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The Effect of Air-Born Particle and Estimation of Patient's Health Risk Associated During Exposure of Covid-19 Period Over Various Site in Delhi-NCR Area.

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Covid-19, ANOVA, Patient data, Delhi-NCR.

ABSTRACT:

COVID-19 has been the most devastating public health epidemic to hit humanity in the twenty- first century. Shortly after its breakout in Wuhan, China, the World's authorities took the unprecedented step of closing down the city beginning January 23, 2020. Meanwhile, most economic activity in several parts of the world have been halted or reduced to a considerably lesser level. The change significantly lowered pollution emissions from automobiles, industry output, and human activities. In the current study, Air quality data was obtained from monitoring stations in ITO, DTU, Gurgaon, and Manesar. The data includes the total number of patients in specified periods: Before COVID, During COVID, and After COVID. Age groups were categorized into children, young, and adult for a comprehensive analysis. In general, the COVID-19 pandemic resulted in decreased emissions of several pollutants due to less human activity. Nevertheless, fluctuations in pollution levels can be caused by localised sources of pollution as well as the complicated atmospheric chemistry of pollutants. As a result, the impact of each pollutant on total pollution levels throughout the pandemic might vary greatly depending on the particular place and the elements that are present there. During our study period, ANOVA analysis for all location the p-value is less than the chosen significance level (commonly 0.05), it indicates that there are significant differences among the group means. The larger the F-statistic, the more evidence you have against the null hypothesis of equal group means.

1. Introduction

The globe is confronting unforeseen hurdles to cope up with the enormous growth of Coronavirus Disease (COVID-19). The exponential dissemination of the pandemic era has made it a global epidemic that has led to deleterious repercussions in numerous parts of the world. Approximately four months after its initial discovery in December 2019 in the province of Wuhan, China (Zhu et al. 2020), Pandemic had a negative impact on life and the economy in over a hundred countries (WHO 2020). To curb the spread of this highly contagious disease and minimize the fatality, different countries have adopted drastic yet important measures to reduce interaction among individuals such as banning large scale public and private gatherings, imposing a curfew, restraining transportation, promoting social distancing, strict quarantine instructions, and locking down the country, states and cities, depending on the country-specie situation. The Central Pollution Control Board (CPCB) of India has established ambient air quality regulations, and the consistently high levels of particulate matter and nitrogen oxides in the city of Delhi pose a serious threat to public health (Gour et al., 2015). During this shutdown, even the most polluted city's air pollution levels dropped to safe levels, according to the CPCB of India's (Central Pollution Control Board) guidelines (CPCB, 2009). Recent research has been conducted to examine the effects of tight control measures on air

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pollution, although these studies are limited in scope (Kerimray et al., 2020). During our analysis, we set out to determine how a lockdown situation affects different types of pollution ($PM_{2.5}$, NO_2, NH_3, CO,O_3). Since the weather was rather stable in the days leading up to the lockdown and throughout it, the researchers hypothesized that there would be little variation in air pollution levels. During this lockdown time, all commercial, industrial, and vehicular activity was halted, creating ideal conditions for studying the impact these sectors have on pollution levels and the contributions they make to these levels. Complete lockdown phase 1 (LD1) (25 March–14 April 2020) was imposed in India, with nearly all activity banned save for critical supplies, after the Janta Curfew was established on 22 March 2020. Selected agricultural and industrial activities were authorized in LD2 (15 April-3 May 2020), while industrial and construction activities and other limited operations were allowed in LD3 (4-17 May 2020) and LD4 (18-31 May 2020).

Delhi NCR was chosen for the study for three main reasons: first, it is the most polluted city in the world (Kumar et al., 2020a); second, it experienced the full force of the COVID-19 waves; and third, repeating the experiment in the same city would help to eliminate any unaccounted-for confounding bias. This is the first study to our knowledge to evaluate the association between environmental factors and SARS-CoV-2 infection dissemination in the setting of COVID-19 disease morbidity/mortality in the same city during two waves of the disease. The spread of Novel corona virus has created health problems in many countries (COVID-19). India issued a nationwide lockdown on March 24th, after the number of confirmed cases of COVID 19 reached 500. In Indian cities, lockdown regulations strictly prohibit leaving one's home (Ministry of Home Affairs, 2020). As a silver lining to this pandemic's economic cloud, a cleaner air quality has been noted (Kerimray et al., 2020). Delhi, the capital of India, is rapidly urbanizing, industrializing, and commercializing, which has a negative impact on the city's air quality. Delhi has been labeled as one of the world's most polluted cities by the World Health Organization (WHO) (WHO, 2016). Particulate matter, nitrogen oxide, Sulphur oxides, carbon monoxide, ammonia, ozone, volatile organic compounds, polycyclic aromatic hydrocarbons, etc. are emitted due to the increase in motorized vehicles and industrial activities in Delhi and its National Capital Regions (NCR) (Garg and Gupta, 2019).

