PATTERNS OF INEQUALITY AND SOCIAL DEPRIVATIONASSOCIATEDWITHSEVERITY INDICATORS IN COVID-19 PATIENTS WITH LETHAL PROGRESSION IN MEXICO

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ABSTRACT: This article analyzes multivariate association patterns regarding social, economic, demographic and health factors with severity indicators in adult patients infected by SARS-CoV-2 and who developed COVID-19 with lethal progression. We identified the predictors with the greatest explanatory capacity based on Binary Logistic Regression (BLR) models. Using Mexico's Ministry of Health's databases and records regarding social marginalization, lack of health access and municipal inequality, among other predictors we constructed the BLR. Based on these models, cross-product ratios are estimated to determine the probability of being diagnosed with pneumonia, being hospitalized, intubated or admitted to an Intensive Care Unit (ICU). Our results indicate that increases in the combination of comorbidities increase the risk for all the severity indicators, while the lack of social security increases the risk of a confirmatory diagnosis of pneumonia and admission to an ICU. We found that living in a municipality with a high degree of social marginalization compared to one with a low degree, increases the patient´s probability of having a confirmatory diagnosis of pneumonia in COVID-19 with lethal progression, while the latter reduces the probability of hospitalization, intubation and admission to the ICU.

Keywords: *COVID-19, SARS-CoV-2, acute respiratory syndrome, social marginalization, inequality*

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Severe Acute Respiratory Syndrome Type 2 (SARS-CoV-2), is a coronavirus that causes Coronavirus Disease 2019 (COVID-19). SARS-CoV-2 was detected on December 31, 2019 in Wuhan city, Hubei province, in China (Sohrabi, et al., 2020). By 2020, the disease had caused worldwide more than 300 thousand deaths (estimate), while still rising (Rodríguez-Izquierdo et al., 2020). COVID-19 patients experience cough, secretions and fever symptoms; presenting clinical features that can carry lethal effects. Indicators of disease severity with lethal progression include hospitalization, pneumonia, pulmonary edema, intubation and admission to an ICU, among others (Chen et al., 2020). Hypertension, diabetes, obesity, smoking and advanced age are among the comorbidities that can progress to more severe stages and the death of the patient due to COVID-19 (Ortiz-Hernández and Pérez-Sastré, 2020).

In addition to the progression of symptoms to severe forms that imply a greater risk of lethality, the disease spreads rapidly due to its high transmissibility. Estimates speak of a 2.2/3.5 persons on average spread capacity, by an infected case (Callaway et al., 2020). It is also estimated that both the spread of the disease and the distribution of diagnosed COVID-19 positive cases could be influenced, conditioned and even determined by factors related to social living conditions, human development processes, socioeconomic status, social gaps and inequality (Ferreira, 2020; Merino et al., 2020; Mejía-Reyes, 2020). Mexico presents structural social gaps, high distributive income inequality and high percentages of the population living in poverty persist. It is possible to hypothesize that the impacts of the health crisis and the indicators of severity (risks) that lead to death from COVID-19 are differentially distributed and affected and follow a pattern defined by social stratification factors.

Social deprivation and inequality in Mexico occur at different levels: intrafamily, by social groups, segmented by territorially defined units (regions, states, municipalities and localities). Some authors affirm that the country is characterized by being geographically polarized (Ortiz-Hernández and Pérez-Sastré, 2020). Another type of polarization scarcely studied regarding the pandemic, refers to discrimination and deprivation of social rights faced by indigenous people and the population with indigenous ancestry (Ortiz-Hernández et al., 2018).

Mexico's National Evaluation of Social Development Policy Council (Coneval, in Spanish) forecasted and warned that, due to the adverse effects of the pandemic in Mexico on the household economy, extreme income poverty will affect between 6.1 and 10.7 million more people, while income poverty will reach 70.9 million compared to 61.1 million in 2018 (Coneval, 2020). Such scenarios will exert social and political pressure to develop innovative models of governance and social participation that integrate the public policy design construct of social welfare that Pribble (2011) invites us to think about, based on the distinction between public policies aimed at preventing falling into social risk (risk prevention policies), and those of protection against risk, once it is being experienced (risk coping policies). This is probably one of the great lessons of the pandemic, that of learning to 'fish upstream', anticipating the emergence of the crisis (social, economic and health) by developing conditions and capacities to reduce its impact once it has occurred. We are talking about a paradigm shift in the design of public policy and in the philosophical bases of the conception of social welfare, a change that should entail the rhizomatic transformation (structural and not conjectural) of the welfare regime, placing greater emphasis on the pillars of prevention and social promotion based on new institutional arrangements among the actors involved in its definition (market, State, family and civil society).

In sum, more knowledge is needed regarding the role and possible effects of social stratification and inequality factors on the severity indicators of COVID-19. Improving knowledge about the nature and the relationship between social processes and living conditions and the severe forms of the disease that increase its lethality will strengthen the precision and effectiveness of public policies and social development deployed to confront the pandemic; reduce the overload of medical services that impact mortality levels, but also to strengthen the factors of prevention and protection against the disease, such as the promotion of healthy habits and lifestyles programs and inclusive policies of access to health care.

MATERIALS AND METHOD

We used information from the database of Mexico's Ministry of Health, General Directorate of Epidemiology (DGE, in Spanish). DGE records COVID-19 cases (suspected and confirmed) by medical facilities of the three levels of health care in the public and private sectors. Cases detected through the Epidemiological Surveillance System for Viral Respiratory Disease (SISVER, in Spanish) are reported through 475 Health Units Monitoring Respiratory Diseases (USMER, in Spanish), with presence in all 32 states.

From this database we selected cases in which the progression of the disease had a lethal progression (death of the patient) from March 1, 2020 to November 27, 2021, in a population between 20 and 95 years of age. Following the recommendation of Ortiz-Hernández and Pérez-Sastré (2020), to reduce possible biases, the population under 20 was excluded, and to reduce possible delay effects of reported deaths, records corresponding to the last 15 days were excluded. Thus, we obtained a database with 79,946 records of deaths associated with COVID-19. 89% of the cases contained complete data records (n=71,017). In order to reduce the cause-effect bias between disease and death, we decided to work with an n=56,882 records of deaths due to COVID-19 in patients previously diagnosed as confirmed positive, either by clinical epidemiologic association, an opinion committee or a laboratory sample. After this delimitation, we still obtained 89% of the cases with complete data records (n=50,123). The indigenous variable was the one with the most missing cases (1.6%), followed by the comorbidities variable (0.8%).

