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Can Risk and Reward Sensitivity to Games Inform about Mood Dynamics and Upcoming Episodes in Bipolar Disorder? *

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Abstract

Lack of information about the upcoming mood episode often hinders the prescription of mood-targeted medication in cases that experience extreme mood swings like in Bipolar disorder between depression and mania. Computational models are yet to seamlessly integrate into the clinical practices, especially for characterizing the phase, severity, and trajectory of mood oscillation dynamics, and personally intervening in people suffering from mood disorders and in particular-bipolar disorder. For our study, we used a dataset collected through the Happiness project initiative at University College London, that prompted the subjects to play two alternate choice task paradigm daily, one option having a higher probability of fetching a reward and the other lower. Mood changes were induced by a wheel of fortune presented in the middle of the game, giving the participants chance for a jackpot or a huge loss. Additionally, the subjects were also asked to rate their Elated, Irritable, Energetic, Sad, Anxious, Angry moods daily. Further, they were also asked to fill in information about their depression, mania symptoms a few times over 2 months. We specifically asked a few questions in our study: 1) Can games be sensitive to mood induction, and how does it inform bipolar disorder? 2) Can a model of subjective reward and risk sensitivity of subjects, along with their ecological momentary input and clinical history, predict the bipolar status of a subject and their precise mood disorder severity? 3) Can the predicted mania and depression severity inform about mood swings in future? Our results broadly suggest that change of happiness reported by Bipolar subjects in a mood induction game significantly differed to that of healthy controls, and the bipolar status along with mood swings for the next 7 days from any time point can be reliably predicted using a combination of extended risk based decision making model of the game and machine learning, statistical models.

Keyphrases

Mood oscillations, computational model, reward sensitivity, risk sensitivity, bipolar disorder, predictive utility.

Introduction

Bipolar disorder is characterized by swings in mood between mania and depressive episodes. The cycle length and periods vary between subjects. The prevalent medical practice as far as we understand for this disorder is self-report, trial and error based suggesting of medications including Lithium, antipsychotics, antidepressants and mood stabilizers. Understanding the basis of moods such as happy, sad, angry, irritated, energetic, has a significant utility in personalized models of mood prediction over time, their monitoring, and strategizing of interventions. Currently there exists a gap in neurocognitive state profiling of the disorder in any patient that is sensitive to the ongoing mood dynamics (Niv et al. 2015; Mason et al. 2017; Rutledge and Adams 2017).

In this study, we apply our risk and reward dependent utility based decision making model (Priyadharsini Balasubramani and Chakravarthy 2020), to understand the changes in behavior in a mood induced decision making paradigm (Eldar and Niv 2015) for subjects with distinct mania, depression mood oscillation profiles. This wholistic framework is novel in explaining the altered appraisal due to mood induction, and that this utility model in a mood induction paradigm can act as a probe to characterize various phases and dynamics in mood disorders, especially bipolar.

Methods

Participants

We had access to data from approximately 88 participants tracked for about 2 months, including demographic information, ecological momentary assessments (EMA), test inventories, and games. These data were collected as part of the Happiness project, courtesy of Dr. Liam Mason, University College London (details below). The total sample consisted of 88 subjects (59 females, 29 males; Age33.78 ± 8.88, Min: 20, Max: 60), where $N = 46$ participants (32 females, 14 males; Age 35.15 ± 8.28, Min: 22, Max: 60) were diagnosed with bipolar disorder (BPD), and $N = 42$ (27 females, 15 males; Age 32.29 ± 9.37, Min: 20, Max: 59) were labeled as Controls. The self-report test inventories analyzed in this study include the Altman Self-Rating Mania Scale (ASRM), Patient Health Questionnaire (PHQ-9), and Quick Inventory of Depressive Symptomatology (QIDS). We further categorized different time points for each subject as euthymic (ASRM ≤ 5 and PHQ-9 ≤ 5), manic (ASRM > 5 and PHQ-9 ≤ 5), depressed (ASRM ≤ 5 and PHQ-9 > 5), or mixed (ASRM > 5 and PHQ-9 > 5) episodes. Of the 46 BPD

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subjects, 7 experienced only euthymic states (i.e., zero sample times of manic, depressed, or mixed states). Thirteen subjects experienced at least one manic state, of which 4 never experienced a depressed or mixed state. Thirty-two subjects experienced at least one depressive state, of which 21 never experienced a manic or mixed state. Twelve subjects experienced at least one mixed state, of which 7 also experienced a manic state and 9 a depressed state. Six subjects experienced at least one manic state and at least one depressed state, of which 4 also experienced at least one mixed state.

