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Neighborhood Walkability, Crime, and Mental Health Service Requests in Missouri: A cross-sectional study

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A capstone project submitted to Washington University in St. Louis, George Warren Brown School of Social Work, in partial fulfillment of the requirements for the award of the degree of Master of Public Health (MPH) in Epidemiology and Biostatistics.

I, Bernard Banda, have neither given nor received unauthorized assistance (as detailed in the Brown School student handbook) in the completion of this work. I certify that this work is authentically my own.

Note: Additional material on spatial analysis were accessed here: https://hughst.github.io

Abstract

Background

Neighborhood characteristics such as walkability, crime rates, and socioeconomic conditions significantly influence mental health outcomes. However, limited research has explored how these factors collectively impact mental health services requests (MHSRs) in Missouri, a state with the highest burden of mental health in the U.S. This study examines the association between walkability, housing occupancy, educational attainment, and MHSRs at the zip code level.

Methods

A cross-sectional study, focusing on the year 2020, was conducted using data from the *211 Counts* database, the U.S. Environmental Protection Agency's Smart Location Database, and the American Community Survey. The outcome variable was the number of MHSRs per zip code. Key predictors included neighborhood walkability, safety, housing occupancy percentage and educational attainment. A Spatial Lag Negative Binomial (NB) model was employed to address overdispersion and spatial autocorrelation, adjusting for socioeconomic indicators such as poverty rates, median household income, and population density.

Results

The Spatial Lag NB model showed good fit (AIC = 1194.5; LRT $\chi^2 = 306.59$, $p < 0.001$). Walkability was positively associated with MHSRs (IRR = 1.23, 95% CI [1.14, 1.34], $p < 0.001$), as were housing occupancy (IRR = 1.05, 95% CI [1.03, 1.06], $p < 0.001$) and educational attainment (IRR = 4.57, 95% CI [1.96, 10.94], $p < 0.001$).

Conclusions

Neighborhood factors such as walkability, housing stability, and education are key predictors of MHSRs Missouri. Targeted policies addressing these issues may improve mental health outcomes and reduce service disparities. Future studies should incorporate longitudinal designs and additional neighborhood-level variables to enhance public health policy development.

List of Abbreviations

AIC - Akaike Information Criterion

ACS - American Community Survey

CI - Confidence Interval

CMD - Common Mental Disorders

CMI - Common Mental Illnesses

EPA - Environmental Protection Agency

HR-QoL - Health-Related Quality of Life

IRR - Incidence Rate Ratio

LRT - Likelihood Ratio Test

MHSRs - Mental Health Service Requests

NB - Negative Binomial

PTSD - Post-Traumatic Stress Disorder

SES - Socioeconomic Status

VIF - Variance Inflation Factor

WHO - World Health Organization

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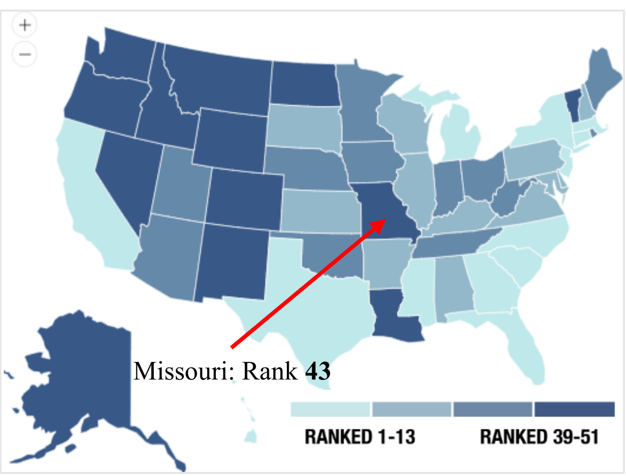
1. Introduction

1.1. Background

Mental health is one of the leading public health challenges both globally and in the United States.[1,2] It contributes significantly to poor health outcomes, premature death, and national economic loss.[3] According to the World Health Organization (WHO), mental health conditions contribute to 1 in 5 years lived with disability globally, with depression alone costing the global economy around US$1 trillion each year.[2] In 2024, mental health remains a significant public health concern in the United States, with over 20% of adults experiencing mental illness and approximately 6% facing severe conditions such as schizophrenia, bipolar disorder, or major depression.[4] The burden of Mental health in the U.S varies across states (Figure 1). Missouri, ranked 43rd out of 51 states, reports a higher prevalence of mental illness and poor overall mental health compared to most other states. [4,5] This challenge is particularly high in urban areas such as St. Louis City, which in 2020 recorded the highest rates of mental health-related emergency room visits across all age groups when compared to St. Louis County and the state average (Figure 2).[6] These patterns highlight a disproportionate mental health burden faced by urban and densely populated areas within Missouri.



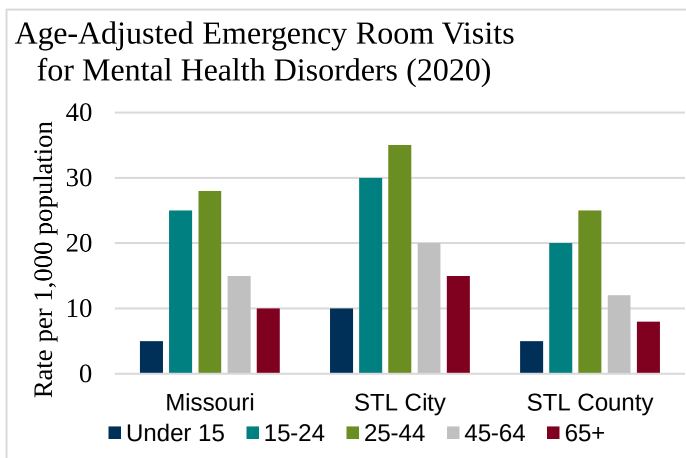


Figure 1:Burden of Mental Illness 2024 by State [i]

Figure 2:Emergency Room Visits for Mental Health Disorder[ii]

[i] Figure 1: Extracted from Mental Health America. *Mental Health and Substance Use Prevalence Data (2024)*. Retrieved from: mhanational.org.

[ii] Figure 2: Adapted from the City of St. Louis Department of Health, *Mental Health Data Brief (2021)*. Retrieved from: https://www.stlouis-mo.gov/government/departments/health/documents/briefs/mental-health-september-2021.cfm.

Despite the significant burden of mental health disorders, the proportion of individuals receiving treatment remains low, partly due to limited resources.[7] In Missouri, only 14.2 % of the need for mental health professionals is met, significantly lower than the national average of 26.6%, highlighting a more pronounced shortage of mental health care providers in the state.[8] Understanding the factors that influence mental health burden can aid in effective resource allocation.

Research has found that neighborhood characteristics are significant determinants of residents' mental health.[9,10] Factors such as walkability and crime rates shape daily experiences, influencing mental well-being.[10] Walkability refers to how friendly an area is for walking, encompassing aspects like the presence of sidewalks, pedestrian crossings, connectivity, and proximity to amenities.[11] Higher walkability is associated with increased physical activity, social interaction, and access to resources, all of which can improve mental health.[12] However, there is limited research specifically examining the association between safety and walkability on mental health in the state of Missouri, where violent crime rates rank among the highest in the United States.[13] Given the high burden of mental health issues in the state, there is a need for comprehensive analysis to understand how these neighborhood characteristics impact mental health burden. Addressing this gap is crucial for developing targeted interventions and public health policies to improve mental health service provision and resource allocation.

