Exploring Unique App Signature of the Depressed and Non-depressed Through Their Fingerprints on Apps

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Abstract. Growing research on re-identification through app usage behavior reveals the privacy threat in having smartphone usage data to third parties. However, re-identifiability of a vulnerable group like the depressed is unexplored. We fill this knowledge gap through an in the wild study on 100 students' PHQ-9 scale's data and 7 days' logged app usage data. We quantify the uniqueness and re-identifiability through exploration of minimum hamming distance in terms of the set of used apps. Our findings show that using app usage data, each of the depressed and non-depressed students is re-identifiable. In fact, using only 7 h' data of a week, on average, 91% of the depressed and 88% of the non-depressed are re-identifiable. Moreover, data of a single app category (i.e., Tools) can also be used to re-identify each depressed student. Furthermore, we find that the rate of uniqueness among the depressed students is significantly higher in some app categories. For instance, in the Social Media category, the rate of uniqueness is 9% higher ($P = .02$, Cohen's $d = 1.31$) and in the Health & Fitness category, this rate is 8% higher ($P = .005$, Cohen's $d = 1.47$) than the non-depressed group. Our findings suggest that each of the depressed students has a unique app signature which makes them re-identifiable. Therefore, during the design of the privacy protecting systems, designers need to consider the uniqueness of them to ensure better privacy for this vulnerable group.

Keywords: Depressed · Non-depressed · Re-identification · Privacy · Unique app signature · Social media · Health & fitness · Smartphone

1 Introduction

Third party apps and websites can collect sensitive information from the users in different ways. Without users' awareness, apps can collect sensitive data such as SMS [4, 5], location [19], phone number [5, 19], even the collection of installed apps from the smartphone [5]. It is possible to uniquely re-identify the users through their data of music preferences [18], app usage [3, 6, 8–11, 23, 32], and mobility [2, 7] which increases the risk of privacy leakage. Moreover, attacks can be designed through the use of leaked data [14]. In fact, study [4] found that malware detects and matches with the users' installed

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apps to perform pre-determined tasks. Due to attacks like cyber-attacks, victims can suffer from various mental illness (e.g., frustration [15]). Therefore, in the case of the people who are already depressed, the situation can worsen. Given the significance of better privacy for vulnerable groups, we explore the unique app signature of the depressed group by which they can be re-identified only from the app usage data.

Scholarly studies [20–22, 29, 33, 41–44, 47] have been conducted regarding depression and technology. A substantial amount of studies [6, 7, 10, 11, 14, 30, 32, 35, 40] also presented the approach to re-identify. Depressed people may have identifiable unique app signatures as previous studies show different preferences of the depressed. For instance, people with major depressive disorder are more likely to prefer sad and low energy music [44]. However, none of these studies have explored the unique app signature of the depressed students by which they can be re-identified from a dataset where any direct identity (e.g., name, email) is not available. If the depressed students are more unique in some app categories, then they are more likely to be vulnerable in having data of those app categories to the third parties which can be a privacy threat. This motivated us to explore the following research questions.

- Can the depressed be uniquely re-identified only from a set of used apps?
- Is there any statistically significant difference between the depressed and non-depressed, in terms of re-identifiability?

To answer the research questions, using our developed app, we collected 7 days' actual app usage data and response of the PHQ-9 scale [12] from 100 Bangladeshi students. Then, following scholarly studies [13, 28, 29], we divided the participants based on their PHQ-9 score. Participants having scores of less than 10 were grouped as the non-depressed and others as the depressed. To understand the re-identifiability, we calculated the hamming distance. Our analysis of regardless app category shows that all of the depressed and non-depressed students are re-identifiable. We also find that students of both groups are more unique on weekdays. However, still, on weekends, about 25 apps are needed to make them anonymous. Our findings also show that using data of the app categories, it is possible to re-identify a significant number of depressed and non-depressed students. In fact, analysis of the Tools category shows that with 12 h data of each day of a week all of the students can be re-identified. It was also interesting to see that depressed students' uniqueness rate is significantly higher in some app categories. For instance, the uniqueness rate among the depressed is 9% higher ($p = .02$) in the Social Media and 8% higher ($p = .005$) in the Health & Fitness category.

Our research has several contributions. Firstly, we explored the depressed students' uniqueness in app signatures which is the first study (to our best knowledge) regarding any group suffering from mental health problems where possibility of re-identification is presented. Secondly, we have presented the differences of this group from the non-depressed in terms of re-identifiability. Thirdly, we have presented that depressed and non-depressed students can be uniquely re-identified through the data of app categories which was not explored previously even in terms of general people. Lastly, through higher uniqueness of the depressed students, we have discussed about their support seeking behavior which can be insightful in designing apps to overcome depression.

2 Related Work

2.1 Difference in Smartphone Usage Among Various Groups of People

Smartphone usage behavior varies between different groups of people, from teens [16] to older [17]. The substantial diversity of smartphone usage behavior is presented by some previous studies [3, 48]. Researchers presented that the number of interactions, number of apps [48], diurnal usage pattern [8, 48], frequency of using apps [3] varies between the users. The usage behavior can vary by place [49] and day of the week [3, 49] also. Bentley et al. found that teens' smartphone usage behavior is different from the general population [16] and Gordon et al. [17] found that smartphone usage of the older adults is different from the younger adults. Indeed, smartphone usage behavior varies by platform. For instance, iPhone users have a higher number of apps per session [40] than the Android users. App usage behavior differ between the risk and non-risk smartphone users also [8]. However, none of the studies explored the behavioral difference between the depressed and non-depressed in terms of re-identifiability.

