INTRODUCTION

Mental illness is a broad term that encompasses a range of disorders that affect an individual's mood, thinking, and behavior. According to the World Health Organization (WHO, 2020), mental illness affects one in four people globally, making it a significant public health issue. Mental illnesses can arise from a variety of factors, including genetics, environmental factors, and lifestyle choices. The most common mental illnesses include anxiety disorders, depression, bipolar disorder, and schizophrenia. These disorders can have a significant impact on an individual's quality of life, leading to impaired functioning, social isolation, and decreased productivity (WHO, 2020). Proper diagnosis, treatment, and management of mental illness are essential to improving an individual's overall well-being and reducing the societal burden of mental illness. This paper will look at the effects of screen time on mental health within the United States.

The use of smartphones has become ubiquitous in modern society, with people using them for various purposes, including communication, entertainment, and information. However, there is a growing concern that excessive smartphone use may contribute to the development or exacerbation of mental health issues, such as anxiety and depression. Studies have shown that individuals who spend more time on their phones are at higher risk of developing symptoms of anxiety and depression, as well as experiencing sleep disturbances and decreased social interaction (Yao, 2020). Additionally, the use of social media on smartphones has been linked to increased feelings of loneliness, anxiety, and depression (Yao, 2020). While the relationship between smartphone usage and mental health is complex and multifaceted, excessive phone use can negatively impact an individual's mental health and well-being.

The field of screen time and its impact on children's well-being has been the subject of much research. Hussain Taylor et al.'s 2018 study, "The internet and children's psychological wellbeing," is one of the earliest works that explored the relationship between internet use and children's well-being. The study found that internet use had a negative impact on children's well-being, with appearance being the most affected domain. Moreover, girls were more impacted than boys. The study also supported the idea that internet use may reduce the time spent on other beneficial activities and highlighted the harmful effects of social media use.

Adrián Nieto and Marc Suhrcke's study (2021), "The effect of TV viewing on children's obesity risk and mental well-being: Evidence from the UK digital switchover," investigated the impact of the transition to digital media on children's mental health and BMI. The study found no significant changes in child mental health and BMI during the years leading up to the digital transition. However, the switch to digital media was found to significantly worsen children's mental well-being, with the negative impact increasing over time. This highlights the importance of investigating the long-term effects of screen time on mental health.

In "An economic theory of depression and its impact on health behavior and longevity", Holger Strulik developed a model to understand the impact of depression on health behavior and longevity. The model showed that depressed individuals tend to consume more unhealthy goods, save less, invest less in their health, and exercise less due to reduced life satisfaction. The endogeneity of health, aging, and longevity in the life cycle model reduced incentives for depressed individuals to engage in healthy activities (Strulik, 2018). This research demonstrates the need to understand the underlying mechanisms that link mental health and health behaviors and the importance of addressing depression as a potential barrier to healthy living.

When conducting a cost-benefit analysis, the correlation between screen time and mental health will be determined. A natural experiment conducted in 2022 by Laura Marciano et al. examines screen time and adolescents' mental health before and after the COVID-19 lockdown in Switzerland has been found. The relevance of using a specific, historical period to compare increased screen time and mental health lies in the fact that it allows researchers to explore the impact of a specific event on screen time and mental health without the need for a controlled experiment. In the case of the study conducted by Laura Marciano et al., the COVID-19 lockdown in Switzerland provided a unique opportunity to examine the effects of increased screen time due to remote learning and social distancing measures on the mental health of adolescents. This type of natural experiment can provide valuable insights into the relationship between screen time and mental health that may not be possible to observe under normal circumstances.

