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Can private cars restriction policy help reduce air pollution in big cities? A case study of Tehran

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ABSTRACT: It is a common understanding that higher traffic volume leads to more pollutant air. Therefore, when the air quality deteriorates, policymakers restrict private vehicles. This study aims to challenge this assumption by using statistical models including multivariate regression and ordered logistic regression models. These models are calibrated by employing datasets on air pollution, traffic quality, and weather conditions, for Tehran the capital of Iran. The results show that the coefficient of the Traffic Quality Index (TQI), representing traffic volume, is not statistically significant. This finding suggests that traffic volume does not significantly impact air quality in Tehran. Among the variables, temperature has the most considerable effect on air pollution with a coefficient of -0.35 and has the highest significant coefficient with the p value of 0.083. The coefficients of all variables align with our previous knowledge. In fact, temperature and wind speed (coefficient is -0.14) show negative significant coefficients, implying that lower temperatures and slower wind speeds leads to higher levels of air pollution. Conversely, TQI and humidity exhibit positive significant coefficients which their values are 0.03 and 0.05 in order, showing that increased traffic volume and higher humidity levels are associated with more polluted air. In conclusion, restricting private cars may not be a practical solution for addressing the issue of air pollution in Tehran.

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1- Introduction

Air quality is defined as a change in the quality of air which is measured by the amount of chemical, biological, and physical pollutants. Therefore, air pollution is associated with the presence of undesirable impurities or an abnormal increase in the proportion of mentioned particles compared to other atmospheric components (National Geographic, 2019) [1]. The harmful effects of air pollution, specifically in large cities, are not hidden to anyone. For instance, according to a report from the World Health Organization in 2018, air pollution has led to the death of more than 4.2 million people in urban and rural areas. Among these, 58% are cardiovascular and stroke diseases, 18% are respiratory diseases, and 6% are lung cancer, which are death-leading diseases caused by air pollution [2].

One of the essential factors causing air pollution in major cities like Tehran is motor vehicles. These vehicles emit pollutant gases like carbon dioxide, carbon monoxide, nitrogen oxides, hydrocarbons, and particulate matter. The gases, unfortunately, cause an increase in harmful suspended particles in the air. In recent decades, the number of motor vehicles has significantly increased which leads to more pollutant air [3]. To be more specific, according to research in 2005, the transportation sector is responsible to 21% of greenhouse gases and 56% of NO_x emissions [4]. As a result, determining the impact of traffic indicators on air pollution has become one of the major concerns for policymakers. Knowing about this effect leads transportation planners and policymakers to make more practical and precise solutions.

In the city of Tehran, air pollution is measured with the help of ground stations located in 22 different areas of the city. At these stations, the levels of pollutants and particles in the air are measured, including CO, O3, NO2, SO2, PM10, and PM2.5. The measurement of these pollutants includes a limited range, and these data should not be used for a wider range [5].

Also, the Traffic Quality Index (TQI) is used to measure traffic conditions for 22 districts of Tehran. This index is based on traffic data from Google Maps and simultaneously considers various factors such as vehicle speed, traffic volume, and queue length. The index serves as a measure of traffic congestion on major highway and arterial network routes, with values ranging from zero (when all routes are green) to 300 (when all routes are dark red).

The city of Tehran ranks high in terms of air pollutants. This situation worsens especially in the fall and winter months, coinciding with the opening of schools and air inversion effects. Therefore, on days when the air quality index is in

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an undesirable state, authorities and relevant organizations take temporary restrictions of private cars aiming to reduce air pollution. The aim of this research is to investigate the impact of traffic density on air pollution levels and whether the restriction of private cars is a rational and practical action or not.

2- Literature review

The impact of traffic control policies on air quality has always been a topic of discussion among policymakers and researchers. This impact can vary in different geographical regions with different weather conditions and specific characteristics of that region.

The articles examining the effect of traffic volume on air pollution can be divided into two categories: those that argue there is a significant relationship between traffic volume and air pollution, and those that conclude there is no significant relationship. The following paragraphs will discuss these two categories.

