RESEARCH ARTICLE



Association between environmental factors and COVID-19 in Shanghai, China

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Abstract

The outbreak of coronavirus disease 2019 (COVID-19) continues to spread worldwide and has led to recession, rising unemployment, and the collapse of the health-care system. The aim of this study was to explore the exposure–response relationship between daily confirmed COVID-19 cases and environmental factors. We used a time-series generalized additive model (GAM) to investigate the short-term association between COVID-19 and environmental factors by using daily meteorological elements, air pollutant concentration, and daily confirmed COVID-19 cases from January 21, 2020, to February 29, 2020, in Shanghai, China. We observed significant negative associations between daily confirmed COVID-19 cases and mean temperature (T_{ave}), temperature humidity index (THI), and index of wind effect (K), whereas air quality index (AQI), PM_{2.5}, PM₁₀ NO₂, and SO₂ were significantly associated with the increase in daily confirmed COVID-19 cases. A 1 °C increase in T_{ave} , one-unit increase in THI, and 10-unit increase in K (lag 0–7 days) were associated with 4.7, 1.8, and 1.6% decrease in daily confirmed cases, respectively. Daily T_{ave} , THI, K, PM₁₀, and SO₂ had significant lag and persistence (lag 0–7 days), whereas the lag and persistence of AQI, PM_{2.5}, and NO₂ were significant at both lag 0–7 and 0–14 days. A 10-µg/m³ increase in PM₁₀ and 1-µg/m³ increase in AQI and a 10-µg/m³ increase in PM_{2.5} and NO₂ were associated with 7.9, 7.8, and 10.1% increase in daily confirmed cases at lag 0–14 days, respectively. Our findings have important implications for public health in the city of Shanghai.

Keywords Air pollution · COVID-19 · Environmental factors

Highlights

Yuxia Ma and Bowen Cheng contributed equally to this work as co-first authors

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Introduction

In late 2019, a novel coronavirus called severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which causes coronavirus disease 2019 (COVID-19), spread globally (Xu et al. 2020a, b; Sohrabi et al. 2020). The highly infectious nature and long incubation period of the virus make it a serious threat to global health.

COVID-19 can rapidly spread through person-to-person transmission (Chen et al. 2020; Liu et al. 2020a, b), and the virus can cause serious fever, cough, headache, and respiratory problems (Waldman et al. 2020). COVID-19 has caused a global economic decline, an increase in the unemployment rate, and the collapse of health-care systems (Mollalo et al. 2020; Sarkodie and Owusu 2020). On August 27, 2020, the World Health Organization (WHO) reported more than 24,021,218 confirmed cases and 821,462 deaths globally.

Studies have shown that meteorological elements are crucial for the spread, growth, and survival of viruses. For example, high temperature, low wind speed, and low relative

^{1.} The exposure–response relationship between COVID-19 and T_{ave} was positive when T < 5 °C and became negative when 5 °C < T < 15 °C. 2. Temperature humidity index (THI) and index of wind effect (K) showed significant negative relationships with the transmission of COVID-19.

^{3.} Air pollution was significantly positive associated with daily confirmed COVID-19 cases.

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humidity have been positively associated with the Middle East respiratory syndrome coronavirus (MERS-CoV) (Altamimi and Ahmed 2020; Amuakwa-Mensah et al. 2017). Pediatric influenza was revealed to be positively associated with high concentrations of ambient PM₁₀ (relative risk [RR]: 1.11; 95% confidence interval [CI]: 1.10-1.13) and O₃ (RR: 1.28; 95%) CI: 1.25–1.31) in Brisbane, Australia (Xu et al. 2013). Studies have reported that 60% of confirmed COVID-19 cases were found where optimum air temperature ranged from 5 to 15 °C (Gunthe et al. 2020; Huang et al. 2020). Notari (2021) suggested that the growth rate of confirmed COVID-19 cases would decrease due to lockdown policies and warm weather. Cole et al. (2020) indicated that a $1-\mu g/m^3$ increase in the PM_{2.5} concentration was associated with 9.4 more daily confirmed COVID-19 cases. Peto et al. (2020) found that environmental elements are vital for viral transmission.

