

Research Article

Biological and Sociodemographic Variables Associated with Covid-19 Outcomes: Bayesian Analysis of Data From 170 Countries Suggests A Cautious Outlook on Obesity Impact

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A B S T R A C T

Background: COVID-19 claimed 6,492,948 deaths from 607,497,755 infections until August 2022. In 2021 and 2022, several SARS CoV-2 variants increased infection/mortality. Objectives: We analysed the impact of nutritional state and epidemiological-sociodemographic factors on the COVID-19 outcome.

Methods: Presently, WHO-defined factors, health/hygiene and metabolic-disorders, i.e., nutritional status (obesity) and lockdown, were considered for association studies with the Total Confirmed Cases/million (TCC/m) and Case-Fatality-Rate (CFR) from COVID-19 in 170 countries. Bayesian-probabilistic analysis was utilised to facilitate intricate hierarchical modelling, effectively managing confounding factors. Normal statistics, including ANOVA, Tukey's post-hoc test, Pearson's correlation, canonical correlation, step-wise/linear-regression, were conducted, and χ^2 -test were performed for non-parametric variables.

Results: CFR positively correlated with air pollution ($r \approx 0.95$), TB incidence ($r = 0.95$), and GDP per capita ($r \approx -0.83$). The contour plot, which shows CFR vs. GDP & Air Pollution, reveals that CFR rises when GDP falls and air pollution rises. Compared to TCC205, CFR205 is tightly controlled ($\sim 0.790-0.815$), indicating little variability. Higher categories of diabetes-obesity are associated with somewhat higher CFR205, suggesting a small rising trend. Instead of at the extremes, TCC205 peaks in communities with mid-level prevalence of diabetes and obesity, which is not definitive. Bayesian critical analysis of posterior distribution suggests no distinct relation between obesity and diabetes with COVID-19 and indicates the interacting influence of other confounding factors. Densely populated

areas are affected more, and that has been significantly restrained by lockdown/quarantine ($\chi^2=85.4$; $p<0.001$ / $\chi^2=58.09$; $p<0.01$).

Conclusions: Environmental pollution, other diseases like severe TB, and lower GDP promoted adverse COVID outcomes. Findings from the Bayesian approach highlight the need for cautious interpretation of the influence of different factors on COVID-19.

Keywords: COVID-19 Pandemic, Health and Hygiene, Socioeconomic Status, Communicable and Non-Communicable Diseases, Correlation

Introduction

The virus that causes COVID-19 is designated as Severe Acute Respiratory Syndrome Corona Virus 2 (SARS-CoV-2). In 2020, WHO declared the COVID-19 outbreak as a public health emergency. The report suggests that travel to or from the affected territories, exposure characteristics, demographic properties and cluster frequencies are associated with the rate of the disease spreading.¹ The primary risk factors for this disease include public transportation, visits and physical interaction.² Marginalised populations with inadequate access to healthcare and other facilities are psycho-socially more affected by severe COVID-19 outcomes.³

Recent research has demonstrated a positive correlation between the outcome of COVID-19 and lower levels of health awareness and medical facilities. A multivariable linear regression model suggests that the >65-year-old age group contributes more to the proportion of African Americans who are sensitive.⁴ Multivariate analysis showed that the spread of COVID-19 was correlated positively with the population density in public transportation systems.⁵ Regarding the role of other diseases, the report reveals that anti-malarial immunity may play a protective role in COVID-19 cases. Individuals with asymptomatic malaria develop IgG antibodies to Plasmodium antigens.

It is known that the people living in endemic areas are designated as 'immune' people, and they manifest less severe symptoms than those of non-immune people. Children are found to be more protected from COVID-19.⁶ The vaccine against some infectious respiratory pathogens primes the "innate" immune system. Some reports reveal that the BCG vaccination confers a nonspecific protective effect against infection with SARS-CoV-2 with lower levels of symptoms.⁷ During oxidative stress, the body is more vulnerable to SARS-CoV-2, which becomes more sensitive in the presence of different comorbidities and confounding factors.⁸

Higher BMI has been associated with respiratory distress, vascular disorders with hypertension and outcomes of COVID-19.⁹ In long COVID syndrome, obesity has been

shown to promote sarcopenia by raising dietary demands and causing a systemic inflammatory condition. 'Long-COVID' is the term for symptoms that persist for a few months even after COVID is cured in a matter of days. The virus can be effectively stored in adipose tissue, which exacerbates the comorbidities linked to obesity, such as fatty liver, diabetes mellitus, dyslipidaemia, and high blood pressure.^{10,11} Nevertheless, in COVID-19 cases, hospitalisation and intensive care unit admission rates were higher among people with obesity. It is clear from a report of a few thousands hospitalised COVID-19 patients with overweight or obesity who had persistently poor O₂ saturation. Globally, major preventative measures were taken as protective, like sanitisation, masking, and nutrient-dense diets; the implementation of partial or total lockdown; and screening, diagnostics/therapeutic interventions, and immunisations.¹²⁻¹⁴ According to epidemiological data, demographically distinct areas had significantly different COVID-19 outcomes. So, community informatics could support policymakers in combating this pandemic situation.

