COVID-19 pandemic and transmission factors: An empirical investigation of different countries

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The present work evaluates the impact of age, population density, total population, rural population, annual average temperature, basic sanitation facilities, and diabetes prevalence on the transmission of COVID-19. This research is an effort to identify the major predictors that have a significant impact on the number of COVID-19 cases per million population for 83 countries. The findings highlight that a population with a greater share of old people (aged above 65) shows a higher number of COVID-19 positive cases and a population with a lower median age has fewer cases. This can be explained in terms of higher co-morbidities and the lower general immunity in the older age group. The analysis restates the widely seen results that a higher median age and greater prevalence of co-morbidities leads to higher cases per million and lesser population density and interpersonal contact helps in containing the spread of the virus. The study finds foundation in the assertion that a higher temperature might lower the number of cases, or that temperature in general can affect the infectivity. The study suggests that better access to sanitation is a certain measure to contain the spread of the virus. The outcome of this study will be helpful in ascertaining the impact of these indicators in this pandemic, and help in policy formation and decision-making strategies to fight against it.

KEYWORDS
co-morbidities, COVID-19, SARS-CoV-2, temperature, transmission

JEL CLASSIFICATION
I-10; I-18; I-19

1 | INTRODUCTION

Towards the very end of 2019, the world entered into an unprecedented global crisis in the form of COVID-19, a disease caused by SARS-CoV-2, a novel strain of corona virus of the SARS species. While the general consensus was that the major impacts on world economy would be from the US-China trade war and Brexit, with the IMF forecasting a moderate global growth rate of 3.4 percent (IMF, 2020); the arrival of this pandemic changed the course of 2020 completely (Yang et al., 2020). There have been a number of considerable pandemics recorded in the human history where pandemic related crises have caused enormous negative impacts on health, economies, and have even caused political and social disruptions. There have been four viral pandemics in the past 130 years: in 1889–1890, 1918–1919, 1957–1958, and 1968–1969.

Between 1889 and 1892 the “Russian Flu,” an H2N2 virus, came in three extended waves and killed around 1 million people worldwide (Herring & Carraher, 2010). In the 1918–1919 “Spanish Flu,” the first cases emerged in Kansas, US in January, spread rapidly in US army camps; and by April, the epidemic was spreading through Europe (Crosby, 2003). It infected 500 million people, about a third of the world’s population. The estimated total number of deaths varies...
between 34.4 and 100 million. The influenza returned in 1920, but was not as severe as in 1918 and 1919. In 1957, the “Asian Flu,” an H2N2 virus, originated in late February in China, became an epidemic in Hong Kong in April, and then reached Japan wherefrom it spread globally. In 1968, “Hong Kong Flu,” the H3N2 virus, originated in Hong Kong in July, and reached the United States and Japan in August, and Britain in September (Crosby, 2003). The SARS (Severe Acute Respiratory Syndrome) outbreak of 2003 was defined as an epidemic, but not a pandemic (Bartlett, 2004; Zhong et al., 2003). In 2009 swine flu (H1N1) was defined as a pandemic, but it was considered a relatively mild version (WHO, 2010).

As for COVID-19, in December 2019, a cluster of cases of a “pneumonia of unknown origin” were reported in Wuhan, China. A few days later, Chinese health authorities confirmed that this cluster was associated with a coronavirus (Li et al., 2020), and the disease caused by it was named the coronavirus disease 2019 (COVID-19) by the World Health Organisation. Emerging at the end of 2019, the coronavirus disease 2019 (COVID-19) has become a public health threat to people all across the globe.

According to early estimates by China’s National Health Commission (NHC) 2020, about 80% of those who died were over the age of 60, and 75% had pre-existing health conditions such as cardiovascular diseases and diabetes. But WHO in its Myth busters FAQs addressed the question: “Does the new coronavirus affect older people, or are younger people also susceptible?” According to WHO, people of all ages can be infected by the novel coronavirus COVID-19 and older people, and people with pre-existing medical conditions (such as asthma, diabetes, and heart disease) were more vulnerable to becoming severely ill with the virus. Reports available to date show that COVID-19 seems to be uncommon in children. Initial data reported from the Chinese Centre for Diseases Control and Prevention (Chinese CDCP) indicated that among the 44,672 confirmed cases of COVID-19 as of February 11, 2020, 0.9% were aged 0–10 years and 1.2% were aged 10–19 years. With each passing day, the number of infected people is increasing at an exponential rate. It is, therefore, safer for people to stay at home. In the last 5 months, a majority of countries have imposed lockdowns to control the spread of disease, either restricting or prohibiting major social and economic activities.

An obvious way in which this unprecedented pandemic is impacting the financial systems is by generating enormous social and economic costs. They closely delineate the global concerns that are now are in the forefront with COVID-19: expense at which both public and private health systems worldwide are providing medical treatments to the affected, while straining to concomitantly deal with more routine checkups.

