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PREDICTING AFFECTIVE EPISODES THROUGH DIGITAL MONITORING OF CIRCADIAN RHYTHM DISTURBANCES: A SYSTEMATIC REVIEW OF MODERN TECHNOLOGY APPLICATIONS

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ABSTRACT

Introduction: Affective disorders are serious, long-lasting, and often relapsing conditions that strike an individual unpredictably. The ideal psychiatric monitoring mechanism would predict coming episodes before their full-blown clinical symptoms develop. This would be a tremendous advance and may be possible using our current understanding of the nature of affective disorders, portable device-based data collection capabilities, and remote data analysis. There are numerous reviews of the literature that cover the symptom recognition of affective disorders using mobile devices, but there are no reviews on the actual prediction of affective episodes. This review aims to cover that gap. **Methods:** A systematic review of five databases (2016-2025) was conducted and included 10 observational studies, mostly designed as prospective cohorts, that concentrated on the prognosis of affective disorders and utilized wearable devices. The variables under study were circadian parameters, sleep metrics, amounts and intensity of physical activity, and light exposure. Although the methodological diversity among the studies made direct comparisons problematic, the studies allowed for the identification of certain findings that appear promising for predicting the occurrence of affective episodes. **Results:** The review encompassed 10 observational studies (1416 subjects). Our synthesis showed that it is possible, even feasible, to predict affective episodes using mathematical models. These models assess the types of characteristic disturbances that individuals with affective disorders have in their circadian rhythms. When we applied some standard methods for doing this kind of analysis (Accuracy Metrics and AUC Values), the results gave us AUC values that ranged from about 0.67 to 0.98, depending on several factors. **Conclusions:** Predicting affective episodes is possible using wearable technology or smartphone app, which can detect disturbances in a person's circadian rhythm. Currently, the best methods for doing this merit a look because they could indeed allow for early intervention before the onset of manic or depressive symptoms.

KEYWORDS

Affective Disorders, Prediction Models, Circadian Rhythms, Mobile Health Monitoring, Digital Psychiatry

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Introduction.

Purpose of The Systematic Review

The subject of the present paper is a literature review regarding the application of wearable devices among patients with affective disorders. Traditional psychiatric methods such as questionnaires, clinical interviews, and observational assessments have limitations in diagnostic capabilities and treatment monitoring. Currently, most psychiatric patients do not require inpatient care; their treatment primarily involves outpatient counseling. This shift is largely due to the development of effective medications with relatively mild side effects. Outpatients are generally capable of societal functioning; however, difficulties arise during episodes of exacerbation or treatment non-adherence. Under these conditions, patients may experience impaired judgment regarding their health status, confusion, and a lack of awareness about the necessity to seek specialist advice for treatment modification or initiation.

The increasing prevalence of mental health conditions has exacerbated challenges related to healthcare accessibility. (Wu, Y., 2024) A potential solution to these issues lies in leveraging rapidly advancing technologies, which have become increasingly affordable to individuals of average income. (Lyu et al., 2024) The intersection of psychiatry and technology has led to extensive research on wearable devices. By registering specific physiological parameters and employing advanced mathematical models, these devices indirectly provide data predominantly on autonomic nervous system functioning, serving as indicators of self-regulation and stress experienced by patients. (Song et al., 2024)

Continuous monitoring facilitates the assessment of functional impairment, even when patients may not fully recognize subtle yet critical changes potentially indicative of an impending disease episode or

exaggerating missing treatment. (Averous, Charbonnier & Dany, 2020) Thus, modern devices—including smartwatches, monitoring bands, and mobile phone applications—can be valuable sources of information for clinicians and patients alike. Current research directions are increasingly focused on biological markers including circadian cycles, sleep patterns, activity patterns, speech patterns, social acitivity changes, heart rate changes, light exposition , temperaturę and galvanic skin response.

These emerging technologies function both by automatically recording objective physiological data and by streamlining the collection, processing, and communication of subjective self-reported data requested from the user, thereby providing a contemporary form of questionnaire assessment. Gathering subjective information through the ecological momentary assessment (EMA) model allows for considering the influence of environmental factors, which can be sources of confounding data. Proper and adequate reactions to life events, without taking subjective information into account, may resemble changes in an individual's homeostasis that mimic changes accompanying disease episodes. (Dunster, Swendsen & Merikangas, 2021)

However, beyond scientifically validated efficacy and affordability, successful implementation of these technologies also depends significantly on meeting users' expectations regarding convenience, ease of use, and resistance to interference from everyday activities, as well as encouraging user engagement, particularly for self-report measures. (Van Til, Youngstrom & Allen, 2019)

Overview of Circadian Rhythms, Mood Regulation, and Affective Disorders

Our internal biological clocks, or circadian rhythms, are intimately linked to mental health, and it's becoming clearer by the day just how much this is the case. These near-24-hour cycles—nearly as long as the Earth takes to spin once on its axis—govern essential patterns of biology and behavior. They make us do things with all the precision an orchestra conductor could muster, and they seem to follow some kind of score that was written a long time ago in some predawn stage of evolutionary history (McCarthy et al., 2022; Takaesu, 2018).

Circadian Dysregulation and Mood Disorders

A multitude of studies connects circadian disruptions to the onset, severity, and recurrence of mood disorders like major depressive disorder (MDD), bipolar disorder (BD), and seasonal affective disorder (SAD) (Lanfumey et al., 2013; McClung, 2013; Takaesu, 2018). Individuals affected by these disorders frequently exhibit disturbed sleep, altered melatonin and cortisol patterns, and shifts in mood that consistently align with the circadian clock (Lanfumey et al., 2013; Wirz-Justice & Benedetti, 2019). In bipolar disorder, for instance, sleep–wake irregularities are evident across manic, depressive, and even euthymic states, suggesting that circadian dysfunction is a core mood disorder feature rather than a mere byproduct of episode presentation (Ng et al., 2015; Armitage, 2007). Manic patients show a reduced need for sleep, increased REM efficiency, and exhibit a number of other unique neurophysiological sleep markers. In contrast, depressive episodes are more likely to be accompanied by insomnia, hypersomnia, or significant circadian phase shifts (Hudson et al., 1988; Takaesu, 2018).

In addition, even in the euthymic phases of BD, trait-like circadian disruptions persist, which are evident in the form of lower overall melatonin levels and a delayed sleep-wake pattern compared to healthy controls (Bradley et al., 2017; Nurnberger et al., 2000; Robillard et al., 2013; Takaesu et al., 2016).

Yet, rhythm instability is not merely a consequence of living with BD. A genetic susceptibility may underlie or partially explain why some individuals with BD have such unstable rhythms. This is particularly true for key clock genes like CLOCK, ARNTL, PER1, and CRY2 (also called CRY). Single-nucleotide polymorphisms in CLOCK have been tied to a propensity to relapse in mood episodes and to shifts in one's chronotype (Benedetti et al., 2003; Lee et al., 2010).

Environmental and Lifestyle Stressors

Environmental stressors also significantly influence circadian stability. Life events that are stressful, which often precede mood episodes in BD, can disrupt social zeitgebers and consequently destabilize internal rhythms (Malkoff-Schwartz et al., 1998). Irregular social routines, as captured by the Social Rhythm Metric, are more common in BD patients even during euthymic phases—and can predict both the first onset and recurrence of mood episodes (Shen, Alloy, Abramson & Sylvia, 2008).

Today's modern lifestyle—characterized by artificial lighting, shift work, and irregular sleep—threatens the very backbone of circadian health (Dobrovinskaya, Alamilla, & Olivas-Aguirre, 2024). For instance, night-shift work ups the odds of depression and anxiety by about 40% over the rates seen in day workers (Lee et al., 2017).

Some studies suggest that evening light exposure may fool the brain into thinking it's daytime, leading to the wired-but-tired feeling and reduced mood that some experience when trying to sleep (Dobrovinskaya et al., 2024).

Underlying Biological Mechanisms

Despite the complexity of circadian disruptions, researchers have begun to elucidate several pathways through which these rhythms intersect with mood regulation including: melatonin and the sleep–wake cycle, neurotransmitter regulation, hypothalamic–pituitary–adrenal (HPA) axis and stress response, neurogenesis and neuroplasticity, immune function and inflammation, energy metabolism and brain connectivity.

Melatonin, secreted by the pineal gland under circadian control, signals the onset of night and helps promote sleep. In many mood disorders, melatonin secretion is abnormally timed, reduced in amplitude, or overly responsive to light suppression (Lewy, Wehr, Goodwin, Newsome & Rosenthal, 1981, Lewy, Sack, Miller & Hoban 1987; Lanfumey et al., 2013). These aberrations likely contribute to sleep disturbances and, in turn, intensify mood instability (Takaesu, 2018; Wirz-Justice & Benedetti, 2019).

Clock genes and the suprachiasmatic nucleus (SCN) orchestrate rhythmic fluctuations in key neurotransmitters such as serotonin, dopamine, and norepinephrine (McClung, 2013). When circadian control falters, these chemical messengers can fall out of sync, promoting either hyperactivation (as in mania) or hypoactivation (as in depression). Notably, mice with CLOCK gene mutations display mania-like behaviors tied to altered dopamine signaling (McClung, 2013), underscoring the gene's pivotal role in mood regulation.

