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Transmission in home environment associated with the second wave of COVID-19 pandemic in India

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ABSTRACT

India has suffered from the second wave of COVID-19 pandemic since March 2021. This wave of the outbreak has been more serious than the first wave pandemic in 2020, which suggests that some new transmission characteristics may exist. COVID-19 is transmitted through droplets, aerosols, and contact with infected surfaces. Air pollutants are also considered to be associated with COVID-19 transmission. However, the roles of indoor transmission in the COVID-19 pandemic and the effects of these factors in indoor environments are still poorly understood.

Our study focused on reveal the role of indoor transmission in the second wave of COVID-19 pandemic in India. Our results indicated that human mobility in the home environment had the highest relative influence on COVID-19 daily growth rate in the country. The COVID-19 daily growth rate was significantly positively correlated with the residential percent rate in most state-level areas in India. A significant positive nonlinear relationship was found when the residential percent ratio ranged from 100 to 120%. Further, epidemic dynamics modelling indicated that a higher proportion of indoor transmission in the home environment was able to intensify the severity of the second wave of COVID-19 pandemic in India.

Our findings suggested that more attention should be paid to the indoor transmission in home environment. The public health strategies to reduce indoor transmission such as ventilation and centralized isolation will be beneficial to the prevention and control of COVID-19.

1. Introduction

Since early March 2021, India has experienced a catastrophic second wave of the coronavirus disease 2019 (COVID-19) pandemic; this outbreak is much more serious than the first wave pandemic, which occurred from July to September of last year (The Lancet, 2021). The number of confirmed COVID-19 cases in India hit a record of more than 400,000 per day in early May, while the daily COVID-19 confirmed cases of most other countries in the Northern Hemisphere did not show a similar change (Dong et al., 2020). This abnormal phenomenon suggests that different transmission characteristics may exist during the second COVID-19 wave pandemic in India.

COVID-19 is a viral respiratory infectious disease that can spread through droplets and aerosols (van Doremalen et al., 2020; Zhang et al., 2020a). Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a member of the human beta coronavirus family, is the causative pathogen of COVID-19 which can remain infectiously active for a long period of several hours to more than a week on aerosols and surfaces (Kampf...
A study based on laboratory experiments had confirmed SARS-CoV-2 was able to retain infectivity and virion integrity in respirable-sized aerosols for about 16 h (Fears et al., 2020). Previous studies have indicated the potential extra infectious risk of COVID-19 in indoor environments, such as classrooms, offices, and hospital (Abbas and Dino, 2021; Borro et al., 2021; Buonanno et al., 2020a; Guo et al., 2020). For hospital environment, more than half of the rooms in hospital with COVID-19 confirmed patients were detected to have environmental surfaces contaminated by SARS-CoV-2 (Chia et al., 2020). In particular, the exposure risk of COVID-19 in the ICUs with confirmed COVID-19 patients was significantly higher than COVID-19 respiratory investigation wards (Ge et al., 2020). Passengers in vehicles with a confined space such as train was also supported to have high infectious risk of COVID-19 (Hu et al., 2021). And for school building environment, infection probability of COVID-19 was supported to strongly depend on ventilation rate (Park et al., 2021).

Accordingly, the enrichment of infectious aerosols (Abouleish, 2021; Buonanno et al., 2020a), contact with contaminated surfaces (Morawaska and Cao, 2020; Mouchtouri et al., 2020), and the changes in human behavioural response to non-pharmaceutical interventions (NPIs) (Xiao et al., 2021) were supported to be associated with the extra infectious risk of COVID-19 in indoor environments. A case report from Singapore found that the toilet bowl, sink and air exhaust outlets in COVID-19 patient’s room were tested positive which suggested contaminated surfaces as a potential medium of COVID-19 transmission (Ong et al., 2020).

Pollutants, such as particulate matter, volatile organic compounds, and polycyclic aromatic hydrocarbons in indoor environments, have also been shown to be associated with the transmission of COVID-19 (Coccia, 2021d; Domingo and Rovira, 2020; Espejo et al., 2020; Lopez-Feldman et al., 2021). The relative humidity in indoor environment was able to affect the transmission of COVID-19 by alter the infectious particle’s aerodynamic diameter, length of time airborne, and viability (Dhand and Li, 2020).

