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Abnormal behavior of following peers in an online game indicates bipolar disorder and manic/hypomanic episodes

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***Abstract*— Early detection of bipolar disorder (BD) is crucial for its ultimate control and prevention. We aim to detect people with BD and their manic/hypomanic episodes through their abnormal behaviors of following peers in Massively Multiplayer Online Game (MMOG) logs. The total participants consisted of 198,605 users of Pigg Party: a popular MMOG in Japan. Their behaviors, including gacha (an online capsule toy game) and purchase in MMOG, were recorded in milli seconds for one month. Of the total participants, 291 responded to the mood disorder questionnaire. Among the questionnaire respondents, 20 were judged as BD group and the other 271 as non-BD group. According to the anomaly scores of the behaviors of following peers, 13,650 of the total participants were estimated as BD group and the other 184,955 participants as non-BD group. Among the total participants, the BD group had significantly more gacha and purchase behaviors than the non-BD group. Further, among this BD group, these behaviors were significantly more prevalent especially during manic/hypomanic episodes. Our findings indicate that behaviors of following peers in MMOG logs is potentially useful for detecting BD and manic/hypomanic episodes.**

Keywords—behaviors of following peers, online game, anomaly detection, bipolar disorder, mania

I. Introduction

Bipolar Disorder (BD) with manic/hypomanic episodes, e.g., abnormally elevated mood states, is associated with a variety of problem behaviors, e.g., excessive gambling and purchasing [1]. People with BD are prone to high medical costs due to the need for high-frequency medical services for a variety of problem behaviors, costing $48 billion annually in the U.S. alone [2]. In order to prevent the rising cost of medical care, it is important to provide simple treatment services to patients with BD before the onset of the disease, thereby eliminating the need for subsequent high-frequency medical services [3]. In other words, BD requires early detection and treatment [4].

While detection of BD has traditionally involved observation during the interview by a specialist [5], in recent years, detection methods using electronic devices have been developed [6]. It has been reported that electrodermal activity during psychological interviews [7], and motion acceleration during daily life [8] are each useful for detecting BD. These findings support that the use of electronic devices to detect BD is a promising approach and may lead to early treatment of BD patients [9].

Another potentially useful approach for detection of BD is analysis of activities in online social networks such as social media and online games. Past studies have shown that users with BD can be predicted by accumulated Twitter chat contents[10], [11]. Further, users with BD have also been shown to be prone to excessive online gaming[12]. However, these studies focus on the behavior of individuals but not on their embedded social networks; since people with BD have been noted to have many social problems[13], [14], it is likely that they also exhibit abnormal behavior during network building in an online game. Therefore, this study will detect abnormalities during network building of MMOG users to estimate their BD and manic/hypomanic episodes.

Our rationale is the interpersonal and social rhythm therapy [15], which assumes that the interpersonal problems of people with BD exacerbate their symptoms, while solving these interpersonal problems improves these symptoms [16]. In fact, their interpersonal problems increased the risks of their suicide attempts [13], whereas solving these problems improved their social functioning [17]. Further, people with BD received lower social support than those without BD [18]. Moreover, frequency of their perceived social support was positively correlated with their recovery from BD [14]. These findings indicate that BD was positively correlated with interpersonal problems and negatively correlated with social support.

Although the correlation between BD and interpersonal problems/social support was mainly identified in offline communities, it is possible that the correlation exists in online

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communities as well, because people with BD used aggressive language and sent the same message repeatedly late at night to their online friends during their manic/hypomanic episodes [19].In fact, people with BD block more friends on Facebook than those without [20]. These findings indicate that people with BD are more likely to have interpersonal problems and less likely to have social support in online communities, and that BD and manic/hypomanic episode duration can be estimated based on their network-building behaviors in a MMOG.

Based on these studies, the present study used behaviors of following peers in a MMOG because following peers online is considered an online networking behavior[21].Abnormal behaviors of following peer could be useful to detect users with BD and aimed to estimate their manic/hypomanic episode duration. We also examined the association between BD and their online behaviors, such as “gacha”(an online capsule toy game), and purchase, which are thought to be increased in BD [22], [23]. Similarly, we distinguished between durations of manic/hypomanic and non-manic episodes among BD users and aimed to confirm that these behaviors were particularly increased during these manic/hypomanic episodes [1].

