THE IMPACT OF COVID-19 OUTBREAK ON AIR POLLUTION LEVELS USING ARIMA INTERVENTION MODELLING: A CASE STUDY OF JAKARTA, INDONESIA

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ABSTRACT

Jakarta is a region with a high number of COVID-19 cases in Indonesia. This study investigates the impact of the COVID-19 pandemic and the resulting large scale social restriction on air pollution levels in Jakarta, Indonesia, by studying particulate matter (PM_{10}) levels. This study employs ARIMA intervention using daily COVID-19 case data from January 1, 2020 to September 30, 2020 (the period before and after the first case of COVID-19 in Indonesia on March 2, 2020). The analysis shows COVID-19 started to impact PM_{10} in Jakarta on the 11th day after confirming the first case in Indonesia, which is indicated by an unordinary increase in PM_{10} level. However, on the 12th day after intervention, the PM_{10} level decreases. This occurred at the beginning of the period when large-scale social restrictions are imposed. However, one month after intervention, PM_{10} increases again and continues to increase until the end of the study. This is allegedly because people are accustomed to being ignorant and bored with the pandemic situation. Social restrictions and movements are no longer effective, which results in the rise of PM_{10} levels again. Hence, it can be concluded that COVID-19 impacts air quality in Jakarta even though the impact is minimal and in the short term.

Keywords: COVID-19, air pollution, PM_{10}, ARIMA intervention

1. Introduction

The first outbreaking COVID-19 was identified in Wuhan, China. World Health Organization characterized it as a pandemic announced on March 11, 2020. On May 4, 2020, COVID-19 had caused more than 3.5 million infected people and 240,000 deaths worldwide. It has been spreading so rapidly throughout the world, including Indonesia [1]. In Indonesia, the first case of COVID-19 was found in Jakarta on March 2, 2020. Jakarta, the capital city of Indonesia, has the highest number of COVID-19 cases. Indonesia COVID-19 Response Acceleration Task Force noted that in the early period of the pandemic, from March 2 until April 9, 2020, Jakarta had the highest number of COVID-19 cases, where 1,632 people were positive and 149 people were died [2].

In order to reduce the spread of that virus, the Indonesian Government had officially announced a social distancing policy called large-scale social restrictions policy in almost all of the regions, including in Jakarta, started from April 10, 2020 until the next two weeks. Later, the large-scale social restrictions policy was extended until the end of June 2020 because the COVID-19 cases were increasing rapidly in Jakarta. Large-scale social restrictions policy obliges people to work from home, schooling from home, worship activities at home, and restrict socio-cultural activities, including the use of public transportation [3].

In the regions that had just been exposed by COVID-19, the government had to make policy to prevent the virus from spreading widely. As a replacement, human mobilities would be restricted, resulting in reduced emissions from transportation, industry and households, and reduced air pollution emissions [4]. This pandemic gives us a chance for measuring the air quality when people spend much more time at home with less of activities [5]. COVID-19 has not only impacted to the health sector in disease burden but also the global economy sector [6], but it allows us to assess changes in air quality caused by reduced industrial and human activities [7].

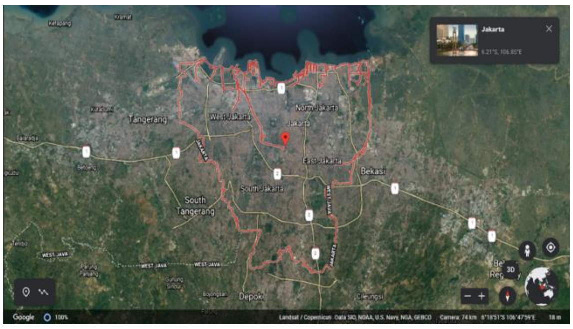
Jakarta has poor air quality. In Southeast Asia, Jakarta was the most polluted capital city for pollution in 2019, closely followed by Hanoi [8]. Jakarta is the most densely populated areas 15,907 residents/km^2 in 2020 [9]. Jakarta is the centre of national business and trade, so the mobilities are very high. Millions of residents from the neighbouring regions generally travel every day.

