Automatic detection of social rhythms in bipolar disorder

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ABSTRACT

Objective To evaluate the feasibility of automatically assessing the Social Rhythm Metric (SRM), a clinically-validated marker of stability and rhythmicity for individuals with bipolar disorder (BD), using passively-sensed data from smartphones.

Methods Seven patients with BD used smartphones for 4 weeks passively collecting sensor data including accelerometer, microphone, location, and communication information to infer behavioral and contextual patterns. Participants also completed SRM entries using a smartphone app.

Results We found that automated sensing can be used to infer the SRM score. Using location, distance traveled, conversation frequency, and non-stationary duration as inputs, our generalized model achieves root-mean-square-error of 1.40, a reasonable performance given the range of SRM score (0–7). Personalized models further improve performance with mean root-mean-square-error of 0.92 across users. Classifiers using sensor streams can predict stable (SRM score ≥ 3.5) and unstable (SRM score < 3.5) states with high accuracy (precision: 0.85 and recall: 0.86).

Conclusions Automatic smartphone sensing is a feasible approach for inferring rhythmicity, a key marker of wellbeing for individuals with BD.

INTRODUCTION

Bipolar disorder (BD) is a serious mental illness that has been recognized worldwide as one of the eight leading causes of years lived with disability.[1] BD affects ~2.6% of the US population aged 18 and older in a given year.[2] It is associated with poor functional and clinical outcomes[3] and high suicide rates.[4] It also induces huge societal cost – the direct and indirect cost associated with BD I and II in 2009 has been estimated to be $151 billion in United States alone.[5]

BD is characterized by disturbances in rhythmicity. A number of theories link disturbances in social rhythms, such as changes in sleep timing and other routines to mood episodes for individuals with BD. The Social Zeitgeber hypothesis[6] suggests that certain life events may lead to episode onset due to their effect on individuals' social routines. Changes in routine, in turn, affect endogenous circadian rhythms leading to mood symptoms and, in vulnerable individuals, to mood episodes.

While there is no cure for BD, effective management can reduce the symptoms and result in better prognosis over time. Substantial evidence indicates that interventions targeting social rhythms, sleep–wake rhythms, and light–dark exposure may markedly improve outcomes.[7] Interpersonal Social Rhythm Therapy is a psychosocial therapy specifically devised to help individuals with BD maintain stable daily social rhythms. Increased regularity of social routines is associated with symptomatic improvement and significantly longer intervals between episodes.[8,9] The work of Interpersonal Social Rhythm Therapy also includes improving interpersonal relations but focuses on the timing of social events for establishing regular social rhythms. To establish and keep track of daily routines, mood and energy, patients use the Social Rhythm Metric (SRM). The SRM, originally developed as a 17-item scale to quantify rhythms of daily life, has subsequently been tested and used as a 5-item therapeutic self-monitoring tool (see Figure 1) in evidence-based psychosocial interventions.[10]

While the SRM has proven effective for assessing stability and rhythmicity of social routines, its paper-and-pencil format has multiple disadvantages as a clinical tool. Longitudinal self-tracking is difficult particularly in light of the inherent characteristics of BD. Even well-intentioned patients often forget to complete it. Additionally, in certain stages of illness, momentary and retrospective recall can be particularly challenging for patients with severe psychiatric disorders, and are sometimes unreliable. Nor is the paper format conducive to summarizing collected data, e.g., creating a visual representation of trends over time that could be used in treatment to enhance patients' self-awareness of their social rhythms. Such issues with paper-and-pencil based tools are well known. For example, Schärer et al.[11] found that for symptom journaling, patients with BD preferred handheld PDA to paper, reported feeling less social stigma and enjoyed having a more involved role in their treatment.

