A Rule Mining and Bayesian Network Analysis to Explore the Link Between Depression and Digital Behavioral Markers of Games App Usage

Md. Sabbir Ahmed[1](✉), Tanvir Hasan[1], Md. Mahfuzur Rahman[2], and Nova Ahmed[1]

[1] Design Inclusion and Access Lab (DIAL), North South University, Dhaka 1229, Bangladesh
msg2sabbir@gmail.com, tanvirfuad00@gmail.com, nova.ahmed@northsouth.edu

[2] Department of Computer Science and Engineering, Eastern University, Dhaka 1345, Bangladesh
dean_et@easternuni.edu.bd

Abstract. Amid the COVID-19 pandemic, spending time on Games increased much, which may impact mental health. While numerous studies were conducted exploring the relation between Games and depression, none of the studies used objective (i.e., actual) Games app usage data which could provide unbiased and real-time insights. To fill this research gap, using our developed app that retrieves the past 7 days' actual app usage data accurately, we conducted a study on Games app users ($N = 60$) in Bangladesh. We extracted the behavioral markers from the foreground and background Games app usage events' data. To explore the relation between Games and depression, we mined rules, did correlation analysis, and built Bayesian networks. Our analyses demonstrated that the students who spent higher time and had a higher launch per Games app on weekends were more likely to be depressed ($p < .05$). In addition, from the Bayesian analysis, we found that while some usage data impacts depression, depression also impacts some usage behavior such as frequency of launching Games apps. Apart from raising awareness about the negative impact of Games, insights from our study can facilitate the design of systems to improve the students' mental health.

Keywords: Smartphone · Games · Depression · Behavioral patterns · Bayesian network

1 Introduction

Amid the pandemic, Games playing time increased and 75% of the rise is estimated to persist in the next two years [11]. However, problematic gaming is found to have a negative impact on mental health [24, 29] which shows the necessity of in-depth exploration of the link between Games and psychological problems. In Bangladesh, the rate of psychological problem depression is higher among university students compared

A. Tsanas and A. Triantafyllidis (Eds.): PH 2022, LNICST 488, pp. 557–569, 2023.
https://doi.org/10.1007/978-3-031-34586-9_37

to other groups of people [10]. The stay at home for the pandemic and the high availability of smartphones where 86% of Bangladeshi university students have smartphones [2] can facilitate them in increasing Games playing.

With great interest, scholarly articles explored the relation between Games and depression where most studies (e.g., [5, 24, 28]) used subjective data. Some of these studies found a positive association of depression with addiction to video gaming [5] and problematic online gaming [24]. However, as subjective data does not present the actual app usage behavior [18, 32], the findings of these studies may not unveil the exact relation.

On the other hand, previous studies also explored objective data on gaming as well as of app categories. In the case of gaming, researchers explored gaming data for purposes such as exploring the feasibility of gamification in having a positive impact on sleep-wake [12], exploring patterns in Games playing behavior [8], to distinguish the gaming events from the sensor-collected data [30], to assess problematic internet use [31], and to find out the factors related with underreported playing time [32]. In a recent study [18], researchers used both subjective and objective data from an online chess platform to explore the relationship with problematic effects (e.g., disrupted sleep). Objective behavioral markers of different app categories such as Communication [1, 15], Health & Fitness, Photo & Video [1], and Social Media [1, 15, 27] have also been explored in different contexts. Researchers [15] observed that depressed and non-depressed students have significantly different app usage duration and frequency of launching Communication apps. In addition, depressed students have significantly higher unique app signatures in the case of Social Media, Health & Fitness app categories [1]. Though some studies explored the behavioral patterns of the depressed [1, 15], Hunt et al. [27] did a causal analysis by keeping students in the control and experimental groups. Their analysis demonstrated that limiting Facebook, Instagram, and Snapchat use reduce depression [27]. Objective behavioral markers regardless of the app categories have also been explored in a recent study [33] to classify the depressed and non-depressed through computational models. However, as far as we know, no study used objective Games app usage data to explore the relation between depression and Games apps usage, although Games is the most popular app category in Google Play Store [6] and amid the pandemic, Games playing time increased significantly [11].

Therefore, we explore the link between objectively measured Games app usage data and depression (i.e., Patient Health Questionnaire-8 (PHQ-8) scale's score [14]) and contribute to the pervasive health research area in the following ways.

