

Spatial Mapping of Hospitalization Rates for Mental Disorders: Community-Level Analysis

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Abstract

Mental disorders are a leading cause of disability and hospitalization in the United States, with Florida ranking among the highest in mental illness prevalence. Despite this, limited research has examined the geographic distribution of mental health-related hospitalizations across the state. This study assessed county-level hospitalization rates for mental disorders in Florida using 2022 data and identified the contextual factors associated with spatial disparities. A Bayesian spatial modeling approach was employed to account for both spatial dependency and variability in socioeconomic, demographic, and environmental covariates. Results revealed substantial geographic variation in hospitalization rates, with elevated burdens in northern and central Florida counties. Counties with higher poverty and obesity rates experienced significantly higher hospitalization rates, while greater health insurance coverage was associated with lower rates. Additionally, the relationship between obesity and hospitalization varied depending on county-level poverty and racial composition, suggesting complex interactions among contextual determinants. Hotspot counties were based on exceedance probabilities, highlighting areas with disproportionately high hospitalization burdens. These findings underscore the value of spatial modeling in public health planning and the need for geographically targeted interventions. Addressing mental health disparities through improved access to care and resource allocation in high-burden areas may enhance equity and reduce avoidable hospitalizations.

Keywords

Mental Health, Hospitalization, Bayesian Spatial Modeling, Geographic Disparities, Socioeconomic Determinants, Public Health Equity

1. Introduction

Mental illness remains a significant public health challenge globally, contributing to considerable morbidity, mortality, and economic burden [1]-[3]. In the United States, mental health disorders are among the leading causes of disability-adjusted life years (DALYs), with millions requiring hospitalization each year due to acute psychiatric episodes or for long-term psychiatric care [4] [5]. Florida, in particular, ranks among the top five states in terms of the prevalence of mental illness [6] [7]. The Floridian aging population structure, rapid population growth, diverse ethnic communities, vulnerability to natural disasters, and county-level variations in healthcare access create unique mental health challenges [8]. Mental disorders such as depression, anxiety, bipolar disorder, and schizophrenia are not only highly prevalent but also among the top contributors to disability and health service utilization, including psychiatric hospitalizations [5] [9].

Hospitalization rates for mental disorders vary considerably across geographic regions and are strongly influenced by socioeconomic inequalities, demographic differences, and environmental exposures [10]. These contextual disparities affect access to mental health services, quality of care, and recovery outcomes. For instance, populations in lower-income or rural areas may face barriers to accessing timely and appropriate treatment, which can lead to more frequent or prolonged hospitalizations [6] [11]. Additionally, environmental conditions, such as exposure to pollution, limited green space, or urban stressors, may not be randomly distributed across space, potentially acting as social determinants of mental health [12] [13].

Despite the recognition of these challenges, limited research has explored the geographic variation in hospitalization rates for mental disorders at granular or county levels. Most existing studies focus on individual-level predictors or broad national trends, often overlooking small-area variation that can reveal important patterns of service need and inequity. Understanding the spatial distribution of mental health-related hospitalizations is essential for identifying regional disparities, informing mental health policy, and optimizing resource allocation. Such insights are particularly critical in a state like Florida, characterized by a heterogeneous population and wide variability in healthcare infrastructure and access.

This study addresses a notable gap by investigating the spatial patterns of mental health-related hospitalizations across counties in Florida. The main research questions guiding this study are:

- 1) What are the spatial patterns and hotspots of hospitalization rates for mental disorders across Florida counties?
- 2) How do socioeconomic, demographic, and healthcare access factors influence these spatial patterns?
- 3) What are the implications of these spatial disparities for mental health policy and targeted resource allocation?

Answering these questions has practical significance. Identifying geographic areas with disproportionate hospitalization burdens can help policymakers and health planners allocate mental health resources more equitably and efficiently, ensuring that services reach communities with the greatest need.