On the other hand, the capacity to automatically track traditionally self-reported behaviors is expanding rapidly. The emergence of novel sensing technologies has opened up new ways to automatically capture behavior that could address the challenges of manual tracking.[12] Recent studies have explored a wide range of sensing for tracking bipolar episodes. Agnes et al.[13] used smartphone-based sensing modalities including phone call duration, speech analysis and movement data to identify manic and depressive states. Using 12 weeks of data from 10 patients, their system detected states with 76% accuracy. In the MONARCA project, Frost et al.[14] developed a smartphone app for collecting data relevant to behavioral trends of BD to provide better disease insights to the patients. In addition to the self-assessed parameters like mood and stress, their system also collected sensor streams including activity, location, and device usage data. Six-month deployment data indicated that patient mood correlates with activity, stress, sleep, and phone usage.

OBJECTIVES

In this work, we focus on using smartphone-based sensing to overcome the limitations of existing self-reporting methods to help patients with BD maintain stability and rhythmicity. To achieve this goal, we provided a customized smartphone app to participants with a confirmed

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Figure 1: Sample paper-based Social Rhythm Metric form that is used as part of Interpersonal Social Rhythm Therapy.

SRM II–5

Directions:

Date (week of): Nov 18 – 24, 2015

- Write the ideal target time you would like to do these daily activities.
- Record the time you actually did the activity each day.
- Record the people involved in the activity: 0 = Alone; 1 = Others present; 2 = Others actively involved; 3 = Others very stimulating

Activity	Target Time	Sunday		Monday		Tuesday		Wednesday		Thursday		Friday		Saturay	
		Time	People	Time	People	Time	People	Time	People	Time	People	Time	People	Time	People
Out of Bed	7:00 am	9:30 am	0	8:30 am	0	7:30 am	0	7:30 am	0	7:15 am	0	7:40 am	0	8:30 am	0
First contact with other person	8:00 am	9:30 am	1	9:30 am	1	8:30 am	1	8:40 am	1	8:15 am	1	8:40 am	1	9:15 am	1
Start work/school/ volunteer/family care	9:30 am	10:30 am	0	10:15 am	2	9:30 am	1	9:50 am	2	9:15 am	0	10:40 am	1	11:30 am	0
Dinner	9:00 pm	11:30 pm	2	9:30 pm	0	9:50 pm	1	9:00 pm	0	9:15 pm	0	10:20 pm	1	9:30 pm	1
To Bed	11:30 pm	12:30 am	0	11:30 pm	0	11:50 pm	0	11:40 pm	0	12:15 am	0	12:40 am	0	12:30 am	0
Rate MOOD each day from −5 to +5 −5 = Very depressed +5 = very elated		+ 1		− 2		− 1		0		−1		+2		+2	

diagnosis of BD for 4 weeks to passively collect behavioral (e.g., speech, activity, SMS, and call log) and contextual data (e.g., location) using smartphone sensors. Based on the collected data, we employ machine learning techniques to model and predict markers of rhythmicity in the daily life of patients with BD that have been shown to reduce the risk of relapse.

While our research shares a basic foundation with previous work in using technology to track behavioral trends and mood, we take a different analytic focus and try to assess a variety of indicators of stability and rhythmicity that might have impact on social rhythms. To our knowledge, this is the first study that automatically infers stability and rhythmicity as assessed from SRM scores using passive sensor data. Since social rhythms are central to the wellbeing of individuals with BD, successfully measuring social rhythms via passive smartphone-based measures has considerable potential for the future monitoring and treatment of BD.

METHODS

Potential participants were identified through the Depression and Manic-Depression Prevention Program at Western Psychiatric Institute and Clinic. Participants were sent information letters to solicit participation. These letters stated project goals, expected duties, and time commitment. Patients interested in learning more were referred directly to the research staff who provided additional information about the study and obtained informed consent from those interested in participating. Only staff who were known to the potential subjects introduced and described the study.

The Institutional Review Board at the University of Pittsburgh approved this research. Inclusion criteria required patients to be already participating in a treatment program at the clinic, to be able to provide informed consent and to have a confirmed diagnosis of BD.