- Firstly, to our best knowledge, using objective data, this is the first study to explore the relation between a psychological problem and digital behavioral markers of Games app usage which can provide unbiased findings.
- Secondly, through rule mining, we present Games app behavioral patterns that are associated with depression which can be potential to understand the nuanced differences between depressed and non-depressed students. In addition, this can facilitate in the development of computational models to predict depression leveraging digital behavioral markers.

- Thirdly, we develop a Bayesian network that shows that all behavioral markers of Games app usage do not impact depression and vice versa which can be useful to design pervasive systems for intervention.

2 Methods

2.1 Participants and Research Ethics

Our study was approved by a university from Bangladesh. We did the study in 2020 during the COVID-19 pandemic where 100 Bangladeshi students from 12 higher educational institutes participated. Among them, 60 students used the Games apps (please, see Sect. 2.2.2 for details) on which we conducted this study. All participants' data were collected through their consent and in the consent form, we specifically mentioned the required permission, collected data, data security, usage of their data, etc. Apart from this, to make the participants more aware of the collected data, our app asked for permission in runtime to access the app usage data before retrieving it.

2.2 Tools and Analysis

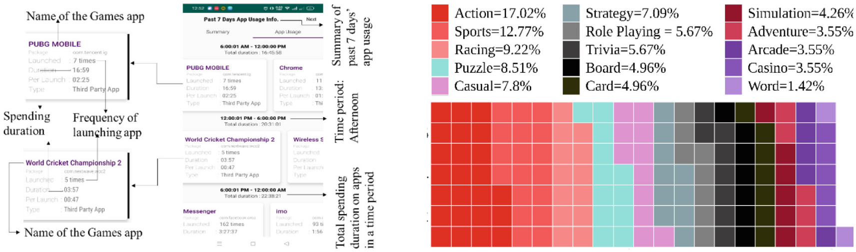
2.2.1 Depression Measurement

To measure the participants' depression, we used the 8-itemed PHQ-8 scale's score [14]. We explored the PHQ-8 scores as the continuous values in the correlation and Bayesian network analysis as described in Sect. 2.2.4 and Sect. 2.2.5 respectively. In addition, to understand the participants' depression and also as a requirement in the rule mining through the classification-based association algorithm (please, see Sect. 2.2.3), we divided the participants based on depression score. In finding major depressive disorder, the sensitivity and specificity are 100% and 95% respectively for a PHQ-8 score of 10 [14]. Hence, the participants who had a PHQ-8 score of 10 or more were grouped as the depressed and others (PHQ-8 $<$ 10) as the non-depressed participants.

2.2.2 Data Collection Tool and Extraction of Games App Usage Markers

As subjective data does not reflect the actual habit [18, 32], we retrieved participants' actual app usage data through our developed Android app (Fig. 1(a)). We used the Java class *UsageStatsManager* [9] to retrieve foreground and background events' data, and to store it, we used the Google Firebase database. We tested the app on 9 phones, and also compared it with the retrieved app usage data of the available such apps (e.g., [17]) in the Play Store. Since the system keeps app usage events' data only for a few days [9], our app can collect the past 7 days' app usage data very accurately.

Our developed app retrieved 817,404 foreground and background events data from 100 participants who used 1,129 apps. Two researchers and one student categorized these apps following the app categories of the Play Store, the app categorization process of previous studies (e.g., [1]), and an understanding of the apps' features. Among 1,129 apps, we found 141 (12.49%) apps in the Games category which consisted of 40,339 foreground and background events. The used Games apps were of 15 subcategories (Fig. 1(b)). Most (17.02%) apps were of Action (e.g., PUBG MOBILE) and the least



(a) Screenshot of the data collection tool showing Games app usage

(b) Number of apps in each of the 15 subcategories

Fig. 1. Data collection tool and participants' Games app usage.

(1.42%) were of Word (e.g., Word Forest) subcategory. On the other hand, among the 100 participants, 60% (N = 60) participants were Games app users who launched at least one Games app in 7 days. Since having the value 0 for the remaining 40% of non-users can make the variables' data distribution highly skewed, their data were excluded from the analysis to have unbiased findings.