The HPA axis normally follows a robust daily rhythm in cortisol secretion, peaking in the morning and tapering by evening. In mood disorders, however, this rhythm can become blunted or reversed, and the axis itself often shows hyperactivity (Havermans, Nicolson, Berkhof & deVries 2010; Lanfumey et al., 2013; McClung, 2013). Disruptions in clock genes can amplify cortisol dysregulation, diminishing stress resilience and perpetuating a vicious cycle of circadian and mood dysfunction (Takaesu, 2018).

Sleep—particularly slow-wave sleep and REM sleep—contributes significantly to synaptic homeostasis, neuronal repair, and adult hippocampal neurogenesis (Armitage, 2007; McClung, 2013). Chronically disrupted sleep and circadian misalignment can hinder these neuroplastic processes, potentially accelerating neurodegenerative changes linked to persistent mood symptoms (Armitage & Hoffmann, 2001; Lanfumey et al., 2013). Encouragingly, interventions that help reset the biological clock, such as light therapy or carefully timed pharmacological treatments, appear to support neurogenesis, offering a mechanistic rationale for their mood-stabilizing effects (Wirz-Justice & Benedetti, 2019).

The immune system and circadian clock engage in ongoing cross-talk, where inflammatory signals can disrupt clock gene expression, and clock genes, in turn, regulate immune responses (McClung, 2013; Wirz-Justice & Benedetti, 2019). Pro-inflammatory states are frequently observed in individuals with MDD or BD, and circadian misalignment can intensify this immune dysregulation, possibly exacerbating mood symptoms (McClung, 2013; Wirz-Justice & Benedetti, 2019).

Cellular energy balance, governed by mitochondrial function, also follows a diurnal pattern under circadian regulation (McClung, 2013). Deficits in mitochondrial efficiency—potentially worsened by circadian disruptions—have been implicated in BD (McClung, 2013). Meanwhile, daily rhythms in brain network connectivity can shift when the clock malfunctions, altering how different regions of the brain interact and compounding the neurobiological basis of mood disorders (Dollish, Tsyglakova & McClung, 2024; Wirz-Justice & Benedetti, 2019).

Underlying Biological Mechanisms

Even though circadian disruptions are quite complex, investigators have begun to clear up a number of pathways that connect these rhythms with mood regulation. Among the pathways are:

- Melatonin and the sleep–wake cycle,
- Neurotransmitter regulation,
- The HPA axis and the stress response,
- Neurogenesis and neuroplasticity,
- Immune function and inflammation,
- Energy metabolism,
- Brain connectivity.

Melatonin, released by the pineal gland under circadian control, signals that night has come and assists in inducing sleep. In many affective disorders, melatonin secretion has been found to be timed abnormally, to

be reduced and/or not to be robust, or to be overly responsive to light suppression (Lewy et al., 1981, 1987; Lanfumey et al., 2013). We suspect that such secretion abnormalities are tied in some necessary way to sleep disturbances, which then contribute to intensified affective instability.

Key neurotransmitters like serotonin, dopamine, and norepinephrine fluctuate rhythmically under the influence of clock genes and the SCN (McClung, 2013). When circadian control weakens, these chemical signals can become desynchronized, pushing the system either into a state of hyperactivation (as in mania) or a state of hypoactivation (as in depression). Notably, chemical messenger dysregulation is also what happens in mice with mutations in the CLOCK gene—all of which suggests a central role for that gene in both circadian timing and mood.

The HPA axis has a robust daily rhythm of cortisol secretion. In people with mood disorders, that rhythm becomes blunted or reversed. There is also evidence that the HPA axis shows hyperactivity in mood disorders (Havermans et al., 2010; Lanfumey et al., 2013; McClung, 2013). Disrupting clock genes can amplify HPA dysregulation and the bad stress resilience that comes with it. HPA dysregulation also perpetuates a downward mood spiral for people who are susceptible (Takaesu, 2018).

The contribution of sleep, especially slow-wave and REM sleep, to synaptic homeostasis, neuronal repair, and adult neurogenesis is substantial (Armitage, 2007; McClung, 2013). If processes integral to sleep's restorative function are disrupted, as can happen when the circadian clock is misaligned or sleep is fragmented, neuroplasticity can take a hit. Fast-forwarding fragmented circadian signals can hinder the messy processes required for the formation of new circuits in the hippocampus and elsewhere (Lanfumey et al., 2013).

The cross-talk between the immune system and the circadian clock is a dialogue that is ever ongoing. Inflammatory signals can and do disrupt the normal expression profile of clock genes. In turn, certain clock genes have been found to regulate various aspects of the immune response (McClung, 2013; Wirz-Justice & Benedetti, 2019).

Methodology

Study Design

Eligibility Criteria

The selection of studies for this systematic review was guided by specific criteria designed to focus on the prediction of affective episodes through digital monitoring technologies. The selection of studies for this systematic review was guided by specific criteria designed to focus on the prediction of affective episodes through digital monitoring technologies. Studies were eligible for inclusion if they involved at least one cohort of participants diagnosed with MDD or BD according to established DSM or ICD diagnostic criteria. All participants were required to be adults, ensuring homogeneity in the developmental stage of the studied population. We specifically sought original research that utilized wearable technology (such as activity trackers or smartwatches) or smartphone applications to collect data related to circadian rhythms. Studies needed to incorporate circadian rhythm parameters—including sleep metrics, activity patterns, heart rate variability, or light exposure—as predictive factors for future mood states or episodes. Our review focused on English language publications from 2016 to 2025, capturing recent technological advances in digital phenotyping.

Studies were excluded if they merely recognized current affective symptoms rather than predicting future episodes, as prediction capability was the central focus of our review. We excluded systematic reviews, meta-analyses, and case-control studies that examined differences between groups without incorporating predictive modeling. Publications that focused solely on technical aspects of measuring devices without reporting clinical outcomes were deemed ineligible. Additionally, we excluded studies lacking clear methodology for prediction or forecasting, non-peer-reviewed publications, and research examining disorders other than MDD or BD as primary conditions.

This review specifically targeted studies that developed predictive models or algorithms to forecast the occurrence of affective episodes before their clinical onset, rather than those merely identifying concurrent symptoms during measurement. This distinction was crucial to evaluate the potential of digital technologies for early intervention in mood disorders.

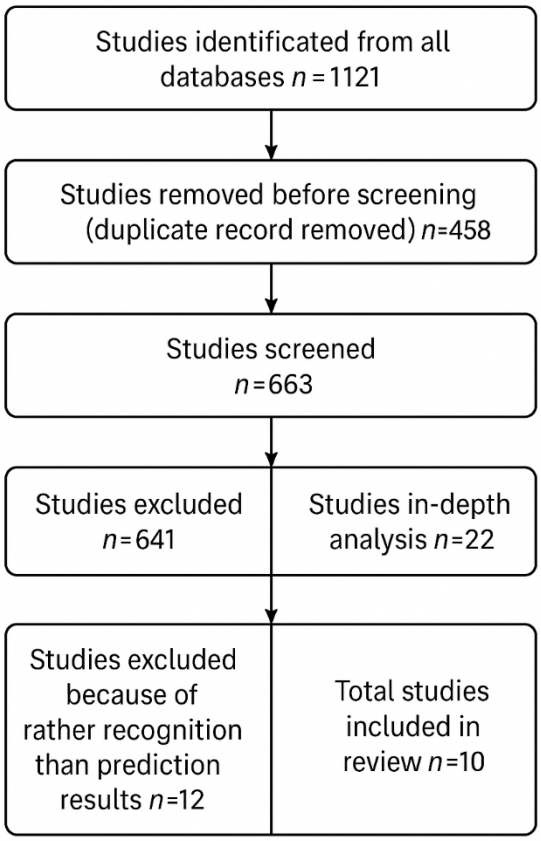

Fig. 1. *Study selection Flowchart*

Data Collection

Search Strategy and Selection Process

Databases searched included PubMed, Google Scholar, PsycINFO, Web of Science, and IEEE Xplore, using keywords and Medical Subject Headings (MeSH) terms such as "wearable devices," "affective disorders," "mood disorders", "depression," "bipolar disorder," "mental health monitoring", "forecast of mental disorders", "prediction of mental disorders".

The selection of studies was performed by all study authors with division of databases and search criteria. The final decision in case of dispute regarding study qualification belonged to the first author. The initial selection was conducted through analysis of the study title, excluding diseases other than depression and bipolar affective disorder.

Subsequently, abstracts were analyzed for depression and bipolar affective disorder criteria. Studies mentioning the use of wearable devices or smartphones in the abstract were included in the next stage. When determination of the used method was impossible, full study texts were reviewed. In cases of doubt about diagnosis criteria, output data were analyzed if studies contained information about registration in the clinicaltrials.com system and indicated the study number.

Next, found systematic reviews were analyzed to identify any omitted studies. Subsequently, systematic reviews were excluded from further analysis. Papers exclusively focusing on technical aspects such as construction and operation of measuring devices or methods of data analysis and research algorithms were excluded unless they contained clear results enabling prediction. The last, but very important stage of analysis involved excluding studies that frequently used the term 'prediction' but in reality only concerned on the recognition of affective disorder symptoms that appeared during measurement.