Air pollution issues has been an essential issue in many urban cities, mainly due to industrialization and vehicle emission pollutions. Air pollution is characterized by major significant pollutants (sulphur and nitrogen oxides, carbon monoxides, volatile organic compounds) and minor pollutants (ozone, non-sea salt sulphate, and minor organic aerosols) [10]. It contributes to the quality of the atmosphere [11]. In 2016, There are about 4.2 million people died because of ambient air pollution [12].

The level of air pollution of the region could be observed by sawing the particulate matter (PM). Particulate matter is an important category of air pollutants, including a natural complex mixture and anthropogenic (human-made) particles. It is suspected that particles with a diameter of less than 10 µm (PM_{10}) and less than 2.5 µm ($PM_{2.5}$) have harmful effects on human health ([13]; [14]).

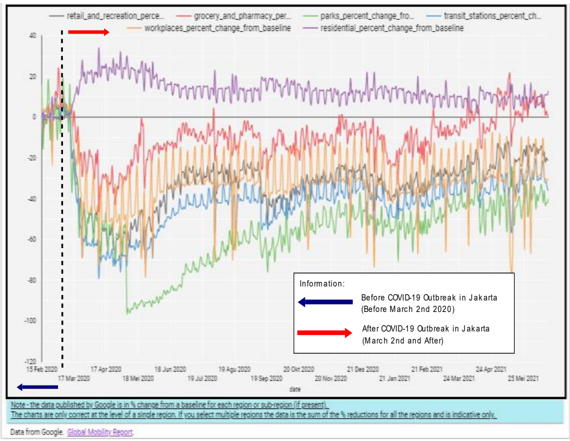
Jakarta's PM_{10} before the COVID-19 outbreak (before March 2, 2020) generally ranged between 50 – 75, which classified as moderate classification. On the other hand, after the COVID-19 attack (March 2, 2020, and after), PM_{10} generally ranged between 25 – 50, classified as good classification [15]. Air pollution might lead to human more vulnerable to exposed COVID-19. A related study showed that particulate matter (PM) and NO_2 contributed to triggering the spread of COVID-19 and lethality [16].

As supporting information, Jakarta public transit mobility reports were analysed. There were differences in mobility pattern before and after the COVID-19 outbreak in Jakarta. A previous study found that the Ozone, NO2, CO, and PM_{10} were decreased at the beginning of the preparation of stay at home orders in many locations in the United States, especially in public places [17]. Similarly, in figure 2. We can see that the transit mobility had decreased at the initial time of positive COVID-19 confirmed cases in the public places of Jakarta, such as in parks, retail and recreations, transit stations, and workplaces compared with baseline. In the other hand, the mobility trends for places of residence did not decrease [18].



Google earth

Figure 1. Jakarta's map.



Source: Google COVID-19 community mobility reports

Figure 2. Jakarta public transit mobility reports before and after the COVID-19 outbreak.

Based on the data and many previous studies, we suppose a difference in air quality before the COVID-19 and after the COVID-19 outbreak. The present study aims to analyze a general description of the level concentration of PM_{10} before and after the first confirmed case of COVID-19 in Indonesia. Moreover, the study will examine the initial time of positive confirmed cases of COVID-19, the impact, the magnitude of the effect, and the endurance of the effect (temporary or permanent) on the level concentration of PM_{10} in Jakarta.

One of the uniqueness of this present study is that we used Arima Intervention Modelling to obtain a more precise model for explaining and analyzing the intervention impacts. This study will help policymakers and researchers to formulate a plan of sustainable environmental management to reduce levels of air pollution in Jakarta. It may improve Jakarta's air quality in a more sustainable post-COVID-19 due to increased public attention to new normal habits.

In recent times, there have been many studies related to the impact of COVID-19 on air quality changes in some regions of the world. A study found that the air quality had improved during the COVID-19 epidemic, but the effect of the COVID-19 outbreak on improving air quality was temporary [19] or in the short term ([20]; [21]).

Furthermore, a study was conducted in South Korea in two domestic cities in Seoul City and Daegu City. The spreading of the COVID-19 was very serious. Compared with the previous three years, during the pandemic, the concentrations of $PM_{2.5}$, PM_{10} and NO_2 dropped by 31 percent, 61 percent, and 33 percent, in respectively [22]. Even though the COVID-19 lock-down had negative impact on social and economy sector, it had positive impact on the environment and the improvement of air quality [23]. A related study in Korea showed that the changes of air quality after the COVID-19 outbreak. All of $PM_{2.5}$, PM_{10}, NO_2, and CO levels were decreased during social distancing for a short period [24].

