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Access to Care, Food Quality Index, and Employment as Predictors of Poor Mental Health Days in Ohio, Louisiana, California, and New York

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Abstract

Objective: Analyze how the availability of mental health providers has changed in Ohio from 2016 to 2020 with relation to changes in mental health outcomes reported. Compare to other regions of the United States (Louisiana, California, New York) in terms of access to healthcare, unemployment status, and food quality index. Lastly, to identify which socioeconomic and health factors are most predictive of poor mental health days.

Methods: Participant data from Ohio (OH), Louisiana (LA), California (CA), and New York (NY) was acquired from countyhealthrankings.org annual survey results that were published from 2016 through 2020. SPSS was utilized for statistical analysis in the form of Student T-tests, linear regression, and ANOVA.

Results: From 2016 to 2020, there was a statistically significant increase in the number of poor mental health days and the percent reporting frequent poor mental health days in OH (4.0 days in 2016 compared to 4.39 days in 2020). In terms of the percentage of the population reporting frequent poor mental health days, OH had a lower percentage compared to LA but a higher percentage compared to CA and NY. The ratio of population-to-provider was found to also have decreased from 2016 to 2020, indicating an increase in the number of providers available per given population; however, OH was found to have a higher population-to-provider ratio when compared to CA and NY. OH has a statistically lower unemployment rate and a higher food environment index than LA, but there was no significant difference when compared to CA and NY. Unemployment was found to be directly correlated with increased number of poor mental health days and increased percentage of population with frequent poor mental health days, while food environment index was inversely related to either one. These two factors were confirmed by linear regression to be predictive of both increased mental health days and increased per4centage of frequent poor mental health days.

Key Words: mental health outcomes, mental health providers, unemployment, food index

Introduction

Mental health is an important topic of concern, particularly in the United States where in 2017 there were over 46.6 million adult American (over the age of 18) reporting a mental illness.[1] Furthermore, this lack of access and poor health outcomes are exacerbated in a time when a viral pandemic has ravaged much of the nation's healthcare infrastructure, let alone shutdown outpatient mental health treatment facilities.[2,3] COVID 19 and the hard reality of quarantine life have become major contributing factors to mental health of populations and its lasting negative impacts in the United States are still yet to be fully determined. Recent epidemiological studies have shown how this pandemic has negatively impacted mental wellbeing of adolescent in China and Italy, two populations that have been already heavily affected since the earliest days of the disease spread.[4,5] Although the long-term impact of this pandemic on the mental health status of populations is still being studied, the concerns for deleterious effects are very real. All of this renews more interests in better understanding which societal factors are predictive of mental health outcomes. Access to mental health providers, employment status, and food quality index are among these factors that have been studied previously for their relation to mental health and have namely been of interest as during these quarantine times.

Access to appropriate mental health providers is an essential aspect of a population's mental health, but it is a challenging aspect to address in areas of the country that have very little available access to care. Previous epidemiological data reveal that among mental disorders, Major Depressive Disorder is the most prevalent in the continental United States as of 2019.[6] The prevalence of mental health and its contributing factors are well studied in the United States.[7] Measures of depression treatment often are based on number of patients reporting active treatment through medication and behavioral therapy—both therapies that require a licensed medical professional to administer. Epidemiologic studies in Brazil and the United States have examined access to mental healthcare and found extensive disparities that exist and prevent those with lower incomes to obtain necessary mental health treatment.[8–10] These socioeconomic disparities and lack of access lead these patients to report poorer outcomes than populations with adequate mental healthcare.[8–10] The disparity in providers is further exacerbated during an epidemic where there is a great shortage of health care providers in general.