1.2. Literature Review

1.2.1. Walkability and Mental Health

Walkability is increasingly recognized as a key determinant of both physical and mental health outcomes, with numerous studies linking it to various aspects of mental well-being.[14–16] Walkability refers to the degree to which a neighborhood is conducive to walking, characterized by elements such as residential density, street connectivity, mixed land use, and the availability of pedestrian infrastructure like sidewalks and pedestrian crossings.[12] A well-designed walkable environment is believed to promote physical activity, reduce social isolation, and improve community engagement, all of which are associated with improved mental health outcomes.[15,17]

Several studies have highlighted the positive relationship between walkability and mental health, particularly in urban settings. Siqueira Junior et al. (2022) observed that older adults residing in neighborhoods with higher walkability scores were less likely to experience cognitive impairment, though no significant relationship was found with depressive symptoms.[15] This suggests that the physical environment, particularly walkability, can influence aspects of cognitive and mental health, particularly in older populations.

Moreover, walkability has been linked to broader neighborhood social health, which also plays a crucial role in mental well-being. Carson et al. (2023) found that higher walkability was positively associated with social interaction and a sense of community, both of which are important for mental health.[16] These social health benefits suggest that walkability not only encourages physical activity but also fosters social cohesion, which can be a protective factor against mental health challenges like anxiety and depression.

In contrast, the relationship between walkability and mental health is not always straightforward. Warner et al. (2022) conducted a scoping review that emphasized the inconsistencies in how walkability is defined and measured across studies, which complicates the ability to draw standard conclusions about its impact on mental health[18]. These findings are further supported by other studies which suggests that the benefits of walkability may be conditional on the presence of other environmental factors, such as safety. Zhu et al. (2023) observed that barriers to walkability, such as crime and traffic, negatively affected mental health-related quality of life (HR-QoL) in Black and Latino communities in New York City.[17] This highlights the complex nature of walkability's influence on mental health, where positive attributes of the built environment must be balanced with considerations of safety and accessibility to improve mental health benefits.

Despite these inconsistencies, the evidence generally supports the idea that improving walkability in urban areas can contribute positively to mental health outcomes by increasing physical activity opportunities and promoting social interaction.[17] However, while walkability is generally associated with improved mental health, the relationship is influenced by various factors, including neighborhood safety, socioeconomic status, and cultural context. Hence, there is a need to further explore factors linking walkability to mental health outcomes and assess how safety and socio-economic status influence mental health outcomes.

1.2.2. Neighborhood safety and Mental Health

Research shows that neighborhood safety plays a key role in influencing mental health. People living in unsafe areas are more likely to experience mental health problems such as depression, anxiety, psychological distress, and post-traumatic stress disorder (PTSD). Baranyi et al. (2021) found that neighborhood crime is linked to higher levels of depression and emotional distress, both directly and indirectly.[10] Similarly, Weisburd et al. (2018) reported that people living in urban areas with high crime rates were more likely to experience depression and PTSD.[19]

Findings from some studies indicate that perceived safety often matters more than actual crime rates. Polling et al. (2014) found that individuals' perceptions of neighborhood disorder were linked to common mental illnesses (CMI), even if crime rates in their area were low.[20] Pearson et al. (2021) supported this finding, showing that people who felt unsafe while walking during the day reported higher levels of stress and depression.[14] This suggests that how safe people feel in their environment can be just as important as the actual level of crime when it comes to mental health.

Socioeconomic status (SES) also plays a role in how neighborhood safety affects mental health. Meyer et al. (2014) found that people with lower incomes tend to feel less safe and have less access to helpful community services, which worsens their mental health.[21] However, not all types of crime have the same impact. Pak & Gannon (2022) found that violent crimes were linked more strongly to poor mental health than property crime, suggesting that the type of crime matters when studying its effects on mental well-being.[22]

1.2.3. Urban-Rural Mental Health Disparities

Research has shown that mental health burdens differ between urban and rural areas due to unique environmental and social factors.[19,23,24] Urban areas are often affected by stressors like high crime rates, overcrowding, and environmental noise, contributing to increased rates of depression and anxiety.[19] In contrast, rural areas face specific challenges such as geographic isolation, limited access to healthcare services, and fewer mental health professionals.[23,24] Munoz (2023) highlights that rural communities experience multiple disadvantages, including social isolation, stigma, and economic hardships, which intensify mental health challenges. Additionally, Maddox et al. (2022) emphasize that stigma and reduced mental health literacy in rural areas deter individuals from seeking help, resulting in a higher prevalence of untreated mental health conditions compared to urban populations.[23] Taking these contextual differences into account is crucial for understanding how neighborhood characteristics influence mental health burdens.

1.3. Conceptual Framework

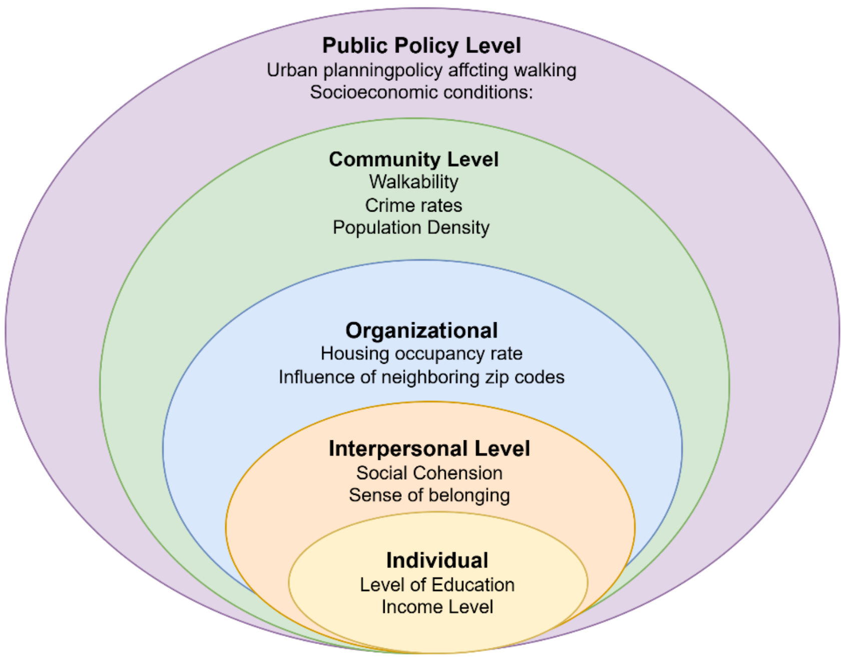


Figure 3: Study Conceptualization Diagram

This study applied the Socio-Ecological Model (SEM) to explore the multi-level factors influencing mental health service requests (MHSRs) in Missouri. At the individual level, factors such as income and educational attainment influence access to care and health literacy. Interpersonal-level factors, including social cohesion and a sense of belonging, play a role in fostering help-seeking behaviors and emotional support. These individual and interpersonal influences interact with community and organizational level factors, such as housing occupancy rates and spatial dependencies, reflecting neighborhood stability and interconnected areas.

While studies highlight a significant treatment gap in mental health care due to limited resources, a shortage of professionals, and the impact of stigma, MHSRs provide valuable insight into the proportion of the population actively seeking help.[25,26] Gao et al. (2024) found that only 42% to 44% of individuals with mental illness access professional care, with rates even lower in resource-constrained settings.[25] Similarly, McLaren et al. (2023) reported that only about half of individuals with depressive symptoms seek mental health services, despite available treatment options.[26] These figures suggest that although MHSRs may underestimate the true burden of mental health issues, they still reflect some community awareness and acknowledgment of mental health challenges. Additionally, service utilization data are often accessible, allowing secondary analysis.