2- 1- Relationship between Traffic Volume and Air Pollution

In a study regarding the impact of traffic volume on air pollution, Magna Aldrin and Ingrid Hoff constructed a non-linear model where they calculated air pollutants hourly using a logarithmic function. They considered pollutants as the dependent variable and independent variables included traffic volume and meteorological variables such as wind, temperature, rain, and snow. Their dataset covered four different regions in Oslo from 2001 to 2003, and according to their results, two significant factors affecting air pollution were related to traffic volume and wind [6]. According to their research, traffic volume has a significant effect on air quality. Moreover, another research was conducted in the summer of 2006. The Middle East conflicts led to a reduction in commercial and personal activities for several weeks in the city of Haifa, Israel. Although large factories and industries continued their operations, activities of small-scale industries, shopping, and personal commuting were significantly reduced. Yuval and his colleagues investigated the impact of this traffic volume reduction on air pollution during this time. Based on their analysis, the decrease in traffic volume resulted in a reduction in levels of NO_2, hydrocarbons, and particulate matter. It is interesting to note that the average decrease in air pollutant concentrations was significantly higher compared to the average decrease in traffic volume [7]. Qi Wang and colleagues have investigated the impact of traffic parameters on air quality quantitatively based on Aerosol Optical Depth (AOD) models and Geographic Weighted Regression (GWR). The main parameters of their model include road network density, road environment occupancy, number of intersections, and bus network density. According to their results, there is a strong positive correlation between peak hour traffic congestion delay index and air quality. Additionally, bus route planning, controlling the reduction of pollutants emitted from buses, road network planning, and optimal scheduling of traffic lights have a greater positive impact on air quality compared to other policies, especially in high-traffic volume areas [8]. In another relevant study, the projection of passenger car (PC) emissions in Tehran by 2035 was explored using econometric and emission models. The research highlighted that PC growth, combined with the continued reliance on gasoline, and would lead to a significant increase in CO_2 and $PM_{2.5}$ emissions. It was concluded that fuel consumption and emissions could be effectively reduced through stricter emission standards and cutting fuel subsidies [9]. Recent studies continue to affirm the significant relationship between traffic volume and air pollution. One example is a study analyzing the effect of reduced traffic flows during the COVID-19 lockdown in Italy. This research demonstrated that the reduction in vehicle movement led to substantial decreases in nitrogen oxides and other pollutants, emphasizing the direct correlation between road traffic and air quality [10]. Moreover, a 2024 study in rapidly urbanizing regions of China used high-resolution emission inventories to explore the spatiotemporal characteristics of CO□ and pollutant emissions from road traffic. The research revealed that trunk roads and low-vegetation areas contributed significantly to pollution, and emissions increased in parallel with the growth of road networks [11].

2- 2- Lack of Significant Relationship between Traffic Volume and Air Pollution

In another research the results were interesting. Gurcan Comert and his colleagues investigated the relationship between traffic volume and air quality in local areas using multi-level mixed linear models and grey systems. Among their models, the LMER+EGM model had the highest accuracy, showing that with an increase in AADT, air pollution levels increased. This effect varies in different regions, to the extent that in some areas, a decrease in AADT leads to an increase in pollution, indicating that other factors are influencing air quality in these regions [12]. In some areas, they use restrictions on private cars to improve air quality. Zhongfei Chen and colleagues examined the impact of these restrictions on air quality during the coronavirus pandemic. According to their results, the effect of traffic restrictions is strongly related to the type of economic growth and other city characteristics. In a region with low economic growth, traffic restrictions have a significant impact on reducing air pollution. On the other hand, in areas with high economic growth and heavy traffic, this impact is reduced and other factors have a greater influence on air pollution levels [13]. In 1989, the Mexican government implemented traffic restrictions to reduce air pollution by allowing vehicles to circulate based on their license plate numbers. Lucas Davis studied this policy and concluded that it did not have a significant impact on air pollution levels and quality [14]. On one hand, Chen and colleagues examined the impact of traffic restriction policies on improving air quality for the 2008 Olympics. According to their findings, implementing strict restrictions can enhance air quality, but the effectiveness depends on the continuity of these policies [15]. For instance, multiple research projects carried out in the United States have shown that enhancing air quality is a gradual journey that heavily relies on the evolving relationship between governmental regulations and private adherence [16-18]. Moreover, extensive research has been conducted on the importance of selecting the appropriate index for measuring air pollution. This index should well represent the level of air pollutants and should not only consider one air pollutant gas in order to achieve accurate results [19, 20]. For example, Viard and Fu utilized two indicators to assess the impact of traffic limitations on air quality, namely API and PM10. Their study revealed that enforcing traffic restrictions resulted in a 19% reduction in API under alternate-day restrictions and a 7% decrease with one-day-per-week restrictions [21]. Ultimately, the effectiveness of traffic restrictions in reducing air pollution is influenced by the specific air pollutant being monitored and the specific attributes of the region under investigation.

