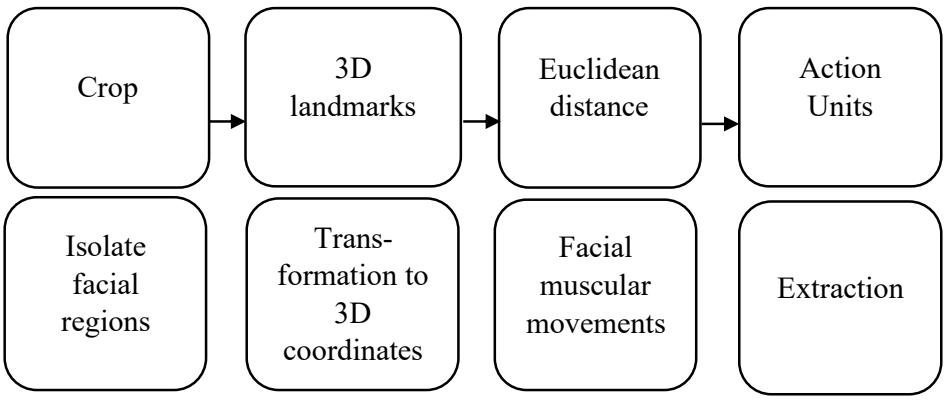


Fig 1 Processing pipeline within OpenFace (Baltrušaitis et al. 2016)

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