In addition to access to appropriate mental health care, employment status has been regarded as a predictor of negative mental health outcomes.[10–12] In a prospective study using an international cohort, Jefferis et al. showed how unemployment lead to moderately raised risks of reporting depressive symptoms and major depression 6 months later.[12] With more and more jobless Americans unable to return due to the health crisis, unemployment is a hot issue that many states and the federal government are zoning in on. In the last 2 months, the employment rate rose to 14.7% according the to the U.S. Bureau of Labor statistics, with a loss of about 20.5million non-farm jobs in April alone.[13] Although the physical damage of unemployment is readily visible in the empty restaurants/bars, closed shopping districts, educational centers, etc., the mental health impact is much more subtle and necessitates closer investigation as a predictor of mental health status.

Food security is also central aspect factor predictive of mental health status as disparities in food access are noted to impact the mental health status of patients. A number of studies using NHANES data shows how household food insecurity is positively correlated with depression among lower-income household and those with underlying chronic disease.[14,15] Upon interview of patients and further clinical inquiry, food insecurity is found to manifest as worsening anxiety and distress in patients as they struggle with their feelings of powerlessness and uncertainty in their ability to manage their nutrition.[14] While food shortages have also started to become a common theme during quarantine, its association with mental health outcomes continues to be studied and will be another essential factor predictive of mental health.

With the mental health impact of the current public health crisis in center stage, we revisit the age-old topic of mental health and its predictors of outcome—this time, in the microcosm that the state of Ohio represents. In this study, we look at the availability of mental healthcare providers, unemployment numbers, food index ratings, and number of poor mental health days reported in Ohio in 2016 and 2020 and compare how they have changed over time. We then look at how these most current Ohio statistics in 2020 compare to other geographically distinct states: Louisiana, California, and New York. Lastly, we analyze the relationships between access to mental healthcare providers, unemployment status, and food index ratings to understand which of these are most predictive of poor mental health days in Ohio, Louisiana, California, and New York in 2020.

Research Questions and Expected Outcomes

1) How has the number of mental health providers significantly changed in 2016 and 2020 for Ohio?
2) How has the number of reported poor mental health days significantly changed in 2016 and 2020 for Ohio?
3) How does unemployment, food environment index, and mental health providers in Ohio compare to following states: LA, NY, CA in 2020?
4) Does unemployment, food environment index, and mental health providers predict the number of reported poor mental health days in 2020?

For RQ1 and RQ2, it is expected that there will be an increasing trend in access to mental health care providers in Ohio. I then expect to see a statistically significant decrease in reported poor mental health days over time from 2016 to 2020. From the literature review, we established that there has been a greater push for mental healthcare and since the inception of the Affordable Care Act, there has been a resurgence in health providers (including mental health).

For RQ3, it is expected that the distribution of the following factors (both dependent and independent) will be similar (no significant difference) among the studied states: Ohio, Louisiana, California, New York. The initial literature review revealed that mental health patients are more concentrated in areas of greater population densities (urban settings). Although these states are geographically distinct, we do not anticipate any major differences in the distribution of socioeconomic status; however, we do expect to see difference in mental health outcomes (e.g. number of poor mental health days and percentage with frequent mental distress) if there are difference in access to mental health providers, unemployment, or food environment index. Specifically, poorer mental health outcomes in those states with poorer access to mental health providers, unemployment, or food environment index.

For RQ4, it is expected that there will be a positive relation between reported poor mental health days and unemployment such that as the rating for a state's unemployment increased, there will be an increase in poor mental health days reported. Conversely, it is expected that there will be a negative relationship between reported poor mental health days and the factors of food index and access to mental health providers such that as the rating of food index and access to providers increases, there will be a decrease in number of reported mental health days in each respective analysis. Numerous literatures and studies cited previously have detailed the effects of employment status, food quality, and access to care to reflect the above expected outcomes.

Methods

Context/Protocol/Data Collection

All data sets were borrowed from the countyhealthrankings.org, a publicly available online database run by County Health Rankings and Roadmaps and created in partnership with in the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute Data provided serves as a "snapshot" of a community's health, a measure of health data in all 50 states. The following are important points with regards to data collection and modeling that

County Health Rankings and Roadmaps noted when compiling their data from 2016 to 2020 for Ohio, Louisiana, California, and New York.