Table 1. Original research by study's design

Study	Year	Design
Grierson et al.	2016	Cross-sectional with prospective elements
Carr et al.	2018	Case-control observational
Cho et al.	2019	Prospective observational cohort
Kumagai et al.	2019	Prospective cohort
Busk et al.	2020	Forecasting study
Esaki et al.	2021	Prospective cohort
Braund et al.	2022	Longitudinal observational
Lee et al.	2023	Prospective cohort
Kim et al.	2024	Prospective cohort with deep learning
Lim et al.	2024	Prospective cohort

Data Collection Process

Data extraction was performed by two independent reviewers using a standardized form without tools or pilot-testing, because the final amount of the eligible studies were small. Discrepancies were resolved through discussion and consensus. For each eligible study, the following data were extracted which may be divided into 5 categories.

Table 2. Types of Data Collected

Study characteristics	• Authors and publication year • Study design (e.g., prospective cohort, randomized controlled trial) • Sample size and participant demographics • Duration of observation period • Clinical diagnosis of participants (MDD, BD I, BD II)
Wearable technology and data collection methods	• Types of wearable devices used (e.g., Fitbit Charge HR, ActiCal, Proteus patch) • Smartphone applications (e.g., eMoodChart, Mood Zoom) • Sensors utilized (accelerometers, light sensors, heart rate monitors) • Self-report instruments and clinical scales (e.g., HDRS, MADRS, YMRS) • Data collection frequency and adherence rates
Circadian rhythm assessment parameters	• Parametric measures (MESOR, amplitude, acrophase, Circadian Quotient) • Non-parametric measures (Interdaily Stability, Intradaily Variability, Relative Amplitude) • Sleep parameters (onset, duration, quality, L5, M10) • Activity patterns (steps, movement, GPS data) • Heart rate parameters (mean, variability, circadian rhythm) • Light exposure data • Self-reported mood and energy data
Analytical approaches	• Mathematical modeling techniques (cosinor analysis, non-parametric circadian rhythm analysis) • Machine learning and deep learning algorithms used (Random Forest, XGBoost, LSTM, GRU) • Feature selection methods • Time window for prediction (next-day, 3-day, 7-day forecasts) • Use of personalized versus general models • Statistical methods for analysis
Outcome measures	• Performance metrics (accuracy, sensitivity, specificity, AUC) • Correlation coefficients between circadian parameters and clinical outcomes • Hazard ratios for mood episode relapses • Differentiation between diagnostic groups • Most significant predictive features

Study Risk of Bias Assessment

The Newcastle-Ottawa Scale (NOS) was used to assess bias of all included studies. For each study, the following domains were assessed: risk of selection bias, risk of information/ measurement bias, risk of attribution bias, risk of reporting bias, risk of confounding, Applicability concerns. Each domain was rated as "Low," "Moderate," or "High" risk of bias. The overall risk of bias was determined based on the individual domain assessments. Study performed by Braund et al. (2022) and Esaki et al. (2021) was included despite of high bias risk, because the studies' limitations were abundantly described in review.

Table 3. Reviewed Studies Risk of Bias

Study	Year	Bias higer or equal to overall	Overall Risk of Bias
Grierson et al.	2016	Selection bias (Low-Moderate): unperfect representation of target population mostly young people (13-25 years) with first-episode mood disorders; Attrition bias: (Low-Moderate) missing physiological data was addressed adequately in statistical analysis	Low-Moderate
Carr et al.	2018	Selection bias (Moderate): small sample, well-characterized clinical groups; Attrition bias (Moderate): data loss addressed but still a significant limitation	Low-Moderate
Cho et al.	2019	Information/Attrition bias (Moderate): missing data handling eg. 43.9% sleep-related, 29.6% heart rate	Low-Moderate
Kumagai et al.	2019	Attrition bias (Moderate): 10% dropout rate; Measurement Bias (Low-Moderate): clinical scale PHQ-9 was administered too far (one per in month); Confounding (Low-Moderate): treatment changes during the study period were not restricted or fully accounted for in the analysis; Information Bias (Low-Moderate): missing data was handled through multiple imputation	Low-Moderate
Busk et al.	2020	Attrition Bias (Low-Moderate): study did not extensively discuss dropout rates	Low
Esaki et al.	2021	Information Bias (High): 7-day measurement period for circadian activity rhythms was a predetermined data collection period without testing different measurement durations; Attrition Bias (High): the loss of nearly 13% of participants; the assessment of circadian rhythm for only 7 days at baseline does not capture changes over the 12-month follow-up period; Confounding (High): the 24-hour baseline assessment period for circadian rhythm is extremely limited, the naturalistic study design meant that therapy during follow-up was not controlled	High
Braund et al.	2022	Information bias (High): reliance solely on GPS data for circadian rhythm; Attrition bias (High): GPS data completeness and handling of missing data not fully described; Confounding (High): 24-hour assessment period for baseline circadian rhythm is very limited	High
Lee et al.	2023	Low in all category	Low
Kim et al.	2024	Low in all category	Low
Lim et al.	2024	Confounding bias (Low-Moderate): the naturalistic observational design means that medication effects could not be fully controlled	Low

Effect Measures

The studies examining the relationship between circadian rhythm disruptions and mood disorders employed various effect measures to quantify their findings, reflecting the diversity of study designs and analytical approaches.

Table 4. Reviewed Studies Types of Effect Measures

Types of effect measures used	Results	Study
Hazard Ratios (HR)	1.109	Esaki et al. (2021)
Accuracy Metrics and AUC Values	AUC ~0.67 up to ~0.98	Cho et al. (2019), Kim et al. (2024), Lee et al. (2023), and Lim et al. (2024)
Correlation Coefficients	r= 0.703; r =-0,4 to +0,28 or insignificant	Carr et al. (2018), Grierson et al. (2016), and Braund et al. (2022)
Forecast Metrics, Regression Models (R^2, RMSE, Panel VAR)	R^2 (≈0.51) and RMSE (≈0.32); PVAR = 0.191- 0.271	Busk et al. (2022), Kumagai et al. (2019)

Assessment of Overall Bias and Uncertainty

GRADE-like qualitative summary was used, beacuse of small sample of studies, which used various designs. Giving to primarly narrative charakter of this systematic review, a **qualitative** approach was chosen and this review focuses on describing risk of bias, inconsistency, indirectness, imprecision, and publication bias narratively, rather than producing formal numeric GRADE scores.

Table 5. GRADE-Like Summary

Domain	Considerations Across the 10 Studies	Overall Assessment
Risk of Bias	➢ Several observational and machine-learning studies (e.g., Carr 2018, Grierson 2016, Kumagai 2019) did not randomize or blind outcomes, thus prone to confounding and selection bias. ➢ In Busk (2020) and Cho (2019), potential bias arises if data are incomplete or self-reported (mood tracking). ➢ Esaki (2021) selected a 7-day measurement period without empirical justification, yet attempted to predict outcomes over 12 months. ➢ Lee/Cho (2023) and Lim (2024) employed more rigorous data collection and sophisticated modeling approaches. ➢ Four studies (Cho 2019, Lee 2023, Lim 2024, Kim 2024) are based on the same Mood Disorder Cohort Research Consortium (MDCRC) database, limiting the independence of evidence sources.	**Moderate to High** (non-RCT designs, possible selective reporting, reliance on self-tracking)
Inconsistency	➢ Studies measured circadian or mood outcomes in varied ways (e.g., activity trackers, daily smartphone reports, or clinical scales). ➢ Diverse analytical approaches produced metrics that aren't directly comparable (machine learning classifications, vector autoregressive models, Cox models). ➢ While circadian disruption consistently correlates with mood symptoms, specific parameters of importance show marked variation.	**Moderate** (heterogeneity of study designs and outcome metrics)

Indirectness	➢ Some studies focus on short-term predictions (within days), others on long-term relapse risks (weeks). ➢ Certain studies (e.g., Kim 2024, Lim 2024) highlight purely digital data for classification, which may not fully capture clinical endpoints. ➢ Most studies use specialized populations (e.g., adults 18–35, or specific BD subtypes), so generalizability might be limited.	**Moderate** (narrow study populations, proxy or digital outcomes in some cases)
Imprecision	➢ Sample sizes vary; some (Kumagai 2019, Grierson 2016) have fewer participants, leading to large confidence intervals or no reported intervals at all. ➢ Machine-learning metrics (e.g., accuracy or AUC) lack confidence intervals in some articles, complicating precision estimates. ➢ For time-to-event data (Esaki 2021), the effect estimates can be narrow but population was still relatively small.	**High** (limited sample sizes & sometimes wide or unstated CIs)
Publication Bias	➢ Only one prospective time-to-event study (Esaki 2021) examines mood relapse; many studies with negative or null findings may remain unpublished. ➢ Funnel plots or Egger's tests are not feasible due to <10 studies per quantitative outcome. ➢ Overall, we cannot exclude publication bias, especially for digital phenotyping approaches that might be prone to "positive result" reporting.	**Uncertain** (few studies, no formal funnel plot possible)
Overall Certainty of Evidence	➢ Across these ten articles, we find consistent signals that circadian disruption is associated with mood dysregulation or relapse, but the methods diverge significantly, and sample sizes often remain small. ➢ Risk of bias and imprecision are notable; no formal meta-analysis is feasible to unify effect estimates.	Actually low with optimistic prognosis

Results

Prediction of Occurrence of Affective Episodes Within Few Days

The investigation by Cho et al. (2019) had the particularity of a very lengthy observation period of 2 years. The sample comprised 55 subjects with mood disorders—18 with MDD, 18 with BD type I, and 19 with BD type II. The apparatus used consisted of either a Fitbit Charge HR or a Charge 2, a smartphone application (eMoodchart), and light sensors in the smartphones. They then employed machine learning algorithms to make sense of the data they had collected.