From the retrieved app usage events, we quantified each participant's behavioral markers of Games app usage by calculating spending duration, frequency of launching apps, number of used apps, duration per app, duration per app launch, and frequency of launch per app of the Games category. In addition, to explore the Games app usage pattern, we calculated entropy $E(j) = \sum_{i=0}^{n} p(i) log p(i)$ where $p(i)$ indicates the probability to use the i^{th} Games app by the j^{th} participant. Since the app usage behavior varies by weekdays and weekends [1], to understand the association of PHQ-8 score with Games app usage data, we explore these 7 variables by calculating each variable's data of weekends (Friday and Saturday), weekdays (Sunday to Thursday), and 7 days (whole week). We divide the days based on the working week in Bangladesh.

2.2.3 Rule Mining and Extraction of Behavioral Patterns

Each of the aforementioned 7 variables presents Games app usage behavior and we denote this set of behavioral items by T_j for j^{th} participant. Using classification-based association (CBA) algorithm [16], we mine the behavioral patterns that are associated with depression in the form of $A_j \rightarrow B_j$ where A_j is the rule body containing a subset of T_j items and B_j is the rule head denoting the class (e.g., depressed) of j^{th} participant. Since CBA works with discrete values, inspired by the previous studies (e.g., [23]), we discretized the values of each behavioral marker into three equal groups where top one-third and bottom one-third percentile were grouped as the high and low users respectively and others were grouped as the medium users. For each rule, there are three parameters namely support, confidence, and lift based on which a rule is selected. Support ($\frac{frequency(rule\ body, rule\ head)}{N}$) denotes the frequency of a set of items appearing among all participants (N) whereas confidence ($\frac{frequency(rule\ body, rule\ head)}{frequency(rule\ body)}$) says how likely the rule head is to occur when the rule body appears. Having lift ($L = \frac{Confidence}{Support(rule\ head)}$;

$Support(rule\ head) = \frac{frequency(rule\ head)}{N}$) greater than 1 means rule body and head are not independent and rule body has an impact on the rule head.

2.2.4 Correlational and Comparative Analysis

Though CBA algorithm can extract unique patterns combining different behavioral data of different levels (e.g., high usage duration with the medium frequency of launch), it cannot present monotonic or linear statistical relation. To overcome the limitation, we did a correlation analysis. We used the nonparametric Spearman rank correlation (r_s) method as our data did not satisfy assumptions of the parametric test. In comparing the demographic data, we did a T-test (t) when data were normally distributed and in other cases, we did a nonparametric Mann-Whitney Test (U). As multiple comparisons can have false positive results, we adjusted p values using the false discovery rate approach.

2.2.5 Bayesian Network Analysis

Though correlation analysis can present the association between variables, it cannot reveal the direction of association between two variables. Therefore, to find the direction of the association, we built a Bayesian network [19] where each variable $V_i \in V$ is denoted by a node of a directed acyclic graph (DAG). In the development of the network, there are structural and parameter learning steps [19, 26] where the structural learning process is similar to the development of classical regression models [26]. For developing the network structure, we used the greedy hill-climbing algorithm which restarts randomly to avoid the local optima. Since the DAG of the network depends on several parameters such as the distribution of the data, we resample the Games app usage data and build the network 10,000 times to measure the strength of the associations and their direction. It can be noted that the strength of each arc was calculated keeping the rest of the network fixed and thus a relation between variables cannot be confounded by others.

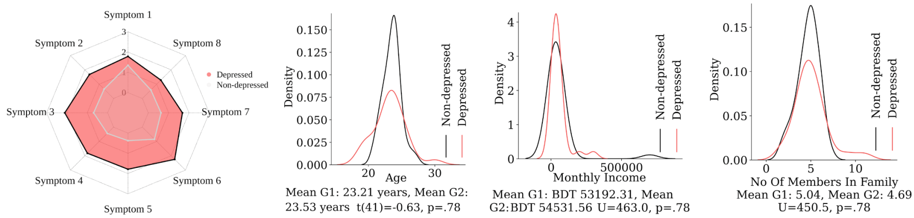
3 Results

3.1 Participants' Depression

Among the 60 Games app users, 46.67% (N = 28) were depressed and 53.33% (N = 32) were non-depressed (details about categorization process is in Sect. 2.2.1). Except for symptom 1 (Little interest or pleasure in doing things), every other symptom's mean score of the non-depressed group was below 1 (Fig. 2(a)) where score 1 presents the symptom's appearance not at all. Between these two groups, there was no statistically significant difference in age (p = .78) (Fig. 2(b)), monthly family income (p = .78) (Fig. 2(c)), and the number of family members (p = .78) (Fig. 2(d)) which could work as confounders in the relation between Games app usage and depression.