Game

The game consisted of two blocks of a probabilistic reward-based choice task with two stimuli, one with a high reward probability (75%) and the other with a low reward probability (25%). The stimuli differed between blocks, but the reward probability for each stimulus remained fixed. Each block comprised 18 trials, with 4 trials being forced-choice (i.e., the subject was given only one option to choose). The game outcomes were either a reward (10 gems) or no reward (0 gems). Subjects reported their happiness level on a slider at points near the start, middle, and end of each block. Between blocks, a wheel of fortune (WOF) offered random outcomes from the set $(-210, -175, -105, -90, 90, 105, 175, 210)$ gems. A total of 1173 games were played by the 88 participants, with a mean of 13.33 ± 10.74 games per person (Min: 1, Max: 70). Several users played multiple games in a day. Considering only one game per day, there were 719 games, with a mean of 8.17 ± 6.51 games per subject (Min: 1, Max: 41).

Ecological Momentary Assessments

As part of the EMA, self-reports of moods (Elated, Irritable, Energetic, Sad, Anxious, Angry, Worthwhile Person) on a scale from 0 to 7 were collected from subjects. A total of 16,611 responses were recorded, with a mean of 188.76 ± 104.67 responses per subject (Min: 3, Max: 340). Considering only one entry per day, there were 3986 entries, with a mean of 44.27 ± 18.51 responses per user (Min: 1, Max: 67).

Ecological Momentary Test Inventories

A total of 613 responses were recorded for the test inventories, with a mean of 6.97 ± 3.81 responses per subject (Min: 1, Max: 22) over the recording period. Some users recorded multiple responses in a day; disregarding duplicates resulted in 590 responses, with a mean of 6.70 ± 3.58 responses per user (Min: 1, Max: 20).

Extended Reinforcement Learning Model

We utilized the computational model reported in Priyadharsini Balasubramani and Chakravarthy (2020) as Model A. Additionally, we simulated the current trial outcome as $r = \eta_r \bar{r} + r_{\text{ins}}$, where r_{ins} is the instantaneous reward. We further use linear regressions, LSTM, random forest classification, and the activation and inhibition model (Cochran et al. 2018) to simulate predictions, statistical dynamics over time, appropriately.

Results

A linear mixed-effects model was used to examine the effects of WOF Outcome, group (clinical vs. control), and pre-WOF happiness on the change in happiness (difference between post-WOF and pre-WOF happiness). The model included 1,173 observations from 88 participants and was fit using restricted maximum likelihood (REML, Figure 11 A,B).

A random intercept for participant was included to account for repeated measurements within individuals across multiple game rounds. Fixed effects included main effects and all two- and three-way interactions among WOF Outcome, group, and pre-WOF happiness. There was a significant main effect of pre-WOF happiness, $b = -0.59$, $SE = 0.05$, $z = -11.64$, $p < .001$, indicating that higher initial happiness was associated with smaller increases (or greater decreases) in happiness following the WOF event. The main effects of group and WOF Outcome were not statistically significant, suggesting no overall differences in happiness change attributable solely to these factors.

A significant two-way interaction between WOF Outcome and group was observed, $b = -0.15$, $SE = 0.05$, $z = -2.86$, $p = .004$, indicating that the effect of WOF Outcome on happiness change differed between the clinical and control groups. A significant three-way interaction emerged among pre-WOF happiness, WOF Outcome, and group, $b = 0.28$, $SE = 0.08$, $z = 3.44$, $p = .001$, suggesting that the joint influence of baseline happiness and outcome on emotional reactivity varied by group. A random intercept was estimated for each participant, with a variance of 0.009 ($SD \approx 0.094$), capturing modest between-subject variability in overall happiness change.

We used the extended reinforcement learning model to optimally estimate the reward hypersensitivity (Ar) and tonic risk sensitivity (k) measures for each subject, with parameters fit to minimize the difference between observed and simulated game choice readouts. Next, we merged the EMA and test inventory data with the game data, using the EMA/inventory sample from the closest available time point. Only one game per user per day was considered, selecting the first game in case of multiple games. We trained a long short-term memory (LSTM) model to predict the current day's PHQ-9 based on 3 previous game days. We observed that the feature "Little interest or pleasure in doing things" (PHQ-9 item 8, 0-3 scale) was the best predictor of PHQ-9 severity in our participants, with an $RMSE = 2.758$ and $R^2 = 0.460$. A random forest model achieved approximately 87% accuracy in a 5-fold cross-validation to predict BPD or control status, with a high F1 score of 0.87 (Figure 1C). Using the model by Cochran et al. (2018), we further optimally fit the transition probability mania and depression scores over the next 7 days (Figure 1D).

Discussion

Our results highlight that the emotional impact of reward, uncertainty in outcomes depends not only on the event itself but also on individual differences in baseline mood and clinical status, with the control group showing greater modulation by both factors. Specifically, individuals in the control group with higher pre-WOF happiness displayed greater emotional sensitivity—both gains and losses—to the WOF outcome than their clinical counterparts. Interestingly, an extended reinforcement learning model to estimate the reward and risk sensitivity of a subject, along with their Ecological Momentary Assessments and test inventory score history during the previous 3 days, was able to reliably inform the current bipolar status of the subject. Further statistical model based estimation of mood oscillations for the next 7 days were also explored.