Experience gained from outbreaks of similar diseases in the past reveals that while human costs are significant, the toll on the economy due to preventive measures and transmission-control policies of governments is also considerably large. With the spread of the novel coronavirus internationally, countries all over the globe are following precautionary policies and closing their borders. The educational institutes are closed, companies and offices are limiting their staff and their working hours, and the government is restricting the mobility of people as much as possible.

Different economic models can be used to examine the consequences of this pandemic. There are direct impacts of reduction in employment, increase in the cost of international transmissions, sharp plummet in the travel and tourism sector, and sudden decline in demand for services that require physical proximity.

It is important to note that it has been around 7 months since the emergence of this virus but the situation across different countries significantly varies in terms of the number of COVID-19 cases per million population, number of deaths per million, and the recovery rate. India’s population is four times larger than the United States, but it has only 2% of the number of cases of the latter, and deaths due to COVID-19 were relatively lower than most of the COVID-19 infected developed countries. Besides, India has a lower per capita income and lesser developed medical facilities. These evidences are not just for India, but also for many other developing countries. How have these countries managed to be relatively less infected compared to the more infected countries? There is enormous literature suggesting measures like successful and timely lockdown to help reduce the impact of this pandemic. These countries may have other protective characteristics that make them less susceptible to the transmission of COVID-19, like lower share of elderly in the total population, higher share of children in total population, median age of the population, higher temperature, share of rural population, population density, share of population with basic sanitation, share of people with comorbidities, etc. There is considerable evidence to show that these variables can have a significant impact on the number of COVID-19 cases per million population.

1.1 Review of literature

Studies attribute the discrepancy in number of reported cases between the economically stronger and weaker countries to better immunity in the latter (Roy, 2020). Lau, Khosrawipour, Kocbach, Mikolajczyk, Ichii, et al. (2020) conducted a study to examine the association between HAQ (Healthcare and Quality) index and COVID-19 virus, and found that countries with lower HAQ Index may underreport the cases or are unable to adequately detect them, which in turn impedes the efforts of containment of the virus. Studies conducted on the major trends of COVID morbidity have found strong links between the prevalence of comorbidities and the overall morbidity rate of COVID (Yang et al., 2020). The highest risk factors in severe patients are hypertension, respiratory diseases and cardiovascular diseases (Shi et al., 2020). In a study of 1590 laboratory confirmed hospitalised patients from 575 hospitals, it was found that people with one or more comorbidities yielded poorer clinical outcomes. The hazard ratio at 95% confidence interval was 1.79 for people with one comorbidity and 2.59 for people with two or more comorbidities (Guan et al., 2020). Several studies highlighted the higher morbidities among the elderly, especially above the age of 85, in the United States, and suggest a more robust and voluntary adherence to social
distancing (Report, 2020). Tsang and Bajpai (2020) have examined the effects of COVID-19 on cancer patients. The researchers suggested stringent controls in attending mass events, following social distancing, using surgical masks, disinfecting their hands and taking a healthy diet and indulging in exercise.

Rocklöv and Sjödin (2020) examined the effect of population density on the spread of the virus. They compare the scenarios between Wuhan and the cruise ship Diamond Princess, and establish that a higher population density leads to a greater contact rate and larger spread of the virus. Lee et al. (2020) have found that the low spread of the Corona virus among children is the result of fewer outdoor activities and international travels. Thus, outdoor activities may be avoided to break the transmission.

Kamron (2020) suggested possible strategies to deal with the virus using decision tree to choose between the strategies of a complete lockdown and a more gradual lockdown. Some studies suggested a stringent confinement of people in high risk areas to slow the spread of the epidemic (Lau, Khosrawipour, Kocbach, Mikolajczyk, Schubert, et al., 2020). As reported by Peeri et al. (2020), inadequate risk management and limited reporting on the epidemic from China has led to the current outbreak. They emphasised the need to use technologies like Internet of Things (IoT) for better mapping the spread of an infection. The authors of yet another study on COVID-19 cases suggest that the incorporation of Social Connectedness Index in modelling can lead to better comprehension of the spread of the epidemic by epidemiologists (Shi et al., 2020). Purnama and Susanna (2020) conducted a perception based analysis of attitude of people towards strategies in Indonesia to control the spread of COVID-19. The study suggests that stay at home, physical distancing, and always using face masks needs to be continued for the public to assist in preventing the transmission of COVID-19.

A study on the relation between the number of positive cases and the temperature for the state capital cities of Brazil depicted a negative relationship between the number of cases and the temperature up to 25.8°C, beyond which the curve flattens out (Prata et al., 2020). The first non-linear study to determine the relation between temperature and confirmed positives, finds the relationship between mean temperature and positivity rate to be positive when the mean temperature is below 3°C, but beyond that there is no evidence of any causality, or correspondence (Xie & Zhu, 2020). A study by Hossain (2018) has found similarity in the measures of average temperature (5–11°C) and RH (44%–84%) in the centres of the epidemic and the laboratory conditions conducive to the virus (4°C and 20%–80% RH). Wang et al. (2020) analysing the relationship between COVID-19 and temperature opined that the daily effective reproductive number R (as a proxy of non-intervened transmission intensity) in a linear analysis is lowered by 0.0225 and 0.0158 by 1°C increase in temperature and relative increase in humidity respectively.