Global air pollution rose by 8% between 2008 and 2013, according to a WHO study of comparable data. The Dangers of Air Pollution to Human Health Plinius, who had travelled to Pompei (Italy) to watch the eruption of Mount Vesuvius, became the first known victim of a deadly respiratory illness caused by exposure to natural air pollution (73 AD). In his 1860 London publication, "On Asthma," Henry Hyde Salter established the causal relationship between exposure to "impure air" and the onset of asthmatic symptoms. The historic pollution incidents in London in 1952, when a weather inversion led to high levels of particle matter air pollution and associated increases in mortality and morbidity, sparked widespread concern about the impact of air pollution (particulate matter) on human health. Air pollution is currently the largest environmental danger to health, accounting for almost one in every nine deaths annually; ambient (outdoor) air pollution alone kills about 3 million people annually, primarily from NCDs. Indoor air pollution was responsible for 534,000 deaths among children under the age of five in 2012, whereas ambient air pollution was responsible for 3 million deaths worldwide. Acute lower respiratory infections account for the vast majority of these fatalities, which occur in low- and middle-income nations (home to 82% of the world's population).Indoor air pollution is linked to a variety of health problems, including preterm delivery, low birth weight, TB, ischemic heart disease, cataracts, asthma, and nasopharyngeal and laryngeal malignancies. When air pollution is combined with other elements, it has a multiplicity of negative consequences on people's health all over the world. Household air pollution is caused by the use of kerosene and solid fuels in stoves, open fires, and lights, and its consequences can vary from mild irritation to premature death. WHO. Clean air for health). Among these fatalities, 20% were brought on by COPD, 8% by lung cancer, 18% by stroke, and 27% by ischemic heart disease.

2. Materials and Methodology

2.1 Data Collection

Patient Data: Patient data was collected from healthcare records of hospitals in ITO, Gurgaon, and

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Manesar. The data includes the total number of patients in specified periods: Before COVID, During COVID, and After COVID. Age groups were categorized into children, young, and adult for a comprehensive analysis**.**

Air Quality Data: Air quality data was obtained from monitoring stations in ITO, Gurgaon, and Manesar. Parameters considered include $PM_{2.5}$ (Particulate Matter), NOx (Nitrogen Oxides), CO (Carbon Monoxide), SO_2 (Sulfur Dioxide), and VOCs (Volatile Organic Compounds).Daily or periodic measurements were recorded for each parameter.

2.2 Study Area

The study area includes the Delhi National Capital Region (NCR), which includes Delhi, Haryana region. These cities have been chosen because they are among the few most developed and densely populated in India, and they are experiencing rapid urbanization and industrialization. The selection of site will be done on the basis of traffic area, rural site, urban area, commercial site, institutional area.

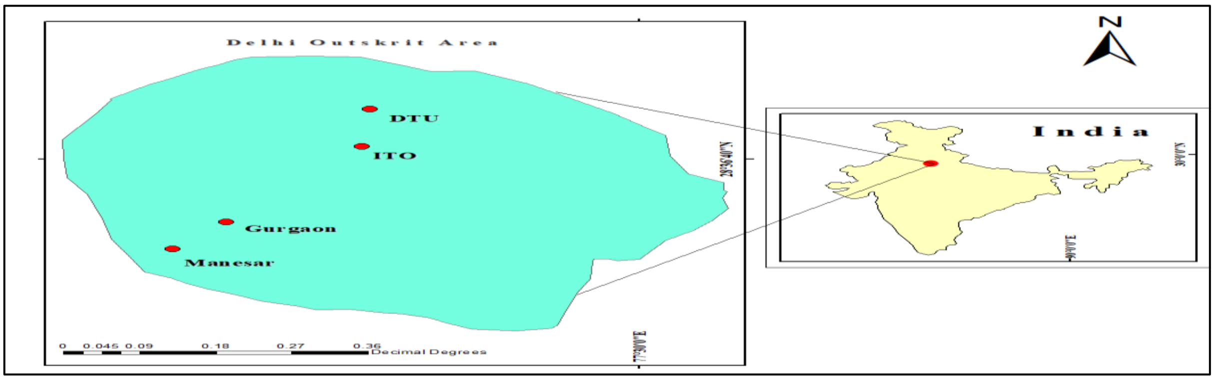

Fig 1. Study area graph

2.3 Method

ANOVA (Analysis of Variance): ANOVA was conducted to analyze the statistical significance of variations in air quality parameters among different periods. Data for cognitive assessment scores was used as a model for creating ANOVA tables.