Tehran is one of the most polluted cities in the world. Every day, many people commute using their private cars, contributing to air pollution and decreasing air quality. To mitigate this, policymakers restrict the use of private cars, especially on highly polluted days, primarily in the fall and winter. However, the effectiveness of these restrictions has not yet been thoroughly studied. According to the literature, the impact of car restrictions depends on the region and the specific characteristics of the area being studied. Therefore, Tehran, as the most important city in Iran, is being examined to determine whether this policy is effective.

3- Methodology

3- 1- Multivariate regression

To assess the influence of the Traffic Quality Index on air pollution, statistical methods such as regression analysis are employed. The Multivariate regression model and ordered logistic regression are briefly explained for this purpose. Regression analysis not only assists in establishing the connection between variables but also aids in making predictions [22, 23]. The Multivariate regression model delves into the correlation between multiple independent variables and a single dependent variable [24]. It establishes a concurrent statistical relationship between the continuous outcome (y) and the predictor variables (x_k) where k ranges from 1 to k as shown in equation 1 [25].

$$Y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + ... + \beta_k x_{i,k} + \varepsilon_i \tag{1}$$

Where:

i = number of observations (i = 1, 2, …, n)

k = number of predictor variables

Y_i = the dependent variable (AQI)

$x_{i,k}$ = explanatory variable (TQI, wind speed, temperature, ...) for i^{th} observation

β_0= the constant coefficient of the regression line

β_k = regression coefficients for each explanatory variable

ε_i = error term

To estimate the parameters of a regression model, the method of ordinary least squares (OLS) is utilized. The OLS procedure involves selecting the values of the unknown parameters so that the residual sum of squares (RSS) $\sum u_i^2$ is minimized. This can be represented symbolically as equation 2:

$$\min \sum u_i^2 = \sum (Y_i - \beta_0 - \beta_1 x_{i,1} - \beta_2 x_{i,2} - ... - \beta_k x_{i,k})^2 \tag{2}$$

In matrix notation, the OLS model is $Y = X\beta + u$ so:

$$\sum u_i^2 = \begin{bmatrix} u_1 & u_2 & ... & u_n \end{bmatrix} \begin{bmatrix} u_1 \\ ... \\ u_n \end{bmatrix} = u^T u \tag{3}$$

The goal is to find β in order to minimize the above function. Therefore, according to equation 4:

$$\begin{aligned} u^T u &= (Y - X\beta)^T (Y - X\beta) \\ &= Y^T Y - \beta^T X^T Y - Y^T X\beta + \beta^T X^T X\beta \\ &= Y^T Y - 2\beta^T X^T Y + \beta^T X^T X\beta \end{aligned} \tag{4}$$

The derivative of the above equation with respect to β must now be taken:

$$\begin{aligned} &\frac{\partial u^T u}{\partial \beta} = -2X^T Y + 2X^T X\beta = 0 \\ &(X^T X)\beta = X^T Y \\ &\beta = (X^T X)^{-1} X^T Y \end{aligned} \tag{5}$$

The above equation gives the OLS estimators.

