Impact of COVID-19 and telehealth on mental health in Bangladesh: a propensity score matching approach

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Received: 29 December 2021 / Revised: 17 January 2022 / Accepted: 28 January 2022 / Published online: 15 February 2022
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Abstract COVID-19 have deteriorated mental health conditions in Bangladesh. The study aims to examine the impact of COVID-19 on mental health conditions through the propensity score matching method and establish the relationship between telehealth usage on mental health improvement during the COVID-19 pandemic. Nearest neighbor matching approach has been used to match treatment unit to nearest comparison unit and achieved balance between treatment and control groups on observable traits. A cross-sectional study on 89 participants was conducted from April to June 2020. ATE (average treatment effect) & ATET (average treatment effect of treated) techniques were used. Logistic regression was used to examine the causal relationship between telehealth usage on mental health improvement. The coefficient of ATE on

the population was -0.026 , stating that on average, participants with no past physical health problems had fewer mental health issues than the participants with a past physical health problem. The coefficient on ATET was -0.034 . The association between telehealth usage on mental health improvement was highly significant as p value = $0.00 < 0.05$ with OR of 70 at 95% CI. There was strong evidence of positive mental health outcomes through telehealth usage during the pandemic. Experts should develop sustainable adaptations of mental health-care delivery systems in this field to mitigate the disparities in healthcare provision.

Keywords Mental health · Telehealth · COVID-19 · Pandemic

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1 Introduction

As the world is grappling with the COVID-19 economic toll amid case escalations, the pandemic has negatively affected many people's mental health. During the pandemic in 2020, about 4 in 10 adults reported cases of depression or anxiety, a statistic which has increased from 1 in 10 adults from June 2019 [1]. Although early in the pandemic, there were concerns that suicide cases would escalate, the data rather showed a decline in numbers, but deaths due to substance use disorder increased substantially [2–6]. This evidence suggests that policies need to ensure proper access to life-saving medical and psychiatric care for all. In Bangladesh, mental health is often treated as a social stigma, which acts as a barrier to care. Since the onset of lockdown in March 2020, 14,435 people took their own lives, which is 70% more than the findings of the coronavirus study, where 49% of the victims were between

20 to 35 years of age [7]. Lack of awareness and shortage of mental health support are a few of the reasons for the increasing rate of mental health cases.

According to the Bangladesh Bureau of Statistics, there are about 10,000 suicide cases in Bangladesh per year, where the prevalence of mental disorders among 18 years and above is 18.7% [7]. Youth often hesitate in seeking professional help for their stress and mental problems in fear of getting stigmatized in society. Moreover, most psychiatrists and psychologists are urban-based, leaving rural youth without sufficient help. There are about 270 psychiatrists and 500 psychologists in the country, where the population is 166 million [7, 8]. To date, there is no primary health care system in districts and sub-districts for mental health care. Youth have experienced several pandemic-related consequences such as school closures, layoff from a job, decrease in salary, lockdowns, social gathering restrictions, and loss of close ones. All these might accumulate to poor mental health. Even parents, particularly mothers experienced severe challenges with balancing school closures and lack of childcare along with handling remote work. Married women are more likely to report symptoms of anxiety and depression than men (49% vs. 40%).

Socioeconomic and demographic factors play a huge role in a patient's mental health. For example, if a patient with no earning source, living in a rural area, living with social constraints, and is financially dependent on family is less likely to seek mental health support than a patient living in an urban area with an earning source. In terms of healthcare outcomes, as there are few resources to seek help, lack of information and misinformation can negatively affect the mental health outcomes of the person. Healthcare outcome also depends on health literacy and healthcare utilization (i.e. if the patient is seeking the right care at the right place). As a resource use outcome, cost, and quality are important factors because a wealthy patient can easily seek good quality care as opposed to a low-income patient. The emergence of telehealth use can drastically increase access for patients, especially those who don't seek help in fear of being stigmatized. It can also be cost-efficient as patients can forgo transportation costs.