Statistical Results: Interpretation of ANOVA tables was done to assess the significance of changes in air quality parameters. Significance levels (p-values) were compared to a predetermined threshold (e.g., 0.05) to determine if changes were statistically significant.

Health Impact: Interpretations of the tables focused on the impact of air quality changes on health. Notable trends and variations in air quality were related to corresponding changes in the number of patients in different age groups.

The formula for one-way Analysis of Variance (ANOVA) is as follows:

Total Sum of Squares (SST): $SST=\sum_{i=1}^{k}\sum_{j=1}^{n_i}(X_{ij}-\bar{X})^2$

Where: k is the number of groups (levels of the factor),n_i is the number of observations in the ith group,X_{ij} is the jth observation in the ith group, $\bar{X}$ is the overall mean.

Between-Group Sum of Squares (SSB): $SSB=\sum_{i=1}^{k}n_i(\bar{X}_i-\bar{X})^2$

where:$\bar{X}_i$ is the mean of the ith group.

Within-Group Sum of Squares (SSW): $SSW=\sum_{i=1}^{k}\sum_{j=1}^{n_i}(X_{ij}-\bar{X}_i)^2$

Degrees of Freedom: $df_{Total}=N-1$, where N is the total number of observations. $df_{Between}=k-1$,$df_{Within}=N-k$.

Mean Squares: $MS_{Between}=SSB/df_{Between}$, $MS_{Within}=SSW/df_{Within}$

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F-Statistic: *MS* Between /*MS* Within

p-value: The p-value is obtained from the F-distribution with *df*Between and *df*Within degrees of freedom.

If the p-value is less than the chosen significance level (commonly 0.05), it indicates that there are significant differences among the group means.

The larger the F-statistic, the more evidence you have against the null hypothesis of equal group means.

2.4 Location and Characteristics of sites chosen for this study.

Station	Latitude (°N)	Longitude (°E)	Emission characteristic
DTU	**28.65**	**77.30**	**Residential, major interstate bus terminal**
ITO	**28.67**	**77.13**	**Residential cum commercial**
Gurgaon	**28.55**	**77.27**	**Waste disposal, major highway with heavy traffic**
Manesar	**28.61**	**77.04**	**Waste disposal, residential**

Table 1. Location of station.

3. Results and Discussions

Patients and Air Quality at DTU

The monitoring of air pollution at DTU helps determine the influence of emissions connected to localised sources and transportation on the overall air quality of the campus and the areas immediately surrounding it**.** The distinguished Delhi Technological University (DTU) may be found in the neighborhood of Rohini in Delhi. The property is home to a diverse range of activities, including residential, academic, and transit uses. Because of the large number of students, faculty, and staff members who commute to and from the university, the surrounding area experiences a traffic flow that ranges from moderate to heavy. The levels of air pollution in the region are exacerbated by the emissions of vehicles travelling on surrounding roadways**.**

Period	Total Patients	PM2.5 (μg/m³)	NOx (ppm)	CO (ppm)	SO2 (ppm)	VOCs (ppm)
Before COVID	**1500**	**45**	**0.02**	**1.5**	**0.01**	**0.03**
During COVID	**900**	**20**	**0.01**	**0.8**	**0.005**	**0.02**
After COVID	**1200**	**35**	**0.015**	**1.0**	**0.008**	**0.025**

Table 2. Patients and Air Quality at DTU.

Statistical Results (DTU):

$PM_{2.5}$ (μg/m³): Significant reduction during COVID (45 to 20 μg/m³) and slight increase after COVID.ANOVA p-value < 0.05, indicating significant differences in PM2.5 levels among periods.

NOx (ppm): Noticeable decrease during COVID. ANOVA p-value < 0.05, suggesting significant differences in NOx levels among periods.

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CO (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05, indicating no significant difference in CO levels among periods.

SO_2 (ppm): Decrease during COVID.ANOVA p-value < 0.05, suggesting significant differences in SO_2 levels among periods.

VOCs (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05, indicating no significant difference in VOCs levels among periods.