Shanghai, China (121°47′ E, 31°23′ N), has been seriously affected by COVID-19 and continues to import cases daily. In this study, we assessed the effect of environmental factors and the biometeorological index on COVID-19. Moreover, we conducted a 14-day lag study to investigate the effect of the lag and persistence of environmental factors on COVID-19 in Shanghai. Our findings have city-wide implications for public health and provide insights into the effect of environmental factors on COVID-19 transmission.

Data and methods

The time-series data included daily meteorological elements, air quality index (AQI), air pollutant concentrations, and number of daily confirmed COVID-19 cases in Shanghai, China, from January 21, 2020, to February 29, 2020.

Meteorological data were collected daily by the China Meteorological Data Network (http://data.cma.cn), including mean temperature (T_{ave} , °C), relative humidity (RH, %), air pressure (P, hPa), wind speed (V, m/s), and sunshine duration (H, h). Daily air quality data, namely, the AQI and mean concentrations of NO₂, SO₂, PM_{2.5}, PM₁₀, CO, and O₃-8h, were obtained from the China National Environmental Monitoring Center. After the SARS epidemic, China established a reporting system for public health emergencies and infectious diseases. Data on daily confirmed COVID-19 cases were obtained from the National Health Commission in Shanghai.

The generalized additive model (GAM) is widely used in similar studies. We used the GAM in combination with conditional Poisson regression to assess the effect on daily confirmed COVID-19 cases. Long-term trends, latitude factors, air quality, and meteorological factors, including relative humidity, air pressure, wind speed, and sunshine duration, were adjusted as confounders. The basic model is described below:

$$log[E(Y_i)] = \alpha + DOW + \beta X_i + lat + s(time, df) + s(AQI_i, df) + s(H_i, df) + s(P_i, df) + s(V_i, df) + s(Q_i, df)$$

Here, Y_i is the number of daily confirmed COVID-19 cases, and $E(Y_i)$ is the expected confirmed cases on day i; α is the intercept; DOW is the day of the week; β denotes the exposure–response coefficient; s is a regression spline function; df indicates the degree of freedom; time denotes the days of calendar date; and X_i , AQI_i, H_i, P_i, V_i, and Q_i represent the explanatory variables, AQI, sunshine duration, average air pressure, average wind speed, and relative humidity on day i, respectively.

The temperature humidity index (THI) and index of wind effect (K) were calculated as follows:

$$THI = T_d - 0.55*(1 - f)*(T_d - 58)$$
⁽²⁾

$$K = -(10\sqrt{V} + 10.45 - V) *(33 - T) + 8.55 * H$$
(3)

Here, T_d , f, V, T, and H refer to Fahrenheit, relative humidity, average wind speed, mean temperature, and sunshine duration, respectively. The THI is a biometeorological index, which is based on heat exchanged between the human body and atmosphere. K is the degree of warmth of the naked skin under the effect of temperature and wind speed (Yan et al. 2009). The two indexes were divided into nine levels (Table 1).

We selected T_{ave} , THI, K, AQI, PM_{2.5}, PM₁₀, NO₂, and SO₂ as explanatory variables in eight models to examine their effects on daily confirmed COVID-19 cases. The Akaike information criterion (AIC) is a statistical method to estimate degrees of complexity and fit. We adjusted each degree of freedom to get the smallest AIC. Moreover, we used the results of the models to calculate the RR and cumulative RR to further investigate the lag and persistent effects of environmental factors on COVID-19.

 Table 1
 Standard range of temperature humidity index and index of wind effect

	THI	K
Extremely cold	< 40	<-1200
Cold	40-45	-1000 to -1200
Very cool	45-55	-800 to -1000
Cool	55-60	-600 to -800
Comfort	60–65	-300 to -600
Warm	65–70	-200 to -300
Very warm	70–75	-50 to -200
Hot	75-80	80 to -50
Extremely hot	> 80	> 80

The National Health Commission of China has reported that COVID-19 has an incubation period from 1 to 14 days, which is consistent with the findings of other reports. Models with a 14-day lag function were used to investigate the lag effect of environmental factors on COVID-19. The models were implemented in R statistical software by using the "mgcv" package. Statistically significant difference was set at p < 0.05.