In measuring "Mental Health Providers" in 2020, the National Provider Identification (NPI) data files from 2019 were used which requires electronic health records to obtain an identification number but not maintain the number. One limitation noted is that these findings may overestimate the number of actual active health providers who may discontinue to practice but remain registered as "active" on NPI. No reported data was provided for the county of Cameron, LA with regards to Mental Health Providers, hence this county was excluded from further statistical analysis.

Data from "Unemployment" in 2020 originates from the 2018 data collected by Local Area Unemployment Statistics (LAUS) program of the Bureau of Labor Statistics which used a variety of modeling techniques: a signal-plus-noise time-series model for states; a building block approach ("Handbook procedure") for labor market areas; and disaggregation procedures for counties and cities. The limitation to this measure is that it does not account from the "discouraged worker", an individual who wants to work but has given up seeking employment

Data from "Food Environment Index" in 2020 originates from the USDA's 2015-2017 "Atlas" survey which collected data on food choices, health and well-being, and community characteristics. Modeling was then used to provide the following data: Limited access (defined as low income households outside the vicinity of a local grocer) and Food insecurity (an estimate of individuals with no reliable access to food in the past year). This data determined the rank that a county would receive on a scale of 0 (worst food index) to 10 (best food index). No limitations were noted for this data set.

Besides the exclusion noted above, I do not intend to use any further data exclusion criteria. All demographical data provided by the countyhealthranking.org will be utilized during the analysis of the independent and dependent variables.

Data Analysis

Data from countyhealthrankings.org was exported as an excel data set that was edited to isolate only the independent and dependent variables to be studied. Statistical analysis was conducted using SPSS version 24.0 (IBM SPSS, IBM Corp., Armonk, NY, USA).

A series of paired T-test between 2016 data and 2020 data will be conducted in the following manner: Access to mental health providers in Ohio 2016 and 2020 will be compared for Research Question 1 (RQ1) and similarly, the number of reported poor mental health days in Ohio 2016 and 2020 will be compared for RQ2.

For RQ3, a series of ANOVAs between 2020 data in Ohio and the comparison states (Louisiana, California, New York) will be conducted in each of the studied factors to assess difference in Access to Mental Health Providers, Poor Mental Health Days, Unemployment, and Food index.

For RQ4: "ANOVA Post-Hoc analysis" between unemployment, food environment index, mental health providers, poor health days will be conducted in for Ohio to assess for statistically significant differences following factors. This will be accomplished by correlation of Poor Mental Health Days to the list of factors above for Ohio 2020 and similarly for the remaining states: Louisiana, California, New York.

Additionally, for RQ4, another analysis will include Linear regression between unemployment, food environment index, mental health providers, poor health days for Ohio 2016 thru 2020

Results

RQ1: How has the number of mental health providers significantly changed in 2016 and 2020 for Ohio?

The ratio of population to mental health providers has decreased (indicating more providers per patient) from 1992:1 (patient:providers) in 2016, to 944:1 in 2020 ($t= 3.533$, $p<.001$) (Table 1, paired t-test).

Table 1: Ratio of Patients to mental health providers in Ohio from 2016 to 2020

Year in Ohio	N	Population:Provider Ratio	SD
2016	88	1992:1	3110
2020	88	944:1	937

Abbreviations: SD, Standard Deviation; N, Number of counties
[a]statistically significant difference from 2016 ($p< 0.001$)

RQ2: How has the number of reported poor mental health days significantly changed in 2016 and 2020 for Ohio?

The number of poor mental health days reported was found to have a statistically significant increase in Ohio from 4.05 days in 2016 to 4.39 days in 2020 ($t= -20.95$, $p < .0001$) (Table 2, paired t-test)

Table 2: Number of Poor Mental Health days reported in Ohio from 2016 and 2020

Year in Ohio	N	Mean Number of Poor Mental Health Days	SD
2016	88	4.05	0.27
2020	88	4.39	0.31

Abbreviations: SD, Standard Deviation; N, Number of counties
[a]statistically significant difference from 2016 ($p< 0.001$)

Additionally, the Percent with Frequent Mental Distress showed statistically significant increase in Ohio from 12.02% in 2016 to 13.48% in 2020 ($t= -41.95$, $p< 0.001$) (Table 3, paired t-test).