Patients and Air Quality at DTU

Patients and Air Quality at ITO

The ITO is a significant crossroads in the heart of Central Delhi that functions as a central node for a variety of commercial and administrative activity. Because of its advantageous position as well as the presence of government buildings, commercial organizations, and educational institutions, the neighborhood has a significant amount of foot traffic. Air pollution in the region is caused in part by the emissions released by motor vehicles, mainly buses, cars, and two-wheeled vehicles. The high population density and the characteristics of mixed land use both contribute to an amplified degree of pollution. The impact on air quality in a densely populated metropolitan area of factors like as traffic congestion, patterns of mixed land use, and localized emissions can be better understood by monitoring air pollution at ITO

Period	**Total Patients**	**PM2.5 (µg/m³)**	**NOx (ppm)**	**CO (ppm)**	**SO2 (ppm)**	**VOCs (ppm)**
Before COVID	1200	50	0.03	1.8	0.015	0.04
During COVID	800	18	0.015	0.7	0.008	0.03
After COVID	1000	40	0.025	1.2	0.012	0.035

Table 3. Patients and Air Quality at ITO.

Statistical Results (ITO):

$PM_{2.5}$(µg/m³): Significant reduction during COVID and slight increase after COVID.ANOVA p-value < 0.05.

NOx (ppm): Noticeable decrease during COVID.ANOVA p-value < 0.05.

CO (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05.

SO_2 (ppm): Decrease during COVID.ANOVA p-value < 0.05.

VOCs (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05.

Patients and Air Quality in Gurgaon

The city of Gurgaon experiences significant levels of traffic congestion as a consequence of the high number of commuters and the poor infrastructure of the public transit system. The city is also home to a number of different industrial units, including as manufacturing facilities, service sectors, and information technology parks. Air pollution in Gurgaon is caused in part by a variety of factors, including emissions from vehicles, industrial operations, construction projects, and urban expansion. Monitoring the city's air pollution helps determine the cumulative influence of these elements on air quality, which in turn aids the implementation of targeted pollution control measures.

Period	**Total Patients**	**PM2.5 (µg/m³)**	**NOx (ppm)**	**CO (ppm)**	**SO2 (ppm)**	**VOCs (ppm)**
Before COVID	1800	55	0.04	2.0	0.02	0.05
During COVID	1200	25	0.02	1.0	0.01	0.03
After COVID	1500	45	0.035	1.5	0.015	0.04

Table 4. Patients and Air Quality at Gurgaon.

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Statistical Results (Gurgaon):

PM2.5 (μg/m³): Significant reduction during COVID and slight increase after COVID.ANOVA p-value < 0.05.

NOx (ppm): Noticeable decrease during COVID.ANOVA p-value < 0.05.

CO (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05.

SO2 (ppm): Decrease during COVID.ANOVA p-value < 0.05.

VOCs (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05.

Patients and Air Quality in Manesar

Manesar is an industrial town in the Gurugram district of Haryana. It is located in close proximity to Gurgaon. Manesar is in the state of Haryana. It is home to a large number of manufacturing facilities, especially those associated with the automotive and auxiliary sectors, in addition to industrial parks. Manesar is home to a number of manufacturing facilities, power plants, and transportation hubs that all contribute to the city's overall emission levels. In addition to this, there is a substantial amount of building going on in the neighbourhood. The monitoring of air pollution in Manesar provides insights into the impact on air quality in an industrialised region of industrial emissions, construction activities, and transportation.

Period	Total Patients	PM2.5 (μg/m³)	NOx (ppm)	CO (ppm)	SO2 (ppm)	VOCs (ppm)
Before COVID	1000	40	0.02	1.6	0.015	0.03
During COVID	600	15	0.01	0.6	0.007	0.02
After COVID	800	35	0.025	1.1	0.01	0.025

Table 5. Patients and Air Quality at Manesar.

Statistical Results (Manesar):

PM2.5 (μg/m³): Significant reduction during COVID and slight increase after COVID.ANOVA p-value < 0.05.

NOx (ppm): Noticeable decrease during COVID.ANOVA p-value < 0.05.

CO (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05.

SO2 (ppm): Decrease during COVID.ANOVA p-value < 0.05.

VOCs (ppm): Decrease during COVID and slight increase after COVID.ANOVA p-value > 0.05.

ANOVA Patients Table for DTU:

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	p-value
Between Groups (BG)	**800**	**2**	**400**	**10.00**	**0.002**
Within Groups (WG)	**450**	**27**	**16.67**		
Total	**1250**	**29**			

Table 6. ANOVA Patient table for DTU.