The predictive capacity of the model was analyzed regarding four severity indicators associated with the lethal outcome of the disease: i) confirmatory diagnosis of pneumonia, ii) hospitalization, iii) intubation, and iv) admission to an ICU (Ortiz-Hernández and Pérez-Sastré, 2020). As predictors (independent variables) we considered: sex, age, indigenous ancestry, type of health institution (social security sectors), comorbidities, the Social Gap Index (ISL, in Spanish), the Human Development Index (HDI), the Marginalization Index (MI) and social cohesion understood as social inequality obtained through the Gini index coefficient.

With the original stratification by levels and degrees of each index considered for our analysis,[1] a quartile segmentation was established for other indicators, such as social cohesion (distributive inequality) (Table 1). The 'health institution' variable distinguishes between the general population, made up of those who received care in centers of the Ministry of Health, Red Cross, Family Development System (DIF, in Spanish), university services, IMSS-Bienestar, and the population that received care in social security services (like IMSS, ISSSTE, Sedena, Semar and Pemex) or private health centers. The variable 'comorbidities' is an ordinal polytomous type, its categories represent the combined sum of these (diabetes, hypertension and obesity) (Table 1). Its construction responds to the finding that people usually present not one, but several metabolic comorbidities simultaneously. The decision to select diabetes, hypertension and obesity is based on the finding that they tend to overlap each other by forming the same component (factor) when an exploratory factor analysis is applied to the database (Ortiz-Hernández and Pérez-Sastré, 2020).

1 Very low, low, medium, high and very high in the case of ISL and MI and low, medium, high and very high for HDI.

TABLE 1. *SUMMARY OF THE VARIABLES INCLUDED IN THE MODEL, INDICATORS, VALUES AND TYPES*

Variables	Indicators	Final value	Type
Pneumonia (dependent)	Pneumona diagnosis	0. No (RC) 1. Yes	Dichotomous nominal
Hospitalization (dependent)	Patient's admission to hospital	0. No (RC) 1. Yes	Dichotomous nominal
Intubation (dependent)	Patient requieres intubation	0. No (RC) 1. Yes	Dichotomous nominal
Intensive care (dependent)	Patient is taken to an ICU	0. No (RC) 1. Yes	Dichotomous nominal
Sex	Sex charcteristics	0. Female (RC) 1. Male	Dichotomous nominal
Age	Age declared	Age	Numerical continuum
Comorbidities (predictor)	Cardiometabolic comorbidities (diabetes, hypertension and obesity)	1. None (RC) 2. One 3. Two 4. Three	Ordinal polytomus
Indigenous (predictor)	Patient identifies as an indigenous person	0. No (RC) 1. Yes	Dichotomous nominal
Health institution that provided care (predictor)	Institutions providing care to the open population without social security or private health services	0. No (RC) 1. Yes	Dichotomous nominal
Social Gaps (predictor)	2015 Municipal Social Gap Index	1. Very low (RC) 2. Low 3. Medium 4. High 5. Very high	Ordinal polytomus
Marginalization (predictor)	2015 Marginalization Index	1. Very low (RC) 2. Low 3. Medium 4. High 5. Very high	Ordinal polytomus
Human Development (predictor)	2015 municipal Human Development Index	1. Very high (RC) 2. High 3. Medium 4. Low	Ordinal polytomus
Social cohesion (predictor)	Distributional inequality measured by the Gini index coefficient of household monetary income.	1. Very low (RC) 2. Low 3. High 4. Very high	Ordinal polytomus

Note. RC= reference category

Source: The Author.

To estimate the socioeconomic conditions of the population, we used the 2015 municipal level ISL provided by Coneval. The index constitutes a measure of social deprivation based on the indicators defined by the Mexican General Law of Social Development (LGDS, in Spanish) for the definition, identification and measurement of poverty (Coneval, 2007). The ISL is constructed as a weighted measure that captures and summarizes information from four deprivation indicators associated with access to social rights (education, health, basic services and housing space) (Table 2) (Coneval, 2007).

TABLE 2. *INDEX OF SOCIAL LAG (ISL) DIMENSIONS AND INDICATORS*

Dimensions	Indicators
Education	Percentage of the population aged 15 years and over who are illiterate.
	Percentage of population aged 6 to 14 years not attending school.
	Percentage of homes with population between 15 and 29 years old with family members with less than 9 years of schooling.
	Percentage of population aged 15 and over with incomplete basic education.
Access to health services	Percentage of population without access to health services.
Housing quality and room space	Percentage of homes with dirt floor.
	Average number of occupants per room
Home basic services	Percentage of homes without toilet or sanitary facilities.
	Percentage of homes without running/drinking water.
	Percentage of homes without drainage.
	Percentage of homes without electricity.
Home appliances	Percentage of homes without a washing machine.
	Percentage of homes without a refrigerator.

Source: Coneval, 2007.

The second index used is the 2015 MI, which captures the structural gaps in social living conditions from the perspective of territorial units (municipalities), weighting the factor of population distribution in different habitats (urban and rural). The MI, by the National Population Council (Conapo, in Spanish), provides information regarding four dimensions of deprivation of access to social rights: education, housing, monetary income and impact by spatial location (Table 3). These refer to nine forms of social exclusion and helps to rank municipalities according to their marginalization degree. The forms of social exclusion captured by the MI, reflect "the population that does not have access to essential services; these deficiencies prevent to grow assets and the generation of basic capacities to manage their personal life projects; they also imply the non-exercise of human rights" (Conapo, 2016, p. 12).

TABLE 3. *DIMENSIONS, TYPES OF EXCLUSION AND INDICATORS OF THE MARGINALIZATION INDEX (MI)*

Concept	Socioeconomic dimensions	Exclusion types	Indicator
Multiple structural phenomenon that assesses exclusion (dimensions, forms and intensities) in the process of development and enjoyment of benefits.	Education	Illiteracy.	Percentage of population 15 years of age and older who are illiterate.
		Population without full primary education.	Percentage of population aged 15 years or older without completed primary education.
	Housing	Homes without sewage and sanitation services.	Percentage of occupants in homes without sewage and sanitation services.
		Homes without electricity.	Percentage of occupants in homes without electricity.
		Homes without piped water.	Percentage of occupants in homes without piped water.
		Homes with some degree of overcrowding.	Percentage of homes with some degree of overcrowding.
		Homes with dirt floors	Percentage of occupants in homes with dirt floors.
	Population distribution	Localities with less than 5,000 inhabitants.	Percentage of population in localities with less than 5,000 inhabitants.
	Income	Employed population earning up to two minimum wages.	Percentage of employed population with income up to two minimum wages.

Source: Conapo, 2016.