Our study has three hypotheses: 1. It would be possible to estimate BD and manic/hypomanic episode from behaviors of following peers in a MMOG. 2. MMOG users estimated to be BD would be more likely to show gacha and purchase behaviors than those who are not. 3. Among those estimated to have BD, durations of manic/hypomanic episodes would be more likely than durations of non-manic episodes to produce gacha and purchase behaviors.

II. Methods

A. Study Design

This study is an observational study with one large population and a small reference population. The large population indicates all the users of MMOG analyzed, which were referred to as total participants. The small reference population indicates the users of questionnaire respondents (see below). The large population was divided into the BD group and the non-BD group, which were estimated through MMOG logs. The small reference population was also divided into the BD group and the non-BD group, which were assessed by Mood Disorder Questionnaire (MDQ).

B. Participants

The total participants were 198,605 users of Pigg Party who had logged in between 7/26/2022 and 8/23/2022 and who had conducted at least two chats (group utterances) or talks (one-on-one utterances) on Pigg Party. The Pigg Party is a popular MMOG in Japan[24]: Each user is provided with a personal avatar and a private room, and users converse with each other using pseudonym (Fig. 1). Among the participants, 291 responded to the 15-item MDQ [25] in Japanese version [26]. Parts of the data from these questionnaire respondents were used in another study [27].

C. Reference Participants

According to the previous study [28], among the questionnaire respondents, those who answered "yes" to six or more questions and had at least minor problems on the MDQ [25] were judged to have BD. Note that the MDQ is a questionnaire used to assess lifetime mania/hypomania, but in this study we wanted to judge mania/hypomania over a one-month period, so all references to "have you experienced ever" were changed to "have you experienced during the past month”. The 20 questionnaire respondents were judged as group with BD; the other 271 questionnaire respondents were judged as group without BD. The rate of BD 6.873% (20/291) was used as threshold to estimate BD in total participants. In other words, these labels were treated as grand truth.

Fig. 1. Players’ behavior in Pigg Party

Notes: Each player has an avatar and a private room, and they can customize his or her avatar and private room and visit the private rooms of other players. To visit a private room, permission to enter must be obtained from the owner of the room in advance. Translation of the figure. a: “I'm going to enter the room.” b: “Hi.” c: “What anime do you watch? Tell me what you're into.” d: “It's a bumper crop this season.” e: “I want to know that too.”

D. Independent Variables

Behaviors of following peers was recorded in milliseconds on the Pigg Party server. The other 26 behaviors of the participants' activities on the Pigg Party (e.g., chatting in a party, sending like to peers, etc.) were also recorded in milliseconds on the Pigg Party server. We collected these records using administrator privileges. All these records were converted into a 24-hour×35-day (5week ×7 day) frequency distribution. (Fig. 2)

E. Outcome Variables

When gacha or purchase behavior is performed on the Pigg Party, these behaviors are recorded. These records were also transformed into a 24-hour×35-day frequency distribution.

F. Statistical Analysis

1) Learning of typical distributions: Typical distributions of 24-hour×35-day frequency were learned for 10 epochs using the Transformer-Variational Autoencoder (t-VAE), and anomalies were detected from the learned t-VAE. AE and VAE is well known as an anomaly detection model [4], [29]. The t-VAE is advanced model of AE and VAE [30]. Hence t-VAE could be useful to detect anomalies in our dataset. Of course, we also tried several anomaly detection algorithms using generative adversarial network, but the results were not stable, so we only describe the results of t-VAE.The hyperparameters of t-VAE were tuned using Optuna [31] with 10 trials. The number of latent dimensions, embedding dimensions, heads, and multi-layer perceptron dimensions of the current t-VAE were 64, 96, 8, and 187, respectively. The learning and dropout rates were also set as 1.4564242176741904e-06 and 2.5114657255747670e-01, respectively.

2) Assignment of anomaly scores and estimation of users with BD: The trained t-VAE calculated anomaly score per user from the frequency distribution of all users. Based on the anomaly scores, Area under the receiver operating characteristic curve (AUC) was estimated. Further, users with anomaly scores in the top 6.873% (20/291) were labeled as group with BD. The others were labeled as group without BD.

