EFFECTS OF SOCIAL DETERMINANTS OF HEALTH ON COVID-19 MORTALITY AMONG ADULTS IN THE METROPOLITAN AREA OF BRASÍLIA

Abstract

The COVID-19 pandemic impacted Brazil amidst an ongoing economic and social crisis, exacerbating pre-existing socioeconomic inequalities and disparities in healthcare access. Vulnerable populations, exposed to social, occupational, and environmental factors, faced greater challenges in adhering to social distancing measures, thus increasing their risk of infection. This cross-sectional study aims to explore the relationship between Social Determinants of Health and COVID-19 mortality among adults in the Metropolitan Area of Brasília, utilizing sociodemographic indicators and death records from the Mortality Information System, aggregated by place of residence. Structural equation modeling results revealed a strong impact of sociodemographic vulnerability, urban infrastructure, and lack of healthcare access indicators on COVID-19 mortality among adults. These findings underscore the need for an analytical framework that can quantify overlapping dimensions of social vulnerability and informing targeted policies and interventions to reduce health inequities and secure equitable access to healthcare services.

Keywords

Social Determinants of Health, Mortality, COVID-19, Structural Equation Modeling.

Introduction

The COVID-19 pandemic severely exacerbated regions already marked by extreme social inequality, spreading the virus unevenly and disproportionately affecting historically marginalized groups.[1] Social determinants of health critically influenced disease transmission and progression, as well as shaped vulnerability.[2]

Brazil was one of the countries most affected by the COVID-19 pandemic globally. The crisis exposed the fragility of the national healthcare system and highlighted socioeconomic and racial inequalities. During the second wave, there was a significant increase in adult mortality among those aged 20 to 59, driven by the high transmissibility of the Gamma variant, early relaxation of social distancing measures, and initial delays in the vaccination campaign.[3]

Metropolitan regions faced heightened vulnerability during the pandemic due to high population density in peripheral areas with inadequate infrastructure, socioeconomic inequality, and limited access to public health services. Brazil's decision to relocate its capital to the Central-West region in the last century aimed to populate the central territory, including Goiás.[4] With urban expansion, these areas integrated into the Administrative Regions, forming the Federal District (DF). Over time, economic connections between Goiás municipalities and the DF fostered the creation of the Metropolitan Area of Brasília (AMB), characterized by pronounced regional inequalities, stark socioeconomic disparities, and significant challenges in healthcare access. During the pandemic, widespread transmission in peripheral areas highlighted the dependency of surrounding Goiás municipalities on Brasília's services.[5]