India has a large population and high population density in urban areas. As human mobility in India has decreased significantly since the second wave of COVID-19 pandemic which is supported by the data from Google Community Mobility Reports, it is obvious that people in India have more opportunities to stay in indoor environments and face the potential health risk of COVID-19 indoor transmission. Therefore, it is important to estimate the health risks of indoor environments and the potential roles of indoor transmission in the second wave of COVID-19 pandemic in India.

Further, some other existing studies which can support the theoretical framework of this study are largely around the transmission characteristics of COVID-19 in urban and in the indoor environment. Low wind speeds and high levels of air pollution were indicated to have association with higher COVID-19 confirmed cases and deaths among Italian cities (Coccia, 2021d). Italian provincial capitals with air pollutant exceeding the limits set over 100 days per year were found to have more COVID-19 confirmed individuals (Coccia, 2020a). Mario Coccia indicated the potential transmission mechanisms were the accumulation of infectious particulate matter air and pollution-to-human transmission (Coccia, 2020a, 2021a, 2021d). Urban ventilation and atmospheric stability played important roles in those transmission dynamics (Coccia, 2021a). Other studies tried to demonstrate the high transmission risk of COVID-19 in confined spaces and the important of ventilation in indoor environment. A Chinese modelling study estimated the infection probability of COVID-19 in confined spaces under different ventilation rates and revealed ventilation rates above the usual value was needed to reduce the infection probability to below 1% (Dai and Zhao, 2020). Ai et al. used tracer gas to investigate the airborne transmission of exhaled droplet nuclei in room environment, according to which, the relative position of the persons in room environment was an unimportant factor for COVID-19 transmission and horizontal air distribution was able to reduce the transmission risk (Ai et al., 2019). Similar discussions were reported by other researchers that proper ventilation can significantly reduce the health risk of COVID-19 transmission in indoor environment (Buonanno et al., 2020b; Park et al., 2021; Sun and Zhai, 2020).

Hence, this study mainly aimed to reveal the potential role and epidemic dynamics of indoor transmission in the second wave of COVID-19 pandemic in India. In order to explore this question, we first evaluated the importance of human mobility in different environments to COVID-19 transmission by using the aggregated boosted tree (ABT) models and the multiple-variable generalized additive model (GAM). Then, based on the results provided by the ABT model, we calculated the correlation and quantitative effects between home environment transmission and COVID-19 growth rate in 30 state-level areas in India during the second wave of COVID-19 pandemic. Subsequently, we used the Susceptible-Exposed-Infectious-Removed model to estimate the epidemic dynamics under different initial conditions to reveal the potential impact of different proportions of indoor transmission in the home environment during the second COVID-19 wave. The findings of our study could help to explain the unusually severe second COVID-19 wave in India from the perspective of the indoor environment and will provide new insights into the characteristics of COVID-19 transmission indoors. This will contribute to future research on the prevention and control of COVID-19.

2. Methods

2.1. Sample and data

Thirty state-level areas, including states and union territories (UTs), which had complete data on both human mobility and COVID-19 daily growth rate from May 1, 2020 to May 13, 2021 were selected as the study areas.

Data on human mobility in India during the period from May 1, 2020 to May 13, 2021 were collected from Google COVID-19 Community Mobility Reports (https://www.google.com/covid19/mobility/). This dataset generated the change rate of the daily requests of Google Maps compared to the average requests of the baseline period (from January 3, 2020 to February 6, 2020). The human mobility data from the Google COVID-19 Community Mobility Reports were collated into six categories (retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential), each of which represented human mobility in a different type of environment. The residential change rate was an important aspect of the human mobility dataset, which was supported as a measurement of the proportion of indoor activities and the corresponding possibility of COVID-19 indoor transmission in the home environment (Saha and Chouhan, 2021; Sulyok and Walker, 2020; Zhu et al., 2020a).