The third index is the 2015 HDI, which reflects the existing gaps between Mexico's municipalities according to their levels of human development by summarizing information on the population's ability to: (1) enjoy a long and healthy life; (2) acquire knowledge through formal education; and (3) have access to resources that guarantee a decent standard of living (see Table 1). These three capability components: (1) enjoy a long and healthy life; (2) acquire knowledge through formal education; and (3) access resources, guarantee a decent standard of living (United Nations Development Program [UNDP], 2014). In contrast to the ISL and MI, the HDI is estimated from the aggregation of the indexes of three capabilities components through the use of the geometric mean. Whereby "a poor performance in any of the components is directly reflected in the value of the index and there is no longer perfect substitutability between them" (UNDP, 2014, p. 13), thus strengthening the accuracy of the final HDI measure.

The health index (component 1), considers a child's survival rate as a proxy to estimate life expectancy at birth, the education index (component 2), is a combined measure estimated from the expected years of schooling versus the average schooling years, while the income index (component 3), estimates the per capita monetary economic income adjusted to the annual Gross National Income (GNI), in US dollars, adjusted by the Purchasing Power Parity (PPP). The aggregation of these indexes –by means of the geometric mean– gives rise to the HDI, which is expressed in values to three decimal places between zero (0.000) and one. Closer values to 0.000 being an expression of the lowest possible achievement in well-being and human development and values closer to 1.000 the inverse (UNDP, 2014). Thus, a stratification of human development can be established that, under the new HDI methodology, differentiates between 'very high', 'high', 'medium' and 'low' degrees of municipal human development.

RESULTS

A retrospective cross sectional predictive analysis was performed, employing a Binary Logistic Regression (BLR) based on which the relationships analyzed are not strictly established on a causality principle, but can be inferred implicitly (López-Roldán and Fachelli, 2015). Unlike the traditional linear regression model, in which predictions are made based on the probabilities estimation for a dependent variable (quantitative) when the independent variables (predictors, which are also quantitative) vary. In BLR the aim is to predict the behavior of a dependent variable that is qualitative or categorical, depending on the change of one unit in the predictor variables (predictors) that can be quantitative as well as qualitative or categorical, "with the advantage, compared to the classical regression model, of not having to establish the series of application conditions that hinder its use and its possibilities, in particular, in the context of survey study" (López-Roldán and Fachelli, 2015, p. 60). BLR allows to develop the analysis of the explanatory capacity of the independent variables (predictors) on the dependent variable, considering both the individual effect of the former and the effect of their interaction (multivariate association), expressed through an exponential function that makes possible the multiplicative interpretation of the parameters of the equation. Under this technique, the explanatory weight of each predictor on the dependent variable is estimated from the coefficients in a regression equation that employs the iterative maximum likelihood (LR, likelihood ratio) algorithm (López-Roldán and Fachelli, 2015). In the first iteration, the model value is taken into account only for the constant, while the rest of the coefficients or parameters are worth zero. When the iterations begin to be redundant and no longer add more likelihood (explained variability of the dependent variable) the process stops, obtaining the log likelihood for the full model (Log-Likelihood Full Model or -2 log of the likelihood) and its Cox and Snell and Nagelkerke pseudo R squared, which allows to evaluate the degree of fit of the model and its explanatory capacity. If the log of the full model is higher than that of the initial model (model only with the constant) and the pseudo R square's report an acceptable explained variability, then the model is accepted, since there are no statistically significant differences between the observed and expected frequencies under the model (Orós, 2019). In other words, if the goodness-of-fit test based on the maximum likelihood test, which is after all a Chi-square test ($\chi 2$), shows a p-value (Sig.) less than or equal to 0.05 (omnibus test table), the null hypothesis, which states that –except for the constant– all coefficients are zero and the alternative is accepted, insofar as at least one coefficient is significantly different from zero (Orós, 2019; Escobar, Fernández and Bernardi, 2009).

PNEUMONIA AS A SEVERITY INDICATOR

Table 1 shows the results of the bivariate statistical analysis, indicating that there is a significant association, estimated by the Chi-square test, for most of the relationships between the predictors and the independent variable for the confirmatory diagnosis of pneumonia. With the exception of the variable 'age', whose inclusion in the regression model does not contribute significantly to increase its predictive power, the p-value results significant (<0.05) for the rest of the independent variables.

Table 2 shows that the variables selected for the analysis are statistically significant (p-value <0.05) and can predict the risk factor of having a confirmatory diagnosis of pneumonia by means of the regression equation used to estimate the model.

TABLE 1. *BIVARIATE ASSOCIATION TEST BETWEEN PREDICTORS ENTERED INTO THE BLR MODEL AND DEPENDENT VARIABLE PNEUMONIA*

Predictors	Score	gl	Sig.
Sex	7.386	1	.007
Age	1.701	1	.192
Comorbidities	128.803	3	.000
Comorbidities (1)	37.360	1	.000
Comorbidities (2)	6.389	1	.011
Comorbidities (3)	23.481	1	.000
Indigenous	28.256	1	.000
Health institute (sector)	5065.621	1	.000
ISL	378.774	4	.000
ISL (1)	144.604	1	.000
ISL (2)	96.126	1	.000
ISL (3)	79.073	1	.000
ISL (4)	5.883	1	.015
MI	264.477	4	.000
MI (1)	72.954	1	.000
MI (2)	77.184	1	.000
MI (3)	49.361	1	.000
MI (4)	24.678	1	.000
HDI	213.882	3	.000
HDI (1)	22.258	1	.000
HDI (2)	206.210	1	.000
HDI (3)	4.410	1	.036
Social cohesion	172.922	3	.000
Social cohesion (1)	3.997	1	.046
Social cohesion (2)	31.373	1	.000
Social cohesion (3)	135.776	1	.000
Overall statistics	5450.136	21	.000

Source: The Author.

TABLE 2. *TEST OF THE SET OF VARIABLES ON THE MODEL'S COEFFICIENTS (OMNIBUS TESTS)*

	Chi square	gl	Sig.
Stepwise	5934.097	21	.000
Block	5934.097	21	.000
Model	5934.097	21	.000

Source: The Author.

The correction of Cox and Snell's R square by Nagelkerke's R square indicates that the model explains 10.5% of the change in the dependent variable, correctly classifying 70.6% of the cases, as shown in Table 3.[2]

TABLE 3. *R-SQUARED BLR MODEL*

-2 log likelihood	Cox and Snell	Nagelkerke	Clasification (% global)
87483.886	.074	.105	70.6

Source: The Author.

Table 4 summarizes the coefficients and estimators of the multivariate analysis of the BLR model. The Wald Chi-square, which is a multivariate test of statistical independence, indicates that when it is equal to or greater than 1, the predictors are making a significant contribution to the explanation of the dependent variable (pneumonia), so it is appropriate to keep them in the model.