While prior studies have documented the role of socio-environmental and demographic factors in shaping mental health outcomes, these investigations often neglect spatial dependencies or clustering effects. Socioeconomic determinants such as poverty, unemployment, and income inequality have consistently been linked to increased risk of mental illness [11]. Similarly, access to care, including the density of mental health professionals, availability of psychiatric beds, and insurance coverage, remains a key barrier in many underserved areas [14]. Environmental stressors, including urban density, pollution, and lack of access to restorative green spaces, have also been found to exacerbate psychological distress [12] [15].

Regarding the role of socio-environmental and demographic factors, spatial epidemiological techniques have been successfully used in other public health contexts—such as cancer mapping [16], cardiovascular outcomes [17], and infectious disease surveillance [18], to detect geographic clusters and inform localized interventions. However, their application to mental health outcomes, particularly hospitalization rates, remains underdeveloped. Recent advances in Bayesian spatial modeling offer promising tools for identifying contextual and spatial effects that influence health outcomes at small-area levels [19].

This study leverages these advanced spatial methodologies to assess the geographic distribution of hospitalization rates for mental disorders in Florida. Specifically, we apply Bayesian spatial models to examine associations between hospitalization rates and county-level socioeconomic, demographic, and environmental variables. By integrating spatial statistics with public health data, we aim to uncover hidden geographic patterns that may otherwise go undetected in traditional analyses, thereby contributing novel insights to the field of mental health services research.

2. Methods: Data and Modeling

2.1. Sources of Data

We were able to get data on inpatient hospitalizations for mental disorders in 2022 from the Florida Department of Health, Division of Public Health Statistics & Performance Management (DPHSM). Mental disorders related to substance use, schizophrenia, mood disorders and anxiety [20]. From the same source, we also obtained covariate data. The covariates were the percentage of owner-occupied housing units (a measure of well-being), incarceration rate (a social determinant that impacts health), racial residential segregation index (unequal access to health care resources), percentage of population living within ½ mile of a healthy food source, median household income, percentages of persons with health insurance, overweight/obese, sedentary, heavy or binge drinking, and poverty rate. These and other covariates were used in Bayesian modeling to assess hospitalization rates of mental disorders. The selection of the covariates for this paper was based on two conditions: 1) based on identification of risk factors for hospitalization due to mental disorder from the literature, and 2) availability of data publicly on those

identified risk factors. Ethical approval was not necessary because this study did not involve individual patients but instead it used publicly available and aggregated data at county-level. The unit of analysis was a county. Consent was not required as data was aggregated.

2.2. Statistical Analysis

We used a Bayesian spatial modeling approach to describe and assess the variations in hospitalization rates of mental disorders. For this approach, the unit of analysis was a county which was the smallest geographical unit where data were available for this study. Such spatial modeling methods analyze and represent data with a spatial component at county level, for the purpose of understanding relationships and patterns between locations and their attributes. While accounting for location (spatial) effects, the relationship between a local outcome attribute and explanatory variables was modeled as follows. The outcome variable (number of hospitalizations due to mental disorders) Y_i has a Poisson distribution with an unknown parameter θ_i which is a county-specific hospitalization rate of mental disorders ($i = 1, \dots, K$). Using the log link, the log-rate is modeled as

$$\log(\theta_i) = \alpha + \mathbf{X}_i \boldsymbol{\beta} + u_i + v_i \quad (1)$$

where, α is the overall log-rate; and a q -dimensional vector \mathbf{X}_i contains county-level covariates with coefficient parameters $\boldsymbol{\beta}$; u_i represents spatially unstructured random effects distributed as, $u_i \sim N(0, \tau^2)$, while v_i denotes spatially structured random effects for neighboring counties [21]-[23], where neighboring counties get a weight of one while non-neighboring counties get a weight of zero. The probability distribution of v_i is defined based on the conditional autoregressive model [24] as

$$v_i | v_j, i \neq j \sim N(\bar{v}_i, \sigma_i^2) \quad (2)$$

where, $\bar{v}_i = \sum_j v_j w_{ij} / \sum_j w_{ij}$ and $\sigma_i^2 = \sigma_v^2 / \sum_j w_{ij}$ and $w_{ij} = 1$, if area i and area j are neighbors, 0, otherwise.

