Spatial distribution of self-reported depression among older adults in Brazil: a generalized additive modeling approach

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Abstract:
Depression in older adults is a growing public health concern in Brazil, often associated with chronic diseases, socioeconomic disparities, and regional inequalities. This study analyzes the spatial distribution of depression among the elderly using data from the 2019 Brazilian National Health Survey (PNS). A cross-sectional design was employed, and Generalized Additive Models (GAMs) were used to assess associations between self-reported depressive symptoms and a set of chronic health conditions and sociodemographic factors at the state level. The modeling approach incorporated spatial smoothing terms to capture geographical patterns in depression prevalence. The analysis revealed that coronary disease was a significant predictor of depression, while other conditions such as hypertension and diabetes showed weaker or non-significant associations. The spatial component was statistically significant, indicating notable regional variations in depression risk. States in the Northeast, North, and Central-West regions showed higher relative risks, suggesting that structural and contextual factors may influence mental health outcomes in the elderly population. The results highlight the importance of integrated care strategies and the need for region-specific public policies that address both mental and cardiovascular health in aging populations. These findings support the application of spatially explicit models in public health research and demonstrate how spatial analysis can inform targeted interventions and policy planning to reduce mental health disparities among older adults in Brazil.
Keywords: Depression; Aged; Chronic Disease; Spatial Analysis; Health Surveys.

Distribuição espacial da depressão autorreferida em idosos no Brasil: uma abordagem com modelos aditivos generalizados

Resumo:

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A depressão em idosos é uma preocupação crescente de saúde pública no Brasil, frequentemente associada a doenças crônicas, desigualdades socioeconômicas e disparidades regionais. Este estudo analisa a distribuição espacial da depressão autorreferida na população idosa, com base nos dados da Pesquisa Nacional de Saúde de 2019. Trata-se de um estudo transversal com aplicação de Modelos Aditivos Generalizados para avaliar associações entre sintomas depressivos e condições crônicas de saúde, além de fatores sociodemográficos em nível estadual. A modelagem incluiu termos de suavização espacial para captar padrões geográficos de prevalência. A doença coronariana foi um preditor significativo, enquanto hipertensão e diabetes mostraram associações mais fracas. O componente espacial foi estatisticamente significativo, com maiores riscos relativos nas regiões Norte, Nordeste e Centro-Oeste. Os resultados sugerem que fatores estruturais e contextuais influenciam os desfechos em saúde mental entre idosos. O estudo destaca a importância de políticas públicas regionais e estratégias de cuidado integradas que abordem conjuntamente a saúde mental e cardiovascular.
Palavras-chave:
Depressão; Idoso; Doença Crônica; Análise Espacial; Inquéritos Epidemiológicos.

Distribución espacial de la depresión autoinformada en personas mayores en Brasil: un enfoque con modelos aditivos generalizados

Resumen:
La depresión en personas mayores es una preocupación creciente de salud pública en Brasil, a menudo vinculada a enfermedades crónicas, desigualdades socioeconómicas y disparidades regionales. Este estudio analiza la distribución espacial de la depresión autoinformada en ancianos utilizando datos de la Encuesta Nacional de Salud de 2019. Se aplicó un diseño transversal con Modelos Aditivos Generalizados para evaluar asociaciones entre síntomas depresivos y condiciones crónicas de salud y factores sociodemográficos a nivel estatal. El modelo incorporó términos de suavización espacial para capturar patrones geográficos de prevalencia. La enfermedad coronaria fue un predictor significativo, mientras que la hipertensión y la diabetes mostraron asociaciones más débiles. El componente espacial fue estadísticamente significativo, revelando mayores riesgos relativos en las regiones Norte, Noreste y Centro-Oeste. Los resultados sugieren que factores estructurales y contextuales influyen en la salud mental de los adultos mayores. El estudio destaca la importancia de políticas públicas regionales y estrategias integradas que aborden la salud mental y cardiovascular.
Palabras clave: Depresión; Anciano; Enfermedad Crónica; Análisis Espacial; Encuestas Epidemiológicas.

Introduction

Depression among the elderly represents a significant public health challenge worldwide, particularly in the context of aging populations and increasing life expectancy. In Brazil, the National Health Survey (PNS) conducted in 2019 provides a comprehensive dataset to explore the prevalence and determinants of depression in older adults. Depression

in this age group often correlates with chronic illnesses, functional limitations, and social vulnerabilities, amplifying its impact on individual well-being and healthcare systems (Barros et al., 2021).

According to the Brazilian National Policy for the Elderly (PNI), established by Ordinance No. 2,528 of October 19, 2006, which serves as the constitutional and regulatory framework for actions directed at the elderly population in Brazil, individuals aged 60 years or older are considered elderly.

