The main goal of this article is to demonstrate the impact of environmental and socio-economic factors on the spreading of COVID-19. In this research, data has been collected from 70 cities/provinces of different countries around the world that are affected by COVID-19. In this research, environmental data such as temperatures, humidity, air quality and population density and socio-economic data such as GDP (PPP) per capita, per capita health expenditure, life expectancy and total test in each of these cities/provinces are considered. This data has been analyzed using statistical models such as Poisson and negative binomial models. It is found that a negative binomial regression model is the best fit for our data. Our results reveal higher population density to be an important factor for the quick spread of COVID-19 as maintenance of social distancing requirements are more difficult in urban areas. Moreover, GDP (PPP) and PM2.5 are linked with fewer cases of COVID-19 whereas PM10, and total number of tests are strongly associated with the increase of COVID-19 case counts.
2. Materials and methods

In this research, data containing the total number of infected cases, death count by COVID-19, population density, GDP (PPP) per capita, per capita health expenditure, life expectancy, total test, monthly average humidity, average high and low temperatures have been collected from 126 cities/provinces of 42 most affected countries around the world from January 18, 2020 to April 24, 2020. Weather data was collected from AccuWeather (http://www.accuweather.com/) in order to get reliable data. Such reliable data is important in order to get the correct and accurate research findings to understand the impact of weather on spreading the COVID-19. Also, population data like area, population density were collected from worldometer (www.worldometers.info/population). In addition, socio-economic data like GDP (PPP) per capita in 2017, life expectancy of people of different country and total number of COVID-19 test are collected from worldometer (http://www.worldometers.info/population) and data for per capita health expenditure in 2017 is collected from Knoema (https://knoema.com/atlas). Also, air quality index, and particulate matters such as PM2.5, PM10 data are collected from plume labs (https://air.plumelabs.com/en/).

USA, France, and a few other countries counted suspected COVID-19 cases as a COVID-19 death to include uncounted fatalities due to the lack of massive testing capacity. Belgium even included flu-like symptomatic deaths as COVID-19 death. Countries are still struggling to scale the testing capacity. Due to this limitation, we verified our data using multiple sources like google coronavirus (COVID-19) statistics data, worldometer (www.worldometers.info/coronavirus) and COVID-19 related pages of government website for different countries. These sources are presented in the appendix.

We had missing values of death count and infected cases for some cities. We really don’t know why they were missing. In our study, we were careful to make our recommendations and refrained making predictions due to this scarcity of the data. Since the presence of missing values in the data can reduce the statistical power of a study, it can lead us to invalid conclusions along with biased estimates. Therefore, we have considered the case deletion method, the most common approach to handle the missing data instead of applying other imputation techniques like maximum likelihood method. After handling missing values, we ended up with 24 countries and 70 cities/provinces. We performed our statistical analysis using these cities/provinces. Our implementations can be reproduced using the code and data made available at our GitLab repository https://gitlab.com/Jishan/covid-19-research-2020.git.

Two different models such as negative Binomial, and Poisson models are considered in this research. These models are assessed using the Akaike Information Criterion (AIC), Cragg & Uhler’s (Oztig and Askin, 2020) pseudo-R², residual deviance, and Pearson statistic. We have used glm() function to fit the Poisson and glm.nb() function to fit the negative Binomial model within the R software (https://cran.r-project.org/src/base/R-4) package MASS (R Core Team, 2017). Two-sided statistical tests were considered along with 5% significance level.