The accuracy achieved by same-day episode classifier was striking: no episode (NE) at 85.3%, depressive episode (DE) at 87%, manic episode (ME) at 94%, and hypomanic episode (HME) at 91.2%. However, the corresponding sensitivity values were rather low. NE had a sensitivity value of 93%, but DE had only 48%, ME had only 25.2% and HME had only 30.6%. Thus, Cho et al. (2019) obtained very good accuracy primarily, because they had a huge predominance of non-episode days mixed in with their overall study time. They also had good specificity. But from a clinical point of view, the low sensitivity may a problem. It would be very hard to use these predictions in a clinical manner when the system had this kind of sensitivity profile. But what is more important from the point of this review, the researchers also tried to predict mood state from 1 to 3 days in advance. The strength of these mood predictions was below the threshold for clinical significance and they did have AUCs ranging between 0.67-0.7.

Cho et al. (2019) undertook an analysis considering several influential factors related to mood prediction across various patient categories and mood episode types. They took data from various sources—light exposure, steps, sleep, and heart rate—and transformed it into specific indexes and factors. They then used machine learning to perform the analysis and assigned weights to the factors, indicating relative importance in predicting the kinds of mood states that can be experienced by different kinds of people.

In general, light exposure during bedtime consistently mattered across most groups, particularly in all patients, MDD patients, BD I patients, and BD II patients with hypomanic episodes. Increasing light exposure

during bedtime positively correlated with mood instability. This suggests that disturbances in the circadian rhythm due to inappropriate light exposure may significantly impact the mood.

Steps taken during bedtime was another critical index across all patients that also correlated with mood instability. Showing a strong positive correlation with the mood index, this suggests that being active during times when one is supposed to be resting is not a good idea for one's mood.

Heart rate circadian rhythm mesor was particularly influential in all patients, BD I patients, and BD II patients. Mensor could be describe as the mid-line around which the heart-rate curve oscillates. Patients who had a higher mesor were typically more unstable and were more likely to have mood episodes.

The most important indexes slightly differed for specific groups. For MDD patients, the most important factors were increased Steps During Bedtime and Light Exposure During Bedtime. Conversely, for BD II Patients, the most influential index was Heart Rate Circadian Rhythm Amplitude, indicating a strong association between heart rate variability and mood states. Additionally, Sleep Quality was positively correlated with mood stability, which was somewhat distinct from other categories. Among less important indexes, Heart Rate Circadian Rhythm Goodness of Fit and Sleep Length were generally less important across all patient groups, with a small exception for BD II patients in the prediction of mood episodes.

A subsequent study performed by Lee et al. (2023) under the direction of the Cho's team that did the earlier work, included a markedly larger number of participants: 495 patients with affective disorders who were followed for a mean observation period of 280 days. Similar devices were used in the study: the Fitbit Charge HR, Charge 2, and Charge 3 along with the eMoodChart application to track participant data. When the researchers compared data collected through the eMoodChart to the Fitbit devices, they reported impressive sensitivity values of 89.8-92.8% and a nice accuracy of 90.1-93.0% three days ahead.

The superior statistical performance of Lee's study compared to Cho's research is attributable to several factors, such as its substantially larger sample size (495 patients versus 55 patients) and different methodological approaches to data collection and analysis. While both studies began recruitment in March 2015, Lee's continued until 2019, whereas Cho's ended in 2017, allowing Lee's study to achieve a longer average follow-up duration per participant. Lee's study appears to have achieved more consistent data collection, with a much higher proportion of their collected data being suitable for comprehensive analysis. Additionally, Lee et al. (2023) implemented binary classification for each episode category - separately for depression, mania, and hypomania - instead of the multiclass classification (NE, DE, ME, HME) used by Cho et al. Interestingly, Cho's study explicitly tested and compared personalized models against general models, finding improved efficiency by approximately 25%, whereas Lee's study didn't indicate any type of personalization.

Lee et al. (2023) used 30 features, whereas Cho et al. (2019) used 14 features in their research. Lee et al.'s work didn't create additional features but instead built upon earlier research to make better optimizations. They did this by using ShapRFECV, a modern statistical method, for more efficient and effective analysis of the features. Lee et al. (2023) rather extraordinarily specified various forms of "step counts" even within various defined parts of the day, even while they themselves had specific definitions of "morning," "afternoon," and "evening." They used forms of these parts of the day in their comparisons; thus, allowing comparisons and analyses of form, duration, and part of the day in much more detail than Cho et al. (2019) could. Using much more precise definitions and forms of the day and by making much more use of statistical definitions and forms of the day, Lee et al. (2023) provided comparisons that are much tighter and more coherent across the specifics of the parts of the day than Cho et al. (2019).

Table 6. Usage of wearable devices, smartphone and mood self-assessment's methods in the review studies

Publication	Wearable devices	Smartphone	Self-assessment of mood
Braund et al. 2022	no	GPS and mood app	Socialise
Busk et al. 2020	no	mood app	yes
Carr et al. 2018	Proteus patch	mood app	Mood Zoom application
Cho et al. 2019	Fitbit Charge HR, Fitbit Charge 2	light sensors and mood app	eMoodchart
Esaki et al.2021	Actiwatch Spectrum Plus	no	no
Grierson et al. 2016	Actiwatch-64/L/2/Spectrum	no	no
Kim et al. 2024	Fitbit Charge 4	light sensors and mood app	EMA
Kumagi et al. 2019	Silmee W20	Kurashi-app	K6
Lee et al. 2022	Fitbit Charge HR, Fitbit Charge 2, and Fitbit Charge 3	light sensors and mood app	eMoodchart
Lim et al. 2024	Fitbit Charge HR, 2 or 3	no	no

In a more recent study, Lim et al. (2024) examined 168 patients diagnosed with affective disorders over a mean observation period of 267 days. Data collected included sleep-wake patterns via Fitbit wearable devices, from which they derived 36 features: sleep windows (comprehensive sleep periods, classifications of sleep windows as long/short (threshold: 3.75h), sleep time (ST) and wake time (WT) within windows, sleep percentage and sleep amplitudę, circadian phase (estimated from core body temperature modeling), circadian amplitudę and daily mood and energy self-assessments collected through the eMoodChart smartphone app. Comparing to Lee' study, Lim' study covers lesser range of concepts, excluding i.a. step counts or light exposure. Lim's study is more structured and statistically detailed, particularly in breaking down sleep metrics into long vs. short windows and analyzing them through Z-scores, Means, and Standard Deviations. Some features directly used in Lee's study were indirectly used, for ex. heart rates in CR parameters.

Lim et al. (2024), similarly to Cho et al. (2019), used both personalized and general models. However, Lim et al., contrary to Cho's findings, observed decreased accuracy with personalization compared to their general model, which achieved AUC values of 0.925 for depressive episodes, 0.984 for manic episodes, and 0.985 for hypomanic episodes. The purpose of Lim et al.'s (2024) study was to present clinically applicable models with short training periods of personal data (30 days and 60 days). Although the intentional shortening of observation periods resulted in poorer prognostic value than their general model, the personalized approach still preserved high accuracy for next-day affective episodes (AUC values of 0.75, 0.98, and 0.95 for depressive, manic, and hypomanic episodes, respectively). This suggests the approach could be valuable even with relatively brief 30-day observation periods. The AUC values for depressive episode prediction rose to 0.8 with 60-day observation periods. It should be noted that Lim et al. (2024) did not provide detailed data for calculating AUC, particularly the test sensitivity parameter; however, the high AUC results are sufficient to consider the model precise, as sensitivity was a main disadvantage in Cho et al.'s study.

Lim et al. (2024) obtained significantly poorer predictive values for depressive episodes, which may result from the lack of subjective mood measurements and the less pronounced relationship between MDD and changes in daily activity, particularly the key indicator in the study: daily circadian phase shifts. Another observation by the researchers is the correlation between delayed circadian cycle and depressive episodes, and acceleration with manic episodes (similar to Moon et al., 2016).

According to Lim's study, the relationship between hypomania and circadian rhythms differs from that of mania and depression, as the linkage is rather non-monotonic, unlike in mania and depression, and non-monotonic analyses like the XGBoost training are necessary to obtain reliable data. This could explain why Song et al. (2024) in their recent study could not find a relationship between diurnal rhythm changes and BP II. Lim's study also points to difficulties with classification of hypomania due to different hypomania symptom

presentations, including dysphoric hypomania, mixed hypomania, and its differentiation from depressive mixed states.

Kim et al. (2024) represent a significant advancement in the early prediction of depressive episodes in mood disorders through the novel application of deep learning techniques to circadian rhythm indicators. This study utilized data from 164 participants. Unlike earlier approaches that primarily focused on three day prediction windows, Kim and colleagues extended the prediction timeframe to seven days, allowing for better preparation and intervention strategies. Kim et al. emphasized DLMO as a primary circadian marker, using two distinct DLMO estimation formulas based on sleep information. Unlike earlier studies, Kim et al. omitted self-assessment data from participants.

The study's methodology employed several deep learning models, including Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and a hybrid LSTM-GRU approach, to analyze time-series features related to sleep, heart rate, activity levels, and light exposure. This approach builds upon previous work but extends it through the application of more sophisticated neural network architectures specialized for sequence data. Previous studies used Ensemble Learning Models, which are machine learning rather than deep learning models, such as random forest and XGBoost.