3) Finding the lowest attention score and estimation of the duration of the manic/hypomanic episode: Since the game logs of those presumed to have BD were displayed over a 24-hour×35-day period (Fig. 2), we estimated the point of lowest transformer attention, i.e., the point that was most difficult to reproduce, as the point with the highest anomaly scores (Fig. 3). The 3.5 days before and after this point, or one week, were estimated as the manic/hypomanic episode duration. The rest of the time was estimated as the period of non-manic episodes (Fig. 4).

4) Comparison analysis: For comparison of gacha or purchase behaviors between groups with and without BD, we used t-test for independent sample and Cohen's d. For comparison of these behaviors during manic/hypomanic and non-manic episodes, we used t-test for paired sample and Cohen's d. These indexes were frequently used to evaluate the difference between two groups [32], [33].

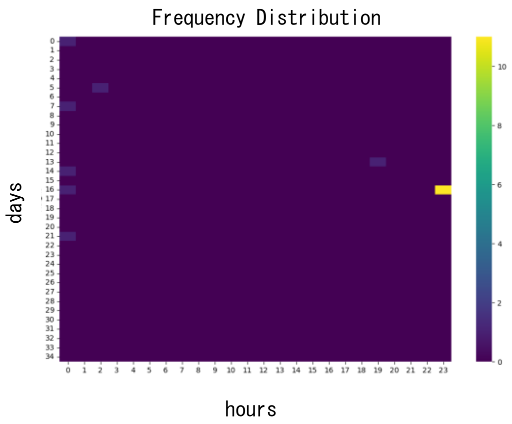

Fig. 2. Frequency distribution of how often a user followed up with a friend in a month (24 hours × 35 days).

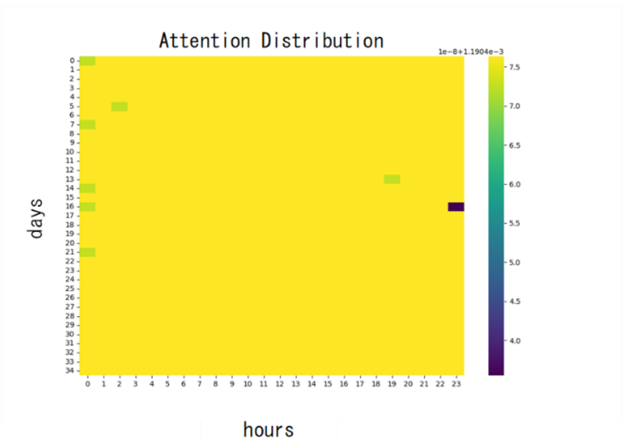

Fig. 3. Attention Distribution when the learned model reads the frequency distribution of Fig. 2 (24 hours × 35 days).

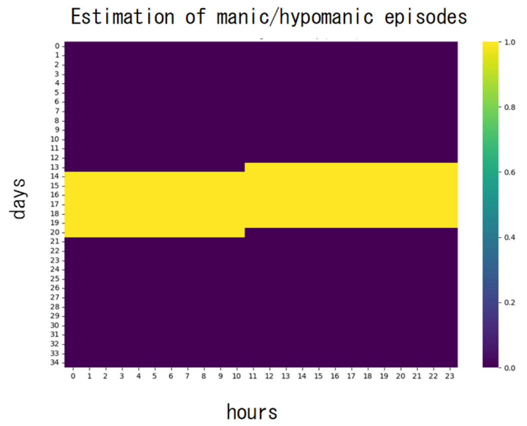

Fig. 4. Estimation of the duration of manic/hypomanic episodes based on the attention distribution of Fig. 3 (24 hours × 35 days).

III. Results

A. Descriptive Statistics of MMOG behaviors

Table I shows descriptive statistics of MMOG behaviors per day. The questionnaire respondents showed higher frequency of these behaviors than the total participants. Hence, the questionnaire respondents were more active users in Pigg party than the total participants. This difference should be kept in mind when interpreting the data.