In this background, we were intended to study the correlations of the World Bank-defined socio-demographic data, nutrition, obesity and other confounding factors like TB and malaria with the total death and COVID-19 case-fatality rate (CFR) in 170 countries. The epidemiological data from the 94th day to the 205th day of COVID-19 exposure were used in this study. The current study will be helpful for the understanding of the influencing factors for COVID-19. The record was collected from several medical/health/demography-related global databases. Extensive analysis was done for verifying the probabilistic disease outcome; correlation and significance levels were analysed by normal (frequentist) and Bayesian statistics.

Materials and Methods

Several open resource databases were utilised to procure the raw data for the current investigation. The data regarding the health, socio-demographic-economic condition and COVID-19 outcomes of ~170 countries were collected from these databases. These parameters include the total number of SARS-CoV-2 infections, the total number of confirmed cases (TCC), the TCC/million populations (TCC/m), the case fatality rate (CFR), the prevalence (total cases) of tuberculosis, malaria, certain nutritional status, obesity and other diseases and some socio-economic factors. Please find below a precise list.

- **Exposure variables:** communicable diseases like tuberculosis, HIV, malaria; drugs like tobacco and alcohol consumptions; metabolic disorder; malnutrition/overnutrition; age of the individuals; income economics; geographical territories; lockdown
- **Outcome variables:** COVID-19 outcomes like total confirmed cases and case fatality rate

- **Confounders (factors that have an impact on both independent and dependent variables):** climate, ecology and environmental factors, status of vaccination to other diseases, social status, medical facilities, health hygiene sanitation, and literacy/education level.

The web-link used for these purposes are:

- <https://www.who.int/emergencies/diseases/novel-coronavirus-2019?>
- <https://www.nih.gov/>
- <https://www.un.org/en/>
- <https://www.unicef.org/>
- <https://www.worldometers.info/coronavirus/>

Other links are mentioned in the reference section.

Patient and Public Involvement Statement

Directly, no patients or the public were involved in the current study.

Ethical consideration

The study was approved by the competent authority and the Institutional Research Ethics Committee (OIST/IRBhu/ Feb/20/02)

COVID-19 outcome analysis

Data from approximately 170 countries were evaluated for all statistical calculations in the current study. All data was procured from WHO, the UN, the World Bank or other registered international organisations.

Total confirmed cases (TCC) and total deaths (TD)

The TCC and Td of COVID-19 were collected from WHO Coronavirus disease (COVID-19) Situation Reports.¹⁵

Case fatality rate (CFR)

CFR measures the risk of persons dying from a certain disease within a given time period. The CFR is calculated as the number of deaths from a specific disease during a specific time period divided by the number of cases of the disease during the same time period, usually expressed per 100 (16). $CFR = (\text{Number of deaths from a specific disease during a specific time period} / \text{Number of cases of the disease during the same time period}) \times 100$.

The total Population and Population Density

Total population of a territory/area and its population density were calculated as population per square kilometre. The information regarding the total population residing in the territory/area and population density of the same geographical area was collected from the reports of the

Department of Economic and Social Affairs Population Dynamics of the United Nations.¹⁷

Income Economies

Gross National Income (GNI) is regarded as the total amount of income by a nation's people and different businesses in that region. According to the recent report of the World Bank, viz., there are different income economics, i.e., low-income economies (GNI per capita $\leq$ \$1,025), lower middle-income economies (GNI per capita = \$1,026-\$3,995), upper middle-income economies (GNI per capita = \$3,996-\$12,375) and high-income economies (GNI per capita $\geq$ \$12,376).¹⁸

GDP

The GDP at purchaser's prices is the gross value added by all resident producers in the economy plus any product taxes and less any subsidies not included in the worth of the items. For the present data, current US dollars are utilised.¹⁸ Region-wise GDP (current US\$) and GDP per capita (current US\$) were collected from the World Bank report.¹⁹

Prevalence of Diabetes

Diabetes prevalence (total occurrence) refers to the territory-wise age-adjusted comparative prevalence in adults aged 20–79 years who have type 1 or type 2 diabetes. This data was collected from the recent publication of IDF.²⁰

Prevalence of communicable diseases and substance abuse

Prevalence of communicable diseases, including HIV (HIV-I), tuberculosis (TB-I), and malaria (Malaria-I), was collected from the report of World Health Statistics 2019.²¹ The alcohol consumption (Alcohol) and tobacco use prevalence (Tobacco-P) were also collected from the same report.²¹ Definitions of health parameters used in the current study were as follows.

Prevalence is defined as the existing cases, while incidence is defined as new cases.

The mathematical way to calculate this would be:

- Prevalence = Number of cases/population $\times$ 100
- Incidence = new cases / total population
- Tb-I: Tuberculosis Prevalence: per 100 000 population
- Malaria-I: Malaria Prevalence: per 1000 population at risk.
- Alcohol: Alcohol consumption: litres of pure alcohol per capita $\geq$ 15 years.
- Tobacco-P=Tobacco use prevalence: age-standardized, among adults 18+ (%).

Population ages 65 and above (% of total population)

Population ages 65 and above as a percentage of the total population. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship.²²

Malnutrition/Obesity Prevalence Rate

Obesity – adult prevalence (total occurrence) rate gives the percent of a regional population considered to have obesity (23). An adult person with obesity is defined by the World Health Organization (WHO) using the Body Mass Index (BMI) calculation, which is $BMI = \text{weight (kg)} / \text{height (m)}^2$. Obesity is defined as having a BMI of 30 or more, whilst overweight is defined as having a BMI of 25 to 29.9.