Keeping in view the existing literature, it is expected that among other factors age, population size, population density, share of rural population, share of older population, temperature, and sanitation facilities of a country may have a significant impact on per million cases of COVID-19 and its mortality rate. But existing literature does not explain the influence of these indicators worldwide. The researchers in the current study have collected information of 83 countries to predict the role of these variables at the macro level on COVID-19 cases. This work covers different types of countries (in terms of large and small populations, developed and undeveloped economic conditions, old and young populations, high and low temperatures, differences in basic sanitation facility, etc.) to evaluate the impact of these indicators on the number of COVID-19 cases per million population. Thus, keeping in view the research gaps, the present study has been undertaken with the objective of examining the impact of median age of the population, total population of a country, annual temperature of a country, share of the rural population, ratio of elderly people in the total population, population density, share of people with access to at least basic sanitation services, percentage of people with diabetes prevalence, and COVID-19 infected death rate on the number of COVID-19 cases per million population and analyse the major predictors. The outcome of this work will help in better understanding the impact of these indicators in this pandemic for policy makers in their decision-making strategy to fight against this pandemic.

2 | RESEARCH METHODOLOGY

There are real-time changes in the world's experience with this virus, and currently, various government and private agencies are engaged in the collection and analysis of COVID-19 data at the local and national levels. This analysis is based on the data of 83 countries. These countries were on priorities in terms of COVID-19 cases and deaths due to COVID-19. The data were collected from the World Data Bank, Johns Hopkins University Centre for System Science and Engineering (JHUCSSE), WHO and Worldometers till 25 May 2020. The data till 25 May 2020 were considered for the study. Here, COVID-19 cases represent total COVID-19 cases either active or recovered.

2.1 | Double log method

The study used country-wise per million cases of COVID-19 as the dependent variable and used a few important variables as explanatory for regression analysis. Model for this work can be written in the following form:

\[
\log Y_i = \alpha + \beta \log X_i + \epsilon_i
\]

In instances where both the dependent variable and independent variable(s) are log-transformed variables, the interpretation is a combination of the linear-log and log-linear cases. In other words, the interpretation is given as an expected percentage change in Y when X increases by one percentage. Such relationships, where both Y and X are log-transformed, the coefficient of log X is referred to as elasticity. In the following statistical model, we regress "Total COVID-19 cases per
million population (TCPM) on ten independent variables (DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP). In this model, total COVID-19 cases per million population is a composite variable that measures total COVID-19 cases per million population in different countries. The ‘DPM’ variable measures the deaths of COVID-19 patient per million population to express contribution in total COVID-19 cases per million population. ‘MAP’ measures the median age of the population and shows variation in ‘TCPM’ by a percentage change in MAP. Similarly the total population in a particular country (TPP), Annual temperature of a particular country (ATP), share of the rural population in a particular country (RPP), population density (people per square km of land area, PDK), population aged 65 and above (SSP), population aged 0–14 (CP), the share of people using at least basic sanitation services (PBS), and diabetes prevalence in population aged 20–79 years (DPP) are indicators in the model used as independent variables. They help explain variance in the dependent variable (TCPM) from a percentage change in their unit.

2.2  Regression model of the study

\[ \ln \text{TCPM}_i = \alpha_0 + \alpha_1 \ln \text{DPM}_i + \alpha_2 \text{MAP}_i + \alpha_3 \text{TPP}_i + \alpha_4 \text{ATP}_i + \alpha_5 \text{RPP}_i + \alpha_6 \text{PDK}_i + \alpha_7 \text{SSP}_i + \alpha_8 \text{CP}_i + \alpha_9 \text{PBS}_i + \alpha_{10} \text{DPP}_i + u_i \]

where ‘\(i\)’ indicates countries.