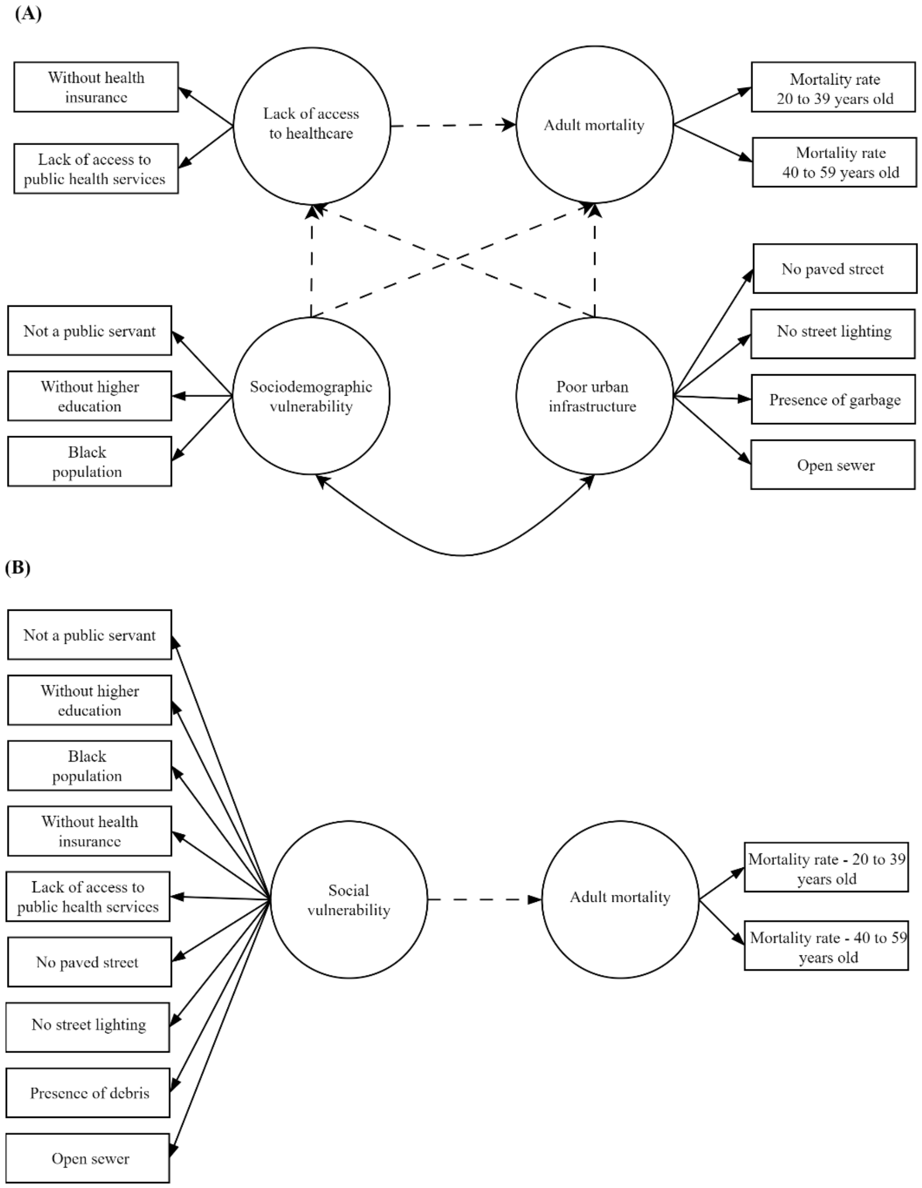
In this context, the present study aims to identify the effects of social determinants of health on COVID-19 mortality in the AMB, focusing on the adult population. The study employs structural equation modeling to analyze and assess the complex relationships between various social factors associated with health and their impact on adult mortality.

Theoretical Framework

Social Determinants of Health and COVID-19 Mortality

Social Determinants of Health (SDH) significantly influence COVID-19 infection risk, disease severity, and mortality, encompassing socioeconomic, cultural and environmental conditions such as income, education, healthcare access, and racial inequalities.[2,3] The model by Solar and Irwin[6] conceptualizes health disparities as arising from interconnected factors beyond individual characteristics, with imbalances in resources and power contributing to health differences across populations. This study employed SDH and Structural Equation Modeling (SEM) to analyze their impact on COVID-19 mortality in adults, examining two hypotheses (Figure 1). Model A draws inspiration from the approach of Rios, Mompart, and Wunsch[7], incorporating the SDH framework in the Brazilian context as outlined by Melo, Costa, and Corso[8]. Model B, in contrast, introduces a single predictive factor, "Social vulnerability," which combines the three dimensions, merging overlapping inequalities into a unified concept of vulnerability. In this model, the convergence of factors is so pronounced that they become indistinguishable.

Figure 1 - Representation of Hypothesis A with 3 predictors and Hypothesis B with one predictor factor



Methods

This cross-sectional ecological study is based on 44 analysis units representing the Brasília Metropolitan Area (AMB), consisting of:

- 32 Administrative Regions (AR) of the Federal District (DF): Plano Piloto, Gama, Taguatinga, Brazlândia, Sobradinho, Planaltina, Paranoá, Núcleo Bandeirante, Ceilândia, Guará, Cruzeiro, Samambaia, Santa Maria, São Sebastião, Recanto das Emas, Lago Sul, Riacho Fundo, Lago Norte, Candangolândia, Águas Claras, Riacho Fundo II, Sudoeste/Octogonal, Varjão, Park Way, Estrutural/Scia, Sobradinho II, Jardim Botânico, Itapoã, Vicente Pires, Fercal, Sol Nascente/Pôr do Sol, and Arniqueira.

- 12 municipalities from the state of Goiás that constitute the Brasília Metropolitan Periphery (PMB): Águas Lindas de Goiás, Alexânia, Cidade Ocidental, Cocalzinho de Goiás, Cristalina, Formosa, Luziânia, Novo Gama, Padre Bernardo, Planaltina, Santo Antônio do Descoberto, and Valparaíso de Goiás.

