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Exploring urban dynamics of crowding with COVID-19 incidence A case study of Mumbai and Bengaluru city in India



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ABSTRACT

Cities are the economic hubs of any country and their production efficiency increases with size and density. However, the rapid spread of COVID-19 in almost all the major cities has raised several questions on the efficacy of urban densification. The objective of this paper is to understand this dynamic interplay between crowding and virus incidence. The research seeks to explain the impact of crowding parameters (population, net and gross density, street crowding, indoor crowding) on the spread of the contagion, together with the confounding explanatory variables (government policies, socioeconomic and environmental characteristics). The study is based on two metropolitan cities of India, namely Mumbai and Bengaluru, which are the hotspots of the infection. At a time when there is a huge debate of compact cities versus sprawling cities, the results are favorable towards densification as the study reveals that other crowding variables have a much higher correlation with the infection transmission than density. In fact, density follows a sub-linear relationship with transmission rate and after a threshold density; the transmission rate is almost independent of the population density. The findings show that contrary to popular belief, dense cities are resilient to pandemics.

1. Introduction

Proximity is the pivotal component on which the efficiency of a city hinges as it enables economy of scale. But with the infectious disease COVID-19 thriving on proximity, densification has suddenly become very undesirable. All the critics of densification have come out of the woods to advocate for sprawling cities as against compact cities. Even the Mayor and Governor of New York have laid the blame for the havoc caused by COVID-19 at the doorstep of the urban planners for creating dense cities (McFarlane, 2020). But it is overlooked that cities being the financial epicenters have the best hospitals and health departments to combat this invisible enemy. They are equipped with socioeconomic connection systems which facilitate the exponential spread of information, create awareness and innovation.

Density and overcrowding seem to be the obvious connection to make with the disease incidence. Though density is an obvious scapegoat, there are many cities that defy that logic. Cities with *lower* population density in China have had more infections than high-density cities. Hong Kong, with an average density of 6,300 people per square kilometer, has 45 cases per 100,000 people (Worldometer, 2020). Many cities with population density as great as or greater than New York City's 10,198 residents per square kilometer (sq.km) have reported much lower case rates. Seoul and Singapore have respectively 16000 and 8358 residents per sq.km. Their case incidence rates per 100,000 residents vary, however, between 9.4 (Seoul) and 635.4 (Singapore), as compared to New York City's rate of 2286

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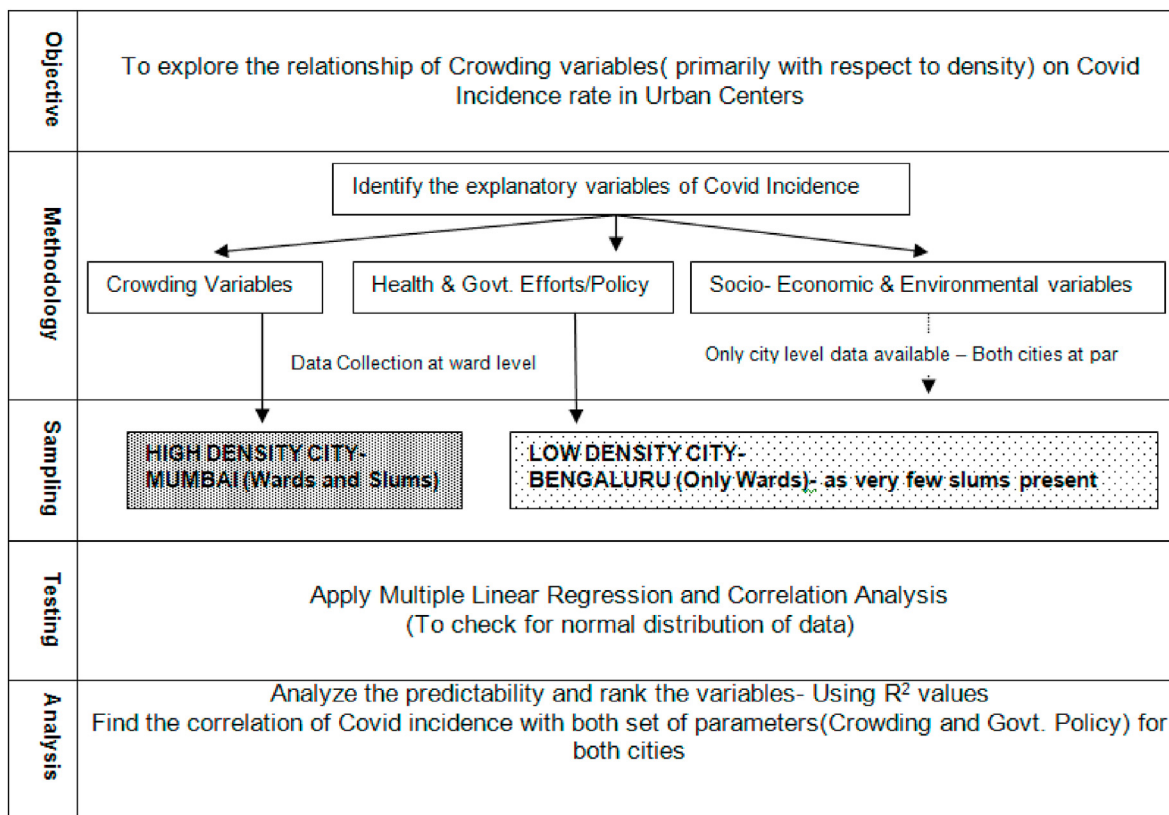


Fig 1. Steps in the Research Process (Source: author, 2021).

cases per 100,000 residents (Federgruen & Naha, 2021).