Additional data was collected from Centers for Disease Control on Prevention (CDC). The CDC has a subdivision named National Center for Health Statistics where they conducted the Research and Development Survey (RANDS). RANDS[[1]](#footnote-1) began in 2015 as a series of cross-sectional surveys from probability-sampled commercial survey panels. Specifically, RANDS is a research project that has conducted seven rounds of surveys with U.S. adults aged 18 and over. Surveys were completed through web and phone administration and examined various health behaviors and conditions. The survey sizes ranged from 2,304 to 6,896 respondents. Each survey was designed to take 15-20 minutes to complete and included existing questions from the National Health Interview Survey, the National Intimate Partner and Sexual Violence Survey, and the National Survey of Family Growth. Topics in each round of RANDS have varied and have included access to healthcare, chronic conditions, food security, general health, health insurance, opioid use, physical activity, psychological distress, smoking, and disability.

BACKGROUND- *Money spent in the insurance industry for mental health*

The high prevalence of mental illnesses in the United States poses significant challenges from a social policy perspective, given that the associated social costs can be substantial. These costs include reduced labor supply, increased public support payments, diminished educational attainment, decreased life expectancy (with a loss of 13 to 32 years), and elevated costs related to other adverse outcomes, such as incarceration or homelessness (Insel, 2008). Of particular concern is the financial impact of mental illnesses, which was estimated at 519.5 billion US dollars in healthcare expenditures, disability payments, and a less productive workforce in 2015 (Insel, 2015). This implies a significant burden on healthcare systems and individuals who require mental health services. Addressing the issue of mental illness has important implications for social welfare policy and economic well-being in the United States (Insel, 2015). One strategy to address mental illness is to analyze the cost-effectiveness of mental health prevention and promotion. While Insel in 2015 estimated that the financial burden of mental illnesses in the United States was over half a trillion dollars, Hsieh's research in 2017 provides evidence of the significant medical costs associated with depression and depressive symptoms among adults in China.

BACKGROUND- *Costs of depression*

This paper provides the first nationally representative estimate of the medical cost attributable to depression and depressive symptoms amongst the adult population in China. Based on the 2012 China Family Panel Studies survey, the results indicate that these mental health conditions have significant impacts on the individual medical expenditure, and they jointly contribute to 14.7% of total personal expected medical spending in China, with depression and depressive symptoms accounting for 6.9% and 7.8%, respectively (Hsieh, 2017).

The baseline model shows that mental health status has a statistically significant impact on both the probability of using health care services and the amount of medical spending among users of health care services. Specifically, the results indicate that individuals with depressive symptoms are 8.8% more likely to have nonzero medical expenditure and will spend 1,029.78 yuan more on health care services in a year compared to individuals without depressive symptoms (Hsieh, 2017). For individuals with depression, the impacts of mental health status on health care costs are even stronger: they are 11% more likely to use health care services and will spend 1,836.52 yuan more on health care (Hsieh, 2017). These results reinforce the findings obtained from previous studies that the cost impacts of mental illness such as depression are high.

The above conclusions shed light on the urgent need for reforming the current mental health system in China, and further government involvement is required to improve the treatment and prevention of mental health conditions. An important priority of the reform is to move away from a hospital-centered health system towards a patient-centered system, in which patients with mental illnesses and other noncommunicable diseases are incentivized to be treated at the community level[[2]](#footnote-2).

BACKGROUND- *The cost-effectiveness of mental health prevention and promotion interventions*

The cost-effectiveness of mental health prevention and promotion interventions has been a topic of interest in the research community. The findings of several studies have highlighted the importance of examining the economic impact of such interventions. For instance, a study conducted in 2020 by Zhang et al., showed that a 2-stage depression screening plus early intervention resulted in the incremental cost-effectiveness ratio (ICER) of $1,726 USD per quality-adjusted life year (QALY) gained. This indicates the potential cost savings associated with early detection and treatment of depression. Below are a few programs that have been successful around the globe.