Participants were excluded if they were unwilling or unable to comply with study procedures or had active suicidal ideation requiring inpatient or intensive outpatient management. Nine participants with a confirmed diagnosis of BD (5 female, 4 male) consented to participate in the study. One participant did not use the app, and we were unable to retrieve another's sensor data, leaving seven participants in the study (see Table 1).

After consent administration, enrolled participants completed an initial questionnaire. We gave each participant an Android smartphone (Nexus 5) with our customized app, MoodRhythm. We also provided an explanation of how to use it. The study lasted 4 weeks. Participants completed a post-study questionnaire and interview. In light of the scale of personal data collection and after discussions with collaborators at the research clinic, each participant was compensated with $50 for each week of participation, $25 for each completed questionnaire and $50 for the final interview. Patient compensation was not contingent on adherence to the daily protocol of use.

Study Instrument

Participants were provided with MoodRhythm to track their social rhythms. MoodRhythm supports both subjective rating and automatically-sensed data collection. It allows patients to track 5 core activities used in the paper version of the SRM-5: (1) waking time, (2) first contact with another individual, (3) starting their day, (4) dinner, and (5) bedtime, and also to add custom activities (see Figure 2). The app allows tracking of mood and energy as well on a −5 (very low) to +5 (very high) scale.

Patients can set daily target times for activities and track how closely they meet these target times. Notes can be used to record additional information such as the amount of medication taken or factors that may have affected a patient's routine or mood. The app is designed to

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provide an at-a-glance summary of the person's successes in meeting their rhythm goals for both the current and preceding days. If the patient completes an activity within their customizable time window (the default is 45 min), then the bar to the left turns green. When the window is about to elapse and an event is not yet recorded, the bar appears yellow (a "warning" that a potential rhythm disruption is occurring). If a target is missed, then the bar turns red. More detailed feedback on weekly patterns is viewable in weekly graphs. MoodRhythm incorporates a series of badges that are given based on adherence to self-report.

The app uses a variety of sensor data sources on the smartphone platform with the ultimate aim of inferring behavioral rhythmicity. Our platform continuously collects data from the phone's light sensor, accelerometers, and microphone, as well as communication patterns and information about phone usage events such as screen unlocks and charging.

The phone's microphone was activated every 2 minute to capture ambient sound. If human speech was detected, the microphone

Table 1: Demographic and clinical characteristics of the participants

Participant	Age	Gender	Diagnosis
1	25–34	Female	BP-I
2	55–64	Female	BP-II
3	45–54	Male	BP-II
4	25–34	Female	BP-II
5	35–44	Male	BP-NOS
6	25–34	Female	BP-II
7	25–34	Female	BP-II

remained active. To filter out false positives including conversation from a TV program, we use energy intensity and distribution likelihood.[15] To protect privacy, we do not record audio recordings, but instead process data in real-time to only extract and store features (e.g., spectral content and regularity, loudness) that are useful for detecting the presence of human voice but insufficient to reconstruct speech content.[16] Using these privacy-sensitive audio features and probabilistic inference techniques, it is possible to reliably estimate the number of conversations an individual engages in, the duration of the conversations, and how much time a given individual speaks within a conversation along with speaking rate and variations in pitch.[16] These features have been used to detect social isolation in older adults.[15]

Activity is captured by the smartphone accelerometer that detects movement. The system generates and stores physical activity status (e.g., active vs sedentary). For location detection, we used the Android location service, which combines the Global Position System, Wi-Fi, and cellular data to provide location estimations. MoodRhythm also collects communication patterns including SMS and call logs. The sensor data are stored in the smartphone and securely transmitted to our remote study server periodically. The impact of our app on battery is reasonable, permitting 16 h of continuous sensing after a full recharge.