B. Estimating BD through MMOG behaviors

The 27 kinds of behaviors in Table I were converted into a 24-hour×35-day frequency distribution as shown in Fig. 2, and the learned t-VAE calculated anomaly scores for each individual frequency distribution. For each kind of these behaviors, the top 6.87% of anomaly scores were estimated as the BD group, and we examined whether this estimation was compatible with the BD group of 20 of the 291 questionnaire respondents. The results showed that anomaly scores for the behavior of following peers predicted the actual BD group. In other words, respondents were estimated to be people with BD if they followed their friends late at night and at high frequency (Fig. 2). As a result, 13,650 of the total participants were categorized into the BD group and 184,955 into the non-BD group.

C. Comparison of Gacha and Purchase Behaviors between Groups with and without BD

To validate the above grouping regarding BD, we compared gacha and purchase behavior between groups with and without BD in total participants. If the BD group reflected people with BD, they would show high number of gacha and purchase behaviors (Table II). As expected, the BD group had significantly higher frequency of gacha and purchase behaviors than the non-BD group ($t = 49.123$, $p < .001$, cohen's $d = 0.436$; $t = 32.366$, $p < .001$ cohen's $d = 0.287$).

To corroborate these findings, we also compared gacha and purchase behavior between groups with and without BD in questionnaire respondents (Table III). While the frequency of purchase behavior did not show a significant difference between the two groups ($t = 0.808$, $p = 0.420$, $d = 0.187$), the questionnaire-based BD group showed marginally higher frequency of gacha than the non-BD group ($t = 1.861$, $p = .064$, $d = 0.43$). These findings provide suggestive, but not conclusive, evidence for the possibility that the estimated BD group reflected people with BD.

D. *Comparison of Gacha and Purchase Behaviors between Manic/Hypo Manic and Non-manic Episodes in the BD Group*

Since we estimated manic/hypo manic episodes of BD groups, we also validated the manic/hypo manic episodes from the perspectives of gacha and purchase behaviors. If the estimated manic/hypo manic episodes reflect actual manic/hypo manic phases of people with BD, manic/hypo manic episode duration would likely to produce higher frequency of gacha and purchase behaviors than non-manic episode duration (Table IV). As hypothesized, manic/hypo manic episode in BD group of the total participants had higher frequency of gacha and purchase than the non-manic phases ($t = 79.120$, $p < .001$, $d = 0.889$, $t=39.660$, $p < .001$, $d = 0.429$).

To corroborate these findings, we also compared gacha and purchase behavior between manic/hypo manic and non-manic episodes in the questionnaire respondents with BD (Table V). While there was no significant difference in the frequency of gacha ($t = 1.273$, $p = .218$, $d = 0.36$), manic/hypo manic episode in questionnaire respondents with BD showed higher

frequency of purchase behavior than non-manic periods ($t = 1.852$, $p = 0.08$, $d = 0.407$). Though not conclusive, these findings partially supported that the estimated manic/hypo manic episodes reflected actual manic/hypo manic episodes of people with BD.

Behavior	Total participants n=198,605		Questionnaire respondents n = 291		AUC[a]
	M	*SD*	*M*	*SD*	
Follow peers	0.54	1.42	0.61	0.92	**0.62**
Feed good add	1.29	11.38	9.34	48.54	0.60
Check user profile	0.81	2.19	1.72	2.60	0.59
Create party	0.12	0.35	0.51	0.83	0.56
Feed post add	0.25	1.04	1.35	3.21	0.56
Chat in a party	24.20	83.10	97.74	170.90	0.55
Change avatars' face	1.80	3.60	7.12	6.82	0.55
Chat in another area	0.04	0.60	0.13	0.53	0.55
Change avatars' clothes	1.80	3.60	7.12	6.82	0.55
Unfollow peers	0.36	1.33	0.88	1.26	0.53
Add item	3.10	4.26	13.53	16.33	0.52
Login	0.35	0.29	0.81	0.06	0.52
Feed comment add	0.34	2.19	2.08	6.43	0.51
Send like to peers	10.06	19.09	51.14	47.60	0.51
Send nice to party	0.97	2.09	3.88	4.64	0.50
Complete mission	2.85	2.96	8.56	2.42	0.49
Change avatar's room	0.26	0.53	1.01	0.92	0.49
Remove posted comments	0.13	0.82	0.85	2.93	0.48
Progress mission	8.56	9.07	23.14	5.67	0.47
Send gift to peers	0.07	0.44	0.51	2.14	0.46
Drop event	7.37	12.03	34.99	20.71	0.46
Chat in a room	15.47	71.35	84.82	147.22	0.46
Ring bell	3.01	7.58	19.64	25.87	0.45
Talk in private channel	1.73	7.33	3.12	7.77	0.44
Tap button	68.29	166.28	307.08	304.42	0.44
Chat in an area	3.30	31.44	27.57	103.34	0.43
Talk in group channel	0.20	1.73	0.17	0.64	0.36