A cognitive dissonance intervention for the prevention of eating disorders (EDs) targeting female university students with high body image concerns was found to have an ICER of $856 USD per additional at-risk person reducing ED symptoms (Zhang, 2020). Preventive interventions targeting employees or nurses with elevated risk of mental health problems were also found to be cost saving, with a return of $1.5 USD to $7 USD per $1 USD invested (Zhang, 2020). Universal mental health promotion programs in community settings in the UK were also found to be cost saving under the societal perspective and more effective and more costly under the health sector perspective, with an ICER of £91 per unit improvement on the depression and anxiety symptom scale (Zhang, 2020). These findings underscore the importance of considering the cost-effectiveness of mental health interventions when making decisions about resource allocation and policy development. The recognition of the importance of mental health and the need for policies to improve mental health services has led to the passing of several laws in the United States.

BACKGROUND- *Successful policies that have been passed for the improvement of mental health.*

Over the past few decades, there has been a growing recognition of the importance of mental health and the need for policies to improve mental health services in the United States. In response, several laws have been passed to address the disparities that have existed between mental and physical health insurance coverage. The Mental Health Parity and Addiction Equity Act is a key piece of legislation that mandates private insurance companies to include mental health benefits on the same terms and conditions as physical health benefits. This law prohibits employers from enforcing annual or lifetime dollar limits on mental health coverage that are more restrictive than those imposed on medical and surgical coverage (Zivin, 2022). The implementation of these laws is aimed at enhancing insurance coverage of mental health services and boosting access to such services. Additionally, the Children's Health Act and 21st Century Cures Act have also been enacted to address the mental health needs of children and adults (Zivin, 2022). The study focused on increasing research and treatment of numerous health issues concerning children including autism, asthma, epilepsy, and oral health to name a few. Overall, these policies demonstrate a commitment to improving mental health services and reducing disparities in access to care. However, continued efforts are needed to ensure that individuals receive adequate access to mental health services and that the policies implemented are effective in improving mental health outcomes. Transitioning to historical events, the COVID-19 pandemic has brought attention to the urgent need to address mental health issues.[[3]](#footnote-3)

BACKGROUND- *Culture and mental health resilience in times of COVID-19*

The COVID-19 pandemic had a profound impact on mental health, with people facing social isolation, uncertainty, and grief. The disparities in health outcomes were also highlighted, with communities of color and those with underlying health conditions experiencing higher rates of hospitalization and death (Tubadji, 2021). Against this backdrop, this study investigated the relationship between cultural activities and mental health during times of crisis.

Tubadji’s study found that engagement in cultural activities before the pandemic was linked to higher levels of happiness during the crisis. Unscripted cultural customs, such as collective singing during times of uncertainty, were also found to be correlated with an increase in pro-social behavior and a willingness to assist others. These findings emphasize the importance of culture as a mechanism for bolstering mental health on an individual level and fortifying social capital resilience at a broader level.

The results suggest that policymakers could use nudging techniques to encourage people to consume more culture and engage with cultural practices to promote mental health during crises. These findings have broad policy implications and suggest that policymakers should consider the role of culture in promoting mental health during times of crisis.

BACKGROUND- *The association between screen time and mental health during COVID-19*

A recent study by Smith et al., has examined the relationship between screen time and various demographic and health factors in a sample of individuals living in England during COVID. The results showed that those who were aged 18-34 years, with high annual income (≥£60,000), living in England, and currently smoking had higher screen time per day (≥6 hours/day) than those with low screen time (<6 hour/days) (Smith, 2020). Moreover, individuals with high screen time reported spending less time in moderate-to-vigorous physical activity per day and had a higher sitting time per day during self-isolation. Interestingly, the overall mean screen time per day was 7.2 (3.8) hours, with younger adults having a higher average screen time of 8.8 (3.7) hours compared to those aged ≥65 years with 5.2 (2.9) hours (Smith, 2020).

The study also investigated the relationship between screen time and mental health outcomes. After adjusting for potential confounding factors, the results showed a positive association between screen time per day and poor mental health in the overall sample. These findings suggest that high screen time may be a risk factor for poor mental health and highlight the need for interventions to reduce screen time in certain populations.