2.2 Smartphone Usage and Mental Health

Smartphones have been widely used in assessing different types of mental health problems such as depression [13, 29, 33, 41, 42, 53, 54] and loneliness [52, 55]. Noë et al. [22] found that smartphone addiction does not correlate with interaction regarding every app category. Rozgonjuk et al. [20] found a negative relation of depression and anxiety with the frequency of unlocking phone screens. However, there are several studies who did not find a negative relation. For instance, a previous study found that addiction to smartphone usage has a significant positive correlation with depression [21]. In another study [29], researchers found that though the depressed and non-depressed students do not differ by total smartphone usage data, they differ significantly in terms of app categories usage data. Using smartphone sensed data, researchers [33, 42] found that students having symptoms of depression and non-depression can be classified accurately. In our study, we discuss the support seeking nature of the depressed students through their unique characteristics of app usage.

2.3 Re-identification of the Users and Privacy Leakage

Most of the ad (advertisement) libraries of the apps collect personal information [5]. Installed apps in users' phones can expose location information to the servers of advertisers without implicit or explicit consent of the users [19]. This is a threat to the privacy of the users as based on location data they can be re-identified [7, 11], and also their demographic attributes can be inferred [14]. The ad libraries [5], popular social media apps like Twitter [36, 37] collect the information regarding installed apps from the users' phone. Moreover, a study [38] showed that 42.55% of the apps share data with Facebook. This data is shared even when the people do not use Facebook [39]. Information collected through different ways can later be used for identification purposes [5]. In fact, combining data that is shared with Facebook can reveal personal information related to activities, interests, health etc. [39]. With the available data, previous studies presented

several ways by which people can be re-identified. Tu et al. [11] investigated the risk of re-identification and privacy leakage through the use of spatial and temporal information. Welke et al. [6] found that 99.67%of the users can be uniquely identified under consideration of 500 most frequent apps. Moreover, they found that even after restricting to 60 most frequent apps, it is still possible to uniquely find out 99.4% users. Surprisingly, few other studies [10, 11, 35] showed that even with 4 random apps, most users can be uniquely re-identified which is a threat to privacy. However, this re-identification varies by season, country [10], mobility, activity in social networks, and gender [11]. Therefore, distinct characteristics regarding fingerprints on apps need to be considered to protect privacy of the users. However, the re-identification of the depressed is unexplored which could be useful in designing technology having better privacy of the depressed.

Apart from the usage of apps' data, previous studies [18, 30] demonstrated some other ways of re-identification. By doing four experiments, Hirschprung and Leshman [18] showed that users can be re-identified by their music selection. Gulyás et al. [32] found that using a combination of font and screen size, users can be re-identified. Their findings also showed that by 100 cameras for 40 lac people, it is possible to re-identify a number of users from the Call Detail Record (CDR) dataset [32]. On the other hand, using data regarding transactions, Montjoye et al. [30] showed that with four spatiotemporal points, 90% credit card users can be uniquely re-identified. Their findings also presented that uniqueness varies by gender, income level. For instance, they found that women can be more easily identified than the men. However, Tu et al. [11] found that men are more distinguishable in terms of app usage data. However, the difference between the depressed and non-depressed is unexplored in terms of re-identification through the app usage data which could be insightful to understand the depressed better and to come up with a better technology ensuring the privacy of this vulnerable group.

3 Methodology

Using our developed automatic logger app (Sect. 3.1), we collected 7 days' actual app usage data (Sect. 3.2). After pre-processing and categorization of the apps (Sect. 3.3), to understand the re-identifiability, we calculated the hamming distance (Sect. 3.3). Apart from this, we did statistical analysis (Sect. 3.3) to explore the difference statistically in uniqueness between the depressed and non-depressed.

3.1 Data Collection Tool

App Usage Data. We developed an Android app to collect actual smartphone usage data and self-reported psychological data. With the proper consent of the user, this app retrieves past 7 days' app usage data very accurately. To get the foreground and background events of the used apps, we used *UsageStatsManager* class of Java and to save the data, we used Google Firebase. Except for the metadata, our app does not collect or store any sensitive data like photo, message etc. We released the app in Google Play store as this app store is known to the Android users (Fig. 1).

Testing the Data Collection Tool. We tested the app in different ways. First of all, we compared the retrieved app usage data of our tool with the manually calculated app usage

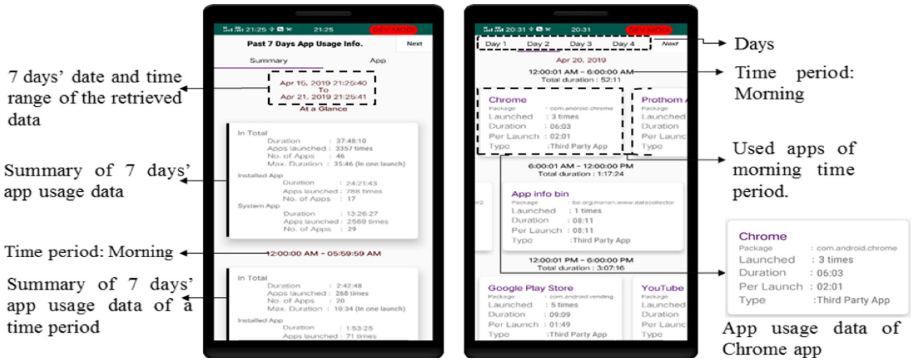


Fig. 1. Screenshots of our developed Android app which was used to collect data.

data. Secondly, we compared the retrieved app usage data of our tool with such apps [57, 58] of Google Play store. Finally, we tested the tool on 9 different smartphones. We find that in each of the mentioned approaches, our data collection tool can calculate 7 days' app usage data (e.g., duration) very accurately.