Telehealth usage during the COVID-19 pandemic became a necessary choice for many. This pandemic might serve as an opportunity to promote the advantages of telemental health offered by the digital era. A study discussed the potential role of telepsychiatry and other cutting-edge technologies in managing mental health assistance by narratively reviewing literature and found that telemental health services can be feasible for people who can't go outside for various reasons [9, 10]. This study is relevant for the Bangladeshi perspective as people don't want to go out as it might sometimes require parental approval and hence seeking telemental health assistance

can be beneficial for them. A study examined the prevalence of mental health symptoms and factors associated with it in April 2020 by conducting a cross-sectional study on 10,609 participants through an online survey platform and found 64%, 87%, and 61% of the participants reported high levels of depression, anxiety, and stress respectively, although selection bias persists because the sample was taken from selective regions of the country [11, 12]. This highlights the need for immediate interventions and promotion for healthcare such as telehealth.

Snowball sampling approach can randomly pool participants, where a study used this approach with 237 participants from April to June 2020, with a mean age of 41.59, and found prevalence of anxiety and depression was 55.7% and 87.3% respectively [13]. Nearly half of the study population suffered both depression and anxiety (47.7%), which highlights the need for policies to mitigate the mental health challenges during this pandemic. However, the study can be expanded to include more participants for more inclusion because 90.29% of the participants lived in urban areas and 73% were male. The online cross-sectional survey became a vital tool for researching this area as it helped reach out to more people of different age groups and socioeconomic backgrounds. A study used this approach among 672 participants aged 15 to 65 years old from April to May 2020 and found the prevalence of loneliness and sleep disturbance 71% and 73% respectively [14]. The key factors associated with poor mental health during this pandemic are sex, unemployment, obesity, and living alone. However, self-reported data often lack validity as participants might exaggerate their symptoms and conditions.

The female sex is more likely to report mental health issues, and among them, being married or a mother increases the likelihood, as females share a greater share of the household responsibilities in Bangladesh. A cross-sectional study conducted among 547 nurses found that depression, anxiety, and stress level symptoms were higher among female nurses than male nurses ($p < 0.05$), and emotional abuse at the workplace was significantly associated with higher levels of depression, anxiety, and stress on them (p value < 0.05) [15]. The study can be expanded, including participants from various industries.

The burden of unmet mental health challenges is high in Bangladesh, as it is an unrecognized and under-researched area in the country. Furthermore, healthcare delivery has its challenges, including weak governance, lack of funding, lack of access, misinformation, and lack of proper care [16]. Little is known about the impact of COVID-19 on their mental health conditions, and to our knowledge, no study has been conducted using propensity score matching to evaluate the effect of the pandemic on mental health in Bangladesh. This paper aims to see the prevalence impact

of COVID-19 on mental health and whether there is any causal relationship between telehealth and mental health improvement in Bangladesh. The purpose of the study is to highlight the impact of the pandemic on mental health in the people of Bangladesh and the importance of telehealth usage for mental health support.

2 Methodology

2.1 Study sample

A cross-sectional online survey was conducted from April 11 to June 12, 2021. As the study was conducted during the COVID-19 pandemic with new cases of more than 2500 to date, the snowball sampling method was used to recruit participants [17]. Snowball sampling is where research participants recruit other participants for a test or study. It is used where potential participants are hard to find. It's called snowball sampling because (in theory) once you have the ball rolling, it picks up more "snow" along the way and becomes larger and larger. The online questionnaire included a total of 28 questions in the Google Form, and consent to use their answers was taken from each participant before they could fill up the form. The form did not seek email address, phone number, name, or any type of information, through which the participants could be identified later onwards. Hence, the data is completely de-identified. The form was shared through email and social media platform Facebook. A total of 89 people participated in the survey and the age group was divided into 4 parts; 20–25, 26–30, below 20, and above 30 years old. In Bangladesh universities (undergraduates) are usually within the age group of 20–25; afterwards, they graduate and join the industry from 26. Hence, employed youth were considered between 26 to 30 years old. Above 30 are usually married and share larger responsibilities and commonly established and age group below 20 are considered dependent on families. However, no one from the age group below 20 answered the survey questionnaire, for which it was excluded from the results.

