EAI Endorsed Transactions
on Pervasive Health and Technology
Research Article EAI.EU

Is There Any Relation Between Smartphone Usage and Loneliness During the COVID-19 Pandemic?: A Study by Exploring Two Objective App Usage Datasets

Md. Sabbir Ahmed*[1], Syeda Shabnam Khan[1], and Nova Ahmed[1]

[1]Design Inclusion and Access Lab (DIAL), North South University, Dhaka-1229, Bangladesh.

Abstract

BACKGROUND: Though smartphone is popular and loneliness is higher among the youth, in low-and-middle income countries (LMICs) such as Bangladesh, the relation of loneliness with actual app usage is unexplored amid pandemic. Also, the studies conducted in developed countries are limited by exploration of some app categories.
METHODS: We conducted two studies in Bangladesh: in 2020 (N_1=100) and 2021 (N_2=105). We collected participant's ULS-8 score and 7 days' actual app usage. We extracted app usage behavioral data from 1.69 million events and did semi-partial and partial correlation analyses.
RESULTS: Our analysis did not present any significant relation which may indicate a negative impact on loneliness. However, we found higher usage of Social Media, Communication, Education, Books, and Shopping apps and higher entropy of Browser apps had significant ($q<.05$) relation with lower loneliness.
CONCLUSION: Smartphone may not negatively impact loneliness. Instead, some app categories can play a role to mitigate loneliness.

Keywords: Smartphone, Loneliness, Students, App categories, Social Media, Communication, Books apps, Education apps

Received on 17 February 2022, accepted on 31 May 2023, published on 02 August 2023

doi: 10.4108/eetpht.9.3663

1. Introduction

Loneliness which has an association with depression [1] and Fear of Missing Out (FOMO) [2] is a global concern where 33% of adults are lonely [3]. The requirement of restricted movement to impede the spread of the COVID-19 virus during the ongoing pandemic period has increased the feeling of loneliness among young adults [4]. At the same time, restrictions for meeting in person resulted in many daily activities such as work, school, shopping, etc. shifting online. Thus, smartphone usage has also increased significantly [5] amid the pandemic.

The association between smartphones and loneliness was investigated in a large number of scholarly articles [2, 6, 7, 8, 9, 10, 12] where several studies found a positive association [6,7,8] in the case of young adults' Social Media app usage indicating a negative impact on loneliness. The main research gap in existing studies is an exploration of mostly the mere frequency or duration and also an exploration of some categories: Social Media [2, 6, 8, 9, 34], Communication [2, 7, 10, 13], Browser, Beautify [9]. However, categories like Education and Books are more popular [11] which remain unexplored. Since the type (positive, negative, or neutral) of relation varies by category [2, 9, 10, 12], exploration of a few app categories may not be sufficient to uncover the exact relation of loneliness with the usage of all app categories. In addition, to our best knowledge, there is no such study that investigated such an association of loneliness with objectively measured smartphone usage data in low-and-

*Corresponding author. Email: msg2sabbir@gmail.com

middle income countries (LMICs) like Bangladesh amid the pandemic where 86.62% of university students have smartphones [48] and also has a high loneliness rate among the young [14].

We fill this knowledge gap by conducting a quantitative study on the university students of Bangladesh where we explore the relation between loneliness and usage data (e.g., duration per launch) of all app categories used by the participants. We collected data in 2020 and 2021 which are two consecutive years of the COVID-19 pandemic. In the study of 2020, 100 students participated; in the second study conducted in 2021, 105 students participated. To measure the participants' loneliness, we used the 8-itemed UCLA Loneliness Scale-8 (ULS-8) scale [21] and to retrieve participants' actual app usage, we used our developed Android app which can retrieve the last 7 days' app usage data very accurately. Since a relation can be confounded by several other data, we do semi-partial and partial correlation analysis by finding and controlling the confounders.

Our findings demonstrate smartphone usage regardless of app category does not have a significant ($q>.05$) association with loneliness. However, we find usage data of several app categories which show statistically significant negative associations ($q<.05$): Books & Reference, Communication, Education, Shopping, and Social Media category. This indicates that the students who use these app categories more are likely to be less lonely. We also find a negative relation in the case of the Browser & Search category's entropy value which indicates that the students who have higher usage of certain apps of the Browser & Search category are more likely to be lonelier. Through this research, we contribute to the human-computer interaction and pervasive health research areas in the following ways:

- As far as we have seen, previous studies relied on the exploration of a single dataset whereas we discussed the findings based on the analysis on two different datasets which can help in reaching out consensus decision regarding the association between app usage and loneliness. Our analysis showed that amid the pandemic, smartphone usage may not negatively impact loneliness, instead, this may play an important role in mitigating students' loneliness.
- We find that usage of Education apps like Zoom and Google Meet which students use for online classes and also usage of Books & Reference, Communication, Shopping, and Social Media, apps may have a positive impact on loneliness.
- We present different app usage behavioral data which have a significant association with loneliness. The insights from our findings can be potential for mental health professionals and researchers to develop parsimonious computational models in identifying loneliness which may contribute in the context of a developing country where wearable devices and other resources are limited.
- Since this is the first study (to our best knowledge) that used objective app usage data in a developing country's context amid the pandemic, our insights can help mental health professionals to understand lonely students better. In addition, our findings can have an impact on how parents and teachers see students' app usage, especially in the South Asian context.

2. Related Work

2.1. Relation between loneliness and retrieved data of the pervasive device

With the advent of pervasive technology, researchers utilized it for assessing and identifying psychological problems. Doryab et al. [23] explored students' smartphones and Fitbit sensed data where they found lower usage of smartphones and also lower activity after midnight has a relation with lower loneliness during the end of the semester. Austin et al. [47] used numerous sensors and explored long-term data of 16 older adults, they found time spent outside has a significant negative association with loneliness. In the StudentLife study [45], researchers used smartphones to collect behavioral and psychological data from 48 students. Their findings show that indoor mobility during the day, travel distance, and duration of activity have a significant negative association with loneliness. In another study [46], researchers assessed whether smartphone-sensed data can work as a behavioral marker. Their findings showed an association of Kinesthetic activity with changes in students' loneliness. On the other hand, several other behavioral data such as total travelled distance, and sleep duration did not show any significant association. However, to retrieve different behavioral data like sleep, an app or system requires access to sensors and also needs to perform computationally complex analysis to extract behavioral data. For example, Wang et al. [45] used an activity classifier, sleep classifier, and audio and speech detector to get different behavioral data. Therefore, in resource-constrained settings, sensed data to assess loneliness may not be feasible due to having cheap smartphones where modern sensors and resources to get quality data and to do complex analysis in the extraction of behavioral information can be very limited.

2.2. Relation between loneliness and app usage

Compared to the sensor-extracted behavioral data, accessing app usage behavioral data is a computationally cheap approach that does not need to access the sensors like GPS and also does not need to run a computationally complex model like a classifier. Scholarly research explored the relation of app usage data with psychological problems. Hunt et al. [6] did a study to understand the causal relation between students' mental health and Social

Media usage. Their findings show that limiting Social Media usage reduces depression and loneliness. In another study, Wetzel et al. [7] found different associations of loneliness with older people and younger people's usage of phone calls and Communication apps. In the case of adults, their findings showed a positive association of loneliness with these apps' usage data. However, Fumagalli et al. [2] found a negative relation of young adults' messaging app usage which indicates a positive impact on loneliness. On the other hand, there are some articles [9, 10, 12] where the direction (positive or negative) regarding the relation of loneliness varied by app category. In a research, Li et al. [10] found a positive association of loneliness with the frequency of launching apps but a negative association with phone call duration in the evening. In another study, Pulekar and Agu [12] found a positive relation of loneliness with the number of messages and the number of calls. However, in that research, authors [12] also found a negative relation between the number of late-night browser searches and the percentage of missed calls. The varying association was found in the study of Gao et al. [9] also where researchers found a positive association of Social Media app usage, but a negative association of phone calls with loneliness. Exploring incoming and outgoing calls, Petersen et al. [13] found a negative relation in the case of incoming calls while not finding a significant association between loneliness and outgoing calls. Apart from exploring the association with loneliness, researchers also explored the association of app usage with other psychological problems like depression. In a study [28] on students, researchers found that depressed and non-depressed students have significantly different app usage signatures in terms of app usage. For example, they found that in the Social Media category, depressed students are significantly more unique than non-depressed students. In another study [49], researchers found significantly higher Communication app usage by depressed students than the non-depressed students. However, as far as we have seen, in previous studies, some of the categories were explored where most of the app categories (e.g., Education, Productivity) remain unexplored for finding an association with psychological problems like loneliness.