Scale to Detect Depression. In the data collection tool, to measure the depression, we include the PHQ-9 scale [12]. In our app, the scale was available in English as well as in native language Bengali. Amid the pandemic, depression increased among the young. In fact, a previous study [34] conducted before COVID found a 69.5% depression rate among the first-year university students of Bangladesh. As a word like dead may worsen the mental health of a depressed student while responding to the questions, we have consulted with three lecturers (one is from the department of CSE and two is from Sociology), and a program coordinator of a university who have good connections with the students. Due to various concerns, all of them suggested removing the word dead. For instance, the program coordinator was concerned about the mental health of the depressed students after being asked a question regarding death. In addition, we talked with 3 more doctors who served the COVID patients. They remarked that the word hurting in the ninth item may present the suicide intention of the depressed one. Moreover, we found that the word dead is not preferable in all cultural contexts. For example, religious participants may not feel comfortable in responding to this item [56]. Therefore, we removed the bold word dead to make the 9th item comfortable for the participants. Finally, we translated the questionnaire in Bengali where three researchers, 2 final year students, and 4 other undergraduate students were involved.

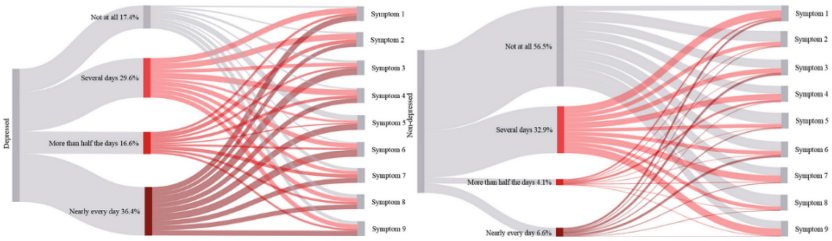
3.2 Data Collection Procedure and Participants

Data Collection Procedure. Using the snowball sampling method [24], the data were collected from 100 students of 12 different higher institutions of Bangladesh and they were from department of BBA (Bachelor of Business Administration), CSE (Computer Science & Engineering), EEE (Electrical & Electronic Engineering), LLM (Master of Laws), MBBS (Bachelor of Medicine, Bachelor of Surgery), Sociology, and Textile

Engineering. But the majority of them were studying in the CSE department. We collected data during COVID period and due to COVID, it was not possible for us to collect all participants' data through a face to face meeting. From most of the participants, we collected data by arranging group meetings and one to one meetings through a virtual platform like Google Meet, Messenger depending participants' availability and their preferences. During data collection, at first we briefly described our research and then asked the participants to read the consent form, download the app from Google Play store. As exams may have an impact on students' mental health, we did not collect data from the students who had mid-term or semester final exams during the data collection time.

Categorization of the Participants. Following previous studies [13, 28, 29], we divide the participants into depressed and non-depressed on the basis of their self-reported response to the PHQ-9 scale. The participants whose score was at least 10 were categorized as depressed and the participants whose score were less than 10 were categorized as non-depressed. For major depression detection, both the sensitivity and specificity of PHQ-9 score 10 was 88% [12].

Depression of the Participants. In the PHQ-9 questionnaire [12], there are 9 symptoms and participants had the option to select the days (not at all, several days, more than half the days, and nearly every day) they bothered each of those symptoms in the past 14 days. In the case of the depressed students, 36.4% responses were nearly every day and 82.6% responses were at least several days (Fig. 2 (a)). On the other hand, in case of non-depressed students more than 50% responses were not at all (56.5%) and only 10.7% responses were more than half the days and nearly every day. (Fig. 2(b)) This presents that in the depressed group, the symptoms appeared at a much higher number of days in comparison to the non-depressed group.

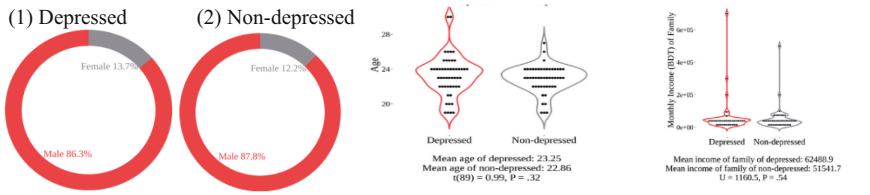


(a) Depressed students (b) Non-depressed students

Fig. 2. The frequency (not at all, several days, more than half the days, nearly everyday) of appearance of different depressive symptoms, in (a) depressed and (b) non-depressed group.

Demographic Characteristics. We explored whether there is any difference between the depressed and non-depressed group in terms of gender, age, and social circumstances such as monthly income as these can be confounders. In the depressed group, there were 13.7% female which is close to the female participants' percentage (12.2%) of the non-depressed group (Fig. 3(a)). There were also almost similar percentages of

male participants (86.3% and 87.8%) in both of the groups. Our statistical analysis also shows that there is no significant difference of age between these two groups of students (Fig. 3(b)). Mean age of the depressed was 23.25 years (SD = 2.33) and non-depressed was 22.86 years (SD = 1.62) which are statistically not different ($t(89) = 0.99$, $P = .32$). We also find that there is no statistically significant difference (depressed: BDT 62,488.9 vs non-depressed: BDT 51,541.7, $U = 1160.5$, $P = .54$) of monthly income (Fig. 3(c)).



(a) Ratio of female and male (b) Age (c) Monthly family income

Fig. 3. Difference between the depressed and non-depressed group in terms of (a) ratio o female and male participants, (b) age, and (c) monthly family income (in BDT: Bangladeshi Taka).