3.2 App Usage Behavioral Patterns' Association with Depression

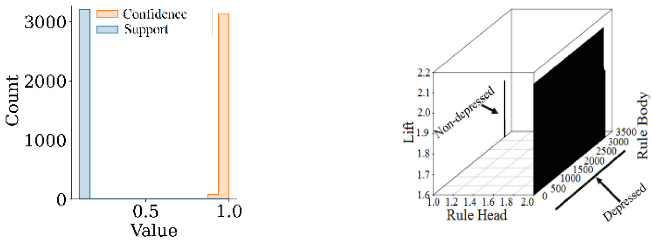
To extract patterns, we used all the behavioral data of weekdays, weekends, and 7 days. But to avoid combinatorial explosion, we set .1 as the minimum support and .9 as the



(a) Depressive symptoms' average score (b) Age (c) Monthly family income (d) Number of family members

Fig. 2. (a) Spider chart showing the difference between the depressed and non-depressed students regarding the mean score of each depressive symptom of the PHQ-8 scale where 0, 1, 2, and 3 scores present Not at all, Several days, More than half the days, and Nearly every day respectively. Kernel Density Estimation (KDE) plot showing the distribution of (b) age, (c) monthly family income (in BDT: Bangladeshi Taka), and (d) number of family members of the depressed (G1) and non-depressed (G2) students.

minimum confidence. In addition, as having a lift value of 1 presents that both the rule body and rule head are independent, we extracted only the rules which had a lift value higher than 1. Satisfying these thresholds, we found 3213 rules which were associated with depression. There were 21 rules where the rule head was non-depressed and in the remaining 3,192 rules, the rule head was depressed. Among these rules, the maximum support, confidence, and lift values were .17, 1.0, and 2.14 respectively (Fig. 3).



(a) Support and confidence (b) Lift

Fig. 3. Distribution of (a) support, confidence, and (b) lift values for the extracted 3,213 rules.

From the extracted behavioral patterns, we found that the higher duration per launching Games app was associated with depressive status (Table 1). For instance, the students whose weekdays' duration per Games app launch and 7 days' spending duration per app were high, they were more likely to be depressed. This behavioral pattern was observed among 17% of students and 91% of them were depressed students (Support = .17, Confidence = .91) (Rule 1, Table 1). The lift value (1.95) regarding this pattern was higher than 1 and this demonstrated that the rule body and rule heads were not independent. Also, we found when the students had medium entropy of using the apps for 7 days, duration per app was high on both weekdays and weekends, they were more likely to be depressed (Support = .17, Confidence = .91, Lift = 1.95) (Rule 5, Table 1).

Table 1. Top-5 (in terms of support and lift) Games app usage behavioral patterns of the depressed and non-depressed students. Con.: Confidence, Sup.: Support.

Depressed	Rules (Rule Body = > Rule Head)	Sup	Con	Lift
	1.{Duration_per_Launch,Weekday = High; Duration_per_App,7_days = High} = > {Depressed = Yes}	.17	.91	1.95
	2.{Duration_per_Launch,Weekday = High; Duration_per_Launch,7_days = High; Duration_per_App,7_days = High} = > {Depressed = Yes}	.17	.91	1.95
	3.{Duration_per_Launch,Weekday = High; Duration_per_App,Weekday = High; Duration_per_App,7_days = High} = > {Depressed = Yes}	.17	.91	1.95
	4.{Entropy,Weekend = Medium;No_of_Apps,7_days = Medium; Duration_per_Launch,Weekday = High} = > {Depressed = Yes}	.17	.91	1.95
	5.{Entropy,7_days = Medium; Duration_per_App,Weekday = High; Duration_per_App,Weekend = High} = > {Depressed = Yes}	.17	.91	1.95
Non-depressed	6.{Duration_per_Launch,7_days = Medium; Duration_per_App,Weekday = Medium} = > {Depressed = No}	.15	.90	1.69
	7.{Duration_per_App,Weekday = Medium; Launch_per_App,7_days = Medium} = > {Depressed = No}	.15	.90	1.69
	8.{Launch,Weekday = High; Launch,7_days = High; Duration_per_Launch,Weekday = Medium} = > {Depressed = No}	.15	.90	1.69
	9.{Launch,Weekday = High; Duration_per_Launch,Weekday = Medium} = > {Depressed = No}	.15	.90	1.69
	10.{Launch,7_days = High; Duration_per_Launch,Weekday = Medium} = > {Depressed = No}	.15	.90	1.69