Since the virus is transmitted most easily when an infected person is in close contact with people for extended periods, the city’s mass transit system is thought to be the obvious culprit. But even cities where the major population moves by cars have had severe infection rates. To explore the connection between health and overcrowding, the scale needs to be chosen correctly. It is important to talk more in terms of square kilometers within a neighborhood rather than the entire city. The unit of measurement may need to be done at an even granular scale—not a region, not a city, but maybe a single ward.

The objective of this paper is to understand the urban dynamics of crowding and virus incidence. The research seeks to explain the impact of crowding parameters (population, net and gross density, street crowding, indoor crowding) on the spread of COVID-19, together with the confounding explanatory variables (government policies and socioeconomic and environmental characteristics). Most research substitute density for contact rate while studying its impact on virus incidence. But this research uses five different metrics of crowding in different density settings, to understand which of the causal variables have the strongest correlation with virus incidence rate. The study is based on two metropolitan cities of India of different densities, namely Mumbai and Bengaluru, which are the hotspots of the infection.

Density is an objective measure and refers to the number of people in any given space. The term has no positive or negative connotations. On the other hand, crowding generally refers to people’s psychological response to density that is, to their feelings of being crowded, having a lack of privacy or an increase in unwanted interactions or psychological distress (Jazwinski, 1998). Although individual studies establish associations between crowding and various illnesses, they are rarely robust enough to establish causality. Indeed, some researchers accept that, given the complex nature of social relationships, a strong association is the best that can be expected (Gray, 2001).

It is not clear from the literature review if density is conclusively responsible for the spread of virus infection and if so to what extent. There are conflicting viewpoints on the nexus between density and virus infection. A recent model to measure the risk of corona virus outbreak in four countries (United States, Australia, Canada and China) shows that the higher is the population density, the higher the risk of transmission of infectious disease from human to human (Islam et al., 2020). Contrary to this another research declares that placing too much blame on urban density is a mistake (Barr & Tassier, 2020).

There is a definite explanation for these conflicting viewpoints. Several other variables could potentially confound contagious disease transmission, including demographic characteristics (Levy & Odoi, 2018), socioeconomic disparities (Quinn & Kumar, 2014), and tourism (Alirol et al., 2011). Connectivity matters more than density in the spread of the COVID-19 pandemic. Large metropolitan areas with a higher number of counties tightly linked together through economic, social, and commuting relationships are the most

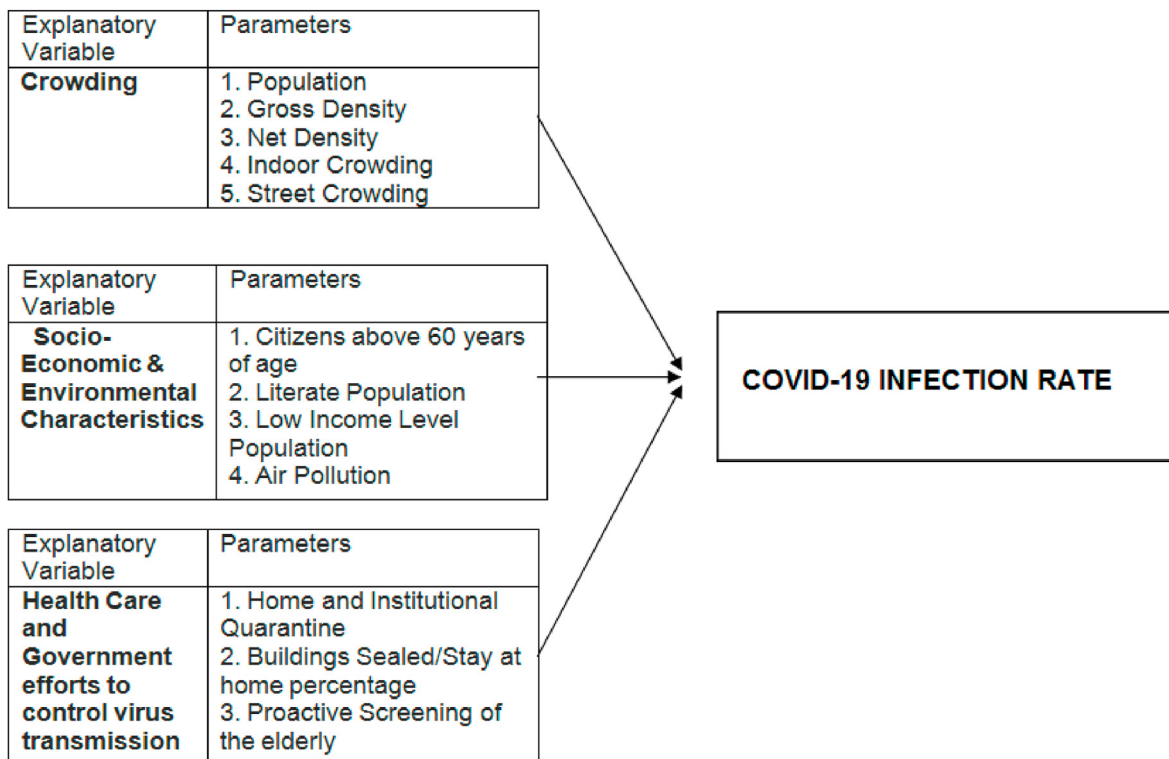


Fig 2. Model showing the Role of explanatory variables on COVID-19 infection rate (Source: author, 2021).

vulnerable to the pandemic outbreak. They are more likely to exchange tourists and business people with each other and with other parts of the world, thus increasing the risk of cross-border infections (Hamidi et al., 2020).

World Health Organization (WHO) has listed down the strategy for countries to combat COVID-19 incidence. Due to rapid transmission, countries around the world should increase attention to disease surveillance systems and scale up country readiness and response operations including establishing rapid response teams and improving the capacity of the national laboratory system (Harapan et al., 2020). In China stringent quarantines, city lockdown, and local public health measures imposed in late January significantly decreased the virus transmission rate (Qiu, Chen, & Shi, 2020).