3. Methods

3.1. Data collection

In Bangladesh, we conduct a cross-sectional study in 2020 (July to October) and also in 2021 (January to June). We used the snowball sampling method and university students were included in the study. Since a large sample size provides greater statistical power, we focused on maximizing the participants by keeping a minimum sample of 30 which is suggested as the minimum sample size for experimental research [35]. We reached out to the participants through close connections and university faculties. Before data collection, we had a meeting with each participant so that they feel comfortable in donating their data. Due to the COVID-19 pandemic, collect data, mostly, we did online meetings through the participants' preferred platforms (e.g., Messenger). All participants voluntarily donated data and provided consent through the e-consent form.

3.2. Data collection tool and loneliness assessment

In Bangladesh, 95.47% users use the Android operating system [16]. We developed an Android app [17] (Figure 1) to retrieve objective data since self-reported responses are different from actual app usage data [18]. App usage events are kept for a few days by the system [19] and we used the Java class UsageStatsManager [19] for retrieving the past 7 days' foreground and background app usage events. We tested our app through manual calculation, compared it with available apps [20], tested it on 9 smartphones, and found that it calculates data accurately. We released the app in Google Play Store which is the largest app store for Android users.

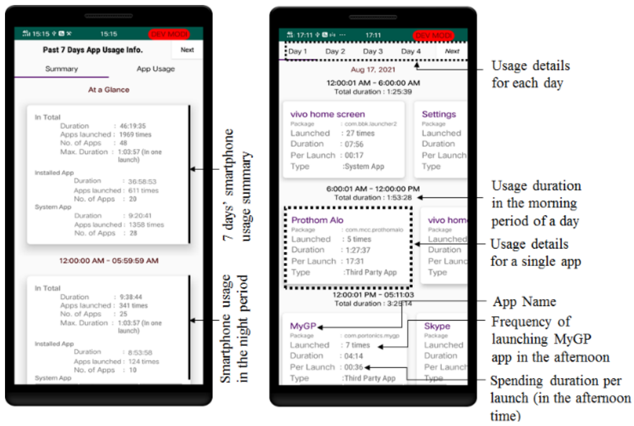


Figure 1. Operation of the data collection tool.

To assess subjective general feelings of loneliness, we used the 8 itemed University of California, Los Angeles (UCLA) Loneliness Scale (ULS-8) [21] which was used in previous studies [14, 22] conducted in Bangladesh. We translated the scale involving 3 researchers, 2 final-year students, and 4 sophomores. In our Android app, this scale was available both in English and the native language Bangla. This scale contains 8 items (Table A.1 of Appendix A) and the score range is 8 to 32. Following studies (e.g., [22, 23]) conducted using different versions of the UCLA loneliness scale, we categorized participants into the lonely category when they had a ULS-8 score of more than 16, and other participants were kept in the non-lonely category.

3.3. Dataset description and study variables

There were 817,404 foreground and background events of 1129 apps in the dataset of the first study and in the dataset of the second study, there were 867 apps' 868,636 events in students' 7 days' app usage. On average, from each participant's phone, we retrieved 8174.2 (SD=4972.53) and 8272.72 (SD=4261.26) events in dataset 1 and dataset 2 respectively. In total, students used 1519 apps which were categorized into 27 categories (Figure 2). We categorized the apps by understanding features, following categorization of previous studies [24, 25] and through a discussion with 2 graduate students of the engineering faculty. In the Play Store, Zoom, Meet, and Team apps were in the Business category. However, we re-categorized those apps in the Education category as students used these apps for online classes during the pandemic [26]. We provide examples of each app category in Appendix B.

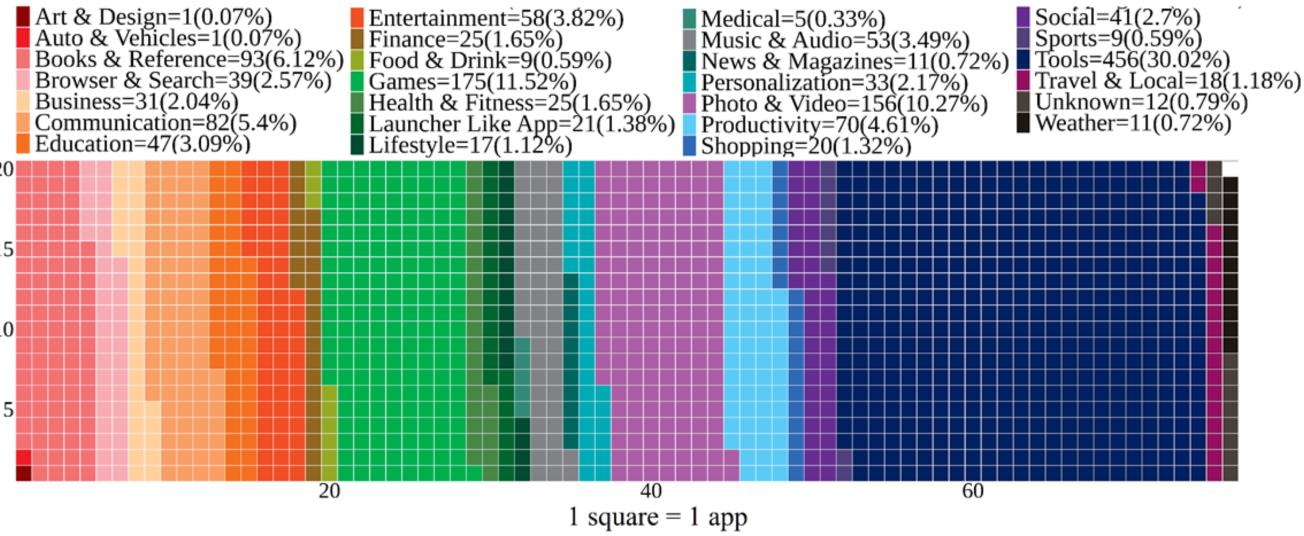


Figure 2. Among the 1519 apps, number of apps and percentage of apps in 27 categories.

For each category, we explore 6 different data of weekdays, weekends, and 7 days (weekdays + weekends): app usage duration, frequency of launch, number of used apps, duration per launch, duration per app, and launch per app. In addition, since app usage uniqueness, measured by hamming distance [27] varies between people [28, 29] (e.g., depressed and non-depressed [28]), we calculate the ratio of hamming distance (details are in Appendix C) for each participant, from the nearest lonely to the nearest non-lonely participant. Also, to understand the app usage pattern and focus on the apps, using Shannon's entropy formula [30], we calculate entropy regarding app usage of each participant j, $E(j) = \sum_{i=0}^{n} p(i) \, log \, log \, p(i)$ where $p(i)$ indicates the probability to use the i^{th} app by the j^{th} user; $p(i) = \frac{duration\ (i)}{\sum_{i=0}^{n} duration\ (i)}$; where $duration(i)$ presents the spending duration on i^{th} app. The entropy E will be lower if there is unequal spending duration on each app. Let's say, participant 1 spent 17 minutes and 3 minutes on two apps whereas participant 2 spent 10 minutes equally on each app. Then, the entropy, E, of the 1st participant will be lower and the app usage pattern will be more skewed, and this will present that she is more focused on certain apps. However, the entropy, E of the 2nd participant will be higher which will present she is equally focused on each app. The entropy (E) will be 0 if a participant uses a single app. We explore these 8 different data as independent variables where the ULS-8 score was explored as an outcome variable in our study.

3.4. Data analysis

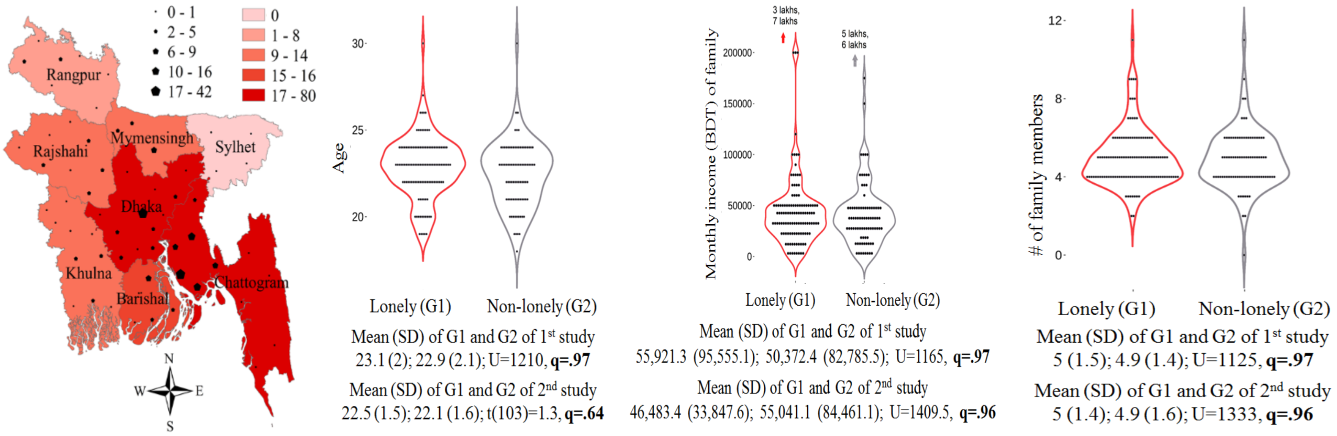
For statistical analysis, we used *ppcor* [31] and *Scipy* [32] packages. To understand the relation between loneliness with app usage, we did both partial and semi-partial correlation analysis since in semi-partial analysis only confounders associated with either dependent or independent variables are controlled whereas, in partial analysis, confounders associated with both types of variables are controlled. Depending on the satisfaction of the assumptions, there, we did Pearson (r) or Spearman correlation (r_s) analysis. When the data were not normally distributed or a variable contained outliers, we did Spearman analysis as it is nonparametric and less sensitive to outliers. For comparison, we performed a parametric T-test (t) or nonparametric Mann-Whitney U Test (U) depending on data distribution. In the case of normally distributed data, we used a parametric T-test and in all other cases, we used a non-parametric Mann-Whitney U Test. To control the false discovery rate, we adjusted p values (q) using Benjamini-Hochberg (BH) approach [33]. We deem those findings as significant where q value was less than .05 and the number of users (N) was larger than 30. Usually, a sample size of 30 is considered as large [15] and is recommended as the minimum sample size in experimental research [35]. In statistical analysis, we did not remove any non-user (i.e., who did not use apps of a category even 1 time) or extreme users' data since the removal of these groups can remove specific groups presumably providing biased findings.