2.3  Partial least squares structural equation modelling (PLS-SEM)

PLS-SEM has also been used to generate and combine features to predict association between dependent and independent variables of the model. It helps suggest where relationships might or might not exist and, recommends propositions. PLS is a statistical technique that allows some associations to principal components regression; instead of finding hyper planes of maximum variance among the response and independent variables, it finds a linear regression model by projecting the predicted variables and the observable variables to a new space. PLS is used to find the fundamental relations among variables to modelling the covariance structures. It was introduced by O.A. Wold (1970–80) and is still dominant in many areas (Sosik et al., 2009). Partial least squares structural equation modelling (PLS-SEM) has become a popular method for estimating (complex) path models with latent variables and their relationships (Sarstedt et al., 2017). The partial least squares structural equation (PLS-SEM) modelling has recently gained increasing attention, especially for the management information systems, operations management, accounting, organisational research, family business research as well as in marketing disciplines (Haenlein & Kaplan, 2004; Kiran & Bose, 2020; Lee et al., 2011; Mateos-aparicio, 2011; Richter et al., 2015; Ringle et al., 2020; Sarstedt et al., 2017; Sosik et al., 2009). PLS-SEM is a comprehensive technique to investigate the association among variables. This study has used PLS-SEM to examine association among variables (TCPM, DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP) from 83 countries. It helps explain TCPM linkage with DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP. Total COVID-19 cases per million (TCPM) has been considered as the dependent variable in this model.

Table 1 presents the summary statistics including mean, median, minimum, maximum, and standard deviation. These descriptive statistics are used to describe the basic properties of all collected variables. They provide simple summaries about the total COVID-19 cases per million population (TCPM), deaths per million population (DPM), median age of population (MAP), population in particular country (TPP), annual temperature of particular country (ATP), share of rural population in the population of the country (RPP), population density (PDK), population aged 65 and above (SSP), population aged 0–14 (CP), share of people using at least basic sanitation services (PBS), and diabetes prevalence in population aged 20–79 years (DPP).

Table 2 presents the hypotheses of the study.

3  RESULTS

This study was undertaken with the objective of understanding the relation among variables (DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP) and per million COVID-19 positive cases of 83 COVID-19 infected countries across the world. Results of this study have been shown through regression (Table 3) and PLS-SEM path coefficients (Figure 2). The study attempts to identify the major variables which make a significant difference in the number of COVID-19 cases per million population. The t-statistics in the model reveal that there are significant results in this data set. The results show that \( F (10,72) = 64.56 \), and \( p \leq .001 \). As per our results, the null hypothesis is rejected with high level of confidence (above 99.99%). Hence, the hypothesis H2 is significant and it significantly explains variance in Total COVID-19 cases per million population (TCPM) is supported.

\( R^2 \) is typically read as the percentage of variance in the dependent variable explained by independent variables. It shows the overall goodness of fit of the model. It is more appropriate to use the adjusted \( R^2 \) while using multiple variables in a model. The value of adjusted \( R^2 \) is .88, which is fairly high. The statistical significance of this estimate is measured by t statistic or p value. If \( p < .05 \), it shows that the result is significant at 95% level. Eight variables (DPM, MAP, TPP, ATP, RPP, SSP, CP, PBS, and DPP) were found to be significant at the 95% level. So, the first point to note is that the regression coefficients (elasticity) of 8 variables are highly significant at 95% level or above 95% level as shown in results (Table 3). Thus, these eight independent variables have a statistically significant effect on the dependent variable (TCPM). Magnitude is the size of the effect, that is, how big the coefficient is in analysed statistics. It shows that if a variable is increased by 1 unit or per cent (in the log–log model), how much does the dependent variable increase (decrease). The interpretation of the coefficient of ‘DPM’ of about 0.74 is that, if DPM increases by 1%, ‘TCPM’ goes up by about 0.74%; similarly, a 1% increase in ‘MAP,’ ‘TPP,’ ‘ATP,’ ‘RPP,’ ‘SSP,’ ‘PBS,’ and ‘DPP’ causes ‘TCPM’ to change by 3.64%, −0.09%, −0.32%, −0.33%, −1.06%, −0.71%, and 0.69%.
respectively. Hence, it supports hypothesis H1a, H1b, H1c, H1d, H1e, H1g, H1i, and H1j.

Total COVID-19 cases per million population (TCPM); Deaths per million population (DPM), Median age of population (MAP), Population in particular country (TPP), Annual Temperature of particular country (ATP), Share of rural population in particular country (RPP), Population density (PDK), Population age 65 and above (SSP), Population age 0–14 (CP), Share of people using at least basic sanitation services (PBS) and Diabetes prevalence of population age 20–79 years (DPP).

Figure 1 has shown the association between TCPM and other variables (DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP). You can see which variables have the strongest influence on per million COVID-19 case (TCPM).

Correlational analyses were used to examine the relationship among variables TCPM, DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP in Table 4.