The study used socioeconomic indicators of the AMB units to analyze the mortality rate of adults aged 20 to 59 during the peak pandemic period, from 2020 to 2021.

COVID-19 Mortality Rates

Mortality data were sourced from the Mortality Information System (SIM)[9], published by the Health Surveillance Secretariats of the Ministry of Health (SVS) and the State Health Department of the Federal District (SES-DF). The data included victims' place of residence, detailed by Administrative Region (RA) or municipality. COVID-19 deaths were identified using the code B34.2, which refers to Coronavirus infection of unspecified location, according to the 10th Revision of the International Classification of Diseases (CID-10).

Population data came from projections by the Brazilian Institute of Geography and Statistics (IBGE) for Brazil and its states (2010-2060); from the Federal District Institute of Research and Statistics (IPEDF) for the Federal District's Administrative Regions (2020-2030); and from the Mauro Borges Institute (IMB) for Goiás municipalities (2011-2020). Mortality rates (per 100,000) were calculated at the level of administrative regions and municipalities. Rates were standardized using the age distribution of the Brazilian population in 2020.

Indicators of Inequalities

Indicators of social determinants of health (SDH) were used, derived from the microdata of the 2021 District Household Sample Survey (PDAD)[10] and the 2019-2020 Metropolitan Household Sample Survey (PMAD)[11]. The selected indicators were grouped by dimension, as detailed in Table 1.

Table 1 – Social Indicators by Dimension

Dimension	Indicator
Sociodemographic vulnerability	Not a public servant (%) Without higher education (%) Black population (%)
Lack of access to healthcare	Without health insurance (%) Lack of access to public health services (z-score)
Poor urban infrastructure	No paved street (%) No street lighting (%) Presence of garbage (%) Open sewer (%)

Access to public health services is assessed through the Index of Access to Health Services (IAHS), which was developed by the authors; values were inverted to reflect barriers to access. Further details on the calculation can be found in the Appendix.

Statistical Analysis

Structural Equation Modeling (SEM) was implemented using robust standard errors and the Satorra-Bentler test statistic, [12–16] selected due to the sample size and the multivariate non-normality of the data. Fit measures included the Chi-square statistic ($p < 0.05$), Tucker-Lewis Index (TLI > 0.95), Comparative Fit Index (CFI > 0.95), Root Mean Square Error of Approximation (RMSEA < 0.06), and Standardized Root Mean Square Residual (SRMR < 0.08).[17] Additionally, McDonald's omega (> 0.7)[18] and the average variance extracted (AVE > 0.5)[19] were calculated.

The measurement model was initially tested through confirmatory factor analysis, followed by SEM. Parameter inclusion and exclusion were guided by the SDH framework, overall model significance, parameter significance, and modification indices. Statistical significance was set at 5%. Modification indices above 10 were considered only when consistent with the theoretical framework, ensuring a balance between data-driven and theory-based modeling. In cases with multiple indices above 10, only the highest, theoretically relevant one was used.[20] Standardized estimates were classified as small, medium, or large based on ranges of 0.10–0.29, 0.30–0.49, and 0.50 or higher.[17] All analyses were conducted using R (version 4.2.2) and the lavaan package (version 0.6-15).

Results

The indicators highlight the following findings for the AMB (Table 2):

- COVID-19 mortality increases with age. In the 20-39 age group, the average mortality rate is about five times lower than in the 40-59 age group.
- The population is predominantly black (64%), with a concentration in peripheral regions.
- The region experiences economic impacts due to the high percentage of the workforce outside the public sector (85%).
- Over 73% of households lack health insurance, with limited access to health services. The highest level of limited access was recorded in Padre Bernardo (GO), at 1.48 standard deviations above the mean, while the lowest level was observed in Park Way (DF), at 1.77 standard deviations below the mean.
- Metrics for lack of street lighting, open sewage, and unpaved roads show high variation (coefficients of variation of 134, 116, and 117, respectively), indicating significant disparities in urban infrastructure across the regions analyzed.
- There is a strong correlation between indicators of sociodemographic vulnerability and lack of access to healthcare. Black population correlates with not being a public servant (0.89) and with lacking higher education (0.78). The absence of health insurance correlates at 0.88 with lack of access to public health services and shows a high correlation with all sociodemographic vulnerability indicators (>0.90). Regarding poor urban infrastructure indicators, presence of

garbage has moderate to high correlations with not being a public servant and lacking higher education (>0.70). Details are in Table 3.