3.5. Research ethics

This study is part of a project which received approval from the Center for Research & Development of a university. In the consent form, along with the description of all necessary things (e.g., data security, usage of the data), we also described each data we collected. We have stored data in secure storage where access is restricted to the researchers only.

4. Results

In our study in 2020, 100 students from 12 educational institutions, and in the study in 2021, 105 students from 8 institutions in Bangladesh participated. In each study, several students did not participate due to their discomfort in installing an app, network issues, and space unavailability. All participants were students, and they were from 7 departments: MBBS (Bachelor of Medicine, Bachelor of Surgery), CSE (Computer Science & Engineering), EEE (Electrical & Electronic Engineering), Textile Engineering, LLM (Master of Laws), BBA (Bachelor of Business Administration), and Sociology. There were 87% and 76.2% male in study 1 and study 2 respectively where the remaining participants were female. The participants were from 45 districts and 7 divisions (Figure 3(a)) covering a large area of Bangladesh which is



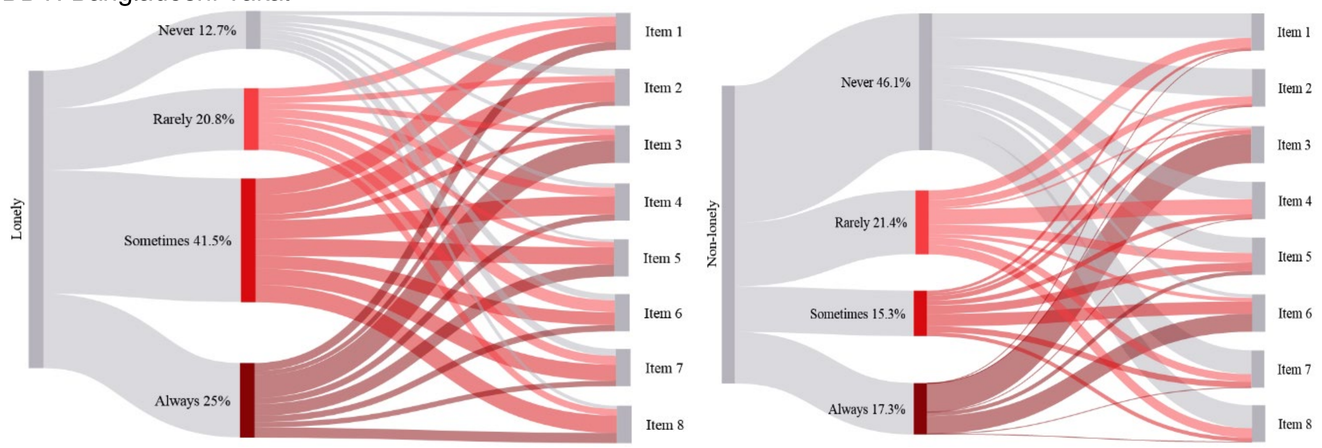
(a) Map of Bangladesh presenting the living location of the participants.

(b) Difference of age between the lonely and non-lonely groups.

(c) Difference in monthly income between the lonely and non-lonely groups.

(d) Difference in number (#) of family members between lonely and non-lonely groups.

Figure 3. Descriptive statistics about lonely and non-lonely students, including all participants of study 1 and study 2. BDT: Bangladeshi Taka.



(a) Lonely participants

(b) Non-lonely participants

Figure 4. Frequency of appearance of ULS-8 scale's items among the lonely and non-lonely participants, on the basis of responses of both datasets.

4.1. Participants' demographic information and loneliness

divided into 64 districts and 8 divisions. To find the difference between lonely (ULS-8 score>16) and non-lonely (ULS-8 score<=16) (details about categorization is in Appendix A) participants in demographic information like age, socio-economic status like family income, we did a comparative study since these can be confounders in relation between loneliness and app usage. We find 2 missing values in the income data and 1 missing value in the data about the number of family members which we removed while exploring the corresponding variable. Our findings show no significant difference ($q>.05$) between the lonely and non-lonely participants in age, monthly family income, and number of family members (Figure 3(b, c, d)).

In the 1st study (N=100) in 2020, 65% participants were lonely whereas in the 2nd study in 2021, 51.4% participants were found to be lonely. On the other hand, 35% participants of 1st study and 48.6% participants of 2nd study were non-lonely and had ULS-8 score below 17. To understand the participants' loneliness, we explored the relation between ULS-8 scale's items and frequency of lonely feelings. We find that whereas lonely students' most responses were sometimes (41.5%) and always (25%) (Figure 4(a)), non-lonely students' most responses were never (46.1%) and rarely (21.4%) (Figure 4(b)). It was interesting to see the ULS-8 scale's item 3 (Appendix A) appearing mostly among the items which the lonely group always felt. This indicates even despite being outgoing people, they are lonely.

4.2. Relation of app usage with loneliness

For total smartphone usage regardless of app category and 27 app categories, we explored 8 app usage data of weekdays, weekends, and 7 days which resulted in exploring 672 variables in total. In Table 1 and Table 2, we present the variables which show significant relation in the case of at least one app category. After finding the significant variables, we do semi-partial and partial correlation analysis (Table 3) for those significant variables by finding and controlling confounders (Table A.3 and Table A.4 of Appendix D).

In study 1, we find students having higher entropy values in Browser & Search category (weekdays: r_s=-.22, $q<.05$; 7 days: r_s=-.23, $q<.05$), have lower loneliness (Table 1). This reveals that students having more focus on a few Browser & Search apps (i.e., low entropy) are more likely to have higher loneliness. We also find higher usage of Books & Reference apps in the weekend is significantly associated with lower loneliness (duration: r_s=-.25, $q<.05$; duration per launch: r_s=-.25, $q<.05$; launch per app: r_s=-.24, $q<.05$; duration per app: r_s=-.26, $q<.05$). In Education category also, we find a negative relation of spending duration (7 days: r_s=-.24, $q<.05$), duration per app's launch (7 days: r_s=-.26, $q<.05$), launch per app (7 days: r_s=-.23, $q<.05$), duration per app (7 days: r_s=-.27, $q<.05$) with loneliness.

Supporting the finding of study 1, in study 2 also, we find that the students who have lower entropy regarding Browser & Search category, are more likely to have higher loneliness (weekday: r_s=-.34, $q<.01$; 7 days: r_s=-.29, $q<.01$) (Table 2). We also find that students having higher duration per Communication apps are more likely to have lower loneliness (weekdays: r_s=-.22, $q<.05$; weekends: r_s=-.27, $q<.05$; 7 days: r_s=-.25; $q<.05$). In addition, students having higher duration per app (weekdays: r_s=-.24, $q<.01$; 7 days: r_s=-.23, $p<.01$), higher duration per app's launch (weekdays: r_s=-.36, $q<.01$; weekends: r_s=-.35, $q<.01$; 7 days: r_s=-.37, $q<.01$) in Social Media are more likely to have lower loneliness. Besides these, we find that compared to the non-lonely students, lonely students are more unique among them in the Social Media category as shown by the positive relation of loneliness with ratio hamming distance (weekdays: r_s=.26, $q<.05$).

However, in the correlation between two variables (e.g., x, y) there may have a third variable (e.g., z) that affects both the variables that are in correlation. We investigate such variables and find there are several confounders affecting 12 among 14 statistically significant ($q<.05$) variables of study 1 and 17 among 19 statistically significant ($q<.05$) variables of study 2 (Table A.3 and Table A.4 of Appendix D for study 1 and study 2 respectively). Besides these, we also find out the confounders which did not affect the ULS-8 score but affected the other variable (e.g., z) in correlation. Both types of confounders can affect the relation even when there is no actual relation between two variables.