Multiple coefficient of determination which is shown by R^2 is the proportion of the variation in Y explained by the variables x_1, x_2, …, x_k. Equation 6 represents the calculation of R^2.

$$R^2 = \frac{ESS}{TSS} \tag{6}$$

Which:

ESS = explained sum of squares,

TSS = total sum of squares

For determining R^2, the following steps should be followed according to Equation 7:

$$R^2 = 1 - \frac{RSS}{TSS} = 1 - \frac{\sum \hat{u}_i^2}{y_i^2} = 1 - \frac{(n-3)\hat{\sigma}^2}{S_y^2} \tag{7}$$

To determine if a specific variable is statistically significant in the model, its association with the dependent variable and its contribution to the model's accuracy are assessed. The t-value for coefficient β is calculated according to equation 8, and its degree of freedom is n - (number of parameters):

$$t = \frac{\beta}{s_b} = \frac{\beta}{s_e \big/ \sqrt{\sum (x-\bar{x})^2}} \tag{8}$$

Which:

S_e = residual standard error = $\sqrt{\frac{SSE}{N-2}}$

The 100(1-α) % confidence interval for β is:

$$\beta \pm t_{\alpha/2} \times \frac{s_e}{\sqrt{\sum (x-\bar{x})^2}} \tag{9}$$

3- 2- Ordered logistic regression

The air quality index is commonly characterized as a categorical variable whose values vary based on the data and conditions, representing different levels of air quality in an ordinal scale. In this research, the air quality index is classified into four categories: "clear", "acceptable", "unhealthy", and "very unhealthy". To analyze the factors influencing air quality, discrete choice modeling is employed, with each day having a specific air quality index.

When dealing with a discrete dependent variable where the value order matters, the ordered logit regression model is a well-established approach. In this study, the air quality index is categorized to enhance the understanding of the relationship between the Total Quality Index (TQI) and the Air Quality Index (AQI). The dependent variable Y, representing air quality, is categorical and holds a meaningful order. Y is determined by another continuous latent variable called Y*, and their relationship is expressed by equation 10:

$$\begin{Bmatrix} Y_i = 1 \quad if \quad Y_i^* \le K_1 \\ Y_i = j \quad if \quad k_j \le Y_i^* \le K_{j-1} \\ Y_i = M \quad if \quad Y_i^* \ge K_{M-1} \end{Bmatrix} \tag{10}$$

The odds of Y being less than or equal to a particular category can be defined as shown in Equation 11:

$$\frac{P_r(Y_i \le j \mid X)}{P_r(Y_i > j \mid X)} = \frac{P_r(Y_i \le j \mid X)}{P_r(1 - P_r(Y_i \le j \mid X))}, j = 1,2,3,4 \tag{11}$$

Having ordered the logit model:

$$\log it(P_r(Y_i \le j \mid X)) = \ln(\frac{P_r(Y_i \le j \mid X)}{P_r(Y_i > j \mid X)}) = \ln(\frac{P_r(Y_i \le j \mid X)}{P_r(1 - P_r(Y_i \le j \mid X))}), j = 1,2,3,4 \tag{12}$$

So, the ordered logit regression is defined as equation 13:

$$\log it(P_r[Y_i > j]) = -\alpha_j + \beta x_i, \begin{Bmatrix} j = 1,2,3,4 \\ i = 1,2,...,n \end{Bmatrix} \tag{13}$$

Where:

α = the slope of the model

β = the coefficient of the model (it is assumed to be the same for all the explanatory variables)

i = the explanatory variable

j = the level of air quality index

The parameters of the above model are estimated using the maximum likelihood estimation technique.

4- Data Description

In any modeling methodology, the primary task involves effectively gathering and processing the required data for the model's utilization. In this study, three datasets were utilized: an air pollution-related dataset, a traffic quality dataset, and a weather condition dataset. In every modeling methodology, data processing is a crucial stage to achieve more accurate results. Given that our dataset lacked normalization and standardization, preprocessing was necessary. To address this, the MinMaxScaler from the "sklearn" library in Python is employed.

4- 1- Air pollution dataset

A publicity available air pollution dataset from the Tehran Air Quality Company was utilized which was accessible for free at the following link: https://airnow.tehran.ir/home/home.aspx. This dataset spans from the 3rd of Mehr to the 30th of Aban (25th September to 21st November), coinciding with the commencement of the school year. It includes the daily average values of CO, O_3, NO_2, SO_2, PM_{10}, and $PM_{2.5}$. Figure 1 illustrates the mean values of each gas over our research period of 58 days.