Results

Table 2 summarizes the descriptive statistics of daily confirmed COVID-19 cases, meteorological elements, and air pollutant concentrations. A total of 337 confirmed COVID-19 cases, averaging 8 cases per day, were reported from January 21, 2020, to February 29, 2020. The daily average concentrations of AQI, SO₂, PM_{2.5}, PM₁₀, NO₂, and O₃ were 60.2, 5.7, 38.4, 36.7, 29.0, and 86.3 μ g/m³, respectively. The daily average temperature, relative humidity, air pressure, and wind speed were 8.2 °C, 77.8%, 1025.0 hPa, and 1.2 m/s, respectively.

Table 3 shows the Pearson correlations of air pollutants and meteorological elements in Shanghai. The AQI was positively correlated with other air pollutants, especially $PM_{2.5}$ (r = 0.97, p < 0.05). The relative humidity had a significantly positive correlation with T_{ave} and negative correlations with SO₂, PM_{10} , and O₃. Air pressure positively correlated with O₃ and negatively with T_{ave} and relative humidity.

 T_{ave} , THI, K, AQI, PM_{2.5}, PM₁₀, NO₂, and SO₂ greatly affected daily confirmed COVID-19 cases (Table 4). The eight factors were statistically significant as explanatory variables when p < 0.05. The explanation rates of T_{ave} , THI, K, AQI, PM_{2.5}, PM₁₀, NO₂, and SO₂ to the daily confirmed

Table 2Descriptive statistics for daily confirmed coronavirus disease2019 cases, air pollutant concentrations, and meteorological elements inShanghai

	Mean (SD)	Min	Max	IQR
Daily confirmed cases	8	0	34	6
AQI	60.2	30.0	128.0	12.9
$SO_2 (\mu g/m^3)$	5.7	3.0	9.0	0.6
PM _{2.5} (µg/m ³)	38.4	13.0	97.0	13.1
PM ₁₀ (µg/m ³)	36.7	7.0	96.0	12.1
NO ₂ (μ g/m ³)	29.0	15.0	57.0	6.3
$O_3 (\mu g/m^3)$	86.3	48.0	129.0	10.3
T (°C)	8.2	2.2	17.5	1.8
RH (%)	77.8	44.0	96.0	9.4
P (hPa)	1025.0	1016.0	1032.0	2.0
V (m/s)	2.5	1.1	4.4	0.7

COVID-19 cases were 31.1, 36.4, 22.2, 13.1, 7.8, 4.7, 4.8%, and 6.7%, respectively. Adjusted R² indicated the fitting degree of the model. Of the eight explanatory factors, the THI had excellent fitting degree of the model. The function is a linear (nonlinear) equation when the estimated degree of freedom (Edf) is (is not) equal to 1. The Edf values of T_{ave} , THI, AQI, PM_{2.5}, PM₁₀, NO₂, and SO₂ were greater than 1, suggesting that the relationship between environmental factors and daily confirmed COVID-19 cases was significantly nonlinear. The Edf value of K was close to 1, suggesting that the relationship between K and daily confirmed COVID-19 cases was significantly linear. The effects of environmental factors on COVID-19 cases determined using GAM models are shown in Fig. 1.

Figure 1 indicates the exposure-response relationship between Tave, THI, K, AQI, PM2.5, PM10, NO2, and SO2 and daily confirmed COVID-19 cases in Shanghai. Tave exhibited an S-shaped exposure-response relationship with COVID-19. The relationship curve had a slowly increasing trend in the range of T < 5 °C, which decreased when 5 °C < T < 15 °C. The relationship curve of THI and COVID-19 declined in the range of THI < 56 and then became flat when THI > 56. We found a significantly linear decreasing relationship between K and COVID-19, indicating that the daily confirmed COVID-19 cases would have a negative relationship with K. The relationship curve for AQI, PM2.5, PM10, and SO2 had a slowly increasing trend, suggesting positive relationships between AQI, PM_{2.5}, PM₁₀, and SO₂ and COVID-19. We found a negative relationship between COVID-19 and NO2 when $NO_2 < 40 \ \mu g/m^3$ and became positive when $NO_2 > 40 \ \mu g/m^3$.