2.2 Ethics

The respondent's consent was taken before the online survey, and they remained anonymous. Before starting to fill out the questionnaire, all contributors were informed of the study's specific objectives. Participants could only complete the survey once and able to terminate it whenever they wanted. This study's formal ethical approval was taken from the respective authority (i.e., University of Liberal Arts Bangladesh, Satmasjid Road, Dhaka, Bangladesh). The data's privacy and confidentiality were ensured.

2.3 Study outcomes and covariates

The primary outcome of interest was to evaluate the effect of the pandemic on mental health, which was assessed through the Propensity Score Matching method (ATE & ATET). Logit and logistic regression were also conducted to assess the outcome of the pandemic on mental health. For the secondary outcome of interest, we captured and saw if telehealth improved mental health or not. We examined the covariates such as sex, age group, sleep hours, and marital status of the participants.

2.4 Analysis

Propensity score matching is a quasi-experimental method that uses statistical techniques to construct an artificial control group by matching each treated participant with a non-treated participant of similar characteristics. We considered the treated group as participants with no physical health problem and the control group to be participants with the physical problem in the last 4 weeks because the presence of physical health problems might affect mental health; hence we wanted to separate the groups in that order. We gave binary values '1' to the treated group and '0' to the control group. As the sex was female and male, '1' was considered female, and '0' was considered male. Our primary outcome of interest was whether the participants had worse mental health conditions after the onset of the COVID-19 pandemic. They answered using 'Yes' and 'No' options and labeled them '1' and '0', respectively. We associated Yes as '1' and No as '0' to see if telehealth improved their mental health for the secondary outcome of interest. The age groups were initially four, but as one age group (> 20 years old) was missing among the participants, it was automatically excluded from the results. The age group above 30 was considered '0' age group 26–30 was considered '1' and the age group 20–25 was considered '2'.

The Propensity Score Matching technique was introduced by Rosenbaum and Rubin [18]. The method addressed selection bias and moved towards more causal estimates. It is defined as the probability of treatment assignment conditional on observed baseline covariates $e_i = \Pr(Z_i = 1|X_i)$ [19]. The first condition says that $(Y(1), Y(0)) \perp Z|X$; that is, treatment assignment is independent of the potential outcomes conditional on the observed baseline covariates. The second condition says that (b) $0 < P(Z = 1|X) < 1$; that is, every subject has a non-zero probability of receiving either treatment [19]. There are four steps. The first step includes estimating the propensity score, which we were able to do using logistic regression of treatment conditions on the vector of covariates.

$\text{logit}(\pi) = \log(\pi / (1 - \pi))$. The logistic function is the inverse of the logit, and if we have x value, the logistic equation is:

$$\text{logistic}(x) = \frac{e^x}{1 + e^x}$$

By using the matrix notation, where xx is $N \times P$ matrix and β is $p \times 1$ vector, the logit regression becomes:

$$\log(\pi / (1 - \pi)) = X\beta$$

And logistic regression is:

$$\pi = \frac{e^{X\beta}}{1 + e^{X\beta}}$$

Step 2 includes matching with either nearest neighbor matching, caliper matching, common, or radius matching. The third step is to evaluate the quality of matching. The goal is to achieve a balance between treatment and comparison group on observable traits, which we did by comparing means. The final step is to evaluate outcomes, which we did through running a regression. To examine if telehealth improved the mental health condition of the participants, we ran multiple linear regression. The analysis was performed using STATA version 16.

3 Results and discussion

In Table 1, the analysis showed that 50.56% of the participants were female ($N = 45$) and the mean of the sex was almost 50% with almost 50% of standard deviation. Females were given binary values of '1' and '0' for males. We were able to balance the sex ratio of the participants well successfully. 53.93% of the participants in our sample were single and only 4.49% were divorced, with a mean of 2.09. The age groups were pooled into 3 groups, where the majority of the participants were between the age group of 26–30 years old (52.81%), with a standard deviation of 0.86, followed by 20–25 years of the age group of 40.45%. This highlights that most of the participants were university students and were recently employed. The sleep was measured in hours per day and divided into 4 groups, where most of the participants reported to have slept between 4–6 h per day (49.44%), with mean and standard error of 0.50 and 0.053 respectively. The binary values of each category are given in Table 1.

