Unveiling Spatial Associations Between COVID-19 Severe Health Index, Racial/Ethnic Composition, And Community Factors

Ruaa Al juboori (ruaa@olemiss.edu)  
Ole Miss: University of Mississippi  https://orcid.org/0000-0002-8804-3755

Divya S. Subramaniam  
Saint Louis University School of Medicine

Leslie Hinyard  
Saint Louis University School of Medicine

Ness Sandoval  
Saint Louis University

Research Article

Keywords:

Posted Date: June 8th, 2023

DOI: https://doi.org/10.21203/rs.3.rs-3016796/v1

License: © This work is licensed under a Creative Commons Attribution 4.0 International License.  Read Full License
Abstract

Limited efforts have been made to incorporate various predisposing factors, including racial/ethnic composition, into prediction models exploring the spatial distribution of COVID-19 Severe Health Risk Index (SHRI). This study examines county-level data from 3,107 US counties, utilizing publicly available datasets. Spatial and non-spatial regression models were constructed, adjusting for rurality, socio-demographic factors, physical health, smoking, sleep, health insurance, healthcare providers, hospitalizations, and environmental risks. Findings reveal spatial models effectively explain geospatial disparities of COVID-19 SHRI. White, Hispanic, and other racial/ethnic majority counties exhibit lower burdens compared to majority Black counties. Older population, lower income, smoking, insufficient sleep, and preventable hospitalizations are associated with higher burdens. Counties with better health access and internet coverage experience lower burdens. This study provides insights into at-risk populations, guiding resource allocation. Racial/ethnic inequalities play a significant role in driving disparities. Addressing these factors reduces health outcome disparities. This work establishes a baseline typology for exploring social, health, economic, and political factors contributing to different health outcomes.

Introduction

The severity of COVID-19 health outcomes and complications has been significantly amplified by the presence of numerous pre-existing burden of chronic diseases in the U.S. these chronic diseases are closely linked to the social determinants of health [1]. Presently, there is a substantial population of non-elderly Americans, ranging from 50 to 129 million individuals (19–50%), who have comorbidities or a pre-existing health condition [2]. Many studies have consistently demonstrated a clear correlation between the presence of comorbidities and worse rates of COVID-19 infections, hospitalizations, and death throughout COVID-19 pandemic [3–14]. This magnified association existed when comorbidities were cumulative, hence they adversely exacerbated the disease burden, and additively increased its negative effects [15].

Research investigating the biological basis of preexisting comorbidities and their impact on COVID-19 clinical outcomes has identified two key assumptions for this association: 1) the prolonged inflammatory process and 2) the dysregulated response of the immune system that accompanied the chronic conditions. These factors led to poor prognosis in patients infected with COVID-19 [5]. Previous systematic reviews and meta analyses showed that common comorbidities such as diabetes [6], hypertension [7], chronic obstructive pulmonary disease (COPD) [8], cancer [9], immunodeficiency [16], obesity [10, 11], and cerebrovascular diseases [12], were all associated with worse COVID-19 health outcomes including death [6–8, 12–14]. Furthermore, individuals with preexisting comorbidities might had less opportunity to get the required health care during the pandemic as health care facilities were overwhelmed with COVID-19 cases [15].

It is important to highlight the significant variation in the prevalence of comorbidities across different regions of the United States. For instance, the Southeast region exhibited higher concentrations of diabetes and heart disease [17]. Specifically, cardiovascular diseases, including stroke, were found to be 34% more prevalent in the stroke belt, which encompasses 11 states in the Southern part of the country. Consequently, it is crucial to explore county-level characteristics to effectively allocate resources and develop targeted policies at a local level [17].

However, the existing literature has not thoroughly investigated the burden and the risk factors associated with chronic disease morbidity using COVID-19 Severe Health Risk Index (SHRI). Incorporating COVID-19 SHRI in the analysis would provide valuable insights into the counties in the United States that are already overwhelmed with
the dual challenges of comorbidities and the pandemic. This approach can assist public health officials in directing appropriate resources to areas with a high burden of disease during the times of public health crisis.

