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How do the urban structure and unequal access to opportunities aggravate the spread of COVID-19 in Brazil?

¿Cómo la estructura urbana y el acceso desigual a las oportunidades agravan la propagación del COVID-19 en Brasil?

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Abstract

This study examines how COVID-19 infections and deaths are linked to the urban structure of Brazilian cities, providing insights to support containment strategies for this and other diseases. Using structural equation modeling (SEM), it explores the direct influence of demographic, mobility, social vulnerability, and urban structure variables on COVID-19 infection and mortality rates. The study also investigates the relationship between urban sprawl and COVID-19 through a multidimensional analysis of urban compactness using the MIMIC model, incorporating demographic factors, social vulnerability, and access to opportunities. Findings reveal that more compact cities experience higher rates of infection and death, although the link between compactness and mortality is weaker. This disparity likely reflects better healthcare access and quality in compact areas. Additionally, variables such as access to opportunities and commuting patterns significantly influence urban compactness. These results underscore the complex interplay between urban structure and pandemic outcomes.

Keywords
COVID-19
Structural Equation Modeling
Urban Sprawl
Compact Cities
Access to Opportunities
Social Vulnerability

Resumen

Este estudio examina cómo las infecciones y muertes por COVID-19 están vinculadas a la estructura urbana de las ciudades brasileñas, lo cual brinda información para respaldar las estrategias de contención de esta y otras enfermedades. Utilizando modelos de ecuaciones estructurales (SEM), explora la influencia directa de las variables demográficas, de movilidad, vulnerabilidad social y estructura urbana en las tasas de infección y mortalidad por COVID-19. El estudio también investiga la relación entre la expansión urbana y el COVID-19 por medio de un análisis multidimensional de la compacidad urbana utilizando el modelo MIMIC, que incorpora factores demográficos, vulnerabilidad social y acceso a oportunidades. Los hallazgos revelan que las ciudades más compactas experimentan tasas más altas de infección y muerte, aunque el vínculo entre compacidad y mortalidad es más débil. Esta disparidad probablemente refleja un mejor acceso y calidad de la atención médica en áreas compactas. Además, variables como el acceso a oportunidades y los patrones de desplazamiento influyen de manera significativa en la compacidad urbana. Estos resultados subrayan la compleja interacción entre la estructura urbana y los resultados de la pandemia.

Palabras clave

COVID-19
Modelado de ecuaciones estructurales
Expansión urbana
Ciudades compactas
Acceso a oportunidades
Vulnerabilidad social

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Introduction

In 2019, the first case of COVID-19 (coronavirus disease) appeared in China, a highly transmissible virus that mainly attacks the respiratory system of individuals, and in 2020, the virus arrived in Brazil. In an attempt to control the spread of the disease, policies were adopted to minimize the rate of infection and the number of deaths. Among the government actions, there was social isolation, which was the main precautionary measure taken to contain the spread of the virus before vaccination became widely available[1] (Júnior, 2020).

The spatial organization of cities follows two models: compact or sprawling (Arbury, 2005; Dieleman and Wegener, 2004). Compact cities have

1 In Brazil, vaccination began in January 2021 (Ministry of Health, 2021). Social isolation, in turn, regulated by law 13.979/2020, was adopted as the main measure to contain the virus.

higher density, less green space, and better public transport, while sprawling cities increase distances between areas, relying on individual transport and causing more pollution (Burton et al., 2003; Júnior, 2017; Leiva et al., 2020; Mesquita et al., 2021; OECD, 2012; Sebbenn and Ruschel, 2019). Public transport development influences access to opportunities, Pereira et al. (2020a) identifying inequalities in work, health, and education access in Brazil's metropolitan regions.

Chauvin (2021) analyzed 2,500 Brazilian municipalities and found higher COVID-19 infection rates in areas with greater density and mobility. Leiva et al. (2020) compared New York (compact) and Los Angeles (sprawling) and observed that initially, areas with greater inequality and sociospatial segregation had fewer cases, as wealthier regions facilitate population agglomeration.

Similarly, Hassell et al. (2017) analyzed the association between urbanization and the spread of zoonoses like avian influenza, tuberculosis, and hepatitis. Soares et al. (2014) examined how location shape and organization influence diseases like leptospirosis. Tauil (2001) studied urban factors in dengue transmission, while Sathler and Leiva (2022), Hamidi et al. (2020), Aguilar et al. (2022), and Yücel et al. (2023) explored how density, infrastructure, mobility restrictions, poverty, and inequality relate to COVID-19 infections and deaths.

The spatial organization of locations can influence COVID-19 contagion. Municipalities with higher density, better transport infrastructure, greater access to jobs, health, and education, less pollution, and fewer green spaces may experience higher infection rates (Gentil, 2015; Leiva et al., 2020). This correlation arises because densely populated areas provide more opportunities for exposure. Hamidi et al. (2020) found that while population density increases infections, it is negatively associated with mortality in North America.

According to the Brazilian Institute of Geography and Statistics (IBGE), Brazil's population grew from approximately 194 million in 2012 to 214 million in 2022, an increase of 20 million people in a decade. This population growth, combined with factors such as continental dimensions and regional disparities, contributed to the asymmetric spread of COVID-19 in Brazil (Bega and Sousa, 2021).

This study aimed to analyze how COVID-19 infections and deaths are related to the urban structure of cities, considering social, demographic, economic, and spatial factors. To understand this process, it was essential to deepen the examination of the main characteristics of compact cities and sprawling cities. Therefore, following Kline (2011), Macana and Comim (2015), Hamidi et al. (2020), and Pereira et al. (2020a), an analysis was initially performed using the structural equation modeling tool to investigate the relationship between spatial, demographic, social, and economic variables and COVID-19 infections and deaths. Next, the relationship between contamination and mortality, as well as the level of urban sprawl, was investigated based on the analysis of the urban compactness index from a multidimensional perspective using the Multiple Indicator Multiple Causes (MIMIC) model. Thus, the territorial units of analysis were the Brazilian municipalities, and the data used were extracted from various national sources. The reference date for cumulative COVID-19 cases and deaths was January 16, 2021, one day before the start of the national vaccination campaign in Brazil, to avoid the influence of immunization on the results. It is noteworthy that despite the empirical relevance of the characterization of Brazilian cities, there is a gap in the literature in terms of investigations that examine the relationship between the typologies of cities and the spread of COVID-19.

Thus, based on Pereira et al. (2020a), Pereira et al. (2020b), Hamidi et al. (2020) and Leiva et al. (2020), the underlying hypothesis of the present study was that compact locations, with higher density indicators and better conditions of accessibility to opportunities, will have a higher infection rate and a lower mortality rate due to COVID-19. This study advances the literature, as it provides new evidence about urban sprawl — through the urban compactness index — and its relationship with the spread of COVID-19, which may be helpful in the design of public policies to combat this and other highly contagious viral diseases.

The COVID-19 pandemic and city models

The way cities are organized is a widely studied phenomenon because it is determinant of both growth and the economic, political, and social development of a location (Eaton and Eckstein, 1997). Cities are places that can be characterized according to their density, political representatives, size, population distribution, transport system infrastructure, and economic model. These urban structures are resilient and change slowly and gradually over time (Bertaud, 2004).

In the horizontal growth model, there are two types of cities: compact and sprawling (dispersed). Compact cities exhibit an urban model characterized by a denser occupancy mechanism. In this type of city, the use of public transportation is greater, leading to its faster development and enabling access to opportunities, such as work, education, and health, to be performed more easily (Burton et al., 2003; Dieleman and Wegener, 2004).

Compact cities are more sustainable due to their higher use of public transportation and shorter distances, which reduce polluting emissions (OECD, 2012). Leiva et al. (2020) highlight New York City as an example of this urban typology. Sebbenn and Ruschel (2019) further emphasize that the compactness of cities allows for more targeted and effective policies, addressing specific problems in smaller geographic areas. As a result, compact cities are often associated with regions offering a better quality of life.