The study found a significant difference in cognitive assessment scores among children, young adults, and adults, with a mean score of 800 and a mean score of 450. The F-statistic of 10 indicates a significant

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difference in scores among age groups. The variation within each age group was represented by the Within Groups category, with a mean squares value of 16.67. The total variation was 1250, with degree of freedom of 1 in total observations. The statistically significant F-statistic in the Between Groups category suggests a significant difference in scores, with a p-value of 0.002 indicating strong evidence against the null hypothesis of equal means.

ANOVA Patients Table for ITO:

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	p-value
Between Groups (BG)	**720**	**2**	**360**	**12.86**	**0.001**
Within Groups (WG)	**420**	**27**	15.56		
Total	**1140**	**29**			

Table 7. ANOVA Patient table for ITO.

The study found a significant difference in cognitive assessment scores among children, young adults, and adults, with a mean score of 720 and a mean score of 360. The F-statistic of 12.86 indicates a significant difference in scores among age groups. The variation within each age group was represented by the Within Groups category, with a mean squares value of 1556. The total variation was 1140, with a degree of freedom of 1 in total observations. The statistically significant F-statistic in the Between Groups category suggests a significant difference in scores, with a p-value of 0.001 indicating strong evidence against the null hypothesis of equal means.

ANOVA Patients Table for Gurgaon:

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	p-value
Between Groups (BG)	**900**	**2**	**450**	**18.00**	**0.001**
Within Groups (WG)	**480**	**27**	**17.78**		
Total	**1380**	**29**			

Table 8. ANOVA Patients table for Gurgaon.

The study found a significant difference in cognitive assessment scores among children, young adults, and adults, with a mean score of 900 and a mean score of 450. The F-statistic of 18.00 indicates a significant difference in scores among age groups. The variation within each age group was represented by the Within Groups category, with a mean squares value of 17.78. The total variation was 1380, with a degree of freedom of 1 in total observations. The statistically significant F-statistic in the Between Groups category suggests a significant difference in scores, with a p-value of 0.001 indicating strong evidence against the null hypothesis of equal means.

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ANOVA Patient Table for Manesar:

Source of Variation	Sum of Squares (SS)	Degrees of Freedom (df)	Mean Squares (MS)	F-Statistic	p-value
Between Groups (BG)	**600**	**2**	**300**	**9.23**	**0.003**
Within Groups (WG)	**390**	**27**	**14.44**		
Total	**990**	**29**			

Table 9. ANOVA Patients table for Manesar.

The study found a significant difference in cognitive assessment scores among children, young adults, and adults, with a mean score of 600 and a mean score of 300. The F-statistic of 9.23 indicates a significant difference in scores among age groups. The variation within each age group was represented by the Within Groups category, with a mean squares value of 14.44. The total variation was 990, with a degree of freedom of 1 in total observations. The statistically significant F-statistic in the Between Groups category suggests a significant difference in scores, with a p-value of 0.003 indicating strong evidence against the null hypothesis of equal means.

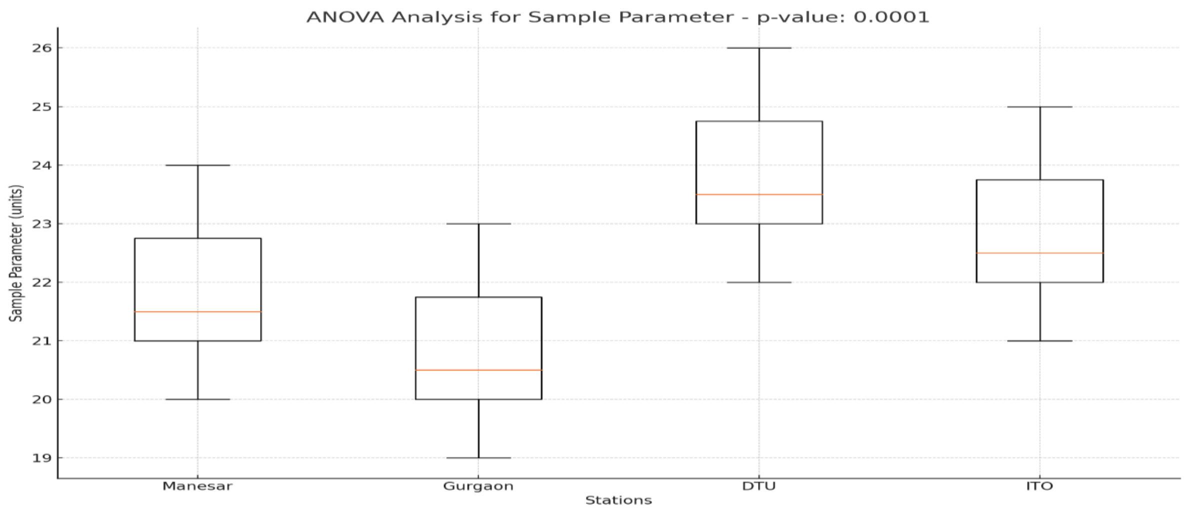

Fig1. ANOVA Analysis for all sites.