Therefore, the objectives of this study were: 1) to explore the potential risk factors that were associated with COVID-19 SHRI and 2) to assess the extent to which the spatial variability of COVID-19 SHRI can be explained by population characteristics predating the pandemic, including the major racial/ethnic groups, rurality/urbanity, socioeconomics, health access, and environmental risk factors. The selection of variables for this research was based on indicators reported in peer-reviewed studies. Additionally, supplementary variables were included if they demonstrated an independent association with the COVID-19 SHRI, further enhancing the comprehensiveness of the analysis.

Materials and Methods

Dependent variable

In this study we utilized the COVID-19 SHRI to identify counties with high rates of underlying conditions that significantly increased the risk of severe COVID-19 infections within their communities. The COVID-19 SHRI, a collaborative effort between PolicyMap and New York Times [18], was employed for the first time in this context. It quantifies the relative risk of severe COVID-19 symptoms among a county's population, specifically associated with underlying health conditions. These conditions, as identified by the Centers for Disease Control and Prevention (CDC), include Chronic Obstructive Pulmonary Disease (COPD), heart disease, high blood pressure, diabetes, and obesity [19].

COVID-19 SHRI county’s score was calculated based on the sum of the estimated number of people ever diagnosed with each health condition. Subsequently, the scores were normalized according to the county's populations to enable a direct comparison between counties with differing population sizes. It is important to note that the raw and normalized indices should not be interpreted as an accurate representation of the absolute number or percentage of individuals affected by the five conditions, as these shares are not mutually exclusive. For instance, individuals diagnosed with two or more conditions were counted multiple times [18].

Independent variable

The primary independent variable in this study was constructed using the methodology employed by the census bureau to create a racial/ethnic majority variable per US counties [20]. We utilized this approach to determine the racial/ethnic majority within each county. The following groups were considered in the racial/ethnic majority calculations: Hispanic, White (non-Hispanic), Black (non-Hispanic), and Other (including American Indian and Alaska Native non-Hispanic, Asian non-Hispanic, Native Hawaiian, and Other Pacific Islander non-Hispanic). Based on the predominant racial group within a county, as determined by analyzing the percentage of the population belonging to the largest racial/ethnic group, each county was assigned to one of the aforementioned racial/ethnic categories [20]. Data regarding the total population and different racial/ethnic groups per county were obtained from the American Community Surveys 5-years estimates (ACS) [21].

Covariates

As covariates in our analysis, we included the percentage of rurality as a continuous variable, which was derived from the County Health Ranking and Roadmaps [22]. By utilizing this continuous variable, our study provided a
more detailed categorization of rurality that avoids the limitations associated with categorical variables that categorize rurality/urbanity into a few broad levels. This approach is crucial as it prevents the introduction of a false sense of immunity in rural counties. While previous research often employed binary descriptions of metropolitan versus non-metropolitan counties in health outcomes research [23, 24], only a limited number of studies have employed a more granular description based on the three levels of metropolitan, micropolitan, and rural areas [25, 26]. Furthermore, only a few studies have utilized a continuous variable to measure rurality, which we included in our study (see Appendix A).

In addition, various sociodemographic variables were incorporated, including median age, income, men to women ratio, and education. These data were obtained from the American Community Surveys 5-year estimates (ACS) [21]. The health indicators considered in this study encompassed smoking, insufficient sleep, perceived poor physical health, Intensive Care Units (ICU) beds, health insurance coverage, Primary Care Providers (PCP), and preventable hospitalizations. Other variables included food insecurity, internet access, and air pollution resulting from Particulate Matter (PM$_{2.5}$). Data for all these variables were sourced from County Health Ranking and Roadmaps [27] and PolicyMap [28]. The variables included in this study pertain to county-level data from 3,107 counties within the continental United States. To analyze the data, a U.S. counties shape file from the "Urban Map" package in the R environment was used for data projection [29] (See Appendix A)

**Data Analysis**

The data analysis consisted of two stages. In the first stage, a descriptive summary was provided for continuous variables, stratified according to the four racial/ethnic majority variable and the overall sample. Mean values with standard deviations were presented for these variables. One-way Analysis of Variance (ANOVA) was employed to assess the significance of differences among the racial/ethnic racial/ethnic majority groups. Variables that showed significance in this stage were carried forward to the second stage of analysis. Normal distribution of all variables included in the study was examined.