Table 1: Summary statistics of the data

| Variables | N  | Mean    | Median | Standard deviation | Min | Max     |
|-----------|----|---------|--------|--------------------|-----|---------|
| TCPM      | 83 | 1366.145| 320    | 2266.754           | 2   | 15,809  |
| DPM       | 83 | 73.40614| 7.5    | 155.9333           | 0.04| 804     |
| MAP       | 83 | 32.70241| 32.4   | 8.998563           | 15.1| 48.2    |
| TPP       | 83 | 73,700,000| 13,000,000| 217,000,000| 287,340| 1,400,000,000|
| ATP       | 83 | 17.61831| 20.2   | 7.600151           | 1.7 | 28.8    |
| RPP       | 83 | 33.69824| 30.058 | 20.50521           | 0.865| 83.575  |
| PDK       | 83 | 172.733 | 92.06711| 279.4273| 3.24787| 2017.27 |
| SSP       | 83 | 10.37604| 8.088393| 6.862699| 1.085| 27.5764 |
| CP        | 83 | 24.91368| 23.17268| 9.814332| 12.6968| 49.9843 |
| PBS       | 83 | 82.37793| 93.3989| 26.11936| 7.31633| 100     |
| DPP       | 83 | 8.063855| 7      | 3.670169| 1.8  | 19.9    |

Source: World Data Bank, Johns Hopkins University Centre for System Science and Engineering (JHUCSSE), WHO and Worldometers till 25 May 2020.

Table 2: Hypotheses of the study

| S. no | Hypotheses of the study                                      |
|-------|-------------------------------------------------------------|
| H1a   | There is a positive relation between deaths per million (DPM) and Total COVID-19 cases per million population (TCPM) |
| H1b   | There is a significant impact of median age of the population (MAP) on Total COVID-19 cases per million population (TCPM) |
| H1c   | There is a significant impact of total population of particular country (TPP) on Total COVID-19 cases per million population (TCPM) |
| H1d   | There is a significant impact of temperature of a particular country (ATP) on Total COVID-19 cases per million population (TCPM) |
| H1e   | There is a significant impact of share of rural population in particular country (RPP) on Total COVID-19 cases per million population (TCPM) |
| H1f   | There is a significant impact of people per square km (PDK) on Total COVID-19 cases per million population (TCPM) |
| H1g   | There is a significant impact of population aged 65 and above (SSP) on Total COVID-19 cases per million population (TCPM) |
| H1h   | There is a significant impact of population aged 0–14 (CP) on Total COVID-19 cases per million population (TCPM) |
| H1i   | There is a significant impact of people using at least basic sanitation services (PBS) on Total COVID-19 cases per million population (TCPM) |
| H1j   | There is a significant impact of diabetes prevalence in population age 20–79 years (DPP) on Total COVID-19 cases per million population (TCPM) |
| H2    | The regression model is significant and it significantly explains variance in Total COVID-19 cases per million population (TCPM) |

Table 3: Regression results

| Observations | 83 | R² | .89 |
|--------------|----|----|-----|
| F (10, 72)   | 64.56 | Adj. R² | .88 |
| Prob > F     | 0 | Root MSE | 0.67 |
| TCPM         | Coefficients | t | p > t |
| DPM          | 0.74 | 16.34 | 0 |
| MAP          | 3.64 | 2.26 | .02 |
| TPP          | −0.09 | −1.9 | .06 |
| ATP          | −0.32 | −1.96 | .05 |
| RPP          | −0.33 | −2.75 | 0 |
| PDK          | 0.01 | 0.15 | .88 |
| SSP          | −1.06 | −4.15 | 0 |
| CP           | 0.75 | 0.79 | .43 |
| PBS          | −0.71 | −2.74 | 0 |
| DPP          | 0.69 | 3.16 | 0 |
| _cons        | −3.24 | −0.42 | .67 |

Note: p values shows the level of significant. Source: World Data Bank, Johns Hopkins University Centre for System Science and Engineering (JHUCSSE), WHO and Worldometers till 25 May 2020.
3.1 Partial least square-structural equation modelling (PLS-SEM)

The study also used PLS-SEM model to establish links among TCPM, DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP. The model has set to capture only the direct effects. The path between TCPM & DPM, TCPM and MAP, TPP and TCPM, ATP and TCPM, RPP and TCPM, PDK and TCPM, SSP and TCPM, CP and TCPM, PBS and TCPM, and DPP and TCPM are explained in a direct association in Figure 2. The results of PLS-SEM in this model support the regression results. The direct effect of variables PBS, SSP, TPP, ATP, and RPP are negatively associated with TCPM and variables DPP, PDK, CP, DPM, and MAP are positively associated with TCPM.

The PLS-SEM results of this study imply that improvement in PBS, SSP, TPP, ATP, and RPP will help reduce the transmission of the number of COVID-19 cases per million population and countries with a higher value of DPP, PDK, CP, DPM, and MAP spread COVID-19 cases more rapidly. As reflected through Table 5 (t statistics and p values), the results were significant for all variables at 5% and 10% level, except for PDK and CP. The results support hypotheses H1a, H1b, H1c, H1d, H1e, H1f, and H1j.

Stone–Geisser Test: Stone (1974) and Geisser (1975) proposed to use the $Q^2$ value for the estimation of predictive relevance of a model. Stone–Geisser’s test uses the value of $Q^2$ by using the blindfolding procedure. The values of $Q^2$ larger than zero for all the reflective endogenous variables in the structural model indicate the predictive relevance for the dependent construct (Stone, 1974; Geisser, 1975; Sarstedt et al., 2017).