Overall, the study sheds light on the factors associated with high screen time and the potential negative impacts on mental health. Future research could investigate the underlying mechanisms driving these relationships and develop interventions to reduce screen time and improve mental health outcomes.

BACKGROUND- *The impact of screen time changes on anxiety during the COVID-19 pandemic*

The COVID-19 pandemic has led to a surge in screen time as individuals spend more time indoors due to lockdown measures. Chen et al.’s study in 2022 aimed to investigate the impact of increased screen time on mental health, sleep quality, and physical activity levels. The results showed that 85.8% of participants reported an increase in their screen time after the pandemic outbreak, with over half (53.3%) indicating higher levels of anxiety than before (Chen et al., 2022). Additionally, 26.1% of participants reported lower sleep quality, while 21.6% reported higher sleep quality than before the pandemic. Furthermore, 36.9% of participants experienced more difficulty falling asleep, and 51.5% reduced their physical activity levels after the virus outbreak (Chen et at., 2022).

Spearman's correlations indicated that higher anxiety levels were associated with longer screen time and longer sleep latency, while lower anxiety levels were linked with better sleep quality and more physical activity. Notably, screen time was significantly correlated with all variables, highlighting its pervasive impact on mental health, sleep, and physical activity.

The findings of this study emphasize the detrimental impact of increased screen time on mental health, sleep, and physical activity levels. These results highlight the importance of monitoring and managing screen time, promoting physical activity, and improving sleep hygiene to mitigate the negative effects of the pandemic and prolonged indoor time.

DATA

The Research and Development Survey (RANDS) is a series of cross-sectional surveys from probability-sampled commercial survey panels that began in 2015. RANDS has been used for methodological research at the National Center for Health Statistics (NCHS). These methodological research efforts include the use of close-ended probe questions and split-panel experiments to evaluate question-response patterns and the development of statistical methodology for the calibration of survey estimates. The survey results have been utilized to evaluate estimation approaches for health outcomes from recruited survey panels, including propensity score adjustment and calibration.

Seven rounds of surveys have been completed, with responses collected during fall 2015, spring 2016, spring 2019, summer 2020, winter 2022, summer 2022, and fall 2022, respectively referred to as RANDS 1 through RANDS 7. RANDS 1 through 3 collected responses using web administration, while RANDS 4 through 7 utilized web and phone administration. Each survey examined a sample of U.S. adults aged 18 and over, with respondent sample sizes ranging from 2,304 (RANDS 1) to 6,896 (RANDS 5). The questionnaires were designed to be completed within 15 to 20 minutes and ask about health behaviors and conditions. The specific topics in each round of RANDS have varied and have included access to and use of health care, chronic conditions, food security, general health, health insurance, opioid use, physical activity, psychological distress, smoking, and disability. For the purpose of this study, data from RANDS 1-3 will be used as pre-COVID-19 data. Other data was collected through the Pew Research Center.

Pew Research Center[[4]](#footnote-4), a nonpartisan think tank located in Washington, D.C., is widely regarded for its systematic and impartial approach to research on a wide range of topics. The center conducts public opinion polling, demographic research, content analysis, and other data-driven social science research, including studies on politics, social issues, religion, technology, and the media.

In the context of this research, locating data on internet usage during the COVID-19 pandemic posed a significant challenge. Many sources provided only percentage changes, and most data was only available on a country-level basis, which was insufficient for this research's objective. However, Pew Research Center's American Trends Panel (ATP) was found to be a valuable source for individual-level data on internet usage.

The ATP is a nationally representative panel survey of the U.S. adult population, initiated in 2014, that is used to study a wide range of topics, including technology use, social and demographic trends, and political views. The ATP dataset[[5]](#footnote-5) is publicly available to researchers and contains detailed demographic information about panelists, as well as their responses to questions asked in multiple waves of the survey.