3.3 Data Analysis

App Categorization. In 7 days, participants used 1129 unique apps in total. To understand their uniqueness regarding app categories, we grouped those apps into 26 categories. During categorization, we considered the features of the apps, volunteers' opinion, developers' referred category in different apps stores, and app categorization of the previous studies (e.g., [1, 40]). For some apps, we did not use the developers' referred category. For instance, though Zoom and Google Meet were categorized as Business apps in the Google Play store, we categorized those as Education apps since participants of our study were students and amid COVID-19, their classes were held virtually using these apps. There were some apps for which detailed information was not available. We kept those in unknown app category like Böhmer et al. [1]. Moreover, in Art & Design category (e.g., Autodesk SketchBook app), there was only 1 participant. Thus, we excluded that app category also keeping 24 categories for statistical analysis.

Analysis to Find the Uniqueness. Finding the uniqueness of a smartphone user, one can be identified easily by an attacker which is a direct privacy leakage [11]. To identify the uniqueness of the both depressed and non-depressed students, we calculate the minimum hamming distance [25] of a user as used by previous studies in case of other groups of people [6, 11, 40]. Let's say, there are two participants named participant 1 and participant 2. The set of apps used by participant 1 is {*WorldGK*, *Wikipedia*} and the set of apps used by participant 2 is {*Dictionary*, *Wikipedia*, *EnglishGrammarFull*}. In terms of app usage, the hamming distance (D) between these two participants can be calculated using the following formula:

$$D = (S_1 \cup S_2) - (S_1 \cap S_2)$$

Here, $S_1 \cup S_2$ presents the set of all the apps used by the participant 1 and participant 2. $S_1 \cap S_2$ presents the common set of apps used by both of these two participants. D represents the distance between participant 1 and participant 2. In the case of the given set of apps, the distance will be 3 ($\{WorldGK, Dictionary, Wikipedia, English GrammarFull\} - \{Wikipedia\}$). In this way, we calculate the hamming distance of a participant from all other participants. After that, to find the uniqueness of a participant (U_i), we find out the user with whom the hamming distance is minimum.

$$U_i = min\{D_1, D_2, D_3, D_4, ..., D_n\}$$

Here, U_i represents the uniqueness of the i^{th} participant. This value will represent the minimum number of apps that will be required to use for the i^{th} participant to be anonymous as described by a previous study [6].

Statistical Analysis. After calculating the minimum hamming distance, we explore whether the uniqueness of depressed and non-depressed students is different. As most of our data were not normally distributed, we did mostly non-parametric Mann-Whitney U Test using scipy library [26]. However, in those cases where data were normally distributed and had equal variance among the groups of students, we did Standard T-Test. In some categories where both groups did not have equal variance, we did the Welch T-Test. As multiple comparisons can produce false positive results, we controlled

Table 1. Brief description about the used phrases in this study.

Phrase	Brief description
App usage fingerprint	The fingerprint on the used set of apps [10, 11]. Here, we used the word fingerprint to denote the touch on the screen of smartphones while using an app
App signature	App signature is defined as the set of mobile apps which were used at least for one time in the participant's phone [6]
Uniqueness	The uniqueness is measured by calculating hamming distance [25] from one participant to another. The higher the hamming distance, the more unique a participant is (for more, please see subsection named "Analysis to Find the Uniqueness") of Methods
Rate of uniqueness	The percentage of participants (e.g., depressed) who used at least one different app from the other participants
Uniqueness through app categories	The uniqueness in terms of the participants' used apps of a particular app category (e.g., Social Media)
Re-identification	Possibility to re-identify [10, 11] a participant. For example, in this study, we used app usage data to present the re-identification of the depressed and non-depressed students, without having any other information (e.g., demographic characteristics)

the type I error using False Discovery Rate (FDR) method [27]. We considered each app category as a separate family as depending on app category, depressed and non-depressed students' smartphone usage behavior varies [29] (Table 1).

3.4 Research Ethics

This study is a part of a research project which was approved by the Center of Research & Development of a university. We collected data with all of the participants' informed consent where we mentioned explicitly details of the study like data we are collecting, data security which we will provide. During the data donation, one had to give two permissions (to access the IMEI number and to access app usage data) which was also mentioned in the consent form.

4 Results

After analysing the response of the PHQ-9 scale [12], we find that among 100 students, 51 participants had depression scores of at least 10. Therefore, based on the classification criteria [13, 28, 29], 51% participants were depressed and 49% participants were non-depressed. We also find that all of the depressed students and non-depressed students can be uniquely re-identified without considering any app category (Sect. 4.1). However, analysis of Tools app category shows that with app usage data of only a single category, it is possible to re-identify each of the depressed and non-depressed students (Sect. 4.2). Moreover, we find that with 24 h data of 7 days, a significant number of participants can be re-identified by the popular app categories such as Communication, Photo & Video, Productivity (Sect. 4.2). After exploring the uniqueness difference between these two groups of students, we find that depressed students are significantly more unique in some app categories (Sect. 4.3). For example, in Social Media, the rate of uniqueness among the depressed students was 9% higher and it was statistically significant ($P = .02$, Cohen's $d = 1.31$).

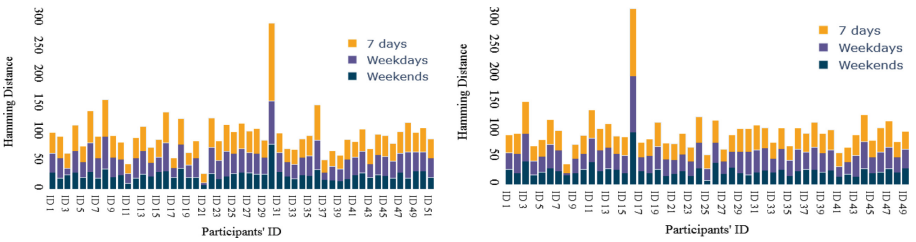
4.1 Uniqueness While Considering Apps of All Categories

About 37 Apps are Needed to Make the Depressed and Non-depressed Anonymous. To understand how unique the depressed and non-depressed students are, we calculated the minimum hamming distance to the nearest participant. Here, during finding the nearest participant, we did not consider that participant's group (e.g., depressed) since we wanted to understand their uniqueness among all participants. From Table 2, we see that under consideration of a week's app usage data only, both in case of depressed and non-depressed students, on average, about 37 apps will be required to be anonymous.