The phenomenon of urban sprawl has been analyzed in studies by Glaeser and Kahn (2004) for the United States and by Nadalin (2010) for the metropolitan region of São Paulo. In São Paulo, sprawl began in the 1980s, contributing to negative externalities such as increased social and spatial inequalities.

Sprawling cities, like Los Angeles (Leiva et al., 2020), are characterized by lower population density and larger geographic areas, which result in greater distances between city centers and peripheries. Public transportation in these cities is often inefficient, leading to a preference for individual transportation, such as cars and motorcycles. This inefficiency, along with longer distances traveled, results in higher emissions of polluting gases like CO_2. The extent of urban sprawl varies across locations, with each city exhibiting different levels of sprawl intensity (Júnior, 2017).

Mesquita et al. (2021) and Leiva et al. (2020) found that a predominance of sprawling cities in Brazil makes it challenging to plan public policies in the fields of transportation, economy, and sustainability. They identified several challenges, including high-income inequality and the intensive use of individual transportation, which hinder the establishment of these policies. Further, there is no precise classification in terms of urban compactness for Brazilian municipalities.

Compact cities have better health care systems than sprawling locations, both in terms of access and supply. This is because, in compact cities, there is a greater diffusion of knowledge and, consequently, a greater number of qualified professionals, such as doctors, nurses, physiotherapists, among others (OECD, 2012; Sebbenn and Ruschel, 2019).

Based on the above, compactness and urban sprawl can be linked to the spread of COVID-19. Leiva et al. (2020), through a case study of Los Angeles and New York, showed that urban structure and organization influenced social isolation measures and, consequently, the spread of the virus. Sathler and Leiva (2022) argue that cities should have been central to discussions on COVID-19 infection, as different urban forms presented distinct challenges and opportunities in addressing the pandemic. Understanding social, spatial, economic, and demographic factors is essential, as they reflect the vulnerabilities of cities.

The urban structure of localities can affect the spread of infectious diseases (Aguilera and Mignot, 2004; Hassell et al., 2017; Soares et al., 2014; Tauil, 2001). Factors such as the use of public transportation, per capita emissions of pollutant gases, size of locations, population distribution, and health indicators are related to the levels of COVID-19 infection (Aguilar et al., 2022).

The problems caused by the new coronavirus are not just sanitary but also political, socioeconomic, and cultural, with varying effects depending on the region (Matta et al., 2021). In Brazil, Cavalcante et al. (2020) reported that by the 20th epidemiological week of 2020, the northern region had the highest relative number of infections. Additionally, Moraes et al. (2020) found that the northeast region was the most affected. These findings highlight that some locations were more impacted than others due to factors such as inadequate hospital infrastructure, spatial organization, and other inefficient systems that hindered the virus containment.

Leiva et al. (2020) found that sprawling cities such as Los Angeles had more decelerated contamination rates than compact cities such as New

York. Mesquita et al. (2021) emphasize that socioeconomic aspects of households are also associated with the way COVID-19 spreads. Thus, even in areas with low population density, the sprawled city model presents issues of greater social inequality and economic precariousness. Individuals in lower-income families are more exposed to the virus in these locations because, in general, they do not have access to private transportation, housing conditions are precarious, and there is a prevalence of multi-family households. Studies indicate that household overcrowding, associated with economic vulnerability, hinders social isolation and increases the transmission of the virus (Demenech et al., 2020; Silva et al., 2023).

Compact cities, due to their higher population density, faced difficulties in implementing preventive measures against COVID-19. This is because in these locations, residences are closer and the use of public transportation is more intense, leading to a greater agglomeration of individuals in the same place, which facilitates the spread of the virus (OECD, 2020).

Yücel et al. (2023), analyzing the metropolitan region of São Paulo, showed that locations with greater centrality have greater difficulty adhering to government policies aimed at delaying the spread of COVID-19, as these locations are closer to the more centralized regions affected by the virus. Aguilar et al. (2022) also examined how the structure of cities is related to the spread of diseases in the United States, showing that dispersed locations tend to have lower numbers of viral infections than compact cities.

Economically large, rich, accessible, and dense regions are more predisposed to a higher incidence of COVID-19; in addition, places that have good government management tend to react faster to the waves of COVID-19. In contrast, places with more outdated health systems and weak government management tend to have higher mortality rates (Matamoros et al., 2021; Rodríguez-Pose and Burlina, 2021).

Hamidi et al. (2020) investigated the direct and indirect effects of population density on the number of COVID-19 cases and deaths in 913 municipalities in the United States. The authors show that in compact cities, the rate of infection tends to be higher, and the mortality rate tends to be lower due to better health services. However, in Brazil, the logic of the health system is regionalized. The municipalities' response to COVID-19 also depends on how the local health network is structured and how each municipality is integrated into the system. Moreover, the large territorial extension of the country, combined with regional inequalities and varying degrees of urban concentration, has contributed to an asymmetric pattern of virus dissemination across Brazilian localities, resulting in distinct infection dynamics depending on the region (Bega and Souza, 2021).

There is a gap in the literature regarding the discussion of how access to opportunities and the theoretical models of cities are jointly related to the spread of COVID-19. In this context, this study advances existing knowledge, producing new evidence about Brazil.

Empirical strategy

Data and definition of variables

The information used in the present study is extracted from the Population Estimates, the Regions of Influence of Cities survey (REGIC) and the 2010 Demographic Census of the Instituto Brasileiro de Geografia e Estatística (IBGE), the United Nations Development Program (UNDP), the System of Estimated Emissions and Removal of the Climate Observatory (SEEG-OC), the Annual Report of Social Information (RAIS) of the Ministry of Economy (ME), the National Registry of Health Establishments (CNES), the School Census of Anísio Teixeira National Institute of Educational Studies and Research (INEP), the Brazilian Agricultural Research Corporation (EMBRAPA) and the COVID Portal of the Ministry of Health (MS). The analysis is conducted for urban Brazil, and the territorial units examined are the municipalities.[2] Table 1 presents a summary of the variables used.

2 Of the 5,570 Brazilian municipalities, only 4,855 are used, due to missing information in the REGIC database and the COVID Portal. The geographic regions of Brazil exhibited missing data in the analyzed dataset, totaling 715 records distributed as follows: North (73), Northeast (163), Center-West (66), Southeast (211), and South (202). The presence of missing values across all regions suggests that their occurrence was random. Therefore, there is no indication of systematic bias, and the randomness of the missing data minimizes the risk of compromising the estimates derived from the dataset.

Table 1. Description of the variables analyzed.

Outcome variables			
Variable	Description of the variable	Year	Database
ln_txinfec	Natural logarithm of the rate of infected persons per 100,000 inhabitants	2020	Ministry of Health (2020)
ln_txobito	Natural logarithm of the death rate per 100,000 inhabitants	2020	
Explanatory variables			
Variable	Description of the variable	Year	Database
ln_popurb	Natural logarithm of the urban population	2010	UNDP (2010)
densR	Residential Density: $densR = \frac{No.of\quad Perm\quad Private\quad Dom}{Urban\quad area}$	2020	IBGE (2020)
densA	Activity Density: $densA = \frac{Qty\quad of\quad active\quad links}{Urban\quad area}$	2020	ME (2020)
densES	Density of Health Facilities: $densES = \frac{no.Health\quad establishments}{Urban\quad area}$	2022	CNES (2022)
densEE	Density of Education Establishments: $densEE = \frac{no.Education\quad Establishments.}{Urban\quad area}$	2021	INEP (2021)
commuting	Flow of intercity commuting (outflow)	2010	IBGE (2010)
Simple hierarchy	Urban hierarchy *dummy*, which captures the centrality of the location: 1 – whether it is a metropolis or regional capital; 0 – if it is a subregional center, zone center, or local center	2018	IBGE (2020)
issuance_pcp	Municipal CO_2 emission per capita: $issuance\_pcp = \frac{total\quad CO2\quad emissions}{Urban\quad population}$	2019	SEEG-OC (2019)
Gini	Gini coefficient	2010	UNDP (2010)
prop_pb	Proportion of individuals with a per capita household income equal to or less than R$ 140.00 per month	2010	
prop_elderly	Proportion of the population over age 60	2010	

Source: Own elaboration. Note: The urban areas of the municipalities in 2015 are used to construct the density indicators, and this information is extracted from the EMBRAPA portal.