2.1. Data observation

Figure 1 shows the distribution of the number of infected people in 70 cities/provinces. Our initial observations suggest that there could be a relationship between the environmental parameters and expansion of COVID-19 across the different geographical locations. Most of the cities/provinces where outbreaks occurred such as Madrid, New York etc., had low temperature and/or low to moderate humidity probably because coronavirus can survive longer on surfaces or respiratory droplets at this environmental condition. Places with relatively high humidity and high temperature such as Banten, Central Luzon etc., showed comparatively less infected people. Another factor, population density and mobility alone can trigger the infection rate logarithmically irrespective of environmental condition. São Paulo, Riyadh etc. cities had high temperature and high humidity but many infected people due to population density and mobility. In cold regions, population density can exacerbate the total COVID-19 infection along with the environment. According to the data analysis, our observation illustrates that there could be a remarkable connection between the environmental, socio-economic parameters and
the nature of the COVID-19 virus. In the next section, we will present statistical analysis and try to understand the above mentioned behavior.

2.2. Statistical analysis

In this paper, a generalized linear model (GLM) framework (Agresti, 2015) for count data has been deployed to analyze the effects of population density, GDP (PPP), health expenditure, life expectancy, total COVID-19 tests, humidity, temperatures and air pollutants on the spreading of COVID-19.

In the Poisson regression model, it is assumed that the variance and mean of the dependent variable are the same. However, this assumption is not always true, especially while studying the environmental risk to human health due to the fact that the variance is higher than average causing the overdispersion of the data. It is challenging to handle overdispersion in the modeling of count response variables like the number of COVID-19 confirmed cases. In our data, the variance of the infected cases is 1,279,339,997 and mean is 14,924.97 - variance is larger than the mean. Also, from Figure 2, we see that our response variable, the count of infected cases is highly skewed. This indicates that our data may be overdispersed. It is convenient to use a negative binomial model to estimate the parameter due to the presence of overdispersion of the data. Therefore, in this study, we have considered the negative binomial model and compared our results with the Poisson model as well to detect overdispersion in our data.

3. Results

3.1. Dataset descriptive analysis

In this work, we considered 70 cities/provinces around the world that had the confirmed cases of COVID-19. Figure 3 shows all explanatory variables through normalized heat map representations. The color scale on the right represents the intensity of the variables according to the saturation level of this scale. For example, New York had the highest number of COVID-19 confirmed cases which is shown in this figure with a highly saturated blue color.

Now, Pearson correlation coefficients are computed as shown in Figure 4 to determine the possible effects of collinearity. It shows that the Pearson correlation between explanatory variables along with the significance measure. There was a strong positive correlation between average high and low temperatures. GDP (PPP), and health expenditure were positively correlated. It was also noticeable that air pollutants PM10, and PM2.5 had positive correlation as well. However, the presence of high correlation among predictor variables does not violate any assumptions of GLMs.

In the following, we presented the summary statistics for infected cases, population density, GDP (PPP) per capita, per capita health expenditure, life expectancy, total test, humidity and average high and low temperatures as shown in Table 1. It is to be noted that the average number of confirmed infected cases was 14,925, the mean value of population density was 4,043.4 per km², the mean values of humidity, average high and low temperatures were 65.28%, 20.42 °C and 9.41 °C.

3.2. Selection and adjustment of the regression models

Since the dependent variable, COVID-19 case count is highly-skewed and non-continuous, standard linear regression models such as ordinary least squares regression are not appropriate for this count data. Therefore, the Poisson log-linear model would be our first-choice modeling technique. The expected COVID-19 infected case count (μi) parameter in the Poisson log-linear model is estimated as

$$\log(\mu_i) = \sum_{j=1}^{p} \beta_j x_{ij}$$

where, \( \beta \) is a vector of estimated coefficients of exploratory variables including the logarithm of the population density, GDP (PPP) per capita, per capita health expenditure, life expectancy and total test along with humidity, average high temperature, average low temperature, AQI, PM2.5, and PM10. For the sake of simplicity, we referred population density as PopDensity, GDP (PPP) per capita as GDPPPP, per capita health expenditure as HealthExpend, average high temperature as AvgHigh, average low temperature as AvgLow, PM10 as PM1, PM2.5 as PM2 during the model building.