On the other hand, the extracted rules regarding the non-depressed students presented that their spending duration per launch was medium (Rule 6 to 10, Table 1). For instance, the students whose spending duration per Games app launch was medium on 7 days and duration per Games app was medium on weekdays, were more likely to be non-depressed (Rule 6, Table1). This behavioral pattern was observed in the case of 15% of students (Support = .15) and 90% (Confidence = .90) of them were non-depressed. We also found that when the weekdays' duration per Games app and 7 days' frequency of launch per Games app became medium, they were also more likely (Confidence = .90, Lift = 1.69) to remain non-depressed (Rule 7, Table 1). Even when the participants had a high frequency of launching the apps, having a medium duration per launch presented a non-depressive status (Rule 10, Table 1).

3.3 Correlation Between Games App Usage and Depression

To explore the statistical relation, we did correlation analysis as discussed in Sect. 2.2.4. We found that the Games app usage data of weekdays and 7 days did not have any statistically significant relation with depression. In relation of depression with weekdays' spending duration ($r_s = .09$, $p = .48$), frequency of launching Games apps ($r_s = .08$, $p = .57$), and the number of used Games apps ($r_s = -.05$, $p = .71$) (Table 2), the p-value was much higher than the significance level .05. However, in case of weekends' spending duration ($r_s = .33$, $p = .026$), duration per launch ($r_s = .29$, $p = .044$), duration per app ($r_s = .39$, $p = .007$), frequency of launch per app ($r_s = .33$, $p = .026$), the p-value was less than .05 which demonstrated the significant association with depression score. This says that the students who spent higher time or have a higher frequency of launch per Games app on weekends were more likely to have a higher depression score.

Table 2. Relation of PHQ-8 score with usage data of Games apps. N denotes the number of users (who launched Games apps at least once in 7 days), in terms of a usage data. Coef.: Coefficient.

Usage data	Days	N	Coef. (r_s)	p	Usage data	Days	N	Coef. (r_s)	p	Usage data	Days	N	Coef. (r_s)	p
Duration	Weekdays	58	.09	.481	Duration per launch	Weekdays	58	.05	.721	Launch per app	Weekdays	58	.13	.326
	Weekends	47	.33	.026		Weekends	47	.29	.044		Weekends	47	.33	.026
	7 days	60	.13	.339		7 days	60	.11	.422		7 days	60	.12	.375
Launch	Weekdays	58	.08	.573	Duration per app	Weekdays	58	.12	.39	Entropy	Weekdays	31	-.31	.095
	Weekends	47	.25	.089										
	7 days	60	.07	.615		Weekends	47	.39	.007		Weekends	20	-.1	.667
# of Apps	Weekdays	58	-.05	.713										
	Weekends	47	-.14	.331		7 days	60	.14	.290		7 days	37	-.28	.098
	7 days	60	-.15	.264										

3.4 Bayesian Network on Games App Usage and Depression

To understand the direction of the found significant associations (Table 2), we built a Bayesian network (Table 3 and Fig. 4) using the variables on weekends' data and by bootstrapping the data 10,000 times. We found that the probability (.61) of having an edge in the direction from Games app usage duration to PHQ-8 was higher than the direction from PHQ-8 to duration (.39) (Table 3). Similarly, the probability of having edges in the direction from duration per launch to PHQ-8 (.67) and from duration per app to PHQ-8 (.74) was higher than the probability in the reverse direction. This presents that the spending duration on Games apps, duration per Games app launch, and duration per Games app impacted depression (Fig. 4).

Table 3. Strength regardless of direction and strength in the specified direction. Gray-colored cells present arcs having more than 50% probability to appear in the specified direction.