The state-level COVID-19 time series and the corresponding state-level population in India from the May 1, 2020 to the May 13, 2021 were collected from the open-source dataset of COVID-19 India (https://github.com/covid19india/api) and India Census in GitHub.

2.2. Measures of variables

The variables in this study were human mobility in six categories (retail and recreation, grocery and pharmacy, parks, transit stations, workplaces, and residential) and the COVID-19 daily growth rate in 30 state-level areas in India. The human mobility was measured with the percent rate of change compared to baseline time period. In this study, to normalize the data and avoid negative values, the percent change of human mobility was transformed into a percent rate.

2.3. Model and data analysis procedure

To determine the effects of human mobility in different
environments on the daily growth rate of COVID-19 confirmed cases in India, an aggregated boosted tree (ABT) was performed using the R package “gbm” with 500 trees for boosting. ABT is a machine learning algorithm based on boosted trees which can be used to quantitatively evaluate and rank the relative importance of each explanatory variable on the response variable (De ath, 2007). This model is better at dealing with nonlinear interactions among variables.

To analyse and compare the correlation between the residential percent rate and the corresponding daily growth rate of COVID-19 confirmed cases, nonparametric Spearman and Kendall rank correlation tests were used to calculate the correlation coefficients among 30 state-level areas in India from May 1, 2020 to May 13, 2021. The generalized additive model (GAM) was used to estimate the descriptive nonlinear relationship between human mobility and the COVID-19 growth rate. Further, piecewise linear regression was used to quantitatively estimate the effect of indoor transmission on the COVID-19 growth rate based on the GAM analysis results.

The Susceptible-Exposed-Infectious-Removed (SEIR) model was used to estimate the dynamic impact of different proportions of indoor transmission on COVID-19 pandemic, as previous studies have suggested (He et al., 2020; Kucharski et al., 2020; Prem et al., 2020). The SEIR model was set as follows,

\[\frac{dS(t)}{dt} = -\beta(t)\frac{S(t)I(t)}{N}\]
\[\frac{dE(t)}{dt} = \beta(t)\frac{S(t)I(t)}{N} - \sigma E(t)\]
\[\frac{dI(t)}{dt} = \sigma E(t) - \gamma I(t)\]
\[\frac{dR(t)}{dt} = \gamma I(t)\]

where \(S(t), E(t), I(t),\) and \(R(t)\) represent the numbers of susceptible, exposed, infectious, and recovered individuals at time \(t;\) \(\beta\) is the effective contact rate or the transmission rate; \(\sigma\) is the incidence of the incubation period patient transformed to an infectious patient; and \(\gamma\) is the recovery rate. The mean incubation period and the mean recovery period were selected as 4.7 days and 10 days according to the literature (Guan et al., 2020; Wiersinga et al., 2020; Zhai et al., 2020), and the corresponding \(\sigma\) and \(\gamma\) values were 0.213 and 0.1, respectively.

To calculate the impact of different proportions of indoor transmission in the COVID-19 pandemic, the transmission of COVID-19 occurs in both indoor and outdoor environments; according to the Bayesian formula, \(\beta\) is given as follows:

\[\beta = (1 - kr_p)\beta_o + kr_p\beta_i - (1 - kr_p)kr_p\beta_o\beta_i\]

where \(\beta_o\) is the transmission rate for the outdoor environment, \(\beta_i\) is the transmission rate for the indoor environment, \(r_p\) is the residential percent rate, \(K\) is the coefficient, and \(kr_p\) represents the proportion of indoor transmission.

The COVID-19 transmission rate for outdoor environments was selected as 0.05, which was calculated based on previous studies (Biswas et al., 2020; Zhang et al., 2021), and the COVID-19 transmission rate for indoor environment was calculated using an online tool provided by the Max Planck Institute (Lelièvred et al., 2020). The corresponding parameters and COVID-19 transmission rates are shown in Table 1, where the \(\beta_i\) in home environment was set to approximately 0.11 (11%). The GAM and SEIR modelling were also finished via R version 3.6.2.