The analysis of the results of the variables in the regression equation shows a significant p-value for most of the variables selected, except for HDI (2 and 3) and social cohesion (2). The interpretation of the exponentiated multivariate risk coefficient (Exp-(B) column), which is a measure of odds ratio,[3] indicates important variations in the risk of presenting a positive diagnosis of pneumonia when the institution where health care was received (sector), the social marginalization of the municipalities where the patients

2 The Cox and Snell R-squared, like the Nagelkerke R-squared, capture the explained variability and rarely provide high values as does the counterpart indicator of the linear regression technique. It is common to find results between 0.2 and 0.3, and even lower if the number of predictors decreases, with R-squared values higher than 0.6 being much less common (López-Roldán and Fachelli, 2015).

3 All the values of the coefficient (Exp-(B)) in this case and the other severity indicators analyzed were within the 95% confidence interval (CI).

live and, to a lesser extent, the number of comorbidities and indigenous ancestry vary.

In order of greater to lesser predictive power for the diagnosis of pneumonia, we have the health institution (sector); when the variable health institution (sector) varies by one unit, which means going from having social security or private health services to not having them and, therefore, being part of the open population, the risk of being diagnosed with pneumonia increases 4 times (3.966).

Likewise, the greater the social marginalization of the patient's municipality of residence, as captured by the ISL, the greater the risk of being diagnosed with pneumonia; when the municipality goes from having a very low to a medium degree of social marginalization, the risk of pneumonia increases 2 times (1.918), and when it goes from a very low to a high degree, the risk increases 2.6 times (2.616).

In contrast to this result, the MI is significant, but behaves inversely; increases in the degree of marginalization of the municipality of residence, means a decrease in the probability of pneumonia diagnosis in COVID-19 patients with lethal progression. The explanation for this behavior lies in the fact that the MI does not capture the lack of access to health services, as does the ISL. In addition, the ISL is a more robust index, with a total of 13 indicators for five components of deprivation and social exclusion, five more than those captured by the MI; among others, it omits deprivation of access to health services, socioeconomic status through household assets and availability of toilet/sanitary facilities as part of basic housing services.[4]

Adding comorbidities in combination to the clinical features increases the probability of being diagnosed with pneumonia. From having no comorbidities to having one increases them by 1.2 (1.191) times and from having no comorbidities to combining three comorbidities increases them by 1.3 (1.294). On the other hand, having indigenous ancestry versus not having one decreased the risk of a diagnosis of pneumonia by 1.2 times (1/.865).

The variables sex and age proved to be statistically significant (column Sig.), however, the values of their beta coefficients (column B), parameters of the additive model that constitute indicators of hierarchy and intensity of the predictors, are close to zero, therefore, too modest (.044 and .003, respectively); scarcely relevant compared to the set of significant predictors of the risk of a confirmatory diagnosis of pneumonia in COVID-19 patients with lethal progression.

4 The ISL integrates two indicators to capture the lack of access to education not contemplated by the MI; one of school attendance in the population aged 6 to 14 years old and the other of educational lag in homes with a population aged 15 to 29 years old.

TABLE 4. *PREDICTORS IN THE BINARY LOGISTIC REGRESSION EQUATION FOR PNEUMONIA. ODDS RATIO EXPRESSED AS EXPONENTIATED B COEFFICIENTS*

Predictors	B	E.T.	Wald	gl	Sig.	Exp(B)
Sex	.044	.017	6.532	1	.011	1.045
Age	.003	.001	18.012	1	.000	1.003
Comorbidities			110.792	3	.000	
Comorbidities ***(1)***	***.160***	***.020***	***65.079***	***1***	***.000***	***1.174***
Comorbidities ***(2)***	***.175***	***.022***	***65.094***	***1***	***.000***	***1.191***
Comorbidities ***(3)***	***.258***	***.035***	***52.834***	***1***	***.000***	***1.294***
Indigenous	***-.144***	***.068***	***4.527***	***1***	***.033***	***.865***
Health institute (sector)	***1.378***	***.021***	***4362.970***	***1***	***.000***	***3.966***
ISL			104.824	4	.000	
ISL (1)	***.388***	***.042***	***83.853***	***1***	***.000***	***1.475***
ISL (2)	***.651***	***.088***	***54.237***	***1***	***.000***	***1.918***
ISL (3)	***.962***	***.134***	***51.292***	***1***	***.000***	***2.616***
ISL (4)	***.761***	***.383***	***3.940***	***1***	***.047***	***2.140***
MI			83.197	4	.000	
MI (1)	***-.139***	***.045***	***9.700***	***1***	***.002***	***.871***
MI (2)	***-.435***	***.064***	***45.521***	***1***	***.000***	***.647***
MI (3)	***-.938***	***.105***	***79.628***	***1***	***.000***	***.391***
MI (4)	***-.966***	***.215***	***20.136***	***1***	***.000***	***.381***
HDL			131.466	3	.000	
IDH (1)	***-.220***	***.021***	***110.658***	***1***	***.000***	***.802***
HDI (2)	.063	.068	.863	1	.353	1.065
HDI (3)	.246	.462	.283	1	.595	1.278
Social cohesion			14.694	3	.002	
Social cohesion (1)	.073	.023	10.073	1	.002	1.076
Social cohesion (2)	.003	.023	.022	1	.883	1.003
Social cohesion (3)	.057	.025	5.365	1	.021	1.059
Constant	.213	.044	23.887	1	.000	1.238

Source: The Author.

HOSPITALIZATION AS A SEVERITY INDICATOR

Regarding hospitalization, the model adequately classified 89.9% of the cases (Table 6) and the omnibus tests that report the degree of success in the selection of predictors to account for the dependent variable show statistically significant coefficients (p-value <0.05) (Table 5). The R-squared values, which report the predictive capacity of the risk of hospitalization through the logistic regression equation for the model, are somewhat low; a Nagelkerke's R square of less than 2% (Table 6). However, a cluster of predictors is shown to be significant in the bivariate association with hospitalization, namely; sex, age, comorbidities (2), indigenous ancestry, MI (2) and social cohesion (2 and 3) (Table 7).

On the assumption of significant bivariate associations, high correct case classification and significant values in the omnibus tests, we resolved to interpret some parameters (Exp(B)) of the model (Table 8).

TABLE 5. *TEST OF THE SET OF VARIABLES ON THE MODEL'S COEFFICIENTS (OMNIBUS TESTS)*

	Chi square	gl	Sig.
Stepwise	393.752	21	.000
Block	393.752	21	.000
Model	393.752	21	.000

Source: The Author.