Bayesian methods are used to estimate the unknown parameters in models (1 - 2). Assessment of prior distributions for the parameters is non-informative and given as follows: $\boldsymbol{\beta} \sim N(0, 100)$; $1/\tau^2$, $1/\sigma_v^2$, each, follows a Gamma (1, 0.001). The posterior distribution of a county-specific hospitalization rate, θ_i , can be used for spatial mapping and computing an exceedance probability. The exceedance probability measures the chance that the i^{th} county's θ_i exceeds a given threshold [25] and can be used to decide whether the county should be classified as having excess risk (hotspot) of mental disorder [26]. The estimation of the unknown parameters of the model in (1) was carried out using the integrated nested Laplace approximation (INLA) software [27]. The software is particularly efficient for fitting spatial mapping models for mortality rates and can easily be used by researchers and practitioners [27]. Comparatively, an unadjusted estimate of θ_i is the standardized hospitalization rate (SHR) which is defined as $SHR_i = Y_i / E_i$

[28] [29], where Y_i is the i^{th} county hospitalization count and E_i is the expected number of hospitalizations of mental disorders per county. When $SHR_i > 1$, it suggests excess hospitalizations due to mental disorders for the i^{th} county, while $SHR_i < 1$, indicates fewer hospitalizations due to mental disorders than expected for the residents in the i^{th} county.

3. Results

Descriptive statistics for the outcome variable (county-level hospitalizations due to mental disorders) and their associated attributes are presented in **Table 1**. In 2022, the average number of hospitalizations for mental disorders across Florida counties was 3069, with considerable variation. The lowest count was recorded in Glades County (35 hospitalizations), while Miami-Dade County had the highest at 28,718. The median age across counties was 44.26 years, and the median household income was \$61,786. The mean obesity prevalence was 68.14%, and the average poverty rate was 14.92%. Across the 67 counties, substantial variability was observed in key sociodemographic and environmental factors, including the

Table 1. Descriptive statistics of county-level variables.

Variables	Mean	SD	Min	Max
Hospital Count	3069	5123.8	35	28718
Median Age	44.26	6.62	31.4	68.3
Health Insurance (%)	87.51	3.24	78.3	94
Immigrant (%)	5.89	5.91	0.7	33.9
Unemployment Rate	5.35	1.54	2.7	9.7
Poverty Rate	14.92	5.17	6.1	28.5
Crime Rate	528.9	199.46	239.2	1086.5
Owner Occupied House (%)	73.47	7.92	51.9	87.2
Education with Bachelor or Higher (%)	24.35	10.65	8	47.5
Healthy Food Store (%)	12.74	12.6	0.2	60
Sedentary (%)	30.66	5.68	19.3	42.7
Personal Doctor (%)	73.65	5.12	57.6	86
Alcohol (%)	16.82	3.32	10.6	26.4
Marriage Rate	7.29	3.86	2.5	30.5
White Population (%)	80.21	9.62	41.71	92.75
Median Income (\$)	61,786	12,903.98	37,221	100,020
Obese (%)	68.14	5.42	54.6	78.5
Severe House Shortage (%)	13.22	2.14	9.2	18.1
Veteran Population (%)	9.864	2.87	2.8	21.7
Segregation Index	0.46	0.12	0	0.7

percentage of adults with at least a bachelor's degree, household income, proximity to healthy food stores, poverty levels, and the demographic composition in terms of White and veteran populations. These differences were also reflected in the Standardized Hospitalization Rate (SHR) values.

The spatial distribution of SHR values is depicted in **Figure 1**, which reveals non-random spatial variation in mental health-related hospitalizations. Higher-than-expected hospitalization rates were clustered in the northern, central, and eastern regions of Florida, as indicated by red and orange shading. However, SHR may be an unstable metric, particularly in counties with small populations, since it assumes homogeneity across counties and does not account for local variability. Therefore, to generate more reliable estimates and assess spatial dependency, we fitted a Bayesian spatial model (BSM), specified in Equation (1).