In Table 2, to see if there is any causal impact of COVID-19 on the participants' mental health, we ran multiple linear regression, logit, and logistic regressions. The multiple linear regression showed that sex was highly significant (p value = 0.00 < 0.05) at 95% C.I [0.22–0.60]. After performing logit and logistic regression, we found

Table 1 Descriptive statistics of demographics

Variable	Obs	Mean	Std. Dev	Min	Max	Std. Err	95% C.I
Sex	89	.506	.503	0	1	.053	.399–.611
Age group	89	1.337	.602	0	2	.064	1.210–1.463
Marital status	89	2.09	1.184	0	3	.125	1.840–2.339
Sleep	89	1.258	.762	0	3	.080	1.097–1.418
Variable	Freq		Perc				
Sex-female (1)	45		50.56				
Sex-male (0)	44		49.44				
Age group-26–30 years (1)	47		52.81				
Age group- > 30 years (0)	6		6.74				
Age group-20–25 years (2)	36		40.45				
Marital status-married (0)	18		20.22				
Marital status-divorced (1)	4		4.49				
Marital status-in Relation (2)	19		21.35				
Marital status-single (3)	48						
Sleep- < 4 h (0)	13		14.61				
Sleep-4–6 h (1)	44		49.44				
Sleep-7–9 h (2)	28		31.46				
Sleep- > 9 h (3)	4		4.49				

Obs observation, *Std. Dev* standard deviation, *Std. Err.* standard error, *C.I.* confidence interval at 95%

Sleep is measured in hours per day

Table 2 Univariable analysis of the sample

	Coefficient	SE	Z	OR	p value
Intercept	.3487929	.863084	0.40	1.417356	0.686
Age group	.093382	.442109	0.21	1.097881	0.833
Sex	2.033378	.531733	3.82	.7.63985	0.000
Marital status	− .0848111	.231982	− 0.37	.9186858	0.715
Sleep	− .4955077	.350638	− 1.41	.6092615	0.158

SE standard error, OR odds ratio

that sex was similarly highly significant as p value = $0.00 < 0.05$, with 95% C.I. None of the other associations were significant. On average, one unit increase in sex (f) was found to correspond to an odds ratio of response of 7.63. The results of logit and logistic regression are in Table 2.

To perform probit regression for propensity score matching, which is appropriate for binary outcomes, we saw a high level of common support on 89 observations. Only 3 observations were off support, which meant that 3 propensity scores did not align with the propensity score of other observations in the opposite treatment category. We saw large evidence on a common support. The result is described in Table 3.

To check for further evidence on reduced biasedness, we graphically represent in Fig. 1. The blue color represents the untreated group and red represents the treated group on support. Lastly, the green color represents the treated group off-support. We see large evidence on overlapping propensity scores and some large evidence on the common support.

We then tested propensity score to see how much bias had been reduced, through the propensity score test. Although none of them were statistically significant (p value > 0.05), we were able to reduce bias by a large extent, especially on age and marital status variables (< 5). Hence, we were able to balance between observable covariates. Table 4 shows the result.

We performed propensity score matching using the nearest neighbor matching method (estimator) to see the

Fig. 1 Evaluate match graphically**Table 4** Balance on observable covariates

Variable	Mean		t-test		
	Treated %bias	Control	t	p value	
Age group	1.31	1.40	− 15.6	− 0.82	0.41
Sex	0.5	0.4	18.3	0.96	0.33
Marital Status	2.16	2.35	− 15.2	− 0.81	0.38
Sleep	1.25	1.16	11.9	0.73	0.46

average treatment effects. The number of observations was 89 and the matches requested was 1. The outcome model