Table 2 – Descriptive Statistics of Selected Indicators

Indicator	Mean	SD	CV	Median	Min	Max	Q1	Q3
Mortality Rate (per 100,000 inhabitants) - Ages 20 to 39	11.21	4.76	42.44	10.50	2.58	23.39	8.28	13.99
Mortality Rate (per 100,000 inhabitants) - Ages 40 to 59	57.63	17.65	30.62	61.70	15.22	96.59	45.76	69.33
Not a public servant (%)	84.64	11.58	13.68	86.40	52.90	98.50	80.00	94.80
Without higher education (%)	65.73	22.37	34.03	71.50	12.80	95.40	62.50	81.50
Black population (%)	63.61	15.70	24.69	63.90	32.70	94.50	56.30	74.00
No paved street (%)	10.00	11.69	116.93	4.30	0.20	43.60	1.60	15.60
No street lighting(%)	10.48	14.04	134.01	5.20	0.30	70.50	2.00	10.10
Presence of garbage(%)	19.78	11.39	57.59	19.40	0.70	48.80	13.10	24.90
Open sewer (%)	9.55	11.08	116.03	7.10	0.80	53.80	3.30	9.10
Without health insurance (%)	72.56	26.00	35.83	83.40	8.80	98.00	64.20	92.00
Lack of Access to Public Health Services (Raw and Z-Score)	3511 (0.00)	1835 (1.00)	52.27 (-)	2963 (0.01)	268 (-1.77)	6227 (1.48)	2034 (-0.81)	4972 (0.80)

SD: Standard Deviation; CV: Coefficient of variation; Min: minimum; Max: Maximum; Q1: First quartile; Q3: Third quartile.

Table 3 – Matrix of Correlations for Selected Indicators

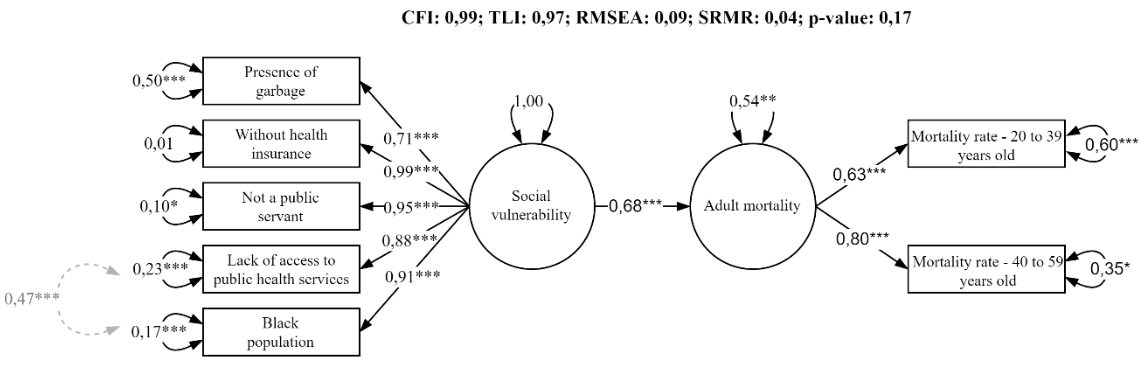
Indicator	1	2	3	4	5	6	7	8	9	10	11
1. Mortality rate - Ages 20 to 39	1										
2. Mortality rate - Ages 40 to 59	0.51	1									
3. Not a public servant	0.43	0.54	1								
4. Without higher education	0.39	0.56	0.89	1							
5. Black population	0.31	0.41	0.86	0.78	1						
6. No paved street	0.02	0.07	0.52	0.44	0.6	1					
7. No street lighting	-0.02	-0.01	0.45	0.32	0.69	0.73	1				
8. Presence of garbage	0.17	0.34	0.72	0.74	0.66	0.49	0.35	1			
9. Open sewer	-0.07	0.1	0.41	0.5	0.24	0.55	0.07	0.63	1		
10, Without health insurance	0.43	0.55	0.95	0.93	0.91	0.49	0.49	0.7	0.33	1	
11. Lack of access to public health services	0.44	0.39	0.81	0.74	0.89	0.59	0.61	0.61	0.22	0.88	1