Given that the unit of analysis is the zip code, the study primarily focused on community-level factors such as walkability, crime rates, and population density, which shape the physical and social environments influencing mental health. Walkable neighborhoods may promote physical activity and social interactions, while high crime rates and population density can increase stress. By integrating these variables, this framework provides a comprehensive approach to understanding how neighborhood characteristics influence mental health burden as represented by MHSRs.

1.4. Objectives of the Study

The primary objective of this study was to examine the association between neighborhood characteristics and MHSRs in the State of Missouri. Specifically, the study aimed to:

1. **Assess the Relationship Between Walkability and MHSRs:**
    - Evaluate how walkability, measured through the Walkability Index, influences mental health service requests by promoting social interaction, physical activity, and access to community resources.
2. **Examine the role of Neighborhood Safety:**
    - Investigate how housing occupancy percentage, as a proxy for residential stability, affects MHSRs, with a focus on differences between urban and rural neighborhoods.
3. **Analyze socioeconomic determinants of MHSRs:**
    - Explore the impact of key socioeconomic indicators, including educational attainment, median household income, poverty rates, and health insurance coverage, on MHSRs.

2. Methods

2.1. Study Design and population

This study used a cross-sectional ecological design to assess the relationship between neighborhood characteristics and MHSRs in Missouri, United States. Neighborhoods, represented by zip codes, served as the unit of analysis, with data aggregated to capture community-level determinants of mental health burden. This approach allowed for the evaluation of neighborhood characteristics as predictors of mental health burden while controlling for key socioeconomic factors and spatial dependencies.

The analysis included all zip codes that had complete data on walkability, socioeconomic indicators, and other covariates. MHSRs were sourced from the *211 Counts* database for 2020, which documents community mental health needs, including crisis intervention and resource utilization. This dataset was appropriate given the difficulties in obtaining accurate mental health data, which is often underreported due to stigma and other factors, resulting in a lack of reliable data sources specifically at neighborhood level.[25] Moreover, the COVID-19 pandemic exacerbated existing mental health conditions, resulting in a significant rise in reported cases of psychological distress globally, making 2020 a particularly relevant year for this analysis.[27] Neighborhoods were classified as urban or rural as defined by the Missouri Department of Health and Senior Services, enabling a stratified analysis to uncover context-specific predictors. [28]

2.2. Data Source and Variables

This study utilized publicly available data from multiple sources to analyze neighborhood characteristics and MHSRs in Missouri. See appendix A for detailed definitions of the variables.

- **Mental Health Service Requests (MHSRs)**: The outcome variable, MHSRs, was obtained from the 211 Counts database for the year 2020. This database records community-level mental health needs, including crisis intervention, substance use, suicide prevention, and other mental health-related services. Data were aggregated at the zip code level to provide neighborhood-level insights into mental health burden. [29]

- **Housing Occupancy Percentage**: The percentage of occupied housing units, used as a proxy for residential stability and safety. Given the challenges of obtaining accurate crime data, which is often reported at the agency level rather than the zip code level due to confidentiality and safety concerns, housing occupancy was selected as an alternative measure for assessing neighborhood stability and safety (ACS).

- **Walkability Index**: Sourced from the U.S. Environmental Protection Agency's (EPA) Smart Location Database, this index measures neighborhood walkability on a scale from 1 to 20, where higher scores indicate greater walkability. It evaluates factors like street connectivity, land use diversity, and proximity to transit. Scores are grouped into four levels: least walkable (1.0–5.75), below average (5.76–10.5), above average (10.51–15.25), and most walkable (15.26–20.0). This study applied this index to assess the walkability of various neighborhoods. [30]

- **Below Poverty Level Percentage**: Percentage of residents living below the federal poverty line (U.S. Census Bureau).

- **Urban or Rural Classification**: Indicates whether a neighborhood is classified as urban or rural based on the Missouri Department of Health and Senior Services definition

- **Spatial Lag**: A spatial lag term was computed using neighboring zip codes' mental health service requests to account for spatial dependencies.

- **Additional Variables**: Covariates were selected based on their relevance to mental health outcomes:

    - **Weighted Education Score:** Sourced from the American Community Survey (ACS), this score measures neighborhood educational attainment on a scale from 1.0 to 4.0, where higher scores indicate greater educational levels. It is calculated by assigning weights to educational attainment levels: less than high school (1), high school graduate (2), some college or associate's degree (3), and bachelor's degree or higher (4). Scores are grouped into four levels: low education (1.0–1.75), below average (1.76–2.5), above average (2.51–3.25), and high education (3.26–4.0). This score was used to examine the role of educational attainment in mental health service requests.[iii]

[iii] The Weighted Education Score calculation is adapted from the methodology described by Barro, R. J., & Lee, J.-W. (2001). International Data on Educational Attainment: Updates and Implications. CID Working Paper No. 42,

- **Population Density**: Number of residents per square mile, reflecting urbanicity (ACS).
- **Insured Percentage**: Proportion of residents with health insurance coverage (ACS).

2.3. Data Analysis

All data management and analyses were conducted using R (version 4.2.3). Processes included data cleaning, descriptive analysis, spatial diagnostics, and inferential modeling, with all processes documented in an R Markdown file and stored on GitHub to ensure reproducibility.

2.3.1. Descriptive Analysis

Descriptive statistics summarized key variables. Continuous variables were described using averages, standard deviations, medians, and ranges. Categorical variables were summarized with counts and percentages.

2.3.2. Spatial Analysis

Spatial clustering of MHSRs was examined to identify geographic patterns. Moran's I test was used to detect spatial dependence in the data, revealing the need for spatial adjustments in the modeling process. A spatial weights matrix was created using k-nearest neighbors (k = 4) to define relationships between neighboring zip codes. A spatial lag term was derived from this matrix to account for the influence of neighboring areas on each zip code.

2.3.3. Inferential Statistics

Multiple models were applied to explore the relationships between neighborhood characteristics and MHSRs. Each step in the modeling process was guided by diagnostic tests and model comparisons to ensure the most appropriate method was employed.

The analysis began with a Poisson regression model, which was used to assess the association between predictors and MHSRs. However, this model exhibited overdispersion, as evidenced by a variance-to-mean ratio greater than 1.5. To address this, a Negative Binomial (NB) regression

Center for International Development at Harvard University. This approach assigns numerical values to different educational attainment levels to create a composite score representing neighborhood educational levels.

model was implemented. The NB model accounted for overdispersion, providing improved fit compared to the Poisson model. However, Moran's I test on residuals from the NB model revealed significant spatial autocorrelation, suggesting the need for a spatially explicit model.

To account for spatial dependencies, a Spatial Lag Negative Binomial model was employed. This model included a spatial lag term, which represented the average MHSRs in neighboring zip codes, in addition to other predictors such as Walkability Index, median household income, and socioeconomic covariates. The spatial lag model significantly reduced residual spatial autocorrelation, as confirmed by Moran's I test, and showed improved fit over the NB model based on Likelihood Ratio Tests and AIC values.

Finally, stratified analyses were conducted to explore urban and rural differences in predictors of MHSRs. In urban settings, Walkability Index and the spatial lag term were significant predictors, reflecting the importance of built environment and spatial dependencies. In rural areas, the spatial lag term had a stronger influence, while housing occupancy percentage emerged as a significant predictor, indicating the role of residential stability in shaping mental health service utilization.