Table 3: Percent with Frequent Mental Distress reported in Ohio from 2016 and 2020

Year in Ohio	N	Mean Percent with Mental Distress	SD
2016	88	12.02%	0.91%
2020	88	13.48%	1.03%

Abbreviations: SD, Standard Deviation; N, Number of counties
[a]statistically significant difference from 2016 ($p< 0.001$)

RQ 3: How does the ratio of mental health providers, the percent with frequent mental distress unemployment, and the food environment index in Ohio compare to LA, NY, CA?

An ANOVA was conducted to compare Ohio's ratio of population to mental health providers in 2020. A statistically significant difference was found between Louisiana, California, and New York ratio of population to providers in 2020 different ($F_{3,267} = 10.067$, $p < 0.001$). Post hoc test showed that a statistically significant difference in the ratio of population to healthcare providers seen in California (354:1) compared to Ohio (944:1) such that the ratio of population to provider was greater in Ohio indicating a lower availability of mental health providers at the $p < 0.001$ level. Additionally, there a statistically significant difference between New York (593:1) and Ohio at the $p < 0.05$ level (Table 4, one-way ANOVA).

Table 4: Ratio of population to mental health providers in Ohio compared to LA, CA, NY

State	N	Population:Provider Ratio	SD
OH	88	944:1	937
LA	64	910:1	905
CA	58	354:1	179
NY	62	593:1	349

Abbreviations: SD, Standard Deviation; N, Number of counties; OH, Ohio; LA, Louisiana; CA, California; NY, New York;
[a]statistically significant difference from CA ($p < 0.001$)
[b]statistically significant difference from NY ($p < 0.05$)

The second ANOVA was conducted to compare Ohio's percent of the population reporting frequent mental distress in 2020. A statistically significant difference was found between Louisiana, California, and New York ($F_{3,268} = 119.1$, $p < 0.001$). Post hoc analysis showed that the difference in percentages was seen between all states such LA had a higher frequency than Ohio (15.66% versus Ohio's 13.48%) at the $p < 0.001$ level; however, CA (12.14%) and NY (12.31%) had lower percentages than Ohio at the $p < 0.001$ level (Table 5, one-way ANOVA).

Table 5: Percent with frequent mental distress in OH, LA, CA, NY

State	N	Mean Percent with Mental Distress	SD
OH	88	13.48%	1.03%
LA	64	15.66%	1.50%
CA	58	12.14%	1.34%
NY	62	12.31%	0.71%

Abbreviations: SD, Standard Deviation; N, Number of counties; OH, Ohio; LA, Louisiana; CA, California; NY, New York.
[a]statistically significant difference from LA, CA, NY ($p < 0.001$)

The next sets of ANOVAS were used to evaluate unemployment and food environment index of the three states and Ohio. For the ANOVA comparing Ohio's unemployment rate in 2020, a statistically significant difference was found between Louisiana, California, and New York ($F_{3,268} = 119.1$, $p < 0.001$). Post hoc analysis showed that the difference in percentages was seen between OH (4.82) and LA (5.60) at the $p < 0.05$ level, indicating that LA had a significantly higher unemployment rate (Table 6, one-way ANOVA).

Table 6: Rate of unemployment in OH, LA, CA, NY

State	N	Mean Unemployment	SD
OH	88	4.82	1.05
LA	64	5.60	1.27
CA	58	5.24	2.65
NY	62	4.50	0.70

Abbreviations: SD, Standard Deviation; N, Number of counties; OH, Ohio; LA, Louisiana; CA, California; NY, New York;
[a]statistically significant difference from LA ($p < 0.05$)

The following ANOVA evaluated the Food Environment Index in 2020. A statistically significant difference was found between Louisiana, California, and New York ($F_{3,268} = 212.22$, $p < 0.001$). Again, post hoc analysis showed that the difference existed between OH (6.04) and LA (9.86) at the $p < 0.001$level; however, the difference was in such a way that LA had a greater Food Environment index that Ohio (Table 7, one-way ANOVA).