The ATP dataset itself comprises 102 waves, with each wave focused on a different topic, such as environmental concerns and activism, technology companies and policy issues, online harassment, race relations, and COVID-19, etc. As a result, locating relevant data from the dataset was a complex and time-consuming process, as each wave must be reviewed individually to obtain the desired information. Specific waves for this research included wave 72[[6]](#footnote-6) and wave 93[[7]](#footnote-7).

EMPERICAL STRATEGY

This study aims to investigate the relationship between increased internet usage and its negative impacts on mental health. To test this hypothesis, the null hypothesis (H0) is formulated as "internet usage does not affect mental health," and the alternative hypothesis (H1) is stated as "internet usage affects mental health." A 95% confidence interval was chosen for conducting the statistical analysis.

By looking at Figure 1, we can see an increasing trend in anxiety symptoms for respondents in the United States who reported symptoms of anxiety disorder in the last seven days or two weeks from April 2020 to January 2023. There tends to be an increase symptoms up until November of 2020. Additionally, if we look at Figure 2, we can see an increase in screen usage during COVID.

For pre-COVID analysis, datasets were obtained from RANDS, as discussed in the Data section. Internet usage values were converted so that units were all the same metric. This was necessary as some responses measured internet usage daily, while others weekly. Without taking this step, results would be skewed and misleading. Notably, the change in the surveying company after round 2 of RANDS resulted in a lack of information on internet usage, which posed a challenge to compare pre-COVID and during COVID values. This is why data from Pew Research Center was used instead of RANDS data for this time period.

For COVID-19 data, datasets from Pew Research Center were used. It is important to note that for internet usage times, responses were qualitative instead of quantitative. The qualitative responses for internet usage made it infeasible to run a normal regression model. Therefore, this study opted for a logistic regression model that created a binary subset for each of the four answer choices a respondent could choose from. This method allowed the analysis of the qualitative responses effectively.

Between pre-COVID and COVID data, a problem of different variable lengths occurred while running logistic regressions. This emerged due to using different datasets to run regressions. Mental health data came RANDS while internet usage data came from PRC. To address this matter, the length of internet usage data was reduced to match the length of mental health variables. Despite the option of forecasting future mental health values, it was not pursued due to time constraints.

EMPERICAL FRAMEWORK

To explore whether the state of one’s mental health can be explained by screen usage pre-COVID, we estimate the following regression model:

*The estimation of internet usage and its effects on mental health used pre-COVID:*

Internet Usageid= µo + β1(ANX\_1)id + β2(ANX\_3)id + β3(MODNO\_N)dt + β4(STRNGNO\_N)id + β5(VIGNO\_N)id + β6(ALC12MNO\_N)id + β7(ACIWTHLS)id + β8(ACISAD)id + β9(ACIRSTLS)id+ β10(ACINERV)id + β11(ACIHOPLS)id + β12(ACIEFFRT)id + εid

Where “i” represents the individuals’ response and “d” represents which dataset the response came from. To explore whether the state of one’s mental health can be explained by screen usage during COVID, we estimate the following regression model:

*The estimation of internet usage and its effects on mental health used during COVID:*

Internet Usageid = µo + β1(ANXFREQ)id + β2(ANXLEVEL)id + β3(DEPFREQ)id + β4(DEPLEVEL)id + β5(SRHPSYCH)id + εid

Where “i” represents the individuals’ response and “d” represents which dataset the response came from. It is important to note the variables differ between the two equations above. This is because different commercial survey panels were used to conduct these surveys. Strategic selection was determined to create as similar equations as possible for the two equations. The extra variables added to the first equation were selected to investigate the effects of internet usage on physical health. While this was not the main focus of this study, it was implemented out of curiosity derived from background research remarking how internet usage as a negative impact on physical health. More specific information on the variables selected for this study can be found in the footnotes[[8]](#footnote-8)[[9]](#footnote-9)[[10]](#footnote-10)[[11]](#footnote-11).