4- 2- Traffic quality dataset

Google Traffic data is utilized to provide real-time traffic reports for Tehran, offering a comprehensive view of traffic

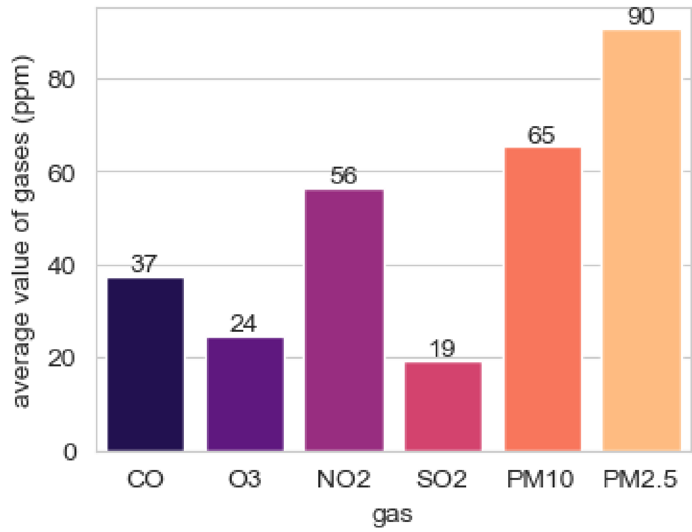

Fig. 1. The mean value of each gas for the research period

congestion across the city. The service generates a color-coded map to visually represent traffic conditions at various locations. This map includes four distinct color categories: green (light traffic), orange (moderate traffic), red (heavy traffic), and dark red (severe congestion).

A Traffic Quality Index (TQI) is derived from this data, calculated daily based on the distribution and intensity of these color categories across the map. The index quantifies overall traffic conditions by assigning weighted values to each color, where darker colors (red and dark red) carry higher weights due to their association with greater levels of congestion. These weights are incorporated into a formula (equation 14) that accounts for both the extent of the affected areas and the severity of congestion.

The Traffic Quality Index was selected for this study because it offers a clear, quantifiable measure of urban traffic conditions, allowing for daily comparisons and trend analysis. By capturing both the spatial distribution of traffic and the intensity of congestion, the index provides a robust tool for assessing the impact of traffic control policies on air quality. Moreover, its simplicity and reliance on widely accessible Google Traffic data make it an effective and practical measure for urban traffic management studies.

$$TQI = (0\times P_0)+(1\times P_1)+(2\times P_2)+(3\times P_3) \tag{14}$$

Which:

P_0 = The percentage of green

P_1 = The percentage of orange

P_2 = The percentage of red

P_3 = The percentage of dark-red

The above formula is stated on the provided link: https://trafficindex.org/how-it-works/.

The mean value of TQI for our research period (58 days) is 25.90.

4- 3- Weather condition dataset

For our weather data, World Weather Online was relied upon for the 58-day period from 3th Mehr to 30th Aban which can be found on the following link: https://www.visualcrossing.com/weather/weather-data. The weather factors of interest were temperature, humidity, and wind speed which is used based on daily average. The mean value of each weather condition for our research period (58 days) is shown in Figure 2.

5- Results

In this section, an analysis of both the multivariate regression model and the ordered logistic regression is presented. These statistical models illustrate the correlation between explanatory variables and air quality levels. Initially, it is ensured that all independent variables are statistically significant and influence the air quality levels. All variables in the models are measured on the same day, except for the traffic quality index (TQI_lag_1) which is evaluated with a one-day lag. This decision is made on the basis of the assumption that pollution generated each day has a more significant impact on the air quality of the following day. This hypothesis is tested prior to constructing the final model, by examining the p-value of the TQI variable. However, the p-value for TQI_lag_1 in both the multivariate regression model and the ordered logistic regression exceeds 0.05, which falls within an accepted confidence interval. More specifically, in the multivariate regression model, the p-value for TQI_lag_1 is 0.77, and for the ordered logistic regression,