3. Results

3.1. Descriptive Analysis

The final cleaned dataset included 218 urban and 724 rural zip codes, totaling 942 geographic units. Urban areas had higher Walkability Index scores (mean = 8.07), and median household income ($63,100) compared to rural areas (mean = 5.12; income = $51,000). Mental health service requests were more frequent in urban areas (mean = 8.66) than in rural areas (mean = 1.37). Urban zip codes also had higher housing occupancy rates (mean = 88.8%), and population density (mean = 1,390 persons/sq. mile) compared to rural zip codes (mean occupancy = 78.6%; density = 209 persons/sq. mile). See Table 1 for additional information.

Table 1:Descriptive statistics for key variables stratified by urban and rural zip codes

Variables	Rural (N=724)	Urban (N=218)	Overall (N=942)
Mental Health Requests			
Mean (SD)	1.37 (6.18)	8.66 (15.1)	3.06 (9.54)
Median [Min, Max]	0 [0, 89.0]	2.00 [0, 84.0]	0 [0, 89.0]
Walkability Index [iv]			
Mean (SD)	5.12 (1.88)	8.07 (3.89)	5.80 (2.78)
Median [Min, Max]	4.74 [2.44, 16.1]	6.24 [2.44, 18.9]	5.00 [2.44, 18.9]
Median Household Income ($)			
Mean (SD)	51,000 (17300)	63,100 (22500)	53,800 (19300)
Median [Min, Max]	49,100 [10,700, 165,000]	61500 [8,620, 161,000]	50,900 [8620, 165,000]
Below Poverty Level (%)			
Mean (SD)	15.2 (9.91)	12.5 (10.4)	14.6 (10.1)
Median [Min, Max]	14.0 [0, 88.0]	10.0 [0, 83.0]	13.0 [0, 88.0]
Insured Population (%)			
Mean (SD)	88.2 (8.95)	90.5 (6.40)	88.7 (8.48)
Median [Min, Max]	90.0 [28.0, 100]	92.0 [66.0, 100]	90.0 [28.0, 100]
Housing Occupancy (%)			
Mean (SD)	78.6 (13.5)	88.8 (9.48)	81.0 (13.4)
Median [Min, Max]	81.0 [25.0, 100]	91.0 [38.0, 100]	84.0 [25.0, 100]
Weighted Education Score[v]			
Mean (SD)	2.47 (0.295)	2.75 (0.326)	2.54 (0.324)
Median [Min, Max]	2.46 [1.35, 3.65]	2.73 [1.98, 3.74]	2.50 [1.35, 3.74]
Population Density (per sq. mile)			
Mean (SD)	209 (715)	1390 (2050)	482 (1270)
Median [Min, Max]	21.8 [2.30, 7500]	472 [12.0, 11500]	30.1 [2.30, 11500]

[iv] The Walkability Index ranges from 1 to 20, with higher scores indicating greater walkability. Scores are categorized as: least walkable (1.0–5.75), below average walkable (5.76–10.5), above average walkable (10.51–15.25), and most walkable (15.26–20.0).

[v] The Weighted Education Score ranges from 1.0 to 4.0, with higher scores indicating greater educational attainment. Scores are categorized as: low education level (1.0–1.75), below average education level (1.76–2.5), above average education level (2.51–3.25), and high education level (3.26–4.0).

To explore patterns in the predictor variables, a histogram was created for the Walkability Index (Figure 4).

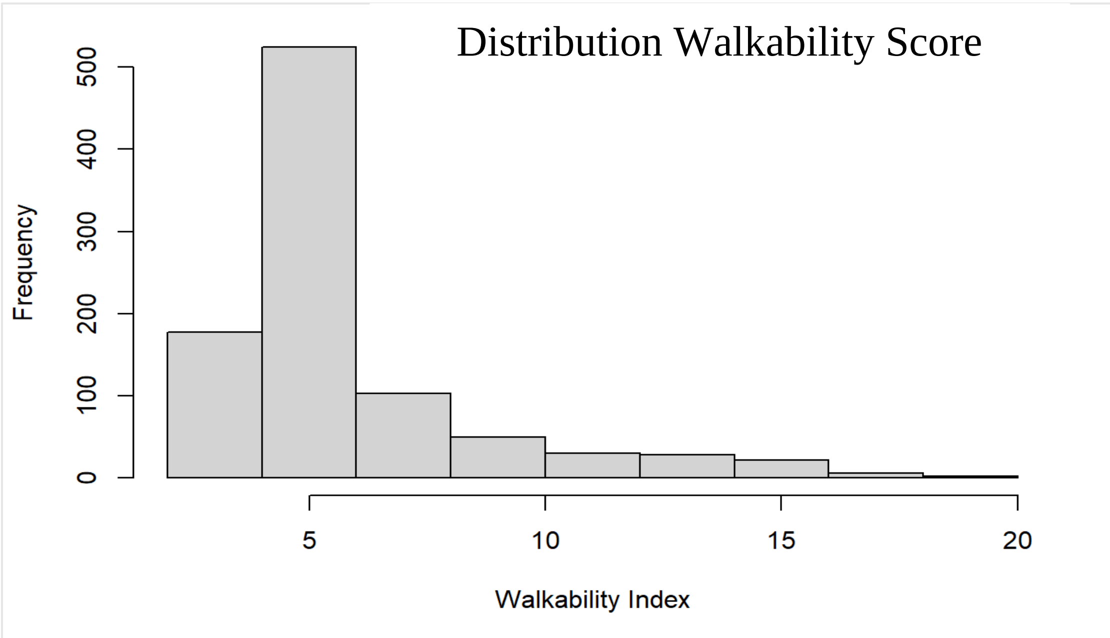


Figure 4: Histogram on the distribution of Walkability scores

The histogram reveals a right-skewed distribution, with most neighborhoods having low walkability scores concentrated between 2.5 and 6.5. Few neighborhoods show high walkability, with the frequency declining beyond a score of 10, suggesting that the majority of the neighborhoods in Missouri have moderate walkability levels.

Building on the exploration of walkability, a scatterplot was created to examine the relationship between Walkability Index and Median Household Income, stratified by rural and urban classifications (Figure 5).