The population for this study consisted of an average age of 48 with a standard deviation of 15.54 as seen in Figure 3. The gender demographic was split evenly (50.78% men, 49.21% female). Many participants either had a full-time job or were retired (combined they accounted for 74.27% of the population) As seen in Figure 4. Approximately 80% of participants have some college experience or a 4-year bachelors degree or more. The remaining population have a high school graduation or less. In terms of income, there was a spread of incomes. In figure 5, we can see that the majority of participants had an income under $15,000.

RESULTS

In this study, an investigation was conducted to examine the impact of internet usage on individuals' mental health. The study employed data from two pre-COVID surveys, namely RANDS1 and RANDS2, as well as two COVID-related surveys, RANDS.COVID1 and RANDS.COVID2, along with supplementary datasets, ATP and ATP2. The aim was to determine the relationship between internet usage and various measures of anxiety, depression, physical activity, and related factors.

The present study utilized regression analysis to examine the association between internet usage and several outcome measures of health. The results showed a negative association between internet usage and ANX\_1, a measure of anxiety, where a 1% increase in internet usage led to a 1.960% decrease in ANX\_1, reaching statistical significance at the 99.9% level. This finding suggests that there is a strong relationship between internet usage and anxiety given a high significance level. Moreover, internet usage was negatively associated with ACIEFFRT and ACINERV, measures of lethargy and nervousness, respectively. Specifically, a 1% increase in internet usage led to a 9.988% decrease in ACIEFFRT and a 1.780% decrease in ACINERV. However, it is noteworthy that these associations were only significant at the 90% level, indicating the need for caution when interpreting these results in future research. Additionally, the results revealed a negative association between internet usage and VIGNO\_N, a measure of vigorous physical activity, where a 1% increase in internet usage led to a 4.662% decrease in VIGNO\_N, reaching statistical significance at the 95% level. Additional results can be seen in Table 1. Taken together, these findings suggest that internet usage may have negative impacts on both mental and physical health.

It is interesting to note that there were some positive relationships between internet usage and other health variables. There was a positive association with STRNGO\_N, a measure of strength-training exercises, and ACISAD, a measure of how often a participant felt so sad that nothing could cheer them up. As internet usage increased by 1%, these variables increased by 3.332% and 1.780% respectively. STRNGO\_N reached a statistical significance at the 99.99% level, and ACISAD reached a statistically significant level at 95%. Further investigation is required to fully comprehend these complex findings.

The RANDS2 data yielded similar findings, indicating that internet usage had a negative impact on ANX\_3 and ACINERV, measures of anxiety and nervousness, respectively. However, a positive relationship was observed between internet usage and MODNO\_N, a measure of light or moderate physical activity. Additional results can be seen in Table 2. The results from both the RANDS1 and RANDS2 datasets suggest a consistent negative association between internet usage and anxiety measures, while also highlighting the potential positive relationship between internet usage and certain physical activity measures and depression levels.

In contrast, the analysis of the COVID-related surveys, RANDS.COVID1 and RANDS.COVID2, did not yield many significant findings when considering any of the subsets. Using RANDS.COVID1 data with ATP data, there was a negative relationship between almost always using internet and depression levels, DEPLFREQ. As internet usage increases by 1%, depression levels negatively decreased by 3.623% at a 95% significance level. Additional results can be seen in Table 3. There were no significant findings using RANDS.COVID2 data with ATP data. This was a disappointment in the world of research, but it highlights the importance of research needed to understand that although internet usage is increasing in the United States, it is not having as significant impacts on mental health as we originally thought.

An examination of the results from RANDS.COVID1 and ATP2 revealed a modest relationship between using the internet several times a week and DEPLEVEL3, with individuals feeling somewhere in between a little and a lot depressed (beta = -0.015%). This reached a statistical significance level of 95%. Additional results can be seen in Table 4. It is important to note that there were no significant findings using RANDS.COVID2 data and ATP2 data. These results were perceived as perplexing as the same variables were used in RANDS.COVID1 and ATP2.