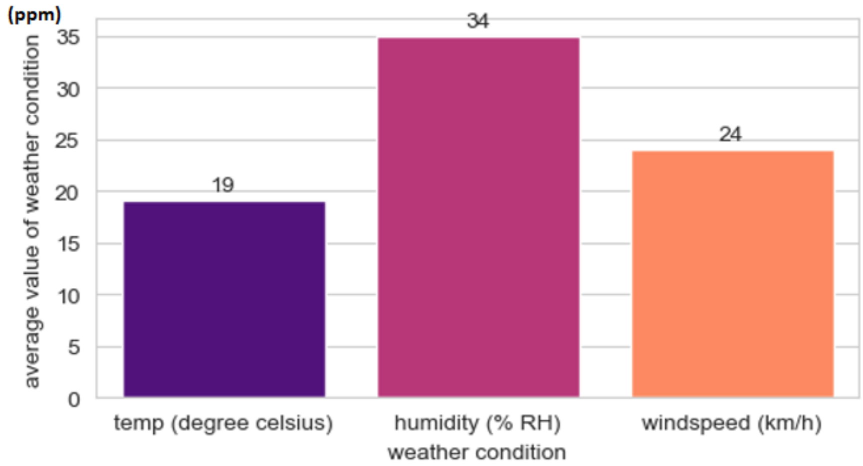

Fig. 2. The mean value of each weather condition for the research period

Table 1. Results of multivariate regression model

Independent variable	Coefficient	Standard Error	t	P > |t|
Constant	0.58	0.185	3.155	0.003
TQI_lag_1	0.03	0.120	0.294	0.770
Temperature	-0.35	0.198	-1.766	0.083
Humidity	0.05	0.204	0.246	0.807
Wind Speed	-0.14	0.118	-1.228	0.225
Holiday	0.00	0.066	0.008	0.994

it is 0.48. In both instances, the models demonstrate that the TQI_lag_1 variable, representing traffic congestion, does not significantly impact the AQI, which represents air pollution. Nonetheless, the positive coefficient sign for TQI_lag_1 suggests that as traffic congestion increases, air pollution also increases, leading to higher AQI levels. In both models, temperature plays the most crucial role in influencing air quality, as indicated by its highest coefficient. The temperature variable has a negative sign, implying that lower (colder) temperatures lead to higher levels of air pollutants. Conversely, the holiday dummy variable is deemed to be the least significant in both cases. In particular, the p-value for this variable in the multivariate regression model (Table 1) is close to 1, suggesting that its coefficient is likely negligible and can be excluded from the model. Following temperature, wind speed emerges as the second most important variable, with a coefficient of -0.14 in the multivariate regression model. This indicates that as wind speed increases by one standard unit, the air quality index decreases by one standard unit, resulting in lower pollution levels. Lastly, humidity is the final variable to consider. Although its significance is relatively low, the positive coefficient suggests that an increase in humidity leads to higher levels of air pollution.

According to the ordered logistic regression model shown in Table 2, when TQI_lag_1 increases by one standard unit, holding other variables constant, the ordered log-odds of belonging to a higher AQI category would increase by 0.81. On the other hand, for temperature and wind speed, which have negative coefficients, the interpretation is reversed. Holding other variables constant, a one-unit increase in

Table 2. Results of ordered logistic regression model

Independent variable	Coefficient	Standard Error	z	P > |z|
TQI_lag_1	0.81	1.133	0.712	0.476
Temperature	-3.19	2.069	-1.542	0.123
Humidity	0.79	1.876	0.420	0.675
Wind Speed	-0.91	1.087	-0.841	0.400
Holiday	0.16	0.602	0.263	0.793
1/2	-2.28	1.842	-1.238	0.216
2/3	0.42	0.219	1.971	0.049
3/4	0.55	0.249	2.229	0.026

Table 3. Evaluation of multivariate regression model

Regression model	RMSE	MAE	RAE	R^2
Multivariate regression model	18.248	13.334	0.150	0.196

temperature would decrease the ordered log-odds of being in a higher AQI category by 3.19, and a one-unit increase in wind speed would decrease the ordered log-odds by 0.91. The positive coefficient for the holiday variable indicates that when all other variables are constant, the ordered logit of being in a higher AQI category on a holiday is 0.16 greater than on a workday. Note from Table 2 that 1/2 is the intercept for AQI in clear situations, 2/3 is the intercept for AQI in acceptable situations, and 3/4 is the intercept for AQI in unhealthy situations.