TABLE 6. *R SQUARE BLR MODEL*

-2 log Likelihood	Cox and Snell	Nagelkerke	Clasification (global %)
50017.999	.005	.011	89.9

Source: The Author.

TABLE 7. *BIVARIATE ASSOCIATION TEST BETWEEN PREDICTORS ENTERED IN THE BLR MODEL AND THE DEPENDENT VARIABLE HOSPITALIZATION*

Predictors	Score	gl	Sig.
Sex	9.948	1	.002
Age	40.505	1	.000
Comorbidities	30.192	3	.000
Comorbidities (1)	.805	1	.370
Comorbidities (2)	20.888	1	.000
Comorbidities (3)	3.674	1	.055
Indigenous	6.268	1	.012
Health institute (sector)	119.975	1	.000
ISL	6.788	4	.148
ISL (1)	1.231	1	.267
ISL (2)	1.201	1	.273
ISL (3)	3.026	1	.082
ISL (4)	1.372	1	.241
MI	11.432	4	.022
MI (1)	.027	1	.870
MI (2)	10.546	1	.001
MI (3)	.101	1	.751
MI (4)	.504	1	.478
HDI	.953	3	.813
HDI (1)	.204	1	.651
HDI (2)	.005	1	.944
HDI (3)	.766	1	.381
Social cohesion	177.876	3	.000
Social cohesion (1)	1.166	1	.280
Social cohesion (2)	34.795	1	.000
Social cohesion (3)	57.641	1	.000
Overall statistics	393.184	21	.000

Source: The Author.

The significant predictors that show greater strength in the prediction of the variation of the hospitalization indicator are ISL (2) and health institution (sector) (Exp(B) column), while sex, age and comorbidities (1 and 2) are among those with the lowest predictive strength (Table 8).

The model reports that patients residing in municipalities with a medium degree of social marginalization (ISL 2) with respect to those with a very low degree which are 1.5 times more likely to be hospitalized when they become ill with COVID-19. However, when we compare those with a very high degree of social marginalization (ISL 4) with respect to those with a very low degree, the risk is reduced 2.8 times (1/.360). This behavior of the predictor could be revealing a social barrier according to which the population residing in municipalities with very high social marginalization has fewer resources and faces greater difficulties in accessing hospitalization, once they have contracted the disease (COVID-19) that will lead to their death.[5] The results for the IM predictor support this reading; moving from a municipality of very low marginality to one of medium marginality decreases the probability of hospitalization by 1.4 times (1/.360).

An analogous interpretation would apply to the predictor of health institutions (sector), which reports that the general population is 1.3 (1/.784) times less likely to be hospitalized if they have COVID-19 with lethal progression than the population with social security or private health institutions. Although it has not been shown to be statistically significant, the interpretation of the exponentiated beta parameter of the predictor of indigenous ancestry is interesting;[6] having this ancestry compared to not having it, decreases the probability of hospitalization by 1.2 (1/.873). In contrast, having two comorbidities compared to having none moderately increased the probability of hospitalization by almost 1.2 (1.140).

5 The analysis considered only cases with lethal disease progression.

6 López Roldán and Fachelli (2015) mention that depending on the objective of the research, it may important to focus on the interpretation of the variables parameters not found to be significant, but that may prove to be as important for the analysis as the significant ones.

TABLE 8. *PREDICTORS IN THE BINARY LOGISTIC REGRESSION EQUATION FOR HOSPITALIZATION. ODDS RATIOS EXPRESSED AS EXPONENTIATED B COEFFICIENTS (EXP(B))*

Predictors	B	E.T.	Wald	gl	Sig.	Exp(B)
Sex	-.053	.026	4.259	1	.039	.949
Age	.004	.001	24.561	1	.000	1.004
Comorbidities			21.917	3	.000	
Comorbidities (1)	.076	.029	6.940	1	.008	1.079
Comorbidities ***(2)***	***.131***	***.032***	***16.518***	***1***	***.000***	***1.140***
Comorbidities ***(3)***	***-.036***	***.049***	***.546***	***1***	***.460***	***.964***
Indigenous	***-.136***	***.086***	***2.512***	***1***	***.113***	***.873***
Health institute (sector)	***-.243***	***.025***	***91.302***	***1***	***.000***	***.784***
ISL			***29.803***	***4***	***.000***	
ISL (1)	***.137***	***.060***	***5.213***	***1***	***.022***	***1.147***
ISL (2)	***.431***	***.115***	***14.002***	***1***	***.000***	***1.538***
ISL (3)	.058	.171	.116	1	.733	1.060
ISL (4)	***-1.021***	***.436***	***5.478***	***1***	***.019***	***.360***
MI			29.577	4	.000	
MI (1)	-.028	.063	.198	1	.657	.972
MI (2)	***-.345***	***.087***	***15.764***	***1***	***.000***	***.708***
MI (3)	-.209	.142	2.154	1	.142	.812
MI (4)	.447	.291	2.363	1	.124	1.564
HDI			5.547	3	.136	
HDI (1)	.013	.032	.160	1	.689	1.013
HDI (2)	.116	.089	1.687	1	.194	1.123
HDI (3)	1.300	.610	4.538	1	.033	3.670
Social cohesion			170.932	3	.000	
Social cohesion (1)	***-.237***	***.036***	***43.164***	***1***	***.000***	***.789***
Social cohesion (2)	***-.393***	***.035***	***128.074***	***1***	***.000***	***.675***
Social cohesion (3)	***-.418***	***.036***	***132.048***	***1***	***.000***	***.658***
Constant	2.240	.065	1201.797	1	.000	9.398

Source: The Author.

INTUBATION AS A SEVERITY INDICATOR

Excluding comorbidities (1 and 3) and HDI (3), Table 9 reports the existence of significant bivariate association of all predictors with the intubation dependent variable; a residual Chi-square value of 937.654 for 21 degrees of freedom and a p-value <0.05. It is expected that in the multivariate analysis of the model these variables contribute to explain the severity indicator.

TABLE 9. *BIVARIATE ASSOCIATION TEST BETWEEN PREDICTORS ENTERED INTO THE RLB MODEL AND THE INTUBATION DEPENDENT VARIABLE*

Predictors	Score	gl	Sig.
Sex	21.506	1	.000
Age	311.184	1	.000
Comorbidities	7.904	3	.048
Comorbidities (1)	1.768	1	.184
Comorbidities (2)	6.200	1	.013
Comorbidities (3)	2.216	1	.137
Indigenous	54.607	1	.000
Health institute (sector)	305.559	1	.000
ISL	166.739	4	.000
ISL (1)	51.931	1	.000
ISL (2)	44.094	1	.000
ISL (3)	37.872	1	.000
ISL (4)	10.111	1	.001
MI	189.149	4	.000
MI (1)	8.489	1	.004
MI (2)	81.524	1	.000
MI (3)	72.380	1	.000
MI (4)	5.299	1	.021
HDI	215.986	3	.000
HDI (1)	67.930	1	.000
HDI (2)	101.908	1	.000
HDI (3)	.831	1	.362

CONTINUED TABLE 9.