RESULTS

On average, participants recorded 36.5 (SD: 11.17) energy instances, 46.12 (SD: 12.71) mood instances, and 144.43 (SD: 43.1) SRM event entries including custom activities (see Figure 2). From sensor data, the overall distance traveled per day by each participant is 8.34 km (SD: 13.34). On average, the ratio of time being sedentary to active per day is 2.09. Participants were around human speech 3.25 h (SD: 3.67) a day, on average. The trend of self-assessed energy scores – computed over seven days (rolling average) – correlates with sensor streams as shown in Table 2. Mood pattern is weakly correlated with

Figure 2: Screens from the MoodRhythm app used by participants for this study.
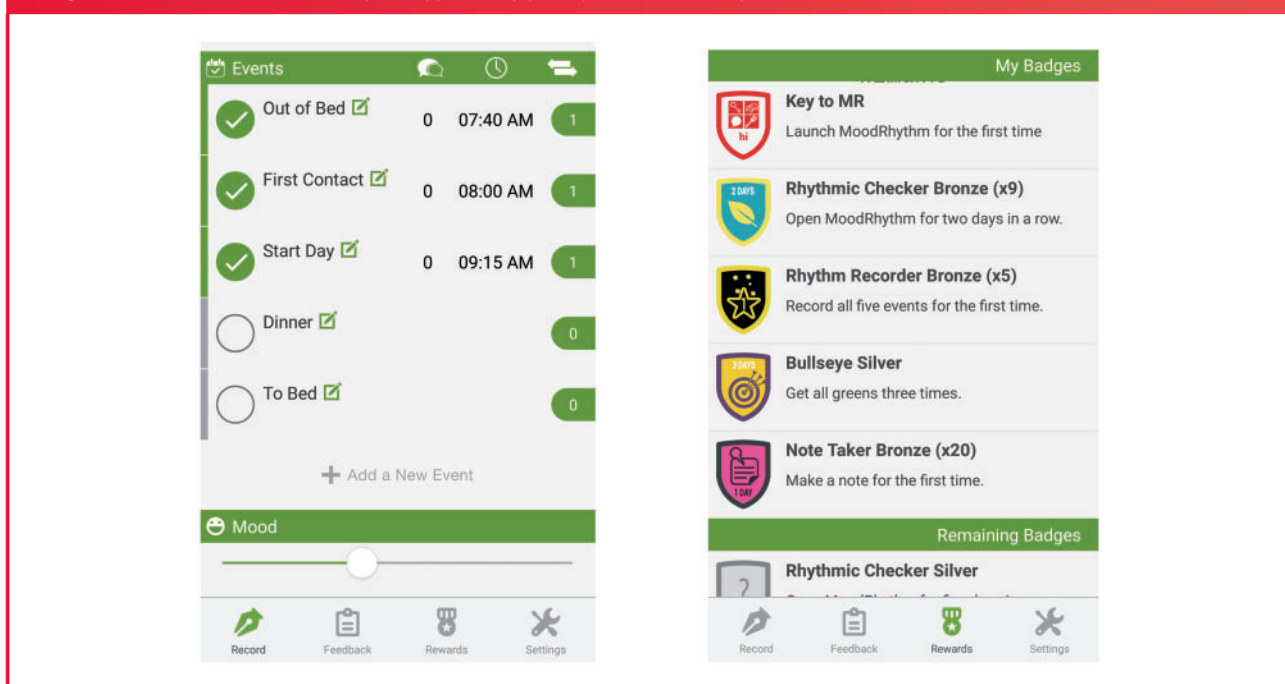
conversation ($r = 0.16$, $P = .06$) and non-sedentary duration ($r = 0.15$, $P = .08$).