To calculate the coefficient \(k\), the average \(\beta\) during the period from 22 February to February 28, 2021 and the corresponding average \(r_p\) during the same period were fitted into the above formula. As a result, the coefficient \(k\) was defined as 0.007302 for the home environment in this study.

### Table 1
The infectious risk in different environments for the condition in India.

| Environment     | Retail | Grocery | Parks | Transit | Workplaces | Residential |
|-----------------|--------|---------|-------|---------|------------|-------------|
| Air exchange rate (/h) | 1      | 0.35    | 6     | 6       | 3          | 2           |
| Floor size (m²)   | 100    | 20      | 200   | 200     | 20         | 40          |
| Height (m)        | 3      | 3       | 3     | 3       | 3          | 3           |
| Duration (h)      | 4      | 0.5     | 3     | 2       | 8          | 12          |
| Susceptible People | 10     | 5       | 100   | 100     | 4          | 2           |
| Transmission rate (%) | 12     | 6.3     | 5.4   | 7.2     | 20         | 11          |

Air exchange rate set as 0.35 for no ventilation and 6 for public places.
Table 2
A. Descriptive analysis of human mobility and COVID-19 daily growth rate in 30 state-level areas in India before the second wave of COVID-19 pandemic in India.

| Category   | Mean    | SD     | Min | Max | P25 | P75 | Skewness | Kurtosis |
|------------|---------|--------|-----|-----|-----|-----|----------|----------|
| Retail     | 85.365  | 53.674 | 24  | 458 | 71  | 82  | 5.064    | 24.964   |
| Grocery    | 122.43  | 83.405 | 31  | 650 | 99  | 119 | 5.009    | 24.601   |
| Parks      | 98.195  | 50.929 | 39  | 476 | 79  | 100 | 4.685    | 23.396   |
| Transit    | 106.061 | 79.231 | 39  | 654 | 85  | 99  | 5.13     | 25.395   |
| Workplaces | 91.81   | 35.499 | 22  | 336 | 80  | 94  | 4.446    | 21.324   |
| Residential| 108.493 | 3.217  | 101 | 123 | 106 | 111 | 0.257    | 0.045    |
| Growth     | 0.101   | 0.128  | 0   | 2.166| 0.032| 0.123| 4.814    | 47.813   |

2021.3.1–2021.5.13

| Category   | Mean    | SD     | Min | Max | P25 | P75 | Skewness | Kurtosis |
|------------|---------|--------|-----|-----|-----|-----|----------|----------|
| Retail     | 77.274  | 61.223 | 13  | 479 | 55  | 83  | 4.674    | 24.178   |
| Grocery    | 119.123 | 91.8   | 15  | 733 | 90  | 124 | 4.698    | 25.408   |
| Parks      | 89.163  | 59.39  | 20  | 567 | 66  | 96  | 4.839    | 24.887   |
| Transit    | 96.784  | 83.271 | 18  | 692 | 69  | 99  | 4.989    | 26.367   |
| Workplaces | 82.912  | 38.773 | 16  | 336 | 64  | 93  | 3.592    | 17.487   |
| Residential| 113.058 | 8.147  | 99  | 141 | 107 | 118 | 0.917    | 0.045    |
| Growth     | 1.001   | 0.996  | 0   | 4.413| 0.112| 1.747| 0.844    | −0.316   |

Fig. 1. The COVID-19 daily growth rate in the 30 state-level areas in India under different human mobility conditions during January 1, 2021 to February 28, 2021.

High mobility Grocery and pharmacy and Residential groups. Moreover, the high mobility group of transit stations corresponded to a lower daily COVID-19 growth rate. During the second wave of COVID-19 pandemic, the high human mobility group in the residential category was significantly associated with a higher daily COVID-19 growth rate, while the other five categories of human mobility were negatively associated with the COVID-19 growth rate.