Table 7: Food environment index in OH, LA, CA, NY

State	N	Mean Food Index	SD
OH	88	6.04	1.05
LA	64	9.86	1.27
CA	58	6.212	2.65
NY	62	4.31	0.70

Abbreviations: SD, Standard Deviation; N, Number of counties; OH, Ohio; LA, Louisiana; CA, California; NY, New York;

[a]Statistically significant difference from LA ($p< 0.001$)

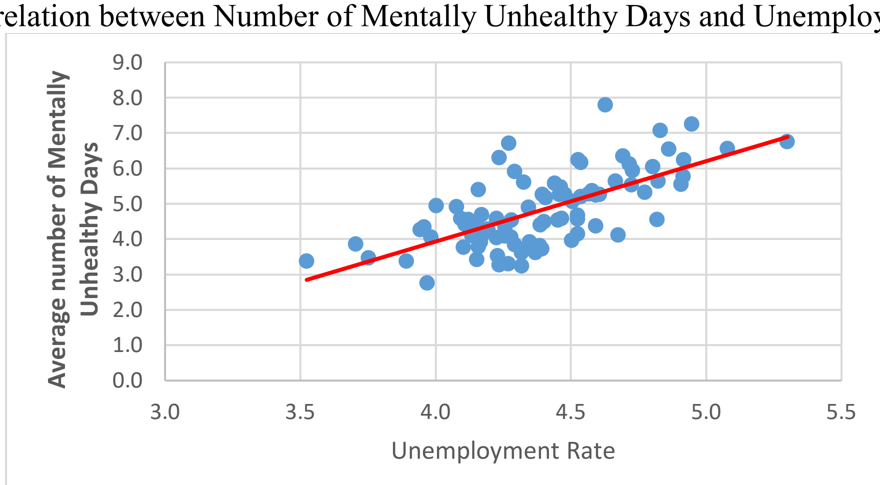
[b]No statistically significant difference was seen between OH and NY (4.31) $p= 0.065$.

RQ 4: Does unemployment, food environment index, and mental health providers predict the number of reported poor mental health days in 2020?

Pearson correlation studies were used to examine which of the above factors (Mental Health provider Ratio, Unemployment, Food Index) are associated with poor mental health outcomes (e.g. increased number of reported poor mental health days or increased percentage of the population reporting frequent mental distress).

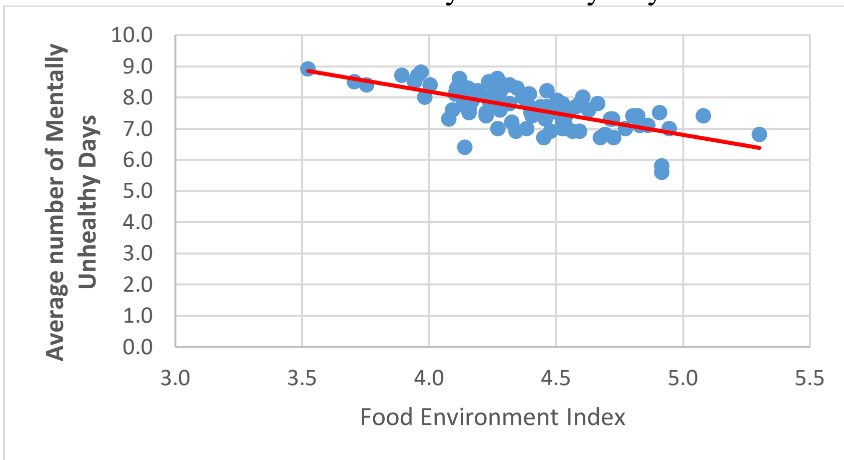
In the first Pearson's correlation study regarding unemployment rate ($r= 0.677$), it was demonstrated that the number of poor mental health days increased as the unemployment rate increased (Figure 1).