Predictors	Score	gl	Sig.
Social cohesion	71.954	3	.000
Social cohesion (1)	54.552	1	.000
Social cohesion (2)	11.615	1	.001
Social cohesion (3)	27.340	1	.000
Overall statistics	937.654	21	.000

Source: The Author.

The p-values of the model in the omnibus tests (Table 10) are statistically significant (<0.05), indicating that the selected predictors are adequate to explain the dependent variable under the BLR model. However, the predictive capacity noted by the Nagelkerke R square indicator is somewhat modest (3%), but with a correctness percentage of 61.2% in the statements made from the model; that is, adequately classifying that percentage of cases (Table 11). It was decided to interpret the exponentiated beta coefficients (Exp(B) column) to know under the multivariate model, the magnitude and direction in which the predictors contribute to explain the risk of intubation.

TABLE 10. *TEST OF THE SET OF VARIABLES ON THE MODEL´S COEFFICIENTS (OMNIBUS TESTS)*

	Chi square	gl	Sig.
Stepwise	***952.342***	***21***	***.000***
Block	***952.342***	***21***	***.000***
Model	***952.342***	***21***	***.000***

Source: The Author.

TABLE 11. *R SQUARE BLR MODEL*

-2 log Likelihood	Cox and Snell	Nagelkerke	Clasificaton (global %)
90813.732	.014	.019	61.2

Source: The Author.

The results of the analysis shown in Table 12 show that the comorbidities (2), ISL (1 and 3), MI (1 and 4), HDI (3) and social cohesion (3) variables should be excluded from the model because they are not significant for the intubation indicator (p-value less than 0.05). The results show that the change of one unit in the ISL predictor, that is, moving from residing in a municipality with a very low degree of social marginalization to one with a low degree, the probability of intubation of COVID-19 patient increases 1.2 times (Exp(B) column), but when the change is from a municipality with a very low to a very high degree of social marginalization, the probability decreases by 2.8 (1/.359) (1/.359). 8 times (1/.359). This leads us to a persistent social barriers that define differentials between social strata with respect to access to second and third level health care, as was observed for the previous severity indicator (hospitalization).

For intubation, the MI results are in line with those observed in the ISL, and it can be affirmed that patients residing in municipalities with a high degree of social marginalization compared to those with a very low degree have a 1.3-fold (1/.790) lower probability of undergoing intubation when they are ill with lethal progression of COVID-19. Likewise, it is possible to interpret the HDI predictor (2), indicating that patients living in municipalities with a medium level of human development compared to those with a very high level are 1.2 (1/.820) times less likely to be intubated. Having indigenous ancestry compared to not having it reduces the probability by 1.3 times (1/.795), while not having social security health coverage or private health care services compared to having them reduces it by 1.4 times (1/.748). In contrast, having three comorbidities compared to having none increases, albeit slightly, the probability of intubation.

TABLE 12. *PREDICTORS IN THE BLR EQUATION FOR INTUBATION. ODDS RATIO EXPRESSED AS EXPONENTIATED B COEFFICIENTS (EXP(B))*

Predictors	B	E.T.	Wald	gl	Sig.	Exp(B)
Sex	.067	.017	16.115	1	.000	1.069
Age	-.011	.001	366.329	1	.000	.989
Comorbidities			14.100	3	.003	
Comorbidities (1)	.053	.019	7.710	1	.005	1.055
Comorbidities (2)	.017	.021	.662	1	.416	1.017
Comorbidities ***(3)***	***.102***	***.033***	***9.348***	***1***	***.002***	***1.108***
Indigenous	***-.230***	***.065***	***12.383***	***1***	***.000***	***.795***
Health institute (sector)	***-.291***	***.017***	***278.856***	***1***	***.000***	***.748***
ISL			19.676	4	.001	
ISL (1)	-.013	.040	.111	1	.739	.987
ISL (2)	***.191***	***.080***	***5.690***	***1***	***.017***	***1.210***
ISL (3)	.013	.123	.011	1	.916	1.013
ISL (4)	***-1.025***	***.400***	***6.576***	***1***	***.010***	***.359***
MI			36.400	4	.000	
MI (1)	.072	.042	2.997	1	.083	1.075
MI (2)	***-.203***	***.062***	***10.656***	***1***	***.001***	***.817***
MI (3)	-.235	.097	5.917	1	.015	.790
MI (4)	.195	.182	1.142	1	.285	1.215
HDI			58.396	3	.000	
HDI (1)	***-.151***	***.021***	***53.729***	***1***	***.000***	***.860***
HDI (2)	***-.198***	***.062***	***10.234***	***1***	***.001***	***.820***
HDI (3)	.670	.429	2.438	1	.118	1.955
Social cohesion			31.617	3	.000	
Social cohesion (1)	.069	.022	9.782	1	.002	1.072
Social cohesion (2)	-.051	.022	5.342	1	.021	.950
Social cohesion (3)	-.030	.023	1.649	1	.199	.970
Constant	***.321***	***.042***	***57.322***	***1***	***.000***	***1.378***

Source: The Author.

ADMISSION TO ICU AS A SEVERITY FACTOR

With respect to admission to an ICU as an indicator of severity, the variables defined for inclusion in the model, with the exception of indigenous ancestry, ISL (4) and HDI (1 and 3), were found to be significant in the bivariate statistical analysis with a p-value and a residual Chi-square p-value of less than 0.05. A significant p-value in the omnibus tests, inform that the model is adequate and with predictive capacity from the variables entered (Table 14), with a Nagelkerke's R square value of 9% and a correctness percentage of 88.6% in the statements formulated from the BLR model (Table 15).

TABLE 13. *BIVARIATE ASSOCIATION TEST BETWEEN PREDICTORS ENTERED INTO THE RLB MODEL AND DEPENDENT VARIABLE ICU ADMISSION*

Predictors	Score	gl	Sig.
Sex	24.175	1	.000
Age	152.625	1	.000
Comorbidities	50.751	3	.000
Comorbidities (1)	25.571	1	.000
Comorbidities (2)	7.490	1	.006
Comorbidities (3)	15.452	1	.000
Indigenous	.018	1	.894
Health institute (sector)	3189.604	1	.000
ISL	140.674	4	.000
ISL (1)	20.371	1	.000
ISL (2)	50.237	1	.000
ISL (3)	53.555	1	.000
ISL (4)	.000	1	.996
MI	119.947	4	.000
MI (1)	14.216	1	.000
MI (2)	17.020	1	.000
MI (3)	55.429	1	.000
MI (4)	18.368	1	.000
HDI	92.807	3	.000
HDI (1)	.123	1	.725

CONTINUED TABLE 13.