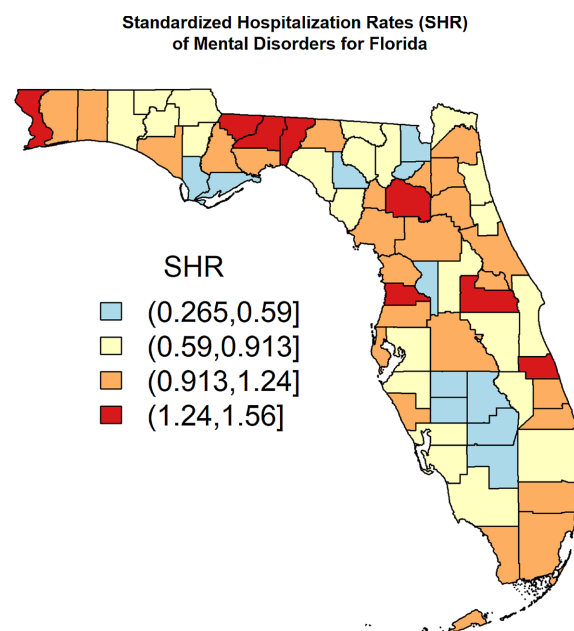


Figure 1. Spatial distribution of standardized hospitalization rates of mental disorders in Florida (2022).

Table 2 summarizes the results of the Bayesian model. Posterior estimates and 95% credible intervals (CIs) were used to evaluate the association between hospitalization rates and county-level covariates. Looking at the 95% credible interval (CI) of parameters of BSM, we observe that counties with higher percentage of people with health insurance had lower hospitalization rates ($\hat{\beta}$: -0.0826 , CI: $(-0.1636, -0.0017)$), which does not include zero) after adjusting for other variables. The results also show that there is a positive and strong relationship between the percentage of poverty and hospitalization rate due to mental disorders ($\hat{\beta}$: 0.2679 , CI: $(0.0608, 0.4768)$) after adjusting for other county-level covariates. Similarly, there is a strong and direct association between the hospitalization rate and percentage of residents who are obese ($\hat{\beta}$: 0.1417 , CI: $(0.0371, 0.2465)$). But this association is moderated by poverty (obesity \times poverty, $\hat{\beta}$: -0.0044 , CI: $(-0.0073,$

–0.0015)) or white (obesity \times white, $\hat{\beta}$: –0.0014, CI: (–0.0025, –0.0003)). These interaction terms suggest that in counties with higher poverty rates or a greater percentage of White residents, the positive association between obesity and hospitalization weakens or even reverses. No statistically significant associations were observed between hospitalization rates and other variables, such as unemployment rate, income level, education level, segregation index, or veteran population percentage.

Table 2. Estimated posterior mean (PM) and standard deviation (SD) of population parameters of Model (1) along with a lower limit (L_{CI}) and upper limit (U_{CI}) of 95% equal-tail credible interval (CI).

Covariates	PM	SD	L_{CI}	U_{CI}
Insurance	–0.0826	0.0411	–0.1636	–0.0017
Median Age	–0.013	0.0071	–0.027	0.001
Poverty	0.2679	0.1056	0.0608	0.4768
Obese	0.1417	0.0532	0.0371	0.2465
Unemployment	–0.9612	0.5916	–2.1263	0.2035
Immigrant	–0.0027	0.0096	–0.0217	0.0163
Median Income	–0.0046	0.0072	–0.0185	0.0097
Alcohol	0.0039	0.0131	–0.0221	0.0295
White	0.0762	0.0394	–0.0014	0.1537
Education	–0.0014	0.0079	–0.017	0.0141
Segregation	0.3697	0.2899	–0.2004	0.9412
Severe Housing	–0.0134	0.0227	–0.0584	0.031
Veteran	0.0206	0.0162	–0.011	0.0527
Insurance:Unemployment	0.0113	0.0069	–0.0023	0.0249
Poverty:Obese	–0.0044	0.0015	–0.0073	–0.0015
Obese:Percent White	–0.0014	0.0006	–0.0025	–0.0003

Using the fitted BSM, we computed posterior hospitalization rates (PHR) for all counties and mapped these in **Figure 2**. The map indicates that counties in the northern and central regions of Florida had the highest hospitalization burdens, defined by PHR values exceeding 1.