Figure 1 Correlation between Number of Mentally Unhealthy Days and Unemployment Rate



Conversely, Pearson's correlation of food environment index ($r= -0.669$) demonstrated that the number of poor mental health days increased as food environment index decreased (Figure 2).

Figure 2 Correlation between Number of Mentally Unhealthy Days and Food environment index



Both correlations were significant at the p< 0.001 level (Table 8).

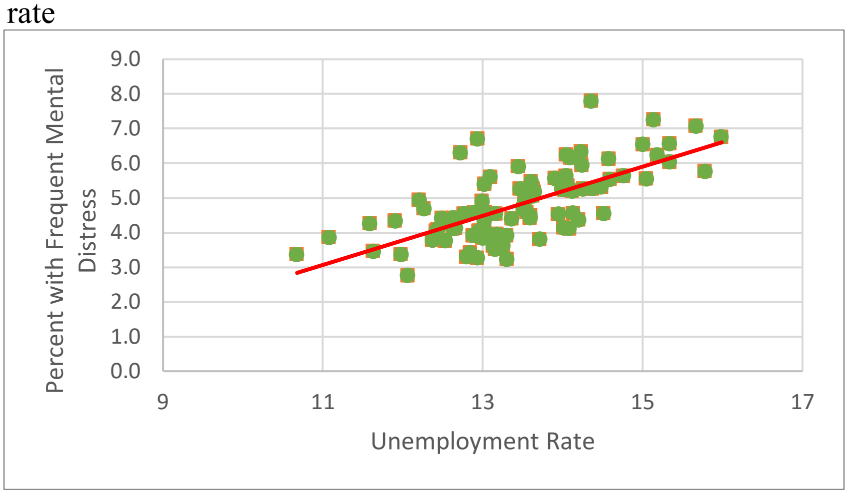
Table 8 Correlations to Average number of Mentally Unhealthy Days

Variable	Number	Pearson Correlation	Significance
Mental Health Provider Ratio	88	-0.096	0.186
Unemployment Rate	88	0.677	0.000[a]
Food Environment Index	88	-0.669	0.000 [a]

[a]Significant at the P<0.001 level

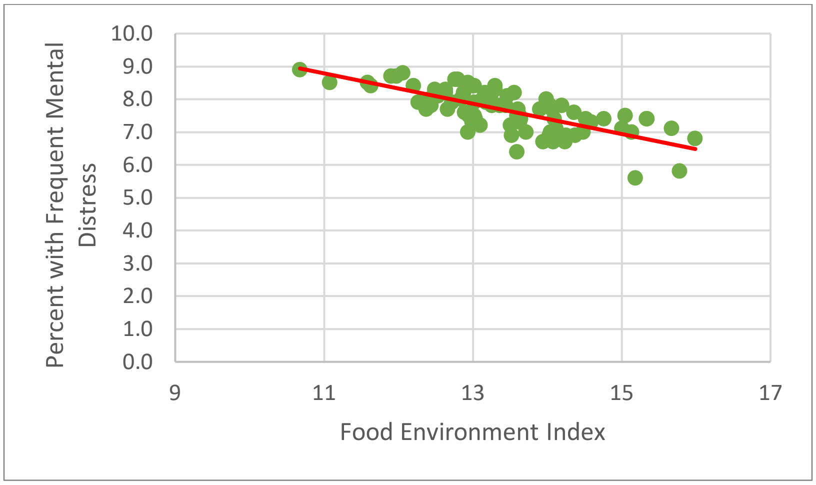
A Pearson's correlation for unemployment rate (r= 0.693) demonstrated that the frequency of mental distress reported increased as the unemployment rate increased (Figure 3).