Lockdown period during COVID-19

The information regarding lockdown in different countries during the COVID-19 pandemic was collected from the Wikipedia literature [https://en.wikipedia.org/wiki/COVID-19_lockdowns]. Due to the COVID-19 pandemic, a number of non-pharmaceutical interventions colloquially known as lockdowns (encompassing stay-at-home orders, curfews, quarantines, cordons and similar societal restrictions) have been implemented.

Statistical Analysis

The statistical analyses were done using the SPSS for Windows statistical software package, special institutional version. Normally-distributed data were tested by the Kolmogorov-Smirnov test. The group means were tested using ANOVA with Tukey's post hoc test. Pearson's chi-squared test (χ^2) is used to assess the likelihood of any observed difference of categorical variables. The Pearson product moment correlation and canonical correlation were done. The P value <0.05 is considered statistically significant. Instead of assigning probabilities to hypotheses, frequentist approaches, i.e., normal statistics, use tools like p-values and confidence intervals, which can be more challenging to understand intuitively than the straightforward probabilistic assertions found in Bayesian analysis. According to Bayesian statistics, probability can be updated by preexisting views (prior distribution) with new information (likelihood) using Bayes' Theorem to produce posterior distribution. In the current study, both statistical procedures are utilised for the evaluation of the present data.

Canonical-correlation analysis will find linear combinations of X and Y. Statistical outcomes and results were visualised by correlation heatmap, contour plot, hierarchical clustering dendrogram, scatter plot and 3D visualisation (surface plot) analysis. The WHO and World Bank defined economic-zone territory-wise and other factors like health/hygiene, socio-demographic profile, some communicable/non-communicable disorders, nutritional status, etc. are tested

in a correlation study employing total confirmed cases/million (TCC/m) and Case-Fatality-Rate (CFR) of COVID-19.

Results

The correlation heatmap interprets that CFR is strongly and positively correlated with air pollution ($r \approx 0.95$) and TB incidence ($r \approx 0.95$) and negatively correlated with GDP per capita ($r \approx -0.83$) and obesity and diabetes (mildly negative). This suggests that low-income, high-TB, and polluted environments correlate with higher case fatality rates (fig. 1, A). The contour plot indicates CFR vs GDP & air pollution, which suggests CFR increases as GDP decreases and air pollution increases (table 1). There is a clear gradient—poorer countries with higher pollution tend to show elevated CFRs (fig. 1B). The hierarchical clustering dendrogram predicts that countries were clustered based on obesity, diabetes, TB, air pollution, GDP, and CFR. In this result section it is demonstrated that distinct clusters emerged: high-income, low-risk countries; middle-income, mixed-risk; and low-income, high-risk countries (e.g., high CFR, pollution, and TB) (fig. 1 C). The 3D visualisation (surface plot) reinforces the contour insights of CFR peaks in regions with low GDP and high pollution. CFR drops off sharply as GDP increases or pollution reduces (fig. 1D).

Figures 2A and 2B demonstrate the Bayesian statistical critical analysis. A Bayesian regression model was assumed in a pattern as $CFR = \beta_0 + \beta_1 \cdot GDP + \beta_2 \cdot TB + \beta_3 \cdot \text{Air Pollution} + \beta_4 \cdot \text{Obesity} + \beta_5 \cdot \text{Diabetes} + \epsilon$. Interpretation of coefficients is mentioned below. The significances of variables represented by coefficients in the Bayesian regression model are defined as follows. β_0 (intercept) means expected CFR when all predictors are at their mean (standardised = 0). β_1 (GDP) denotes the change in CFR per standard deviation increase in GDP. β_2 (TB) is the change in CFR per standard deviation increase in TB. β_3 (Air Pollution) is defined as the effect of air pollution on CFR. β_4 (Obesity) represents the impact of obesity prevalence on CFR. β_5 (Diabetes) represents the influence of diabetes on CFR (table 2).

The Bayesian analysis was performed using bootstrapped samples to approximate posterior distributions for key predictors of CFR₂₀₅ (Case Fatality Rate at day 205). The predictors analysed were obesity and diabetes (table 2). The histogram plots display the approximate posterior distributions of the regression coefficients derived from 1000 bootstrap samples. These distributions provide insight into the uncertainty surrounding the estimated effects of the predictors. The credible intervals, which represent the Bayesian equivalent of confidence intervals, were calculated at the 95% level. For obesity, the interval ranges from -0.23 to 0.20, and for diabetes, from -0.57 to 0.13 (fig. 2A). Narrower distributions for Europe suggest lower variability, while wider ones for African regions indicate

greater uncertainty in mean TCC levels. These results provide probabilistic insight into regional differences and strengthen confidence in ANOVA findings (fig. 2B). Figure C demonstrates the 3D surface plot models on TCCpM205 as a function of alcohol and tobacco consumption. Figure: D: The contour plot illustrates density zones of TCCpM205 relative to alcohol and tobacco use. High-density regions (darker contours) correlate with moderate to high consumption levels, again hinting at lifestyle influences on COVID-19 outcome.