Table 3 presents the RMSE, MAE, RAE, and R^2 values of the multivariate regression model. RMSE represents the root mean square error and is a common method for assessing model accuracy. A lower RMSE value indicates a better fit of the model to the data. MAE stands for mean absolute error, which calculates the average absolute difference between the actual and predicted data. RAE, or relative absolute error, is determined by dividing the absolute error by the absolute value of the actual data. As previously mentioned, R^2 signifies the goodness of fit of the regression model.

Table 4 displays the confusion matrix from an ordered logistic regression analysis. A confusion matrix aids in evaluating the model's performance by indicating its ability to correctly classify various levels of the ordinal dependent variable. As per the table, the model exhibits an accuracy rate of nearly 40%, with a predominant focus on clear air quality.

In summary, while the models provide valuable insights into the factors influencing air quality in Tehran, they also highlight some limitations. The relatively low R^2 value in the multivariate regression model (0.196) suggests that a significant portion of the variability in air quality remains unexplained by the selected variables. This points to the possibility that other unmeasured factors, such as industrial emissions or geographical conditions, may play a more substantial role in determining air pollution levels. Moreover, the ordered logistic regression model, with an accuracy of around 40%, indicates moderate predictive power but also reveals room for improvement in correctly classifying more extreme pollution levels. These results suggest that while temperature and wind speed are key drivers of air quality, further research should explore additional variables and more advanced modeling techniques to enhance the accuracy and comprehensiveness of air pollution predictions.

Table 4. Evaluation of ordinal logistic regression model

True AQI	Predicted AQI			
	clear	acceptable	unhealthy	Very unhealthy
clear	11	6	2	1
acceptable	11	5	2	0
unhealthy	2	5	7	0
Very unhealthy	0	3	3	0

6- Conclusion

This study employed regression models to investigate the relationship between traffic volume and air pollution in Tehran, a city plagued by frequent air quality issues. The results reveal that contrary to common assumptions, traffic volume does not have a significant direct impact on air pollution levels. These findings suggest that traditional traffic-related interventions, such as limiting private vehicle use or closing schools, may not effectively reduce air pollution, particularly during severe pollution episodes.

One of the most critical insights from the analysis is that temperature plays a dominant role in influencing air quality, with lower temperatures linked to heightened pollution levels. This points to the need for policymakers to consider seasonal factors and develop weather-responsive strategies for managing air pollution. For example, heightened monitoring and more aggressive mitigation efforts may be required during colder months when air quality typically worsens.

Wind speed also emerged as a significant factor, with higher wind speeds contributing to the dispersion of pollutants. This finding underscores the importance of natural factors in air quality management and suggests that enhancing urban design to improve ventilation and air circulation could be a valuable long-term solution. The insignificance of humidity and holiday variables further refines our understanding of the specific conditions that influence pollution levels, suggesting these variables may not need to be prioritized in future models.

Interestingly, the Traffic Quality Index (TQI), which reflects daily traffic congestion levels, showed no significant impact on air pollution. This result suggests that the traffic-related contribution to air pollution may be less substantial than other sources, such as industrial activities or energy production, particularly in Tehran. Future research could benefit from a more detailed examination of these other sources and their interactions with environmental factors.

Despite these insights, the study has limitations. The regression models used, while effective for identifying correlations, may not capture the full complexity of factors influencing air quality. Non-linear relationships or long-term cumulative effects of traffic on air pollution may require more advanced modeling techniques. Additionally, the study relies on available traffic and environmental data, which may have its own limitations in terms of precision and coverage.

In conclusion, while the study highlights important environmental variables like temperature and wind speed as key drivers of air pollution, it challenges the assumption that traffic volume is a major contributor to Tehran's air quality issues. Policymakers should therefore reconsider traffic-centered approaches and focus on more comprehensive, multifaceted strategies to address air pollution, potentially involving industrial emissions control, energy consumption patterns, and urban planning initiatives designed to enhance air circulation. Future research could explore these alternative pathways and refine the models used to predict air quality dynamics.

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