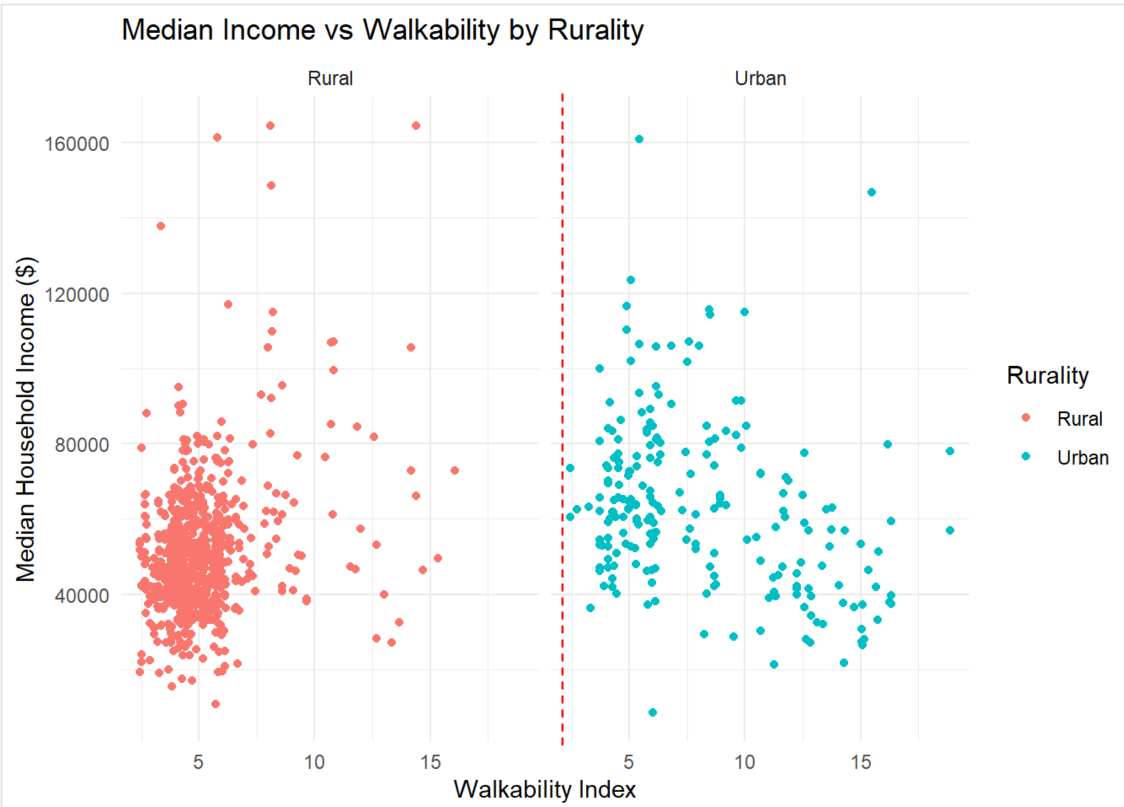


Figure 5:Scatter plot of Walkability vs. Median Income by Rural and Urban

The plot reveals distinct patterns between rural and urban areas. In rural areas, there is a narrower distribution of walkability scores, mostly below 10, and median household incomes clustered around lower to moderate levels. In contrast, urban areas exhibit a broader range of walkability scores, with higher median household incomes concentrated in neighborhoods with moderate to high walkability. This distinction suggests that urban neighborhoods with better walkability may have greater socioeconomic resources compared to their rural counterparts.

3.2. Statistical Modelling

I conducted a series of statistical models to examine the relationship between neighborhood characteristics and MHSRs. Each model's performance was assessed through diagnostic tests and fit statistics, ultimately leading to the selection of a Spatial Lag Negative Binomial (NB) model.

This model accounted for and improved the spatial dependencies in the data while addressing overdispersion in MHSRs.

3.3. Initial Modeling: Poisson Regression

The analysis began with a Poisson regression model, appropriate for count data. However, this model exhibited overdispersion, as the variance of MHSRs significantly exceeded the mean (variance-to-mean ratio > 1.5). Overdispersion was confirmed by a likelihood ratio test (LRT), prompting the transition to a Negative Binomial (NB) regression model.

3.4. Negative Binomial Regression Model

The NB model adjusted for overdispersion by introducing a dispersion parameter. Covariates included Walkability Index, median household income, insured percentage, housing occupancy percentage, weighted education score, and population density. While this model improved fit compared to the Poisson model (LRT: $\chi 2= 938.73$, $P<0.001$), residuals exhibited significant spatial autocorrelation, as revealed by Moran's I test (Moran's $I = 0.078$, $P<0.001$). Spatial autocorrelation was further supported by a Delaunay Triangulation chart (Figure 4), which visualizes the spatial connectivity of neighborhoods in Missouri.

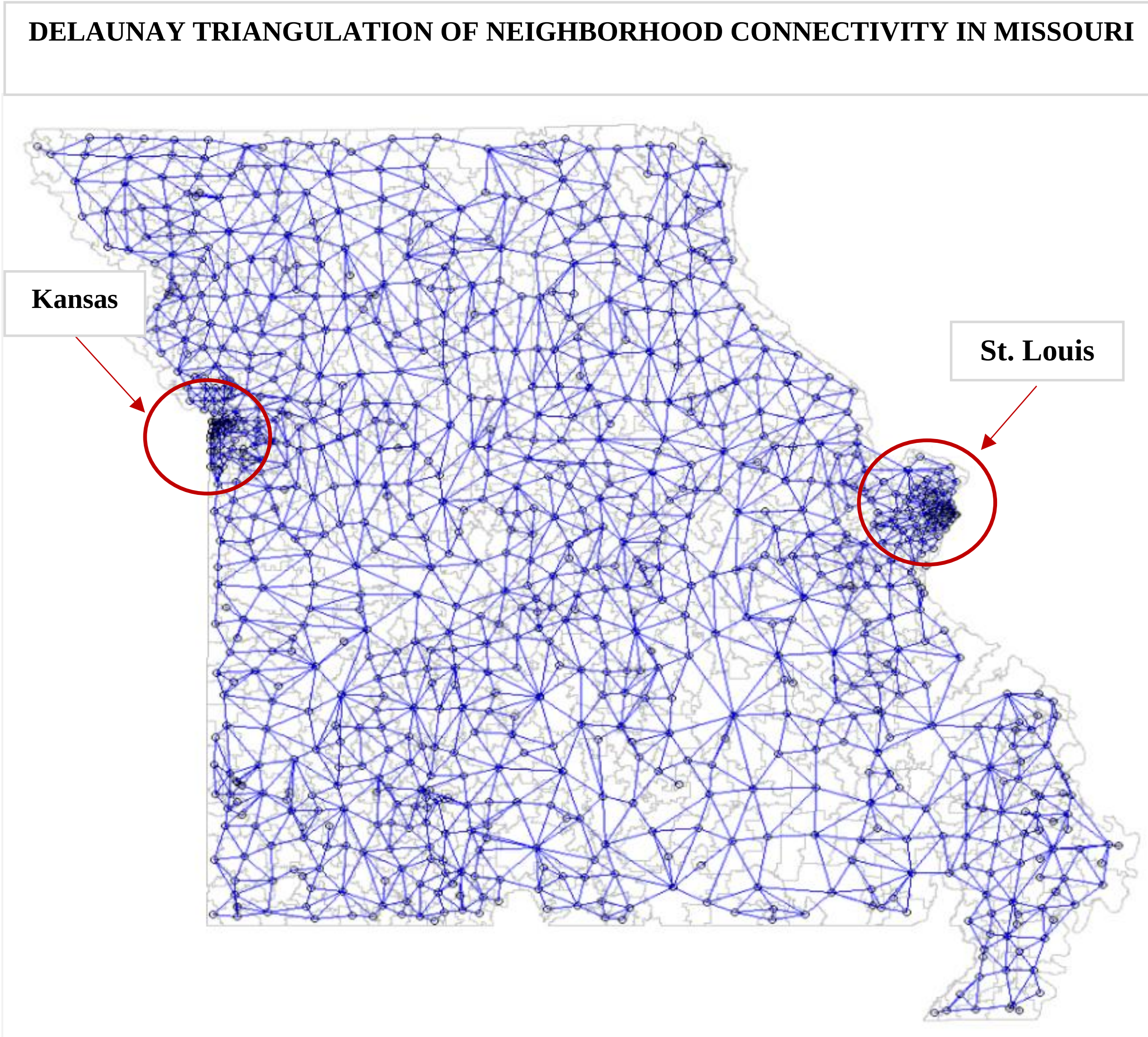


Figure 6:A Delaunay Triangulation chart showing the spatial connectivity of neighborhoods in Missouri.

The chart, constructed using centroids of zip-code polygons from the dataset, shows more dense spatial connections in urban centers like St. Louis and Kansas City compared to rural areas. These clusters suggest a lack of spatial independence, as nearby zip-codes are likely to share similar characteristics or influence each other. This supports the results from the Moran's I test above, indicating spatial autocorrelation in variables. To address this, spatial adjustments using a spatial lag model were applied to ensure accurate analysis.