Figure 3 Correlation between Percent with Frequent Mental Distress reported and Unemployment rate



In contrast, Pearson's correlation of food environment index (r= -0.732) demonstrated that the frequency of mental distress increased as food environment index decreased (Figure 4).

Figure 4 Correlation between Percent with Frequent Mental Distress and Food environment index



Both correlations were significant at the p< 0.001 level (Table 9).

Table 9 Correlations to the Frequency of mental distress

Variable	Number	Pearson Correlation	Significance
Mental Health Provider Ratio	88	-0.104	0.168
Unemployment Rate	88	0.693	0.000[a]
Food Environment Index	88	-0.732	0.000 [a]

[a]Significant at the P<0.001 level

Lastly, a stepwise linear regression was conducted to examine which of the above factors to (Mental Health provider Ratio, Unemployment, Food Index are predictive of poor mental health outcomes (e.g. increased number of reported poor mental health days or increased percentage of the population reporting frequent mental distress). In analysis of predictors of poor mental health days, a best fitting model involving Unemployment rate and Food Environment index was found to be significant ($F_{2,85}$= 21.654, p< 0.001) and accounts for 56.8% of the variance. Unemployment (B= 0.129, t= 4.868, p< 0.001) and Food Environment index (B= -

0.199, t= -4.653, p< 0.001) contributed equally to the model while the mental health providers ratio showed no statistically significant contribution.

With regards to the predictors of the percentage of frequent poor mental health days, a second set of linear regression revealed the best fitting model that was significant ($F_{2,85}$= 74.827, p< 0.001) and accounts for 62.9% of the variance in the percentage of frequent poor mental health days. Like the first linear regression, this model involved Food environment index (B= -0.783, t= -0.732, p< 0.001) and unemployment rate (B= 0.389, t= 4.906, p< 0.001) with both contributing equally. The ratio of Mental Health providers did not contribute significantly to the model.

Discussion

Changes in Ohio Over Time

In the context of a global pandemic, public health should involve examining both the physical health aspect as well as the mental health aspect. This study was used to assess the mental health status of Ohio in 2020 compared to Ohio in 2016 as well as in comparison to other geographically distinct states in 2020. With regards to RQ1, this study did find that the ratio of population to mental health providers has decreased since 2016 (from 1992:1 to 944:1, Table 1), indicating that there has indeed been an increase in the number of mental health providers since 2016. The number of poor mental health days and percentage of population with frequent poor mental health days has increased from 2016 (Table 2 and 3). These two findings suggest that despite an increase in the number of providers, there is still a statistically significant increase in poor mental health outcomes. Therefore, given just these first findings, they are in conflict as literature has shown that more availability of providers should lead to better mental health outcomes.[8–10] Regardless, the reason for this increase may yet to be revealed in the form of socioeconomic factors, namely unemployment and food environment index, which may have changed since 2020.

<u>Ohio Compared to Other States</u>

RQ 3 focused on comparing Ohio in 2020 to other states based on provider ratio, unemployment, food environment index, and percentage with frequent poor mental health days. Overall, the results represent a mixed bag with regards to comparison's to Ohio. In terms of percentage of population with frequent mental distress, Table 5 illustrates that California and New York have the lowest compared to Ohio, while Louisiana have greater percentages than all the other states. Ohio seems to serve as a middle ground when it comes to mental health outcomes. The availability of providers seems to corroborate that same trend as table 4 illustrates the provider ratio in both California and New York is lower than Ohio while the Louisiana has the greater of the ratios. From these first two ANOVAs, there seems to be a trend in the how the number of providers (lower provider ratios) also coincide with better mental health outcomes (lower percentage of population with frequent mental distress) and thus affirming previous literature. Yet, when it comes to evaluating unemployment and food index, the expected outcomes for RQ3 cease as no clear trends are revealed. In comparing unemployment (with Ohio at our "middle ground" at 4.82), New York had a smaller mean unemployment at 4.50 while Louisiana had a higher mean at 5.6; however, California had a higher mean than Ohio as well at 5.24 despite have a less detrimental mental health outcome and much better provider ratio ($p < 0.05$, Table 6). Food environment index followed an even more irregular trend as Louisiana held the best food index at 9.86 (despite having the worse provider ratio and mental health outcomes), while New York's index at 4.31 was worse than Ohio at 6.04 ($p< 0.001$,Table 7).