An in-depth analysis to understand the gap in literature review reveals that more granular data is required from cities and that too in a variety of density settings to pinpoint the role of density and crowding in the spread of an infectious disease like COVID-19.

2. Methodology

To explore the relationship between crowding variables and COVID-19 infection rate the research followed the following methodology:

1. Obtaining a model for explanatory variables which will determine the outcome variable (COVID-19 incidence rate)
2. Studying the effect of explanatory variables through Regression analysis and Correlation Coefficient in a case study for 2 cities (Mumbai and Bengaluru) with wards as the unit of analysis.
3. A deeper analysis of the Correlation Coefficient of density with COVID-19 incidence rate for slums of Mumbai.
4. Discussion and analysis to explain the polar differences in results for both cities.

The Research steps followed have been illustrated in Fig. 1 (given below).

The smallest administrative unit in a city for which COVID-19 infection data is available is a ward. Collecting data ward wise is suitable as it doesn't suffer from aggregation bias. The infection transmission occurs with the interactions and movement of people, and peoples' movements in times of lockdown rarely extend beyond their immediate neighborhoods except for persons working for essential services.

2.1. Explanatory variables

The choice of explanatory variables to predict the COVID-19 incidence rate variable is based on common sense and early theories on

the spread of the virus. Explanatory variables for the major determinants of a pandemic outbreak have been grouped under crowding, socioeconomic characteristics, health care facilities and government efforts to control the virus. Since the study was done at a time (July 2020) when complete lockdown had been imposed in India, tourism and travel is expected to have minimal impact.

The objective of the paper is to study the impact of crowding on the virus infection rate; hence the study of crowding metrics and Government efforts will be done at a more granular level i.e. at the ward level and other variables grouped under “socio-economic cum environmental characteristics” will be done at the metropolitan level.

Social-demographic variables (Population in urban agglomerations of more than 1 million, PM_{2.5} air pollution mean annual exposure, life expectancy, hospital beds available, urban population, global health security detection index and restrictions on international movement) are strongly associated to the initial growth rate of COVID-19 (Duhon et al., 2021). Factors associated with community-level vulnerability included age, disability, language, race, occupation, and urban status (Andersen et al., 2021). Patients with COVID-19 living in areas with the greatest socioeconomic deprivation had a higher frequency of critical care admission and a higher adjusted 30-day mortality (Lone et al., 2021).

Human-mobility reduction had a significant impact on reducing COVID-19 related deaths, thus providing crucial evidence in support of such government measures (Hadjidemetriou et al., 2020). Transport modes are amongst the most critical platforms for the rapid spread of infection in high-density and mixed-use urban environments (Moslem et al., 2020).

Fig. 2 shows the model to identify the explanatory variables for COVID-19 infection rate. It is based on the above literature study and the steps that have been taken by the Government to control the virus incidence.

Using the above model, the data was collected for two major cities (Mumbai and Bengaluru) which are ranked first and sixth in density. The relationship of crowding variables (with respect to density) on COVID-19 incidence in urban centers was then tested and analyzed using Multiple Linear Regression and Correlation analysis.

2.1.1. Dynamics and metrics of crowding

Crowding as a metric can be applied to a range of needs in an urban area. Crowding could happen in the streets, workplace, residential space, commercial space or industrial space. This research will take five metrics of crowding to understand the entire gamut and dimensions of human interactions and their effect on virus transmission. The first three metrics are commonly used and do not need much explanation.

1. *Population* is the total number of people in that locality
2. *Gross Density* is very simply, the total population of the area divided by the total area of the locality. The total area includes the street area, open spaces and water bodies.

Gross Density (GD) = Population of locality/Total Area of locality

3. *Net Density* is the population of a locality divided by the buildable plot area. Alternatively, it is called Plot Density. The buildable plot area is obtained by excluding street areas, open spaces and water bodies from the locality area.

Net density (ND) = Population of locality/ Buildable Plot Area

4. *Indoor Crowding* is the number of people indoors per square kilometer of built area. The built area is obtained by buildable plot area times the Floor Space Index (FSI) of that locality. This includes all built area under residential, commercial, institutional and industrial use.

Indoor Crowding(IC) = Indoor Population/ Built Area (where Built Area = Buildable Plot Area x FSI)

Since most cities in India are under lockdown with the working population and students working from home, the Indoor population is assumed at 90% of the population.

5. *Street Crowding* is the number of people on the streets per sq.km of street area. This would be a critical measure to evaluate how crowded the street life is likely to be. By street area we mean the public, shared space, used for circulation of pedestrians and vehicles. Since streets are the vectors for virus transmission, it is a very important metric for measurement. However mass transit systems have not been included as these transit systems are working in a restricted manner in the lockdown phase.

Street Crowding (SC) = Population on Street /Street Area

2.1.2. Socioeconomic and environmental characteristics

The key socioeconomic and environmental variables affecting the transmission rate for this research are:

1. *Citizens above the age of 60* are the percentage of population in that locality whose age is above the age of 60. The aged population is assumed to have lesser immunity.
2. *Literate Population* is the percentage of population in that locality who is literate and able to comprehend the guidelines and expected to follow the social distancing norms.