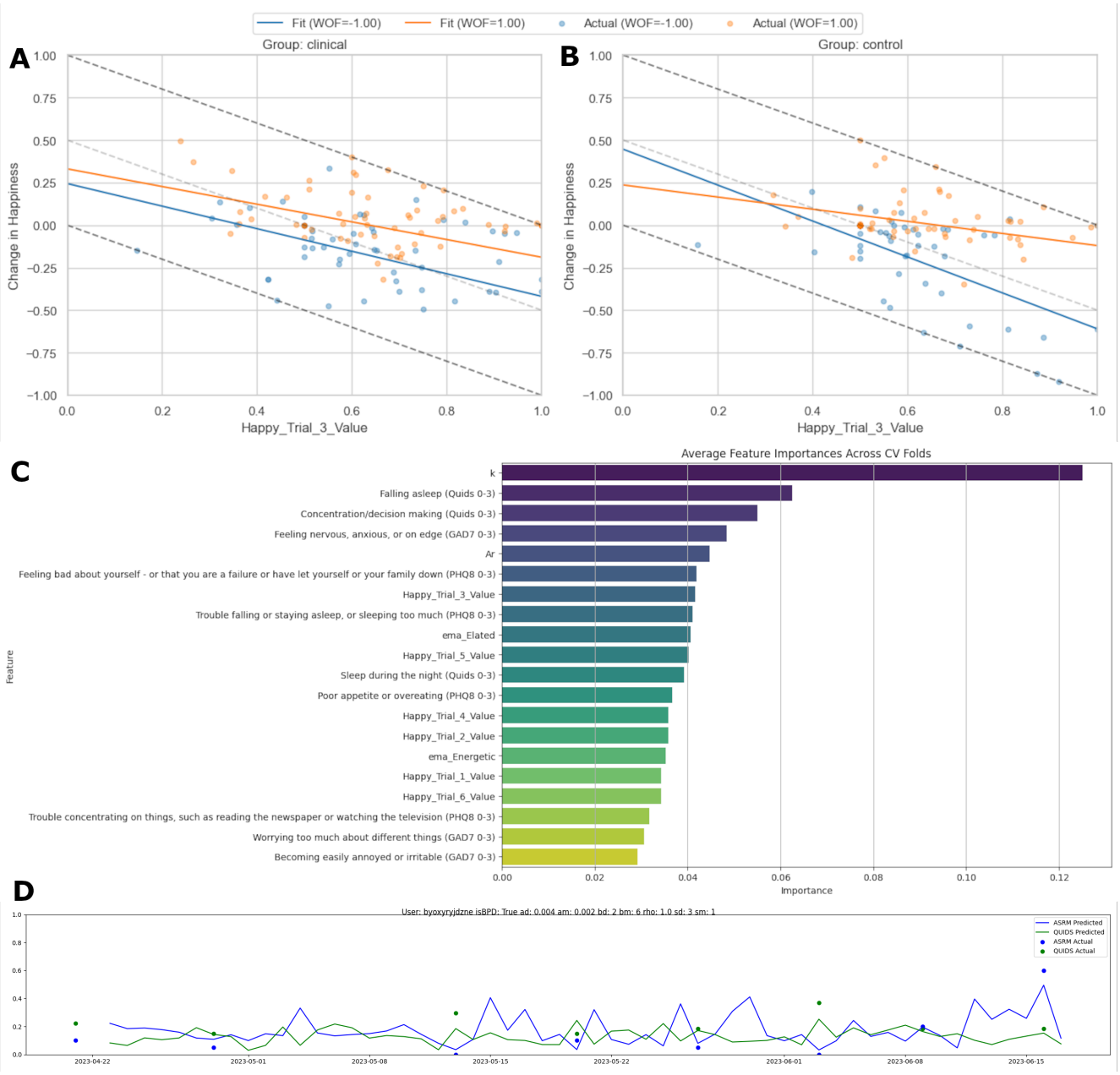

Figure 1: Happiness Mood Induction effect, reward and risk sensitivity model to predict Bipolar mood oscillations. We observe strikingly increased change in happiness in controls especially during negative induction of mood through wheel of fortune compared to Bipolar subjects (see, A for clinical, B for control subjects). c) Presents the importance wise sorted bar diagram of the features able to predict bipolar status of the subjects. Here (Ar) and (k) represents the reward hypersensitivity and tonic risk sensitivity of the subjects optimized for every subject using the reinforcement learning model. D) Statistical model based prediction of mood oscillations in an illustrative subject.

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Contributions

All authors contributed equally to the paper.

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