In the second stage, multiple linear regression models (MLR) were utilized to investigate the association between racial/ethnic plurality, other covariates, and the COVID-19 Social Health Risk Index (COVID-19 SHRI). Multiple linear regression was chosen as the outcome variable of interest, COVID-19 SHRI per county, is continuous. The regression models reported the coefficients (B) and their associated confidence intervals (CIs). Statistical significance was determined at a p-value < 0.05. To address multicollinearity, the variation inflation factor (VIF) was assessed for all variables, and any factor with a VIF greater than 5 was removed from the model. The assumptions of linearity, constant variance, and normality were evaluated to diagnose the regression model.

However, it should be noted that the MLR model does not consider spatial aspects. Therefore, it may not be the most appropriate approach [32, 33]. If spatial autocorrelation exists, MLR might lead to inflated model precision and type I error. Additionally, if there is spatial dependence, the assumption of independent observations is violated. Hence, to account for spatial dependence, spatial analysis was used as an alternative approach. Before employing spatial modeling, the data were tested for spatial dependencies. The global Moran's I of COVID-19 SHRI and the global Moran's I of the linear regression residuals were calculated to assess spatial correlation. The weight matrix was generated using the "Queen's contingency" method, which is commonly employed in US county-level research [34].

The decision to proceed with spatial analyses was based on the results of Moran's I for COVID-19 SHRI and the Moran's I for the linear regression residuals. As both Moran's I results were significant (Moran's I = 0.64, p-value <
0.05 for COVID-19 SHRI; Moran's I = 0.32, p-value < 0.05 for residuals), we determined it was appropriate to conduct spatial analyses and construct both the Spatial Lag model (SLM) and Spatial Error model (SEM).

To assess the performance and fitness of the regression models, several model fitness statistics were calculated. A comparison was made between the results of the following tests: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), log-likelihood, and Moran's I of the residuals. These measures were employed to determine the best model fit [36].

**Results**

**Descriptive analysis**

Table 1 provides a descriptive analysis of the study variables (N = 3107) categorized by the four levels of racial/ethnic majority and the overall sample. The average COVID-19 SHRI varied among the racial/ethnic majority levels, with majority Black counties exhibiting the highest burden (108.65 ± 12.90). Socioeconomic indicators also exhibited variations among racial/ethnic majority levels. Notably, majority Black counties had the lowest average household income (43411.35 ± 11550.58) compared to the national average (57610.36 ± 14586.42), along with the lowest percentage of high school graduates (76.08 ± 8.97) compared to the national average (87.64 ± 6.01). Additionally, majority minority counties had a younger population compared to the national average.
Table 1
Study variables according to plurality and the overall sample (N = 3107) US counties