Both of the Depressed and Non-depressed are More Unique on Weekdays. We present the uniqueness of each student on 7 days, weekdays, and on weekends. We find that both the depressed and non-depressed students are more unique on weekdays in comparison to weekends. On weekdays, the average distance to the nearest user is about 34 whereas on weekends, this distance is about 25 (Table 2).

Table 2. Depressed and non-depressed students' hamming distance. SD: Standard Deviation.

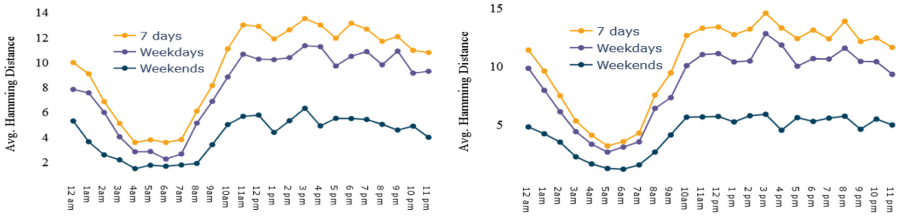
Days	Depressed students' Hamming distance				Non-depressed students' Hamming distance			
	Minimum	Maximum	Mean	SD	Minimum	Maximum	Mean	SD
7 days	16.0	137.0	37.73	17.84	16.0	122.0	36.7755	14.995
Weekdays	4.0	76.0	33.53	11.98	4.0	101.0	34.20	12.94
Weekends	7.0	79.0	24.61	9.898	7.0	94.0	24.61	12.055



(a) Depressed students (b) Non-depressed students

Fig. 4. Hamming distance to the nearest user for each of the depressed and non-depressed.

In Each Hour, Depressed and Non-depressed Can Be Uniquely Re-identified. Supporting the findings of each individual student's uniqueness as presented in Fig. 4, Fig. 5 also shows that in each hour of the day, on weekdays, their uniqueness level is higher. The difference in uniqueness between weekdays and weekends becomes higher from mid day. In addition, Fig. 5 shows that as we move from morning (6 AM) to afternoon both the depressed and non-depressed students use more unique apps. However, from 10 PM, their uniqueness begins to move downwards and in case of the non-depressed students (Fig. 5(b)), this decrease is approximately linear on weekdays. On the other hand, in case of depressed students (Fig. 5(a)), from 7 AM on weekdays, their average uniqueness increment is almost linear.



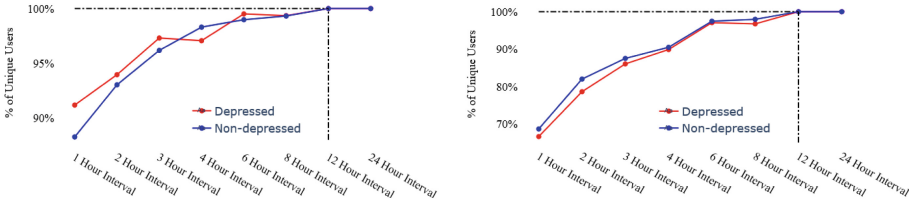
(a) Depressed students (b) Non-depressed students

Fig. 5. Average hamming distance of the depressed and non-depressed students in each hour of weekdays, weekends, and 7 days (weekdays + weekends).

4.2 Uniqueness Through App Categories

To understand how many students can be uniquely re-identified if adversaries have only an app category's data of particular hours of 7 days, we calculate the average percentage of unique students in terms of 8 different hour intervals (1 h, 2 h, 3 h, 4 h, 6 h, 8 h, 12 h, 24 h). To do this analysis, at first, we calculate the percentage of students that are unique in terms of each time range (e.g., 12 AM–2 AM, 2 AM–4 AM) of 7 days under consideration of a particular interval (e.g., 2 h interval). After that, we calculate the average percentage of students that are unique, in terms of the corresponding interval.

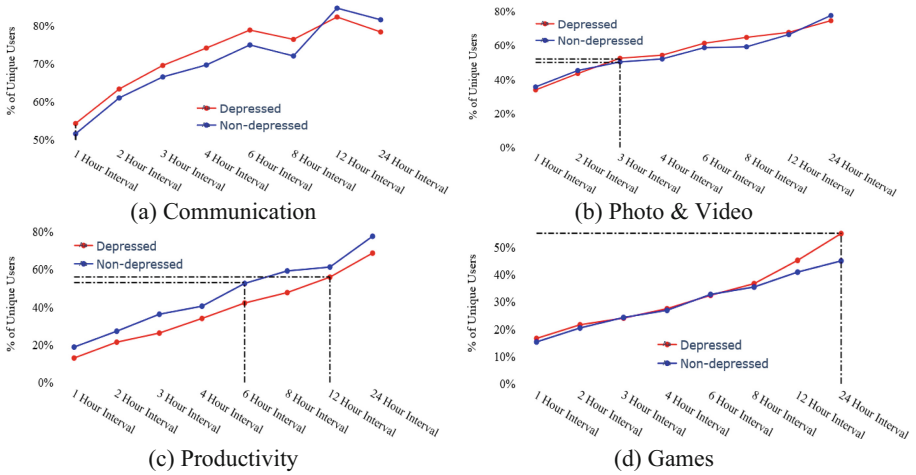
Tools Category's Data Can Re-identify Each of the Depressed and Non-depressed. Our findings show that regardless of the app category, all of the participants can be uniquely re-identified using 12 h' data of each day of a week (Fig. 6(a)). In fact, considering 1 h's data of each day of a week, our findings show that on average 91% depressed and 88% non-depressed students are unique (Fig. 6(a)). This motivated us to explore how uniquely both the depressed and non-depressed students can be re-identified with app categories usage data. Analysis of the Tools app category shows that like the findings of regardless app category, each of the students of both groups can be re-identified when we consider the 12 h interval's data of this app category. Our findings also show that if an attacker gets just 1 h's data of each day of a week (i.e., 7 h data of a week), about 70% of students can be re-identified through the Tools category (Fig. 6(b)).