At first, we do a semi-partial correlation analysis for the significant variables (Table 1), after controlling the confounders. We find that among the 14 significant variables regarding the Books & Reference, Browser & Search, Education, and Shopping app categories of study 1, 11 variables still significantly ($q<.05$) relate to the loneliness score (Table 3). However, in the case of 7 days' entropy values of the Browser & Search (q=.052), 7 days' frequency of launch per Education app (q=.061), and weekdays' frequency of launch per Education app (q=.061), q value was higher than .05. It can be due to the fact that in semi-partial correlation, the effect of the confounder is not removed from the ULS-8 score. Therefore, we do partial correlation analysis also which removes the effect from both of the variables that are in correlation. After doing a partial analysis, we find that each of the 14 variables of study 1 is significantly negatively related to the ULS-8 score (Table 3).

In the case of study 2 also, after controlling the confounders, we analyze the relation between loneliness score and 19 significant variables as found in Table 2. We find that the relation of smartphone usage duration per app launch was confounded by other variables and there is no significant relation (partial analysis- 7 days: r_s=-.07, q=.477; weekdays: r_s=-.02, q=.477, weekends: r_s=-.01, q=.477) (Table 3). We also find that the entropy value of Social Media apps was confounded by other variables and there is no significant relation with loneliness score and weekdays' (r_s=.12, q=.154), weekends' (r_s=.19, q=.096), and 7 days' entropy values (r_s=.14, q=.137). However, in the case of 13 other variables regarding Browser, Communication, Launcher, Productivity, and Social

Media, we find significant results after doing both semi-partial and partial correlation analysis.

5. Discussion

Our first study conducted in 2020 showed 65% of university students were lonely which was 51.4% in the second study conducted in 2021. A recent study conducted in Bangladesh found a loneliness rate of 71% [22] and 64% [14] in 2020 and 2021 respectively which also indicates a lower loneliness rate in 2021. The lower loneliness in 2021 can be due to the fact that the students coped with the new normal situation in different ways such as support from teachers and student clubs [52].

In investigating the relation of loneliness with app usage after finding and controlling the confounders, our findings demonstrate students having higher duration per launch of Communication and Social Media apps are less lonely which shows the supportive nature of these apps amid the pandemic. These findings contrast with studies that found positive associations with Social Media [6, 8] and Communication [7] apps. However, exploring our two logged datasets having a sample size of at least 100 in each, we did not find any statistically significant positive relation (i.e., negative impact) of these two categories with loneliness. One of the reasons for not having a negative impact can be students' willingness for using Social Media to overcome loneliness [54] and to regulate emotion [53, 54]. Additionally, as offline interaction decreased during the pandemic [36], Social Media and Communication apps can help the young to be more connected. Having a connection with friends and family help students to mitigate loneliness [54]. These findings can be potential insights for mental health professionals in early intervention and also in mitigating the negative impact of the pandemic on mental health.

We found students using the Education category's apps more on the weekdays are less lonely. However, in previous research, the study duration was found to relate positively to the psychological problem of depression [37]. During the pandemic, educational institutes were closed for a long time and teachers used Zoom, Meet, or Teams for delivering lectures [26] and students could interact with teachers and peers through these apps of the Education category. The platforms also helped the students in getting support from their peers [55]. These can facilitate the students to overcome loneliness since peer support has a positive effect on mental health [56]. Meanwhile, we find lower loneliness in students' higher usage of Books & Reference apps. Higher reading habits are associated with higher mindfulness [38] and also reading printed books reduces loneliness [39]. Our finding highlights that books are the best companions regardless of the type (i.e., printed or app). To our best knowledge, we are the first to present the association of objectively measured Education and Books app usage data with loneliness. It can be noted that, unlike the results from our first study, our findings show no association with these two app categories in the second study. This opens up opportunities for the researchers to explore the association in more depth to reach a clear conclusion.

Our statistical analysis on datasets of both studies shows that higher loneliness is associated with a lower entropy value of the Browser & Search category. Having a lower entropy value says that the app usage pattern is skewed, and that group of users is more focused on certain apps. This finding suggests that exploring the mere duration and launch as was largely studied [40] may not reveal all app usage patterns that are associated with loneliness. In addition, this finding along with the findings of other app categories (e.g., Books & Reference, Social Media, Shopping) showing significant association can be used for machine learning models to improve the performance in loneliness identification. However, in previous studies where researchers explored behavioural markers from smartphone usage to identify loneliness, data of the app categories remained unexplored (e.g., in [23]). Our findings suggest features presenting the app categories can be used with the other behavioural and physiological data to more accurately identify the students having loneliness. Besides these, to find viable targets for clinical intervention, insights from our study can be used to develop a minimal and parsimonious computational model which can be useful for resource-constrained settings. For example, following a recent study [57] conducted on depression, using only variables having a significant association with loneliness as presented in our study can be used to develop a Bayesian network to find out the possible viable targets for intervention regarding loneliness.

Exploring eight different smartphone usage data, we found no statistically significant relation between loneliness and total smartphone usage regardless of the app category. This finding differs from a study [41] which found a positive relation. Amid the pandemic, loneliness increased [4] and while staying alone, people use smartphones believing the smartphone to be supportive for removing stress and boredom [42]. As we find app categories where higher spending duration is associated with lower loneliness showing supportive nature, the negative impact of smartphones can be mitigated. There is a social perception of the negative impact of the smartphone on young users [43]. Given students' higher smartphone usage during the pandemic for both academic and non-academic purposes [5], parents and teachers are also concerned about it [5]. Therefore, insights from our findings can be potential for the caregivers, parents, and teachers who affect the decision-making of young people, especially in the South Asian context [44].

6. Limitations

In both of our studies, the percentage of male participants was higher compared to the female participants which can affect the generalizability of the findings. In addition, our study showing an association between the variables does not present a causal relation. Currently, we are conducting a countrywide large-scale study in Bangladesh, and we are expecting to overcome these limitations in our future study through exploration of that dataset. In addition, we hope to explore in-depth the app usage behavior of the lonely and non-lonely students to unveil the nuanced differences between them.

7. Conclusion

Our exploratory study demonstrates that higher usage of Education, Books, Social Media, and Communication app categories have an association with lower loneliness. These findings suggest smartphones may not negatively impact loneliness amid the pandemic. Instead, this can support students to mitigate the negative consequences of the difficult time. Insights from our findings can be valuable for mental health professionals in clinical intervention to reduce students' loneliness. In addition, our findings can be useful in developing minimal computational models for identifying students' loneliness in real-time.

Table 1. In case of study 1 (Sample Size=100), relation of loneliness with usage data of 27 categories and total smartphone usage data. Gray colored cells present the variables having significant association. N/A: number of users (N)<2. ** q<.01 and N>30; * q<.05 and N>30; $ q<.05 and N<30; # q<.1. q: adjusted p value.