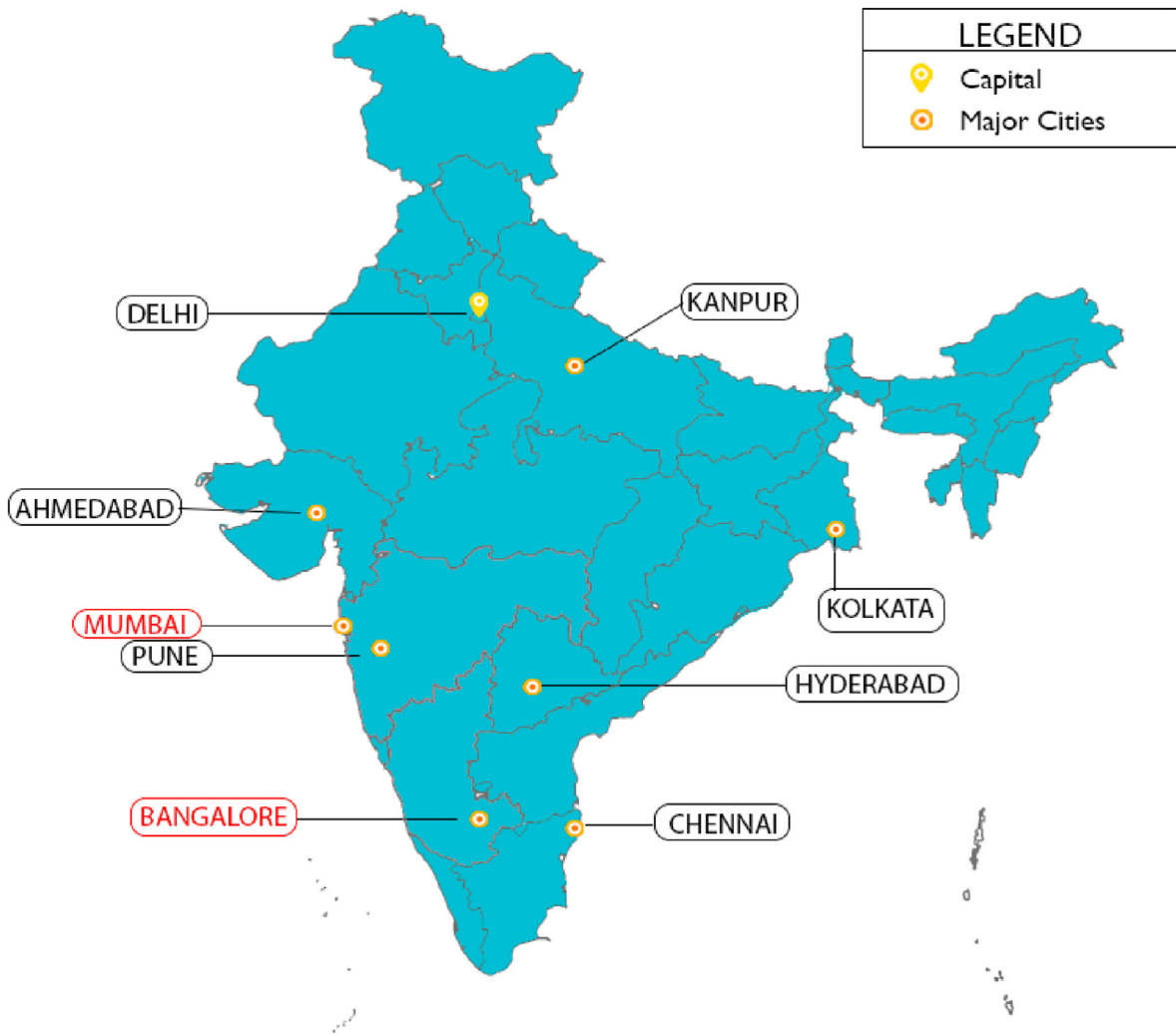


Fig 3. -Major cities of India.

3. *Low income level population* is the percentage of population in that locality who are below the national poverty line. Disadvantaged groups including people in poverty, often living in overcrowded conditions which make social distancing difficult.
4. *Air Pollution* is measured by $PM_{2.5}$ per cubic meter (micrograms per cubic meter). The safe limit is $60\mu\text{g}/\text{m}^3$. Air pollution aggravates respiratory disease and lowers natural immunity.

2.1.3. Health care and government efforts to control the virus transmission

WHO (World Health Organization) recommends that each country must continue to implement National Action Plans based on a realistic appraisal of what is feasible to achieve slowing down of transmission (find, test, isolate and care for cases and quarantine contacts to control transmission) and these plans must be flexible enough to react to rapidly changing epidemiological situations in different parts of the country, and take into account the local contexts and capacities to respond. (WHO Report, 2020)

In this research the key variables for Government efforts to trace, test, isolate and quarantine contacts for controlling transmission are:

1. *Home and Institutional Quarantine* is the number of corona positive patients who have been put under home quarantine and in COVID-19 care centers.
2. *Buildings Sealed* is the number of Containment zones and sealed buildings (help to control the virus from spreading to adjacent areas).
3. *Proactive Screening of the Elderly* is the number of elderly cases who were proactively screened for early detection, timely treatment and recovery.

Table 1
Demographic variables and COVID-19 cases for the six most populated cities in India.

	Density	COVID-19 Cases	Population
Mumbai	25771	100014	12442273
Chennai	21000	92206	4681087
Hyderabad	18,172	33902	3943323
Delhi	11320	127364	16349831
Kolkata	7,480	23837	14112536
Bengaluru	4378	23911	8425970

(Data Source: [Census \(2011\)](#) and www.mygov.in/COVID).

Table 2
Socioeconomic and Environmental variables for Mumbai and Bengaluru.

Cities	Senior citizens (above 60 years)	Literate Population %	PM 2.5 per cubic metre(microgram) Safe limit 60µg/m3
Mumbai	6.48	89.9	100
Bengaluru	7.76	88.68	123

(Data Source: Census 2011 and COVID-19 data from www.mygov.in/COVID (as of 15, July 2020)).