Another study found that air quality was improved after the publication of social distancing guidelines in Seoul, South Korea [25]. With a more extensive scope, social distancing policy also had a significant impact on reducing air pollutant levels, although it had a weaker effect compared with the lockdown policy [4]. Particulate matter (PM_{10}) concentrations were significantly dropped during stay at home orders in the United States even if the reduction is moderate and short-lived [26]. Similarly, the impact of lockdown in 12 cities within the globe were assessed during the pandemic showed that a notable improvement in air quality [27]. Furthermore, the study of air quality data in four metros in India showed that there was a different pattern in air quality during the COVID-19 lock down policy. The mobility had been restricted in many locations by India Government. The lock down had brought fine changed to the natural environment in the decreasing of two particulate matters ($PM_{2.5}$ and PM_{10}) pollutions. The metros cities had cleaner air than before [28].

Many previous researches focusing discussion about the impact of COVID-19 to air pollution were also carried out in East Asian, European countries, and American countries ([29]; [30]; [31]). This research fills the gap, the impact of COVID-19 on air pollution in Indonesia, especially in Jakarta as Indonesia's most populous metropolitan cities. Besides, this study analyzes the effect using the intervention time series model approach to observe how the impact pattern occurs and make short-term predictions of the model obtained.

2. Methods

Data. This study has used secondary data obtained from the world air quality index project (AQICN) website https://aqicn.org/city/indonesia/jakarta/us-consulate/central/ in the form of daily time series data on PM_{10} concentration in Jakarta with a research period from January 1, 2020, to September 30, 2020. The data used has been validated and used in several previous studies ([32]; [33]; [34]). Jakarta is the most populous cities in Indonesia that belongs to a large industrial area and prone to congestion caused by many motor vehicles. This causes Jakarta until now has not been able to escape the problem of air pollution. On March 2, 2020, Indonesia announced the first confirmed case of COVID-19 in Indonesia. For several months after the announcement of the first case, Jakarta became one of the regions with the highest number of COVID-19 cases in Indonesia.

Methods. The analysis method used in this study is descriptive analysis in the form of graphs and inference analysis in the form of the ARIMA (Autoregressive Integrated Moving Average) Intervention model. Intervention analysis is used to measure the impact of an intervention (an event that impacts a forecasting variable) and to estimate the impact of such interventions in the future [35]. In this study, the processed data were divided into two groups: before the intervention and after the intervention. The intervention in this study is the first confirmed case of COVID-19 in Indonesia that occurred on March 2, 2020.

ARIMA is a time series modelling by adding an Integrated term to the ARMA model that shows the stationarity of data [36]. Meanwhile, the ARIMA Intervention model is the development of the ARIMA model by adding interventions. Stationarity checking can be done through Dicky Fuller Test or the Augmented Dicky Fuller Test to determine whether the root unit is available. Dicky Fuller Test delivers good results in a variety of applications [37]. The null hypothesis in the ADF and DF Test is that there is a root unit (not stationary), while the alternative hypothesis is that there is no root unit. Thus, the ARIMA model has three components, namely AR(p), I(d), and MA(q). The p and q value are determined based on the cuts off on the p-lag on the PACF and the cuts off at the q-lag on the ACF, while the d value is determined from the difference value of the differencing process. The selection of ARIMA models is determined based on the smallest AIC (Akaike's Information Criterion) and BIC (Bayesian Information Criterion) values. Using the help of backshift operators, the ARIMA(p,d,q) model can be written as follows [38]:

$$Y_p(B)(1-B)^d Z_t = \varepsilon_q(B) e_t \qquad (1)$$

$\phi_p(B)$ indicate AR(p), $(1-B)^d Z_t$ indicate the d-th difference, and $\theta_q(B)$ indicate MA(q). An event that appears suddenly is one form of intervention that will cause a change in data patterns. Steps function is the simplest form of intervention. Intervention function with one intervention variable can be written as follows:

$$f(\mathrm{I}_t) = y_t(s,r,b) = \frac{\omega_s(B)}{\delta_r(B)} \qquad (2)$$

Thus, the general formula of ARIMA Intervention steps function is:

$$Z_t = f(\beta, \mathrm{I_t}) = \frac{\omega_s(B)}{\delta_r(B)} B^b S_t^{(T)} + N_t \qquad (3)$$