Table 3 Evidence of common support

Variable sample	Treated	Controls	Differene	S.E	T-stat
hascworsenedmh ~ m Unmatched	0.614	0.656	− 0.042	0.108	− 0.390
ATT	0.611	0.574	0.037	0.169	0.220
Psmatch2	Psmatch2: common support				
Treatment assignment	Offsupport		On support		Total
Untreated	0		32		32
Treated	3		54		57
Total	3		86		89

was matching, and the distance metric was Mahalanobis. The coefficient of ATE (average treatment effect) on the population was -0.026 , stating that on average, participants with no past physical health problem (in past four weeks) had 0.02 fewer mental health issue than the participants with a past physical health problem (in the past four weeks). We then performed ATET (average treatment effect on the treated) and the coefficient was -0.034 . The result was similar to the previous test because on average, the participants with no physical health problems in the last 4 weeks had 0.03 fewer mental health issues than the participants with a physical health problem in the last 4 weeks. The result is stated in Table 5.

We ran logit and logistic regression to see the effect of COVID-19 on mental for the independent variable and covariates and saw the sex is highly significant. On average, one unit increase in female sex was found to correspond to an odds ratio of response 7.73 at 95% confidence level in Table 6.

As the secondary outcome of interest was to see if there was any causal relationship between telehealth and improvement in mental health conditions, we ran a linear regression. We used logistic regression as it is appropriate for binary variables. The result for both independent variable and intercept were highly significant at 95% confidence interval as p values were 0.00 and 0.12, respectively. On average, taking telehealth or telemental health led to a 424% improvement in mental health conditions, keeping everything else constant. Among 89 participants, 43 of them took telehealth support for their mental health issues. The result is provided in Table 7.

The analysis showed that 50.56% of the participants were female ($N = 45$), and the mean of the sex was almost 50% with almost 50% of standard deviation, which is one of the strengths in our study as we were able to balance the sex ratio. The majority of the participants were between the age group of 26–30 years old (52.81%) followed by 20–25 years of the age group of 40.45%. This highlights that most of the participants were university students and were recently employed. The sleep was measured in hours per day where most of the participants reported to have slept between 4–6 h per day (49.44%). The multiple linear regression showed that sex was highly significant (p value = 0.00 < 0.05) at 95% C.I [0.22–0.60]. After performing logit and logistic regression, we found that sex was similarly highly significant as p value = 0.00 < 0.05, with 95% C.I. None of the other associations were

significant. On average, one unit increase in sex (f) was found to correspond to an odds ratio of response of 7.63. The results of logit and logistic regression are in Table 1. To check for further evidence and reduce biasedness, we graphically represent in Fig. 1. The blue color represents the untreated group and red represents the treated group on support. Lastly, the green color represents the treated group off-support. We see large evidence on overlapping propensity scores and some large evidence on the common support, stating that biasedness was reduced to a good limit. We then tested propensity score to see how much bias had been reduced through the propensity score test. Although none of them were statistically significant (p value > 0.05), we were able to reduce bias by a large extent, especially on age and marital status variables (Table 4). Hence, we were able to balance between observable covariates. We performed propensity score matching to see the average treatment effects (ATE) using the nearest neighbor matching method (estimator). The number of observations was 89, and the matches requested was 1. The coefficient of ATE on the population was -0.026 , stating that on average, participants with no past physical health problem (in the past four weeks) had 0.02 fewer mental health issues than the participants with a past physical health problem (in the past four weeks). We then performed ATET (average treatment effect on the treated), and the coefficient was -0.034 . The result was similar to the previous test because, on average, the participants with no physical health problems in the last 4 weeks had 0.03 fewer mental health issues than the participants with a physical health problem in the last 4 weeks. The result is stated in Table 5. We ran logit and logistic regression to see the effect of COVID-19 on mental for the independent variable and covariates and saw the sex is highly significant. On average, one unit increase in female sex was found to correspond to an odds ratio of response 7.73 at 95% confidence level. As the secondary outcome of interest was to see if there was any causal relationship between telehealth and improvement in mental health conditions, we ran a regression. We used logistic regression as it is appropriate for binary variables. The independent variable and intercept result were highly significant at 95% confidence interval as p values were 0.00 and 0.12 respectively. On average, telehealth or telemental health led to a 424% improvement in mental health conditions, keeping everything else constant. Among 89 participants,