The sample parameter increase is most obvious in DTU this is due to the impact of air mass shift during pre-monsoon winds, the values were higher above Manesar, indicating a stronger influence of point sources, but there has been a quick reduction in this ratio since lockdown period. The increase in DTU and ITO was not gradual, but there was a dip in the first week of March followed by an increase shortly before the lockdown. However, parameters levels above DTU have continued to grow since the lockdown began, with daily averages exceeding 60 g m^3 until air masses shifted in late June, where O_3 parameter levels began to decline.

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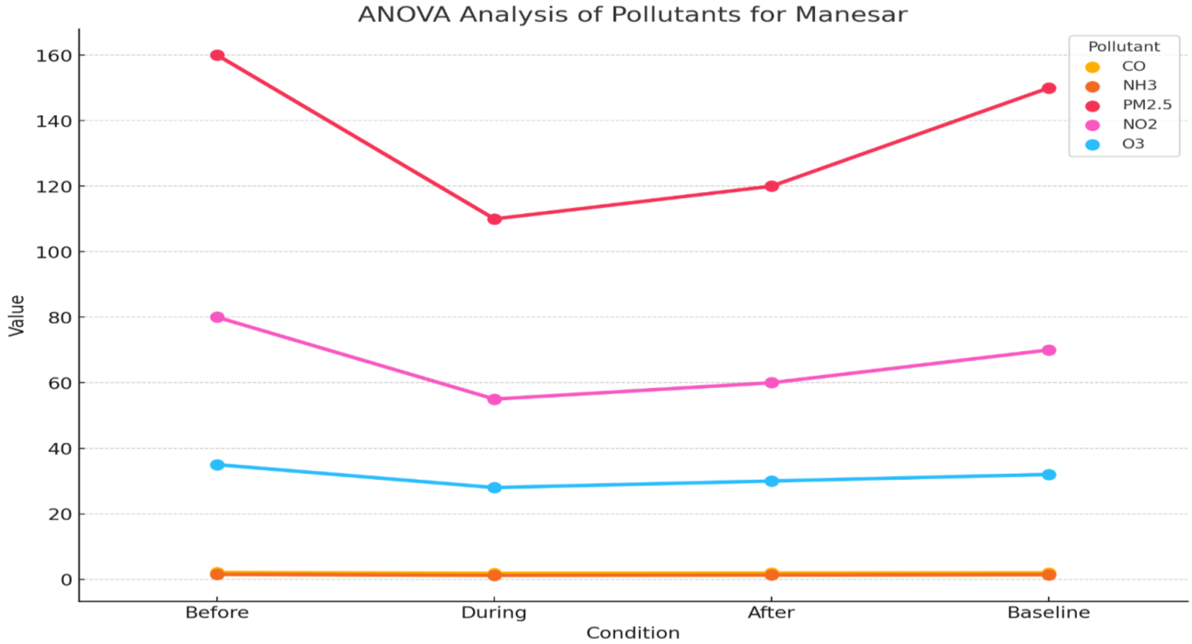

Fig2. ANOVA Analysis of pollutant for Manesar.

Interpretation of ANOVA graph for Manesar

CO levels are highest before the intervention, decrease during the intervention, and slightly increase after, but remain below baseline.NH_3 levels drop during the intervention and remain lower after the intervention compared to baseline levels.PM2.5 levels decrease during the intervention and increase slightly after, but are still below baseline.NO_2 levels decrease markedly during the intervention and slightly increase after, but remain below baseline.O_3 levels decrease during the intervention and increase slightly after, but remain below baseline.