Low: Human mobility in the percentiles range of 0%–25%;
Moderate: Human mobility in the percentiles range of 25%–75%;
High: Human mobility in the percentiles range of 75%–100%;

*p*-value was given by one-way ANOVA test.
COVID-19 daily growth rate in the 30 state-level areas in India before and during the second COVID-19 wave. The results of this analysis are shown in Fig. S2 and Fig. S3 in Appendix, and indicate that the relationship between human mobility and the COVID-19 daily growth rate had significant differences before and during the second wave of COVID-19 pandemic in India. In general, before the second COVID-19 wave, human mobility in three categories (grocery and pharmacy, workplaces, and residential) showed a positive correlation with the corresponding COVID-19 daily growth rate, while human mobility in the other two categories (retail and recreation, and transit stations) was negatively correlated with the COVID-19 daily growth rate. In addition, human mobility in the categories of Parks showed an uncertain relationship with the COVID-19 daily growth rate, with an approximate horizontal exposure-response curve and a wide 95% confidence interval. During the second COVID-19 wave, human mobility in two categories (grocery and pharmacy, and residential) showed a positive correlation with the corresponding COVID-19 daily growth rate, while human mobility in the other two categories (retail and recreation, and parks) was negatively correlated with the COVID-19 daily growth rate. However, human mobility in the categories of workplace and transit stations did not show an association with the COVID-19 daily growth rate.

Subsequently, we used the ABT model to determine the importance ranking and the relative influence of these six categories of human mobility in the COVID-19 pandemic. The results are presented in Fig. 3. Human mobility in the Residential categories was supported as the most important variable affecting the COVID-19 daily growth rate, especially during the second COVID-19 wave, with a relative influence of 24.85% before the second wave of COVID-19 pandemic and 68.46% during the second wave.

A: The relative influence of six categories of human mobility before the second wave of COVID-19 pandemic in India (January 1, 2021 to February 28, 2021).

B: The relative influence of six categories of human mobility during the second wave of COVID-19 pandemic in India (March 1, 2021 to May 13, 2021).

As the above results indicated the importance of human mobility in the residential category during the second wave of COVID-19 pandemic, we next focused on the relationship between the residential percent rate and the corresponding COVID-19 daily growth rate in 30 state-level areas in India. The Spearman and Kendall correlation coefficients

![Fig. 2. The COVID-19 daily growth rate in the 30 state-level areas in India under different human mobility conditions during March 1, 2021 to May 13, 2021.](image1)

![Fig. 3. Aggregated boosted tree analysis showing the relative influence of human mobility on the daily growth rate of the COVID-19 confirmed cases in India.](image2)
between the COVID-19 daily growth rate and the residential percent rate in 30 state-level areas in India are summarised in Fig. S1D in Appendix. Among the 30 states and UTs of India involved in this study, 29 showed a significant positive correlation between daily growth rate and the corresponding residential percent rate with a Spearman correlation coefficient in the range of 0.138–0.822, and a Kendall correlation coefficient in the range of 0.075–0.626. These results demonstrated that the daily growth rate of COVID-19 confirmed cases in most state-level areas in India were significantly associated with the corresponding residential percent rate, suggesting that a higher proportion of indoor transmission in the home environment was associated with a faster increase in COVID-19 confirmed cases in India.

To further reveal the effect of residential indoor transmission on the COVID-19 daily growth rate in India, single-variable analyses for three different periods (from May 1, 2020, January 1, 2021, and March 1, 2021 to May 13, 2021) of daily residential percent rate were conducted by GAM. The results are presented in Fig. 4. According to the GAM results, the daily residential percent rate in India was significantly and positively correlated with the corresponding daily COVID-19 growth rate during all three periods. Among them, the residential percent rate had an approximately linear relationship with the COVID-19 growth rate of COVID-19 confirmed cases in most state-level areas in India during the second wave (from March 1, 2021 to May 13, 2021). The results are summarised in Table 3. These results indicate that a 1 percent change in the residential percent rate was significantly related to a range of 0.045–0.282 percent per day increase in COVID-19 daily growth rate among the 30 state-level areas in India. However, the effect of the residential percentage rate on the daily growth rate of COVID-19 in the range of 120–145% was uncertain and non-significant because the sample point in that range was too few or even did not appear.

A: Time period from May 1, 2020 to May 13, 2021.
B: Time period from January 1, 2021 to May 3, 2021.
C: Time period from March 1, 2021 to May 13, 2021.