Node (From)	Node (To)	Strength (Regardless direction)	Strength in the specified direction (From → To)	Node (From)	Node (To)	Strength (Regardless direction)	Strength in the specified direction (From → To)
PHQ-8	Duration	.13	.39	Duration	PHQ-8	.13	.61
PHQ-8	Entropy	.35	.60				
PHQ-8	Launch	.19	.69	Entropy	PHQ-8	.35	.40
PHQ-8	# of used apps	.44	.88	Launch	PHQ-8	.19	.31
PHQ-8	Duration per launch	.26	.33	# of used apps	PHQ-8	.44	.12
PHQ-8	Duration per app	.15	.26	Duration per launch	PHQ-8	.26	.67
PHQ-8	Launch per app	.10	.71	Duration per app	PHQ-8	.15	.74

Unlike duration, in the frequency of launching the Games apps, we found that the probability (.69) of having the edge in the direction from PHQ-8 to launch was higher than the probability of having the edge in the reverse direction (launch to PHQ-8: .31) (Table 3). In the same way, the probability of having the edge in the direction of PHQ-8 to the number of used apps (.88), launch per app (.71), and entropy (.60) were higher than the probability of having the edge in the reverse direction. This reveals that depression also impacted the frequency of launching of Games apps, number of used Games apps, launch per Games app, and entropy regarding Games app usage (Fig. 4).

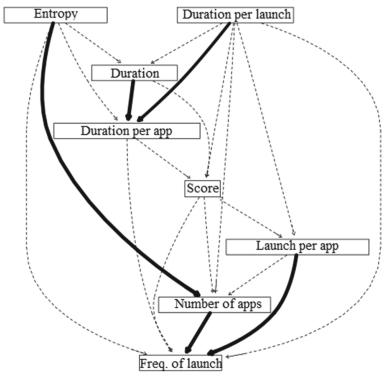


Fig. 4. Bayesian network presents the direction of the relation between PHQ-8 score and weekends' Games apps usage data.

From the Bayesian network (Fig. 4), it is also apparent that the frequency of launch node does not have any outgoing edge whereas the duration per app launch node has 6 outgoing edges which is the maximum among all nodes. This node is directly linked with the PHQ-8 score and also with the 5 behavioral markers, namely, duration, duration per app, number of used apps, launch per app, and frequency of launch. This presents that the duration per app launch can be a plausible target node to control the 5 behavioral markers and also depression.

4 Discussion

In our study on Games app users, we found a depression prevalence of 46.67% which is close to the depression prevalence of 47.3% found in a previous study conducted on Bangladeshi students [25]. Our analysis showing the negative impact of weekends' usual usage of Games apps on depression extends previous studies [24, 29] which used subjective data and found a negative impact of problematic gaming. To our best knowledge, this is the first study to present this impact using the objective app usage behavioral data and also using data of all the used Games apps by a participant. Our findings suggest raising awareness to reduce gaming time for their well-being, especially during this pandemic when gaming time increased significantly [11]. One of the plausible reasons for having a negative impact is that gaming makes a poor connection with family and friends [4] and this may have a significant negative impact on the students amid the pandemic. During alone time, people use smartphones to seek support [7] and on weekends, as students do not have classes and also as the pandemic restricted movement, higher usage of Games apps can present their effort to overcome loneliness through playing Games. Therefore, having a good connection with the parents, caregivers, or friends on the weekends may reduce their interest in the Games apps which in turn may reduce their spending time on Games. Moreover, our findings suggest parents and caregivers need to be aware of the weekend depression [20] since this has become a rising concern and also as we found a negative impact on weekends' Games app usage.

In our developed Bayesian network, we found some association in the opposite direction also, i.e., depression also impacts some weekends' behavior regarding Games apps. For instance, we found that depression has an impact on behavioral markers such as frequency of launching and number of used Games apps. In previous studies (e.g., [5, 24]), researchers showed how gaming is associated with depression. However, our analysis based on the Bayesian network where directed acyclic graphs were constructed 10000 times, showed the link in both directions depending on behavioral markers (e.g., duration, launch) which was unexplored even in subjective data-based studies [5, 24, 28]. Therefore, the insights from our findings can contribute to a better understanding of the smartphone usage behavior of the people [1, 15], especially the vulnerable group's Games playing behavior which can be potential in research to develop systems for better mental health. The plausible reasons for having such an impact of depression can be smartphone users' willingness to be distracted through apps upon facing negative emotions [21]. Higher launch and higher number of Games apps used by depressed students as shown in our study can present their multitasking behavior which can also present their distracting behavior. Therefore, these insights can facilitate in designing systems to regulate the Games app usage for promoting well-being.