According to the Brazilian regulations, an older person is defined as a person who is over 60 years of age. However, as defined by the World Health Organization (WHO), the classification of elderly status varies depending on a country's level of development: in developing countries, individuals are considered elderly from the age of 60 years, whereas in developed nations, this threshold is set at 65 years (Pereira et al., 2019). About 16% (33 million) of Brazilians are elderly (IBGE, 2024), a trend expected to rise to nearly 70% by 2070.

The etiology of depression in late life is multifaceted, involving biological, psychological, and sociocultural factors. According to the DSM-5-TR (Cortés, 2022), depression is characterized by Major Depressive Disorder (MDD), in which an individual experiences at least five symptoms for a minimum of two weeks, including either depressed mood or loss of interest/pleasure. Other symptoms include changes in sleep, appetite, energy, concentration, feelings of guilt, psychomotor agitation or retardation, and suicidal thoughts. The symptoms must cause significant distress and cannot be explained by another medical condition or disorder. Gender differences are particularly pronounced, with elderly women often exhibiting higher prevalence rates of depressive symptoms than men, influenced by both historical life course factors and age-specific vulnerabilities (Girgus et al., 2017). Additionally, socioeconomic inequalities and limited access to mental health care exacerbate the challenges faced by this population (Neto et al., 2023).

Depression is strongly associated with chronic health conditions, such as diabetes, hypertension, and arthritis, which are highly prevalent among older adults. These conditions impose not only a significant physical burden but also intensify psychological distress, further increasing the risk of depressive symptoms (Silva et al., 2017). Studies have shown that comorbidities exacerbate healthcare demands, leading to poorer health outcomes and underscoring the necessity of integrated treatment approaches (Taylor, 2014; Zhou et al., 2021). Furthermore, social isolation and the absence of community support networks have been identified as major risk factors for depression in this demographic (Sguerri et al.,

2024).

Given that the prevalence of depression and its associated risk factors can vary significantly across regions, understanding the geographical distribution of depressive symptoms is crucial. Brazil, characterized by stark regional disparities in healthcare access, socioeconomic conditions, and environmental factors, presents a unique context for exploring how these factors may influence depression among older adults. Such disparities make spatial analysis an essential tool for identifying areas with higher rates of depression and the specific local conditions that exacerbate the problem.

Spatial analysis methods, especially those that employ Generalized Additive Models (GAMs), provide an innovative approach to understanding the geographical distribution of depression and its associations with sociodemographic and environmental variables. GAMs allow the identification of non-linear relationships and spatial patterns that might be overlooked by traditional modeling techniques (Souza-Junior et al., 2015; Didoné et al., 2020). This methodology is particularly relevant in Brazil, a country marked by significant regional disparities in healthcare access, socioeconomic conditions, and environmental factors (Silva et al., 2018).

This study expands on existing research by incorporating spatial analysis to examine the distribution of self-reported depressive symptoms and their association with chronic health conditions, as well as sociodemographic and environmental factors, in the elderly population of Brazil. Leveraging data from the 2019 PNS, this research aims to address critical gaps in understanding the geographical and contextual factors influencing depression in older adults. However, it is important to clarify that the focus here is on self-reported symptoms of depression rather than diagnosed cases, which may lead to different implications for understanding how chronic health conditions influence depression.

Methods

Study Design and Data Collection

This is a cross-sectional study using secondary data from the 2019 National Health Survey (PNS), proposed by the Ministry of Health and conducted in 2019 by the Brazilian Institute of Geography and Statistics (IBGE). The PNS-2019 was approved by the National Research Ethics Commission for Human Beings, under the Ministry of Health.

The PNS samples are representative of residents in permanent households located in urban and rural areas across municipalities in all five major geographic regions of Brazil, encompassing the 26 states and the Federal District. The PNS-2019 included a sample of 94,114 individuals interviewed in 185,268 households, using three data collection forms, referring to the household, residents, and individuals. For the present study, only data from individuals aged 60 years or older (n = 20,340) were used, collected from the Chronic Diseases Module (Módulo Q) of the Selected Resident Questionnaire. Among the elderly participants, 2,365 self-reported symptoms of depression (Souza-Júnior et al., 2015; IBGE, 2014).

Data collection for the PNS-2019 was conducted by trained interviewers using handheld electronic devices for real-time data storage. Further details regarding the sampling process and weighting, as well as the data collection methods, can be found in the PNS-2019 methodological report (Szwarcwald et al., 2014).