Figure 2E demonstrates the scatter points are spread across obesity (0–7 categories) and diabetes (0–4 categories). Most points cluster at lower values of TCC205 (0–2 range), suggesting that high values of TCC205 are relatively rare. There is no clear visible linear trend: TCC205 values fluctuate irregularly across obesity and diabetes categories. Figures 2F and C describe the trends of TCC and CFR values in critical analysis. This analysis examines the temporal progression of TCC and CFR at different time points. Figure 2H suggests the surface is smooth and nearly planar, sloping gently across the obesity and diabetes axes. CFR205 values are tightly constrained (~0.790–0.815), suggesting low variability compared to TCC205. There appears to be a slight upward trend: higher obesity and diabetes categories correspond to marginally higher CFR205. CFR205 shows a more systematic relationship with obesity and diabetes than TCC205. As obesity and diabetes categories increase, CFR205 tends to

increase slightly, meaning case fatality worsens.

Figure 3, panel A, demonstrates a contour plot on TCC205 vs obesity & diabetes. The highest density (green–yellow region) is centred on moderate obesity and moderate diabetes categories. The contours spread outward, showing fewer cases at the extremes of both obesity and diabetes. Panel B is the boxplot (CFR205 by Population Density Groups). Median CFR205 is fairly consistent across density groups, with small variation. Panel C explains the Canonical Correlation Analysis (CCA) that WHO regions (different colours) overlap considerably — no clear separation. This suggests weak but detectable multivariate associations between the predictor set (risk factors) and outcome set (TCC205, CFR205). Panel D is the boxplot (TCC205 by Population Density Groups). The correlation between lockdown and the epidemiology of COVID-19 (TCC, TCCpM, CFR) is shown to be highly significant (Figure 4) (Table 3). ANOVA results indicated that the increasing number of total confirmed cases ($F=5.472$; $P<0.01$) and total confirmed cases per million ($F=2.980$; $P<0.05$) were directly influenced by the number of days of lockdown in the countries, but no such association was noted with case fatality rate ($F=0.639$; $P>0.05$). The Pearson Product Moment Correlation (r) result also supports the findings: TCC ($r=0.309$; $P<0.01$), TCCpM ($r=0.272$; $P<0.01$) and TD ($r=0.339$; $P<0.001$) are positively related with days of lockdown, while lockdown did not influence the CFR (0.107 ; $P>0.05$) (figure 4).

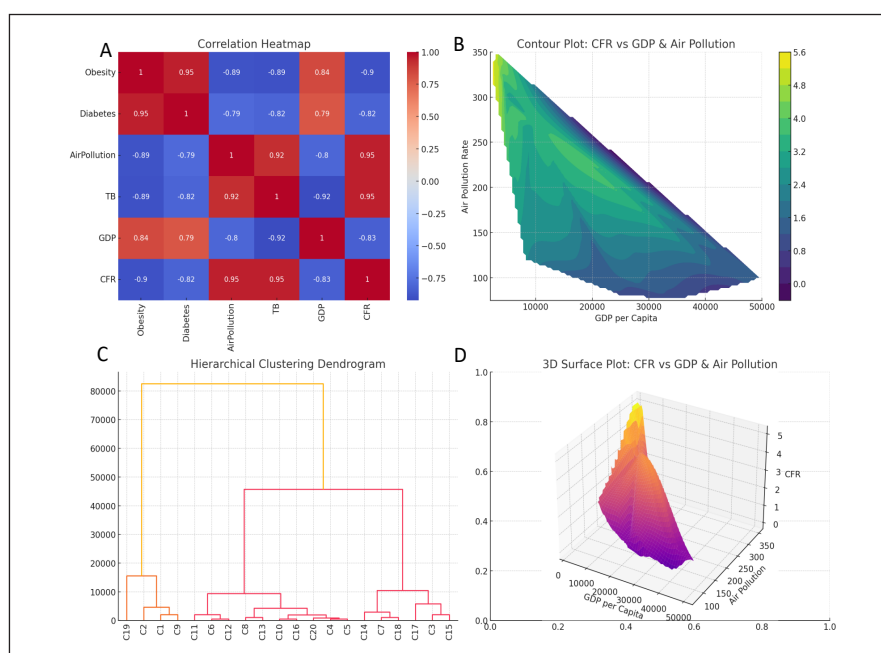


Figure 1. A Correlation Heatmap interpret the CFR relations with different confounding factors related to socio-demography and biological states. B: Contour Plot indicates CFR vs GDP & Air Pollution. C: Dendrogram predicts, Countries were clustered based on Obesity, Diabetes, TB, Air Pollution, GDP, CFR. D: The 3D visualization (surface plot) reinforces the contour insights CFR peaks in regions with low GDP and high pollution