To identify hospitalization hotspots, we calculated the exceedance probability, defined as the posterior probability that a county's hospitalization rate exceeds a given threshold (e.g., PHR > 1). **Figure 3** displays exceedance probabilities for all 67 counties. High exceedance probabilities (close to 1) indicate counties where hospitalization burdens are significantly above the expected level, while values near 0 suggest below-threshold rates. Looking at **Figure 3**, one sees that the identified hotspots (red color) for hospitalization burden due to mental disorders are

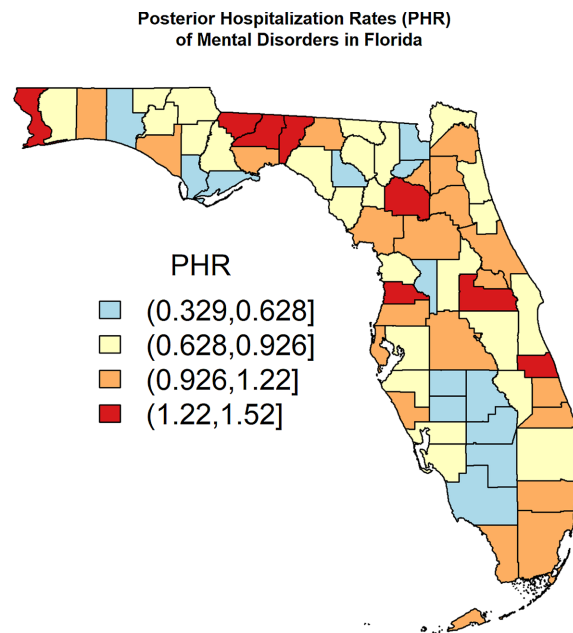


Figure 2. Spatial distribution of posterior hospitalization rates of mental disorders in Florida (2022).

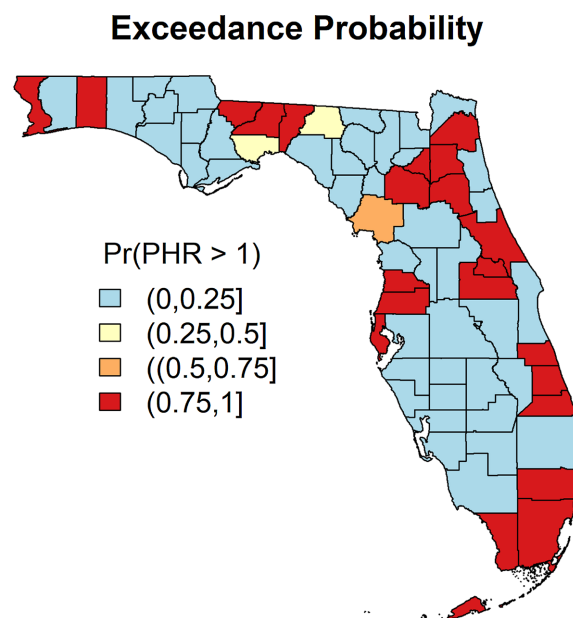


Figure 3. Exceedance probability that a county's hospitalization rate for mental disorders is greater than expected.

scattered across Florida. In the northwest, the hotspot counties in 2022 were Escambia, Gadsden, Jefferson and Sant Rosa. Likewise, in the northeast, the counties were Alachua, Bradford, Clay, Duval and Putnam. Hotspot counties in the central east region were Indian River, Martin, Orange, Seminole and Volusia. In the central west part, Hernando, Pasco and Pinellas counties were identified as having high hospitalization rates, and the southeast Broward, Miami-Dade and Monroe happened to have high burden of hospitalization rates for mental disorders. These

spatial patterns underscore the geographic inequities in the burden of mental health hospitalization across the state. Identifying such hotspots is vital for targeted interventions, enabling policymakers and public health practitioners to prioritize high-burden areas for resource allocation, prevention strategies, and expanded access to mental health care services.