3.5. Spatial Lag Negative Binomial Regression Model

To account for spatial dependencies, a Spatial Lag Negative Binomial (NB) model was employed, integrating a spatial lag term representing MHSRs from neighboring zip codes. The model significantly improved over the standard NB model (LRT: $\chi^2 = 306.59$, $p < 0.001$) and reduced residual spatial autocorrelation, though some dependency remained (Moran's I = 0.039, $p < 0.05$).

Table 2: Key Predictors of Mental Health Service Requests in the Spatial Lag NB Model

Predictor	Estimate (β)	Std. Error	z-value	p-value	IRR (Exp(β))	95% CI (IRR)
Intercept	-8.098	1.092	-7.413	<0.001***	0.000	(0.000, 0.003)
Walkability Index	0.211	0.040	5.188	<0.001***	1.235	(1.141, 1.342)
Below Poverty Level (%)	-0.000	5.4E-06	-2.562	0.010*	0.999	(1.000, 1.003)
Insured (%)	-0.008	0.012	-0.688	0.491	0.992	(0.960, 1.023)
Housing Occupancy (%)	0.048	0.008	6.382	<0.001***	1.049	(1.031, 1.062)
Weighted Education Score	1.520	0.385	3.951	<0.001***	4.574	(1.961, 10.940)
Population Density	0.000	8.42E-05	0.747	0.455	1.000	(1.000, 1.002)
spatial lag	0.067	0.012	5.580	<0.001***	1.069	(1.041, 1.102)

Significance codes: *** P < 0.05.

Key predictors in the Spatial Lag NB model (Table 3) showed that a one-unit increase in the Walkability Index was associated with a 23% higher rate of MHSRs (IRR = 1.23, 95% CI [1.14, 1.34], $P < 0.001$). A 1% increase in housing occupancy corresponded to a 5% increase in requests (IRR = 1.05, 95% CI [1.03, 1.06]). Higher educational attainment resulted in 4.5 times the rate of requests (IRR = 4.57, 95% CI [1.96, 10.94], $P < 0.001$). Conversely, there was a marginal but significant association between median household income and MHSRs (IRR = 0.99, 95% CI [1.00, 1.00], $P < 0.05$). The spatial lag effect was significant, with a 7% increase in MHSRs linked to one-unit increases in requests based on the characteristics of neighboring zip codes (IRR = 1.07, 95% CI [1.04, 1.10], $P < 0.01$). Population density and insured percentage were not significant, suggesting possible indirect influences through other variables.

Table 3:Stratified Results of Mental Health Service Requests by Urban and Rural Areas

	Predictor	Estimate (β)	Std. Error	z-value	p-value	IRR (Exp(β))	95% CI (IRR)
Urban Areas	**Intercept**	-8.871	1.216	-7.293	<0.001***	0.0001	(0.00, 0.00)
	Walkability Index	0.207	0.0409	5.063	<0.001***	1.23	(1.13, 1.34)
	Below Poverty Level (%)	1.406	0.9828	1.431	0.1525	4.08	(0.41, 45.20)
	spatial lag	0.0664	0.0119	5.571	<0.001***	1.07	(1.04, 1.10)
	Insured (%)	-0.4398	1.185	-0.371	0.7104	0.644	(0.036, 11.9)
	Housing Occupancy (%)	4.901	0.7603	6.446	<0.001***	134	(31.4, 621)
	Weighted Education Score	1.516	0.3865	3.923	<0.001***	4.56	(1.94, 10.9)
	Population Density	0.0001	0.0001	0.73	0.4652	1	(1.00, 1.00)
Rural Areas	**Intercept**	-7.725	1.57	-4.92	<0.001***	0.0002	(0.00,0.011)
	Walkability Index	0.1693	0.0841	1.91	0.0561	1.1743	(0.99, 1.40)
	Below Poverty Level (%)	1.03	0.0123	2.396	0.0166	1.03	(0.99, 1.06)
	spatial lag	0.0892	0.0224	4.139	<0.001***	1.0971	(1.04, 1.18)
	Insured (%)	-0.0143	0.0153	-0.66	0.5095	0.9899	(0.95, 1.03)
	Housing Occupancy (%)	0.0365	0.0097	3.68	<0.001***	1.0363	(1.02, 1.06)
	Weighted Education Score	2.008	0.5835	3.441	0.0006	7.45	(1.64, 17.23)
	Population Density	0.0001	0.0002	0.495	0.6207	1.0001	(0.99, 1.00)

Significance codes: *** P < 0.05.

As shown in Table 4, stratified results show distinct patterns in urban versus rural contexts. In urban areas, housing occupancy demonstrated a notably large effect on MHSRs (IRR=134, p<0.05), followed by walkability (IRR=1.23, p<0.05) and educational attainment (IRR=4.56, p<0.05). In rural areas, housing occupancy still had a positive but more modest effect (IRR=1.04, p<0.05), while educational attainment was strongly associated with MHSRs (IRR=7.45, p<0.05). Although walkability was significant in urban settings, it was not statistically significant in rural settings (p = 0.056). Spatial dependence persisted in both contexts (urban: IRR=1.07, p<0.05; rural: IRR=1.10, p<0.05), indicating that areas with higher MHSRs influence neighboring communities. Insurance coverage and median household income did not show significant direct effects. These findings highlight the importance of tailoring interventions and policies to local built-environment and socioeconomic conditions.

3.6. Model Diagnostics and Comparison

The diagnostics of the Spatial Lag Negative Binomial (NB) model confirmed its better fit compared to the standard NB model. The model showed significant improvement in model fit with an AIC of -1194.5 compared to -1041.2 for the standard NB model. The Likelihood Ratio Test (LRT) yielded a chi-square value of 306.59 ($p < 0.001$), confirming that the spatial lag term significantly enhanced explanatory power. Moran's I Test for residuals indicated some spatial autocorrelation (Moran's I = 0.0398, p = 0.011), suggesting reduced but persistent autocorrelation. Multicollinearity diagnostics showed acceptable VIF values (<5), with the highest being 3.05 for the Walkability Index, indicating that no variable required removal. Residual maps further highlighted that the Spatial Lag NB model effectively reduced clustering and improved prediction accuracy, making it better suited for modeling MHSRs in Missouri (Appendix B).

4. Discussion

This study provides valuable insights into how neighborhood factors particularly walkability, housing occupancy, and educational attainment are associated with MHSRs in Missouri. By applying a Spatial Lag Negative Binomial (NB) model, I addressed several analytical challenges, including overdispersion and spatial autocorrelation, thus applying a more robust and conventional approaches. This comprehensive methodology represents one of the key strengths of my study. By incorporating a spatial lag term, I not only accounted for the non-independence of observations across geographical areas, but also improved model fit and provided a more detailed understanding of how mental health service utilization can be influenced by neighboring communities.