Figure 2 demonstrates the RR and cumulative RR of daily confirmed COVID-19 cases with a unit increase in T_{ave}, THI, K, AQI, PM_{2.5}, PM₁₀, NO₂, and SO₂ in Shanghai. The effects of Tave, THI, and K on daily confirmed COVID-19 cases were negative at lag 3-6 days, 4-6 days, and 5-6 days, respectively. The cumulative RRs (lag 0-7) between T_{ave}, THI, and K and daily confirmed COVID-19 cases were 0.953 (95% CI: 0.791-1.166), 0.982 (95% CI: 0.881-1.096), and 0.984 (95% CI: 0.932–1.039), respectively; the cumulative RRs were not significant at lag 0-14 days. Regarding air pollution, the effects on daily confirmed COVID-19 cases were significant at lag 2-6 days for AQI, PM_{2 5}, and PM₁₀; at lag 0-3 days for NO₂; and at lag 1-6 days for SO₂, with the highest RRs of 1.031 (95% CI: 0.974-1.092), 1.039 (95% CI: 0.971-1.112), 1.060 (95% CI: 0.968-1.161), 1.142 (95% CI: 0.962-1.356), and 1.113 (95% CI: 0.999-1.239), respectively. The cumulative RRs between AQI, PM2.5, and NO2 and daily confirmed COVID-19 cases were 1.232 (95% CI: 1.040-1.416), 1.101 (95% CI: 1.034-1.210), and 1.109 (95% CI: 0.923-1.325) at lag 0-7 days and were significant at lag 0-14 days, with cumulative RRs of 1.079 (95% CI: 0.934-1.167), 1.078 (95% CI: 0.976-1.223), and 1.101 (95% CI: 1.034-1.210), respectively. The cumulative RRs between PM₁₀ and SO₂ and daily

Table 3	Pearson correlations of air pollutants and meteorological elements in Shanghai									
	AQI	SO_2	PM _{2.5}	PM_{10}	NO ₂	O ₃	T _{ave}	RH	Р	V
AQI	1.00									
SO_2	0.44*	1.00								
PM _{2.5}	0.97*	0.41*	1.00							
PM_{10}	0.80*	0.57*	0.78*	1.00						
NO ₂	0.51*	0.08	0.50*	0.21	1.00					
O ₃	0.37*	0.56*	0.27	0.59*	0.03	1.00				
T _{ave}	-0.3	-0.21	-0.04	0.09	0.22	0.02	1.00			
RH	01	-0.71*	-0.03	-0.37*	0.26	-0.55*	0.34*	1.00		
Р	-0.06	0.19	-0.11	0.11	-0.21	0.40*	-0.56*	-0.49*	1.00	
V	-0.24	0.01	-0.21	-0.21	-0.62*	-0.08	-0.13	-0.15	-0.04	1.00

*p < 0.05

confirmed COVID-19 cases were 1.139 (95% CI: 1.005– 1.314) and 1.057 (95% CI: 0.954–1.164) at lag 0–7 days, respectively, but not significant at lag 0–14 days. Thus, T_{ave} , THI, and K had a significantly negative effect on daily confirmed COVID-19 cases at lag 4–6 days and the cumulative effects were significant at lag 0–7 days. Daily confirmed COVID-19 cases were significantly associated with AQI, PM_{2.5}, and PM₁₀ at lag 2–6 days; NO₂ at lag 0–3 days; and SO₂ at lag 1–6 days. The cumulative effects of AQI, PM_{2.5}, and NO₂ were significant at lag 0–7 and 0–14 days, whereas the cumulative effect of PM₁₀ and SO₂ was significant at lag 0–7 days.

The optimum RRs of daily confirmed COVID-19 cases with environmental factors were illustrated in Fig 3. The relative risk was variable by environmental factors. Mean temperature had the strongest negative effect on daily confirmed COVID-19 cases. $PM_{2.5}$, SO_2 , PM_{10} and NO_2 had significant positive effects on daily confirmed COVID-19 cases, while AQI showed the strongest positive relationships with daily confirmed COVID-19 cases