2.2. Sampling

Fig. 3 below shows some of the largest cities of India based on population. The study sample to explore the relationship between crowding variables and COVID-19 infection rate was selected from the six most populated cities of India as shown in **Table 1**.

The study is based on Mumbai and Bengaluru (earlier known as Bangalore) which are ranked 1st and 6th in terms of density among the six most populated cities of India. The COVID-19 incidence rates were taken during the peak period of COVID-19 infection transmission i.e. July 2020.

The densest and least dense city along the continuum of density has been selected to get a better understanding of the relationship between crowding and the virus infection. Since density and crowding are used interchangeably in most studies ([Chang, 1999](#)) density has been used as a criterion for city selection. Both cities are in the same stage of infestation.

With a population of 12.4 million, Mumbai is the densest city of India and the second most populated city after New Delhi ([Census, 2011](#)). What is more alarming is that 52.5 % of this population lives in slums which hardly occupy 7% of the city area ([MCGM, 2011](#)) making it an obvious candidate for a COVID-19 hotbed.

On the other hand, Bengaluru the 4th most populated city with a population of 8.42 million is the least dense city in the list of the top six populated cities of India. It was hailed as a model city in India practicing rigorous tracing, testing and treatment but after the lockdown was lifted, it has had a sudden surge.

3. Data analysis

Since a ward-wise data for socioeconomic and environmental variables was not available, it was necessary to examine the city-level data for those variables. **Table 2** reveals that both cities are almost at par on all variables. However, the testing rate of Mumbai at 35610 persons per one million population is much higher than Bengaluru at 22610 persons per one million population.

Table 3 (below) shows the ward wise data of Mumbai with the independent variable (No of COVID-19 positives per 1 million population) against dependent variables for “Crowding” (Population, Gross Density, Net Density, Indoor Crowding, Street Crowding) and “Government Efforts to control the virus” (Quarantined cases (home and institutional), Sealed Buildings, Proactive Screening of Elderly).

Table 4 shows the ward wise data of Bengaluru with the independent variable (No of COVID-19 positives per 1 million Population) against dependent variables for Crowding (Population, Gross Density, Net Density, Indoor Crowding, Street Crowding) and Government Efforts to control the virus(Quarantined cases (home and institutional), Sealed Buildings, Proactive Screening of Elderly).

4. Statistical analysis and discussion

In the analysis, the main focus will be given to correlation and regression analysis. In the simple linear regression model, the dependent variable is COVID-19 incidence rate and the independent variables will be from the “Crowding variables” group and “Government efforts to control the Virus”. In this way, it will be possible to detect the size and impact of correlation between COVID-19 with “Crowding variables” and “Government efforts variables”. To study the effects of density on COVID-19 incidence a further study has been done on the slums of Mumbai. However, the Bengaluru slums have been omitted from the discussion as only 10% of Bengaluru population lives in the slums and the number of slums is also very less (597 government notified). Most of these slums are in the fringe areas of the city and not much data is available on COVID-19 incidence in the Bengaluru slums.

Table 3
Showing ward wise data of Mumbai with Independent variable vs Dependent Variables.

Ward name	Ward Area	No of COVID-19 positives per 1 million Population(as of 15 July,2020)	CROWDING VARIABLES					HEALTH CARE AND GOVERNMENT EFFORTS TO CONTROL VIRUS		
			Population (Census 2011)	Gross Density (persons/Sq km)	Net Density (persons/Sq km)	Indoor Crowding (persons/Sq km)	Street Crowding (persons/Sq km)	Quarantined (home and institutional)	Sealed Buildings	Proactive Screening of Elderly
A	Colaba	12640	185014	14801	17243	4240	9026	7805	54	5031
B	Sandhurst Road	7140	127290	50916	69557	34587	20205	1925	57	5888
C	Marine Lines	8430	166161	92312	159770	69131	26635	3711	0	12078
D	Grant Road	10660	346866	52555	70789	35792	39692	23933	295	9941
E	Byculla	10120	393286	53147	67808	30211	34197	12750	0	20941
FN	Matunga	7800	529034	40695	48138	51576	48985	22574	252	20021
FS	Parel	14030	360972	25784	27767	25763	51841	48266	185	13292
GN	Dadar	10250	599039	65828	72000	25920	133120	19856	199	15612
GS	Elphinstone	11990	377749	37775	47756	17192	44127	20372	186	40739
HE	Khar	7010	557239	41277	45304	16309	80935	16860	109	10442
HW	Bandra	8620	307581	26516	30820	11095	27403	5461	152	11884
KE	Andheri E	7760	823885	33221	37012	13324	57214	38537	748	46799
KW	Andheri W	8970	748688	31995	39178	14104	41250	20571	359	9248
L	Kurla	5360	902225	56744	65856	23708	65643	38414	90	218795
ME	Chembur E	4660	807720	24853	26500	9540	55605	10699	101	39026
MW	Chembur W	7390	411893	21123	25776	9279	36308	32012	101	14224
N	Ghatkopar	8570	622853	23956	26104	9398	64881	19894	352	31731
PN	Malad	6760	941366	49286	58616	21102	71970	26933	493	15544
PS	Goregaon	6960	463507	18996	22051	7938	20089	22434	221	24121
RC	Borivli	8160	562162	11243	11678	4204	62987	32009	704	11755
RN	Dahisar	5750	431368	23965	26910	9688	39257	9624	211	20814
RS	Kandivili	6350	691229	38833	44682	16085	51598	17620	557	15750
S	Bhandup	7960	743783	11622	12628	4546	42501	34000	135	15276
T	Mulund	12340	341463	7521	10064	3623	32062	11558	441	12729

(Data Source: MCGM, Census 2011 and BMC COVID-19 Response War Room Dashboard, July 15, 2020).