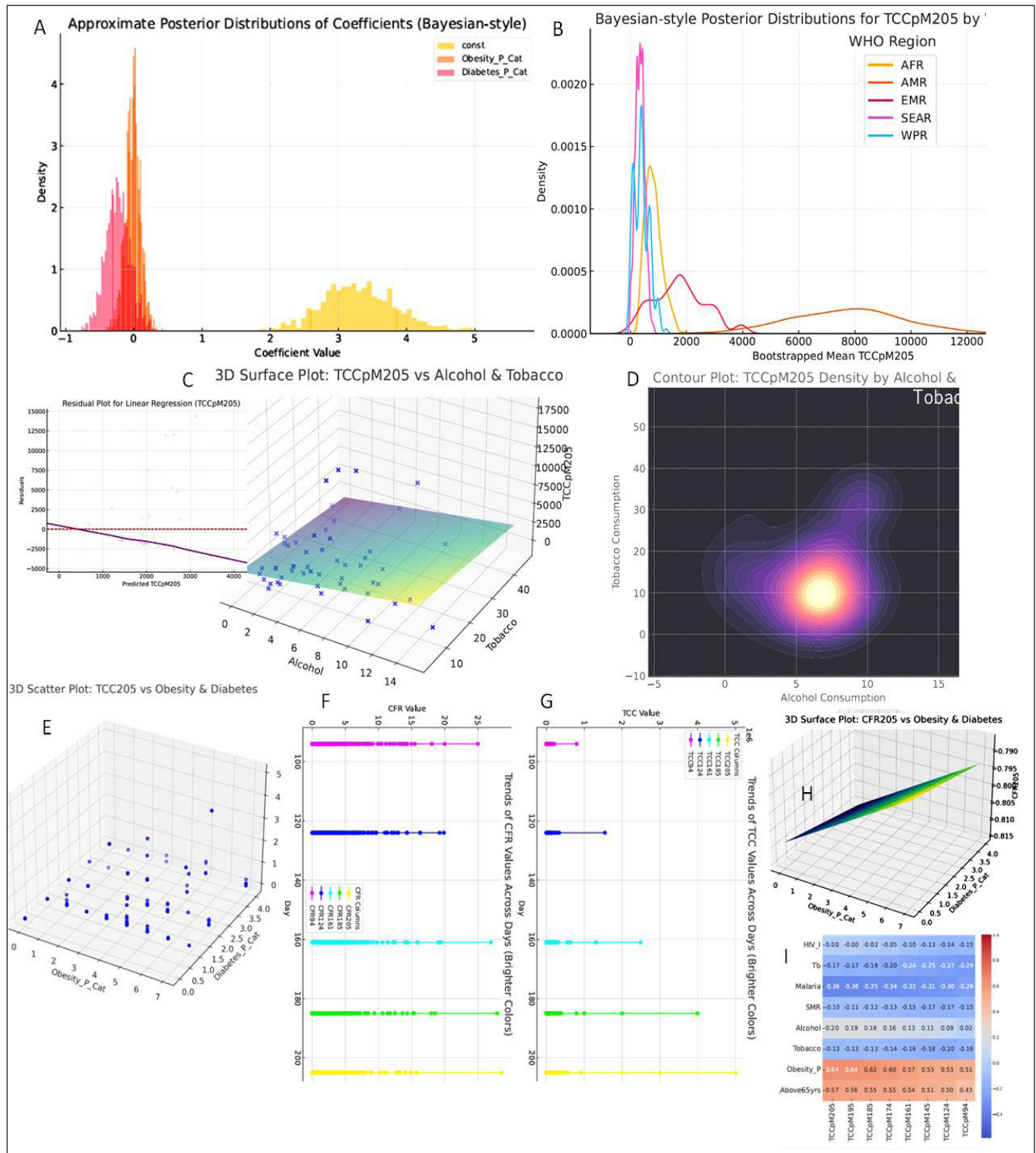


Figure 2. Figure A. and B: Bayesian Statistics Critical Analysis; Bayesian analysis was performed using bootstrapped samples to approximate posterior distributions for key predictors of CFR205 (Case Fatality Rate at day 205). Figure C: 3D Surface Plot: TCCpM205 vs Alcohol & Tobacco. Residual regression plot for TCCpM205 are presented (inset). Figure D: The contour plot illustrates density zones of TCCpM205 relative to Alcohol and Tobacco use. Figure E: The scatter points are spread across obesity (0–7 categories) and diabetes (0–4 categories). Figure F and G: Trends of TCC and CFR Values Critical Analysis. Figure H: 3D surface plot of CFR205 vs obesity and diabetes. Figure I: Correlation Heatmap of different time points of TCC94 to TCC205 vs multiple confounding factors of COVID-19 outcome