The dataset described in Table 1 presents temporal variation, with information referring to the years 2010, 2018, 2019, 2020, 2021, and 2022. The use of variables from different reference years was due to the availability of the most recent data for each indicator, ensuring greater timeliness and completeness of the information used. Moreover, some variables — such as the Gini index — exhibit lagged effects, meaning their impact on socioeconomic outcomes tends to persist over time. Although this temporal heterogeneity represents a limitation, it is acknowledged and justified by the nature of the available data and was duly considered in the methodological procedures adopted in the analysis. The use of variables from different years is supported in the literature, particularly in studies involving socioeconomic indicators, whose effects are known to persist over time or manifest with a delay (Barro, 1991; Deininger and Squire, 1996; Wooldridge, 2010).

Specifically, the outcome variables are the natural logarithm of the infection rate (confirmed cases per 100,000 inhabitants up to the reference date) and the death rate (confirmed cases per 100,000 inhabitants up to the reference date). It is important to note that in these accumulated case data, there is underreporting of the number of people infected with COVID-19 due to the scarcity of diagnostic tests and the absence of symptoms in some individuals. Confirmation of infection was made when the individual tested positive using a test administered by a health professional. The number of deaths reflects the number of deaths reported by the health departments on the date they were confirmed by laboratory or clinical epidemiological findings (Ministry of Health, 2020).

The reference date for capturing the accumulated cases of infection and mortality from COVID-19 is 01/16/2021. This date was deliberately chosen for being prior to the start of vaccination in Brazil (Ministry of Health, 2020), in order to avoid the influence of territorial heterogeneities in vaccine distribution and to reflect better the natural spread and impact of the virus before vaccine control measures were implemented.

Regarding the explanatory variables of the model, some information needs to be highlighted. The per capita CO_2 emission level was computed using municipal information on the total gross CO_2 emission level in tons. In summary, a per capita CO_2 emission indicator, *emission_pcp*, was created taking into account the urban population of the municipalities. The variable is normalized on a scale of 0 to 1. This variable was used to capture the level of municipal sustainability.

The mobility variable *commuting*, constructed with microdata from the 2010 census, captured intercity commuting due to work, precisely identifying the flow of individuals residing in one municipality and commuting to another municipality for work (outflow). The analysis was also conducted with the normalized indicator on a scale between 0 and 1.

The urban hierarchy variable comprised five major levels: 1) metropolises; 2) regional capital; 3) subregional center; 4) zone center, and 5) local center. Simões and Amaral (2011) showed that the definition used in the REGIC study to characterize the levels of urban hierarchy considered not only the classification of territorial management centers but also the size of the region and its influence. Thus, the municipalities categorized as metropolises, regional capitals, subregional centers, zone centers, and local centers were composed of 15, 97, 352, 398, and 4,037 Brazilian municipalities, respectively (IBGE, 2020).

In this study, a simplification of the urban hierarchy indicator was performed, making it a dummy variable that took the value 1 when the municipality was in the category of metropolis (1) or regional capital (2) and the value 0 if it was included in the other categories. The urban hierarchy dummy was expected to capture the centrality of locations, as the higher the level of urban hierarchy was, the greater the supply of highly complex services, the denser and more complex the urban network, and the easier to access opportunities. That is, the site tended to be more compact (Christaller, 1966; Moura et al., 2021).

The density variables linked to work, health, and education weigh the issues associated with unequal access to these opportunities in the municipalities. Pereira et al. (2020a) used each of these densities to estimate travel time matrices for the 21 largest Brazilian cities. As it was not possible to calculate these matrices for all Brazilian municipalities, we chose to use the densities themselves as a proxy for accessibility to opportunities.

Residential density, in turn, was used in the models, given its relevance to urban mobility, especially concerning home-work commutes. One of the main characteristics of a compact location is the high residential density, which highlights how individuals are distributed within the urban space (Leiva et al., 2020; Neuman, 2005). The descriptive statistics for the variables used are presented in Table 2.

Table 2. Descriptive statistics of the model variables.

Variable	Mean	Standard deviation	Minimum	Maximum
ln_txinfec	5.7542	.6730	2.1913	7.9361
ln_txobito	1.7637	.7119	-1.1897	3.5395
ln_popurb	9.0743	1.3190	5.3566	16.2272
densES	6.6196	5.0501	.1868	104.3771
densR	1336.8450	1016.7400	77.3748	27682.6900
densA	546.9462	418.5968	4.7436	6754.5480
Dense	9.1814	12.1461	.0016	264.4231
Commuting	.0112	.0492	0	1
simple_hierarchy	.1022	.3029	0	1
issuance_pcp	.0273	.0411	0	1
prop_elderly	.1194	.0320	.0260	.2709
Gini	.4966	.0655	.2800	.8000
prop_pb	.2311	.1796	.0000	.7823

Note: The number of observations is 4,855 municipalities. For information on the variables, see Table 1.
Source: Own elaboration.

Table 3 shows that the average infection rate per 100,000 inhabitants was highest in regional capitals (531.4174), followed by subregional centers (483.1441) and metropolises (453.0339). Smaller locations, such as zonal centers (409.5722) and local centers (343.0872), had lower infection rates. This indicates that areas with a higher urban hierarchy, which have larger populations and more interconnected urban networks, tend to have higher infection rates, likely due to their larger regions of influence (IBGE, 2020).

Table 3. Average infections and deaths by COVID-19
by classes of urban hierarchy.

Urban Hierarchy	Rate of Infections per 100,000 inhabitants (16/01/2021)			Rate of Deaths per 100,000 inhabitants (16/01/2021)		
	Observations	Mean	Standard deviation	Observations	Mean	Standard deviation
Metropolis	203	453.0339	243.8237	203	11.8012	4.3311
Regional Capital	295	531.4174	294.1703	295	10.5343	4.9337
Sub-Regional Center	481	483.1441	269.2335	481	8.6708	4.7325
Zone Center	435	409.5722	265.2186	435	6.8331	4.3833
Local Center	3,859	343.0872	248.6956	3,859	5.8989	4.5930

Note: The number of observations is 4,855 municipalities.
Source: Own elaboration.

The regional capitals and subregional centers had a higher average rate of infection compared to the metropolises, which may be because in Brazil, especially in the northern region, there are places with low density but a high number of infections. In addition, there are locations in metropolitan areas that have low rates of infection (see Figure 3 in the Results section).

The average death rate per 100,000 inhabitants behaved similarly to the infection rate, such that a higher death rate is observed in locations with a higher urban hierarchy class. In summary, in larger urban hierarchies, that is, in locations with a higher level of regional influence, the average death rate was higher. Such evidence suggests that the hypothesis, based on Hamidi et al. (2020), that more central and compact locations would have a reduced COVID-19 mortality rate may not be a reality in Brazil. In this context, understanding the relationships between site organization and infection and mortality is essential. Thus, in the following subsection, the empirical models used to verify these associations are presented.

Methodology

Structural equation modeling (SEM) is a cross-sectional multivariate statistical technique widely used in the most diverse areas of scientific research (Neves, 2018). In the present study, this methodological procedure is used to analyze the processes that influenced the spread of COVID-19 and the number of deaths, and how the advancement of the disease was interconnected with the spatial organization structure of cities in Brazil.

The estimation of structural equation models involves solving a set of equations in which there is an equation for each output variable (endogenous) of the system that affects and is affected by other variables. Variables that are only predictors of others are called influences (or exogenous variables); they may be correlated with each other but are determined outside the system (Hamidi et al., 2020).