Table 4

Showing Zone wise data of Bengaluru with independent variable versus dependent Variables.

Zone Area	No of COVID-19 positives per 1 million Population(as of 15 July,2020)	CROWDING VARIABLES					HEALTH CARE AND GOVERNMENT EFFORTS TO CONTROL VIRUS		
		Population (Census 2011)	Gross Density (persons/Sq km)	Net Density (persons/Sq km)	Indoor Crowding (persons/Sq km)	Street Crowding (persons/Sq km)	Quarantined (home and institutional)	Sealed Buildings	Proactive Screening of Elderly
Yelahanka	2000	545799	5496	7878	4052	1818	1560	306	Data Not available
Dasarahalli	770	445604	15971	29239	11696	3571	263	127	
Rajarajeshwari	2160	742411	6743	10986	4394	1631	277	654	
East	3130	1684175	18366	31825	9547	4458	1731	280	
West	4250	1275992	32386	69879	20964	6036	1637	783	
Mahadevapura	1620	878991	5125	6866	3090	2022	190	490	
South	3330	1961797	27438	63162	18948	4851	1415	2765	
Bommanahalli	2440	908906	29776	15946	5740	2233	410	924	

(Data Source: Census 2011 and BBMP COVID-19 War Room Booklet, July 2020).

4.1. Analysis by Multiple Linear Regression analysis using SPSS

4.1.1. Effect of crowding variables on COVID-19 rate for Mumbai and Bengaluru

The output of the multiple linear Regression analysis and Correlation using SPSS (Results in Annexure 1) has been comparatively analyzed for both cities to study the difference in the effect of crowding variables on COVID-19 incidence rate. The effect of Crowding variables on COVID-19 incidence is weaker in the densely populated urban conglomeration of Mumbai ($R = 0.602$) compared to Bengaluru ($R = 0.980$).

Correlation explains the linear association between two quantitative variables. The degree of association is measured by a correlation coefficient. In the case of a densely populated city like Mumbai there is a very weak association of crowding variables (Gross and Net Density, Indoor and Street Crowding). But in both the cities, it is seen that Gross Density has the lowest correlation with COVID-19 incidence among all crowding variables.

Interpretations	Model Summary & Anova	Standardized Coefficients	Unstandardized Coefficients	Pearson Correlation & Multi Collinearity
Mumbai Crowding Variables (Reasonably Normal distribution of Residuals in histogram and P-P chart. Linearity in relationship checked)	The prediction of COVID-19 rate by crowding variables is statistically significant and $R = 0.602$, 36.2 percent (variance)of COVID-19 rate predicted by crowding variables	Ranking of order of importance of crowding variables on its effect on COVID-19 rate 1. Population 2. Street Crowding 3. Gross Density 4. Indoor Crowding 5. Net Density	Indoor & Street Crowding have a positive relationship with COVID-19 rate. Population, Gross and Net Density have a negative relationship with COVID-19 rate.	Strongest correlation between COVID-19 rate and Population. Rest all is weak. (population-0.514,Gross Density -0.111, Net Density -0.069, Indoor Crowding 0.027, Street Crowding -0.132) Extremely High multicollinearity (VIF> 10)with Gross & Net Density
Bengaluru Crowding Variables (Reasonably Normal distribution of Residuals in histogram and P-P chart. Linearity in relationship checked)	The prediction of COVID-19 rate by crowding variables is extremely significant and $R = 0.980$, 96 percent (variance)of COVID-19 rate predicted by crowding variables	Ranking of order of importance of crowding variables on its effect on COVID-19 rate 1. Net Density 2. Indoor Crowding 3. Population 4. Gross Density 5. Street Crowding	Indoor Crowding is negatively correlated and others have weak positive correlation	Pearson Correlation shows extremely high correlation between COVID-19 rate and all crowding variables(Population-0.757,Gross Density 0.656, Net Density 0.736, Indoor Crowding 0.656, Street Crowding 0.704) Extremely high multicollinearity between Net Density and Indoor Crowding

4.1.2. Effect of government policy variables on COVID-19 rate for Mumbai and Bengaluru

The output of the multiple linear Regression analysis and Correlation using SPSS (Results in Annexure 1) has been comparatively analyzed for both cities to study the effect of Government policy on COVID-19 incidence rate.

The effect of Government policy variables on COVID-19 incidence is weaker in the densely populated urban conglomeration of Mumbai($R = 0.432$) rather than Bengaluru($R = 0.792$). Again, the correlation (Pearson Correlation) of COVID-19 rate with all the crowding variables is positive in Bengaluru but is very weak in the highly dense city of Mumbai. In the case of a densely populated city like Mumbai, there is a very weak association of government efforts variables (quarantined - home and institutional, and sealed buildings) but a moderately strong association with Population and proactive screening of the elderly. On the other hand, the less dense

Table 5
Showing ward wise Mumbai's slum distribution and COVID-19 incidence rate.

Ward Area	COVID-19 positive rate (Persons per 1 million Population)	Slum Population 2011	Slum Density	Slum % Population
Colaba	12640	22282	139263	12.04
Sandhurst Road	7140	12711	1166147	9.99
Marine Lines	8430	16571	103569	9.97
Grant Road	10660	34699	54217	10.00
Byculla	10120	124194	116069	31.58
Matunga	7800	238128	158752	45.01
Parel	14030	180128	281450	49.90
Dadar	10250	361674	196562	60.38
Elphinstone	11990	124306	327121	32.91
Khar	7010	388923	153119	69.79
Bandra	8620	82552	161867	26.84
Andheri E	7760	572818	170482	69.53
Andheri W	8970	215678	205408	28.81
Kurla	5360	758108	165888	84.03
Chembur E	4660	685994	193238	84.93
Chembur W	7390	164992	120432	40.06
Ghatkopar	8570	249229	91293	40.01
Malad	6760	708247	161332	75.24
Goregaon	6960	230829	181755	49.80
Borivli	8160	172,849	131946	30.75
Dahisar	5750	281151	159745	65.18
Kandivili	6350	414395	187509	59.95
Bhandup	7960	408442	94766	54.91
Mulund	12340	85560	161434	25.06

(Data Source: MCGM, Census 2011 and BMC COVID-19 Response War Room Dashboard, July 15, 2020).

city of Bengaluru shows a moderately high degree of association with “Government efforts to control the virus”.