Model of Social Determinants of Death

First, we tested the measurement model according to Models A and B. Model A, showed inadequate fit, with improper solutions stemming from high multicollinearity between factors (>0.85) across all combinations of indicators within the same dimension, even after adjusting indicators based on methodological criteria. In contrast, Model B, which used a single predictive factor, did not face these issues and was further refined by adjusting the model based on methodological criteria until achieving an adequate fit: The final measurement model showed a good fit with the following metrics: CFI of 0.99, TLI of 0.97, RMSEA of 0.09, p-value of 0.17, omega coefficients of 0.96 and 0.71, and AVE of 0.90 and 0.63 for "Social vulnerability" and "Adult mortality," respectively.

Based on these results, a Structural Equation Model (SEM) was subsequently developed (Figure 2).

Figure 2 – SEM Model with a Single Predictor Factor



*** p<0.001; ** p<0.05; * p<0.1; the estimates are completely standardized.

In the structural model, social vulnerability had a significant positive impact on adult mortality. An increase of one standard deviation in social vulnerability was associated with a 0.68 standard deviation increase in adult mortality. However, the disturbance term linked to adult mortality was large (0.54).

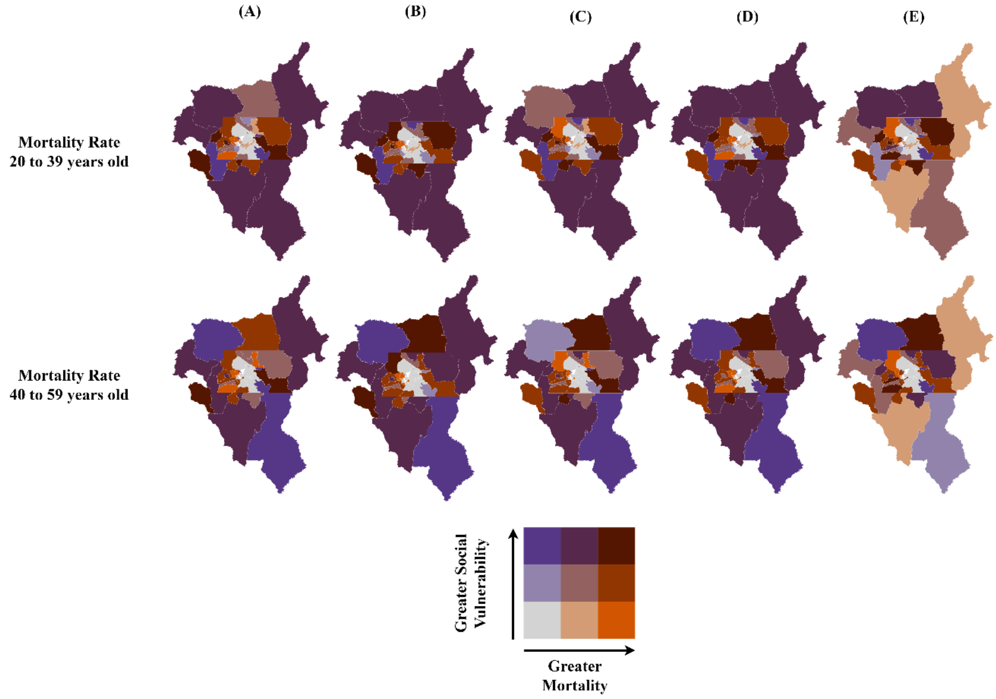
The measurement model indicated that factors such as lack of health insurance, limited healthcare access, low public sector employment, a higher prevalence of the black population, and a greater accumulation of garbage were strongly and positively correlated with social vulnerability. All items were statistically significant at the 5% level with low standard errors. Furthermore, social vulnerability explained a high proportion of variance across all indicators, except for the presence of garbage.

The mortality rate among individuals aged 40 to 59 showed a higher correlation (0.80) compared to the 20 to 39 age group. The mortality rate for the 20 to 39 age group had a low variance explained by the adult mortality factor, accompanied by a high measurement error.

Finally, the coefficient of 0.47 for the correlation between the errors of lack of access to public health services and the black population is significant and may indicate an underlying additional factor.