Thus, SEM can be represented as follows:

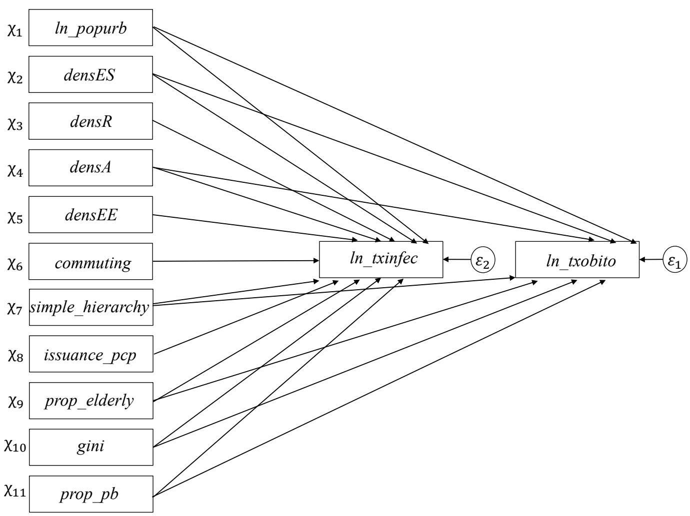
$$\boldsymbol{Y} = \boldsymbol{BY} + \boldsymbol{\Gamma X} + \boldsymbol{\alpha} + \varsigma \tag{1}$$

where $\boldsymbol{X}$ is the vector of all exogenous variables, $\boldsymbol{Y}$ is the vector of all endogenous variables, $\boldsymbol{B} = [\beta_{ij}]$ is the matrix of the coefficients of the endogenous variables, $\boldsymbol{\Gamma} = [\gamma_{ij}]$ is the matrix of the coefficients of the exogenous variables, $\boldsymbol{\alpha} = [\alpha_i]$ is the intercept vector, and ς is the error term with a mean of zero and $Cov(\boldsymbol{X}, \varsigma) = 0$.

According to Kline (2011), SEM is based on maximum likelihood (ML) estimation, which assumes normal distribution for all endogenous variables existing in the model. As the variables examined in the present study did not pass the Kolmogorov-Smirnov normality test,[3] it was decided to use the maximum pseudolikelihood estimation method, which removes the requirement of normality, making the model viable (Kline, 2011; Macana and Comim, 2015).

Figure 1 shows the relational path diagram for the SEM dependent variables, namely, COVID-19 infection and mortality. This diagram shows the relationship of each of the exogenous variables with the endogenous variables of the model. This model is used because it allows us to understand the relationship between social, demographic, economic, and spatial variables with the COVID-19 infection and mortality rate, and to observe the direct and indirect relationships of each variable in the context of the study.

Figure 1. Relational path diagram between endogenous and exogenous variables.



Source: Own elaboration.

3 In this test, when the p-value is significant, the assumption of normality of the variable is rejected. For the variable of infected the p-value = 0.004, and for the variable of deaths the p-value = 0.000.

A limitation of the proposed model, in theoretical terms, is that despite the urban hierarchy *dummy* trying to capture the level of urban compactness, it is known that there are other aspects, not considered at the hierarchy level, that are fundamental to characterizing compact cities, such as sustainability, access to opportunities and a higher level of economic interaction (Breheny, 1992; Jenks, 1996; Neuman, 2005). Thus, to advance the analysis, the MIMIC model developed by Joreskog and Goldberger (1975) was used.

MIMIC belongs to a kind of SEM. In the present study, the aforementioned model allows capturing the level of urban compactness, constituting a latent variable that represents a common construct of a set of observable indicators. This is composed of two stages, with two different types of models (Joreskog and Goldberger, 1975):

(i) a structural model that shows the relationship between latent variable $\boldsymbol{\eta}$ and exogenous observable variables $\boldsymbol{\chi}$. In the present study, latent variable $\boldsymbol{\eta}$ refers to the level of urban compactness, which is determined by the set of exogenous variables $\boldsymbol{\chi}(j{=}1,...,J)$:

$$\boldsymbol{\eta} = \gamma_1 \chi_1 + ... + \gamma_J \chi_J + \epsilon \text{ (structural equation)} \quad (2)$$

(ii) a measurement model in which the latent variable is a construct measured by observable indicators that linearly determines each of the indicators. Thus, $\boldsymbol{y}_{\mathbf{i}}$ $(i = 1,...,m)$is the vector of observable indicators, to mention, in this analysis, the COVID-19 infection and mortality associated with the level of urban compactness $\boldsymbol{\eta}$.

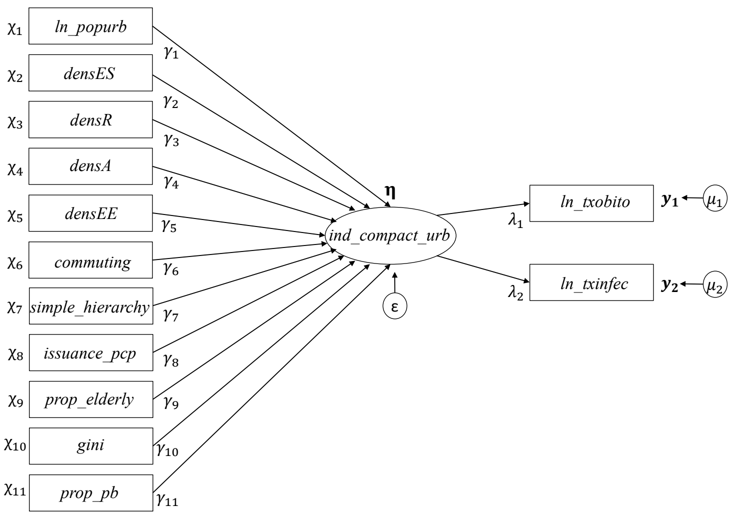
$$\boldsymbol{y}_{\boldsymbol{m}} = \lambda_m \boldsymbol{\eta} + \mu_m \text{ (measurement model)} \quad (3)$$

The model of multiple indicators and multiple causes is divided into two processes, with $\boldsymbol{\eta}$ being latent. The parameters must be estimated using the link between variances and covariances of the observable variables of causes and indicators. The regression coefficients influence the unobservable variable and, proportionally, all the indicators. These relationships are evidenced through a system of three equations:

$$\begin{aligned} \boldsymbol{y}_{\mathbf{1}} &= \lambda_1 \boldsymbol{\eta} + \mu_1 \\ \boldsymbol{y}_{\mathbf{2}} &= \lambda_2 \boldsymbol{\eta} + \mu_2 \end{aligned} \quad (4)$$

In Equation (4), y_1 and y_2 are the death and infection rates, respectively. The λ's are the factor loadings used to estimate the latent variable of urban compactness level. In the structural equation $j = 11$ means that the structural model has 11 exogenous variables that determine the level of urban compactness. Figure 2 schematically shows the application of the MIMIC model in the context of the present study.

Figure 2. MIMIC model for analysis of the relationship between urban compactness and COVID-19 infection and mortality rates.



Source: Own elaboration.

After specifying the MIMIC model, it is necessary to evaluate its identification property, which is defined by the degree of freedom after the specification of the parameters to be estimated. For it to be guaranteed, it is necessary that (i) the model has at least zero degrees of freedom ($df_M \geq 0$) and (ii) a metric scale is assigned to every latent variable (including residuals).

Regarding item (i), the degree of freedom is calculated by $df_M = p - q$, in which p shows the number of observations and q represents the number of parameters estimated in the model. It is important to note that in this type of modeling, the number of observations is not equivalent to the sample size (Macana and Comim, 2015). Thus, the number of observations is given by $p = \frac{l(l+1)}{2}$, where l is the number of observed variables existing in the model. In the estimated model, $l = 13$ (11 exogenous variables and 2 endogenous variables), so the number of observations is $p = 91$.