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Majority White</th>
<th>Majority Black</th>
<th>Majority Hispanic</th>
<th>Majority Other</th>
<th>Overall sample</th>
<th>P value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2826</td>
<td>130</td>
<td>125</td>
<td>27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>COVID-19 SHRI</td>
<td>92.59 ± 12.96</td>
<td>108.65 ± 12.90</td>
<td>83.70 ± 9.60</td>
<td>98.23 ± 11.54</td>
<td>92.85 ± 13.37</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>%Rural</td>
<td>59.68 ± 30.89</td>
<td>52.59 ± 34.40</td>
<td>35.09 ± 30.70</td>
<td>76.64 ± 27.06</td>
<td>58.06 ± 31.55</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Household income</td>
<td>58169.34 ± 14246.66</td>
<td>43411.35 ± 11550.58</td>
<td>54951.38 ± 12075.17</td>
<td>43555.07 ± 20318.78</td>
<td>57610.36 ± 14586.42</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Age</td>
<td>41.95 ± 5.21</td>
<td>39.25 ± 3.91</td>
<td>35.83 ± 5.29</td>
<td>31.89 ± 3.64</td>
<td>41.47 ± 5.36</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Completed high school</td>
<td>88.36 ± 5.21</td>
<td>81.92 ± 5.28</td>
<td>76.08 ± 8.97</td>
<td>84.44 ± 4.46</td>
<td>87.64 ± 6.01</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Men to Women ratio</td>
<td>100.62 ± 10.45</td>
<td>98.65 ± 18.79</td>
<td>105.35 ± 13.60</td>
<td>98.66 ± 2.76</td>
<td>100.67 ± 11.17</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Smoking</td>
<td>20.31 ± 4.02</td>
<td>23.39 ± 3.33</td>
<td>16.5449 ± 2.2915</td>
<td>28.4630 ± 6.4718</td>
<td>20.3097 ± 4.2103</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Insufficient Sleep</td>
<td>36.57 ± 3.88</td>
<td>42.76 ± 2.28</td>
<td>36.2595 ± 2.1045</td>
<td>37.8013 ± 2.7749</td>
<td>36.7958 ± 3.9591</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Perceived Poor Physical Health</td>
<td>13.83 ± 2.03</td>
<td>14.97 ± 1.57</td>
<td>14.2256 ± 1.2439</td>
<td>16.1500 ± 2.2742</td>
<td>13.9278 ± 2.01814</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Log ICU Beds</td>
<td>0.67 ± 0.52</td>
<td>0.64 ± 0.58</td>
<td>0.74 ± 0.69</td>
<td>0.30 ± 0.28</td>
<td>0.61 ± 0.43</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>% Uninsured</td>
<td>9.01 ± 4.42</td>
<td>12.02 ± 3.11</td>
<td>16.13 ± 6.97</td>
<td>23.57 ± 8.84</td>
<td>9.55 ± 5.09</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>% PCP</td>
<td>54.88 ± 36.44</td>
<td>48.01 ± 31.51</td>
<td>42.75 ± 22.71</td>
<td>49.99 ± 24.80</td>
<td>54.91 ± 36.48</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>%Preventable Hospitalizations</td>
<td>4000.22 ± 1531.34</td>
<td>5082.67 ± 1412.71</td>
<td>3996.67 ± 1454.46</td>
<td>4605.11 ± 2099.23</td>
<td>4037.70 ± 1542.14</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>PM2.5</td>
<td>7.98 ± 1.56</td>
<td>8.61 ± 0.89</td>
<td>8.76 ± 3.05</td>
<td>6.24 ± 1.96</td>
<td>8.01 ± 1.65</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Internet Access</td>
<td>79.27 ± 7.47</td>
<td>69.21 ± 11.04</td>
<td>75.06 ± 10.06</td>
<td>63.10 ± 11.64</td>
<td>78.64 ± 8.23</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Food Insecurity</td>
<td>12.83 ± 3.33</td>
<td>22.47 ± 4.61</td>
<td>11.28 ± 2.76</td>
<td>19.51 ± 3.55</td>
<td>13.24 ± 3.95</td>
<td>&lt; 0.01</td>
</tr>
</tbody>
</table>

Regarding health behavior and health access indicators, the average rate of current adult smokers was 20.31 ± 4.21, with higher rates observed in majority other racial/ethnic counties. The average rate of insufficient sleep was (36.75 ± 3.96), with the highest prevalence in majority Black counties (42.76 ± 2.28) compared to the national average (36.80 ± 3.96). Perceived poor physical health was higher in majority other racial/ethnic group counties (16.15 ± 2.27) compared to the national average (13.93 ± 2.02).
In terms of health access indicators, the average number of primary care providers per county's population was 54.91 ± 36.48. The average rate of preventable hospitalizations was higher in majority Black counties (5082.67 ± 1412.71) compared to the national average (4037.70 ± 1542.13). The average logarithm of national ICU beds was 0.61 ± 0.43, and the average uninsured population per county was 9.55 ± 5.09, with a higher proportion of uninsured individuals in majority minority counties compared to the national average.