To estimate the dynamic impact of different proportions of indoor transmission on the second wave of COVID-19 pandemic in India, we used the SEIR model to simulate the impact of three levels of residential percent rate (100%, 110%, and 120%, based on the piecewise linear regression results) under different average contact numbers (the number of close contacts to a single infected individual, set as 2, 4, and 8, or a =

Table 3

| Area          | Residential percent ratio ≤ 120 | Residential percent ratio > 120 |
|---------------|---------------------------------|---------------------------------|
|               | Percent change (%)              | 95% CI                           | Percent change (%)              | 95% CI                           |
| Andhra Pradesh| 0.111**                         | 0.098–0.123                      | -0.119                          | -0.303–0.065                     |
| Assam         | 0.117**                         | 0.102–0.133                      | 0.118                           | -0.048–0.283                     |
| Bihar         | 0.230**                         | 0.197–0.263                      | -0.235                          | -0.283–0.236                     |
| Chandigarh    | 0.083**                         | 0.062–0.105                      | 0.013                           | -0.073–0.100                     |
| Chhattisgarh  | 0.198**                         | 0.168–0.227                      | 0.075                           | -0.007–0.157                     |
| Delhi         | 0.173**                         | 0.144–0.201                      | -0.115                          | -0.403–0.173                     |
| Goa           | 0.143**                         | 0.121–0.164                      | 0.102                           | -0.168–0.371                     |
| Gujarat       | 0.202**                         | 0.164–0.240                      | 0.016                           | -0.057–0.090                     |
| Haryana       | 0.153**                         | 0.140–0.167                      | -0.234                          | -0.660–0.192                     |
| Himachal      | 0.157**                         | 0.136–0.177                      | -0.567**                        | -0.875–0.259                     |
| Jammu and Kashmir | 0.105**                     | 0.091–0.118                      | 0.129*                          | 0.005–0.253                      |
| Jharkhand     | 0.162**                         | 0.122–0.202                      | 0.146                           | -0.101–0.392                     |
| Karnatak      | 0.143**                         | 0.125–0.161                      | 0.024                           | -0.177–0.224                     |
| Kerala        | 0.104**                         | 0.077–0.131                      | 0.022                           | -0.032–0.075                     |
| Ladakh        | 0.075**                         | 0.030–0.121                      | 0.001                           | -0.022–0.034                     |
| Madhya        | 0.091**                         | 0.056–0.125                      | -0.038                          | -0.124–0.049                     |
| Maharashta    | 0.116**                         | 0.080–0.153                      | 0.014                           | -0.033–0.061                     |
| Manipur       | 0.045**                         | 0.033–0.057                      | 0.081**                         | 0.029–0.133                     |
| Meghalaya     | 0.075**                         | 0.048–0.101                      | 0.054                           | -0.022–0.129                     |
| Mizoram       | 0.130**                         | 0.107–0.153                      | -0.025                          | -0.579–0.529                     |
| Odisha        | 0.134**                         | 0.108–0.16                      | 0.071                           | -0.014–0.156                     |
| Puducherry    | 0.135**                         | 0.114–0.155                      | 0.026                           | -0.055–0.107                     |
| Punjab        | 0.079**                         | 0.065–0.093                      | -                        | -                        |
| Rajasthan     | 0.225**                         | 0.199–0.250                      | -0.083*                         | -0.159–0.007                     |
| Tamil Nadu    | 0.121**                         | 0.095–0.147                      | 0.012                           | -0.045–0.069                     |
| Telangana     | 0.104**                         | 0.083–0.125                      | -0.073                          | -0.199–0.053                     |
| Tripura       | 0.056**                         | 0.046–0.066                      | -                        | -                        |
| Uttar Pradesh | 0.282**                         | 0.251–0.312                      | 0.015                           | -0.196–0.226                     |
| Uttarakahand  | 0.272**                         | 0.243–0.300                      | -0.018                          | -0.296–0.260                     |
| West Bengal   | 0.174**                         | 0.150–0.197                      | -0.010                          | -0.076–0.057                     |
| India         | 0.119**                         | 0.112–0.125                      | -0.010                          | -0.028–0.007                     |

- The sample points were too few or did not or not appear in the range of values.
- *p < 0.01.
- **p < 0.001.
2, 4, 8, the corresponding reproduction number was in the range of 0.84–3.83). The SEIR modelling results are shown in Fig. 5. Higher peak incidence rates and faster increases in cumulative incidence were observed when the residential percent rate increased under all three conditions. These simulation results further indicated that a higher proportion of indoor transmission could intensify the severity of the second wave of COVID-19 pandemic in India.