Furthermore, adding the 13 coefficients estimated with the variances of the two endogenous variables and the latent variable, one obtains the number of parameters $q = 16$. Therefore, the number of degrees of freedom in this model is given by $df_M = 91 - 16 = 75$. Therefore, the model is characterized as identified (or overidentified), as it has a greater number of observations than parameters, i.e., $df_M > 0$.

Regarding item (ii), the metric scale in every latent variable is important because the latent constructs do not have a specific form of measurement; therefore, it is necessary to establish the metric scale that can be satisfied through normalization. In this way, the latent variable will use one of the endogenous variables as a constraint or reference and normalize the others based on it. In the present study, the rate of COVID-19 infections was determined, and the death rate was used as a reference (Kline, 2011; Macana and Comim, 2015).

Results and discussions

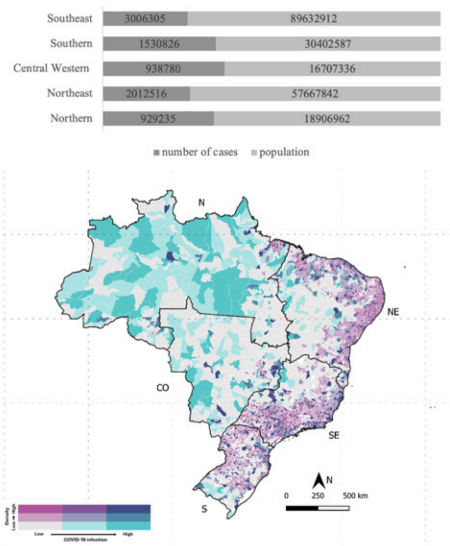
Analyzing COVID-19 infections in Brazil up to January 2021 (Figure 3), the Southeast had the highest number of cases, as it concentrates the largest population – 89,632,912 inhabitants or 42 % of the country's total (IBGE, 2021). In contrast, the Northern region, with the lowest number of infections, is the least populated, with 18,906,962 inhabitants, representing 9 % of the Brazilian population.

In relative terms, the central western region had the highest percentage of COVID-19 infections (5.62 % of its population), while the Southeast had the lowest (3.35 %). Figure 3 illustrates the relationship between population density and infection rates, a key factor identified in multiple studies as a major determinant of COVID-19 spread globally (Hamidi et al., 2020; Leiva et al., 2020).

The high population density-high infection rate condition is primarily found in Brazilian coastal metropolitan municipalities, such as São Gonçalo do Amarante (CE), Caucaia (CE), Fortaleza (CE), Recife (PE), Salvador (BA), and cities in the Rio de Janeiro metropolitan area, among others. Municipalities with low population density and low infection rates do not follow a clear spatial pattern, though this trend is more evident in the interior of the country. In the North, for example, places like northern

Pará, Amapá, and southeastern Rondônia have low population density but high infection rates.

Figure 3. Spatial distribution of the cumulative number of individuals infected with COVID-19 and population density.



Source: Prepared by the authors, using data from the Ministry of Health (01/16/2021) and IBGE (2021). QGIS software.

In addition, on the outskirts of metropolitan areas, there are places with medium population density and a low infection level, such as the metropolitan region of São Paulo, Florianópolis, and João Pessoa. Thus, regional differences may be related to the unequal number of individuals infected with COVID-19 in Brazil. Wong and Li (2020) found that these regional inequalities dictated the speed of infection, as more connected and compact locations had higher numbers of infections in the early stages of the pandemic, and more remote and widespread locations had a lower rate of contamination.

The results of the estimations of the structural equations model are presented in Table 4. The dependent or endogenous variables, the natural logarithm of the COVID-19 infection rate and the natural logarithm of the COVID-19 death rate, seek to capture the spread and lethality of the virus. In Table 4, Column 1 shows the coefficients of the model estimation for the infected rate and Column 2 for the death rate, whereas Columns 3 and 4 show the standardized coefficients.

Table 4. Results of the structural equations model (SEM).

Variables	(1) ln_txinfec	(2) ln_txobito	(3) Standardized coefficients of Column 1†	(4) Standardized coefficients of Column 2†
ln_popurb	.0359*** (.0095)	.0513*** (.0081)	.0704*** (.0186)	.0951*** (.0151)
densES	.0219*** (.0029)	-.0047** (.0021)	.1644*** (.0219)	-.0333** (.0149)
densR	-.0002*** (.0000)		-.3098*** (.0349)	
densA	.0002*** (.0000)	.0001*** (.0000)	.1140*** (.0175)	.0389** (.0149)
Dense	.0038** (.0018)		.0686** (.0322)	
Commuting	-1.2360*** (.1770)		-.0903*** (.0129)	
simple_hierarchy	.1356*** (.0312)	.2983*** (.0283)		
issuance_pcp	.0001 (.0001)		.0175 (.0134)	
prop_elderly	-3.9060*** (.3779)	.9600*** (.3279)	-.0186*** (.0176)	.0432** (.0147)
Gini	.5550*** (.1875)	-.1629 (.1820)	.0540** (.0182)	-.0150 (.0167)
prop_pb	-.7992*** (.0982)	-.0797 (.0754)	-.2133*** (.0260)	-.0201 (.0190)
ln_txinfec		.4976*** (.0145)		0.4704*** (.0119)
Intercept	5.7936*** (.1251)	-1.6162*** (.1358)	8.6094*** (.2145)	-2.2705*** (.1854)
Observations	4,855			
R^2	.201			
SRMR	.005			

*Note: † Standardized coefficients of dummy variables are not presented because they do not allow an interpretation of the results, so the interpretation of the urban hierarchy is provided by the non-standardized coefficients (Columns 1 and 2). Robust standard deviations are shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Source: Own elaboration.

The model's degree of fit is measured by the standardized root mean square residual (SRMR), with a result of .005 indicating a good fit (Chang et al., 2009). The coefficient of determination of .201 shows that 20.1 % of the variation in endogenous variables is explained by the model. The analyses use standardized coefficients (Columns 3 and 4), presenting results in standard deviation units to allow for a comparable magnitude of explanatory power between endogenous and exogenous variables (Kline, 2011; Macana and Comim, 2015).

In the infection model, the urban hierarchy variable (.1356) indicates that more developed locations and larger populations are associated with a higher rate of COVID-19 infection. Batella and Miyazaki (2020) argue that the urban network is directly linked to the spread of the virus, particularly due to factors like centrality, connections between centers, and circulation infrastructure. Duarte and Schumann (2022) also highlight that the spread of COVID-19 followed a reticular but uneven pattern, with locations closer to and more economically integrated with more developed central municipalities experiencing an increase in cases earlier than more remote areas.

The urban population variable (.0704) has a statistically significant positive relationship with the spread of COVID-19. This result was expected because in more populous locations, greater contact between individuals tends to increase the chances of transmission of any contagious disease. This association is mainly related to the level of urban sprawl, as more compact locations tend to have higher numbers (Hamidi et al., 2020; Wong and Li, 2020).

The variables density of health facilities (.1644), education (.0686), and activity (.1140) capture access to opportunities. The more central, compact, and developed a particular location is, the more intense the presence of these opportunities per square kilometer, and consequently, a higher level of accessibility is expected (Pereira et al., 2020a; Scott and Horner, 2008). The estimated coefficients for the three density indicators corroborate the idea that better access to opportunities is related to a higher rate of contagion. This is because the better this accessibility is, the more displacements tend to occur in these locations, thus increasing the degree of exposure of individuals (Leiva et al., 2020; Pereira et al., 2020b).

Residential density (-.3098) is significantly and negatively related to the rate of COVID-19 infections, indicating that a lower density of households is associated with a higher rate of COVID-19 infections. This result was persistent but was not expected. A plausible explanation for this result is that places with higher residential density tend to be more central, and in large centers, and the daily exchange ratio between individuals tends to be reduced, especially in neighborhoods (Willems, 2019).