This study focuses on the automatic inference of rhythmicity in the daily life of patients with BD. We use the sensed data to build a statistical inference and prediction model using machine learning techniques. The patient-reported SRM score is used as ground-truth. In other words, the goal is to develop a predictive model that can infer the SRM score from smartphone-based sensor data alone. In particular, we use the number of location clusters, distance traveled, frequency of conversation inferred from audio data, and duration of non-sedentary activity calculated over each day as inputs to the model (i.e., feature set). For location clustering, we use a density-based algorithm[17] with a radius of 0.5 km. We selected these features because they are good indicators of social and physical functioning, which are crucial in tracking symptomatic behavior of patients with BD. A number of recent studies also have found these parameters to be highly useful for assessing mental health. Speech and conversation features have been used for determining states of individuals with BD.[13,18,19] Recent studies[14,20,21] have also found that the level of physical activity, location, and mobility can indicate state change in this disorder. Moreover, as we describe in Table 2, these features correlate with self-reported energy.

While traditionally SRM scores have been computed over non-overlapping weeks, given the higher granularity of our sensed data, we calculate SRM scores using a rolling window of 7 days. The value of the SRM score ranges from a theoretical 0 to a theoretical 7 where higher values indicate greater rhythmicity. SRM scores are in a continuous range, so to model them we use Support Vector regression,[22] a well-known machine learning framework. The accuracy of the model is evaluated using 10-fold cross-validation – a widely used model validation technique in statistical analysis. For this, data is randomly partitioned into 10 equal sized subsets. For each round, a single subset is retained for model validation and the other nine subsets are used for training the model. This process is repeated 10 times to use each subset for validation and the averaged result is then computed. Using test set independent of training data can help assess the generalizability of model. From our analysis, we find that the average root mean square error (RMSE) is 1.40. RMSE is calculated by taking the square root of average of squared errors — the difference between predicted and actual SRM scores. Given the range of SRM scores (0–7), the low RMSE value indicates that our model achieves reasonably good accuracy. Personalized models trained on each individual can significantly improve performance with a mean RMSE of 0.92 across all participants. Model performance is likely to improve further with the collection of more data enabling better adaptation to idiosyncratic trends over a longer period of time.

Beyond raw SRM scores, we also focus on being able to infer status of rhythmicity from sensor data. From a large study on representative healthy population ($n = 1249$), Tienoven et al.[23] found that the mean population SRM score was close to 3.5. Following their finding of "normal social rhythm", we considered a SRM score lower than 3.5 as an unstable state while any score greater or equal to 3.5 is indicative of a stable state. In this formulation, it is a binary (i.e., unstable and stable) classification problem. We use a Support Vector Machine for prediction. Based on input features, Support Vector Machine constructs decision boundary separating different classes (i.e., stable and non-stable states in this case). For training the model, we use the same feature set as before. Over 10-fold cross-validation, our model achieves high performance with a precision score of 0.85 and recall score of 0.86.

We also perform feature ranking to assess the importance of each feature in predicting SRM stability from sensor data. We use recursive feature elimination[24] for this. At each step of recursive feature elimination, a model is trained on the entire dataset and the feature least contributing to the model is discarded. This procedure is recursively continued until there is only one feature left. The most important features for prediction are the location cluster and total distance traveled over a day as shown in Table 3.

We compute class probability estimates that provides more granular information than prediction output alone. Probability estimations are easily interpretable and particularly useful in conveying uncertainty associated with outputs from a statistical model. In particular, the confidence score associated with predictions made by the model could help clinicians make informed decisions. For example, depending on the potential cost associated with misclassification in a given context, clinicians could choose to discard predictions with high uncertainty.

To calculate the probability distribution from the outputs of our classification model, we use Platt scaling.[25] To calculate probability, it fits a logistic regression model to the classifier output. From the calculated probability estimates, we find that 75.89% of correctly classified labels have a probability ≥ 0.7 – an indicator of high confidence in predictions from the learning model. In other words, for the majority of the correctly classified labels, the learning model has high confidence. This shows that our prediction model is quite robust against noise.