It is assumed in Poisson distribution that the mean and the variance are equal to the \( \mu_i \) parameter. However, this assumption was not satisfied for the data used in this study. The greater ratio of variance to mean leads to overdispersion. The problem of overdispersion is evident from the Poisson model fit as the ratio of residual deviance and degrees of freedom is 9311.293 which is greater than the dispersion parameter limit 1. Pearson statistic and the deviance statistic were used as well to assess the overall performance of the fitted model. In Table 2a, the p-values suggest that the Poisson model is not adequate suggesting a poor fit. We cannot even trust the p values due to the presence of substantial overdispersion in our Poisson model. Since the negative-binomial (NB) model is a different generalization of the Poisson that allows for over-dispersion, we apply the NB model to overcome this problem of over dispersion. A gamma-distributed error term (Oztig and Askin, 2020) is included to Eq. (1) to relax the Poisson model assumption by introducing additional randomness as

$$\log(\mu_i) = x_i^T \beta + \epsilon_i$$

where \( \epsilon_i \) follows a gamma distribution with mean 1 and variance \( \alpha \).

The NB model has a mean \( \mu_i \) and variance \( \mu_i + a \mu_i^2 \), where \( \alpha \) is the overdispersion parameter which is used as a measure of dispersion. Therefore, we have considered the following NB regression model,
In the NB model, we have found that the ratio of residual deviance and degrees of freedom is approximately equal to the dispersion parameter limit 1. The high Pseudo-$R^2$ values in Table 2b clearly indicate no evidence of lack-of-fit. It is to be mentioned here that the AIC score for the NB model was 1373.1.

### 3.3. Negative binomial model assessment

Diagnostic plots were used to check the performance of the negative Binomial model. In Figure 5, the jackknife deviance residuals vs. the fitted values are displayed on the top left panel, and normal QQ plots of the standardized deviance residuals are shown on the top right panel. The dotted line of the normal QQ plots represents the expected line if the standardized residuals are normally distributed (Davison and Snell, 1991). Cook statistics are shown in the bottom two panels. The bottom left plot shows the Cook statistics vs. the standardized leverages. The horizontal line is drawn at $8/(n-2p)$, and the vertical line is drawn at $2p/(n-2p)$, where $n$ represents the number of observations and $p$ represents the number of estimated parameters. Points above the horizontal line may be points which have high influence on the model. On the other hand, high leverage points correspond to the right side of the vertical line. We had 70 cities with COVID-19 confirmed cases, and 11 parameters were estimated. Here, we get a pretty accurate picture from the Figure 5 that our model is adequately describing the over dispersion in the count data when we use the negative binomial regression, but we may have some issues with extreme data points. Since the deletion of extreme data points may cause the other problems of over-fitting, it is not convenient to delete the outliers to increase the goodness-of-fit and power of explanation. However, we investigated these extreme data points in Figures 6 and 7 to detect the influential observations using the Cook distance. In Figure 6, we see from the influence plot that observations 30 (Jakarta, Indonesia), and 45 (Khyber Pakhtunkhwa, Pakistan) stand out with large positive residuals whereas observations 16 (Guangdong, China) have large negative residuals. Observations 42 (Mexico City, Mexico), and 58 (Riyadh, Soudi Arabia) have a large leverage. However, it is evident from the residuals vs leverage plot (Figure 7) that none of them are influential observations. We evaluated our model without these outliers as well to see their impact. We found that outliers had no impact on the model performance as well. It does make sense because Jakarta had really extreme values of AQI, PM$_{2.5}$, and PM$_{10}$, Mexico had high values of AQI, PM$_{2.5}$, and PM$_{10}$ values were not available for Khyber Pakhtunkhwa, and Riyadh had low humidity with high values of AQI, PM$_{2.5}$, and PM$_{10}$.