This counterintuitive result may be related to the fact that areas with higher residential density are generally located in more organized and hierarchical urban centers, with better infrastructure and institutional capacity. Recent studies suggest that, in this type of city, lockdown measures were more effective, mainly because they directly targeted mobility and social contact hotspots, which helped slow the spread of the virus. In contrast, in less dense and more decentralized areas, mobility tends to be more dispersed and control less effective, which may have contributed to higher infection rates even with lower physical density (Aguilar et al., 2022; Yang, 2021).

The outflow of commuters (-.0903) has an inverse relationship with the rate of infections, indicating that places with a higher outflow of commuters have lower infection rates. This relationship was not expected because, due to the greater movement of individuals in larger and more developed cities, the expected transmission of COVID-19 cases from these cities to those of origin would be. Because large city centers have a greater dissemination of the care needed to prevent the spread of the virus, the estimated negative coefficient of this variable may be associated with the greater degree of information available to individuals who circulate in these central areas (Matta et al., 2021).

The proportion of elderly individuals (-.1863) also exhibits an inverse relationship with the rate of infected individuals. In general, municipalities with the highest proportions of elderly people were not those with the greatest spread of the disease; the highest COVID-19 transmission rate occurred in the 20-49 age group (Monod et al., 2021).

Regarding social vulnerability measures, the Gini coefficient (.0540) and the proportion of poor people (-.2133) show an inverse relationship, where income inequality was positively associated with the spread of COVID-19. In contrast, the proportion of the poor was inversely related. Koudjom et al. (2022) analyzed how poverty and income inequality, specifically the Gini coefficient, influenced COVID-19 spread in 52 African countries, finding that both were positively related to the virus spread. The different results for Brazil may be partially associated with the coexistence of high income inequality and the presence of higher income groups in more central urban areas, which could mask poverty conditions when measured solely by income (Salata and Ribeiro, 2021).

Regarding the model for deaths, the main determinant was the municipal infection rate (.4707). It is noteworthy that higher mortality rates were related to higher rates of infections. In fact, the fatality rate of a virus, by its nature, is linked to the rate of infection by it (Hamidi et al., 2020).

The urban hierarchy (.2983) was also a significant determinant of the lethality of the virus, showing that places with a higher level of urban hierarchy (metropolis and regional capitals) were associated with a higher mortality rate due to COVID-19. Even though there are better mechanisms for the functioning of the health system in more central locations, in general, locations characterized as metropolises and regional capitals tended to have higher rates of COVID-19 infections, which, in turn, were related to higher mortality rates (Leiva et al., 2020).

Júnior et al. (2020) determined that three situations can lead to an increase in mortality in regions with a lower urban hierarchy (subregional centers and zone centers), namely, when the city is a tourist destination; when the medium- and small-scale traffic nodes[4] have more accurate indices than the large centers; and when these smaller urban centers participate in alternative productive, business or migratory circuits. However, these exceptions are not able to counterbalance the effect of urban centrality in this process.

The positive and statistically significant relationship between the activity density variable (.0389) and the death rate indicates that locations with higher employment density or better access to employment opportunities are associated with a higher unemployment rate and mortality from COVID-19. This is because, due to better access conditions, there is a greater degree of exposure on the home-work journey (Sathler and Leiva, 2022).

The density of health care facilities (-.0333) has an inverse relationship with the death rate; that is, municipalities with higher densities of health care facilities, on average, have lower mortality rates. The greater the availability of local health facilities is, the faster emergency care is provided and the greater the chances that the individual will recover (IBGE, 2020;

4 Medium- and small-scale traffic nodes are supports for the road integration of meso- and micro-regions.

Noronha et al., 2020). In addition, the higher density of health facilities facilitates access to health care, which speeds up emergency assistance (Leiva et al., 2020; Pereira et al., 2020a).

The proportion of elderly individuals (.0432) shows that there is a positive relationship between this variable and the mortality rate due to COVID-19. The elderly population is more vulnerable to the virus due to a weakened immune system, which generates greater risks of complications; consequently, locations with a greater share of elderly individuals have, on average, greater lethality of the virus (Barbosa et al., 2020; Kang and Jung, 2020).

Regarding the urban population (.0951), places with greater urban populations are associated with higher mortality rates due to COVID-19. This result is consistent with the literature, as COVID-19 began and was strongly concentrated in large urban centers. Thus, the greater the degree of urbanization is, the greater the number of individuals living and circulating in this locality, which culminates in a greater number of infections and, consequently, deaths (Viezzer and Biondi, 2021).

The results of the structural equations model in Table 4 show the relationship between economic, demographic, and social variables and the COVID-19 infection and mortality rates. However, such a model is still not able to sufficiently present the relationship between the urban structure and these rates because it is necessary to advance the design of the model through the estimation of a MIMIC.

The results for the MIMIC are shown in Table 5, where the endogenous variable is the urban compactness index, influenced by all the variables already described (Table 1). Column 1 presents the coefficients of each of the predictor variables, that is, those that compose the urban compactness index. Column 2 shows the standardized coefficients, and as in the previous model, the analyses were performed using the standardized coefficients. The degree of fit of the model, as measured by the SRMR, was .020, indicating a good quality of fit. The coefficient of determination of .222 shows that 22.20 % of the variation in the endogenous variable is explained by the model.

Table 5. Results of the multiple indicators and multiple causes model (MIMIC).

Variables	(1) Urban compactness index	(2) Standardized coefficients of Column 1†
ln_popurb	.0448*** (.0091)	.1081*** (.0228)
densES	.0171*** (.0031)	.1578*** (.0259)
densR	-.0002*** (.0000)	-.3013*** (.0404)
densA	.0002*** (.0000)	.1283*** (.0183)
Dense	.0024 (.0016)	.0537 (.0354)
Commuting	-.8523*** (.1594)	-.0766*** (.0134)
simple_hierarchy	.2005*** (.0305)	
issuance_pcp	.0001 (.0001)	.0247 (.0162)
prop_elderly	-3.2827*** (.4117)	-.1921*** (.0212)
Gini	.4821*** (.1821)	.0577** (.0216)
prop_pb	-.7754*** (.0893)	-.2547*** (.0290)
Observations	4,855	
R^2	0.222	
SRMR	0.020	

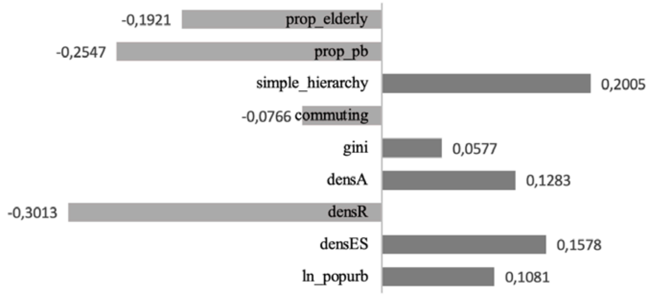
*Note: † Standardized coefficients of dummy variables are not presented because they do not allow an interpretation of the results, so the interpretation of the urban hierarchy will be given through the non-standardized coefficients (Column 1). Robust standard deviations are shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Source: Own elaboration.

Figure 4 illustrates the impact of significant determinants on the urban compactness index. The variable with the greatest positive impact is the urban hierarchy *dummy* (.2005), indicating that cities with higher urban centrality (metropolises and regional capitals) tend to have a higher compactness index. This result aligns with the expectation that larger urban hierarchies, which feature more structured and interconnected urban networks, are characteristic of compact cities (IBGE, 2020; Leite et al., 2015).

The density of health care facilities (.1578) has a positive association, showing that the more health care facilities there are per square kilometer, the higher the indicator of urban compactness. This is evident because, due to demand, compact locations tend to have a greater supply of this type of service. In addition, given the greater supply of jobs, there is a retention of qualified professionals in these places, including health professionals. In addition, access to health services is facilitated in these locations (Leiva et al., 2020; Pereira et al., 2020a).

Figure 4. Ranking of the impact of significant determinants of the urban compactness index.



Note: 4,855 Brazilian municipalities were observed.
Source: Own elaboration.