Interpretations	Model Summary & Anova	Standardized Coefficients	Unstandardized Coefficients	Pearson Correlation & Multi Collinearity
Mumbai Government Policy Variables (Normal distribution of Residuals in the histogram and P-P chart. Linearity in relationship checked)	The prediction of COVID-19 rate by government policy variables is statistically insignificant and $R = 0.432$, 19.2 percent (variance) of COVID-19 rate predicted by crowding variables	Ranking of the order of importance of government policies 1. screening 2. quarantined 3. sealed buildings	All three variables are weakly effective	Value of Pearson correlation is quite weakly negative with all 3 variables No multicollinearity
Bengaluru Government Policy Variables (Normal distribution of Residuals in histogram and P-P chart. Linearity in relationship checked)	The prediction of COVID-19 rate by government policy variables is statistically significant and $R = 0.792$, 62.7 percent (variance) of COVID-19 rate predicted by crowding variables	Ranking of order of importance of government policies 1. Quarantine 2. Sealed Buildings	Both variables are moderately positive	Value of Pearson correlation is positive with all 3 variables No multicollinearity

4.1.3. Mumbai slums

A lot has been reported about slums being a fertile ground for the rapid transmission of the virus. So to explore the density dimension further, a study of the COVID-19 incidence in Mumbai slums is done. Dharavi in Mumbai, the biggest slum of Asia has been often quoted as a ticking time bomb. Mumbai's slums accommodate approximately 380 households per hectare as compared to 175 households per hectare in non-slum areas. So observing the infection rate in slums which are compounded with the high-density overcrowded settlements and unsanitary living conditions could help us understand the relationship better.

Looking at Table 5 (below), we can see that Dadar which houses the Dharavi slum has quite a high level of COVID-19 incidence. Kurla and Chembur(E) which have a very high percentage of slum population, however, do not have a very high COVID-19 infection rate.

The output of the multiple linear Regression analysis and Correlation using SPSS (Results in Annexure 1) has been analyzed in the table below for the slums of Mumbai.

Interpretations	Model Summary & Anova	Standardized Coefficients	Unstandardized Coefficients	Pearson Correlation & Multi Collinearity
Mumbai Slums Crowding Variables (Reasonably Normal)	The prediction of COVID-19 rate by crowding	Ranking of the order of importance of crowding	Density does not affect (positive or	Pearson correlation is quite strongly negative at-0.603 with

(continued on next page)

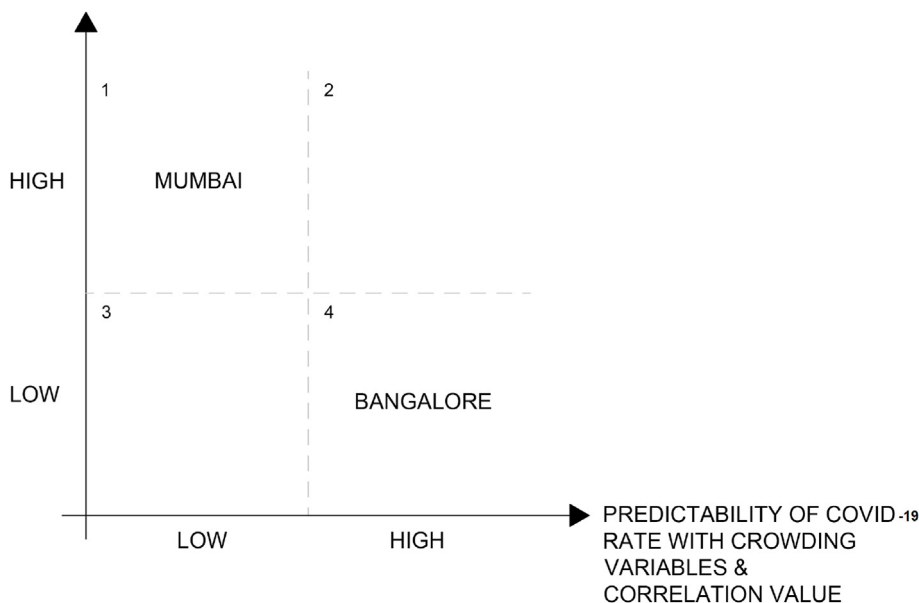


Fig 4. Positioning of Mumbai and Bengaluru on Density versus Predictability of COVID-19 with respect to Crowding variables and Correlation strength (Source: author, 2021).

(continued)

Interpretations	Model Summary & Anova	Standardized Coefficients	Unstandardized Coefficients	Pearson Correlation & Multi Collinearity
distribution of the Residuals in histogram and P-P chart. Linearity in relationship checked)	variables is statistically significant and R = 0.629 , 39.5 percent (variance) of COVID-19 rate predicted by crowding variables	variables on its effect on COVID-19 rate 1.Population(0.640) 2.Gross Density(0.184)	negative) Population weakly negative	Population but very weakly negative with Gross Density at -0.053 No multicollinearity

A look at the densest parts of Mumbai city which are the slums shows that R value is 0.629. Here too there is some correlation of COVID-19 incidence with Population but not with density.