DISCUSSION

To our knowledge, this is the first study that automatically infers stability and rhythmicity as assessed from the SRM score using passive sensor data. Our model can distinguish between stable and unstable states with high precision. The probability estimation also indicates that the model is quite robust. We now discuss the implications of our findings for an early warning system to predict relapses. The ability to automatically detect departures from rhythmicity as described here can open up ways of providing instantaneous interventions beyond the current capabilities of existing clinical systems.

Managing BD requires constant and lifelong vigilance against relapse. Interventions targeting the regularity of social rhythms can

Table 2: Correlation between sensor stream and trend of self-assessed energy scores computed as rolling average over 7 days

Sensor	Correlation
Cluster	0.31***
Distance	0.23**
Conversation	0.25**
Non-sedentary duration	0.39***

**$P < .01$, ***$P < .001$.

Table 3: Ranking of feature importance for the stable and unstable status classification using recursive feature elimination (RFE). It also shows weights assigned to features in a support vector machine using a linear kernel.

Feature	Ranking	Weight
Distance Traveled	First	1.56×10^{-2}
Location Cluster	Second	3.27×10^{-3}
Non sedentary duration	Third	-3.79×10^{-4}
Conversation frequency	Fourth	7.69×10^{-5}

lower the risk of relapse and improve long-term prognosis. However, maintaining self-tracking over a long period of time using the existing paper-and-pencil SRM is understandably challenging. People can forget to complete entries, and there is no way to recover lost records. More important, relying on an individual's ability to recall events, whether the self-report measure is administered on a paper form or a smartphone, often fails to capture the subtler details of behavioral and contextual patterns that may be particularly difficult to track for people with severe psychiatric disorders.

Our findings suggest the viability of overcoming the limitations of existing clinical tools. For example, our predictive model does not rely on individual recall of events and thereby removes the risk of non-adherence and stigma. The wide ranging data collection capabilities combined with the unobtrusive nature of smartphone-based sensors means that behavioral and contextual tracking of daily patterns can be much more comprehensive and continuous. The original SRM scale had 17 items and was reduced to 5-items because of the difficulty in manually tracking so many items. A smartphone-based automatic sensing system can track a wide array of trends, without placing additional burden on users. This approach also has the potential to identify individualized cues that might be more accurate idiosyncratic markers of clinical status than the five self-rating items in the SRM. Over long periods of time, this data could also be helpful in identifying person-specific disruptors of routines and prodromes of episode onset.

Automatic and unobtrusive sensing of rhythmicity as described here can also address issues with longitudinal data tracking. In contrast to paper-and-pencil measures, active user interaction is not necessary to track daily trends. This might be particularly useful when the patient is very symptomatic – remembering to complete SRM items is understandably more unlikely during the depths of depression and the heights of mania, and this is precisely the time when symptom tracking is most crucial. Thus, automated data collection and trend detection before relapse onset can provide invaluable insights for immediate intervention and clinical actions for the long run. For example, a low conversation level for an extended period of time might be indicative of the onset of a depressive state while an increased number of location clusters and distance traveled might signal the beginning of a manic phase. Such early detection of relapse signatures can enable preemptive care.

Another problem with how existing tools are used in practice is the lag in intervention. The delay between recording SRM entries and clinicians having access to them can be longer than ideal. Being able to automatically assess stability and rhythmicity can help in the provision of more timely feedback to individuals outside of clinical settings by identifying and sharing disruptions in routines in real time. Beyond just a tracking tool, smartphones can also be an intervention delivery tool – providing care to patients when and where they need it.

The data provided by passive sensing of contextual and behavioral trends for longitudinal wide-ranging tracking can enable a better understanding of individualized symptom cues for both patients and clinicians. The automated sensing and prediction that has been described here could thus empower patients and also enable clinicians to create more effective personalized treatment plans. For example, the clinicians could combine the output from sensed data with other subjective measurements. Along with classifier decisions, the confidence score from the probability estimates could also help clinicians to make informed decisions about the uncertainty.