The variables urban population (.1081) and activity density (.1283) show that, on average, the larger the urban population and the greater the density of employment, the more compact the location will be. Such evidence for Brazil corroborates the findings of Leiva et al. (2020), Hamidi et al. (2020), Sathler and Leiva (2022), and Neuman (2005).

In terms of access to health and employment opportunities, places with better levels of accessibility have a higher level of urban compactness; consequently, the sprawl of these municipalities is lower. This is evident because the urban network and the collective public transport system work in synergy (Leiva et al., 2020; Scott and Horner, 2008).

The outflow of commuters (-.0766) indicates that locations with lower outflows of commuters tend to be more compact. Sprawling locations, with fewer job opportunities, have a higher rate of commuting evasion of individuals to centers and subcenters that absorb this labor (Aguilera and Mignot, 2004).

The municipal proportion of elderly people (-.1921) is negatively related to the level of urban compactness. This result can be explained by two phenomena: first, the economically active population is usually concentrated in large centers due to the higher level of job opportunities; second, elderly individuals tend to seek more dispersed and quieter places, usually located in the countryside (Carvalho, 2011; Moura, 1987). Therefore, locations with a lower proportion of elderly individuals are associated with a higher urban compactness index.

Regarding social vulnerability measures, the proportion of the poor (-.2152) shows that locations with a lower proportion of individuals living below the poverty line tend to have higher urban compactness indicators. The Gini coefficient (.0577) suggests that more income-unequal societies are associated with more compact locations. This observation ties into the discussion of suburbanization, where lower-income individuals often settle on the periphery due to the higher cost of living in central areas (Batty et al., 1999; Koudjom et al., 2022).

Residential density (-.3013) is significant and shows an inverse relationship with urban compactness in an unexpected and persistent result. One possibility is that compact cities attract more individuals to work and study; further, due to the higher costs of living in these places, these commuters may choose to live further away from opportunities and use transportation to access them (Aguilera and Mignot, 2004; Sathler and Leiva, 2022).

Table 6 presents the measurement model results for the latent variable (urban compactness index). In this model, the infection rate carries more weight within the urban compactness index compared to the death rate. The lower weight of the death rate may be due to the effectiveness of the health system in reducing mortality in these locations. For example, the natural logarithm of the infection rate per 100,000 inhabitants is expected to increase by approximately .8126 standard deviations with a one standard deviation increase in the urban compactness index.

Additionally, Table 6 shows that the latent construct of the urban compactness index explains 66.03 % of the variation in the COVID-19 infection rate and 39.96 % of the variation in the death rate. These findings suggest that contagion and death mechanisms were linked to urban sprawl and influenced by factors specific to each location. The results are robust to variations in reference dates, maintaining consistency in both magnitudes and signs.[5]

Table 6. Results of the measurement model, a multiple indicators and multiple causes model (MIMIC).

Endogenous variable	Coefficient	Standardized coefficient	R^2
ln_txinfec	1.0000 (constrained)	.8126*** (.0263)	.6603
ln_txobito	.8229*** (.0531)	.6322*** (.0216)	.3996

*Note: A total of 4,855 Brazilian municipalities were observed. The coefficient of ln_txinfec is 1 because this indicator was the reference for the normalization of the urban compactness index construct, ensuring the identification property of the model. Robust standard deviations are shown in parentheses. Significance levels: *p<0.10, **p<0.05, ***p<0.01.*

Source: Own elaboration.

Final considerations

This study aimed to analyze the role of urban structure in the process of COVID-19 infection and mortality in Brazil. An analysis was performed using structural equation models to capture the relationship between the variables of density, mobility, social vulnerability, and urban structure with the rates of spread and mortality by COVID-19. Then, using the model of multiple indicators and multiple causes, an investigation was conducted on the association of these rates with the level of urban sprawl through the indicator of urban compactness.

The literature used in this study showed that the geography of COVID-19 cases and deaths does not follow a homogeneous pattern, i.e., each location may have differences in the process of contamination, prevention, deaths, and information about the disease. Studies such as this one are important for public policy planners to devise the best strategies to contain the spread of highly contagious diseases, such as COVID-19.

The results of the econometric models indicate that because compact cities have a greater urban hierarchy and offer better access to

5 The results considering the flexibility in the dates for the accumulated infections and deaths, for three reference dates (01/16/2021, 12/22/2020 and 12/31/2020), are contained in the Appendix.

opportunities, the mortality and death rates due to COVID-19 were higher compared to sprawling cities. This indicates that more interconnected and dense cities are more susceptible to virus risks, despite having greater infrastructure and a faster response to threats.

Another interesting result observed is that two indicators of social vulnerability – the Gini index and the proportion of poor people – showed opposite effects: the former was positively associated with infection rates and urban sprawl, while the latter was negatively associated with both outcomes. This may reflect the presence of areas in Brazil where higher-income individuals are concentrated, potentially leading to a lower observed prevalence of income-based poverty. However, this does not necessarily capture the full extent of multidimensional poverty. We suggest that future research explore more deeply the relationship between different dimensions of social vulnerability and the patterns of COVID-19 spread and lethality across Brazilian municipalities.

The outflow of commuters indicates that commuting evasion is more pronounced in cities characterized by greater urban sprawl. This agrees with the literature used in this study, as fewer compact locations have, on average, fewer opportunities for access to work, education, and health opportunities. In this sense, a good part of commuting is related to the search for access to better opportunities.

This study contributes to addressing the gap in research on the urban structure of localities and their relationship with COVID-19 infection and mortality rates in Brazil. This work will serve as a foundation for developing guidelines for public policy planners to understand better and address COVID-19 and future viral infections, both in Brazil and globally. The results highlight clear links between the spread and lethality of COVID-19 and factors such as access to opportunities, commuting, and population density.

It is essential to discuss strategies that promote social and economic well-being, whether through sustainable development or by expanding access to critical services such as healthcare, education, and employment. These actions are crucial for improving the quality of life and reducing disease lethality in contexts marked by deep social inequalities.

As a research agenda, additional variables could be incorporated into the model to enrich the analysis. Among them, noteworthy are education level, essential occupations, and more detailed indicators of social vulnerability and vaccination coverage over time. An important limitation of the current set of variables is that, in many cases, the available data do not accurately reflect local realities or are temporally outdated. A possible future development of this study would be to deepen the analysis using spatial econometrics tools. This approach would allow for a more precise observation of dissemination and lethality patterns during both the pre- and post-vaccination periods. Furthermore, another critical advancement would be to explore more deeply the relationship between social vulnerability indicators and rates of virus transmission and mortality, especially considering the Brazilian context, which is marked by profound socioeconomic inequalities and limited access to essential public services.

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Appendix

The results considering the flexibility in the dates for the accumulated infections and deaths, for three reference dates (01/16/2021, 12/22/2020 and 12/31/2020) are presented in the tables below.

Table 7. Results of the structural equation model for the infection rate.