Notably, Kim et al.'s results revealed that the GRU model achieved the highest sensitivity (0.767) for predicting depressive episodes, while the LSTM model demonstrated superior robustness across metrics with an average recall of 0.748. These results provide a different perspective compared to the AUC values reported by Lim et al. for depressive episodes (0.925), though the extended prediction window in Kim's study presents additional challenges that may account for the differences in performance metrics.

The study by Busk et al. (2020) examined the feasibility of forecasting mood in bipolar disorder using smartphone-based self-assessments. The research involved 84 participants with bipolar disorder, collecting a substantial dataset of 15,975 daily self-assessments and 280 clinical evaluations over approximately 9 months as part of the MONARCA II randomized clinical trial. This corresponds to an average of 190.2 self-assessments per participant with a high adherence rate of 82.8%.

Participants used an Android smartphone app to evaluate subjective measures of illness activity through a daily self-assessment questionnaire. The items included mood (scored from -3 to +3), activity level, alcohol consumption, anxiety, irritability, cognitive difficulty, medicine adherence, mixed mood, sleep, and stress. The optimal window size for forecasting was determined to be 4 days of historical data. Feature importance analysis revealed that historical mood was the most important predictor variable (4.53), followed by anxiety (2.78), irritability (2.74), and mixed mood (2.09). For 1-day forecasts, the model achieved R^2=0.51 and RMSE=0.32, and for 7-days (RMSE=0.375). The lack of other statistical data presentation, it cannot be compare to accuraty measure from other studies.

The study found significant correlations between self-reported mood scores and clinical assessments, like HDRS and YMRS scores. Unlike some other studies in this field that focused on classification of mood states, and did not incorporate objective smartphone sensor data such as physical activity metrics, GPS location data or passive measures of sleep patterns.

Braund et al. (2022) conducted a longitudinal observational study examining the relationship between circadian rhythm, extracted from smartphone GPS data, and mental health symptoms among adults diagnosed with major depressive disorder (MDD) or bipolar disorder (BD). This 10-week study with 121 clinically diagnosed participants provides important insights into the limitations of sigle circadian measures for forecasting future mood trayectory and affective episodes. The researchers collected GPS data from participants' smartphones and calculated circadian rhythm as the regularity of location changes in a 24-hour pattern. Unlike previous studies that aimed to predict the occurrence of mood episodes, Braund et al. focused on examining relationships between baseline circadian rhythm and changes in clinical symptoms over time. Interestingly, the study found no significant association between circadian rhythm at baseline and mental health symptoms over 10-weeks period. The limitations of this study exemplify the challenges in using insufficient theoretical approach by rather estalish baseline circardian rythms than characteristic changes. Other limitations inculde choice of single type of data (GPS) and insufficent observation period (24-hours).

Table 7. Number of participants in the reviewed studies

Study	Total Participants	MDD (n)	BD (n)	Additional Notes
Braund 2022	121	79	42	Participants with MDD or BD; no exact split stated.
Busk 2020	84	0	84	All diagnosed with BD
Carr 2018	54	0	20	Others: 14 borderline personality + 20 healthy controls.
Cho 2019	55	18	37	BD: 18 BD I + 19 BD II; korean Mood Disorder Cohort Research Consortium (MDCRC)
Esaki 2021	189	0	189	All with BD
Grierson 2016	63	33	30	
Kim 2024	168	57	111	BD: 42 BD I + 69 BD II; korean Mood Disorder Cohort Research Consortium (MDCRC)
Kumagi 2019	89	89	0	All had MDD.
Lee 2022	495	95	175	BD: 78 BD I + 97 BD II; korean Mood Disorder Cohort Research Consortium (MDCRC)
Lim 2024	168	57	111	BD: 42 BD I + 69 BD II; korean Mood Disorder Cohort Research Consortium (MDCRC)

Prediction of Affective Disorder Severity

Grierson et al. (2016) conducted a study on a group of 63 individuals aged 13-25 years with a first episode of mood disorder within the diagnosis of MDD or BD. The authors recruited individuals with 'emerging mood disorders,' i.e., at an early stage of the disease. The measurement of disease severity for correlation purposes was performed during, immediately before/after the two-week period of actigraphic recording. The study was based on a simple indicator for assessing circadian rhythm using wrist actigraph data, and the following parameters were distinguished: amplitude, acrophase (hour of greatest activity), and rhythmicity index. The observation period was 14 days. Longer duration of illness was associated with reduced amplitude in daily activity patterns ($r = -0.25$, $p = 0.045$). Youth who had experienced symptoms for a longer period demonstrated weaker circadian rhythmicity ($r = -0.33$, $p = 0.01$). Only higher manic symptom scores corresponded with a delay in the timing of maximum daily activity ($r = 0.28$, $p = 0.03$). The circadian rhythmicity index significantly differentiated between MDD and BD groups after controlling for potential confounders ($F = 2.34$, $df = 6, 56$; $p = 0.044$). Additionally in participants with bipolar disorder specifically, both increasing depressive and manic symptoms severity were accompanied by diminished circadian rhythm robustness, a pattern not observed in unipolar disorder cases. These findings suggest that disrupted circadian rhythmicity, particularly when associated with symptom severity, may serve as a distinguishing characteristic of young people at elevated risk for a bipolar illness trajectory.

Forecasting of Increased Chance For Future Affective Episodes

Kumagai, Esaki, & Lee (2019) conducted an explanatory feasibility study to investigate whether lifelog data collected through smartphones and wearable devices could identify warning signs of depression recurrence. The study employed a panel vector autoregressive (PVAR) approach to analyze the bidirectional relationships between lifestyle factors and depression symptoms.

The researchers collected digital data consisting of individual activity records (lifelog data) from 89 patients who were on maintenance therapy for recurrent depression over a one-year period. All participants were in remission at baseline as defined by Beck Depression Inventory-II scores of 9 or less. Data collection utilized a smartphone application called Kurashi-app ("life" in Japanese) on iPhones and a wearable device

(Silmee W20). The Kurashi-app helped track 16 types of activities, including meeting friends/family, bathing, childcare, commuting, domestic work, exercise, hospital visits, meals, shopping, sitting idly, sleep, study/work, hobbies, media consumption, reading, and other activities.

Depression symptoms were assessed using both the Kessler Psychological Distress Scale (K6), which participants completed weekly through the app, and the Patient Health Questionnaire-9 (PHQ-9), which clinical coordinators administered monthly by phone. For the analysis, the researchers developed a five-variate PVAR model that examined the relationships between K6 scores, sleep patterns (long/short sleep time), standardized variable of missed lunches, UV light exposure (as a proxy for outdoor activity), and sitting idly.

The panel vector autoregressive analysis revealed that long sleep time was a significant risk factor for depression recurrence. They identified long sleep based on when a person's sleep duration exceeded their own 7-day average plus the standard deviation. Long sleep was defined relative to each person's own typical weekly pattern. The 3-week lagged effect was statistically significant with a coefficient of 0.271 for all age groups except 50-59 years. The p-value associated with this coefficient was <0.001. The predictive factor is the opposite of the characteristic symptom, which is insomnia and was reported by 75% of patients according to the review of the research results, confirming that it is a pure predictive factor and not an early symptom of depression. Other factors initially considered, including not eating lunch regularly, sitting idly, and UV exposure (as a measure of outdoor activity), were not significant predictors when analyzed jointly with long sleep time. As the authors stated, this might have been due to the relatively small sample size. Specifically, long sleep predicted depression recurrence after a 3-week lag.

When participants were stratified by age, long sleep in patients aged 50-59 years predicted depression recurrence after 4 weeks, while in other age groups it predicted recurrence after 3 weeks with a coefficient of 0.240.

The study employed several methodological innovations, including the use of PVAR models to account for bidirectional relationships between lifestyle factors and depression symptoms, and the application of both K6 and PHQ-9 assessments to enhance data completeness. The researchers also carefully addressed missing data through multiple imputation techniques.

This research furnishes important knowledge about the possible use of digital phenotyping for the early detection of recurrent depression. In its manifestations, depression can be either unipolar or bipolar. In the case of bipolar illness, the more serious affects can be compounded by potential long term health and mental problems related to the depressive phases. Even when not as serious, disruptions to sleep on a regular insomnia cycle and/or hypersomnia (long sleep and/or depression) every night can lead to problems with the following: (1) physical health (fatigue and potential obesity); (2) mental health (potential increased depression and not improving condition); and (3) potential serious long-term cognitive problems.

Esaki et al. (2021) conducted a 12-month prospective cohort study to examine the relationship between circadian activity rhythms and mood episode relapses in patients with bipolar disorder. The researchers recruited 189 outpatients with bipolar disorder who participated in the "Association between the Pathology of Bipolar Disorder and Light Exposure in Daily Life (APPLE) cohort study." Participants' physical activity was objectively assessed using a wrist-worn accelerometer over 7 consecutive days for the baseline assessment and then at the 12-month follow-up for mood episode relapses.

The levels and timing of the circadian activity rhythms were estimated using a cosinor analysis and a nonparametric circadian rhythm analysis. Of the 189 participants, 88 (46%) experienced mood episodes during the 12-month follow-up. The Cox proportional hazards model adjusting for potential confounders showed that a robust circadian activity rhythm, including midline-estimating statistic of rhythm (MESOR) and amplitude by cosinor analysis and 10 consecutive hours with the highest amplitude values (M10) by the nonparametric circadian rhythm analysis, was significantly associated with a decrease in mood episode relapses (MESOR, 0.993; amplitude, 0.994; and M10, 0.996).