Study variables

The response variable in this study was the number of self-reported depression cases among elderly individuals in each federative unit of Brazil. We select socioeconomic and clinical factors as potential independent variables associated with depression prevalence. These factors were chosen based on scientific references on mental health determinants in older adults and data available from the 2019 National Health Survey (PNS) at the federative unit level. The following explanatory variables were selected as potential predictors:

- Proportion of elderly people with stroke: Several factors indicate that stroke can lead to the occurrence of depression due to pathophysiological changes and not just psychological factors. The psychological impact caused by the limitations imposed by stroke may already be a sufficient condition to trigger a depressive condition (Dias, 2015; Robinson and Jorge, 2016; Villa et al., 2018).
- Proportion of elderly individuals with high cholesterol levels: Evidence suggests that elevated cholesterol levels may be linked to depressive symptoms due to chronic inflammation and alterations in neurotransmitter pathways. Additionally, lipid metabolism dysregulation has been associated with increased vulnerability to mood disorders (Persons and Fiedorowicz, 2016; Wagner et al., 2019; Fittipaldi et al., 2020; Zhou et al., 2025).
- Prevalence of hypertension among elderly individuals: Hypertension is

known to contribute to cognitive decline and vascular depression, with studies indicating that increased blood pressure is associated with a higher risk of late-life depression. Furthermore, individuals with poorly controlled hypertension exhibit higher depressive symptoms and lower quality of life (Boima et al., 2020; Zhang et al., 2024; Gan et al., 2023; Lim et al., 2023).

- Mean income per capita (in BRL): Socioeconomic disparities play a crucial role in mental health outcomes among the elderly. Research has shown that lower income levels are significantly correlated with higher depression rates, likely due to financial stress, reduced access to healthcare, and social isolation (Domènech-Abella et al., 2018; Xue et al., 2021; Sánchez-Moreno and Gallardo-Peralta, 2022; Costantini et al., 2024; Sánchez-Moreno et al., 2024).
- Proportion of elderly individuals diagnosed with coronary disease: Cardiovascular diseases, particularly coronary heart disease (CHD), are strongly associated with depression in older adults. Studies indicate that individuals with CHD have a twofold increased risk of developing depression, possibly due to shared pathophysiological mechanisms such as systemic inflammation, endothelial dysfunction, and autonomic nervous system dysregulation (Zhang et al., 2018).
- Prevalence of diabetes mellitus among the elderly: Diabetes has been identified as an independent predictor of depression, with research indicating that older adults with diabetes are twice as likely to develop depressive symptoms compared to non-diabetics (Dziedzic et al., 2020; Andrade et al., 2022; Zhang et al., 2023; Zheng et al., 2024). The bidirectional relationship between diabetes and depression is linked to chronic inflammation, oxidative stress, and lifestyle factors such as sedentary behavior and poor dietary habits.

Spatial Model Specification

Generalized Additive Models (GAMs) were used to assess the association between the number of self-reported depression cases and independent variables while accounting for spatial dependencies. The model was specified as follows:

$$\log(\psi_i) = \alpha + \sum_{j=1}^{p} \beta_j x_{ij} + f_1(z_{1i}, z_{2i}) + \sum_{j=1}^{p} f_{2j}(z_{1i}, z_{2i}, x_{ij}) + \sum_{j<k}^{p} f_3(x_{ij}, x_{ik}) \quad (1)$$

where f_1 represents the smooth function for spatial coordinates, f_{2j} accounts for interaction

effects between spatial location and each covariate, and f_3 captures interactions between covariates. This approach builds on the theory of spatial models in GAMs, which allow for the incorporation of spatial autocorrelation and the modeling of smooth functions in geospatial data (Wood, 2006).

The spatial variables, corresponding to the *x* and *y* coordinates of the centroids of the federative units, were incorporated to analyze the spatial pattern of risk. Conditioned on the relative risk ψ_i, we assumed that the number of self-reported depression cases in the i-th federative unit follows a Poisson distribution with mean $\mu_i = E_i\psi_i$, which can be expressed as:

$$y_i \mid \psi_i \sim \text{Poisson}(E_i\,\psi_i), \quad i = 1,2,\ldots,27.$$

The expected rates were computed as $E_i = N_i R$, where $R = \sum_{i=1}^{27} y_i / \sum_{i=1}^{27} N_i$, and N_i represents the number of elderly individuals in the i-th federative unit.

The model described in Equation (1) offers a high degree of flexibility, allowing it to be adapted to diverse study contexts. It effectively captures both linear and nonlinear effects, as well as complex interactions among spatial and non- spatial covariates, enhancing its applicability in spatial epidemiology and public health risk assessments (Wood, 2006).

Estimation and Model Selection

The Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were employed to identify the most suitable model (Gill, 2015; Sutherland et al., 2023). The relative contribution of each variable in the best-fit model was assessed by iteratively removing individual variables with lower significance and calculating the change in total explained deviance (DE) between the full model and the model with the discarded variables. The explained deviance (DE) was used to measure the explanatory power of the model's variables, where a higher DE value indicates greater explanatory capacity.