(a) Regardless app category (b) Tools app category

Fig. 6. Percentage of the users that can be re-identified while considering (a) Without consideration of app category and (b) Tools app category.

Through Data of Popular App Categories Also, Depressed Can Be Uniquely Re-identified. As the popular app categories are used more by the students, we explored how the popular app categories can be used to uniquely re-identify the depressed and non-depressed students. Here, we visualize the app categories which can be used for re-identification of at least 50% users. Our findings show that in the case of Communication (Fig. 7(a)), Photo & Video (Fig. 7(b)), and Productivity (Fig. 7(c)) app categories, more than 75% users can be uniquely re-identified with usage data of only a single app category. In fact, in the Communication category, with 7 h data of a week (1 h interval), it is possible to re-identify more than 50% depressed and non-depressed students (Fig. 7(a)). We also find in terms of Games category, more than 50% depressed students are unique (Fig. 7(d)).



(a) Communication (b) Photo & Video

(c) Productivity (d) Games

Fig. 7. Percentage of users that can be re-identified while considering (a) Communication (b) Photo & Video (c) Productivity (d) Games app categories. The dashed line indicates the interval using which one can uniquely re-identify at least 50% of students of a group (e.g., depressed).

4.3 Difference in Uniqueness Between the Depressed and Non-depressed Students

Depressed are Significantly more Unique in 7 App Categories. To understand whether there is any difference in uniqueness between the depressed and non-depressed students, we did a comparative study (for methodology, please see Sect. 3.3). After analyzing the data of 26 app categories, we find that in the Finance ($P = .01$, $d = 1.7$), Food & Drink ($P = .004$, $d = 1.69$), Health & Fitness ($P = .005$, $d = 1.47$), Launcher Like App ($P = .003$, $d = 3.4$), Lifestyle ($P = .005$, $d = 1.77$), Social Media ($P = .02$, $d = 1.31$), and Sports ($P = .0004$, $d = 3.13$) app categories, there is a significant difference in percentage of uniquely identifiable students between the depressed and non-depressed group (Table 3). In each of these app categories, more depressed students can be re-identified. As these percentages are based on hamming distance, higher uniqueness represents that the depressed students use a diverse set of apps than the non-depressed students. For instance, in the Health & Fitness category, we find that a student of the depressed group uses an app (Quit Tracker: Stop Smoking) to quit her/his smoking habit. Few others of that group use apps to create and communicate with replica friends (by an app, Replika: My AI Friend), to concentrate more, to reduce body weight etc. However, these types of apps were not used by the the non-depressed students.

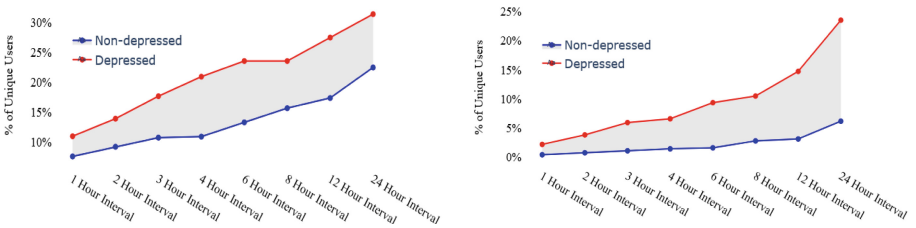
Depressed are 9% More Unique in Social Media and 8% More Unique in the Health & Fitness Category. Our findings also show that in terms of Social Media category, after considering all of the 8 different hour intervals' percentage, on average 21% students can be uniquely re-identified (Table 3). However, analysis of the same app category shows that on average 13% students can be uniquely re-identified in case of non-depressed students which is 9% less ($P = .02$). Moreover, we find that in the Health & Fitness

Table 3. App categories which show significant differences between the depressed and non-depressed groups in percentage of re-identifiable students. Here, mean represents the average percentage of uniqueness after considering the percentages of 8 different hour intervals.

App Category	Example Apps	% of Depressed		% of Non-depressed		Statistics Value	*P* Value	Cohen's d
		Mean	Max.	Mean	Max.			
Finance	ALLEX, bKash	6	12	2	3	t(51) = 3.41	0.01	1.7
Food & Drink	eFood, CoSRe	2	4	0.9	2	t(98) = 3.38	0.004	1.69
Health & Fitness	Replika: My AI Friend	10	24	2	6	U= 59	0.005	1.47
Launcher Like App	System UI, Launcher3	9	10	4	8	U = 61	0.003	3.4
Lifestyle	SmartThings, Athan	5	10	1	4	U = 59	0.005	1.77
Social Media	Instagram, Facebook	21	31	13	22	t(98) = 2.62	0.02	1.31
Sports	Goal News, CricBall	6	10	0.6	1	t(52) = 6.26	0.0004	3.13

app category, 8% more (P = .005) students of the depressed group can be re-identified. Though in some other app categories (e.g., Food & Drink), we find that depressed students are significantly (P < .05) more unique (Table 3), in this section and the following sections of this paper, we will talk about Social Media and Health & Fitness app categories as using other app categories (which show significant difference) very less number (less than 10%) of students can be re-identified.