Like the correlation analysis, in mined behavioral patterns through the CBA algorithm [16], we did not find link of depression with a single weekdays' or 7 days' behavioral marker. Instead, through mining rules, we found high usage of Games apps in terms of multiple behavioral markers was associated with depression. It is due to the fact that to find a relation with a class (e.g., depressed), the CBA algorithm [16] uses values of several variables in different combinations while the Spearman correlation [22] uses data of a single variable to find out the monotonic relation with another variable. This demonstrates the strength of the data mining technique in extracting Games app usage behavioral patterns of the students having psychological problems. In a study [23], researchers presented the application of mined behavioral patterns to develop machine learning models to identify depression with higher accuracy. However, Games app usage data was unexplored as features for the models. Our findings suggest that as Games app category's behavioral patterns are linked with depression, this app category's data can be leveraged to develop better computational models for real-time identification of depressed individuals.

From our developed Bayesian network, we found that the duration per Games app launch data has the maximum outgoing edges, and also this node is directly linked with depression. Hence, this can be a plausible target for limiting Games app usage behavior and also lowering depression. This finding extends the recent study on psychological problems where researchers discussed the interaction of depressive symptoms [3] presenting a plausible target for intervention. Moreover, as we found that the higher Games apps usage duration per launch had a negative relation with depression, Games developers may take this into account for the well-being of the students. They may integrate different interventions (e.g., intervention through the input [13]) which was found to be effective in minimizing app usage. But the Games should have the option to integrate students' self-defined rules since pre-defined intervention can create frustration [13].

5 Limitations

This study is limited by a small number of Games app users (N = 60) and 7 days' Games app usage data. In addition, due to having fewer participants in each sub-category of Games, we could not explore the sub-categories to analyze the relation with depression.

6 Conclusion

Using the objective app usage data, we explored the relation between depression and Games app usage behavior. From the Bayesian network-based analysis, we found that the relation is not in a single direction. Also, our mined class association rules through the CBA algorithm showed that depressed and non-depressed students have unique behavioral patterns. Insights from our findings can be potential for the caregivers to be aware of the negative impact of Games app usage. Researchers, developers, and healthcare professionals can also use these insights to design systems for well-being.

References

1. Ahmed, M.S., Ahmed, N.: Exploring unique app signature of the depressed and non-depressed through their fingerprints on apps. In: Lewy, H., Barkan, R. (eds.) PH 2021. LNICSSITE, vol. 431, pp. 218–239. Springer, Cham (2022). https://doi.org/10.1007/978-3-030-99194-4_15
2. Ahmed, M.: 86pc university students own smartphones in Bangladesh: Survey. https://en.prothomalo.com/youth/education/86pc-university-students-own-smartphones-in-bangladesh-survey. Accessed 21 Sept 2022
3. Briganti, G., Scutari, M., Linkowski, P.: Network structures of symptoms from the Zung Depression Scale. Psychol. Rep. **124**, 1897–1911 (2021)