A later timing of the circadian activity rhythm (M10 onset time) was significantly associated with an increase in the depressive episode relapses (per hour; 1.109 [1.001–1.215]). These findings complement the study by Grierson et al. (2016), who observed that in young people with bipolar disorder, both increasing depressive and manic symptom severity were accompanied by diminished circadian rhythm robustness. Esaki et al. (2021) further demonstrated that temporal parameters of circadian activity rhythm, particularly delayed phase, may be specifically associated with depressive episode relapses.

It is worth noting that similar to Grierson's study, which showed that longer duration of illness was associated with reduced amplitude in daily activity patterns ($r = -0.25$, $p = 0.045$), Esaki's study suggests that reduced physical activity level is associated with a higher risk of mood episode relapse.

Differentiation Between Mood-Associated Disorders in Stable Period

Carr et al. (2018) investigated the relationship between diurnal rhythm variability and mood fluctuations in BD, Borderline Personality Disorder and control groups for four days using a Proteus patch (recording heart rate and acceleration), actigraphy, and a smartphone app called Mood Zoom (MZ). Additionally, participants were studied during euthymic or relatively stable states rather than during acute mood episodes.

The MZ app collected self-reported mood ratings (anxious, elated, sad, angry, irritable, and energetic) ten times daily. Variability in these mood scores was quantified using standard deviation, TKEO (Teager-Kaiser Energy Operator), entropy, and RMSSD (Root Mean Squared Successive Differences).

The results obtained in the study were not very spectacular. They showed that people with BPD have a statistically significant decrease in mood (daily MZ variability measures with delayed sleep phase. (coefficiency of 0.703, p-level = 0.05) Such an effect was not shown for people with BD, while the trends were 0.384 for BD and -0.134 for HC, respectively. The observation lasted only 4 days. However, Carr's study is significant in the context of the need to differentiate BD and BPD, especially in the case of short measurements, which may be more significant for BPD for some parameters. Additionally, a trend can be observed from healthy people for whom the sleep phase shift improved mood, through people with BD in whom it worsened, to BPD in whom it strongly worsened mood.

When comparing BD and BPD specifically, several key differences emerged. While BPD showed strong correlations between heart rate variability and mood measures (particularly irritability), BD patients demonstrated no such relationship. This suggests that BD may be characterized primarily by sleep rhythm disturbances, while BPD demonstrates broader dysregulation across multiple physiological systems..

The study was limited by its short observation period (4 days) and the Proteus patch's inability to capture beat-to-beat heart rate variability (HRV) like traditional ECG monitors do. Instead, it recorded less sofiticated parameters an average heart rate over 5-minute intervals with 1-minute sampling.

Discussion

The presented studies demonstrate the possibility of significant advancement in the field of psychiatry, as they showcase the application of technology not only for diagnosing but also for predicting future affective episodes. The possibility of applying this technology stems from prior development of knowledge about factors that trigger episodes of affective disorders, specifically the dysregulation of circadian rhythms. Identifying risk factors and their constant systematic measurement represents a particularly important direction for the advancement of psychiatry. Studies by Lee et al. (2022), Lim et al. (2024), Cho et al. (2019), and Kim et al. (2024) demonstrated robust evidence that circadian rhythm metrics (e.g., amplitude, phase shifts, rhythm stability) predict mood episode relapse with significant accuracy. Particularly, Lim et al. (2024) provided strong evidence that delays or advances in circadian phase effectively predict depressive and manic/hypomanic episodes, respectively. Continuous passive monitoring through wearable technologies and smartphones offers an unprecedented opportunity to predict mood episodes before clinical onset. Such technology could significantly reduce healthcare burdens and improve patient quality of life by enabling early interventions.

Psychiatry, as a field of science predominantly based on periodic meetings, subjective criteria, and reactive intervention, may transform to continuous monitoring based on digital phenotyping data, prevention of deterioration, and highly personalized interventions (Lanata, Valenza, Nardelli, Gentili & Scilingo, 2015; Lipschitz, Lin, Saghafian, Pike & Burdick, 2025).

Methods of data collection varied greatly among studies, ranging from smartphone self-assessments, wearable devices tracking physiological parameters, and a combination of lifelogging technologies such as GPS and sleep trackers as showed in tabel no. 6. Observation periods spanned from relatively short-term (4-14 days, Carr et al., 2018; Grierson et al., 2016) to long-term follow-up (~2 years, Cho et al., 2019), significantly influencing the reliability and generalizability of predictions. Although promising, current evidence calls for standardized protocols, larger and more diverse sample sizes, longer-term observational periods, and real-world replication to confirm the reliability, validity, and generalizability of predictive models across various clinical settings.

The separation of training and validation datasets was explicitly addressed in most studies, enhancing methodological rigor. For instance, Kim et al. (2024), Lim et al. (2024), and Lee et al. (2022) specifically utilized distinct validation datasets, increasing confidence in their predictive models' real-world applicability. However, the clinical validity varied; shorter-duration studies (Carr et al., 2018; Grierson et al., 2016) provided valuable insights but limited long-term clinical predictive power. While highly predictive models (e.g., Lim et al., 2024; Lee et al., 2022) demonstrate readiness for clinical translation, their routine clinical implementation

still requires validation through large-scale, multi-center trials and practical assessments in diverse healthcare environments.

The capability to apply technology is a result of prior development of knowledge about factors triggering episodes of affective disorders through circadian rhythm dysregulation. Achieving these capabilities derives from technological advancement, particularly user-friendly commercial technologies that eventually become available to a wide audience. This review excellently exemplifies the development of modeling and algorithmization. The diverse data analysis methods employed by study authors demonstrate broad possibilities for improving indicator values using various statistical methods, machine learning, and deep learning techniques.

One of the primary challenges present in most studies of this type is patients' non-compliance with recommendations. Cho et al. (2019) included only 11% of complete data, while Lee et al. (2023) applied mathematical models to supplement data for approximately 38% of the database. Kumagai et al. (2019) utilized data completion methods with validation. Kim et al. (2024) employed a dual approach for estimating missing data through deep learning and SMOTE, a technique used in machine learning to address unbalanced datasets. Busk et al. (2020) assessed their method of estimating missing data as insufficient and had to limit the number of observations included in their analysis.

Wenze & Miller (2010) note that individuals with affective disorders show reduced willingness to follow instructions due to their symptoms; some consider wearable devices unaesthetic, too large, or uncomfortable during sleep. Notably, due to the nature of collected data, sleep information is often crucial for assessing circadian rhythms. Van Til et al. (2019) points out that data loss frequently results from participants forgetting to wear their bands, smartwatches, or charge batteries. For FitBit bands specifically, users may forget to enable Bluetooth during synchronization. Additionally, changes in participants' daily routines (often related to symptoms) may result in failure to adjust application settings to new sleep or activity schedules. Other objective obstacles to data collection include network access problems or smartphone incompatibility.

As reported by Van Til et al. (2019), some participants found daily EMA cumbersome or "annoying" and grew tired of frequent notifications to complete smartphone questionnaires. Some patients reported uncertainty about correctly assessing their mood; interestingly, the act of mood assessment itself expanded patients' emotional awareness (Mughal, Raffe, Stubbs, Kneebone & Garcia, 2022). Nevertheless, the overall assessment of wearable devices was positive. Van Til et al. (2019) indicated that most participants evaluated using Fitbit more favorably compared to actively completing smartphone applications, noting that bands are less engaging and require less effort for daily monitoring. Similarly, Ringeval, Wagner, Denford, Paré & Kitsiou (2020) observed that wearing Fitbit-type bands typically does not overly burden participants. In another study, Mughal et al. (2022) reported that 78% of participants described the tested procedure (combining device-based activity monitoring with online questionnaires) as "not very burdensome" and even beneficial for increasing self-awareness. Participants generally tolerated both band and smartwatch measurements and mobile application assessments well, especially when systems were designed with user convenience and clear instructions in mind (Lipschitz et al., 2025).

The early detection of circadian rhythm disorders enables timely contact between mental health specialists and patients to propose appropriate treatment (Lanata et al., 2015). In comparative studies, Cho et al. (2020) demonstrated significant improvement in patients who received mood monitoring with feedback and warnings about deterioration risks related to circadian rhythm disorders. Improvements included less frequent affective episodes and shorter episode durations, resulting from enhanced patient self-awareness. Other researchers reported increased patient engagement in treatment processes and improved self-discipline associated with feedback (Mughal et al., 2022; Van Til et al., 2019). Treatment monitoring may facilitate more tailored appointment scheduling with mental health specialists or identify needs for treatment modification (Lanata et al., 2015). Hickman, D'Oliveira, Davies & Shergill (2024) advocates for integrating monitoring systems with remote care and proactive physician engagement through messaging, online consultation offers, or other interventions.