The models were estimated using the Restricted Maximum Likelihood (REML) method, as proposed by Patterson and Thompson (1971) (see Wood et al. (2016) for further details). Additionally, verification tests were conducted to determine the optimal spline function for the spatial variables. The smoothing parameter was selected by balancing the likelihood function and overfitting, ensuring the convergence of the iterative algorithm.

To assess the goodness of fit and overall model performance, we employed several statistical metrics widely used in environmental and social sciences, including root mean

square error (RMSE), mean absolute error (MAE), and the coefficient of determination (R^2) (Chai and Draxler, 2014). Employing multiple measures of model performance is a common practice in machine learning and statistics. This approach provides a more nuanced evaluation of the model's performance by considering different aspects such as the average magnitude of errors, sensitivity to outliers, and the overall goodness of fit.

Residual Analysis and Model Verification

Model verification ensures the model's correctness. To assess its validity, we performed residual analysis using deviance residual plots and QQ-plots. Deviance residuals highlight differences between observed and expected values, while graphical diagnostics help detect model misfits.

We also examined spatial autocorrelation in the residuals using Moran's I index (Moran, 1950), computed with the `spdep` package (Bivand et al., 2017). Moran's I values range from −1 to 1, indicating the degree of spatial dependence.

Models were implemented using R version 4.4.3 (R Core Team, 2025) with the `mgcv` package (Wood et al., 2016). Maps were created using the `tmap` package (Tennekes et al., 2025) with IBGE shapefiles (2022) (https://portaldemapas.ibge.gov.br/portal.php#homepage).

Ethical considerations

The PNS project was submitted for ethical review and approved by the National Research Ethics Commission (Comissão Nacional de Ética em Pesquisa - CONEP), which is affiliated with the Brazilian National Health Council. The study was approved under Protocol Numbers 10853812.7.0000.0008 (2013) and 3.529.376 (2019). All participants provided written informed consent before participation. The PNS dataset is publicly available, and no personal identifying information is disclosed.

Results

Exploratory Analysis

Table 1 presents descriptive statistics for the health conditions investigated, based on prevalence estimates calculated separately for each of Brazil's 27 federative units. The estimates were obtained using complex survey design methods, incorporating sampling weights, as implemented in the `survey` package in R (Lumley, 2020). These unit-level prevalence values were then summarized using standard descriptive measures, to characterize the distribution of each health condition across the country. Income, expressed in Brazilian reais (BRL), was the only socioeconomic variable considered in this analysis.

Table 1 - Summary statistics for the prevalence of health conditions and average income by federative unit.

Variable	Mean	SD	Min	1st Q	Median	3rd Q	Max
Depression	9.66	3.96	4.93	7.00	8.61	10.86	20.19
Hypertension	54.79	3.66	45.45	53.58	54.54	57.69	60.26
Diabetes	19.20	2.71	13.93	17.36	19.19	20.36	26.27
Cholesterol	25.24	4.22	16.19	23.12	25.17	27.48	38.13
Coronary disease	11.61	2.79	6.92	9.61	11.71	13.48	17.93
Stroke	6.15	1.57	4.15	5.04	5.81	6.47	11.19
Income	119.78	50.62	34.58	94.98	108.13	138.75	267.62

Source: Authors (2025).

The descriptive statistics provide important insights into the distribution and variability of key health and socioeconomic variables among the elderly population studied. Depression presents a mean score of 9.66 (SD = 3.96), with values ranging from 4.93 to 20.19. The median (8.61) and third quartile (10.86) suggest that a considerable portion of individuals experience moderate to high levels of depressive symptoms, with some cases reaching severe levels. Hypertension is highly prevalent, with a mean of 54.79% (SD = 3.66). The median (54.54%) is close to the mean, and values are concentrated between 45.45% and 60.26%, indicating a relatively homogeneous distribution across the population. Diabetes shows a mean prevalence of 19.20% (SD = 2.71), with most cases falling within a narrow range (1st quartile = 17.36%, 3rd quartile = 20.36%), suggesting moderate variability and no extreme outliers. Cholesterol levels have a mean of 25.24 (SD = 4.22), with a minimum of 16.19 and a maximum of 38.13. The quartile values (1st Q = 23.12, 3rd Q = 27.48) indicate that the majority of individuals have moderate cholesterol levels, although a subset shows significantly elevated values. Coronary disease presents a mean prevalence of 11.61% (SD = 2.79), with values ranging from 6.92% to 17.93%. The median (11.71%) being slightly above the mean suggests a possible right-skewed distribution, where

some individuals exhibit notably higher prevalence. Stroke has a relatively low prevalence, with a mean of 6.15% (SD = 1.57) and values ranging between 4.15% and 11.19%. The quartiles (1st Q = 5.04%, 3rd Q = 6.47%) show that most cases cluster around the mean, indicating low variability. Income, however, exhibits the greatest variability, with a mean of 119.78 (SD = 50.62) and a wide range from 34.58 to 267.62. The median (108.13), coupled with the high third quartile (138.75) and large maximum value (267.62), suggests that a subset of individuals has significantly higher income levels, contributing to an asymmetrical distribution and reinforcing economic disparities within the sample.