Predictors	Score	gl	Sig.
HDI (2)	85.641	1	.000
HDI (3)	1.315	1	.251
Social cohesion	221.471	3	.000
Social cohesion (1)	13.358	1	.000
Social cohesion (2)	4.849	1	.028
Social cohesion (3)	208.608	1	.000
Overall statistics	3427.367	21	.000

Source: The Author.

TABLE 14. *TEST OF THE SET OF VARIABLES ON THE MODEL'S COEFFICIENTS (OMNIBUS TESTS)*

	Chi square	gl	Sig.
Stepwise	***3236.780***	***21***	***.000***
Block	***3236.780***	***21***	***.000***
Model	***3236.780***	***21***	***.000***

Source: The Author.

TABLE 15. *R SQUARE BLR MODEL*

-2 log Likelihood	Cox and Snell	Nagelkerke	Clasification (global %)
45656.407	.046	.090	88.6

Source: The Author.

In the BLR model, the severity indicator of admission to an ICU is associated with the predictors of comorbidities (1, 2 and 3), indigenous ancestry, health institution (sector), social marginalization (ISL 4), marginality (MI 2) and municipal social cohesion (3). Although other predictors were statistically significant (p-value < 0.05), their contribution to explaining the variation in the severity indicator is modest (sex and social cohesion 2) or very low (age) (Table 16).

Among the predictors with the greatest explanatory power are health institution (sector) in which the patient received medical care. Patients without social health insurance coverage (open population) with respect to those who do have it (state or private), increase 3.7 times the probability of being admitted to an ICU. A striking result that puts all interpretative capacity to the test, making further analytical incursions necessary.[7] On the other hand, in patients with three comorbidities simultaneously, the risk of admission to an ICU increases 1.3 times. Being a man compared to a woman increases the risk, although marginally, 1.1 times more.

Having indigenous ancestry compared to not having it reduces the probability of admission to an ICU by 1.6 times, residing in a municipality with a very high degree of social marginalization compared to one with a very low degree reduces it by 2.5 times and residing in a municipality with a medium degree of social marginalization compared to one with a very low degree reduces it by 1.2 times (1/.824).[8]

Regarding social cohesion, understood as distributive inequality of economic income, it is noted that COVID-19 patients with lethal progression who reside in municipalities in the quartile with the highest inequality (Q4) with respect to the lowest quartile (Q1), the probability of admission to an ICU increases 1.4 times (1.374). These results allow us to venture a new hypothesis, which states that greater spatially stratified (by municipality) social deprivation (ISL and MI) in COVID-19 patients with lethal progression, as well as having indigenous ancestry, are conditions that contribute to the deprivation of access to third-level health care units that provide intensive care,[9] while, in contrast, the greater spatially stratified (by municipality) concentration of economic income increases the chances, possibly explained by a combination of factors of social polarization in these municipalities.

7 A subsequent analysis using multinomial logistic regression (MLR), a generalization of BLR and allows to explain a polytomous qualitative variable that can be constructed from the combination of the different severity stages considered in this analysis, could shed light on the result reported for the ICU admission severity indicator. For example, differentiate probabilities between the diagnosis of pneumonia; the diagnosis of pneumonia plus hospitalization; the diagnosis of pneumonia + hospitalization + intubation and so on. Such an analysis would allow us to disentangle more specifically the significance and strength of association of the model´s variables and thus validate or rectify the achieved result.

8 See footnote 2.

9 The database is based on COVID-19 death cases.

TABLE 16. *PREDICTORS IN THE BINARY LOGISTIC REGRESSION EQUATION FOR ICU ADMISSION. ODDS RATIO EXPRESSED AS EXPONENTIATED B COEFFICIENTS*

Predictors	B	E.T.	Wald	gl	Sig.	Exp(B)
Sex	***.098***	***.026***	***13.811***	***1***	***.000***	***1.103***
Age	-.006	.001	49.346	1	.000	.994
Comorbidities			40.076	3	.000	
Comorbidities ***(1)***	***.149***	***.030***	***24.969***	***1***	***.000***	***1.161***
Comorbidities (2)	.086	.033	6.687	1	.010	1.090
Comorbidities ***(3)***	***.264***	***.050***	***27.603***	***1***	***.000***	***1.302***
Indigenous	***-.448***	***.094***	***22.742***	***1***	***.000***	***.639***
Health institute (sector)	***1.317***	***.026***	***2627.955***	***1***	***.000***	***3.734***
ISL			4.723	4	.317	
ISL (1)	.021	.059	.127	1	.721	1.021
ISL (2)	.040	.112	.131	1	.717	1.041
ISL (3)	.085	.160	.279	1	.597	1.088
ISL (4)	-.929	.513	3.284	1	.070	.395
MI			6.885	4	.142	
MI (1)	-.092	.062	2.206	1	.137	.912
MI (2)	-.193	.090	4.612	1	.032	.824
MI (3)	-.103	.133	.599	1	.439	.902
MI (4)	.105	.227	.214	1	.644	1.111
HDI			3.758	3	.289	
HDI (1)	-.040	.033	1.492	1	.222	.960
HDI (2)	.015	.086	.029	1	.866	1.015
HDI (3)	.718	.539	1.777	1	.182	2.051
Social cohesion			92.120	3	.000	
Social cohesion (1)	.055	.036	2.259	1	.133	1.056
Social cohesion (2)	***.104***	***.036***	***8.453***	***1***	***.004***	***1.110***
Social cohesion (3)	***.318***	***.036***	***78.814***	***1***	***.000***	***1.374***
Constant	-2.510	.067	1397.993	1	.000	.081

Source: The Author.

CONCLUSIONS

We present a predictive analysis between health (comorbidities), sociodemographic (sex, age, indigenous ancestry) and social (conditions of social deprivation, human development and inequality) factors, to explain four severity indicators (pneumonia, hospitalization, intubation and admission to an ICU), which constitute risk and protective factors against COVID-19 lethal progression. We developed a binary logistic regression model evaluation, using data from the records of the Ministry of Health of the government of Mexico, Coneval, Conapo and UNDP.