Table 3 shows the associations of GDP (PPP) per capita, life expectancy, per capita health expenditure, total test, population density, humidity, average high temperature, average low temperature, AQI, PM$_{2.5}$, PM$_{10}$ with COVID-19 infected incidence. The results show that population density (Coefficient estimate: 0.135; 95% CI: (0.019, 0.255), p-value = 0.021), and GDP (Coefficient estimate: $/C01.631$; 95% CI: ($/C02.931$, $/C00.375$), p-value = 0.021), PM$_{10}$ (Coefficient estimate: 0.017; 95% CI: ($/C00.002$, $/C00.033$), p-value =0.011), PM$_{2.5}$ (Coefficient estimate: $/C00.022$; 95% CI: ($/C00.037$, $/C00.006$), p-value = 0.001), total test (Coefficient estimate: 0.809; 95% CI: (0.610, 1.008), p-value = 0.000) were significantly associated with COVID-19. The results indicate that the “baseline” average, infected case count is 8142.499. We can interpret the other exponentiated coefficients multiplicatively as well.

Our results clearly demonstrate that for every unit increase in GDP, we estimated a significant decrease in COVID-19 infected case count of 80.4%. There is evidence to suggest that the percent change in the incident rate of COVID-19 infected case count is a 2.2% decrease for
every unit increase in PM2.5. However, for every unit increase in population density, we could expect to see a 14.5% rise in COVID-19 infected case count. It is noticeable that each unit increase in PM10 multiplies the COVID-19 infected case count by 1.017, a 1.7% increase. It is to be mentioned that the number of tests played a significant role to rise in the infected cases. It is even clearer from our result that for every unit increase in total test, we estimated a significant increase in COVID-19 infected case count of 124.6%.

4. Discussion

In this study, we attempted to answer the question of why some cities/provinces have higher numbers of COVID-19 infected people compared with others. In this study, we found from Table 3 that the population density, and GDP, PM10, PM2.5, and total tests were significantly associated with the COVID-19 confirmed infected cases.

Since COVID-19 is a highly contagious virus, population density can contribute to the spread of this virus (Coskun et al., 2020). Oztig and Askin (2020) examined the link between human mobility and the number of COVID-19 infected people in countries. They reported that countries that have higher population density (IRR = 2.403, p < 0.01) are found to be more likely to have higher numbers of COVID-19 infected cases than other countries. We also found statistically significant evidence that an increase of 1 unit in population density is associated with an 14.5% increase in the COVID-19 infected case count. It is difficult to maintain social distance in densely populated metropolitan cities and countries with tourist attractions. New York, New Jersey, Lombardy, Hubei, Madrid and Catalonia were the epicenter of the COVID-19 due to their dense population. New York, Lombardy, Madrid and Catalonia are popular tourist destinations as every year millions of tourists visit these cities. Taking the number of tourists into account when modeling the association between population density and COVID-19 could substantially improve the performance of our models. However, we did not consider the number of tourists as an explanatory variable due to the lack of reliable data.

Our results also indicate a positive association between the PM10 and high numbers of COVID-19 infected patients. It was surprising to see that countries with high values of air pollutants PM2.5 are less likely to have more COVID-19 cases than other countries. Associations between short-

| Variables               | Mean    | SD      | Min    | Max    |
|-------------------------|---------|---------|--------|--------|
| Infected cases          | 14925   | 35767.86| 181    | 263000 |
| Population density (/km²)| 4043.4  | 10563.71| 6.0    | 71263.0|
| GDP (PPP) per capita    | 29715   | 17902.62| 5539   | 66307  |
| Life expectancy         | 77.98   | 5.01    | 67.79  | 85.03  |
| Per capita health expenditure | 2322.7 | 2917.15 | 45.0   | 10224.0|
| Humidity (%)            | 65.28   | 12.92   | 26.00  | 90.00  |
| Avg high temperature (°C)| 20.42   | 9.05    | 6.00   | 38.09  |
| Avg low temperature (°C)| 9.414   | 9.48    | 3.230  | 26.25  |
| AQI                     | 50.4    | 45.47   | 19.0   | 274.0  |
| PM2.5                   | 32.17   | 40.18   | 0.00   | 148    |
| PM10                    | 31.92   | 40.66   | 0.00   | 170    |
| Total test              | 815174  | 2021204 | 3359   | 9800000|