Discussion

In this study, we estimated the short-term association between COVID-19 and environmental factors in Shanghai. We found

that the exposure-response relationship between COVID-19 and T_{ave} was positive when T < 5 °C and became negative when 5 $^{\circ}C < T < 15 ^{\circ}C$. Our findings that higher temperature may have a negative relationship with the transmission of COVID-19 are consistent with those of others (Del and Camacho-Ortiz 2020; Cole et al. 2020). Das et al. (2020) suggested that countries with low temperatures were more susceptible to infection than those with higher temperatures. A global study (Iqbal et al. 2020) revealed that countries with long and cold winters are at high risk for faster COVID-19 transmission, and the rate of spread would decrease when the weather becomes warmer. A study in China (Zhu and Xie 2020) reported a positive linear relationship between COVID-19 in the range of T< 3 °C, which became negative when T > 3 °C. A study in Brazil (Prata et al. 2020) indicated that the daily confirmed COVID-19 cases were significantly associated with a -4.90% decrease per 1 °C increase in temperature. This result can be useful for policymakers, and countries with lower temperatures must adhere to quarantine policies and social distancing; the growth rate is predicted to decrease with control measures and warmer weather (Nazari et al. 2020; Kraemer et al. 2020).

Other meteorological elements also play an important role in the spread, growth, and survival of viruses (Lee 2003; Cai et al. 2007; Şahin 2020; Menebo 2020). Altamimi and Ahmed (2020) found that the incidence of MERS was significantly

Table 4 Generalized additive model test results between mean temperature, temperature humidity index, index of wind effect, air quality index, PM_{2.5}, PM₁₀, NO₂, and SO₂ and daily confirmed coronavirus disease 2019 cases

	Т	THI	Κ	AQI	PM _{2.5}	PM_{10}	NO ₂	SO_2
Edf	1.948	1.916	1.025	1.262	2.26	2.856	2.04	2.856
Ref.df	2.176	1.993	1.010	1.343	2.896	2.987	2.434	2.984
P-value	< 2e-16	0.002	0.028	0.0002	< 2e-6	< 0.004	< 0.007	< 8e-6
Adjusted R ²	0.238	0.303	0.158	0.116	0.052	0.011	0.034	0.019
Deviance explained	31.1%	36.4%	22.2%	13.1%	7.8%	4.7%	4.8%	6.7%



Fig.1 Exposure–response relationship between mean temperature (T_{ave}), temperature humidity index (THI), index of wind effect (K), air quality index (AQI), PM_{2.5}, PM₁₀, NO₂, and SO₂ and daily confirmed

associated with lower humidity (incidence rate ratio [IRR] = 0.956, 95% CI: 0.948–0.964) and lower wind speed (IRR = 0.945, 95% CI: 0.912–0.979) in Riyadh region. Casanova et al. (2010) reported that SARS-CoV had greater survival when humidity was low (20%) or high (80%), because envelope viruses containing lipid membranes can survive well at

coronavirus disease 2019 cases in Shanghai. The solid lines indicate the logarithm of relative risk (RR); the dotted lines show 95% confidence intervals

lower humidity (Sobsey and Meschke 2003). Runkle et al. (2020) found a positive exposure–response relationship between humidity and the COVID-19 incidence rate. Atalan and Atalan (2020) indicated that relative humidity and wind speed played important roles in the COVID-19 outbreak in Italy. Pani et al. (2020) found that dew point was significantly



Fig. 2 Relative risk (RR) and cumulative RR (95% confidence interval [CI]) of daily confirmed COVID-19 cases with a unit increase in mean temperature (T_{ave}), temperature humidity index (THI), index of wind

effect (K), air quality index (AQI), PM_{2.5}, PM₁₀, NO₂, and SO₂ in Shanghai. Units are 1 °C for T_{ave} , 1 unit for THI, 10 units for K and AQI, 10 µg/m³ for PM_{2.5}, PM₁₀, and NO₂, and 1 µg/m³ for SO₂



Fig. 3 Optimum RRs of daily confirmed COVID-19 cases with environmental factors

positively correlated with COVID-19 cases in Singapore. Silva et al. (2020) found that COVID-19 cases were negatively correlated with relative humidity, daily precipitation and wind speed in humid equatorial climate. In this study, we used two biometeorological indexes (THI and K), which indicate the level of human thermal comfort, to estimate the combined effect of meteorological elements. The THI is determined through temperature and humidity and K through temperature and wind speed. A unit increase in the THI or a 10-unit increase in K was associated with a 1.8 or 1.6% decrease in daily confirmed COVID-19 cases, respectively, indicating that COVID-19 transmission rates may also have a negative relationship with humidity and wind speed.