App category	Duration		Duration Per Launch		Launch per # of App			Duration per # of App			Entropy	
	Week end	7 Days	Week end	7 Days	Week day	Week end	7 Days	Week day	Week end	7 Days	Week day	7 Days
Art & Design	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Auto & Vehicle	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Books & Reference	$-.25^{*}$	-.08	$-.25^{*}$	-.03	-.08	$-.24^{*}$	-.15	-.06	$-.26^{*}$	-.09	0	-.01
Browser & Search	.02	.01	.05	.09	-.11	0	-.08	0	.04	.04	$-.22^{*}$	$-.23^{*}$
Business	.14	0	.14	0	0	.14	0	0	.14	0	.01	.01
Communication	.02	.04	-.05	-.02	-.01	.03	0	0	.05	.03	-.05	0
Education	-.14	$-.24^{*}$	-.15	$-.26^{*}$	$-.23^{*}$	-.15	$-.23^{*}$	$-.24^{*}$	-.15	$-.27^{*}$	-.02	-.04
Entertainment	.04	.07	.04	.08	.07	.04	.05	.1	.04	.07	.06	.01
Finance	.1	-.02	.08	-.02	-.16	.07	-.05	-.13	.1	-.02	.03	.08
Food & Drink	$.2^{\#}$	$.19^{\#}$	$.2^{\#}$	$.2^{\#}$	.14	$.2^{\#}$	$.19^{\#}$	.15	$.2^{\#}$	$.19^{\#}$	N/A	N/A
Games	.07	.09	.07	.05	.1	.07	.1	.07	.07	.07	.04	.04
Health & Fitness	$.19^{\#}$	$.27^{\$}$	$.19^{\#}$	$.27^{\$}$	$.2^{\#}$	$.19^{\#}$	$.26^{\$}$	$.2^{\#}$	$.19^{\#}$	$.27^{\$}$	$.23^{\$}$	$.24^{\$}$
Launcher	-.05	-.05	.11	.09	-.08	-.06	-.09	0	0	-.02	-.13	-.1
Lifestyle	.02	.08	.02	.08	.08	.01	.08	.07	.02	.07	N/A	N/A
Medical	0	.01	0	.01	.06	0	.01	.06	0	.01	N/A	N/A
Music & Audio	-.01	-.09	0	-.07	-.16	-.03	-.11	-.12	-.02	-.09	-.01	0
News & Magazine	.02	.06	.02	.07	-.04	.02	.06	-.05	.02	.06	N/A	N/A
Personalization	.05	-.05	.05	-.06	-.05	.05	-.08	-.03	.05	-.06	.1	.01
Photo & Video	-.16	-.14	-.06	.01	-.14	$-.23^{\#}$	-.17	-.09	-.16	-.09	-.13	-.06
Productivity	-.18	-.17	-.13	.03	-.09	$-.22^{\#}$	$-.2^{\#}$	0	-.19	-.13	-.16	-.13
Shopping	-.16	-.17	-.16	-.15	$-.22^{*}$	-.16	$-.23^{*}$	$-.21^{\#}$	-.17	$-.19^{\#}$	-.01	.02
Social Media	-.02	.09	-.01	.02	-.03	-.08	-.05	.05	-.05	.03	-.03	-.02
Sports	.09	.17	.1	.18	.13	.09	.17	.13	.09	.17	N/A	N/A
Tools	-.2	-.11	-.16	-.03	.03	-.03	.01	-.05	-.21	-.08	-.14	-.16
Travel & Local	-.05	-.11	-.05	-.13	-.06	-.05	-.12	-.06	-.05	-.12	-.02	.07
Unknown	N/A	-.05	N/A	-.05	N/A	N/A	-.05	N/A	N/A	-.05	N/A	N/A
Weather	0	-.06	0	-.06	-.03	0	-.05	-.03	0	-.06	N/A	N/A
Total Smartphone Usage Data	-.06	-.01	.03	.1	-.05	-.09	-.06	.02	-.01	-.03	-.14	-.11

Table 2. In case of study 2 (Sample size=105), relation of loneliness with usage data of 27 categories and total smartphone usage data. Gray colored cells present variables having significant association. N/A: number of users (N)<2. ** q<.01 and N>30; * q<.05 and N>30; $ q<.05 and N<30; # q<.1. q: adjusted p value.

App Category	Duration per Launch			Duration per # of App		Entropy			Ratio of H. Distance
	Week day	Week end	7 Days	Week day	7 Days	Week day	Week end	7 Days	Week day
Art & Design	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Auto & Vehicle	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Books & Reference	.03	-.02	.03	.01	.03	.1	.07	.1	.19
Browser & Search	-.05	-.06	-.05	.08	.1	$-.34^{**}$	-.12	$-.29^{**}$	-.14
Business	.04	-.05	.02	.03	.01	-.01	-.17	-.01	-.02
Communication	$-.22^{*}$	$-.27^{*}$	$-.25^{*}$	-.06	-.1	.14	.03	.14	.05
Education	-.11	-.06	-.13	-.03	-.05	-.05	.04	-.08	.01
Entertainment	.08	.1	.15	.07	.13	.04	0	.02	-.03
Finance	0	0	.01	0	0	.09	.03	.1	.06
Food & Drink	.02	.05	.02	.01	.01	N/A	N/A	N/A	N/A
Games	.09	.04	.08	.09	.08	.09	-.06	.04	.02
Health & Fitness	-.19	N/A	-.14	-.19	-.13	N/A	N/A	N/A	-.18
Launcher	-.16	$-.25^{*}$	-.18	-.09	-.12	.06	.04	.09	.07
Lifestyle	$-.22^{\#}$	-.03	$-.2^{\#}$	$-.22^{\#}$	$-.19^{\#}$	N/A	N/A	N/A	0
Medical	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Music & Audio	-.11	-.11	-.13	-.1	-.13	.01	.04	.05	-.03
News & Magazine	-.18	-.04	-.18	-.18	-.18	N/A	N/A	N/A	$-.2^{\#}$
Personalization	.06	.07	.04	.07	.06	.07	N/A	.07	-.03
Photo & Video	-.08	-.08	-.06	-.08	-.07	-.03	.01	-.01	-.13
Productivity	-.09	.06	-.05	.03	.04	$.24^{*}$	.05	$.19^{\#}$	.11
Shopping	.13	.13	.13	.16	.16	.11	.11	.13	.11
Social Media	$-.36^{**}$	$-.35^{**}$	$-.37^{**}$	$-.24^{*}$	$-.23^{*}$	$.2^{*}$	$.22^{*}$	$.21^{*}$	$.26^{*}$
Sports	.05	-.02	.07	.05	.06	N/A	N/A	N/A	N/A
Tools	$-.18^{\#}$	$-.21^{\#}$	$-.21^{\#}$	-.12	-.13	.14	.08	.16	$-.19^{\#}$
Travel & Local	.13	.21	.09	.14	.12	N/A	N/A	$.18^{\#}$	-.09
Unknown	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Weather	-.01	.01	-.02	0	-.01	N/A	N/A	N/A	-.07
Total Smartphone Usage Data	$-.24^{*}$	$-.24^{*}$	$-.24^{*}$	-.05	-.04	.13	.03	.11	-.15

Table 3. Partial and semi-partial correlation analysis showing relation of ULS-8 score with the significant variables, after controlling the confounders. Sign.: Statistically significant results, Coef.: Coefficient. q: adjusted p value. Con. Var. : Control Variables.

Study 1 (Sample size=100)							**Study 2 (Sample size=105)**						
14 Significant Variable of study 1	# of Con. Var.	Semi-partial correlation		Partial correlation		Sign.	19 Significant Variable of study 2	# of Con. Var.	Semi-partial correlation		Partial correlation		Sign.
		Coef.	q	Coef.	q				Coef.	q	Coef.	q	
Books_Duration_Weekends	4	-.2	.025	-.21	.022	✓	Browser_Entropy_7 days	11	-.3	.002	-.33	.001	✓
Books_Duration_per_Launch_Weekends	2	-.19	.032	-.19	.029	✓	Browser_Entropy_Weekdays	2	-.33	.001	-.33	.001	✓
Books_Duration_per_App_Weekends	4	-.21	.02	-.22	.017	✓	Communication_Duration_per_Launch_7 days	36	-.23	.057	-.29	.023	✓
Books_Launch_per_App_Weekends	7	-.2	.031	-.2	.027	✓	Communication_Duration_per_Launch_Weekdays	35	-.2	.057	-.25	.028	✓
Browser_Entropy_7 days	5	-.18	.052	-.18	.045	✓	Communication_Duration_per_Launch_Weekends	24	-.18	.057	-.21	.028	✓
Browser_Entropy_Weekdays	8	-.17	.052	-.18	.045	✓	Launcher_Durati_per_Launch_Weekends	19	-.19	.043	-.21	.027	✓
Education_Duration_7 days	12	-.22	.022	-.22	.019	✓	Productivity_Entropy_Weekdays	34	.18	.065	.22	.035	✓
Education_Duration_per_Launch_7 days	4	-.27	.004	-.28	.003	✓	Smartphone_Duration_per_Launch_7days	52	-.05	.482	-.07	.477	×
Education_Duration_per_App_7 days	0	-.27	.006	-.27	.006	✓	Smartphone_Duration_per_Launch_Weekdays	39	-.02	.482	-.02	.477	×
Education_Duration_per_App_Weekdays	5	-.2	.027	-.21	.023	✓	Smartphone_Duration_per_Launch_Weekends	48	-.01	.482	-.01	.477	×
Education_Launch_per_App_7 days	40	-.2	.061	-.24	.032	✓	Social_Duration_per_Launch_7 days	17	-.29	.004	-.34	.001	✓
Education_Launch_per_App_Weekdays	35	-.23	.061	-.27	.027	✓	Social_Duration_per_Launch_Weekdays	14	-.31	.004	-.35	.001	✓
Shopping_Launch_per_App_7 days	31	-.23	.032	-.26	.015	✓	Social_Duration_per_Launch_Weekends	10	-.28	.004	-.3	.002	✓
Shopping_Launch_per_App_Weekdays	41	-.26	.032	-.32	.013	✓	Social_Duration_per_App_7 days	25	-.22	.026	-.26	.015	✓
							Social_Duration_per_App_Weekdays	18	-.21	.026	-.23	.015	✓
							Social_Entropy_7 days	17	.13	.17	.14	.137	×
							Social_Entropy_Weekdays	26	.1	.19	.12	.154	×
							Social_Entropy_Weekends	8	.18	.108	.19	.096	×
							Social_Hamming_Distance_Weekdays	18	.2	.03	.22	.02	✓

Appendix

Appendix A. Participants' loneliness

To detect perceived loneliness, different versions of the UCLA Loneliness Scale are widely used. Some previous studies (e.g., [23]) used the 20-itemed UCLA Loneliness Scale-20 (ULS-20) and some other studies [50, 51] used a 3-itemed ULS-3 scale to detect loneliness. In the ULS-20 scale, researchers classified the participants into the high loneliness category when the score was more than 40 [23] and in the case of ULS-3, this score was 6 and more [51]. In a study, Mezuk et al. [50] used USL-3 scale and grouped the participants into the moderate and high loneliness categories when the score was at least 4 and 6 respectively. In our study, we used the ULS-8 scale [21] which was previously used for loneliness detection in study [22] conducted on the Bangladeshi people. This scale contains 8 items (Table C.1) and the response for each item is never (score 1), rarely (score 2), sometimes (score 3), and always (score 4). Having a score of more than 16 means there is at least one symptom which was bothered by the participant sometimes. Therefore, following studies [22, 23, 50, 51], we kept students into the lonely group when they had a ULS-8 score more than 16 and others were kept in the non-lonely group.