In this study, results highlight that the Stone–Geisser’s $Q^2 (1 - \frac{SSE}{SSO})$ values generated are more than zero (0.802), thereby confirming adequate predictive relevance of the model (Geisser, 1975; Sarstedt et al., 2017; Stone, 1974). The results of Stone–Geisser test is explained in Table 6.

4 DISCUSSION

The results highlight that the variables (DPM, MAP, TPP, ATP, RPP, SSP, PBS, and DPP) are major characteristics that help explain the transmission of total number of COVID-19 cases per million population. Our findings relate to the role and magnitude of these indicators in shaping the characteristics of TCPM.
The regression results resonate with the widely held medical beliefs and facts. The results observed that the median age of the total population (MAP) of a particular country has a relatively high influence than any other variable in the model; a 1% increase in median age has led to an increase of 3.64% in the number of COVID-19 cases per million population of a country. A lower median age will result in a lower TCPM and vice versa, as has been already observed in Italy, where a higher median age coupled with the widespread prevalence of comorbidities has led to high fatality rate and COVID-19 cases. The relations might also be due to the higher immunity among younger people (Roy, 2020; Singhal, 2020). WHO has interpreted that while people of all ages can be infected by the COVID-19 virus, older people appear to be more vulnerable (Brooke & Jackson, 2020; Day, 2020; Henri, 2020; Nikolich-Zugich et al., 2020; Sattar et al., 2020). Generally, the immune system of older people becomes weaker with an increase in their age, which could be a major cause of this result.

The population size of a country was found to be a significant factor in reducing per million number of COVID-19 cases. It is important to note that in this situation the absolute number of COVID-19 cases can be higher. A fall in the number of positive cases and deaths was also expected with an increase in temperature. This is an interesting result to explain; the annual temperature of countries was reported as a significant factor negatively associated with the number of COVID-19 cases per million population and 1% increase in annual temperature helps reduce per million transmission of COVID-19 cases by 0.32%. But despite all the speculation, there has been no concrete study or definite proof that a rise in temperature would make any difference in the behaviour of the virus (Prata et al., 2020; Wang et al., 2020; Xie & Zhu, 2020).

In addition, the results show that coefficient value for the percentage of rural population was negative (−0.33%) which could be due to lower population density, and distance from cities and international travellers. A look at the performance of the rural population in this pandemic is important (with its distinct characteristics, in terms of lower population density, fewer testing, a lower degree of sanitation, etc.) in complementing and extending established work (Rocklöv & Sjödin, 2020).

The COVID-19 outbreak has shown the importance of basic sanitation facilities and clean water. There is a need for taking precautionary measures like frequently washing hands, covering the face, avoiding touching the face, etc. It is grievous and morally unacceptable that billions of people around the world do not have access to clean water and basic sanitation. The World Health Organisation

| TABLE 4  | Correlation |
|----------|-------------|
|          | TCPM | DPM | MAP | TPP | ATP | RPP | PDK | SSP | CP | PBS | DPP |
| TCPM     | 1    |     |     |     |     |     |     |     |     |     |     |
| DPM      | 0.89 | 1   |     |     |     |     |     |     |     |     |     |
| MAP      | 0.63 | 0.66| 1   |     |     |     |     |     |     |     |     |
|          | 0.66 | 0.09|     |     |     |     |     |     |     |     |     |
|          | 1    |     |     |     |     |     |     |     |     |     |     |
| TPP      | −0.15| −0.05| −0.19|     |     |     |     |     |     |     |     |
| ATP      | −0.39| −0.45| −0.52| 0.17| 1   |     |     |     |     |     |     |
| RPP      | −0.55| −0.41| −0.41| 0.22| 0.23| 1   |     |     |     |     |     |
| PDK      | 0.13 | 0.13| 0.20| 0.16| 0.12| 0.02| 1   |     |     |     |     |
|          | 0.23 | 0.25| 0.06***| 0.15| 0.27| 0.85|     |     |     |     |     |
| SSP      | 0.42 | 0.6 | 0.84| −0.09***| −0.61| −0.17| 0.11| 1   |     |     |     |
| CP       | −0.64| −0.62| −0.97| 0.19| 0.48| 0.46| −0.25| −0.74| 1   |     |     |
| PBS      | 0.53 | 0.53| 0.73| −0.22| −0.31| −0.48| 0.11| 0.54| −0.69| 1   |     |
| DPP      | 0.21 | 0.04| 0.18| 0.01| 0.21| −0.2| 0.22| −0.09| −0.21| 0.49| 1   |
|          | 0.05**| 0.73| 0.10| 0.89| 0.05*| 0.06*| 0.04*| 0.44| 0.06*| 0   |     |