4.2. Result analysis

To summarize, the statistical analysis reveals that for a densely populated city of Mumbai, there is a low to moderate correlation and predictability between COVID-19 incidence rate and the crowding variables(Gross Density being the lowest of all 5 variables) and low predictability with government efforts (except screening of elders which has a moderate correlation). For a less dense city like Bengaluru, there is an extremely high correlation and predictability between COVID-19 incidence rate and the crowding variables (Gross Density again being the lowest of all 5 variables) and moderately high predictability with government efforts.

Fig. 4 shows a matrix where City density has been plotted versus its predictability of COVID-19 incidence rate. Mumbai, a city with high density is expected to have a high COVID-19 incidence rate and be positioned in Quadrant 2. Similarly, Bengaluru with a lower density is expected to have a low COVID-19 incidence rate and be positioned in Quadrant 3 in the matrix. However, Mumbai and Bengaluru are found to be in the 1st and 4th quadrant instead of the expected 2nd and 3rd quadrant (Fig. 4).

These strangely contradicting results can be explained by recent research (done by Epidemiological Modeling (EMOD) Group, Intellectual Ventures Laboratory) that after a threshold density the sub-linear relationship between density and infection rate flattens. The findings of this research are corroborated by the explanation given by Hu, H., et al., (2013).

Substantial evidence indicates that when Population density is at the scale of general activities, the transmission mode of respiratory diseases is likely to follow an initial sub-linear density-dependent pattern until the saturation of transmission rate transitions to a frequency-dependent pattern independent of Population density (Fig. 5). For high-density clusters, such as crowds at mass gatherings, the random movement and contact of individuals initially increase the frequency of contacts. However, the contact rate decreases at extremely high density, when it becomes difficult for people to move and make contact with others (Hu, H., et al., 2013).

Contact rate increases with higher density but after a certain level of density, the contact rate saturates and does not result in increased disease incidence. This explains the reason why Mumbai lying beyond the threshold level of density has reached a stage where

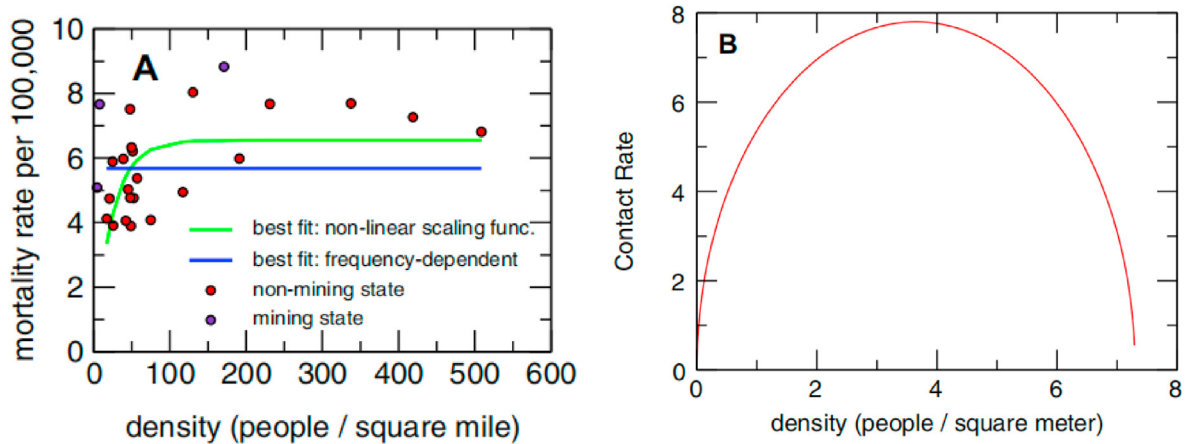


Fig 5. A. Relationship between Population density and 1918 Influenza mortality B. Relationship between Contact Rate and Population density. Data Source: Study by Epidemiological Modeling (EMOD) Group, Intellectual Ventures Laboratory, USA.

the contact rate is on a decreasing trend and hence the disease incidence correlation with density is negative. Whereas Bengaluru has not yet reached the threshold density level and due to the increasing contact rates there is a positive correlation between disease incidence and density.

5. Conclusion

The objective of the research was to explore the relationship between crowding variables and COVID-19 infection rate. The findings of the research contradict viewpoints put forward by various researches that denser cities are more vulnerable to pandemics. The different metrics of crowding are important to examine rather than simply substituting density for contact rate when exploring the causes for the transmission rate of a respiratory disease like COVID-19. Furthermore, density follows a sub-linear relationship with transmission rate and after a threshold density; the behavior of transmission is almost independent of the Population density. The findings of the highly dense Mumbai slums (where there was aggressive testing and containment zones than in the more affluent sections of the city for obvious reasons) further strengthen the observed independent behavior of density with transmission rate. One size does not fit all. Mumbai, a city with very high density levels has a significantly weaker relationship with causal variables (both “Crowding” and “Government effects to control the virus”) than Bengaluru, a city with moderate density levels.

The limitations of this research are that these findings need to be corroborated with cities of different densities across similar ethnic races, with studies at a more granular level, to find the threshold density where the curve flattens out. For the western world where the infection rate is higher, it would be reasonable to presume that the threshold density would be different as people respect personal space more and interpersonal contact rates are lesser except in mass transit use. The number of tests conducted is also important to curb the transmission rate and there should be random sampling-based mapping to make a reliable diagnosis of the causal variables.

Compact denser cities not only have a lower carbon footprint but also provide for economy of scale due to efficient use of resources. Rather than rejecting dense settlements, it is more important to take care that the density level is optimal so that there is no added pressure on existing transport infrastructure, utilities (water, sanitation, sewage treatment and disposal), open recreational spaces, public health and amenities.

Declaration of competing interest

The authors declare that there is no conflict of interest whatsoever.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.jum.2021.08.002>.

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