The spatial analysis revealed a heterogeneous geographical distribution of depression cases across Brazil. Mapping the cases by state showed a higher concentration in the South and Southeast regions, whereas the North region exhibited the lowest number of cases (Figure 1).

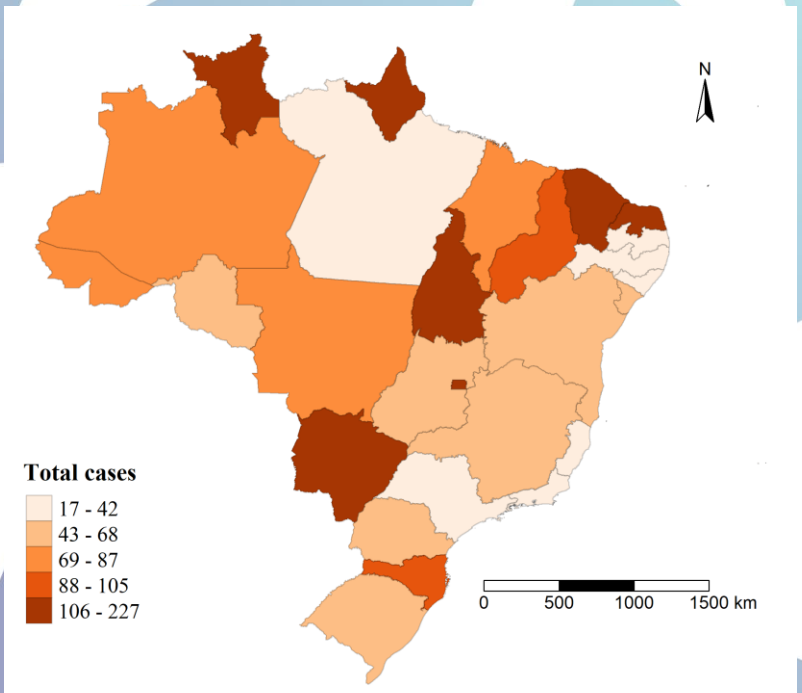

Figure 1 - Spatial distribution of depression cases across Brazil. **Source:** Authors (2025).

This spatial variation suggests that regional-specific factors may influence disease prevalence, potentially linked to socioeconomic conditions, cultural aspects, and access to mental health services. Regions in the mid-range (43–105 cases) display a moderate prevalence, likely reflecting a mix of rural and urban populations where mental health outcomes are influenced by varying levels of healthcare accessibility and socio-economic conditions. In contrast, areas with the fewest reported cases (17–42) are predominantly less densely populated or rural regions, where lower case numbers may result from

underreporting, limited mental health services, or reduced access to healthcare rather than a truly lower prevalence of depression.

Spatial Analysis

A total of ten Generalized Additive Models (GAMs) were considered to identify the determining factors and their spatial relationships with the prevalence of depression. The analysis of Table 2 allows for the comparison of different fitted models (M1 to M10) based on statistical performance metrics, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Coefficient of Determination (R^2), and Explained Deviance (DE). These metrics are essential for assessing model fit quality and predictive capacity.

Table 2 - Fitted Models and Evaluation Metrics.

Model	RMSE	MAE	AIC	BIC	R^2	DE
M1	14.21	10.79	246.25	255.32	0.93	0.94
M2	11.93	8.57	224.89	241.91	0.93	0.97
M3	8.66	6.56	221.36	245.41	0.95	0.98
M4	8.87	6.77	220.54	243.24	0.95	0.98
M5	9.23	6.97	219.83	240.93	0.95	0.98
M6	9.26	6.95	218.78	238.93	0.95	0.98
M7	9.72	7.33	218.05	237.03	0.95	0.98
M8	4.52	3.6	207.95	232.26	0.99	0.99
M9	4.45	3.46	208.21	232.88	0.99	0.99
M10	4.82	3.77	205.57	227.95	0.99	0.99

Source: Authors (2025).