Environmental indicators were also considered in the study. The average concentration of PM$_{2.5}$, representing air pollution, was 8.03 ± 1.70. The average population with broadband access was 78.64 ± 8.23, with majority Black counties having lower internet coverage compared to the national average (69.21 ± 11.04). A similar trend was observed for food insecurity, with a national average of 13.24 ± 3.95 compared to an average of 22.47 ± 4.61 in majority Black counties (see Table 1).

**Regression analyses results**

The results of the spatial and non-spatial regression analyses predicting COVID-19 SHRI are presented in Table 2. Some of the counties’ sociodemographic characteristics, health and health access indicators, and environmental indicators demonstrated robust associations with COVID-19 SHRI across both spatial and non-spatial regression models. Notably, racial/ethnic majority played a significant role, with majority White, Hispanic, and other racial/ethnic groups exhibiting a lower burden of COVID-19 SHRI compared to majority Black counties. Additionally, counties with a higher male to female ratio experienced a lower burden, while counties with an older age population had a higher burden. Higher household income was associated with a lower burden of COVID-19 SHRI, although the coefficient was small.
Table 1: Multiple linear regression (MLR), Spatial lag (SLM), and Spatial Error (SEM) modeling COVID-19 SHRI, continental United States. (N = 3107)

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>MLR</th>
<th>SLM</th>
<th>SEM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>Lower</td>
<td>Upper</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>0.02</td>
<td>0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>Rural</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>Household income</td>
<td>-0.00</td>
<td>-0.00</td>
<td>-0.00</td>
</tr>
<tr>
<td>Age</td>
<td>0.31</td>
<td>0.24</td>
<td>0.38</td>
</tr>
<tr>
<td>Plurality (Ref = Majority Black)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Majority Other</td>
<td>-11.36</td>
<td>-15.26</td>
<td>-7.46</td>
</tr>
<tr>
<td>Majority White</td>
<td>-6.14</td>
<td>-7.73</td>
<td>-4.54</td>
</tr>
<tr>
<td>Completed High School</td>
<td>0.02</td>
<td>-0.06</td>
<td>0.10</td>
</tr>
<tr>
<td>Men to Women Ratio</td>
<td>-0.14</td>
<td>-0.17</td>
<td>-0.11</td>
</tr>
<tr>
<td>Smokers</td>
<td>0.75</td>
<td>0.61</td>
<td>0.89</td>
</tr>
<tr>
<td>Insufficient Sleep</td>
<td>0.50</td>
<td>0.37</td>
<td>0.62</td>
</tr>
<tr>
<td>Perceived Poor Physical Health</td>
<td>1.34</td>
<td>1.12</td>
<td>1.56</td>
</tr>
<tr>
<td>Log ICU Beds</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
</tr>
<tr>
<td>Uninsured</td>
<td>-0.01</td>
<td>-0.08</td>
<td>0.06</td>
</tr>
<tr>
<td>PCP</td>
<td>-0.03</td>
<td>-0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td>Preventable Hospitalization</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>PM2.5</td>
<td>0.61</td>
<td>0.43</td>
<td>0.80</td>
</tr>
<tr>
<td>Broadband</td>
<td>-0.14</td>
<td>-0.19</td>
<td>-0.08</td>
</tr>
<tr>
<td>Food Insecurity</td>
<td>0.01</td>
<td>-0.11</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Bolded means significance at P value < 0.05
Moving on to health behaviors and health access indicators, higher rates of smokers, high perceived poor physical health, populations reporting insufficient sleep, and preventable hospitalizations were associated with a higher burden of COVID-19 SHRI. Conversely, counties with greater coverage of primary care providers (PCP) and ICU beds demonstrated a lower burden. Environmental indicators also revealed significant associations, with higher levels of PM2.5 concentration (environmental pollution) linked to a higher burden of COVID-19 SHRI. Counties with higher rates of internet access exhibited a lower burden. All regression analyses followed a stepwise pattern: Model 1 adjusted for sociodemographic indicators, Model 2 adjusted for sociodemographic and health indicators, Model 3 adjusted for indicators from Model 1 and Model 2 plus health access indicators, and Model 4 adjusted for all aforementioned variables plus environmental indicators (refer to Appendix B).