In this study I used mental health requests as a proxy for mental health burden. My findings highlight that walkability is positively associated with MHSRs, suggesting that environments that promote social interaction and walking are likely to have high mental burden. These findings are inconsistent with findings from Siqueira Junior et al. (2022) who reported that greater walkability is associated with improved cognitive function and reduced depression in older adults, underscoring the benefits of walkable built environments in mental health outcomes.[31] A possible explanation for this inconsistency is that while high demand for mental health services indicates a greater burden, it may also reflect overreporting or easier access to services due to better resource availability in some communities. Besides, walkable neighborhoods are likely to have more and better services, enabling improved marketing of mental health related services such as the 211 helplines, thus increasing service utilization. This view is supported by Carson et al. (2023), who suggested that higher walkability promotes social cohesion and increases help-seeking behaviors.[16]

In addition, the absence of significant findings related to income and insurance coverage was unexpected. Prior research, such as Kan et al. (2022), highlighted the importance of socioeconomic indicators in shaping mental health outcomes, suggesting that higher income and insurance coverage should reduce mental health conditions or burden.[9] The lack of significance in this study could be attributed to potential collinearity with housing occupancy or education levels, which were strong predictors

The results also revealed that educational attainment had the largest effect on MHSRs in rural areas, which is consistent with Meyer et al. (2014), who reported that higher education correlates with better health literacy and access to services.[21] However, this effect was higher than expected, potentially reflecting broader structural inequalities in rural areas, such as limited-service availability or cultural norms affecting help-seeking behaviors. Additionally, residual spatial autocorrelation persisted even after using a Spatial Lag Negative Binomial model, suggesting unmeasured contextual factors like community support networks or healthcare facility accessibility.

Overall, my findings highlight the importance of tailored urban and rural policies aimed at enhancing mental health services in communities. Policies promoting walkable neighborhoods, reducing crime, and expanding educational opportunities could reduce mental health burdens. Future studies should explore longitudinal data to assess causal relationships and include direct measures of perceived neighborhood safety, crime statistics, and social support networks. Expanding spatial models to capture additional socio-environmental variables may also provide deeper insights into neighborhood-driven mental health disparities

5. Strengths and Limitations

In addition to the inclusion of spatial effects in the statistical analysis, other strengths of this study include the use of publicly available data sources. I integrated a range of neighborhood-level indicators that allowed me to capture a multifaceted view of community contexts. By stratifying the analysis by urban and rural areas, the study further clarified that the determinants of mental health service requests differ across geographic contexts, providing more detailed findings. Additionally, since the study was conducted for Missouri, the approach could be applied to other states with available 211 Counts data, allowing for broader comparisons and deeper policy insights.

However, the study had several limitations. First, despite the use of spatial lag adjustments, some residual spatial autocorrelation remained, indicating that areas with high MHSRs can still influence neighboring areas, and vice versa. This suggests that other unmeasured spatial factors, such as cultural norms or other unobserved neighborhood characteristics, may have affected the results. Consequently, the relationships observed should be interpreted with care, and future studies may benefit from even more refined spatial methodologies or the inclusion of additional contextual variables.

Second, MHSRs derived from the 211 Counts database may underestimate the true mental health burden. Similar to previous research on 211 helplines and other social services data, individuals experiencing mental health challenges may not always seek help through these channels. People with ongoing mental health conditions or established community resources may already know where to go and therefore may not need to contact 211 for referrals. Additionally, variability in how different 211 helplines categorize, and code service requests could introduce measurement inconsistencies. While these data provide a trackable measure of mental health service needs and allow for community-level comparisons, they should be viewed as one piece of the overall mental health landscape. The complexities of help-seeking behaviors, local referral patterns, and resource availability all play a role in shaping 211 Counts' MHSR data.

Finally, the cross-sectional design of this study limits our ability to infer causality. We cannot determine whether neighborhood characteristics lead to increased service. Furthermore, using the zip code as unit of analysis may mask important within-neighborhood variations and individual-level disparities in mental health services request.

6. Conclusion

Despite these limitations, this study offers valuable insights into the ways that built environment factors, neighborhood stability, educational attainment, and spatial dependencies influence mental health service utilization at zip code level. My spatial modeling approach, combined with a focus on both urban and rural areas, provides a more comprehensive understanding of how zip-code characteristics shape mental health needs and access to care. While data from 211 helplines may not capture the full extent of mental health needs, it remains a practical, trackable source, especially given the challenges of obtaining granular mental health data at the local level.

In moving forward, policymakers and public health practitioners should consider the specific neighborhood characteristics patterns that influence mental health service use. Efforts to enhance walkability, stabilize housing, and improve educational opportunities may be key strategies for increasing mental health service access. Ultimately, by integrating spatial, social, and environmental perspectives, we can better inform resource allocation, tailor interventions, and promote more equitable mental health outcomes across diverse communities.

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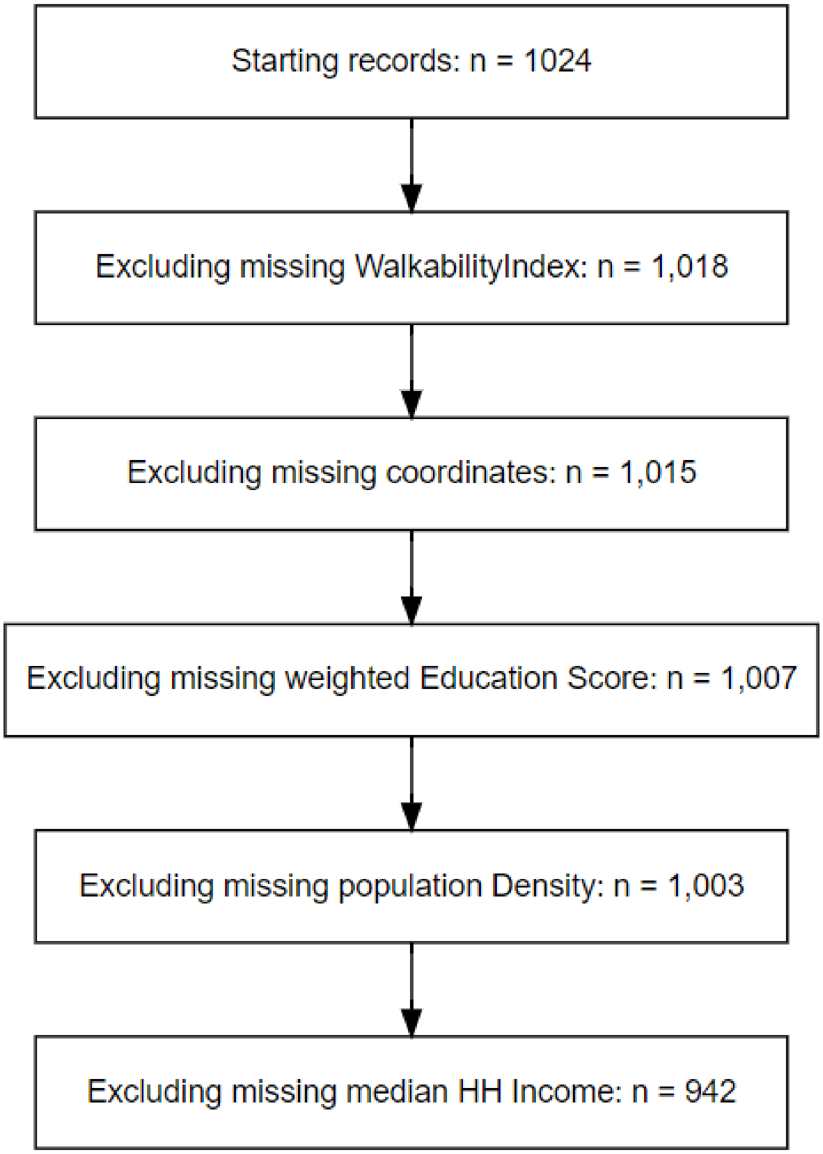
Appendices