Supporting the findings mentioned in Table 3, Fig. 8 also shows that in the case of Social Media and Health & Fitness app categories, depressed students are more unique in both of these app categories. In fact, considering 24 h data of 7 days, in the Health & Fitness category, 6% non-depressed students are unique whereas in the depressed group, 24% are unique (Fig. 8(b)).



(a) Social Media (b) Health & Fitness

Fig. 8. Difference between depressed and non-depressed students in percentage of users that can be re-identified while considering (a) Social Media (b) Health & Fitness app categories.

As using Social Media category, a significantly higher percentage of depressed students can be re-identified, we were motivated to explore this app category more. To understand whether in this app category, two groups of students have different diurnal usage patterns or not, following previous studies [3, 8], we divide a day into four equal periods taking 6 h as an interval: Night: 12:01 AM to 6:00 AM; Morning: 6:01 AM to 12:00 PM; Afternoon: 12:01 PM to 6:00 PM; Evening: 6:01 PM to 12:00 AM.

Depressed are More Unique in the Afternoon and Evening Time Period. Table 4 shows that considering Social Media usage of the night and morning time, there is no significant

Table 4. Difference of hamming distance between the depressed and non-depressed students, in terms of their Social Media app category usage data of different time ranges.

Time Range	Distance of Depressed		Distance of Non-depressed		Statistics Value	P	Cohen's d
	Mean	Maximum	Mean	Maximum			
Night	0.24	3	0.16	2	U=1250.5	0.995	0.15
Morning	0.18	1	0.1	1	U=1342.5	0.385	0.27
Afternoon	0.41	5	0.1	1	U=1475	0.046	0.47
Evening	0.35	3	0.1	2	U=1490	0.046	0.47

difference in hamming distance between the depressed and non-depressed students. However, in the afternoon time, the hamming distance of the depressed students to the nearest user is much higher than the non-depressed students and the difference is statistically significant (dep. 0.41 vs non-dep. 0.1, $P = .046$). Cohen's d of 0.47 also shows that the effect is not smaller. After analysing data of evening time range also, we find that depressed students can be more uniquely re-identified than the other group (dep. 0.35 vs non-dep 0.1, $P = .046$, Cohen's $d = 0.47$) using Social Media category usage data. Higher hamming distance of the depressed students in the afternoon and evening time ranges reveal that they use a more diverse set of apps in these time periods. Moreover, this analysis also presents that in terms of unique signature on apps of Social Media, depressed students have significantly different diurnal usage patterns than the non-depressed students.

In Several App Categories, Though Both the Depressed and Non-depressed are Unique, There is No Significant Difference. Several app categories do not show any significant difference between the depressed and nondepressed students' groups. Though using data of Tools app category, a large number (more than 90%) of students of each group can be uniquely re-identified, there is no significant difference (dep. 89% vs non-dep 90%, $P = .84$, Cohen's $d = -0.1$) in percentage of uniqueness between these two groups of students (Table 5). We also find similar insignificant ($P > .05$) differences in the case of several other app categories (Table 5). For instance, from analysis (Table 5 and Fig. 7(c)) of the Productivity category, it seems that a higher number of non-depressed students can be uniquely re-identified. However, the difference is not statistically significant (dep. 39% vs non-dep. 47%, $P = .41$, Cohen's $d = -0.42$). This says that in terms of percentage of uniquely re-identifiable students, the depressed group is more likely to be similar to the non-depressed group, in case of the app categories as presented in Table 5.

Table 5. App categories which do not show statistically significant differences between the depressed and non-depressed in percentage of uniquely re-identifiable students. Here, mean is the average percentage of uniqueness after considering the percentages of 8 different intervals.

App category	Example apps	% of Depressed		% of Non-depressed		Statistics value	P	Cohen's d
		Mean	Max.	Mean	Max.			
Books & Reference	World GK, Translate	16	24	18	29	$t(98) = -0.73$	0.48	−0.36
Browser & Search	Browser, Search	27	35	32	47	$t(98) = -1.03$	0.32	−0.51
Business	Pymetrics, TallyKhata	5	10	8	16	$t(98) = -1.27$	0.22	−0.64
Communication	TalkSign, Messenger	72	82	70	85	$t(98) = 0.38$	0.71	0.19
Education	ZOOM, Learn PHP	6	14	10	18	$t(98) = -1.62$	0.13	−0.81
Entertainment	Football TV, Adere	13	27	10	16	$t(98) = 0.97$	0.35	0.49
Games	Among Us, Archero	32	55	30	45	$t(98) = 0.39$	0.7	0.19
Medical	Daktarbhai, Patient Aid	2	2	0.8	2	$U = 47$	0.12	1.04
Music & Audio	Harmonium, i Music	15	25	16	35	$t(98) = -0.3$	0.77	−0.15
News & Magazines	Reddit, Job Circular	5	8	3	6	$t(98) = 1.97$	0.07	0.98
Personalization	Theme Store, Themes	7	10	5	9	$t(98) = 1.51$	0.15	0.75
Photo & Video	Camera, Collage Maker	57	75	56	78	$t(98) = 0.14$	0.89	0.07
Productivity	Scanner, Calendar	39	69	47	78	$t(98) = -0.84$	0.41	−0.42
Shopping	Pickaboo, AliExpress	6	14	6	7	$t(60) = 0.27$	0.79	0.14
Tools	Settings, Download Mp3	89	100	90	100	$t(98) = -0.2$	0.84	−0.1

(*continued*)

Table 5. (*continued*)