The initial models (M1 to M3) exhibit inferior performance compared to the others, as evidenced by higher RMSE and MAE values. For example, M1 shows an RMSE of 14.21 and an MAE of 10.79, indicating higher prediction errors. As additional adjustments are incorporated, there is a progressive reduction in errors and AIC/BIC values, reflecting an improvement in model performance. In M3, the explained deviance reaches 98%, and R^2 increases to 0.95, suggesting a more precise model compared to the previous ones.

In the intermediate models (M4 to M7), the RMSE and MAE values stabilize around 9.0 and 6.9, respectively, while the AIC remains between 218 and 220. This indicates that, although these models continue to explain 98% of the deviance, they do not

provide substantial additional improvements in model performance.

Conversely, the final models (M8 to M10) exhibit the best performance, with a significant reduction in prediction errors (RMSE ≈ 4.5 and MAE ≈ 3.6) and lower AIC and BIC values, suggesting more efficient and well-fitted models. The R^2 reaches 0.99, and the explained deviance (DE) rises to 99%, indicating that nearly all the data variability is accounted for by the model. Among these, M10 stands out as the best-performing model, presenting the lowest AIC (205.57) and BIC (227.95), as well as the lowest prediction errors (RMSE = 4.82 and MAE = 3.77), ensuring higher precision and efficiency. Thus, the results indicate that while simpler models (M1 to M3) exhibit inferior performance, more complex models (M8 to M10) yield substantial gains in predictive capability. M10 emerges as the best choice, as it achieves the optimal balance between model fit, prediction accuracy, and complexity penalization, making it the most robust option for modeling the count of depression cases among the elderly. The model performance was evaluated based on residual deviance, degrees of freedom, deviance reduction, and statistical significance.

We conducted a comprehensive series of diagnostic tests to assess the adequacy of the final model (M3), which incorporates both fixed and smooth effects. The results indicated: (1) normality of the residuals (Shapiro-Wilk test, p = 0.5391), (2) homoscedasticity (F-test, p = 0.2713), (3) independence of residuals (Durbin-Watson test, p = 0.356), and (4) absence of influential data points. Spatial analysis (Moran's test) confirmed the presence of significant spatial autocorrelation, supporting the inclusion of spatial components in the model. These findings reinforce the usefulness of spatial Generalized Additive Models (GAMs) for capturing nonlinear patterns and spatial dependencies in epidemiological research. The diagnostic assessments, including Q-Q plots, residual histograms, and complementary analyses, were conducted, but the details will not be presented.

Parameter Estimates and Model Interpretation

Table 3 summarizes the parameter estimates for the fixed effects and smoothed terms from the Generalized Additive Model (GAM). The results include coefficient estimates, standard errors, t-values, and p-values, allowing for an assessment of the impact of different variables on depression risk.

The analysis of the coefficients for depression prevalence in elderly individuals in

Brazil reveals that coronary disease and the spatial term $s(x,y)$ are statistically significant, with p-values below 0.05. This indicates that individuals with coronary disease have an increased risk of depression, while the significance of the spatial term confirms the presence of relevant geographical patterns in the distribution of the disease.

Table 3 - Estimates of fixed effects and smoothed terms with 95% confidence intervals for depression prevalence in the elderly, Brazil, PNS 2019.

Parameter	Estimate	Std. Error	t-value	p-value
Intercept	-0.1427	0.0258	-5.5264	< 0.0001
Hypertension	-0.0131	0.043	-0.3054	0.7601
Coronary	0.171	0.0743	2.3027	0.0213
Diabetes	-0.061	0.0406	-1.5038	0.1326
Cholesterol	0.0271	0.0453	0.5974	0.5503
Stroke	0.0301	0.0552	0.5458	0.5852
Income	-0.042	0.0348	-1.2084	0.2269
$s(x, y)$	10.4733	12.5259	30.7426	0.0016

Source: Authors (2025).

The intercept of the model is also statistically significant and negative, suggesting that, in the absence of the considered factors, the expected depression rate tends to be lower. However, variables such as hypertension, diabetes, cholesterol, stroke, and income did not show statistical significance individually, as their p-values are greater than 0.05 and their confidence intervals include zero. This suggests that these factors, in isolation, may not be direct determinants of depression or that their effects might be mediated or confounded by other variables in the model.

The spatial term $s(x,y)$ stands out with a high coefficient and a very low p-value (0.0016), reinforcing the influence of geography on depression prevalence. This finding suggests that the distribution of depression among the elderly is not homogeneous across Brazil and that there may be regional factors not directly captured by the model, such as disparities in access to mental health services, local socioeconomic conditions, and cultural characteristics.

Figure 2 presents the spatial relative risk (RR) map for depression among the elderly by state. Darker shades represent areas with a higher relative risk of depression, predominantly concentrated in parts of the Northeast, Central-West, and North regions of Brazil. In contrast, lighter shades indicate areas with a lower relative risk, primarily observed in portions of the Southeast and South.