Table A.1. Eight items of UCLA loneliness Scale - 8 (ULS-8) [21]

Item	Participant's response for each item
1. I lack companionship	• Never (score 1) • Rarely (score 2) • Sometimes (score 3) • Always (score 4)
2. There is no one I can turn to	
3. I am an outgoing person	
4. I feel left out	
5. I feel isolated from others	
6. I can find companionship when I want it	
7. I am unhappy being so withdrawn	
8. People are around me but not with me	

Appendix B. Examples of app categories

Table A.2. Example of apps, percentage of apps in each of the 27 app categories.

App category	Example of apps	App category	Example of apps
Art & Design	Autodesk SketchBook	Lifestyle	SmartThings, Prayer Time Quran Qibla Dua Tasbih, My Galaxy
Auto & Vehicles	Android Auto	Medical	Medical, Maya, Patient Aid
Books & Reference	Al-Quran Bangla, Higher Math Solution	Music & Audio	Gaana, Google Play Music, Music, Spotify
Browser & Search	Chrome, Firefox, UC Browser	News & Magazines	Briefing, Job Circular, Medium
Business	Fiverr, Kormo, REDX Delivery	Personalization	Live Wallpaper Picker, Silver Luxury Watch Wallpaper and Keyboard, Lockscreen magazine
Communication	Duo, Gmail, Messenger	Photo & Video	Camera, Gallery, Photo Editor
Education	Learn C++, Udemy, Zoom, Meet	Productivity	Excel, GitHub, PDF Reader
Entertainment	Netflix, Hotstar, IMDb Movies & TV Shows:	Shopping	Evaly, AliExpress, Daraz
Finance	bKash, City Bank, GPAY	Social	Facebook, Twitter, LinkedIn
Food & Drink	foodpanda, Uber Eats: Order Food Delivery,	Sports	Live Football Tv, Cricbuzz, Goal News
Games	PUBG MOBILE, Free Fire	Tools	App Lock, Bluetooth, Clock
Health & Fitness	Mi Health, Step Tracker & Pedometer, Home Workouts Gym Pro (No ad)	Travel & Local	Biman Bangladesh Airlines, BDTICKETS, Uber
Launcher	Launcher3, My Launcher, POCO Launcher	Weather	Weather, Weather Bangladesh, Windy
		Unknown	N/A

Table A.3. Confounders which show significant association with both loneliness score and each of the 14 significant variables of dataset of study 1. Here, inside the round brackets, we present the correlation coefficient regarding the relation between a confounder and a significant variable. ** q (adjusted p) < .001.

Significant Variables	**Confounders**
Education,Duration_per app 7 days	Education category's data of 7 days' duration(0.97**), duration per launch (0.89**), launch per app (0.89**). Weekdays' duration per app (0.95**), launch per app (0.87**)
Books & Reference,Duration_per app weekends	Books & Reference category's weekends duration (1.0**), launch (0.99**), Duration per Launch (0.99**);Launch app (0.98**)
Books & Reference,Duration weekends	Books & Reference,Launch weekends (0.99**), duration per launch (0.99**), duration per app (1.0**), launch per app (0.98**)
Education,Duration 7 days	Education 7 days' duration per launch (0.84**), duration per app (0.97**), launch per app (0.9**) Weekdays' duration (0.96**), launch per app (0.89**), Duration_per app (0.94**)
Shopping,Launch_per app 7 days	Shopping weekdays' launch per app (0.95**)
Education,Launch_per app weekdays	Education category's 7 days' duration (0.89**), duration per lunch (0.62**), duration per app (0.87**), launch per app (0.96**). Weekdays' duration (0.91**), Duration per app (0.91**)
Books & Reference,Launch_per app weekends	Books & Reference category's weekends' duration (0.98**), launch (1.0**), duration per launch (0.95**), duration_per app (0.98**)
Shopping,Launch_per app weekdays	Shopping,Launch_per app 7 days ;0.95**
Education,Duration_per app weekdays	Education category's 7 days' duration (0.94**), duration per launch (0.83**), duration per app (0.95**), launch per app (0.86**). Weekdays' launch per app (0.91**)
Books & Reference,duration per launch weekends	Books & Reference weekends' Duration (0.99**), Launch (0.96**), duration_per app (0.99**, launch_per app (0.95**)
Education,duration per launch 7 days	Education 7 days' duration (0.84**), duration per app (0.89**), launch per app (0.64**). Weekdays' launch per app, (0.62**), Education duration per app (0.83**)
Education,Launch_per app 7 days	Education 7 days' duration (0.9**), duration per launch (0.64**), duration per app (0.89**). Weekdays' launch_per app 0.96**, Duration_per app (0.86**) Duration (0.87**)
No confounders found for Browser & Search,Entropy weekdays and Browser & Search,Entropy 7 days	

Appendix C. Ratio of hamming distance

Table A.4. Confounders which show significant association with both loneliness score and each of the 19 significant variables of dataset of study 2. Here, inside the round brackets, we present the correlation coefficient regarding the relation between a confounder and a significant variable. **q< 0.001 and *q<0.05. q: adjusted p.

Significant Variable	Confounders
Browser,Entropy, 7 days	Browser,Entropy weekdays 0.87**, Social,Duration per app weekdays 0.28*
Browser,Entropy weekdays	7 days' entropy values of Browser (0.87**). Duration per Social app launch data of weekdays' (0.3*) and 7 days' 0.29*
Smartphone,duration per launch 7 days	Duration per Communication app launch data of weekends (0.53**) and 78 days (0.54**) Duration per launch weekends' data of Launcher category 0.47**. Smartphone's duration per launch data of weekdays' (0.92**) and weekends (0.92**). Weekdays (0.52**), weekends (0.42**), 7 days (0.52**) data of Social
Social,Entropy weekdays	Social weekdays' data of hamming distance (0.42**) and duration per app (-0.34*)
Social,duration per launch weekends	Social,duration per launch data of weekdays (0.75**) and 7 days (0.84**)
Social,duration per launch 7 days	Browser category's entropy values for weekdays (0.29*) Social duration per launch data of weekdays (0.98**). Social categor's duration per launch data of weekends (0.84**)
Smartphone,duration per launch weekdays	Weekends duration per launch data of Communication (0.47*)* and Launcher category (0.41**). Smartphone's duration per launch data of weekends (0.78**) and 7 days (0.92**). Social category's duration per launch data of weekdays (0.59**), weekends 0.43** and 7 days (0.57**)
Social,Duration per app 7 days	Browser apps' entropy values 7 days (0.29*). Social category's entropy values of weekends (-0.23*) and 7 days (-0.37**), hamming distance data of weekdays (-0.35**), duration per launch data of weekdays (0.55**), weekends 0.47**, and 7 days (0.53**). Social apps' duration per app data of weekdays (0.98**)
Social,Duration per app weekdays	Social entropy values weekends (-0.22*) and 7 days (-0.37**) and hamming distance of weekdays -0.34**. Social category's duration per launch data of weekdays (0.58**), weekends 0.46**, and 7 days (0.56**). Social data of duration per app of7 days (0.98**)
Communication,duration per launch weekends	Communication,duration per launch 7 days ;0.87**. Social,duration per launch weekends 0.31*. Social,duration per launch 7 days ;0.26*
Social,Hamming_Distance weekdays	Social,Duration per app weekdays (-0.34**) and 7 days (-0.35**).
Social,duration per launch weekdays	Browser apps entropy values of weekdays (0.3*). Social duration per launch data of weekends (0.75**) and 7 days (0.98**).
Communication,duration per launch weekdays	Duration per launch of weekends (0.71**), 7 days (0.93**) data of Communication, weekends (0.25*) data of Launcher , weekdays (0.5**) data of Smartphone, weekdays (0.31*), weekends (0.34*), and 7 days (0.31*) of the Social Media category.
Smartphone,duration per launch weekends	Communication category's duration per launch data of weekends (0.58**) and 7 days (0.54**). Launchers' duration per launch data of weekends (0.47**). Smartphone's duration per launch data of weekdays (0.78**), and 7 days (0.92**). Social duration per launch data of weekdays (0.4**), weekends 0.46**, and 7 days (0.44**).
Social,Entropy 7 days	Social,Hamming_Distance weekdays 0.4**. Social,Duration per app weekdays -0.37**
Communication,duration per launch 7 days	Communication duration per launch data of weekends (0.87**), Launcher's data of duration per launch weekends (0.28*). Smartphone's duration per launch of weekdays (0.51**), weekends 0.54**, and 7 days (0.54**). Social category's duration per launch data of weekdays (0.28*), weekends (0.32*), and 7 days (0.3*)
Social,Entropy weekends	Social,Hamming_Distance weekdays 0.33*

We did not find any variable which significantly relates with both of the ULS-8 score and Productivity,Entropy weekdays , Launcher,duration per launch weekends.