4. Brigham Young University: Video games linked to poor relationships with friends, family (2009). https://www.sciencedaily.com/releases/2009/01/090123075000.htm
5. Brunborg, G.S., Mentzoni, R.A., Frøyland, L.R.: Is video gaming, or video game addiction, associated with depression, academic achievement, heavy episodic drinking, or conduct problems? J. Behav. Addict. **3**, 27–32 (2014). https://doi.org/10.1556/JBA.3.2014.002
6. Google Play most popular app categories 2021. https://www.statista.com/statistics/279286/google-play-android-app-categories. Accessed 23 Sept 2021
7. Diefenbach, S., Borrmann, K.: The Smartphone as a pacifier and its consequences: Young adults' smartphone usage in moments of solitude and correlations to self-reflection. In: Proceedings of the CHI 2019. ACM, New York, NY, USA (2019)
8. Drachen, A., Riley, J., Baskin, S., Klabjan, D.: Going out of business: auction house behavior in the massively multi-player online game glitch. Entertain. Comput. 5, 219–232 (2014)
9. UsageStatsManager. https://developer.android.com/reference/android/app/usage/UsageStatsManager.html. Accessed 21 Sept 2022
10. Hosen, I., Al-Mamun, F., Mamun, M.A.: Prevalence and risk factors of the symptoms of depression, anxiety, and stress during the COVID-19 pandemic in Bangladesh: a systematic review and meta-analysis. Glob. Ment. Health (Camb.) **8**, e47 (2021)
11. 75% of pandemic-driven increase in mobile gaming activity will persist indefinitely, according to new IDC and LoopMe report. https://www.idc.com/getdoc.jsp?containerId=prUS47906621. Accessed 21 Sept 2022
12. Ilhan, A.E., Sener, B., Hacihabiboglu, H.: Improving sleep-wake behaviors using mobile app gamification. Entertain. Comput. **40**, 100454 (2022)
13. Kim, J., Park, J., Lee, H., Ko, M., Lee, U.: LocknType: lockout task intervention for discouraging smartphone app use. In: Proceedings of the CHI 2019 (2019)
14. Kroenke, K., et al.: The PHQ-8 as a measure of current depression in the general population. J. Affect. Disord. **114**, 163–173 (2009)
15. Ahmed, M.S., Rony, R.J., Hasan, T., Ahmed, N.: Smartphone usage behavior between depressed and non-depressed students: an exploratory study in the context of Bangladesh. In: Adjunct Proceedings of the UbiComp-ISWC 2020 (2020)
16. Liu, B., Hsu, W., Ma, Y.: Integrating classification and association rule mining. In: Proceedings of the KDD 1998, pp. 80–86. AAAI Press (1998)
17. App usage - manage/track usage. https://play.google.com/store/apps/details?id=com.a0soft.gphone.uninstaller. Accessed 21 Sept 2022
18. Mok, L., Anderson, A.: The complementary nature of perceived and actual time spent online in measuring digital well-being. Proc. ACM Hum. Comput. Interact. **5**, 1–27 (2021)
19. Nagarajan, R., Scutari, M., Lèbre, S.: Bayesian Networks in R (2013)
20. Owl, B.: Weekend depression. https://www.kindmindonline.com.au/blog/weekend-depression-ecmh9. Accessed 21 Sept 2022
21. Sarsenbayeva, Z., et al.: Does smartphone use drive our emotions or vice versa? A causal analysis. In: Proceedings of the CHI 2020 (2020)
22. Chalmer, B.J.: Understanding Statistics. CRC Press, Boca Raton, FL (1986)
23. Xu, X., et al.: Leveraging routine behavior and contextually-filtered features for depression detection among college students. Proc. ACM IMWUT **3**, 1–33 (2019)
24. Yazici, Z.N., Kumcagiz, H.: The relationship between problematic online game usage, depression, and life satisfaction among university students. Educ. Proc. Int. J. **10**, 27–45 (2021)
25. Koly, K.N., et al.: Prevalence of depression and its correlates among public university students in Bangladesh. J. Affect. Disord. **282**, 689–694 (2021)
26. Scutari, M., Auconi, P., Caldarelli, G., Franchi, L.: Bayesian networks analysis of malocclusion data. Sci. Rep. **7**, 15236 (2017). https://doi.org/10.1038/s41598-017-15293-w

27. Hunt, M.G., Marx, R., Lipson, C., Young, J.: No more FOMO: Limiting social media decreases loneliness and depression. J. Soc. Clin. Psychol. **37**, 751–768 (2018)
28. Wei, H.-T., Chen, M.-H., Huang, P.-C., Bai, Y.-M.: The association between online gaming, social phobia, and depression: an internet survey. BMC Psychiatry **12**, 92 (2012)
29. Lin, H.-C., Yen, J.-Y., Lin, P.-C., Ko, C.-H.: The frustration intolerance of internet gaming disorder and its association with severity and depression. Kaohsiung J. Med. Sci. **37**, 903–909 (2021)
30. McMahan, T., Parberry, I., Parsons, T.D.: Modality specific assessment of video game player's experience using the Emotiv. Entertain. Comput. **7**, 1–6 (2015)
31. Caplan, S., Williams, D., Yee, N.: Problematic Internet use and psychosocial well-being among MMO players. Comput. Hum. Behav. **25**, 1312–1319 (2009)
32. Kahn, A.S., Ratan, R., Williams, D.: Why we distort in self-report: Predictors of self-report errors in video game play. J. Comput. Mediat. Commun. **19**, 1010–1023 (2014)
33. Opoku Asare, K., et al.: Predicting depression from smartphone behavioral markers using machine learning methods, hyperparameter optimization, and feature importance analysis: Exploratory study. JMIR mHealth uHealth **9**, e26540 (2021)