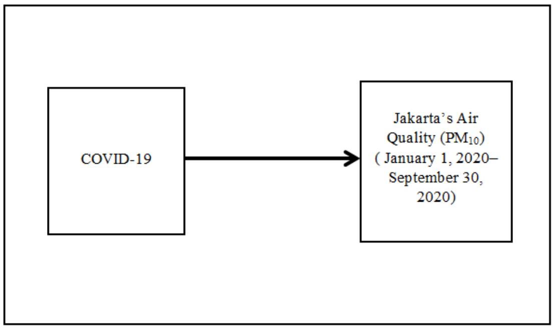


Figure 3. Research framework.

ARIMA intervention's equation if the result of transformation (λ) is:

$$Z_t(\lambda) = f(\beta, I_t) = \frac{\omega_s(B)}{\delta_r(B)} B^b S_t^{(T)} + N_t \quad (4)$$

$$\omega_s(B): \omega_0 - \omega_1(B) - \cdots - \omega_s B^s \quad (5)$$

$$\delta_r(B) : 1 - \delta_1(B) - \cdots - \delta_r B^r \quad (6)$$

b is the number of periods before I_t input affects Z_t, s is the amount of I_t value that affect Z_t, r is number of periods before I_t inputs related to Z_t, ω_s is the magnitude of level increase or decrease (mean), δ_r is a form of delay as a result of the influence of intervention. The research framework can be seen in Figure 3.

3. Result and Discussions

Overview of PM_{10} concentrations in Jakarta. Data on Jakarta's Concentration PM_{10} from January 1, 2020 until September 30, 2020, will be analyzed using the ARIMA intervention step function.

Figure 4 shows the pattern of data before and after the intervention. Prior to the intervention, PM_{10} concentrations had decreased. Although the first confirmed case of COVID-19 in Indonesia occurred on March 2, 2020, the public has been alerted to the spread of COVID-19 by not often doing activities outside the home. This is because the virus has struck in several countries other than Wuhan, China, by the end of 2019. Figure 5 shows the decrease in people's mobility to retail &recreation, grocery & pharmacy, parks, transit stations, workplaces, except residential compared to the regular days before the occurrence of COVID-19.

The data pattern after the intervention, as shown in Figure 4, shows the concentration of PM_{10} was first still low. For example, on March 3, 2020, the concentration of PM_{10} in Jakarta was 33 μg/m^3, but slowly the concentration increased and on September 30, 2020, it reached 53 μg/m^3. The Jakarta Government has carried out several policy restrictions on activities both in small and large scopes in reducing the number of positive cases of COVID-19. However, over time the restriction policy is getting looser so that people have become accustomed to doing activities outside the home even though the COVID-19 pandemic is not over.

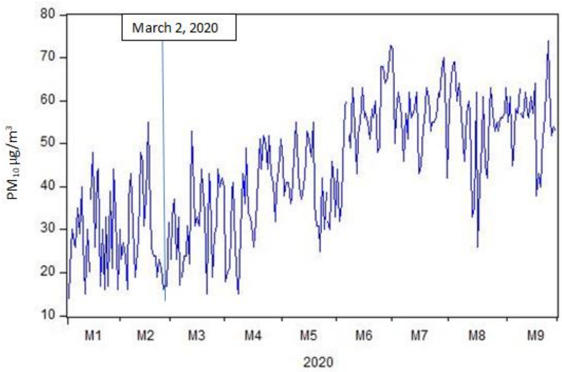


Figure 4. The plot of Jakarta's Concentration PM_{10} data before and after the intervention.