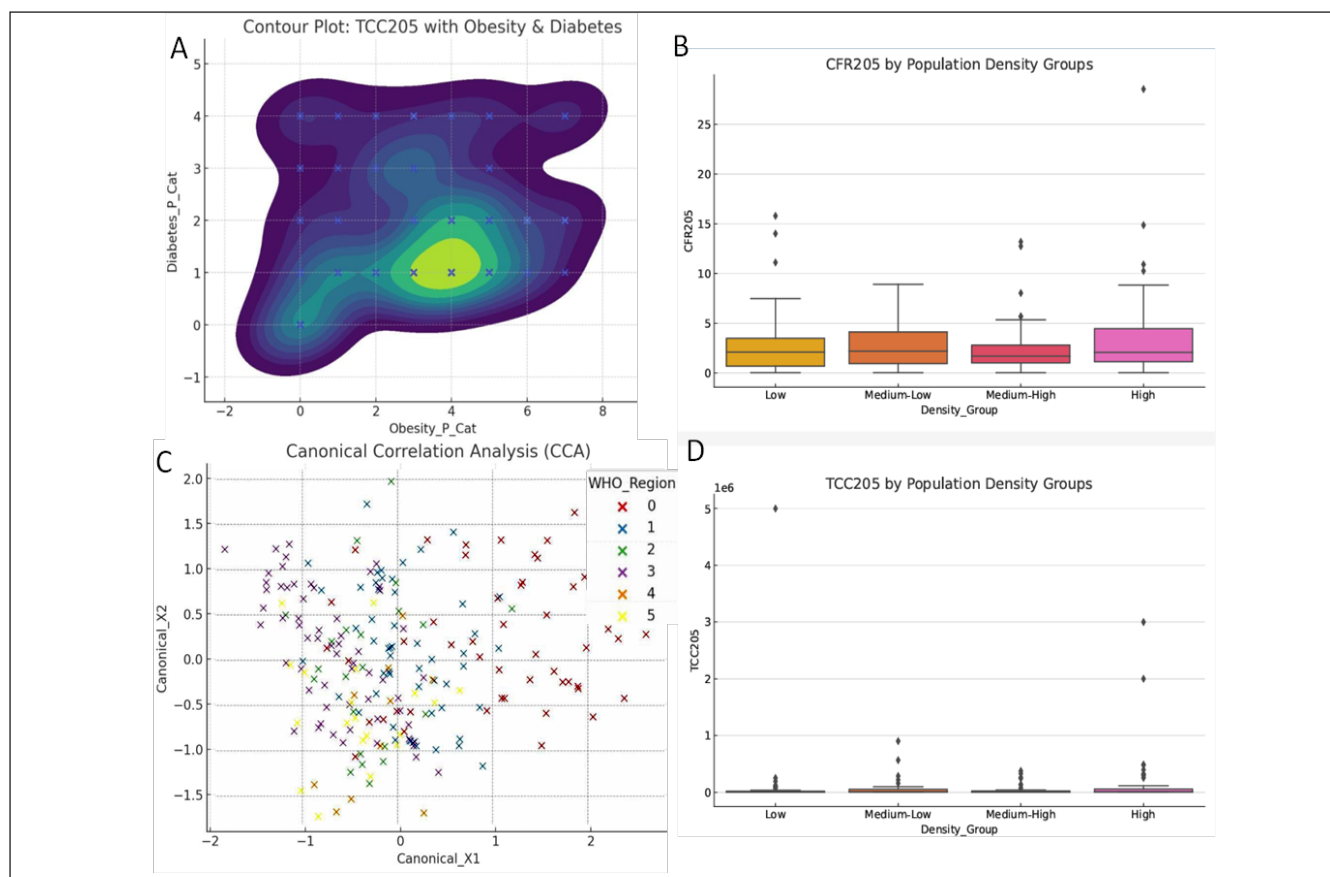


Figure 3. Panel A: Contour Plot (TCC205 vs Obesity & Diabetes), Panel B: Boxplot (CFR205 by Population Density Groups), Panel C: canonical correlation analysis of CFR vs different WHO regions. Panel D: Boxplot (TCC205 by Population Density Groups)

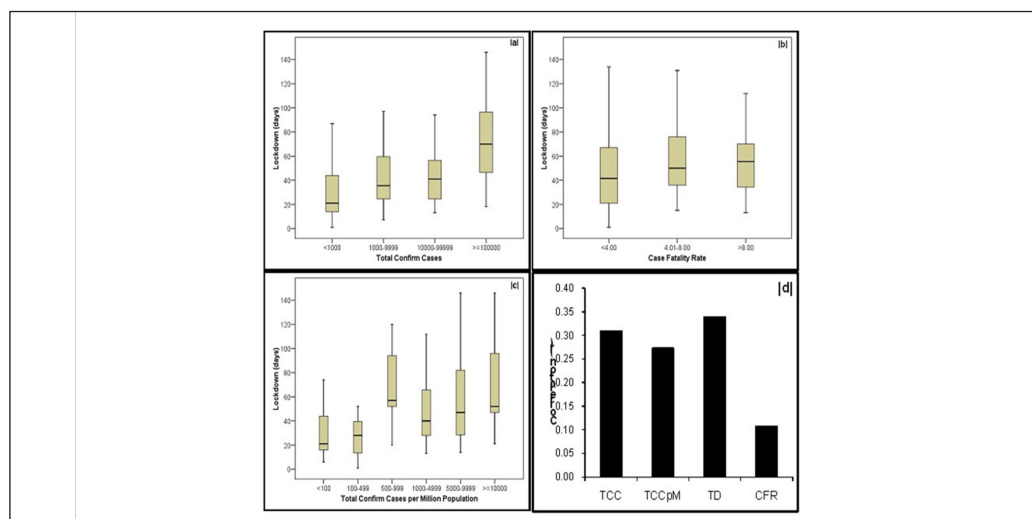


Figure 4. Association between Lockdown and epidemiology of COVID-19 disease (TCC, TCCpM, CFR). ANOVA results indicated that the increasing number of total confirmed cases ($F=5.472$; $P<0.01$) and total confirmed cases per million ($F=2.980$; $P<0.05$) were found to be directly influenced by the number of days lockdown in the countries but no such association was noted with case fatality rate ($F=0.639$; $P>0.05$). The Pearson Product Moment Correlation (r) result also support the findings, TCC ($r=0.309$; $P<0.01$), TCCpM ($r=0.272$; $P<0.01$) and TD ($r=0.339$; $P<0.001$) are positively related with days of lockdown while lockdown did not influence the