A: The existing incidence rate under a parameter of $c = 2$.
B: The existing incidence rate under a parameter of $c = 4$.
C: The existing incidence rate under a parameter of $c = 8$.
D: The cumulative infection rate under a parameter of $c = 2$.
E: The cumulative infection rate under a parameter of $c = 4$.
F: The cumulative infection rate under a parameter of $c = 8$.

4. Discussion

As the indoor environment is an important component of daily life, people remain indoors for extended periods of time, and a large proportion of human activities occur within the indoor environments. The importance of the transmission characteristics of COVID-19 in indoor environments has been indicated in previous studies (Azuma et al., 2020; Guo et al., 2020; Kohanski et al., 2020; Morawska and Cao, 2020). Indoor respiratory aerosol transmission has been considered to be the reason for several COVID-19 superspreading events in the United States and Japan (Furuse et al., 2020; Miller et al., 2021; Qian et al., 2021). Other studies have indicated an association between regional human mobility and COVID-19 spread (Chen et al., 2020; Kraemer et al., 2020; Xiong et al., 2020). In addition, digitally sourced datasets such as Apple Mobility Trends Reports (Shao et al., 2021), Twitter location (Huang et al., 2020), and Google Community Mobility Reports (Sulyok and Walker, 2020) have been widely used to reveal the potential relationship between human mobility and COVID-19 transmission. However, to the best of our knowledge, indoor transmission and its effect on the second wave of COVID-19 pandemic in India were not deeply investigated in previous studies.

Our study aimed to reveal the impact and intensifying effect of indoor transmission in the second wave of COVID-19 pandemic in India by using state-level human mobility and the corresponding COVID-19 surveillance data. According to our analysis results, human mobility in the categories of residential was the most important and most relative variable influencing COVID-19 daily growth rate among all six categories of human mobility, while human mobility in other indoor environments, such as retail and recreation, grocery and pharmacy, and workplaces did not show a similar importance during the second wave of COVID-19 pandemic in India. This indicated that although the transmission rate in other indoor environments, such as offices, shops, and entertainment venues, were also higher than in the outdoor environment, the impact and effect of indoor transmission in the second wave of COVID-19 pandemic in India might mainly occur in the home environment. Therefore, we focused on estimating the effect and impact of indoor transmission in the second wave of COVID-19 pandemic in India. The residential percent rate, which represents the level of staying in the home environment and the proportion of COVID-19 indoor transmission in the home environment, showed a significant positive correlation with the daily growth rate of COVID-19 confirmed cases in 29 state-level areas in India from May 1, 2020 to May 13, 2021. The GAM analyses indicated an approximately linear positive relationship between the residential percent rate and the corresponding COVID-19 daily growth rate when the residential percentage rate ranged from 100 to 120% in India, while flat and more uncertain relationships were indicated in the range of 120–140%. Based on the results of the GAM single-variable analysis, we calculated the COVID-19 infection risk under different residential percent rates.
percent rates by using piecewise linear regression. These results suggest that indoor transmission in the home environment had a significant enhancement effect on the COVID-19 pandemic when the residential percentage rate ranged from 100 to 120% in 30 state-level areas in India. Further, we estimated the impact of several proportions of indoor transmission on the second wave of COVID-19 pandemic in India using the SEIR model. The modelling results also demonstrated that the increase in indoor transmission in the home environment was able to intensify the severity of the second wave of COVID-19 pandemic in India.