TABLE I. AVERAGE DAILY FREQUENCY OF IN-GAME BEHAVIOR

NOTE. AUC: AREA UNDER THE RECEIVER OPERATING CHARACTERISTIC CURVE. [A]: THE THRESHOLD FOR CALCULATING THE AUC WAS SET AT THE PERCENTAGE OF BIPOLAR DISORDERS INCLUDED IN THE QUESTIONNAIRE RESPONDENTS, I.E., 6.87%. M AND SD INDICATE THE MEAN AND STANDARD DEVIATION OF THE FREQUENCY WITH WHICH EACH BEHAVIOR OCCURS PER DAY.

IV. DISCUSSION

A. Principal Findings

This study used behaviors of following peers in MMOG logs to estimate people with BD and their manic/hypomanic episodes. Similar to previous studies that estimated BD using logs via electronic devices [6], this study shows that anormal behaviors of following peers in online games are useful for estimating BD and manic/hypomanic episodes. Past studies have shown the association between the BD and excessive purchase behavior in offline communities. The present study extended these findings in online communities by taking advantage of the analysis on large datasets (i.e., approximately 200k users) where gacha and purchase behaviors are recorded. These findings indicate that the analysis of network building behaviors in MMOG is potentially useful for detecting BD and manic/hypomanic episodes.

This study also confirmed that people estimated to be BD in the MMOG showed significantly more gacha and purchase behaviors. It also confirmed that these behaviors were significantly more prevalent especially during their manic/hypomanic episodes. These findings indicate that problem behaviors of people with BD are not confined to offline communities [22], [23] but are also observed in online communities [19], [20]. This is not surprising given that addictive behaviors such as excessive shopping are observed online as well as offline [1]. Therefore, online behavior monitoring will become more important for BD assessment in the future [4].

Behavior	BD group n = 13650		Non-BD group n = 184955				
	M	***SD***	***M***	***SD***	***t***	***p***	***d***
Gacha	1.32	1.43	0.83	1.10	49.12	0.00 ***	0.43
Purchase	0.35	0.68	0.19	0.53	32.36	0.00 ***	0.28

TABLE II. COMPARISON OF GACHA AND PURCHASE BEHAVIOR BETWEEN GROUPS WITH AND WITHOUT BD AMONG TOTAL PARTICIPANTS

Behavior	BD group n = 20		Non-BD group n = 271				
	M	***SD***	***M***	***SD***	***t***	***p***	***d***
Gacha	2.69	4.54	1.84	1.65	1.86	0.06 +	0.43
Purchase	1.28	4.12	0.85	2.09	0.80	0.42	0.18

TABLE III. COMPARISON OF GACHA AND PURCHASE BEHAVIOR BETWEEN GROUPS WITH AND WITHOUT BD AMONG QUESTIONNAIRE RESPONDENTS

Behavior	Manic/hypo manic period n = 13650		Non manic period n = 13650				
	M	***SD***	***M***	***SD***	***Paired-t***	***p***	***d***
Gacha	3.76	4.67	0.75	1.10	79.12	0.00 ***	0.88
Purchase	0.82	1.79	0.24	0.61	39.66	0.00 ***	0.42

TABLE IV. COMPARISON OF GACHA AND PURCHASE BEHAVIOR BETWEEN MANIC/HYPO MANIC AND NON-MANIC PERIODS IN THE BD GROUP AMONG TOTAL PARTICIPANTS

Behavior	Manic/hypo manic period n = 20		Non manic period n = 20				
	M	***SD***	***M***	***SD***	***Paired-t***	***p***	***d***
Gacha	2.06	3.67	1.08	0.92	1.27	0.21	0.36
Purchase	1.04	1.70	0.52	0.62	1.85	0.08 +	0.40

TABLE V. COMPARISON OF GACHA AND PURCHASE BEHAVIOR BETWEEN MANIC/HYPO MANIC AND NON-MANIC PERIODS IN THE BD GROUP AMONG QUESTIONNAIRE RESPONDENTS

NOTE. ***: P < .001, +: P <. 10, M AND SD IN TABLE IV AND V INDICATE THE MEAN AND STANDARD DEVIATION OF THE FREQUENCY WITH WHICH EACH BEHAVIOR OCCURS PER DAY.