App category	Example apps	% of Depressed		% of Non-depressed		Statistics value	P	Cohen's d
		Mean	Max.	Mean	Max.			
Travel & Local	NOVOAIR, Rail Sheba	6	10	5	12	$t(98) = 0.44$	0.67	0.22
Weather	Weather	2	6	3	4	$U = 16$	0.1	−0.43
Regardless App Category	Browser, Weather	97	100	97	100	$t(98) = 0.29$	0.78	0.14

5 Discussion

Our findings show that 51% of the students (N = 100) are depressed which is close to the depression rate found in the previous studies [50, 51]. Our analysis on re-identification shows that using only 7 h of data a week, 91% of the depressed and 88% of the non-depressed students can be re-identified. Moreover, in comparison to the non-depressed, depressed students' rate of uniqueness is 9% (P = .02) and 8% (P = .005) higher in the Social Media and Health & Fitness app categories respectively. Our findings are novel and to our best knowledge, this is the first study which explored the re-identification of a group suffering from mental disease. We believe that our findings will be worthwhile to bring better privacy to the depressed one.

5.1 Depressed and Non-depressed Students Can Be Uniquely Re-identified

Based on only 7 days' data, on average, both the depressed and non-depressed students' minimum hamming distance to the nearest user is about 37 apps which represents that a higher number of apps will be needed to make them anonymous. This finding showing the uniqueness of the depressed extend the previous studies [6, 10, 11] which were conducted on the general people. Going beyond the previous studies, we also explore the app categories and find that using data of a single app category named Tools, it is possible to uniquely re-identify all of the depressed and non-depressed students. This highlights the possible threat to privacy, if the adversaries get data even of a single app category. Thus, to ensure better privacy, instead of focusing only on total set of used apps, researchers and designers need to utilize the data of app categories also.

It was interesting to see that depressed students have more uniqueness on weekdays than the weekends. Previous studies found that app usage behavior varies by days of a week [3, 49] and on weekdays people are more unique [11]. Researchers [11] also remark that this difference can be due to variation in profession. However, our findings suggest that despite being in the same group and having similar characteristics (student, no significant difference in age, monthly family income) of the depressed participants, they can be more uniquely re-identified on weekdays than the weekends. This indicates that during designing systems to protect privacy of the depressed, their uniqueness on weekdays should get more weight in differential privacy [60].

5.2 Depressed Students Are More Unique in Some App Categories

Through statistical analysis, we find that the depressed students are significantly more unique in some app categories, notably in the Social Media category. This finding contrast with the previous study [29] which did not find any significant difference in terms of total usage duration, frequency of launcing Social Media apps. We speculate about depressed students' less energy to do real world interaction [43] which may encourage them to use a more diverse set of Social Media apps to communicate with others. In fact, we find that a depressed student having a PHQ-9 score of 17 uses an AI based app (Replika: My AI Friend) which is used to create and communicate with a replica friend. Meanwhile, we find that depressed students use significantly more diverse set of Social Media apps in the afternoon (12 PM–6PM] and evening (6 PM–12AM] time period of weekdays which are peak time for class and self-study respectively in Bangladesh. Supporting our findings, previous study also shows that depressed have peak usage Social Media during the working hour [43]. A plausible reason for having peak during the class time can be due to having online classes instead of on-campus class amid the pandemic. Moreover, negative emtions can cause higher apps use to find distraction [62]. Going beyond our study's focus of re-identification, these findings demonstrate the support seeking nature of the depressed students which opens up opportunities for the researchers to explore further.

Our findings show that in the Health & Fitness category also, more depressed students can be uniquely re-identified and it is significantly more than the non-depressed. Wang et al. [33] show that physical activity has a negative relation with depression score. However, findings of another previous study [47] shows that the relation of physical activity with a patient's state can vary by person as well as time period of a day. Different app usage behavior of the depressed students of our study regarding Health & Fitness category represents that they may want to improve their situation since we find that depressed students use such apps of this category which are usually used to improve health. For example, a depressed student uses an app which has a feature to stop smoking and another student uses an app which is used to concentrate more. Therefore, our findings suggest to integrate the the physical and mental health professionals in the Health & Fitness apps, as having proper guidance (e.g., through counselling [61]) based on medical sciences can help the depressed to overcome their depression.

Since our findings demonstrate that the depressed students use statistically significantly more unique apps in some categories, specially, in the Health & Fitness and Social Media categories, more noises [59] can be added to the data of these app categories to make the depressed anonymous. Moreover, our findings present that the depressed are significantly more unique in the afternoon and evening usage of Social Media. Therefore, a higher weight to the noise can be added for those time periods to preserve depressed students' privacy.

6 Limitations

Though we have several novel contributions as mentioned in the introduction section, we have some limitations also. Since mental health is a taboo topic in Bangladesh [45, 46], it was difficult to collect such data from a large number of participants. In addition, we used

the snowball sampling method [24] and thus, a research through random sampling is required to inspect the generalizability of the findings. Beside these, though we removed the dead word from the 9th item of the PHQ-9 scale [12] through an approach (Sect. 3.1), having a clinical validation will increase the reliability. However, without the 9th item of the PHQ-9 scale, still all of the depressed participants remain depressed in PHQ-8 scale [31] and this may present the efficacy of our findings.

7 Conclusion

In our in the wild study, using the 100 students' actual smartphone usage data, we present how uniquely the depressed and non-depressed students can be re-identified. We find that using fingerprints of 7 days' usage data regardless of app category, it is possible to re-identify each of the depressed and non-depressed students. Moreover, we find that using data of a single category named Tools, we can get the same (100%) percentage of re-identification. Our findings also show that depressed students are significantly more unique in case of some app categories. The reason behind their uniqueness is the use of a diverse set of apps as presented by the value of hamming distance. These reveal that during designing the privacy protection system, designers should consider the high uniqueness of the vulnerable group like the depressed students.

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