Discussion

There is limited evidence on the socioeconomic impacts on the pandemic situation raised by COVID-19. Some recent reports indicates that low-income regions are more sufferers with high infection and mortality rates due to their inadequate medical facilities.²⁴ According to a certain report, on the contrary, high-income regions have also a higher incidence of COVID-19 due to higher population density with different co-morbidity factors.²⁵ The present analysis of data from approximately 170 countries indicates that COVID-19 outcomes were related to a combination of environmental, socioeconomic, demographic and health-system factors rather than to a single biological determinant. The strongest associations reported in the present analysis were the positive correlation of CFR with air pollution ($r \approx 0.95$) and tuberculosis incidence ($r \approx 0.95$), together with an inverse correlation with GDP per capita ($r \approx -0.83$). The contour, clustering and surface-plot analyses were concordant with this pattern. These findings should, however, be interpreted as country-level associations and not as evidence of causality.³³ Differences in testing intensity, case ascertainment, reporting practices, vaccination coverage, age structure, access to healthcare and timing of epidemic waves can all influence national CFR estimates. During the last part of 2021, several new

variants (D614G, Delta omicron etc.) of SARS-CoV-2 have sharply increased its TCC/m and CFR in different countries. Further, the increased prevalence of comorbidities such as cardiovascular disease, diabetes and nutritional disorders in the older people may be another reason for the higher risk of mortality.²⁵

The obesity finding is the most important point requiring careful interpretation. In the present dataset, obesity and diabetes showed only weak or negative correlations in the heatmap, while the Bayesian bootstrap analysis produced 95% credible intervals of -0.23 to 0.20 for obesity and -0.57 to 0.13 for diabetes. Because both intervals include zero, the analysis does not provide strong evidence for a distinct independent association in this particular country-level model. This does not contradict the much larger clinical literature showing that obesity and diabetes can increase the risk of severe COVID-19 and death at the individual level. A systematic review and meta-analysis of 145 observational studies estimated adjusted mortality risk ratios of 1.39 for obesity and 1.43 for diabetes, although residual heterogeneity remained substantial. But in some advanced conditions individuals with class III obesity demonstrated an increased risk of venous thrombosis, which might have been attributed to an adverse outcome in the pandemic condition.²⁶

Table 1. Summary of correlation with other diseases and air quality in the Results section

Outcome/analysis	Predictor	Reported statistic	Interpretation
CFR	Air pollution	$r \approx 0.95$	Strong positive ecological correlation
CFR	TB incidence	$r \approx 0.95$	Strong positive ecological correlation
CFR	GDP per capita	$r \approx -0.83$	Strong inverse ecological correlation
CFR	Obesity/diabetes	Weak/mild negative in heatmap	No clear independent relation established

Table 2. Bayesian bootstrap results for obesity and diabetes

Predictor	Outcome	Bootstrap samples	95% credible interval	Interpretation
Obesity	CFR205	1000	-0.23 to 0.20	Interval crosses zero; direction remains uncertain
Diabetes	CFR205	1000	-0.57 to 0.13	Interval crosses zero; direction remains uncertain

Table 3. Reported lockdown analyses

Outcome	ANOVA F	P value	Pearson r with lockdown days	P value	Interpretation
Total confirmed cases (TCC)	5.472	<0.01	0.309	<0.01	Significant positive association

TCC per million (TCCpM)	2.980	<0.05	0.272	<0.01	Significant positive association
Total deaths (TD)	Not reported	Not reported	0.339	<0.001	Significant positive association
Case-fatality rate (CFR)	0.639	>0.05	0.107	>0.05	No significant association

Table 4. Variables and their role in the present ecological analysis.

Variable/domain	Role in analysis	Main reported result
Air pollution	Predictor/confounder	Strong positive correlation with CFR
TB burden	Predictor/confounder	Strong positive correlation with CFR
GDP per capita	Socioeconomic predictor	Strong inverse correlation with CFR
Obesity	Metabolic predictor	Weak/uncertain independent association
Diabetes	Metabolic predictor	Weak/uncertain independent association
Population density	Demographic/contextual factor	More closely related to case magnitude than CFR
Lockdown duration	Public-health intervention/context	Associated with TCC/TCCpM/TD, not CFR

Another meta-analysis reported increased risk of severe disease among people with obesity and a smaller but statistically significant increase in mortality.³² Thus, the present result should not be interpreted as evidence that obesity is biologically unimportant. Rather, it suggests that an ecological country-level association can be attenuated or obscured when obesity prevalence is considered together with socioeconomic, demographic, environmental and healthcare variables.

Country-level obesity studies and the ecological scale have been considered in the present analysis. A particularly relevant comparison is the country-level study by Foo et al.³¹, which analysed 168 countries and reported that each 1% increase in obesity prevalence was associated with an 8.3% higher COVID-19 mortality rate and a 6.6% higher case rate after multivariable adjustment. The difference from the present Bayesian result may reflect differences in outcome definition, pandemic period, covariate selection, modelling strategy and the treatment of regional heterogeneity. It also demonstrates why country-level obesity analyses require cautious interpretation. Individual-level obesity measures, hospital admission cohorts and country-level prevalence estimates answer different questions. Ecological analyses can identify population patterns but cannot establish that an individual with obesity has a higher probability of death because of obesity itself. The present Bayesian analysis therefore adds a useful complementary perspective by emphasising uncertainty around the independent country-level contribution of obesity and diabetes.