Further, online treatment of BD will be prevalent in the future once online estimation of BD is possible. In fact, randomized controlled experiments on MMOG for people with BD have been conducted [27]. Further, intervention studies via smartphone apps have become more frequent in recent years [9]. By applying online findings sfrom this study to the traditional treatment of BD to date [13]–[18], online treatment of BD will be boosted in the future [6], [7]. Online treatment will help control health care costs because it is less costly in terms of labor than in-person services [9].

B. Limitations

Limitations of this study are low AUC scores and the lack of significant differences in purchase behavior between the BD and non-BD groups of questionnaire respondents. Both of them could be attributed to the fact that the questionnaire respondents were more active users than the total participants. Because some of the questionnaire respondents were very active, our t-VAE trained on data from less active total participant incorrectly estimated these active participants as having BD, which lowered the AUC. In addition, the number of respondents classified as BD was relatively small, which leads to unbalanced samples and may have made it difficult to find significant differences Although the grand truth data in this study was based on questionnaire data, grand truth data based on face-to-face and experimental data will be needed in the future [4], [10].

V. CONCLUSIONS

Despite these limitations, the present findings based on the data from approximately 200 k MMOG users are valuable for detection of BD [34]. The accuracy of BD estimation can be enhanced by combining not only individual behaviors from other electronic devices [7], [8], [10], [11] but also network building behaviors from MMOG logs. Such highly accurate BD estimation will promote early detection and treatment of BD [4], and may contribute not only to the well-being of people with BD[3] but also to the reduction of healthcare costs [2].

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References

[1] C. Varo et al., "Behavioral addictions in bipolar disorders: A systematic review," Eur. Neuropsychopharmacol., vol. 29, no. 1, pp. 76–97, Jan. 2019, doi: 10.1016/j.euroneuro.2018.10.012.

[2] L. Bessonova, K. Ogden, M. J. Doane, A. K. O'Sullivan, and M. Tohen, "The Economic Burden of Bipolar Disorder in the United States: A Systematic Literature Review," Clin. Outcomes Res., vol. 12, pp. 481–497, Dec. 2020, doi: 10.2147/CEOR.S259338.

[3] F. Iorfino et al., "Clinical Stage Transitions in Persons Aged 12 to 25 Years Presenting to Early Intervention Mental Health Services With Anxiety, Mood, and Psychotic Disorders," JAMA Psychiatry, vol. 76, no. 11, pp. 1167–1175, Nov. 2019, doi: 10.1001/jamapsychiatry.2019.2360.

[4] A. Ortiz et al., "Identifying patient-specific behaviors to understand illness trajectories and predict relapses in bipolar disorder using passive sensing and deep anomaly detection: protocol for a contactless cohort study," BMC Psychiatry, vol. 22, no. 1, p. 288, Apr. 2022, doi: 10.1186/s12888-022-03923-1.

[5] M. Berk et al., "Setting the stage: from prodrome to treatment resistance in bipolar disorder," Bipolar Disord., vol. 9, no. 7, pp. 671–678, 2007, doi: 10.1111/j.1399-5618.2007.00484.x.

[6] A. Ortiz, M. M. Maslej, M. I. Husain, Z. J. Daskalakis, and B. H. Mulsant, "Apps and gaps in bipolar disorder: A systematic review on electronic monitoring for episode prediction," J. Affect. Disord., vol. 295, pp. 1190–1200, Dec. 2021, doi: 10.1016/j.jad.2021.08.140.

[7] G. Anmella et al., "Exploring Digital Biomarkers of Illness Activity in Mood Episodes: Hypotheses Generating and Model Development Study," JMIR MHealth UHealth, vol. 11, no. 1, p. e45405, May 2023, doi: 10.2196/45405.