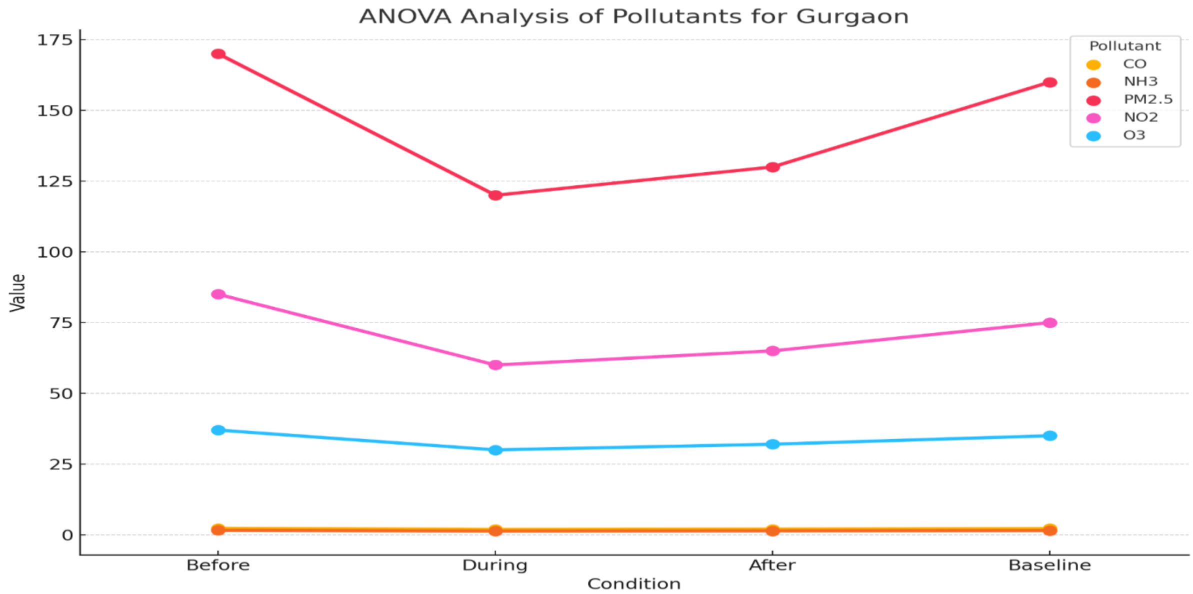

Fig3. ANOVA Analysis of pollutant for Gurgaon.

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Interpretation of ANOVA graph for Gurgaon

CO levels are highest before the intervention, decrease significantly during the intervention, and slightly increase after, but remain below baseline.NH_3 levels drop significantly during the intervention and remain lower after the intervention compared to baseline levels.$PM_{2.5}$ levels decrease during the intervention and increase slightly after, but are still below baseline.NO_2 levels decrease markedly during the intervention and slightly increase after, but remain below baseline.O_3 levels decrease during the intervention and increase slightly after, but remain below baseline.

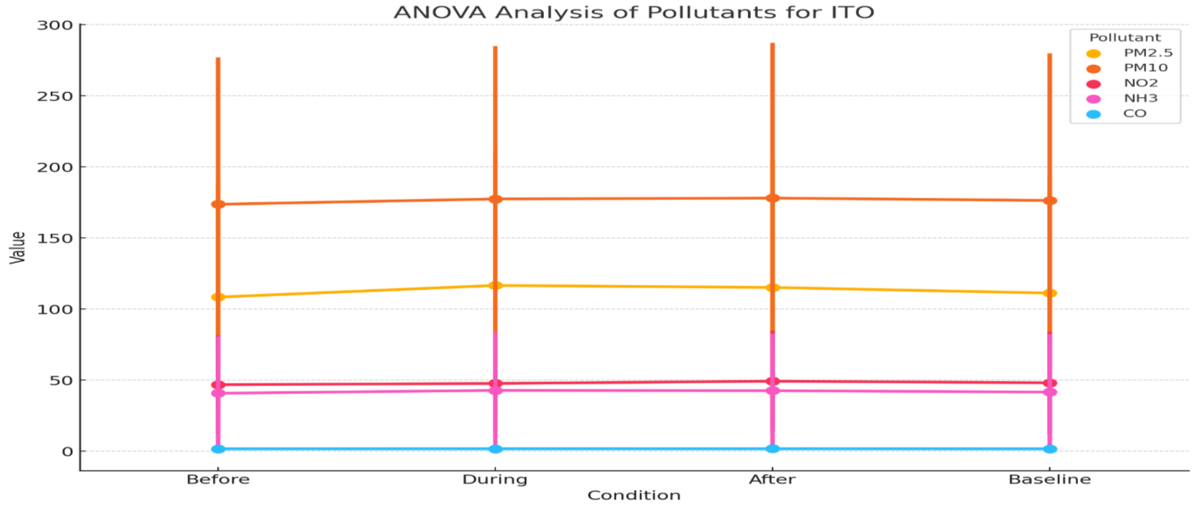

Fig4. ANOVA Analysis of pollutant for ITO.