4. Discussion

This study examined the spatial distribution of hospitalization rates due to mental disorders across counties in Florida and explored their associations with key socioeconomic, demographic, and environmental covariates. Our findings reveal significant geographic variation in mental health-related hospitalizations, with elevated rates concentrated in the northern and central regions of the state. These spatial disparities suggest that mental health burdens are not evenly distributed and may reflect underlying social and environmental inequities.

Consistent with previous research emphasizing the role of contextual determinants in mental health outcomes [5] [11], our study found that counties with higher poverty rates exhibited significantly greater hospitalization rates for mental disorders. This supports the notion that economic deprivation contributes to poor mental health through pathways such as chronic stress, inadequate housing, food insecurity, and limited access to preventive care [1] [10]. In contrast, higher levels of health insurance coverage were associated with reduced hospitalization rates, underscoring the protective role of access to healthcare services. These findings highlight the urgent need for interventions that expand coverage and reduce structural barriers to care in underserved areas.

A notable contribution of this study is the identification of obesity as a significant positive predictor of hospitalization rates for mental disorders. This aligns with literature indicating a bidirectional relationship between obesity and mental illness, potentially mediated by stigma, inflammation, and comorbidities such as diabetes or cardiovascular disease [9]. However, we found that the strength and direction of this association varied by county-level poverty and racial composition, suggesting that obesity's impact on mental health is context-dependent. In counties with higher poverty or a larger White population, the positive association between obesity and hospitalization was attenuated or reversed. These moderating effects point to complex interdependencies between physical health, socioeconomic status, and social environments that warrant further investigation. Environmental and socioeconomic factors have been found to significantly impact mental health in various mechanisms [30]-[32]. Though not clearly known, some mechanisms may explain moderation of race and poverty for the association of obesity and higher rates of hospitalization for mental disorder.

Our application of Bayesian spatial modeling provides a methodological advantage by accounting for spatial dependencies and heterogeneity in population structure, issues that may bias estimates based on traditional standardized rates.

The identification of high-burden counties through posterior hospitalization rates and exceedance probabilities offers a more robust understanding of localized mental health challenges. Hotspot counties, particularly in the northwest (e.g., Escambia, Gadsden, Jefferson), northeast (e.g., Duval, Putnam), and central regions (e.g., Orange, Hernando), should be prioritized for targeted mental health interventions and capacity-building efforts.

These findings have practical implications for public health planning. By identifying geographic areas with disproportionate hospitalization burdens, state and local health agencies can tailor interventions that improve service accessibility, invest in community-based preventive care. Moreover, spatial epidemiology can complement ongoing mental health surveillance systems by uncovering patterns that are not visible through aggregate state-level analyses.

Several limitations should be acknowledged. First, the ecological nature of the study precludes causal inferences at the individual level. Second, while we included several important county-level covariates, unmeasured confounders such as mental health stigma, health workforce shortages, or behavioral health service quality may also influence hospitalization rates. Third, the cross-sectional design captures spatial patterns at a single time point and may not reflect temporal trends. Future studies employing multilevel modeling of small-area level and individual level variables would enhance understanding of evolving mental health disparities. Evaluation of the association between mental disorder and hospitalization at a finer spatial unit would be useful in future study. In addition, potential confounders, for instance, a county-level density of mental health providers, are worth including in a future study as well.

In conclusion, this study provides new evidence on the spatial distribution and contextual determinants of mental health-related hospitalization rates across Florida counties. Using Bayesian spatial modeling, we identified significant geographic disparities, with elevated hospitalization burdens in the northern and central regions of the state. Higher poverty rates, lower insurance coverage, and obesity prevalence were found to be key drivers of hospitalization, with important moderating effects from racial composition and socioeconomic conditions. These findings underscore the importance of spatially targeted mental health strategies that account for both place-based and population-based factors.

Investments in public health infrastructure, particularly in hotspot counties, are critical to reducing the burden of mental disorders and promoting mental health equity. Our study highlights the value of integrating spatial epidemiological tools into mental health surveillance and planning efforts, ultimately contributing to more effective and equitable mental health systems.

Data Availability

The datasets were obtained from publicly archived located at:

<https://www.flhealthcharts.gov/ChartsReports/rdPage.aspx?rdReport=NonVitalInd.Data>.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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