[8] N. Sangha, L. Lyall, C. Wyse, B. Cullen, H. C. Whalley, and D. J. Smith, "The nosological status of unipolar mania and hypomania within UK Biobank according to objective and subjective measures of diurnal rest and activity," Bipolar Disord., vol. 24, no. 7, pp. 726–738, 2022, doi: 10.1111/bdi.13237.

[9] G. Anmella et al., "Smartphone-based interventions in bipolar disorder: Systematic review and meta-analyses of efficacy. A position paper from the International Society for Bipolar Disorders (ISBD) Big Data Task Force," Bipolar Disord., vol. 24, no. 6, pp. 580–614, 2022, doi: 10.1111/bdi.13243.

[10] Y.-H. Huang et al., "Leveraging Linguistic Characteristics for Bipolar Disorder Recognition with Gender Differences." arXiv, Jul. 17, 2019. Accessed: May 11, 2023. [Online]. Available: http://arxiv.org/abs/1907.07366

[11] Y.-H. Huang, L.-H. Wei, and Y.-S. Chen, "Detection of the Prodromal Phase of Bipolar Disorder from Psychological and Phonological Aspects in Social Media." arXiv, Dec. 26, 2017. Accessed: May 11, 2023. [Online]. Available: http://arxiv.org/abs/1712.09183

[12] M. M. Ohayon and L. Roberts, "Internet gaming disorder and comorbidities among campus-dwelling U.S. university students," Psychiatry Res., vol. 302, p. 114043, Aug. 2021, doi: 10.1016/j.psychres.2021.114043.

[13] C. J. R. Sewall et al., "A Bayesian multilevel analysis of the longitudinal associations between relationship quality and suicidal ideation and attempts among youth with bipolar disorder," J. Child Psychol. Psychiatry, vol. 62, no. 7, pp. 905–915, Jul. 2021, doi: 10.1111/jcpp.13343.

[14] L. Dunne, T. Perich, and T. Meade, "The relationship between social support and personal recovery in bipolar disorder," Psychiatr. Rehabil. J., vol. 42, pp. 100–103, 2019, doi: 10.1037/prj0000319.

[15] E. Frank, H. A. Swartz, and D. J. Kupfer, "Interpersonal and social rhythm therapy: managing the chaos of bipolar disorder," Biol. Psychiatry, vol. 48, no. 6, pp. 593–604, Sep. 2000, doi: 10.1016/S0006-3223(00)00969-0.

[16] E. Frank et al., "The Role of Interpersonal and Social Rhythm Therapy in Improving Occupational Functioning in Patients With Bipolar I Disorder," Am. J. Psychiatry, vol. 165, no. 12, pp. 1559–1565, Dec. 2008, doi: 10.1176/appi.ajp.2008.07121953.

[17] C. Lam and M.-H. Chung, "A Meta-Analysis of the Effect of Interpersonal and Social Rhythm Therapy on Symptom and Functioning Improvement in Patients with Bipolar Disorders," Appl. Res. Qual. Life, vol. 16, no. 1, pp. 153–165, Feb. 2021, doi: 10.1007/s11482-019-09740-1.

[18] P. Studart-Bottó, G. Léda-Rêgo, P. Abbade, I. D. Bandeira, and Â. Miranda-Scippa, "Social support among individuals with bipolar disorder during euthymic phase: A systematic review," Clin. Psychol. Psychother., vol. 30, no. 2, pp. 270–280, 2023, doi: 10.1002/cpp.2805.

[19] M. Matthews et al., "The double-edged sword: A mixed methods study of the interplay between bipolar disorder and technology use," Comput. Hum. Behav., vol. 75, pp. 288–300, Oct. 2017, doi: 10.1016/j.chb.2017.05.009.

[20] J. P. do Nascimento, L. Borges, and R. Meneses, "Is There Any Difference between Bipolar and Non-bipolar Individuals in the Use of Facebook?," Bipolar Disord. Open Access, vol. 2, Jan. 2016, doi: 10.4172/2472-1077.1000104.