Air pollution showed the strongest positive correlation with CFR in the present analysis. This finding is broadly compatible with a systematic review of 116 studies from Europe and North America^{33,34}, in which positive associations between air pollutants and COVID-19 mortality were frequently reported, particularly for PM_{2.5} and NO₂. Importantly, that review also noted substantial confounding and outcome-measurement concerns. Therefore, the present correlation should not be described as proof that air pollution directly caused higher CFR (table 4). Countries with high pollution may simultaneously differ in age structure, cardiopulmonary disease burden, urbanisation, occupational exposure, healthcare access and socioeconomic conditions. The most defensible interpretation is that air pollution is a marker of an adverse environmental and population-health context that warrants further investigation.

The influence of tuberculosis and infectious-disease burden on the present outcome has been studied. The strong positive association between TB incidence and CFR is biologically and epidemiologically plausible, but it also requires distinction between population-level TB burden and individual TB–COVID coinfection. Recent systematic reviews indicate that TB–COVID coinfection is associated with adverse outcomes and substantial fatality, although estimates vary widely and study heterogeneity is high.³⁵ The present analysis used country-level TB incidence/prevalence information rather than individual-level documentation of active TB in COVID-19 patients. Consequently, the observed $r \approx 0.95$ should be interpreted as an ecological association.

High TB burden may also identify countries with constrained health-system resources, higher poverty and greater vulnerability to delayed diagnosis or treatment, creating important pathways for confounding. Some influences from malaria-prone regions are reported also. Primed immune system following a malarial attack; anti-malarial medications' preventive anti-inflammatory effects may be helpful in COVID-19 instances also. All these events promote vaso-vascular anomalies, which are the predominant risk factors in COVID-19 patients.³⁰

Socioeconomic status and GDP demonstrated appreciable influence on the disease outcome. The inverse correlation between GDP per capita and CFR is consistent with broader evidence that socioeconomic conditions and geographic context contribute to COVID-19 outcomes. A cross-sectional ecological analysis of 184 countries found associations between COVID-19 outcomes and socioeconomic variables, including human development, urbanisation and unemployment, with geographic region explaining part of the variation.³³ Lower GDP may therefore be acting through several interconnected mechanisms, including reduced healthcare capacity, diagnostic access, availability of oxygen and critical-care resources, public-health infrastructure and social protection. At the same time, GDP should not be described as a direct protective biological factor. Higher-income countries also experienced high case burdens because greater testing, older populations, international mobility and earlier detection can increase reported cases and alter CFR denominators.

Population density and transmission of infections are clearly evident in the present study. The present figures suggest that population density was more clearly related to the magnitude of confirmed cases than to CFR. This distinction is epidemiologically reasonable: density primarily facilitates opportunities for contact and transmission, whereas fatality is additionally shaped by age, comorbidity, healthcare capacity, clinical management and ascertainment. An ecological study from Malaysia found a strong positive association between population density and active COVID-19 cases³⁶, although other studies have shown that the relationship can weaken under stringent control measures. Thus, density should be considered a context-dependent driver of transmission rather than a universal determinant of mortality.

Lockdown and interpretation of positive correlations are considered here. The lockdown analysis showed significant positive correlations between days of lockdown and TCC ($r=0.309$), TCC per million ($r=0.272$) and total deaths ($r=0.339$), while CFR was not significantly related to lockdown duration ($r=0.107$; $P>0.05$). These results should not be interpreted as evidence that lockdown

increased infections or deaths. Reverse causation is highly plausible: countries experiencing larger outbreaks may have introduced longer or more intensive restrictions. Ecological studies have nevertheless reported reductions in incidence after implementation of lockdown-type measures in several countries.³⁷ The present findings therefore indicate that the number of lockdown days is strongly entangled with epidemic severity and timing and that a simple cross-sectional correlation cannot estimate intervention effectiveness.

The Bayesian component strengthens the manuscript by shifting the interpretation from a binary significant/non-significant framework toward the magnitude and uncertainty of plausible effects. The bootstrap posterior intervals for obesity and diabetes cross zero, indicating that both positive and negative effects remain compatible with the data under the reported model. This is consistent with the broader pattern of the study: several variables are correlated with COVID-19 outcomes, but their apparent effects are intertwined. The Bayesian result therefore supports a cautious conclusion rather than a categorical rejection of obesity or diabetes as risk factors.

Several limitations should be acknowledged. Firstly, the several ecological and geographical factors are associated with disease prevalence and its final outcomes. Second, CFR is affected by testing and reporting practices, case definitions, healthcare access, vaccination, age distribution and the timing of epidemic waves. Third, the analysis combines information originating from different databases and years, which can introduce temporal mismatch. In the current study the Bayesian analysis is based on 1000 bootstrap samples, which provides an approximation to uncertainty rather than a substitute for a fully specified hierarchical Bayesian model with explicit prior distributions and likelihood assumptions.

Taken together, the findings suggest that COVID-19 outcomes at the national level are shaped by interacting environmental, infectious-disease, socioeconomic, demographic and public-health factors. Obesity and diabetes may contribute to adverse clinical outcomes at the individual level, as supported by substantial clinical and meta-analytic evidence, but their independent contribution to country-level CFR in the present dataset is uncertain after consideration of concordant influence from other factors. Future studies should integrate individual-level BMI and diabetes status with age, sex, vaccination, healthcare utilisation, pollution exposure and socioeconomic indicators in longitudinal multilevel models. Such designs would provide a stronger basis for distinguishing direct biological effects from population-level confounding.

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