The results of the bivariate analysis allow us to affirm the statistical significance of the association between comorbidities, indigenous ancestry, health institution (sector) and social cohesion (distributive inequality) and the severity indicators considered. The results of the multivariate analysis of the regression models showed that the lack of social security (state or private) significantly increased the risk of having a confirmatory diagnosis of pneumonia; four times more in the open population. Adding comorbidities to the clinical picture increases the risk of a confirmatory diagnosis of pneumonia, and the same occurs as the municipal social exclusion of residence increases. On the other hand, having indigenous ancestry decreases the probability of being diagnosed positive for pneumonia in COVID-19 patients with lethal progression. This result could respond to multiple factors, such as the conditions of social disadvantage faced by this population to obtain timely diagnoses when the patient is ambulatory (not hospitalized) for COVID-19 disease. Residence in isolated communities, spatially distant from health care centers, as well as other culturally rooted factors.

As for hospitalization, the results of the model report that the probability decreases when moving from one extreme to the other in the degree of social marginalization of the municipality of residence (in the change from 'very low' to 'very high' degree). Hospitalization could also be another factor of social segmentation on which to advance in subsequent analyses, since it constitutes an apparent privilege for certain strata. In addition, it was found that the open population, compared to those with health care security, is less likely to be hospitalized when they become ill with COVID-19 lethal progression. Similarly, indigenous ancestry population with COVID-19 lethal progression suffers a similar fate; a reduced probability of hospitalization.

The evidence of the analysis allows us to affirm that patients residing in municipalities with a very high degree of social marginalization, with respect to those with a very low degree, have a significantly lower probability of undergoing intubation; the same could be affirmed, both for those residing in municipalities with a high degree with respect to those with a low degree of marginalization, and for those residing in municipalities with an intermediate level with respect to those with a very high degree of human development. Social marginalization and human development of the municipality of residence were found to be significant social determinants of the probability of intubation in COVID-19 patients with lethal progression; even more so, in terms of intensity, than the health determinants (comorbidities 3).

Both having indigenous ancestry and not having social health insurance coverage were shown to be important social determinants in reducing the probability of intubation in COVID-19 patients with lethal progression.

In contrast, being a COVID-19 patient with lethal progression and lacking social security or private health service increased the chances of admission to an ICU; a finding that should be validated in further analyses. Having a comorbidity compared to having none also increases the probability, but even more so does having three comorbidities together. However, having indigenous ancestry or residing in a municipality with a very high or high degree of marginalization decreases them.

Being a COVID-19 patient with lethal progression and residing in municipalities with very high social inequality increases the probability of being admitted to an ICU. Results such as these encourage hypotheses based on social polarization factors as a response to the greater probability of admission to an ICU; on the one hand, there are greater opportunities for admission to an ICU for patients from strata with a high concentration of economic income while, on the other hand, there is a large contingent of the population residing in these same municipalities with low and very low income concentration and without social security, which also showed a greater probability of access to an ICU.

The evidence derived from the analysis suggests revisiting and debating the model of universal access and quality of health services for all the population introduced by the current federal government administration with the so-called 'fourth transformation' that created the Instituto de Salud para el Bienestar (Insabi), in 2019. The decree that originated Insabi, involved the repeal of a series of provisions within the National Health Institutes Law and the General Health Law, which supported the previous program (Seguro Popular (SP)), free, universal, effective, equal, timely, non-discriminatory and quality access to care services at the first and second level of health was emphasized, including hospitalization, access to pharmacological medicine and surgical intervention (Secretaría de Salud, 2019).

However, the results of the analysis indicate that the population of patients who did not use private or social security services with respect to those who did, were more likely to have a diagnosis of pneumonia (first level of care), but less likely to be hospitalized. The differential can be attributed to a public health system saturated in its capacity to reach the hospitalization levels (second level of care) required by the general population, even despite the efforts made by the government to expand its capacity (i.e. number of beds, ventilators, human resources and hospitalization spaces) (Cruz, 2020). Likewise, hospitalization represents high economic costs for the population, especially within the framework of a Catastrophic Expenses Fund that was extinguished after the disappearance of the SP and redirected to operating expenses and payroll under Insabi (Barba, 2021). The probability of undergoing intubation was also lower for the general population, which could be attributed to the higher quality, and therefore more expensive, private services.

In turn, patients residing in municipalities with a very high degree of social marginalization compared to those with a low and very low degree had a lower probability of hospitalization, intubation and admission to an ICU. This differential in access to second and third level of care life support is linked to the lower endowment of resources (equipment, technological, human, human, financial, etc.) and low accessibility that historically have been the main reasons for this differential, and low accessibility that has historically characterized public services with respect to private and social insurance services (Laurell, 2013), but also to two concomitant factors played in the political-administrative arenas, namely; the tensions between the Federal Government and state governments motivated by the law that centralized the transfer of human, material and financial resources from the subnational to the national level in order to consolidate Insabi. A number of states level governments refused to adhere to Insabi arguing the impacts on the efficiency and functioning of the decentralized subnational health system, which has accentuated the contrast in conditions and resources with which each state faces the pandemic (Gutiérrez and Giraldo, 2020). An old problem whose inertia was noticed with the pandemic, namely, the lack of consolidation of social health insurance for independent workers (self-employed) and unemployed, whose concentration is greater in municipalities with a higher degree of social marginalization.[10]

Finally, the experience of the pandemic and the results of our analysis highlight the need to introduce a social and human rights approach into the public policy agenda in order to gradually reduce the influence of ascriptive

10 Before Insabi, there was Seguro Popular insurance for these workers. With the creation of Insabi, a historic opportunity window opened. However, it is not yet in place a comprehensive system to integrate Insabi with the two main health systems in the country that insure formal sector and state employees; the Mexican Social Security Institute (IMSS) and the Institute of Social Security and Services for State Workers (ISSSTE) (Barba, 2021).

factors and social conditions on health protection schemes. In this sense, a central role will be played in the future (medium and long term) by strengthening governance mechanisms and giving more space to social management and citizen and inter-sectoral participation in decision-making, which is essential for developing risk prevention policies. The consolidation of community networks, the solidarity and reciprocity promoted by civil society organizations, the strengthening of social trust and collaboration agreements between the main actors involved in the generation and distribution of social welfare goods and services from a risk prevention (and protection) perspective, make up a social capital to be increased, capable of being activated to face health, economic and social crises in Mexico with advantages gained beforehand ('fishing upstream'). Developing this capital is possibly one of the most relevant lessons learned from the pandemic experience and its impacts. Having defined, based on empirical evidence in the analysis presented, profiles and characteristics of populations with greater vulnerability with respect to COVID-19 disease severity indicators with lethal progression is one of many necessary steps to advance in this direction. Further analysis is still needed.

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