By combining the self-reported SRM with smartphone sensing for a short period of time, these models could be individualized to each patient. This would improve the accuracy of the clinical information. Since BD is a life-long condition characterized by common and idiosyncratic symptoms, this training period could be very helpful.

Although passive smartphone sensing of social rhythms based on our generalized model could provide valuable, otherwise unobtainable, clinical information, it is vital to consider whether any positive therapeutic elements might be lost by using a fully automated system in clinical practice. In a sensor-supported system, there is a risk that positive elements associated with self-tracking such as having a sense of involvement in treatment and control over one's illness may be lost. This is particularly relevant in the case of the SRM, which is both a measure of social rhythms and a tool for helping individuals structure their days by explicitly setting target times for each event. While our approach means clinicians do not have to rely entirely on self-reported measures of social rhythmicity, participants could still continue to self-track if deemed therapeutically beneficial. In this case, it could then be possible to pivot the focus of patient tracking from event tracking to focus on more qualitative aspects of individual experience.

The results presented here have several limitations. The study population is small and data were collected for only 4 weeks. Sensor data collection was also dependent on participants carrying the phone. If a participant were to forget to carry their phone, then the data would not represent the context and activity of the user. Participants did not use their own phones, which might result in different usage patterns. All the patients were euthymic when recruited. Since adherence to SRM tracking could be very low during relapse onset, having euthymic patients ensured enough data coverage to compare with sensor streams and also can help establish individual baseline, departure from which can be used as early-warning sign. Future work should investigate the use of this approach across mood states and over a longer period of time.

Our analyses focused on the SRM, but another important factor is social activity. Someone with BD is typically less involved in social activity during a depressive episode and much more involved than normal during a manic episode. Future studies could investigate whether there are connections between patient self-report involvement in social activity and sensor data.

CONCLUSIONS

In this work, we investigated the feasibility of automated assessment of the SRM score – a clinically validated marker of stability in patients with BD – using sensor data streams from smartphones. By employing statistical learning techniques, we find that sensor data can be used to successfully distinguish between stable and unstable states (precision: 0.85 and recall: 0.86). The confidence score associated with the output also indicates that the predictive model is quite robust.

Since maintaining stability in daily routine can significantly reduce risk of relapse in individuals with BD, being able to automatically assess rhythmicity without requiring active user engagement can have considerable impact on clinical care. In particular, our findings could help overcome issues with existing paper-and-pencil based clinical tools by significantly lowering the user burden of manual tracking.

As passive sensing can result in much more granular and wide-ranging data than manual and subjective tracking, these results can be extended to an early warning system for relapse detection. Such a system could open up novel ways to provide interventions – enabling preemptive care at the right moment and the right place. By lowering user burden, the use of automated sensing could make longitudinal tracking significantly easier, which, in turn, could provide crucial and subtle clues to inform clinical decisions on individualized treatment course.

In addition to BD, the SRM has also been used in a number of clinical conditions including stroke,[26] Parkinson's disease,[27] myoclonic epilepsy,[28] anxiety disorders,[29] and unipolar depression.[30] The predictive model to automatically infer stability and rhythmicity as developed in this work can potentially be applied to these conditions as well,

which would greatly enhance the practicality of social rhythm theory as a clinical tool and research instrument.

CONTRIBUTORS

S.A. contributed to the conception, design, implementation, analysis, and drafting the work. M.M. initiated the collaborative process, helped designing the study and writing the manuscript. E.F. revised the draft. G.G. helped in the design of the study. G.D. revised the draft. T.C. contributed in study design, analysis and revising the draft. All authors contributed to refinement of the study protocol and approved the final manuscript.

COMPETING INTERESTS

M.M., E.F., and T.C. co-founded and have equity interest in HealthRhythms. G.G. serves on the advisory board for HealthRhythms.

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RESEARCH AND APPLICATIONS