The geographic distribution of the indicators selected for the final model is illustrated in Figure 3. The maps reveal that areas predominantly populated by white individuals, employed in the public sector, and with access to quality urban infrastructure and healthcare services exhibit lower rates of mortality and social vulnerability (represented in gray on the map).

Figure 3 – Geographic Distribution of Inequality Based on Social Vulnerability and Mortality Indicators in the Metropolitan Area of Brasília



(A) Without health insurance, (B) Lack of access to public health services, (C) Not a public servant, (D) Black population and (E) Presence of garbage.

Discussion

The study reveals SDH shape a network of inequalities in the Metropolitan Area of Brasília (AMB), highlighting significant and interrelated socioeconomic and spatial disparities. A primary factor identified is the barrier to healthcare access, with social vulnerability primarily affecting the black population, who face significant challenges in accessing healthcare, depend heavily on the public health system (SUS), and are often engaged in informal employment with lower educational attainment. This group not only encounters reduced access to hospital resources but also endures longstanding healthcare inequities, including discrimination and economic obstacles, leading to delayed treatment and higher mortality rates.[23-24] Additionally, urban infrastructure issues, such as inadequate waste management reflected in garbage accumulation, are tied to housing conditions that exacerbated the pandemic's spread in the most vulnerable areas.[21-22]

Our results indicate that an approach considering multiple overlapping social vulnerabilities — race, socioeconomic status, and housing conditions — is necessary to understand how these factors combine to heighten vulnerability to COVID-19 and its outcomes. In the context of the AMB, the black population, particularly affected by precarious living conditions and restricted access to essential services, faces unique challenges that intensify the pandemic's impact. This multidimensional perspective underscores that increased COVID-19 mortality is not driven by a single factor, such as race or class, but by the convergence of multiple disadvantages.[25,26] This perspective underscores the need for public policies that address social inequalities in all their complexity, advocating for solutions that account for these intersecting vulnerabilities to reduce the unequal burden of the pandemic.

Limitations

This observational study relies on secondary data, meaning the authors did not design the data collection instrument, which presents challenges for model construction. The small sample size limits the ability to test models with more indicators and complexity. These conditions increase the risk of non-convergence and improper solutions, and often result in underestimated standard errors, inflating Type I error rates. Although the Satorra-Bentler adjustment[27] is recommended to mitigate this issue,[13–14] results should be interpreted cautiously.

Despite the Mortality Information System (SIM) achieving nearly 100% coverage[28] and the Health Secretariat of the Federal District conducting thorough investigations into causes of death, there remains a potential underreporting of COVID-19 deaths, particularly in 2020.

Conclusion

The regions within the Metropolitan Area of Brasília (AMB) were affected by the pandemic in varying ways, highlighting the existing social vulnerability across the territory. This underscores the need for measures that acknowledge the role of social determinants of health in mitigating pandemic risks, with actions that not only ensure quicker responses in the future but also enhance their effectiveness. Addressing this issue requires the government to be better equipped to identify and tackle the multiple and intersecting factors that drive health inequalities. Additionally, a coordinated effort between public and private institutions is essential for the implementation of cross-sectoral policies. Such policies should integrate various fields, including healthcare, education, housing, and social assistance, considering how different forms of discrimination and inequality intersect and affect the health of the most vulnerable groups.

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Appendix

The Index of Access to Health Services (IAHS) was developed by combining metrics on the availability of specialized care services at public health facilities within the Unified Health System (SUS), alongside data on the distance and travel time needed for the population to reach these establishments. This indicator helps to reveal the challenges people face in accessing specialized care and evaluates the capacity of hospital services to meet these needs.

Data Sources and Variables

Active records from December 2019 from the National Register of Health Establishments (CNES) were used to map the availability of hospital services within the Metropolitan Area of Brasília (AMB), focusing specifically on facilities with potential capacity to treat severe COVID-19 cases, defined by the availability of Type II ICU beds. Geographic accessibility variables were obtained using the Google Distance Matrix API, utilizing the Gmapsdistance package (version 4.0.4) in R, with measurements conducted on November 15, 2023, from 18:05 to 18:10 (Brasília time, GMT -3). Data on the percentage of households owning a vehicle were derived from the microdata of the 2021 District Household Sample Survey (PDAD) and the 2019-2020 Metropolitan Household Sample Survey (PMAD).