*Significant at 1% level.
**Significant at 5% level.
***Significant at 10% level.
Source: Self calculated.
WHO reported in June 2019 that around 2.2 billion people across the world do not have access to clean drinking water, while 4.2 billion people do not have basic sanitation services while lack of basic hand washing facilities was found in 3 billion people. A lack of these facilities can be a significant roadblock in containing the transmission of the virus, the coefficient value for which is 0.71. If countries have larger proportion of people with access to basic sanitation (PBS), they may be able to limit COVID-19. Moreover, the results are statistically significant, meaning that 0.71% of the difference in ‘TCPM’ in the different countries are explained by ‘PBS.’ Transmission of this virus and higher mortality rates in patients with morbidities, including diabetes, heart disease, obesity, and hypertension, increases concern over the consequences of COVID-19, and it is more dangerous to be severely ill if infected with COVID-19 virus. When people with diabetes develop a viral infection, it can be harder to treat due to fluctuations in blood glucose levels and the presence of diabetes complications (Cristelo et al., 2020; Klatman et al., 2020). Similarly, results found in this study show that 1 percent increase in diabetes

**FIGURE 2**  PLS-SEM model examining the influence of various variables (DPM, MAP, TPP, ATP, RPP, PDK, SSP, CP, PBS, and DPP) on per million Total COVID-19 cases (TCPM)
prevalence in population aged 20–79 years (DPP) increases the transmission of COVID-19 cases by 0.69 percent.

Variable “Population aged 65 & above” (SSP) with a coefficient of −1.06 shows a negative impact on TCPM, which is surprising, when almost all researches suggest that there is higher possibility of COVID-19 infection in people aged 65 & above. However, it may be seen that in countries like Japan and Russia immunity is higher; and as the infection is spreading across many countries, the relation may have become negative which was otherwise positive. Better immunity in poor countries due to the warm, weaker strain of the virus, climate, and protection by malaria and habituation to living in lesser hygienic condition have been put forward as reasons for lower COVID-19 death rates. And with lower medical attention throughout their lifetime; they naturally acquire better immunity and higher resilience against many infective diseases (WHO, 2020). Thus, it is in line with the new evidence, people of African ancestry usually show stronger immune responses than Europeans do (CellPress, 2016; University of Montreal, 2016).

PLS-SEM results also suggest that improvement in PBS, SSP, TPP, ATP, and RPP will help reduce the transmission of the number of COVID-19 cases per million population and countries with a higher value of DPP, PDK, CP, DPM, and MAP spread COVID-19 cases more rapidly. Purnama and Susanna (2020) through PLS-SEM perceptual model highlighted that stringent rules should still be followed to prevent the spread of COVID-19. Sannigrahi et al. (2020) used PLS-SEM model for European Countries and supported that the socio-demographic factors have a substantial impact on the overall casualties caused by the Coronavirus (COVID-19). They found that the selected demographic and socio-economic components, including total population, poverty, and income are the key factors in regulating overall casualties of COVID-19 in the European region.

Overall, the results suggest that a higher median age and greater prevalence of co-morbidities leads to higher deaths and cases per million ratios, while lower population density and interpersonal contact will help contain the spread of the virus.

### Table 5

| Path coefficients of constructs | Original sample (O) | Sample mean (M) | Standard deviation (STDEV) | T statistics (O/STDEV) | p values |
|---------------------------------|---------------------|----------------|---------------------------|-----------------------|---------|
| Average temperature of country ≥ Total COVID-19 cases per million | −0.1 | −0.099 | 0.055 | 1.837 | .067 |
| Basic sanitation services ≥ Total COVID-19 cases per million | −0.199 | −0.185 | 0.075 | 2.661 | .008 |
| Death per million due to COVID-19 ≥ Total COVID-19 cases per million | 0.864 | 0.865 | 0.057 | 15.072 | .000 |
| Diabetes prevalence of population age 20–79 ≥ Total COVID-19 cases per million | 0.167 | 0.163 | 0.055 | 3.027 | .003 |
| Median age of population ≥ Total COVID-19 cases per million | 0.546 | 0.561 | 0.288 | 1.896 | .058 |
| Population density (people per square km) ≥ Total COVID-19 cases per million | 0.006 | 0.005 | 0.058 | 0.111 | .912 |
| Population age 65 and above ≥ Total COVID-19 cases per million | −0.419 | −0.425 | 0.131 | 3.185 | .002 |
| Share of population age 0–14 ≥ Total COVID-19 cases per million | 0.143 | 0.149 | 0.218 | 0.656 | .512 |
| Share of rural population ≥ Total COVID-19 cases per million | −0.134 | −0.116 | 0.062 | 2.163 | .031 |
| Total population in country ≥ Total COVID-19 cases per million | −0.077 | −0.073 | 0.044 | 1.759 | .079 |

Note: p values shows the level of significant.

Source: Self calculated.