Table 2a. Goodness-of-fit (GOF) results for the Poisson model.

| Test      | Value | df | p-value |
|-----------|-------|----|---------|
| Deviance  | 540055.4 | 58 | 0       |
| Pearson   | 774514.4 | 58 | 0       |

Table 2b. Goodness-of-fit (GOF) result for the negative-binomial (NB) model.
term PM$_{2.5}$ exposure and poor infectious disease outcomes for influenza, pneumonia, and acute lower respiratory infections were reported by several previous studies (Croft et al., 2020; Horne et al., 2018). Therefore, we were expecting to see the positive association of PM$_{2.5}$ with COVID-19 like previous studies. Unfortunately, our study design cannot provide clear insight into the mechanisms underlying the negative relationship between PM$_{2.5}$ and COVID-19 infected case counts. We think that socio-economic indicators played a significant role here. For example, Jakarta, Indonesia had 140 $\mu$g/m$^3$ for PM$_{2.5}$. In contrast, they have conducted only 27,075 tests due to the lack of testing equipment. We have seen from our results that the numbers of tests administered to individuals are significantly associated with the increased number of COVID-19 infected cases.

To stop the spread of the COVID-19, it is required to test more people and enable contract tracing. It is also equally important to incorporate mitigation techniques such as “Stay at Home” orders, frequent hand washing, and social distancing. However, it is quite impossible to implement such mitigation techniques for a country like India due to the widespread poverty and unequal distribution of income compared to a wealthy nation like Switzerland. Thus, we have attempted to explore the relationships between COVID-19 incidence with the socio-economic indicators such as GDP (PPP) per capita, life expectancy, and per capita health expenditure. We have found statistically significant evidence that GDP is associated with a decrease in the COVID-19 incident rate. It makes sense as people living in countries with higher GDP are likely to attend a
larger number of social events and to spend more time travelling foreign countries possibly paving the way for easier virus diffusion. Also, the higher efficiency of national health systems allow them to administer more tests and that could affect the number of COVID-19 confirmed cases.

We observed fewer COVID-19 cases in warmer cities like Delhi and Mecca. Seasonal flu epidemics usually occur yearly during the colder months. COVID-19 is primarily spread from person to person through close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. Therefore, seasonal close contact. We can become infected from respiratory droplets when an infected person coughs, sneezes, or talks. However, we did not see the surge of massive COVID-19 cases. Also, average low temperature could drive the spread of virus through respiratory droplets. However, our model shows there is very little or no role of humidity in spreading of COVID-19 in different countries. In addition, cities with higher population density pose extreme risk, which provides useful guidelines for policymakers and the public to control the COVID-19 pandemic. Most importantly, our research showed that GDP and PM$_{2.5}$ has a positive effect on the slowdown of spreading of COVID-19 infection whereas PM$_{10}$ and total tests significantly contributed to the rise of COVID-19 infection.

### Declarations

**Author contribution statement**

J. Ahmed: Performed the experiments; Analysed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Md. Hasnat Jaman: Contributed reagents, materials, analysis tools or data; Wrote the paper.

G. Saha: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

P. Ghosh: Contributed reagents, materials, analysis tools or data.

### Funding statement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

### Data availability statement

Data associated with this study has been deposited at [https://gitlab.com/Jishan/covid-19-research-2020.git](https://gitlab.com/Jishan/covid-19-research-2020.git).

### Declaration of interests statement

The authors declare no conflict of interest.

### Additional information

Supplementary content related to this article has been published online at [https://doi.org/10.1016/j.heliyon.2021.e06979](https://doi.org/10.1016/j.heliyon.2021.e06979).

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