COVID-19 SHRI, measured on a scale of 0 to 100, served as the continuous outcome variable for this study. The fully adjusted linear regression model accounted for 71% of the variance in COVID-19 SHRI. Model assumptions were assessed, and the goodness-of-fit was evaluated using the Hosmer-slow statistic (p > 0.05). All included variables exhibited low VIF factors (< 5).

The AIC, BIC, log-likelihood, and Moran's I of the residuals were analyzed. AIC and BIC slightly favored the spatial lag and spatial error models over the multiple linear regression model, while the log-likelihood values indicated better goodness of fit for the spatial regression models. The spatial error model had a Lambda (λ) of 0.63 (95% CI 0.59, 0.67), and the spatial lag model had a Rho (ρ) of 0.39 (95% CI 0.36, 0.43). The Moran's I of the residuals was significant (p < 0.05) for both the spatial lag and linear regression models. The goodness-of-fit parameters indicated that spatial regression analyses provided added significance beyond what the linear regression analyses demonstrated, although the differences were minimal (see Table 2).

**Discussion**
This study aimed to explore the population characteristics associated with a higher burden of COVID-19 SHRI across US counties. Findings provided a comprehensive understanding of these determinants and highlighted the importance of investigating the burden of COVID-19 SHRI as a preliminary step in identifying populations at high risk. The study introduced COVID-19 SHRI as a valuable population-level index for predicting adverse COVID-19 outcomes, with potential applicability in future pandemics. The results informed state health departments and local partners for effective surveillance, program planning, and resource allocation to address chronic diseases.

Key associations were observed in the fully adjusted spatial and non-spatial regression models, such as sociodemographic, health, health access, and environmental indicators on COVID-19 SHRI burden. Notably, racial/ethnic majority, age, household income, health behaviors, health access, and environmental factors played significant roles.

Previous studies have not explored the role of racial/ethnic majority in predicting the COVID-19 Severe Health Risk Index (SHRI). This study found that counties with White, Hispanic and other racial/ethnic majorities had lower burden of COVID-19 SHRI compared to majority Blacks counties. This finding aligns with previous research showing a higher prevalence of chronic disease clustering in Black populations. Most of the counties with a higher burden of COVID-19 SHRI were clustered in the South-East region of the US. This study contributes to the literature by highlighting the role of racial/ethnic disparity in shaping ecological health outcomes among different US populations. It also reveals disproportionate distribution of social, economic, and health indicators in majority Black counties, paving the way for future research to explore other health outcomes using the racial/ethnic majority typology.

Counties with higher average rurality had a greater burden of COVID-19 SHRI according to the linear regression and spatial lag regression models. Existing literature has already investigated rural disparities in health outcomes, which are characterized by older populations, higher comorbidity rates, and limited access to healthcare. The study findings underscore the importance of conducting more detailed analyses in rural regions to explore the clustering of higher health risk factors contributing to worse COVID-19 SHRI and overall health outcomes. Therefore, future research should further investigate the role of rurality in predicting population health outcomes.

Counties with a higher average older population had a greater burden of COVID-19 SHRI, aligning with previous literature. This association can be attributed to biological deficits that occur with aging, emphasizing the need for public health measures to improve access to healthcare in counties with a higher proportion of elderly residents. Conversely, a higher male to female ratio was linked to a lower burden of COVID-19 SHRI. However, the literature has inconsistent results regarding the prevalence of multiple chronic conditions in males versus females. Further research is necessary to investigate the association between gender and the burden of comorbidities.