From the perspective of digital phenotyping technology development, key priorities include maintaining maximum patient privacy while preserving high model predictive capabilities, establishing trust in monitoring entities, and addressing legal data protection issues. Health data, particularly mental health information, constitutes a special category of sensitive data. Various authors note that geolocation data and voice recordings generate greater resistance among patients compared to heart rate or step count monitoring (Lipschitz et al., 2025). Building patient trust in proposed solutions requires transparent policies regarding data storage and deletion, options for patients to opt out of monitoring, and clear data retention periods. This directly addresses

concerns expressed by study participants (Mughal et al., 2022). Antosik-Wójcińska et al. (2020) highlights that the two primary smartphone operating systems (iOS and Android) may not fully integrate with research applications, and some research applications lack clearly established privacy policies.

Conclusions

This systematic review demonstrates that the edifice of empirical research has arisen to show that tech we can wear and the smartphone we can hold can do a good job of predicting when we might be about to have an affective episode. As in, they can tell when there's a disturbance in our circadian rhythms and thus predict when we're going to be in danger of having a mood episode. Because these are the first methods we've had with the reliability necessary for the consistent clinical use hinted at by their potential in the studies we've reviewed, it's worth diving into the specific findings of the studies themselves.

Main findings are: (1) predicting episodes of affective disorder within 1 to 28 days before the clinical event occurs; (2) the use of models that are personalized and account for a person's baseline pattern; (3) the combination of monitoring a person's physiology in a passive manner with ecological momentary assessment; and (4) using machine learning and deep learning to obtain a greater predictive accuracy.

If these predictive models are to be fully implemented in the clinical setting, several obstacles will need to be cleared first. For one, obtaining the necessary data is a challenge; issues of data completeness have already been problematic in the past, and there's no indication that this will improve soon. If we want to use user data to predict user behavior, we must first collect that data—and in a diverse user way—that is also neat and tidy, so to speak. User adherence to the platform and privacy concerns are also significant challenges. Conversations around these two topics could fill several books, so I'll leave them at that. Altogether, if we want to make these models work in a clinical context, we must first prove that they are valid and reliable across all involved parameters.

Digital phenotyping technologies are changing. They are being integrated into psychiatric practice, and we see this as a promising development. When we say "affective disorders" in this context, we are referring to the kinds of illnesses that largely make up what is commonly called "mental illness." The two examples we gave were depression and bipolar disorder.

REFERENCES

1. Antosik-Wójcińska, A. Z., Dominiak, M., Chojnacka, M., Kaczmarek-Majer, K., Opara, K. R., Radziszewska, W., Olwert, A., & Święcicki, Ł. (2020). Smartphone as a monitoring tool for bipolar disorder: A systematic review including data analysis, machine learning algorithms and predictive modelling. *International Journal of Medical Informatics*, 138, Article 104131. https://doi.org/10.1016/j.ijmedinf.2020.104131
2. Armitage, R., & Hoffmann, R. F. (2001). Sleep EEG, depression and gender. *Sleep Medicine Reviews*, 5(3), 237-246. https://doi.org/10.1053/smrv.2000.0144
3. Armitage, R. (2007). Sleep and circadian rhythms in mood disorders. *Acta Psychiatrica Scandinavica*, 115(s433), 104–115. https://doi.org/10.1111/j.1600-0447.2007.00968.x
4. Averous, P., Charbonnier, E., & Dany, L. (2020). Relationship between illness representations, psychosocial adjustment, and treatment outcomes in mental disorders: A mini review. *Frontiers in Psychology*, 11, Article 1167. https://doi.org/10.3389/fpsyg.2020.01167
5. Benedetti, F., Serretti, A., Colombo, C., Barbini, B., Lorenzi, C., Campori, E., & Smeraldi, E. (2003). Influence of CLOCK gene polymorphism on circadian mood fluctuation and illness recurrence in bipolar depression. *American Journal of Medical Genetics Part B: Neuropsychiatric Genetics*, 123B(1), 23-26. https://doi.org/10.1002/ajmg.b.20038
6. Bradley, A. J., Webb-Mitchell, R., Hazu, A., Slater, N., Middleton, B., Gallagher, P., McAllister-Williams, H., & Anderson, K. N. (2017). Sleep and circadian rhythm disturbance in bipolar disorder. *Psychological Medicine*, 47(9), 1678-1689. https://doi.org/10.1017/S0033291717000186
7. Braund, T. A., Zin, M. T., Boonstra, T. W., Wong, Q. J. J., Larsen, M. E., Christensen, H., Tillman, G., & O'Dea, B. (2022). Smartphone sensor data for identifying and monitoring symptoms of mood disorders: A longitudinal observational study. *JMIR Mental Health*, 9(5), Article e35549. https://doi.org/10.2196/35549
8. Busk, J., Faurholt-Jepsen, M., Frost, M., Bardram, J. E., Vedel Kessing, L., & Winther, O. (2020). Forecasting mood in bipolar disorder from smartphone self-assessments: Hierarchical Bayesian approach. *JMIR mHealth and uHealth*, 8(4), Article e15028. https://doi.org/10.2196/15028
9. Carr, O., Saunders, K. E. A., Bilderbeck, A. C., Tsanas, A., Palmius, N., Geddes, J. R., Foster, R., De Vos, M., & Goodwin, G. M. (2018). Desynchronization of diurnal rhythms in bipolar disorder and borderline personality disorder. *Translational Psychiatry*, 8(1), Article 79. https://doi.org/10.1038/s41398-018-0125-7

10. Cho, C., Lee, T., Kim, M., In, H., Kim, L., & Lee, H. (2019). Mood prediction of patients with mood disorders by machine learning using passive digital phenotypes based on the circadian rhythm: Prospective observational cohort study. *Journal of Medical Internet Research*, 21(4), Article e11029. https://doi.org/10.2196/11029
11. Cho, C. H., Lee, T., Lee, J. B., Seo, J. Y., Jee, H. J., Son, S., An, H., Kim, L., & Lee, H. J. (2020). Effectiveness of a smartphone app with a wearable activity tracker in preventing the recurrence of mood disorders: Prospective case-control study. *JMIR Mental Health*, 7(8), Article e21283. https://doi.org/10.2196/21283
12. Dobrovinskaya, O., Alamilla, J., & Olivas-Aguirre, M. (2024). Impact of modern lifestyle on circadian health and its contribution to adipogenesis and cancer risk. *Cancers*, 16(21), Article 3706. https://doi.org/10.3390/cancers16213706
13. Dollish, H. K., Tsyglakova, M., & McClung, C. A. (2024). Circadian rhythms and mood disorders: Time to see the light. *Neuron*, 112(1), 25-40. https://doi.org/10.1016/j.neuron.2023.09.023
14. Dunster, G. P., Swendsen, J., & Merikangas, K. R. (2021). Real-time mobile monitoring of bipolar disorder: A review of evidence and future directions. *Neuropsychopharmacology*, 46(1), 197-208. https://doi.org/10.1038/s41386-020-00830-5
15. Esaki, Y., Obayashi, K., Saeki, K., Fujita, K., Iwata, N., & Kitajima, T. (2021). Association between circadian activity rhythms and mood episode relapse in bipolar disorder: A 12-month prospective cohort study. *Translational Psychiatry*, 11(1), Article 525. https://doi.org/10.1038/s41398-021-01652-9
16. Gershon, A., Ram, N., Johnson, S. L., Harvey, A. G., & Zeitzer, J. M. (2016). Daily actigraphy profiles distinguish depressive and interepisode states in bipolar disorder. *Clinical Psychological Science*, 4(4), 641-650. https://doi.org/10.1177/2167702615604613
17. Grierson, A. B., Hickie, I. B., Naismith, S. L., Hermens, D. F., Scott, E. M., & Scott, J. (2016). Circadian rhythmicity in emerging mood disorders: State or trait marker? *International Journal of Bipolar Disorders*, 4(1), Article 3. https://doi.org/10.1186/s40345-015-0043-z
18. Havermans, R., Nicolson, N. A., Berkhof, J., & deVries, M. W. (2010). Mood reactivity to daily events in patients with remitted bipolar disorder. *Psychiatry Research*, 179(1), 47-52. https://doi.org/10.1016/j.psychres.2009.10.020
19. Hickman, R., D'Oliveira, T. C., Davies, A., & Shergill, S. (2024). Monitoring daily sleep, mood, and affect using digital technologies and wearables: A systematic review. *Sensors*, 24(14), Article 4701. https://doi.org/10.3390/s24144701
20. Hudson, J. I., Lipinski, J. F., Keck, P. E., Jr., Aizley, H. G., Lukas, S. E., Rothschild, A. J., Waternaux, C. M., & Kupfer, D. J. (1992). Polysomnographic characteristics of young manic patients. Comparison with unipolar depressed patients and normal control subjects. *Archives of General Psychiatry*, 49(5), 378-383. https://doi.org/10.1001/archpsyc.1992.01820050042006
21. Jeong, S., Seo, J. Y., Jeon, S., Cho, C., Yeom, J. W., Jeong, J., Lee, J., Lee, T., & Lee, H. (2020). Circadian rhythm of heart rate assessed by wearable devices tends to correlate with the circadian rhythm of salivary cortisol concentration in healthy young adults. *Chronobiology in Medicine*, 2(3), 109–114. https://doi.org/10.33069/cim.2020.0022
22. Kim, B., Chae, M., Kim, Y., Kong, S., Kim, Y., Jung, T., Jeong, J., Park, S., Cho, C., Yeom, J. W., Lee, T., Lee, H., & Lee, H. (2024). Early prediction of depressive episodes in mood disorders using circadian rhythm indicators and deep learning. *2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, 6411–6418. https://doi.org/10.1109/bibm62325.2024.10822654
23. Kumagai, N., Esaki, T., & Lee, H. (2019). Predicting recurrence of depression using lifelog data: An explanatory feasibility study with a panel VAR approach. *BMC Psychiatry*, 19(1), Article 391. https://doi.org/10.1186/s12888-019-2382-2
24. Lanfumey, L., Mongeau, R., & Hamon, M. (2013). Biological rhythms and melatonin in mood disorders and their treatments. *Pharmacology & Therapeutics*, 138(2), 176-184. https://doi.org/10.1016/j.pharmthera.2013.01.005
25. Lanata, A., Valenza, G., Nardelli, M., Gentili, C., & Scilingo, E. P. (2015). Complexity index from a personalized wearable monitoring system for assessing remission in mental health. *IEEE Journal of Biomedical and Health Informatics*, 19(1), 132-139. https://doi.org/10.1109/JBHI.2014.2360711
26. Lee, Y., Lee, J., Kwon, I., Nakajima, Y., Ohmiya, Y., Son, G. H., Lee, K. H., & Kim, K. (2010). Coactivation of the CLOCK-BMAL1 complex by CBP mediates resetting of the circadian clock. *Journal of Cell Science*, 123(20), 3547-3557. https://doi.org/10.1242/jcs.070300
27. Lee, A., Myung, S. K., Cho, J. J., Jung, Y. J., Yoon, J. L., & Kim, M. Y. (2017). Night shift work and risk of depression: Meta-analysis of observational studies. *Journal of Korean Medical Science*, 32(7), 1091-1096. https://doi.org/10.3346/jkms.2017.32.7.1091
28. Lee, H. J., Cho, C. H., Lee, T., Jeong, J., Yeom, J. W., Kim, S., Jeon, S., Seo, J. Y., Moon, E., Baek, J. H., Park, D. Y., Kim, S. J., Ha, T. H., Cha, B., Kang, H. J., Ahn, Y. M., Lee, Y., Lee, J. B., & Kim, L. (2023). Prediction of impending mood episode recurrence using real-time digital phenotypes in major depression and bipolar disorders in South Korea: A prospective nationwide cohort study. *Psychological Medicine*, 53(12), 5636-5644. https://doi.org/10.1017/S0033291722002847