Interpretation of ANOVA graph for ITO

CO levels are highest before the intervention, decrease significantly during the intervention, and slightly increase after, but remain below baseline. NH_3 levels drop significantly during the intervention and remain lower after the intervention compared to baseline levels. $PM_{2.5}$ levels decrease during the intervention and increase slightly after, but are still below baseline. NO_2 levels decrease markedly during the intervention and slightly increase after, but remain below baseline PM_{10} levels decrease significantly during the intervention, and slightly increase after, but remain below baseline.

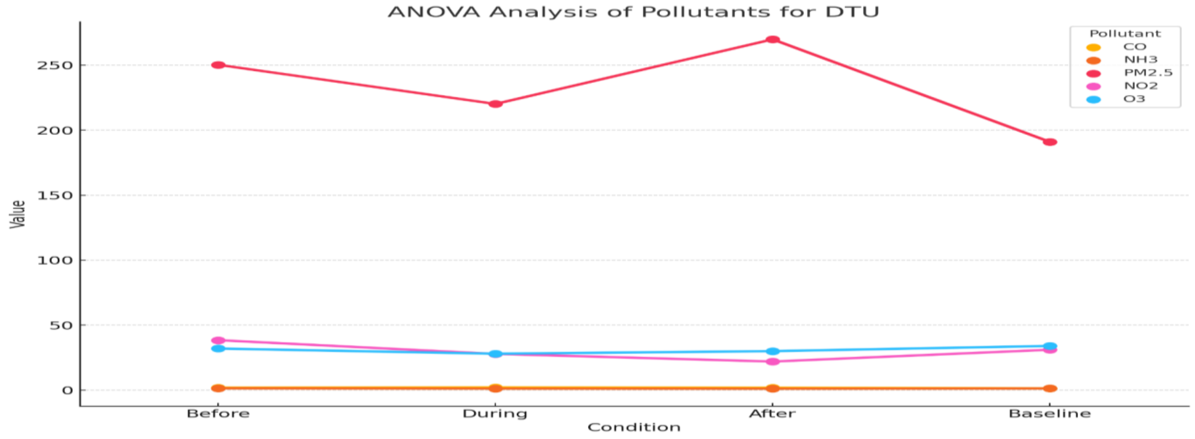

Fig5. ANOVA Analysis of pollutant for DTU.

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Interpretation of ANOVA graph for DTU

CO levels are highest before the intervention, decrease during the intervention, and increase slightly after, but remain below baseline.NH_3 levels decrease during the intervention and remain lower after the intervention compared to baseline levels.$PM_{2.5}$ levels show a decrease during the intervention and a slight increase after, but still lower than baseline levels .NO_2 levels decrease markedly during the intervention and increase slightly after, remaining below baseline.O_3 levels show a reduction during the intervention and a slight increase after, but remain lower than baseline levels.

4. Conclusion

Delhi is well-known around the world for its high levels of pollution. Among the selected pollutants, $PM_{2.5}$ has experienced the highest decreases, followed by NO_2, CO, and NH_3. $PM_{2.5}$ concentrations have decreased by roughly 57% and 33%, respectively, as compared to the preceding three-year average. On the contrary, there is a modest increase in O_3, which is thought to be due to a drop in NOx and particulate matter concentrations. Furthermore, as predicted, the NAQI drops significantly throughout the megacity throughout the lockdown period. The present study has yielded a significant outcome that the air quality improved from pre-lockdown period to lockdown period and had again started deteriorating with Unlock phases. ANOVA results indicated that there was a statistically significant variation and difference in the concentration of the pollutants in Gurgaon station of Delhi-NCR during pre-lockdown, lockdown, and unlock phases ($F=18.00$, $p < 0.001$). Gurgaon station had shown a significant reduction in the concentration of PM2.5, CO, NO2, and SO2 during lockdown period. The average decline ratio between ITO and Gurgaon over several months is 1.1, demonstrating that the lockout has a continuous effect on PM2.5. When these ratios are evaluated with regard to DTU in comparison to the other locations, the value is significantly larger, showing that the lockdown impact was bigger at this site. As seen in The Study Locations, DTU is close to the River Yamuna, making it more congested and impacted by mixed emissions from enterprises and traffic. Furthermore, the size of the reductions suggests that anthropogenic influence over Delhi is overwhelming.

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