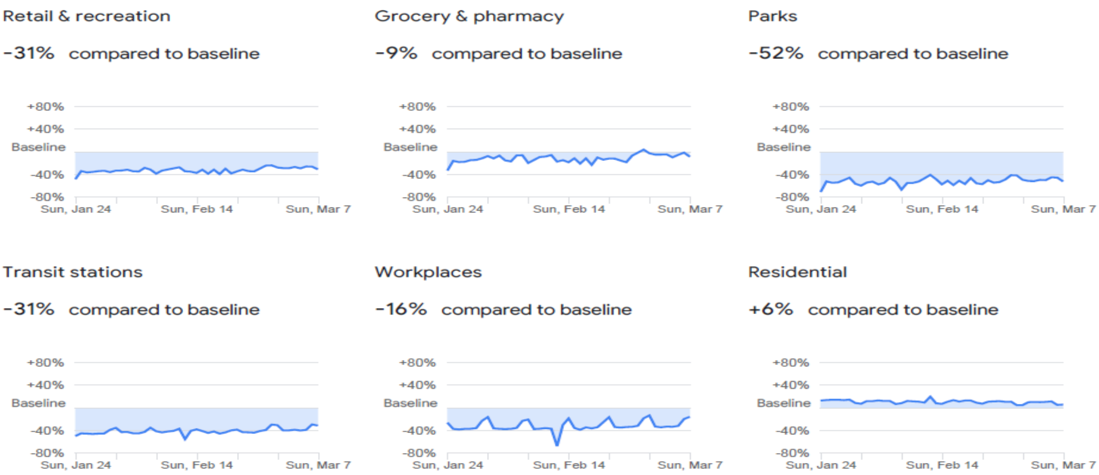


Figure 5. Mobility of people in Jakarta.

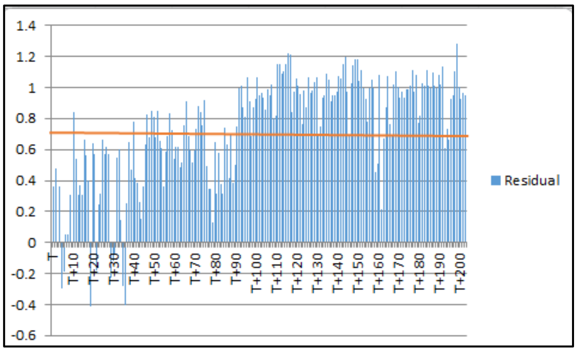


Figure 6. The plot of residual data.

Table 1. Parameter estimation and diagnostic tests ARIMA model

Parameter		White Noise Checking	
Estimasi	P-value	Lag	P-value
$\emptyset$ = 0.99982	<.0001*	6	0.4422
θ =0.83519	<.0001*	12	0.6789
		18	0.7571
		24	0.9251

*Significant at α = 1 percent

Table 2. Parameter estimation and diagnostic tests ARIMA intervention model.

Maximum Likelihood Estimation		
Parameter	Estimation	P-value
θ_1	0.76535	<,0001*
$\emptyset_1$	0.99986	<,0001*
ω_0	0.78152	0,0020*
ω_1	0.44060	0,0812

*Significant at α = 1 percent

ARIMA and ARIMA Intervention. One of the conditions in analysing using the ARIMA method is that the data used must be stationary on variance and average. If the data is not stationary on variance, then data transformation is done, while if the data is not stationary on average, then the differencing process is carried out. In this study, the data has been stationary at the average level so that no differencing process is carried out. Therefore, it is only necessary to transform the data into a natural logarithmic form to become stationary.

The results of statistical tests using the Ljung-Box test presented in Table 1 show the results of ho reject failure at α = 0.01. This means that the residual value for the ARIMA model (1, 0, 1) has tested the white noise assumption test to be used in this study. Determining the order b, s, and r in the intervention ARIMA is done by looking at residual chart patterns out of bounds ±2 σ with a value of σ = 0.3549. Figure 6 shows at lag 11 (T+11) is the first-time residuals cross the ±2 σ limit so that it can be expected that the value of order b is 11. The value for the order s is 1 (T+12) because there is an increase after the order b=11. Furthermore, the value for the order r is expected to be zero (r=0) because the residual has no pattern. The determination of the order b, s, and r in this study also involved a trial and error process.