29. Lewy, A. J., Wehr, T. A., Goodwin, F. K., Newsome, D. A., & Rosenthal, N. E. (1981). Manic-depressive patients may be supersensitive to light. *The Lancet*, 1(8216), 383-384. https://doi.org/10.1016/s0140-6736(81)91697-4
30. Lewy, A. J., Sack, R. L., Miller, L. S., & Hoban, T. M. (1987). Antidepressant and circadian phase-shifting effects of light. *Science*, 235(4786), 352-354. https://doi.org/10.1126/science.3798117
31. Lipschitz, J. M., Lin, S., Saghafian, S., Pike, C. K., & Burdick, K. E. (2025). Digital phenotyping in bipolar disorder: Using longitudinal Fitbit data and personalized machine learning to predict mood symptomatology. *Acta Psychiatrica Scandinavica*, 151(3), 434-447. https://doi.org/10.1111/acps.13765
32. Lyu, H., Huang, H., He, J., Zhu, S., Hong, W., Lai, J., Gao, T., Shao, J., Zhu, J., Li, Y., & Hu, S. (2024). Task-state skin potential abnormalities can distinguish major depressive disorder and bipolar depression from healthy controls. *Translational Psychiatry*, 14(1). https://doi.org/10.1038/s41398-024-02828-9
33. Malkoff-Schwartz, S., Frank, E., Anderson, B., Sherrill, J. T., Siegel, L., Patterson, D., & Kupfer, D. J. (1998). Stressful life events and social rhythm disruption in the onset of manic and depressive bipolar episodes: A preliminary investigation. *Archives of General Psychiatry*, 55(8), 702–707. https://doi.org/10.1001/archpsyc.55.8.702
34. McCarthy, M. J., Gottlieb, J. F., Gonzalez, R., McClung, C. A., Alloy, L. B., Cain, S., Dulcis, D., Etain, B., Frey, B. N., Garbazza, C., Ketchesin, K. D., Landgraf, D., Lee, H. J., Marie-Claire, C., Nusslock, R., Porcu, A., Porter, R., Ritter, P., Scott, J., ... Murray, G. (2022). Neurobiological and behavioral mechanisms of circadian rhythm disruption in bipolar disorder: A critical multi-disciplinary literature review and agenda for future research from the ISBD task force on chronobiology. *Bipolar Disorders*, 24(3), 232-263. https://doi.org/10.1111/bdi.13165
35. McClung, C. A. (2013). How might circadian rhythms control mood? Let me count the ways. *Biological Psychiatry*, 74(4), 242–249. https://doi.org/10.1016/j.biopsych.2013.02.019
36. Moon, J. H., Cho, C. H., Son, G. H., Geum, D., Chung, S., Kim, H., Kang, S. G., Park, Y. M., Yoon, H. K., Kim, L., Jee, H. J., An, H., Kripke, D. F., & Lee, H. J. (2016). Advanced circadian phase in mania and delayed circadian phase in mixed mania and depression returned to normal after treatment of bipolar disorder. *EBioMedicine*, 11, 285-295. https://doi.org/10.1016/j.ebiom.2016.08.019
37. Mughal, F., Raffe, W., Stubbs, P., Kneebone, I., & Garcia, J. (2022). Fitbits for monitoring depressive symptoms in older aged persons: Qualitative feasibility study. *JMIR Formative Research*, 6(11), Article e33952. https://doi.org/10.2196/33952
38. Ng, T. H., Chung, K. F., Ho, F. Y. Y., Yeung, W. F., Yung, K. P., & Lam, T. H. (2015). Sleep–wake disturbance in interepisode bipolar disorder and high-risk individuals: A systematic review and meta-analysis. *Sleep Medicine Reviews*, 20, 46–58. https://doi.org/10.1016/j.smrv.2014.06.006
39. Nurnberger, J. I., Jr., Adkins, S., Lahiri, D. K., Mayeda, A., Hu, K., Lewy, A., Miller, A., Bowman, E. S., Miller, M. J., Rau, L., Smiley, C., & Davis-Singh, D. (2000). Melatonin suppression by light in euthymic bipolar and unipolar patients. *Archives of General Psychiatry*, 57(6), 572-579. https://doi.org/10.1001/archpsyc.57.6.572
40. Ringeval, M., Wagner, G., Denford, J., Paré, G., & Kitsiou, S. (2020). Fitbit-based interventions for healthy lifestyle outcomes: Systematic review and meta-analysis. *Journal of Medical Internet Research*, 22(10), Article e23954. https://doi.org/10.2196/23954
41. Robillard, R., Naismith, S. L., Rogers, N. L., Ip, T. K. C., Hermens, D. F., Scott, E. M., & Hickie, I. B. (2013). Delayed sleep phase in young people with unipolar or bipolar affective disorders. *Journal of Affective Disorders*, 145(2), 260–263. https://doi.org/10.1016/j.jad.2012.06.006
42. Shen, G. H. C., Alloy, L. B., Abramson, L. Y., & Sylvia, L. G. (2008). Lifestyle regularity and cyclothymic symptomatology. *Journal of Clinical Psychology*, 64(4), 482–500. https://doi.org/10.1002/jclp.20440
43. Song, Y. M., Jeong, J., de Los Reyes, A. A., 5th, Lim, D., Cho, C. H., Yeom, J. W., Lee, T., Lee, J. B., Lee, H. J., & Kim, J. K. (2024). Causal dynamics of sleep, circadian rhythm, and mood symptoms in patients with major depression and bipolar disorder: Insights from longitudinal wearable device data. *EBioMedicine*, 103, Article 105094. https://doi.org/10.1016/j.ebiom.2024.105094
44. Takaesu, Y. (2018). Circadian rhythm in bipolar disorder: A review of the literature. *Psychiatry and Clinical Neurosciences*, 72(9), 673–682. https://doi.org/10.1111/pcn.12688
45. Takaesu, Y., Inoue, Y., Murakoshi, A., Komada, Y., Otsuka, A., Futenma, K., & Mishima, K. (2016). Prevalence of circadian rhythm sleep-wake disorders and associated factors in euthymic patients with bipolar disorder. *PLOS ONE*, 11(7), Article e0159578. https://doi.org/10.1371/journal.pone.0159578
46. Van Til, K., Youngstrom, E. A., & Allen, N. B. (2019). A comparative study of engagement in mobile and wearable health monitoring for bipolar disorder. *Bipolar Disorders*, 21(3), 284–294. https://doi.org/10.1111/bdi.12849
47. Wenze, S. J., & Miller, I. W. (2010). Use of ecological momentary assessment in mood disorders research. *Clinical Psychology Review*, 30(6), 794–804. https://doi.org/10.1016/j.cpr.2010.06.007
48. Wirz-Justice, A., & Benedetti, F. (2019). Perspectives in affective disorders: Clocks and sleep. *European Journal of Neuroscience*, 51(1), 346–365. https://doi.org/10.1111/ejn.14362
49. Wu, Y. (2024). The impact of circadian rhythm on bipolar disorder. *Proceedings of ICBioMed 2024 Workshop: Computational Proteomics in Drug Discovery and Development from Medicinal Plants*. https://doi.org/10.54254/2753-8818/65/2024.LA18038