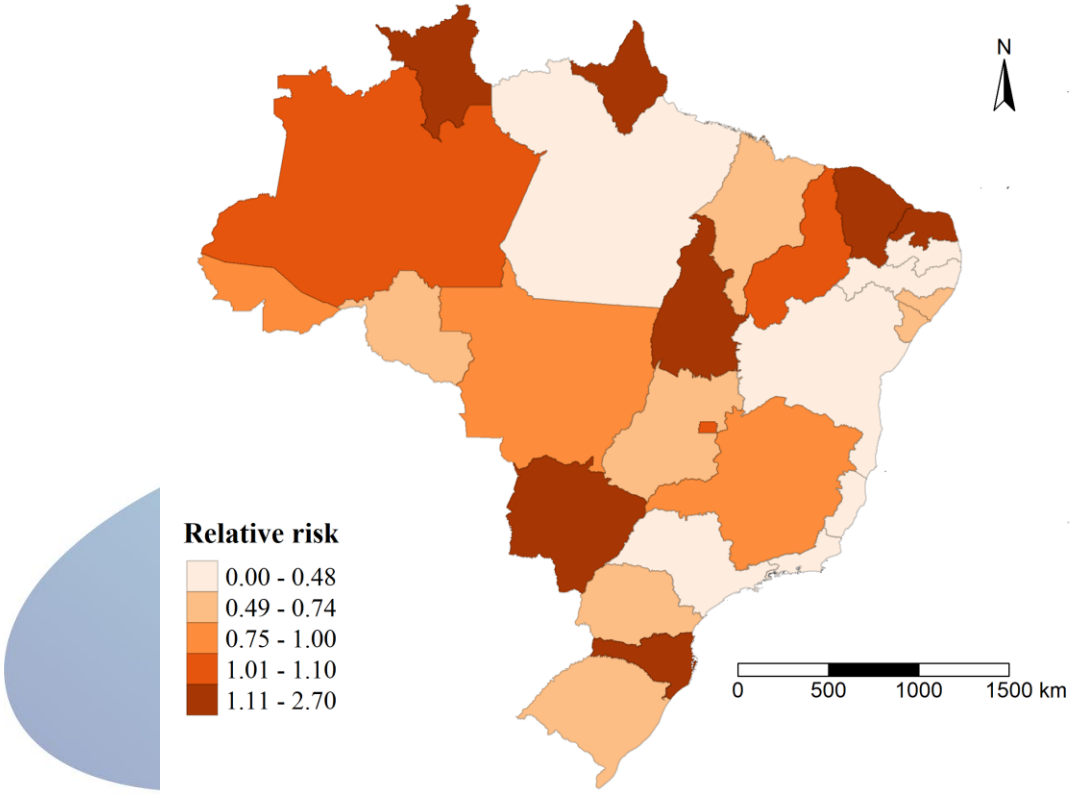

Figure 2 - Spatial distribution of the relative risk of self-reported depression cases in the elderly population across different regions of Brazil, PNS 2019. **Source:** Authors (2025).

The observed variation in relative risk may be driven by regional disparities, including differences in access to healthcare services, socioeconomic conditions, and other social determinants of health. A relative risk above 100 indicates that individuals in these regions face an increased risk compared to the national average, which may be influenced by structural, environmental, or behavioral factors specific to these areas. Conversely, states with relative risk below 70 exhibit lower vulnerability, potentially due to better socioeconomic conditions, access to healthcare, and more effective public policies.

The adjusted Generalized Additive Model (GAM) identified significant spatial patterns in the distribution of depression cases. Coronary disease had a statistically significant impact on depression risk. The model performance metrics confirmed an excellent fit, demonstrating the effectiveness of the additive model in capturing the complexity and variability of the data.

Discussion

The findings of this study reinforce the association between depression in the elderly Brazilian population and the presence of chronic health conditions, corroborating

previous research that highlights the interplay between physical and psychological factors in this age group (Barros et al., 2021; Silva et al., 2017; Taylor, 2014). Spatial analysis revealed a heterogeneous geographic pattern, indicating that depression prevalence is not uniformly distributed across the country. Regions with higher incidences of cardiovascular diseases, diabetes, and hypertension exhibited elevated rates of depressive symptoms, suggesting an overlap of vulnerabilities in specific areas (Silva et al., 2017; Zhou et al., 2021).

The literature suggests that aging is frequently accompanied by an increased burden of chronic diseases, which can directly impact the emotional well-being and quality of life of older adults (Blazer, 2003; Taylor, 2014). This study confirms this trend by identifying a statistically significant association between depression and conditions such as coronary artery disease, diabetes, and hypertension, even after adjusting for socioeconomic factors. These findings support the hypothesis that comorbidities act as aggravating factors for the development of depressive symptoms, not only due to their physiological implications but also because of the functional limitations they impose (Silva et al., 2017; Sguerri et al., 2024).