Correlations to Poor Mental Health in Ohio

While the previous ANOVA findings cannot exactly be used as a measure of correlation, studies have shown that unemployment and food quality are predictors of mental health.[11,12,15] To investigate whether this is the case for the state of Ohio, Pearson correlations were drawn from 2020 data with significant findings seen in the unemployment group and the food environment index group. Using the measure of the number of average numbers of poor mental health days, unemployment showed a positive correlation at 0.67 suggesting that as unemployment increased, the number of poor mental health days also increased ($p< 0.001$, Figure 1, Table 9). The converse was found for food environment index which had a significant negative correlation at -0.669 suggesting that lower food environment index was associated with increased number of poor mental health days ($p< 0.001$, Figure 2, Table 9). A second set of correlations involving the percent with frequent mental distress was also significant with regards to findings for unemployment and food environment index and a followed the same trend as the previous correlation. Unemployment was positively correlated while food environment index was negatively correlated with percentage of the population reporting mental distress (Figure 3 and 4, Table 9). These findings suggest that increased unemployment and low food environment index are indeed correlated to poor mental health outcomes such as increase in the number of poor mental health days or an increase in the percent with frequent mental health distress. These findings corroborate literature regarding the effects of employment status and food quality on a population, and thus, affirm the expected outcomes for RQ3.[9,12,14] On the other hand, correlation studies did not find any significant correlation between the ratio of health provider in either of the two poor mental health outcomes. This finding contrasts with literature findings that the availability of providers is in fact correlated to with mental health outcomes such that higher provider rates lead to better mental health outocomes.[8–10]

Predictors of Poor Mental Health in Ohio

The final portion of this study was to evaluate the predictors of poor mental health outcomes, again using the 2020 population of Ohio. Echoing the results of the correlation studies, a stepwise linear regression found that unemployment and food environment index are significant predictors of both the number of poor mental health days and the percentage of the population with frequent mental distress (all findings significant at $p < 0.001$). With these findings add to the correlational studies by now suggesting that unemployment status and poor food environment index are not only correlated with poor mental health outcomes, but they serve as predictors of those mental health outcomes as well and thus, answers RQ 4. Like the correlational studies, the ratio of mental health providers was not found to be a statistically significant predictor which contrasts with literature that indicated availability of providers as predictive of mental health outcomes as well.[8,10] Taking the data into account, unemployment and poor food environment index have been shown to both predict and be significantly correlated with poor mental health outcomes in Ohio while the availability of mental health providers does not significantly correlate or predict poor mental health outcomes in Ohio. These results can help explain the finding in RQ1 regarding the increase in poor mental health outcomes from 2016 to 2020 despite an accompanying increase in the ratio of mental health providers. More measures of mental health care availability may also yield different results.

Conclusion

While these 2020 findings are still being collected, it is interesting to note how data collected from just halfway through the year can still serve as a basis to examine the correlation and predictiveness of these health and social factors with regards to poor mental health outcomes. However, it is important to note that they are limited in the sense that the 2020 data is still not complete and some measures (e.g. unemployment and food environment index) are based on modeling from previous years' data. Although the goal of this study was to evaluate mental health in 2020, the most current health and economic crisis may have yet to show their effects as data collection is incomplete for the year. Furthermore, since the findings are limited to the immediate 4 states: Louisiana, California, New York, and Ohio. A future point of improvement may be to use more states from each geographically distinct regions of the country and increasing the sample size. Other mental health outcomes outside of the number of poor mental days and the percentage of population with frequent mental distress can also be utilized in future progressions of this study. Additionally, other socioeconomic factors may prove to be predictors of mental health and provide another avenue of improvement for this study.

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