Uniqueness in terms of app usage varies between different groups of people [28, 29]. Inspired by that, for each participant, we calculated the ratio of hamming distance from the nearest lonely to the nearest non-lonely participant. However, to get an unbiased model, we did not consider the group (e.g., lonely) of that participant for which we calculated the distance each time. The main motivation behind using ratio, instead of global distance (minimum distance among all participants) is that it gives us information regarding how much or less a participant is unique in comparison to the lonely and non-lonely group which is intuitively more informative. The distance is calculated by the formula: $UL_{ij} = (A_i \cup A_j) - (A_i \cap A_j)$ where UL_{ij} indicates the distance of the i^{th} participant from the j^{th} user of the lonely group and A_i and A_j present the set of apps used by the i^{th} and j^{th} participant respectively. After calculating distance from each participant of the lonely group in this way, we calculate the minimum distance of the i^{th} user in the lonely group: $UL_i = min\{UL_{i1}, UL_{i2}, UL_{i3}, \ldots\ldots, UL_{in}\}$ where n is the number of lonely participants. Similarly, we calculate the minimum distance of the i^{th} user in the non-lonely group, UNL_i. After that, we calculate the ratio of hamming distance for i_{th} user, $RH_i = \frac{UL_i}{UNL_i}$.

Appendix D. Finding the confounders for variables of study 1 and study 2

Table A.3 and Table A.4 show the confounders which we controlled in partial correlation analysis due to confounding the significant relations. For example, Education_Duration_per_app_7_days has significant relation (q<.05) with loneliness (Table 1). However, Education category's duration data of 7 days has significant relation with loneliness and also with Education_Duration_per_app_7_days (Table A.3). Therefore, that variable (Education category's duration data of 7 days) is a confounder which we control in partial correlation analysis while exploring the relation between Education_Duration_per_app_7_days and loneliness. Apart from this, through semi-partial correlation analysis, we controlled the variables which had significant association with one of the two variables that are in relation, but do not have relation with both of the variables.

Acknowledgements.
We thank all of the participants of our study for their time in data donation. Additionally, we thank Tanvir Hasan Fuad and the faculties of different universities, particularly Eastern University, for their cordial support in the data collection phase.

References

[1] Killgore WDS, Cloonan SA, Taylor EC, Dailey NS. Loneliness: A signature mental health concern in the era of COVID-19. Psychiatry Res. 2020;290(113117):113117. http://dx.doi.org/10.1016/j.psychres.2020.113117
[2] Fumagalli E, Dolmatzian MB, Shrum LJ. Centennials, FOMO, and loneliness: An investigation of the impact of social networking and messaging/VoIP apps usage during the initial stage of the Coronavirus pandemic. Front Psychol. 2021;12:620739. http://dx.doi.org/10.3389/fpsyg.2021.620739
[3] Varrella S. Loneliness among adults worldwide by country 2021. Statista. [accessed 29 Jan 2022] Available from: https://www.statista.com/statistics/1222815/loneliness-among-adults-by-country/
[4] Lee CM, Cadigan JM, Rhew IC. Increases in loneliness among young adults during the COVID-19 pandemic and association with increases in mental health problems. J Adolesc Health. 2020;67(5):714–7. http://dx.doi.org/10.1016/j.jadohealth.2020.08.009
[5] Serra G, Lo Scalzo L, Giuffrè M, Ferrara P, Corsello G. Smartphone use and addiction during the coronavirus disease 2019 (COVID-19) pandemic: cohort study on 184 Italian children and adolescents. Ital J Pediatr. 2021;47(1):150. http://dx.doi.org/10.1186/s13052-021-01102-8
[6] Hunt MG, Marx R, Lipson C, Young J. No more FOMO: Limiting social media decreases loneliness and depression. J Soc Clin Psychol. 2018;37(10):751–68. http://dx.doi.org/10.1521/jscp.2018.37.10.751
[7] Wetzel B, Pryss R, Baumeister H, Edler J-S, Gonçalves ASO, Cohrdes C. "how come you don't call me?" smartphone communication app usage as an indicator of loneliness and social well-being across the adult lifespan during the COVID-19 pandemic. Int J Environ Res Public Health. 2021;18(12):6212. http://dx.doi.org/10.3390/ijerph18126212
[8] Bonsaksen T, Ruffolo M, Leung J, Price D, Thygesen H, Schoultz M, et al. Loneliness and its association with social media use during the COVID-19 outbreak. Soc Media Soc. 2021;7(3):205630512110338. http://dx.doi.org/10.1177/20563051211033821
[9] Gao Y, Li A, Zhu T, Liu X, Liu X. How smartphone usage correlates with social anxiety and loneliness. PeerJ. 2016;4(e2197):e2197. http://dx.doi.org/10.7717/peerj.2197
[10] Li Z, Shi D, Wang F, Liu F. Loneliness Recognition Based on Mobile Phone Data. In: Proceedings of the 2016 International Symposium on Advances in Electrical, Electronics and Computer Engineering. Paris, France: Atlantis Press; 2016.
[11] Ceci L. Google Play most popular app categories 2021. Statista. [accessed 29 Jan 2022] Available from: https://www.statista.com/statistics/279286/google-play-android-app-categories/
[12] Pulekar G, Agu E. Autonomously sensing loneliness and its interactions with personality traits using smartphones. In: 2016 IEEE Healthcare Innovation Point-Of-Care Technologies Conference (HI-POCT). IEEE; 2016. http://dx.doi.org/10.1109/hic.2016.7797715
[13] Petersen J, Thielke S, Austin D, Kaye J. Phone behaviour and its relationship to loneliness in older adults. Aging Ment Health. 2016;20(10):1084–91. http://dx.doi.org/10.1080/13607863.2015.1060947
[14] Islam MR, Jannath S, Moona AA, Akter S, Hossain MJ, Islam SMA. Association between the use of social networking sites and mental health of young generation in Bangladesh: A cross-sectional study. J Community Psychol. 2021;49(7):2276–97. http://dx.doi.org/10.1002/jcop.22675
[15] LaMorte WW. Mann Whitney U test (wilcoxon rank sum test). Bumc.bu.edu. [accessed 2 Feb 2022] Available from: https://sphweb.bumc.bu.edu/otlt/mph-modules/bs/bs704_nonparametric/BS704_Nonparametric4.html
[16] Mobile operating system market share Bangladesh. StatCounter Global Stats. [accessed 16 Feb 2022] Available from: https://gs.statcounter.com/os-market-share/mobile/bangladesh
[17] Ahmed MS. Info bin. Google.com. [accessed 29 Jan 2022] Available from: https://play.google.com/store/apps/details?id=bd.me.sabbireubdesh.www.datacollector
[18] Felisoni DD, Godoi AS. Cell phone usage and academic performance: An experiment. Comput Educ. 2018;117:175–87. http://dx.doi.org/10.1016/j.compedu.2017.10.006
[19] UsageStatsManager. Android Developers. [accessed 29 Jan 2022] Available from: https://developer.android.com/reference/android/app/usage/UsageStatsManager.html
[20] Mindefy Labs. YourHour - phone addiction tracker & controller. Google.com. [accessed 29 Jan 2022] Available from: https://play.google.com/store/apps/details?id=com.mindefy.phoneaddiction.mobilepe