Moreover, the statistical modeling approach, based on Generalized Additive Models (GAMs), revealed that spatial interactions play a fundamental role in understanding the distribution of depression among older adults. The presence of significant spatial patterns suggests that contextual factors, such as access to healthcare services, socioeconomic inequalities, and social support networks, may modulate the manifestation of depression in different regions of Brazil (Souza-Junior et al., 2015; Silva et al., 2018). These results align with previous studies indicating that social determinants of health, such as income and access to medical care, directly influence the prevalence of mental disorders in older populations (Girgus et al., 2017; Neto et al., 2023; Zhou et al., 2021).

The results also indicate that the impact of chronic diseases on depression may be amplified by the interaction between multiple clinical conditions. Models that accounted for disease interactions, such as the combination of hypertension and diabetes, demonstrated higher predictive performance, reinforcing the need for integrated approaches to elderly healthcare management (Taylor, 2014; Zhou et al., 2021). In this regard, multidisciplinary care strategies and continuous monitoring could contribute to better management of depressive symptoms and improve the quality of life of this population (Taylor, 2014).

The presence of spatial autocorrelation in the model residuals suggests that unobserved variables may still be influencing the distribution of depression among elderly

Brazilians. This underscores the need for future research incorporating environmental factors, community support networks, and cultural aspects for a more comprehensive understanding of the phenomenon (Silva et al., 2018).

This study makes a significant contribution to literature by integrating spatial and epidemiological analyses, providing robust evidence on the determinants of depression in old age. The findings underscore the importance of public policies that address regional disparities and the interactions between clinical and socioeconomic factors, aiming for a more effective planning of interventions focused on mental health among the elderly population in Brazil.

This study has notable strengths and limitations that should be considered when interpreting its findings. A key strength is the innovative spatial analysis approach using Generalized Additive Models (GAMs) to capture non-linear relationships and spatial patterns, providing a detailed understanding of depression distribution among the elderly. The study also benefits from a nationally representative dataset from the 2019 National Health Survey (PNS), enhancing result robustness and generalizability. By integrating clinical factors (e.g., hypertension, diabetes, and coronary disease) with socioeconomic determinants, it offers a comprehensive perspective on depression risk factors. Additionally, identifying high-risk geographic areas through spatial autocorrelation analysis enables targeted public health interventions. The model's performance metrics (AIC, BIC, RMSE, and Explained Deviance) confirm an excellent fit, reinforcing result reliability.

Despite these strengths, certain limitations exist. Cross-sectional design prevents causal inference between chronic diseases, socioeconomic factors, and depression, making it unclear whether these conditions precede or result from depression. The reliance on self-reported data introduces potential recall bias or underreporting, affecting prevalence estimates. Moreover, the study does not account for all contextual variables influencing depression distribution, such as access to mental health services, cultural factors, or social support networks. Some residual spatial autocorrelation suggests unmeasured spatial determinants may still influence depression prevalence. Lastly, as the study is based on 2019 data, its findings may not fully reflect recent socioeconomic or healthcare changes.

In summary, while this study provides important insights into the spatial distribution of depression among Brazilian older adults, future research should consider longitudinal analyses, alternative depression assessment methods, and additional contextual variables to further refine and expand these findings.

Conclusions

This study demonstrates that depression among the elderly in Brazil exhibits a heterogeneous spatial distribution, influenced by a complex interplay of clinical, socioeconomic, and geographic factors. Spatial analysis revealed higher depression prevalence in the South and Southeast regions, where the burden of chronic diseases, such as hypertension, diabetes, and coronary disease, is significant.

The application of Generalized Additive Models (GAMs) provided a flexible and robust framework for identifying spatial patterns and their interactions with individual characteristics. The findings confirm that both individual and structural factors contribute to regional variations in depression, while the presence of spatial autocorrelation in residuals suggests the influence of unmeasured contextual determinants, warranting further investigation.

These results underscore the need for targeted interventions that consider regional disparities and social determinants of health to mitigate the impact of depression in the elderly population. Public health strategies should prioritize equitable access to mental health services, particularly in high-vulnerability areas. Additionally, policies that promote integrated and interdisciplinary approaches in elderly care could play a crucial role in the prevention and management of depression.

Finally, the study highlights the value of advanced statistical methods and spatial analysis in generating evidence-based insights for policymaking. Identifying high-risk areas through spatial modeling can support the development of effective strategies to reduce the burden of depression among older adults in Brazil.

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Conflict of interest

The authors declare no conflicts of interest in this study.

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