It then tests the parameters of the order and shows significant results at the significance level α =0.01 shown in Table 2. Based on Table 2 shows the result of failed reject H_0 at the significance level α = 0.01. This suggests that the ARIMA intervention model has met the assumption of white noise. Therefore, the ARIMA intervention model can be written as follows:

$$\hat{Y}_t = (0.78152 + 0.44060)B^{11}S_{1t} + \frac{0.99986\hat{Y}_{t-1}}{0.76535\hat{\varepsilon}_{t-1}} \quad (7)$$

with ARIMA model:

$$\hat{Y}_t = 0.99982\hat{Y}_{t-1} + 0.83519\hat{\varepsilon}_{t-1} \quad (8)$$

Intervention b=11, precisely in mid-March 2020 shows the first impact resulting from the first confirmed case of COVID-19 in Indonesia with PM_{10} concentration of 53 μg/m^3. PM_{10} concentrations improved than usual but did not last long. This is indicated in T+12 residual data decreased again. On March 22, 2020 (T+19) PM_{10} concentrations decreased at their lowest point during the research period with a concentration value of 15 μg/m^3. This is because the date is a weekend so there are not many people who do activities outside the home. If studied further, on March 22, 2020, based on data from the Committee for Handling COVID-19 and National Economic Recovery confirmed cases in Jakarta had reached 18 people while the number recovered as many as three people.

From mid-April 2020 (T+47) to early June 2020 (T+90), PM_{10} concentrations were volatile. For example, on April 10, 2020 the PM_{10} concentration was 43 μg/m^3. This is because the Jakarta government implemented a large-scale social restriction policy. Since the implementation of Work From Home (WFH) and large-scale social restrictions in Jakarta to reduce the mobility of people to work. Since WFH was implemented, people's mobility to work has decreased by 15 percent, while when large-scale social restrictions occur, there has been a decrease of 73 percent [39]. However, after the end of the first policy of large-scale social restrictions ended precisely on April 24, 2020, PM_{10} concentration again increased out of the ordinary with a concentration value of 52 μg/m^3. Similarly, conditions in late April and early May, from April 30, 2020 to May 1, 2020 PM_{10} concentrations increased with concentration values of 51 μg/m^3 and 46 μg/m^3. Although the COVID-19 pandemic is not over yet, labour protest is still taking place in some areas of Jakarta.

Currently, the COVID-19 pandemic is unknown when it ends, so people are getting used to doing activities outside the home. This is evidenced that

PM_{10} concentration tends to increase from the beginning of June 2020 (T+91) until the end of the study, namely the end of September (T+203). This is allegedly because people are accustomed to being ignorant and bored with pandemic situations so that social restrictions and movements are no longer effective, which results in the rising of PM_{10} concentrations levels again. Therefore, COVID-19 has an impact on air quality in Jakarta even though the impact is minimal. As well as the impact of COVID-19 on small particulate matter concentrations in some areas ([40]; [41]; [42]; [43]; [44]; [45]). This is because in some areas of Jakarta there are still corporate or industrial activities, so an increase in PM_{10} concentration is inevitable [40]. Besides, research [45] shows that particulate matter has a positive correlation with transportation and industry. There are still activities of companies or industries during the COVID-19 pandemic; this aims to safeguard the Indonesian economy. For example, during large-scale social restrictions, the types of businesses that are still allowed to work in the office are health, finance, energy, foodstuffs, telecommunications and informatics technology, hospitality, logistics, basic services, construction, and others. In addition, factors that affect PM_{10} concentration include season, wind speed, rain, and relative humidity. PM_{10} concentration increases at two times, namely morning (7-10 AM) and afternoon (16.00 – 17.00 PM), then decreases at night. The study also stated that relative humidity has a significant and negative effect on PM_{10}, while CO has a positive relationship with the increase in PM_{10} [46]. Based on accuweather.com data shows that at the September 2020 the air temperature around Jakarta was in the range of 30℃ until 34℃ Temperature and wind speed have a positive correlation to PM_{10} concentrations [47].

4. Conclusion and Suggestion

The impact of COVID-19 on air pollution in Jakarta began to be felt after one week of confirmation of the first case. The increase in PM_{10} concentration increased out of the ordinary since the 11th day after the announcement of the first case. COVID-19 intervention against PM_{10} concentration as a proxy for air pollution is gradually temporary, meaning that the intervention affects PM_{10} concentration gradually and temporarily. After the 11th day, the decrease in PM_{10} concentration continued to occur until it reached its lowest point after the 19th day after the PM_{10} concentration again increased after the 91st day. Therefore, COVID-19 has an impact on air quality in Jakarta, even though the effect is minimal. Our findings suggest that efforts to significantly reduce air pollution in this short period of time may suggest that in a more sustainable post the pandemic public awareness of a new healthy environment and a new normal is increasing.

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