The internal validity of the study could have been affected by several factors, including the method of response measurement used in RANDS.COVID data and ATP data. If the participants had given numerical responses like the pre-COVID data, the results could have been different. Moreover, the perception of categorical measurements varies among individuals, which could have also influenced the results. Another factor that could have impacted the internal validity of the study is the change in instruments used. The shift in procedures from pre-COVID to COVID times could have had an impact on the results due to the measurement of different variables, leading to inconsistent findings over time. In conclusion, these factors should be taken into account when interpreting the results of the study.

From an external validity perspective, the findings from this study can be generalizable to other populations during pre-COVID and during COVID. The samples used in this study reached all walks of life in the United States. If this study only focused on a single state, the results would be less generalizable to greater populations. Additionally, the context in which this study was conducted made the results more generalizable. These surveys were conducted at the comfort of one’s home via web and phone administration. If this study was conducted in a laboratory setting, it may not generalize to real-world settings. It is important to note the time period in which a study was conducted. This study looked at data pre-COVID and during COVID. If more time was allotted for this research, I would have looked at data post-COVID pertaining to internet usage and mental health rates. Because of this, this study is cannot be representative of post-pandemic times.

Overall, the results of this study suggest that the impact of internet usage on individuals' well-being may vary depending on the context in which it is considered. These findings may have implications for public health interventions aimed at promoting physical activity and mitigating the negative effects of internet usage on mental health. Further research in this area may shed more light on the underlying mechanisms that drive the observed associations.

CONCLUSION

Mental illness is a significant public health issue affecting millions of people globally. The most common mental illnesses include anxiety disorders, depression, bipolar disorder, and schizophrenia, and they can have a profound impact on an individual's quality of life. While the causes of mental illness are multifaceted, excessive smartphone use has been linked to increased symptoms of anxiety and depression, sleep disturbances, and decreased social interaction. The negative impact of excessive screen time has been found to be more pronounced in children, highlighting the importance of addressing screen time as a potential barrier to healthy living. Studies such as Karl Taylor et al.'s study and Adrián Nieto and Marc Suhrcke's study have investigated the relationship between screen time and mental health, with varying results. Holger Strulik's research highlights the importance of addressing depression as a potential barrier to healthy living. Natural experiments such as Laura Marciano et al.'s study can provide valuable insights into the relationship between screen time and mental health. Additional data from the Centers for Disease Control and Prevention's Research and Development Survey (RANDS) have also provided intriguing findings, indicating a negative association between internet usage and symptoms of anxiety and depression. Proper diagnosis, treatment, and management of mental illness are crucial to improving an individual's overall well-being and reducing the societal burden of mental illness. Therefore, more research is needed to understand the complex relationship between screen time and mental health and to develop effective interventions to address this issue.