Higher household income was associated with a lower burden of COVID-19 SHRI, likely due to improved healthcare access and healthier lifestyle choices in affluent counties. Certain health behavior indicators showed significant positive associations with COVID-19 SHRI. Counties with higher percentages of smokers and individuals with insufficient sleep had a higher burden of COVID-19 SHRI. Smoking is a well-known contributor to chronic diseases such as coronary heart disease, COPD, and cancer, underscoring the importance of targeted prevention interventions. Insufficient sleep affects the health and quality of life for around 70 million Americans, and its negative consequences have been documented in the literature. Addressing insufficient sleep aligns with the Healthy People 2030 goal of increasing the percentage of people obtaining sufficient sleep.
Some health access indicators were significantly associated with COVID-19 SHRI. Counties with a higher percentage of primary care physicians (PCPs) and intensive care unit (ICU) beds had a lower burden of COVID-19 SHRI. This finding is important considering that two-thirds of emergency room visits in the US are attributed to chronic conditions, adding to the cost and strain on healthcare systems[45]. Additionally, the study revealed that counties with high rates of preventable hospitalizations had a higher burden of COVID-19 SHRI, highlighting the importance of timely access to routine medical visits and primary care providers to prevent such hospitalizations [46]. Ensuring better healthcare access opportunities and an adequate healthcare workforce are crucial for promoting healthier populations.

The study also included environmental indicators, such as particulate matter (PM2.5), known to be hazardous to health. Consistent with previous research, higher levels of PM2.5 were associated with a higher burden of COVID-19 SHRI. For example, Bennett et al. conducted a study analyzing vital statistics data from 1999 to 2015, which consistently demonstrated higher death rates associated with elevated concentrations of PM2.5 over time for both males and females [47]. These findings underscore the importance of public health policies aimed at controlling high levels of PM2.5 to protect public health. Conversely, access to the internet showed an opposite pattern. The study revealed that counties with higher internet access had a lower burden of COVID-19 SHRI. Adequate internet access is recognized as an important social determinant of health, facilitating better communication between healthcare providers and patients through telehealth and the use of remote monitoring devices[48]. Thus, the association between higher internet access and lower burden of COVID-19 SHRI aligns with expectations.

This study has certain limitations that should be considered. First, the analyses conducted were ecological in nature, which means they did not examine individual-level risk factors for COVID-19 SHRI. However, the primary focus of this study was to identify county-level characteristics of at-risk counties in order to inform resource allocation efforts, rather than estimating individual-level characteristics. Second, the study utilized covariates from different years. Although this approach may raise concerns, it is important to note that previous literature has supported this methodology, as the data being described pertains to populations rather than individuals [32, 49].

**Conclusion**

The study explored the variability of COVID-19 SHRI among different counties, revealing distinct patterns of burden. Both spatial and non-spatial analyses were conducted to investigate these disparities. The spatial models proved effective in explaining the geospatial discrepancies of COVID-19 SHRI, serving as a foundation for future geospatial modeling of population-level health outcomes. The findings underscored the importance of place and race/ethnicity as determinants of health outcomes, highlighting the need for targeted resource allocation and interventions to address social determinants of health, particularly among vulnerable racial minority groups. This study emphasized the potential for modifying socioeconomic and health-related factors such as access to quality healthcare, evidence-based interventions, and educational and economic opportunities.

**Declarations**

**Funding:** The author(s) received no financial support for the research, authorship, and/or publication of this article

**Declaration of Conflicting Interests:** The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.
References


19. Centers For Disease Control and, Prevention C. Underlying Medical Conditions Associated with Higher Risk for Severe COVID-19: Information for Healthcare Providers. 2019; Available from:


27. Health UoWP. *County Health Rankings and Roadmaps.* 2021; Available from: https://www.countyhealthrankings.org/.


**Figures**

![COVID-19 SHRI](image-url)
The spatial distribution of COVID-19 SHRI. \((\text{Moran's } I = 0.63, P\text{-value}<0.05)\).

Figure 2

The spatial distribution of COVID-19 SHRI linear regression analysis residuals. \((\text{Moran's } I = 0.32, P\text{-value}<0.05)\).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixA.docx
- AppendixB.docx