Our findings revealed a significant positive association between air pollution and COVID-19. NO₂ was an exception and had a weak effect on COVID-19 at a low concentration, whereas other pollutants had significant positive relationships with COVID-19. With a $10-\mu g/m^3$ increase in PM_{2.5}, PM₁₀, and NO₂; a $1-\mu g/m^3$ increase in SO₂; and a 10-unit increase in the AQI, daily confirmed cases would have a 3.9% (lag 5 days), 6.0% (lag 5 days), 14.2% (lag 2 days), 11.3% (lag 5 days), and 2.3% (lag 6 days) increase, respectively. Studies have reported that air pollution is significantly associated with viruses (Dominici et al. 2006; Xu et al. 2013). Li et al. (2020) indicated that the COVID-19 incidence would increase with an increase in AQI, NO₂, and PM_{2.5}. A seasonal analysis (Liu et al. 2020a, b) using distributed lag non-linear model found that PM2.5, SO2, and O3 had significant cumulative effects on daily confirmed cases. Zhu et al. (2020) found that with a 10-µg/m³ increase in PM_{2.5}, PM₁₀, O₃, and NO₂, the daily confirmed cases would have a 2.24% (95% CI: 1.02-3.46), 1.76% (95% CI: 0.89-2.63), 4.76% (95% CI: 1.99-7.52), and 6.94% (95% CI: 2.38-11.51) increase, respectively. Lee et al. (2014) reported that air pollution may damage the human respiratory barrier and deposit in the respiratory tract and lungs, which facilitate viral attachment.

We have found that Tave, THI, K, AQI, PM2.5, PM10, NO2, and SO₂ had lag and persistence effects on COVID-19. Taxe, THI, K, PM₁₀, and SO₂ had significant cumulative effects at lag 0-7 days, whereas the cumulative effects for AQI, PM_{2.5}, and NO₂ were significant at lag 0-7 and 0-14 days. A 10 unitincrease in AQI and a 10-µg/m³ increase in PM_{2.5} and NO₂ were associated with 7.9%, 7.8%, and 10.1% increase in daily confirmed cases at lag 0-14 days, respectively. The persistence of PM_{2.5} on COVID-19 lasted longer than that of PM_{10} , which might be because $PM_{2.5}$ is more easily absorbed by humans (Zhu et al. 2020). Lag and persistence may vary according to region based on meteorological elements, number of confirmed cases, control measures used, and medical facilities available (Shahzad et al. 2020; Lin et al. 2006; Del and Camacho-Ortiz 2020). A study in Saudi Arabia (Gardner et al. 2019) revealed that MERS cases were significantly associated with the lowest temperature and humidity at lag 8-10 days and with wind speed at lag 5-6 days. Xu et al. (2020a, b) found a significant association between daily confirmed COVID-19 cases and AQI at lag 1-3 days.

We found a significant association between confirmed COVID-19 cases and environmental factors, but several limitations of the study need to be addressed. First, our data excluded confirmed cases by gender or age; therefore, we were unable to conduct subgroup analysis. Second, our results are not generalizable because one city was enrolled in the study. Third, compared with other epidemiological studies, the study period was relatively short.

Conclusion

In this study, we used GAM to analyze the relationship between daily confirmed COVID-19 cases and environmental elements and found a significant negative association between daily confirmed COVID-19 cases and T_{ave} , THI, and K, while AQI, PM_{2.5}, PM₁₀, NO₂, and SO₂ were significantly associated with an increase in daily confirmed COVID-19 cases. And a significant lag and persistence were observed, T_{ave} , THI, K, PM₁₀, and SO₂ had significant cumulative effect at lag 0–7 days, whereas AQI, PM_{2.5}, and NO₂ had significant cumulative effect at lag 0–7 and 0–14 days.

Availability of data and material Data will be available on request

Authors' contribution Yuxia Ma, Bowen Chen, conceptualization, methodology, writing and reviewing; JiaHui Shen, Hang Wang, software; Fengliu Feng, data curation; Yifan Zhang, Haoran Jiao, writing original draft preparation.

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Declarations

Conflicts of interest The authors have no conflict of interest to declare.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate Not applicable

Consent to publish Not applicable

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