[21] Hays RD, DiMatteo MR. A short-form measure of loneliness. J Pers Assess. 1987 Spring;51(1):69–81. http://dx.doi.org/10.1207/s15327752jpa5101_6
[22] Das R, Hasan MR, Daria S, Islam MR. Impact of COVID-19 pandemic on mental health among general Bangladeshi population: a cross-sectional study. BMJ Open. 2021;11(4):e045727. http://dx.doi.org/10.1136/bmjopen-2020-045727
[23] Doryab A, Villalba DK, Chikersal P, Dutcher JM, Tumminia M, Liu X, et al. Identifying behavioral phenotypes of loneliness and social isolation with passive sensing: Statistical analysis, data mining and machine learning of smartphone and Fitbit data. JMIR MHealth UHealth. 2019;7(7):e13209. http://dx.doi.org/10.2196/13209
[24] Böhmer M, Hecht B, Schöning J, Krüger A, Bauer G. Falling asleep with Angry Birds, Facebook and Kindle: A large scale study on mobile application usage. In: Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services - MobileHCI ’11. New York, New York, USA: ACM Press; 2011. http://dx.doi.org/10.1145/2037373.2037383
[25] Zhao S, Ramos J, Tao J, Jiang Z, Li S, Wu Z, et al. Discovering different kinds of smartphone users through their application usage behaviors. In: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing. New York, NY, USA: ACM; 2016.
[26] BSS. BUET to take term-final exams online. The Daily Star. 2021. [accessed 16 Feb 2022] Available from: https://www.thedailystar.net/youth/education/news/buet-take-term-final-exams-online-2141496
[27] Wikipedia contributors. Hamming distance. Wikipedia, The Free Encyclopedia. 2021. Available from: https://en.wikipedia.org/w/index.php?title=Hamming_distance&oldid=1054348646
[28] Ahmed S, Ahmed N. Exploring unique app signature of the depressed and non-depressed through their fingerprints on apps. In: Proceedings of 15th EAI International Conference on Pervasive Computing Technologies for Healthcare. 2022. DOI: 10.1007/978-3-030-99194-4_15
[29] Tu Z, Li R, Li Y, Wang G, Wu D, Hui P, et al. Your apps give you away: Distinguishing mobile users by their app usage fingerprints. Proc ACM Interact Mob Wearable Ubiquitous Technol. 2018;2(3):1–23. http://dx.doi.org/10.1145/3264948
[30] Shannon CE. A mathematical theory of communication. ACM SIGMOBILE Mob Comput Commun Rev. 2001;5(1):3–55. http://dx.doi.org/10.1145/584091.584093
[31] Kim S. Ppcor: An R package for a fast calculation to semi-partial correlation coefficients. Commun Stat Appl Methods. 2015;22(6):665–74. http://dx.doi.org/10.5351/CSAM.2015.22.6.665
[32] Virtanen P, Gommers R, Oliphant TE, Haberland M, Reddy T, Cournapeau D, et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. Nat Methods. 2020;17(3):261–72. http://dx.doi.org/10.1038/s41592-019-0686-2
[33] Benjamini Y, Hochberg Y. Controlling the false discovery rate: A practical and powerful approach to multiple testing. J R Stat Soc. 1995;57(1):289–300. http://dx.doi.org/10.1111/j.2517-6161.1995.tb02031.x
[34] Park S, Kim I, Lee SW, Yoo J, Jeong B, Cha M. Manifestation of depression and loneliness on social networks: A case study of young adults on Facebook. In: Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing. New York, NY, USA: ACM; 2015.
[35] Hill R. WHAT SAMPLE SIZE is “ENOUGH” in INTERNET SURVEY RESEARCH. Pbworks.com. [accessed 29 Jan 2022] Available from: http://cadcommunity.pbworks.com/f/what%20sample%20size.pdf
[36] Chou W-P, Wang P-W, Chen S-L, Chang Y-P, Wu C-F, Lu W-H, et al. Voluntary reduction of social interaction during the COVID-19 pandemic in Taiwan: Related factors and association with perceived social support. Int J Environ Res Public Health. 2020;17(21):8039. http://dx.doi.org/10.3390/ijerph17218039
[37] Yeo SC, Tan J, Lo JC, Chee MWL, Gooley JJ. Associations of time spent on homework or studying with nocturnal sleep behavior and depression symptoms in adolescents from Singapore. Sleep Health. 2020;6(6):758–66. http://dx.doi.org/10.1016/j.sleh.2020.04.011
[38] Miyata H. Impacts of reading habits on mindfulness and psychological status: A further analysis. WASEDA RILAS JOURNAL. [accessed 29 Jan 2022] Available from: https://www.waseda.jp/flas/rilas/assets/uploads/2020/10/207-218_Hiromitsu-MIYATA.pdf
[39] Rane-Szostak D, Herth KA. Pleasure reading, other activities, and loneliness in later life. Journal of Adolescent & Adult Literacy. 1995;39(2). Available from: https://www.jstor.org/stable/40034518
[40] Schønning V, Hjetland GJ, Aarø LE, Skogen JC. Social media use and mental health and well-being among adolescents – A scoping review. Front Psychol. 2020;11. http://dx.doi.org/10.3389/fpsyg.2020.01949
[41] Twenge JM, Haidt J, Blake AB, McAllister C, Lemon H, Le Roy A. Worldwide increases in adolescent loneliness. J Adolesc. 2021;93:257–69. http://dx.doi.org/10.1016/j.adolescence.2021.06.006
[42] 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 2019 CHI Conference on Human Factors in Computing Systems. New York, NY, USA: ACM; 2019. http://dx.doi.org/10.1145/3290605.3300536
[43] Hiniker A, Schoenebeck SY, Kientz JA. Not at the dinner table: Parents’ and children’s perspectives on family technology rules. In: Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing. New York, NY, USA: ACM; 2016. http://dx.doi.org/10.1145/2818048.2819940
[44] Ahmed N, Urmi T, Tasmin M. Challenges and opportunities for young female learners in STEM from the perspective of Bangladesh. In: 2020 IEEE International Conference on Teaching, Assessment, and Learning for Engineering (TALE). IEEE; 2020.
[45] Wang R, Chen F, Chen Z, Li T, Harari G, Tignor S, et al. StudentLife: Assessing mental health, academic performance and behavioral trends of college students using smartphones. In: Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing. New York, NY, USA: ACM; 2014. http://dx.doi.org/10.1145/2632048.2632054
[46] Ben-Zeev D, Scherer EA, Wang R, Xie H, Campbell AT. Next-generation psychiatric assessment: Using smartphone sensors to monitor behavior and mental health. Psychiatr Rehabil J. 2015;38(3):218–26. http://dx.doi.org/10.1037/prj0000130
[47] Austin J, Dodge HH, Riley T, Jacobs PG, Thielke S, Kaye J. A smart-home system to unobtrusively and continuously

assess loneliness in older adults. IEEE J Transl Eng Health Med. 2016;4:2800311. http://dx.doi.org/10.1109/JTEHM.2016.2579638
[48] Ahmed M. 86pc university students own smartphones in Bangladesh: Survey. Prothomalo. Prothom Alo English; 2020. [accessed 29 Jan 2022] Available from: https://en.prothomalo.com/youth/education/86pc-university-students-own-smartphones-in-bangladesh-survey
[49] Ahmed MS, Rony RJ, 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 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers. New York, NY, USA: ACM; 2020.
[50] Mezuk B, Choi M, DeSantis AS, Rapp SR, Diez Roux AV, Seeman T. Loneliness, depression, and inflammation: Evidence from the multi-ethnic study of atherosclerosis. PLoS One. 2016;11(7):e0158056. http://dx.doi.org/10.1371/journal.pone.0158056
[51] Jackson SE, Hackett RA, Grabovac I, Smith L, Steptoe A. Perceived discrimination, health and wellbeing among middle-aged and older lesbian, gay and bisexual people: A prospective study. PLoS One. 2019;14(5):e0216497. http://dx.doi.org/10.1371/journal.pone.0216497
[52] Zhang H, Yang J, Li Y, Ren G, Mu L, Cai Y, et al. The patterns and predictors of loneliness for the Chinese medical students since post-lockdown to new normal with COVID-19. Front Public Health. 2021;9:679178. Available from: http://dx.doi.org/10.3389/fpubh.2021.679178
[53] Sarsenbayeva Z, Marini G, van Berkel N, Luo C, Jiang W, Yang K, et al. Does Smartphone Use Drive our Emotions or vice versa? A Causal Analysis. In: Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. New York, NY, USA: ACM; 2020.
[54] Shi Y, Koval P, Kostakos V, Goncalves J, Wadley G. "Instant Happiness": Smartphones as tools for everyday emotion regulation. Int J Hum Comput Stud. 2023;170(102958):102958. Available from: http://dx.doi.org/10.1016/j.ijhcs.2022.102958
[55] Morris ME, Kuehn KS, Brown J, Nurius PS, Zhang H, Sefidgar YS, et al. College from home during COVID-19: A mixed-methods study of heterogeneous experiences. PLoS One. 2021;16(6):e0251580. Available from: http://dx.doi.org/10.1371/journal.pone.0251580
[56] Suresh R, Alam A, Karkossa Z. Using peer support to strengthen mental health during the COVID-19 pandemic: A review. Front Psychiatry. 2021;12:714181. Available from: http://dx.doi.org/10.3389/fpsyt.2021.714181
[57] Ahmed MS, Hasan T, Rahman M, Ahmed N. A rule mining and Bayesian network analysis to explore the link between depression and digital behavioral markers of Games app usage. In: Proceedings of PervasiveHealth'22 [In Press]. 2022. DOI: 10.1007/978-3-031-34586-9_37