5. Conclusion

In conclusion, our results indicate that indoor transmission in the home environment played an important role in the second wave of COVID-19 pandemic in India. Some implications can be drawn based on our study. First, indoor transmission in the home environment plays an important role in the second COVID-19 wave in India, while indoor transmission in other environments, such as offices, shops, and entertainment venues, might not have the same importance and impact. This may be a new transmission characteristic especially considering the high proportion of the delta variant of SARS-CoV-2 during the second wave of COVID-19 pandemic in India. The reason for the importance of indoor transmission in the home environment may be related to the exposure time, NPIs, and undetected infected individuals. Although the COVID-19 transmission rate in several common indoor environments is believed to be higher than that in the outdoor environment, only human mobility in the home environment increased during the second wave of COVID-19 pandemic, while human mobility in other indoor environments, such as offices, shops, and entertainment venues, decreased during the same period. The exposure time in the home environment was obviously much longer than the time spent in other indoor environments, especially under some public health policies, such as lockdown and stay-at-home orders during the second wave of COVID-19 pandemic. In addition, NPIs in the home environment might be different from those in other indoor environments. For example, people would tend to wear masks in indoor environments, such as offices, schools, and shops, rather than in home environments. Such behavioural changes in NPIs in different indoor environments could also affect the actual COVID-19 transmission rate. Second, since the start of the global spread of COVID-19, there has been a wide debate on whether home isolation or centralised isolation is more effective (Ju et al., 2021; Xu et al., 2020; Zhu et al., 2020b). The extra infection risk in indoor environments and its intensifying effect on COVID-19 pandemic, indicated by our study, seem to provide some positive evidence on the advantage of centralised isolation, especially when a large number of initially infected individuals already exists. Third, although the aerosol transmission of COVID-19 and the effects of air pollutants on the COVID-19 pandemic have been recognised by previous researchers (Filippini et al., 2021; Lopez-Feldman et al., 2021; Zhang et al., 2020b; Zhu et al., 2020c), their roles in indoor environments are still poorly understood. Our study can provide some clues about the effects of these environmental factors in indoor environments, which will contribute to future studies. The last and the most important, more attention should be paid to the indoor transmission of COVID-19 especially to the public health strategies and worthy to be considered (Coccia, 2021e; Coccia, 2021f). Therefore, understanding the transmission characteristics of the COVID-19 in indoor environment will facilitate the development of more efficient and less economically impact public health policies. Several studies have indicated the effectiveness of public health policies to control the COVID-19 indoor transmission such as air pollution control (Coccia, 2021b; Domingo et al., 2020), natural ventilation (Park et al., 2021) and to increase healthcare investments. Our study provided some evidence of the effectiveness of these public health policies and some explanations of the mechanisms and the epidemiological dynamics.

However, our study had two main limitations. First, although the relationship between the residential percent rate and COVID-19 daily growth rate was significant and definite when the residential percent rate was in the range of 100–120 percent, a similar relationship did not appear when the residential percentage rate was over 120 percent. This is mainly caused by the lack of simplicity in this range. More study on the residential percent rate in the range of over 120 percent is needed in the next period. Second, the potential seasonality (Choi et al., 2021; Liu et al., 2021) and outdoor environmental factors (Guo et al., 2021; Iqbal et al., 2020; Kumar, 2020; Paraskevis et al., 2021) may also have some effects on the second pandemic wave in India, which was not included in our present study due to the lack of data. However, we will focus on this study area once the data become available in the future.

Author contributions section

Research concept and design were contributed by Jing Tian and Weiren Huang; data collecting was contributed Jinghong Chen, Xinwei Liu and Xilin Wu; statistical analysis was contributed by Min Liu and Liwei Tang; drafting of manuscript was contributed by Liwei Tang, Min Liu, and Bingyu Ren.

All authors read and approved the final manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2021.111910.

References

Abbas, G.M., Dino, I.G., 2021. The Impact of Natural Ventilation on Airborne Biocontaminants: a Study on COVID-19 Dispersion in an Open Office. Engineering Construction and Architectural Management.

Aboulieh, M.Y.Z., 2021. Indoor air quality and COVID-19. Pabl. Health 191, 1–2.