Computation of the Indicator

The IAHS is characterized by two dimensions, based on a set of variables described below:

- Supply: Type II ICU beds; life-support equipment; and healthcare professionals (doctors and nurses).
- Geographic Accessibility: Distance by car and public transport (in meters); travel time by car and public transport (in seconds).

The geographic locations of the headquarters of the 32 Administrative Regions of the Federal District and the 12 municipalities in Goiás that form the Brasília Metropolitan Periphery (PMB) were used as origin points. Fourteen healthcare facilities, which met the pre-established selection criteria, were identified as destination points.

Each geographic unit l has two matrices: A, containing the variables for the Supply dimension, and B, containing the variables for the Geographic Accessibility dimension. The following formulas are applied to these matrices:

$$A_l = \begin{bmatrix} a_{11} & \cdots & a_{13} \\ \vdots & \ddots & \vdots \\ a_{14,1} & \cdots & a_{14,3} \end{bmatrix}$$

$$B_l = \begin{bmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ b_{14,1} & \cdots & b_{14,4} \end{bmatrix}$$

To align the variables, higher values in distances and times (Matrix B) are converted to represent lower performance.

$$v'_i = max(V) + min(V) - v_i \quad (1)$$

The next step involves transforming the variable scales from both dimensions into a single scale, using deciles.

Consider $X_j = \{x_1, x_2, \dots, x_n\}$ as the data vector representing the observations of variable j. Initially, X_j is sorted in ascending order, and the deciles $D_0, D_2, \dots, D_{10}$, are calculated, where D_0 is the minimum value and D_{10} is the maximum value in X_j.

Based on these deciles, 10 intervals I_k are defined for $k = 1,2,\dots,10$. Each interval is given by $I_k = (D_{k-1}, D_k]$, indicating that it starts immediately after D_{k-1} (excluding D_{k-1}) and extends up to D_k, including this value. The first interval, I_1, is an exception, including both of its limits $I_1 = [D_0, D_1]$.

For each observation x_i in X_j, a score $N(x_i)$, ranging from 1 to 10 is assigned based on the interval to which it belongs:

$$N(x_i) = k \; se \; x_i \in I_k \quad (2)$$

When deciles have repeated values, the score for observations within these intervals is the average of the possible positions, calculated as: $N(x_i) = \frac{\sum_{k=m}^{n} k}{n-m+1}$ (2.1), where m and

n are the starting and ending positions (inclusive) of the duplicated intervals that x_i could occupy.

Thus, formulas (2) or (2.1) are applied to matrices A e B for each geographic unit l, resulting in the score matrices A' e B'.

$$A'_l = \begin{bmatrix} a'_{11} & \cdots & a'_{13} \\ \vdots & \ddots & \vdots \\ a'_{14,1} & \cdots & a'_{14,3} \end{bmatrix}$$

$$B'_l = \begin{bmatrix} b'_{11} & \cdots & b'_{14} \\ \vdots & \ddots & \vdots \\ b'_{14,1} & \cdots & b'_{14,4} \end{bmatrix}$$

After evaluation, the scores for Supply and Accessibility are summed, forming a column matrix consolidating these components:

$$\sum A'_l = A'_l \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} a^*_{11} \\ \vdots \\ a^*_{14} \end{bmatrix} = A^*_l \tag{3}$$

$$\sum B'_l = B'_l \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} = \begin{bmatrix} b^*_{11} \\ \vdots \\ b^*_{14} \end{bmatrix} = B''_l \tag{4}$$

For Geographic Accessibility, a weighting factor λ, is applied, indicating the percentage of households that own a car in unit l.

$$B'_l \times \lambda_l = B^*_l \tag{5}$$

The index for each observed unit l is calculated by multiplying the components:

$$IAHS_l = (A^*_l)^T B^*_l \tag{6}$$

Finally, the scores $IAHS_l$.

$$IAHS\ standardized_l = \frac{IAHS_l - mean(IAHS)}{standard\ deviation\ (IAHS)} \tag{7}$$

The resulting values are standardized to reflect standard deviations relative to the mean of the geographic units: High (above 1 standard deviation), Moderate-High (0.5 to 0.99), Moderate (-0.49 to 0.49), Moderate-Low (-0.5 to -0.99), and Low (below -1 standard deviation). It is important to note that geographic units near the boundaries between groups may not show significant qualitative differences, suggesting that small variations in classification do not necessarily imply substantial changes in access to health services.

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