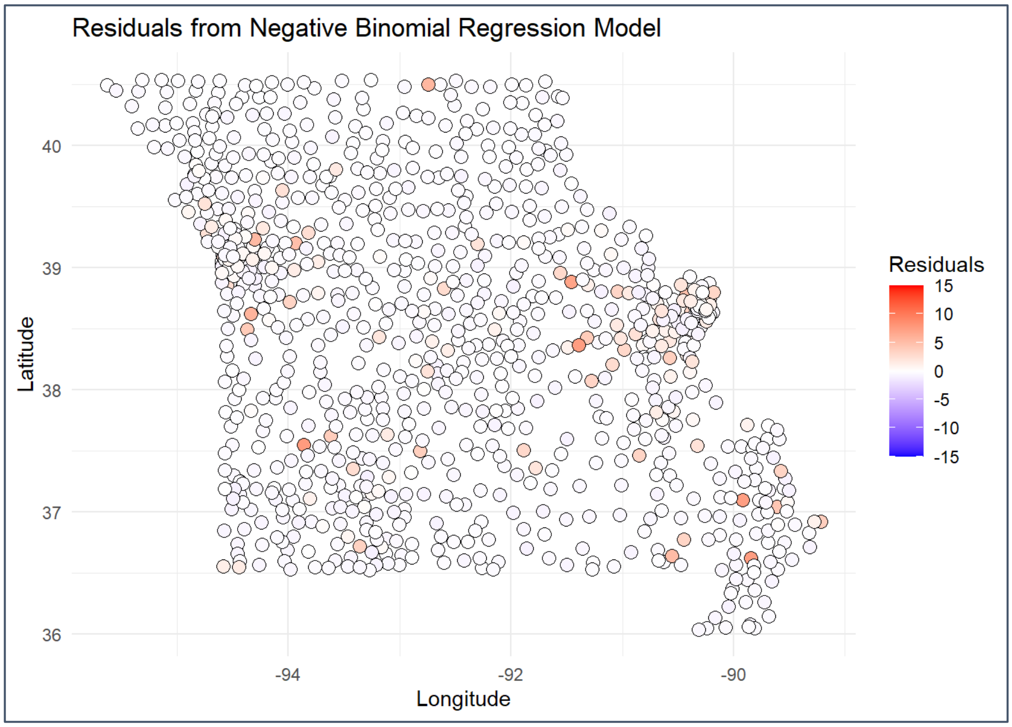
Appendix A: Variables and Definitions

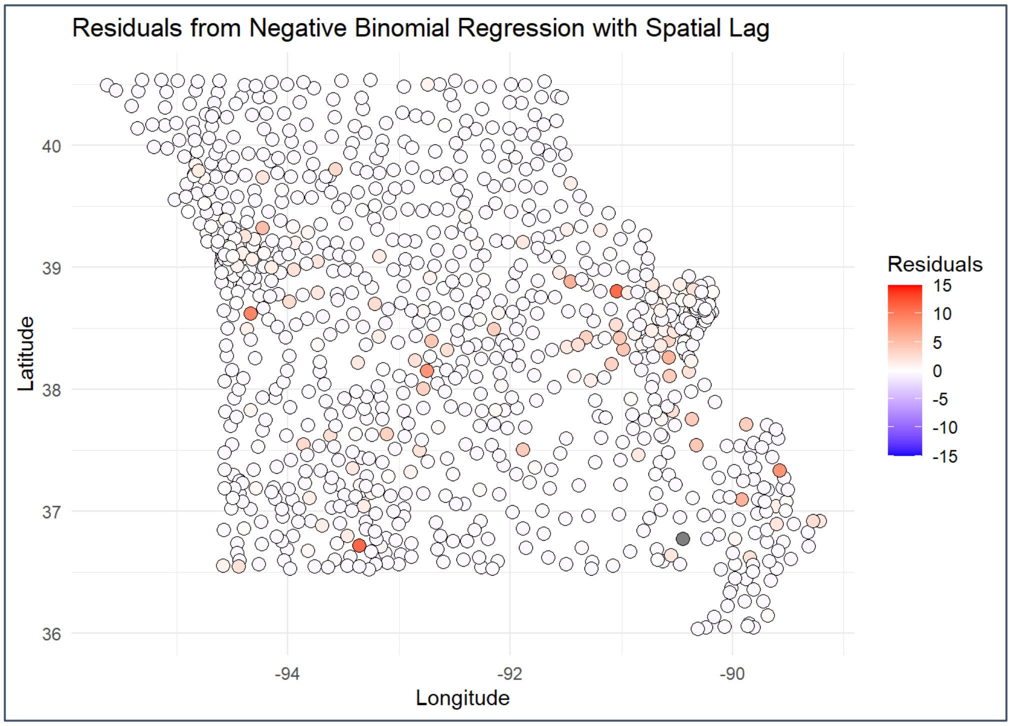
Category	Variable	Definition
Outcome	Mental Health Service Requests (MHSRs)	Total number of MHSRs per zip code, treated as a count variable to reflect the burden of mental health needs.
Predictors	Walkability Index	Higher values represent greater walkability, indicative of better street connectivity and access to resources.
	Median Household Income	Measured in U.S. dollars, capturing neighborhood-level socioeconomic status.
	Housing Occupancy Percentage	Proxy for residential stability and Safety, measured as the proportion of occupied housing units.
	Spatial Lag	Calculated using a spatial weights matrix, representing the average MHSRs in neighboring zip codes.
Covariates	Below Poverty Level Percentage	Reflects economic hardship in neighborhoods.
	Insured Percentage	Proportion of residents with health insurance coverage, indicating access to healthcare resources.
	Weighted Education Score	Composite measure of educational attainment; higher scores indicate better educational outcomes.
	Population Density	Number of residents per square mile, reflecting urbanicity or rurality of neighborhoods.

Appendix B:Listwise Deletion Summary



Appendix C:Residual map standard versus Spatial NB Model





The colors in the charts represent the residuals, with blue indicating areas where the model underestimates mental health service requests (negative residuals), red showing areas where the model overestimates requests (positive residuals), and white representing areas with near-zero residuals (good model fit).

In the spatial lag model (bottom chart), the colors are more evenly distributed, reflecting reduced clustering of extreme residuals compared to the original model (top chart), which shows stronger clustering of red and blue regions. The spatial lag model is better suited for this analysis as it accounts for spatial autocorrelation, reducing the residual clustering observed in the original model. By incorporating spatial dependencies, it not only improves prediction accuracy but also provides a more realistic representation of how mental health service utilization is influenced by surrounding areas, making it more effective.

Appendix D:MPH Competencies addressed

Below is a list of competencies that I plan to demonstrate and how they will be addressed through this capstone project.

Competency Area	Competency
3.1 Foundational Competencies Addressed	
i. Apply epidemiological methods to the breadth of settings and situations in public health.	The study analysis involves the application of epidemiological methods, including assessing and controlling for confounding through regression if applicable.
ii. Interpret results of data analysis for public health research, policy, or practice.	This paper demonstrated competency on the interpretation of analyzed data, statistical models and summarizing the results in the discussion and conclusion section.
iii. Assess population needs, assets and capacities that affect communities' health.	The study assessed community needs by examining socioeconomic and built-environment indicators that influence mental health service utilization.
3.2 Epi/Biostat Specialization Competencies	
i. Apply and interpret common statistical methods for inference (e.g., ANOVA, linear and logistic regression, survival analysis) found in public health studies.	The data analysis approach for the project involved inferential statistical tests, particularly linear regression, which will require competency in data interpretation and assessing if the data meets the required assumptions/conditions.
ii. Apply preferred methodological alternatives to commonly used statistical methods when assumptions are not met.	The final data analysis method in this study was informed by the model diagnostic test and assessing whether the data meets the assumptions/conditions for specific statistical tests.
diii. Demonstrate an understanding of the components of reproducible research.	The study will use data from publicly available sources, and all data consolidation, cleaning, and analysis will be conducted in R with a well-documented R-markdown file.