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**APPENDIX**

**Chart, histogram

Description automatically generatedFigure 1:**

**Chart, line chart

Description automatically generatedFigure 2:**

**Chart, bar chart

Description automatically generatedChart, histogram

Description automatically generatedFigure 3:**

**Figure 4:**

**Chart, bar chart, histogram

Description automatically generatedFigure 5:**

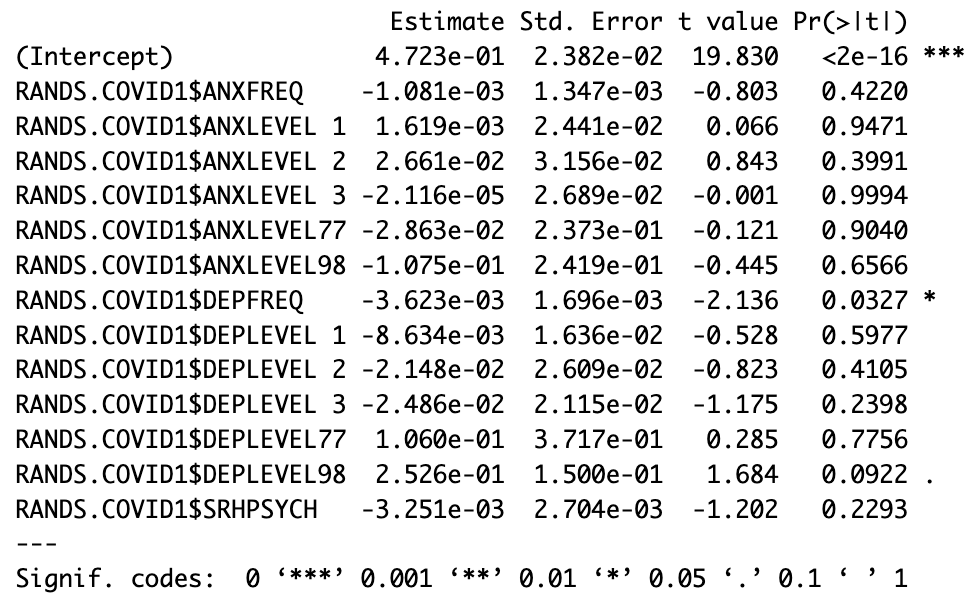
**TABLES**

**Text, table

Description automatically generatedTable 1:**

**Table

Description automatically generatedTable 2:**

**Table 3:**

**Table 4:**

**Table

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1. <https://www.cdc.gov/nchs/rands/data.htm> [↑](#footnote-ref-1)
2. Additional topics include “The development of mental health care in Guangzhou, China” This paper discusses the development of mental health services in Guangzhou, a major city in China. It covers the historical trajectory of mental health care in Guangzhou and how it reflects the development of mental health services across China. The paper also highlights the current mental health care delivery system and resources in Guangzhou, including the psychiatric specialist hospitals, psychiatric units of general hospitals, and community mental health care. The paper then focuses on community mental health care in Guangzhou, discussing its organizational setup, management, and services. The paper also explores the design of community mental health service models and the challenges in the post-covid-19 era. Finally, the paper provides considerations and recommendations for mental health service delivery in Guangzhou in the future (Li et al., 2023) [↑](#footnote-ref-2)
3. Additional topics include the article “Mental health law, policy & program in India”. The paper discusses the history of mental health legislation in India and highlights the influence of colonial laws on the country's mental health policies and programs. The growth of community psychiatry and international developments such as the UN Convention on Rights of Persons with Disabilities and the Movement for Global Mental Health have significantly impacted the mental health sector in India. However, the paper notes a disjuncture between the progressive mental health law and policy framework and the national and district mental health programs. The paper also raises critical questions about the dominance of western biomedical psychiatry and the potential of technology-assisted solutions for mental health care in India (Ranade et al., 2022). [↑](#footnote-ref-3)
4. <https://www.pewresearch.org/about/> [↑](#footnote-ref-4)
5. <https://www.pewresearch.org/american-trends-panel-datasets/> [↑](#footnote-ref-5)
6. <https://www.pewresearch.org/journalism/dataset/american-trends-panel-wave-72/> [↑](#footnote-ref-6)
7. <https://www.pewresearch.org/politics/dataset/american-trends-panel-wave-93/> [↑](#footnote-ref-7)
8. <https://www.cdc.gov/nchs/rands/files/RANDS1_codebook.pdf> [↑](#footnote-ref-8)
9. <https://www.cdc.gov/nchs/rands/r1probsample.htm> [↑](#footnote-ref-9)
10. <https://www.pewresearch.org/journalism/dataset/american-trends-panel-wave-72/> [↑](#footnote-ref-10)
11. <https://www.pewresearch.org/politics/dataset/american-trends-panel-wave-93/> [↑](#footnote-ref-11)