	SEM 16/01/21		SEM 22/12/20		SEM 31/12/20	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	ln_txinfec	Standardized Coefficients of Column 1 †	ln_txinfec	Standardized Coefficients of Column 3 †	ln_txinfec	Standardized Coefficients of Column 5 †
ln_popurb	.0359*** (.0095)	.0704*** (.0186)	.0387*** (.0104)	.0711*** (.0191)	.0385*** (.0101)	.0721*** (.0189)
densES	.0219*** (.0029)	.1644*** (.0219)	.0197*** (.0032)	.1388*** (.0226)	.0219*** (.0031)	.1577*** (.0222)
densR	-.0002*** (.0000)	-.3098*** (.0349)	-.0002*** (.0000)	-.2945*** (.0335)	-.0002*** (.0000)	-.3082*** (.0339)
densA	.0002*** (.0000)	.1140*** (.0175)	.0002*** (.0000)	.1209*** (.0174)	.0002*** (.0000)	.1193*** (.0176)
dense	.0038** (.0018)	.0686** (.0322)	.0041** (.0019)	.0701** (.03216)	.0039** (.0018)	.0676** (.0320)
Commuting	-1.2360*** (.1770)	-.0903*** (.0129)	-1.2079*** (.1828)	-.0838*** (.0126)	-1.1932*** (.1798)	-.0840*** (.0126)
simple_ hierarchy	.1356*** (.0312)		.1768*** (.0331)		.1647*** (.0326)	
issuance_ pcp	.0001 (.0001)	.0175 (.0134)	.0001 (.0001)	.0754** (.0141)	.0001 (.0001)	.0133 (.0130)
prop_elderly	-3.9060*** (.3779)	-.0186*** (.0176)	-4.5184*** (.4086)	.0146 (0,0130)	-4.2486*** (.3980)	-.1924*** (.0176)
Gini	.5550*** (.1875)	.0540** (.0182)	.4109** (.2059)	-.2004*** (.0177)	.4428** (.2005)	.0413** (.0186)
prop_pb	-.7992*** (.0982)	-.2133*** (.0260)	-.4797*** (.1024)	.0376** (.0188)	-.5413*** (.1011)	-.1383*** (.0257)
ln_txinfec				-.1203*** (.0256)		
Intercept	5.7936*** (0.1251)	8.6094*** (0.2145)	5.6635*** (.1355)	7.9021*** (.2165)	5.6866*** (.1324)	8.0806*** (.2158)
Observations	4,855	4,855	4,748	4,748	4,789	4,789
R^2	0.201	0.201	0.356	0.356	0.373	0.373
SRMR	0.005	0.005	0.086	0.086	0.086	0.086

*Note: † Standardized coefficients of dummy variables are not presented because they have no interpretation, so the interpretation of the urban hierarchy is presented as the non-standardized coefficients (Column 1). Robust standard deviations are shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Source: Own elaboration.

Table 8. Results of the structural equation model for the death rate.

	SEM 16/01/21		SEM 22/12/20		SEM 31/12/20	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	ln_txobito	Standardized Coefficients of Column 1†	ln_txobito	Standardized Coefficients of Column 3†	ln_txobito	Standardized Coefficients of Column 5†
ln_popurb	.0513*** (.0081)	.0951*** (.0151)	.0443*** (.0087)	.0796*** (.0156)	.0473*** (.0084)	.0862*** (.0154)
densES	-.0047** (.0021)	-.0333** (.0149)	-.0071*** (.0022)	-.0488** (.0159)	-.0061*** (.0021)	-.0426** (.1497
densR						
densA	.0001*** (.0000)	.0389** (.0149)	.0001*** (.0000)	.0543*** (.1504)	.0001*** (.0000)	.0488 (.0121)
densEE						
commuting						
simple_ hierarchy	.2983*** (.0283)		.3329*** (.0298)		.3177*** (.0292)	
issuance_ pcp						
prop_elderly	.9600*** (.3279)	.0432** (.0147)	.6029* (.3488)	.0261* (.0151)	.8574** (.3400)	.1449** (.0149)
Gini	-.1629 (.1820)	-.0150 (.0167)	-.1304 (.1898)	-.0117 (.0169)	-.1516 (.1849)	-.0137 (.0167)
prop_pb	-.0797 (.0754)	-.0201 (.0190)	.0879 (.0804)	.0215 (.0197)	.0539 (.0780)	.0134 (.0193)
ln_txinfec	.4976*** (.0145)	.4704*** (.0119)	.4844*** (.0152)	.4426*** (.0123)	.4967*** (.0149)	.4602*** (.0121)
intercept	-1.6162*** (.1358)		-1.6241*** (.1431)	-2.2155*** (.1896)	-1.6859*** (.1402)	.4602*** (.0121)
Observations	4,855	4,855	4,748	4,748	4,789	4,789
R^2	0.201	0.201	0.356	0.356	0.373	0.373
SRMR	0.005	0.005	0.086	0.086	0.086	0.086

*Note: † Standardized coefficients of dummy variables are not presented because they do not allow an interpretation of the results, so the interpretation of the urban hierarchy will be presented as the non-standardized coefficients (Column 1). Robust standard deviations are shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Source: Own elaboration.

Table 9. Results of the structural model for the three dates – multiple indicators and multiple causes model (MIMIC).

	MIMIC 16/01/21		MIMIC 22/12/20		MIMIC 31/12/20	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Urban Compactness Index	Standardized Coefficients of Column 1†	Urban Compactness Index	Standardized Coefficients of Column 3†	Urban Compactness Index	Standardized Coefficients of Column 5†
ln_popurb	.0448*** (.0091)	.1081*** (.0228)	.0441*** (.0098)	.0999*** (.0230)	.0454*** (.0096)	.1045*** (.0230)
densES	.0171*** (.0031)	.1578*** (.0259)	.0142*** (.0035)	.1231*** (.0276)	.0165*** (.0034)	.1456*** (.0270)
densR	-.0002*** (.0000)	-.3013*** (.0404)	-.0002*** (.0000)	-.2776*** (.0413)	-.0002*** (.0000)	-.2943*** (.0411)
densA	.0002*** (.0000)	.1283*** (.0183)	.0002*** (.0000)	.1377*** (.0182)	.0002*** (.0000)	.1348*** (.0184)
densEE	.0024 (.0016)	.0537 (.0354)	.0026 (.0017)	.0543 (.0358)	.0024 (.0017)	.0522 (.0355)
simple_ hierarchy	.2005*** (.0305)		.2434*** (.0327)		.2295*** (.0324)	
issuance_ pcp	.0001 (.0001)	.0247 (.0162)	.2955 (.2267)	.0211 (.0163)	.3024 (.2204)	.0218 (.0160)
prop_elderly	-3.2827*** (.4117)	-.1921*** (.0212)	-3.8747*** (.4737)	-.2117*** (.0215)	-3.5939*** (.4590)	-.1997*** (.0215)
Gini	.4821*** (.1821)	.0577** (.0216)	.3966** (.1985)	.0447** (.0223)	.4097** (.1936)	.0468** (.0220)
prop_pb	-.7754*** (.0893)	-.2547*** (.0290)	-.4985*** (.0932)	-.1540*** (.0292)	-.5517*** (.0916)	-.1730*** (.0290)
Observations	4,855	4,855	4,748	4,748	4,789	4,789
R^2	0.222	0.222	0.185	0.185	0.190	0.190
SRMR	0.020	0.020	0.019	0.019	0.019	0.019

*Note: † Standardized coefficients of dummy variables are not presented because they do not allow an interpretation of the results, so the interpretation of the urban hierarchy will be given through the non-standardized coefficients (Column 1). Robust standard deviations are shown in parentheses. Significance levels: * p<0.10, ** p<0.05, *** p<0.01.*

Source: Own elaboration.

Table 10. Results of the measurement model for the three dates - multiple indicators and multiple causes model (MIMIC).

MIMIC 16/01/21			
Endogenous Variable	Coefficient	Standardized Coefficient	R^2
ln_txinfec	1.0000 (constrained)	.8126*** (.0263)	.6603
ln_txobito	.8229*** (.0531)	.6322*** (.0216)	.3996
MIMIC 22/12/20			
Endogenous Variable	Coefficient	Standardized Coefficient	R^2
ln_txinfec	1.0000 (constrained)	.8117*** (.0325)	.6589
ln_txobito	.7964*** (.0648)	.6316*** (.0264)	.3990
MIMIC 31/12/20			
Endogenous Variable	Coefficient	Standardized Coefficient	R^2
ln_txinfec	1.0000 (constrained)	.8150*** (.0312)	.6642
ln_txobito	.8025*** (.0619)	.6355*** (.0255)	.4038

*Note: The coefficient of ln_txinfec is 1 because this indicator is the reference for the normalization of the urban compactness index construct, ensuring the identification property of the model. Robust standard deviations are shown in parentheses. Significance levels: *p<0.10, **p<0.05, ***p<0.01.*

Source: Own elaboration.