[21] N. B. Ellison, C. Steinfield, and C. Lampe, "The Benefits of Facebook 'Friends:' Social Capital and College Students' Use of Online Social Network Sites," J. Comput.-Mediat. Commun., vol. 12, no. 4, pp. 1143–1168, 2007, doi: 10.1111/j.1083-6101.2007.00367.x.

[22] J. Laloyaux et al., "Performance on a computerized shopping task significantly predicts real world functioning in persons diagnosed with bipolar disorder," Psychiatry Res., vol. 210, no. 2, pp. 465–471, Dec. 2013, doi: 10.1016/j.psychres.2013.06.032.

[23] L. Jones et al., "Gambling problems in bipolar disorder in the UK: Prevalence and distribution," Br. J. Psychiatry, vol. 207, no. 4, pp. 328–333, Oct. 2015, doi: 10.1192/bjp.bp.114.154286.

[24] K. Yokotani and M. Takano, "Avatars' Social Rhythms in Online Games Indicate Their Players' Depression," Cyberpsychology Behav. Soc. Netw., vol. 25, no. 11, pp. 718–732, Nov. 2022, doi: 10.1089/cyber.2022.0058.

[25] R. M. A. Hirschfeld et al., "Development and Validation of a Screening Instrument for Bipolar Spectrum Disorder: The Mood Disorder Questionnaire," Am. J. Psychiatry, vol. 157, no. 11, pp. 1873–1875, Nov. 2000, doi: 10.1176/appi.ajp.157.11.1873.

[26] Tanaka T., Inoue T., Suzuki katsuharu, Masui T., and Koyama T., "Unipolar Depression? Bipolar Depression? A Study of the Usefulness of a Self-Administered Rating Scale(In Japanese)," Bipolar Disord., vol. 5, pp. 21–27, 2007, Accessed: Jan. 23, 2023. [Online]. Available: https://jglobal.jst.go.jp/detail?JGLOBAL_ID=200902233253603662

[27] Yokotani K., Takano M., and Abe N., "Likes returned within a day prevents depression: a randomized controlled experiment in an online game," in Information Processing Society of Japan, Tokyo, Mar. 2023. Accessed: May 17, 2023. [Online]. Available: https://www.ipsj.or.jp/event/taikai/85/index.html

[28] T. Nagata, H. Yamada, A. R. Teo, C. Yoshimura, Y. Kodama, and I. van Vliet, "Using the mood disorder questionnaire and bipolar spectrum diagnostic scale to detect bipolar disorder and borderline personality disorder among eating disorder patients," BMC Psychiatry, vol. 13, no. 1, p. 69, Feb. 2013, doi: 10.1186/1471-244X-13-69.

[29] K. Yokotani and M. Takano, "Predicting cyber offenders and victims and their offense and damage time from routine chat times and online social network activities," Comput. Hum. Behav., vol. 128, p. 107099, Mar. 2022, doi: 10.1016/j.chb.2021.107099.

[30] J. Jiang, G. G. Xia, D. B. Carlton, C. N. Anderson, and R. H. Miyakawa, "Transformer VAE: A Hierarchical Model for Structure-Aware and Interpretable Music Representation Learning," in ICASSP 2020 - 2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), May 2020, pp. 516–520. doi: 10.1109/ICASSP40776.2020.9054554.

[31] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A Next-generation Hyperparameter Optimization Framework," in Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining, in KDD '19. New York, NY, USA: Association for Computing Machinery, Jul. 2019, pp. 2623–2631. doi: 10.1145/3292500.3330701.

[32] P. Mishra, U. Singh, C. M. Pandey, P. Mishra, and G. Pandey, "Application of Student's t-test, Analysis of Variance, and Covariance," Ann. Card. Anaesth., vol. 22, no. 4, pp. 407–411, 2019, doi: 10.4103/aca.ACA_94_19.

[33] A. Lovakov and E. R. Agadullina, "Empirically derived guidelines for effect size interpretation in social psychology," Eur. J. Soc. Psychol., vol. 51, no. 3, pp. 485–504, 2021, doi: 10.1002/ejsp.2752.

[34] K. Yokotani and M. Takano, "Effects of suspensions on offences and damage of suspended offenders and their peers on an online chat platform," Telemat. Inform., vol. 68, p. 101776, Mar. 2022, doi: 10.1016/j.tele.2022.101776.