### Table 6

| Assessment | Purpose | Tests | Evaluation criteria | Reference | Results |
|------------|---------|-------|---------------------|-----------|---------|
| Predictive relevance | Predictive validity of the model | Stone–Geisser's Test | The Q2 value should be >0 | Stone (1974), Geisser (1975), Wold (1982), Chin (1998), Tenenhaus et al. (2005), Henseler et al. (2009) | The model was confirmed to have good predictive relevance as all the Q2 values were greater than zero. |
Table 7 summarised the findings of the study, accordingly, the acceptance or rejection of hypotheses is presented in Table 2.

Table 7 Status of hypotheses

| S. no. | Hypothesis of the study                                                                 | Accepted/rejected |
|--------|-----------------------------------------------------------------------------------------|-------------------|
| H1a    | There is a positive relation between deaths per million (DPM) and Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1b    | There is a significant impact of median age of the population (MAP) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1c    | There is a significant impact of total population of a particular country (TPPM) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1d    | There is a significant impact of temperature of a particular country (ATP) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1e    | There is a significant impact of share of rural population in particular country (RPP) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1f    | There is a significant impact of the number of people per square km (PDPK) on Total COVID-19 cases per million population (TCPM) | Rejected          |
| H1g    | There is a significant impact of population aged 65 and above (SPP) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1h    | There is a significant impact of population aged 0–14 (CP) on Total COVID-19 cases per million population (TCPM) | Rejected          |
| H1i    | There is a significant impact of people using at least basic sanitation (PBS) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H1j    | There is a significant impact of diabetes prevalence in population aged 20–79 years (DPP) on Total COVID-19 cases per million population (TCPM) | Accepted          |
| H2     | The regression model is significant and it significantly explains variance in Total COVID-19 cases per million population (TCPM) | Accepted          |

There are several ways in which the findings of this work can support a move towards a better management to fight against the virus. In particular, there may be policy implications for younger and elderly people. This is an initial level study focusing on factors that are important and need to be focused on. As suggested by the model, it is important to provide basic sanitation, because it helps to reduce spread of this virus. Policy makers should be very careful about high-density areas. The results reinstate the widely seen results that a higher median age and greater prevalence of comorbidities leads to a higher number of COVID-19 cases and lesser population density and interpersonal contact will help contain the spread of the virus. Pandemics need special focus and there is a need to have greater mone tary resources to cater to critical situations. Almost all developed and developing countries have reported shortage of health professionals and health infrastructure. There is an urgent need to look into these. It is very important to focus and have more concern for the patients with morbidities like diabetes, heart disease, hypertension, etc.

Here we have used the data for 83 COVID-19 infected countries. In current scenario cases of this virus are changing frequently therefore we have taken data till 25 May 2020 for this particular work. This covers the initial spread, however currently the developing economies are bearing the brunt of virus. An extension of time period and region wise analysis could shed more light on this emerging problem, which has in fact made the entire world stagnate in this age of technological breakthroughs.

**5 | CONCLUSION**

There can be two ways of going about the conclusion of this result. The two scenarios differ widely based simply on the level of testing; a greater old age population share is going to result in a higher number of positive cases. A lower median age country has a higher positive COVID-19 cases and vice versa, as has been already observed in Italy. A lower median age has also been found to correspond with a lower number of cases. It could be due to the higher immunity among younger people. A fall in the number of positive cases was also expected with an increase in temperature. This work has also found similar results. The per million population COVID-19 cases are relatively low in rural and low-density area, which results simply due to the lower population density and fewer interpersonal physical contact in rural area. It also has been found from the data highlighting the widely seen results that a higher median age and greater prevalence of comorbidities leads to higher cases per million. In addition, lack of basic sanitation facilities can be a significant pathway in the transmission of the virus, if systematic and proper hygiene is not being followed. The coefficient of 0.71 for countries with a higher percentage of people using basic sanitation shows that such people are able to evade or reduce the impact of COVID-19.

**6 | POLICY IMPLICATIONS AND LIMITATIONS**

There are several ways in which the findings of this work can support a move towards a better management to fight against the virus. In particular, there may be policy implications for younger and elderly people. This is an initial level study focusing on factors that are important and need to be focused on. As suggested by the model, it is important to provide basic sanitation, because it helps to reduce spread of this virus. Policy makers should be very careful about high-density areas. The results reinstate the widely seen results that a higher median age and greater prevalence of comorbidities leads to a higher number of COVID-19 cases and lesser population density and interpersonal contact will help contain the spread of the virus. Pandemics need special focus and there is a need to have greater monetary resources to cater to critical situations. Almost all developed and developing countries have reported shortage of health professionals and health infrastructure. There is an urgent need to look into these. It is very important to focus and have more concern for the patients with morbidities like diabetes, heart disease, hypertension, etc.

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AUTHOR CONTRIBUTIONS
All authors have contributed equally to this paper.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are openly available in worldometers at https://www.worldometers.info/coronavirus/, and World Bank at https://data.worldbank.org/.

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