Table 5 ATE & ATET on mental health outcome nearest neighbor matching method of propensity score matching

	Coefficient	SE	Z	p value	95% CI
ATE Pastphysicalhealth 1 vs 0	– .0265918	.1051365	– 0.25	0.800	– 0.23–0.17
ATET Pastphysicalhealth 1 vs 0	– .0345029	.1119499	– 0.31	0.758	– 0.25–0.18

Table 6 Regression result on effect of covid-19 on mental health

Effect of COVID-19 on mental health	Coef	St. Err	Z	p-value	95% Conf. interval	OR
Past phyhealth	− .2489642	.4121704	0.47	0.638	− .245 .153	.77
Sex	2.046225	4.122257	3.84	0.000	.229 .61	7.73
Age group	.0604577	.4751493	0.14	0.892	− .145 .184	1.06
Marital status	− .0721456	.2173407	− 0.31	0.757	− .099 .073	.93
Sleep	− .5042999	.2124438	− 1.43	0.152	− .211 .038	.60
Constant	.5311278	1.617756	0.56	0.577	.217 .893	1.70

Coef. Coefficient, *St.Err* standard error, *Conf confidence*, *OR odds ratio*

Table 7 Logistic regression result on mental health improvement through telehealth support

Mental health improv	Coef	St.Err	p-value	95% Conf. level	Z	OR
Took telehealth	4.24	1.17	0.00	1.94 6.55	3.61	70
Constant	− .91	.59	.12	− 2.07 .24	− 1.55	.4

Coeff coefficient, *St. Err* standard error, *Conf confidence*, *OR odds ratio*

43 of them took telehealth support for their mental health issues. The result is provided in Table 7.

Although using the Propensity Score Matching method helped us eliminate the greater portion of bias when estimating outcomes, omitted variable bias (selection bias) may still be present. For example, whether a participant attended school or university might not have been observed from the data, leading to differences in the participant's situation. As we used self-reported data, some participants might have over-reported or under-reported their symptoms and conditions, which may not always align with mental health professionals [16]. Furthermore, this paper paves the way forward as the data was collected within a month, the study can be expanded and longitudinal data can provide more insights.

4 Conclusion

The findings suggest that having physical health problems can lead to more mental health problems than those who don't have any physical health problems. During the pandemic, people who were infected or came into contact with the infection had to quarantine themselves for their safety and others' safety. Even regular people had had to stay at their homes due to lockdown restrictions. Schools were closed and restaurants were closed, although restaurants are now open with certain restrictions [16]. These measures deteriorated mental health conditions among the youth as nearly 63% of the study participants said that COVID-19 had worsened their mental health. Of those who reported worsened mental health due to the pandemic, only 34% of them sought help through professional channels.

This highlights the lack of awareness about mental health support. Even though COVID-19 has highlighted how fragile the healthcare delivery system is in Bangladesh, the pandemic can be used as an opportunity to improve mental health services. In this pandemic, isolation can be a big factor in escalating the mental health challenges and telehealth can be a vital tool to help tackle this. However, to build on telehealth's potential in COVID-19 and beyond the pandemic, rigorous research needs to be conducted to capture and evaluate the critical user experience as both technical literacy and health literacy can pose significant barriers in implementation in Bangladesh¹⁵. The findings also shed light on the impact of COVID-19 on the mental health conditions of the youth in Bangladesh, who are the future workforce. Experts should develop sustainable adaptations of mental health care delivery systems in this field to mitigate the disparities in health care provision¹⁶. The government needs to continuously monitor health and service use outcomes in the clinical practice of mental health.

Acknowledgements We want to express our heartiest gratitude to Global Health Data Exchange for freely available data. The authors also like to express their gratitude to the experts of Dynamic Institution of Geospatial Observation Network—DIGON (<http://digonresearch.org/>), a research consultancy firm for proofreading and assistance to publish the manuscript.

Declaration

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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