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Atmospheric particulate matter effects on SARS-CoV-2 infection and spreading dynamics: A spatio-temporal point process model

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ABSTRACT

Particulate matter (PM) may play a role in differential distribution and transmission rates of SARS-CoV-2. For public health surveillance, identification of factors affecting the transmission dynamics concerning the endemic (persistent sporadic) and epidemic (rapidly clustered) component of infection can help to implement intervention strategies to reduce the disease burden. The aim of this study is to assess the effect of long-term residential exposure to outdoor PM_{10} \leq 10 \mu m concentrations on SARS-CoV-2 incidence and on its spreading dynamics in Marche region (Central Italy) during the first wave of the COVID-19 pandemic (February to May 2020), using the endemic-epidemic spatio-temporal regression model for individual-level data. Environmental and climatic factors were estimated at 10 km^2 grid cells.

10-years average exposure to PM_{10} was associated with an increased risk of new endemic (Rate Ratio for 10 \mu g/m^3 increase 1.14, 95%CI 1.04–1.24) and epidemic (Rate Ratio 1.15, 95%CI 1.08–1.22) infection. Male gender, older age, living in Nursing Homes and Long-Term Care Facilities residence and socio-economic deprivation index increased Rate Ratio (RR) in epidemic component. Lockdown increased the risk of becoming positive to SARS-CoV-2 as concerning endemic component while it reduced virus spreading in epidemic one. Increased temperature was associated with a reduction of endemic and epidemic infection.

Results showed an increment of RR for exposure to increased levels of PM_{10} both in endemic and epidemic components. Targeted interventions are necessary to improve air quality in most polluted areas, where deprived populations are more likely to live, to minimize the burden of endemic and epidemic COVID-19 disease and to reduce unequal distribution of health risk.

1. Introduction

Coronavirus disease (COVID-19) spread rapidly from China in December 2019 to the rest of the world and was declared pandemic by the World Health Organization (WHO) in March 2020. The COVID-19 was caused by a novel coronavirus, named Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) (WHO, 2020a).

Transmission rates and host’s susceptibility to influenza and other viral diseases are influenced by several factors, such as demography, age, gender, socio-economic status, education, and comorbidities. These elements can explain the differential distribution and transmission rates of SARS-CoV-2 (Arsalan et al., 2020; Wu et al., 2020). It has been recently shown how contaminated surfaces, in particular in hospital wards, and environmental factors, including atmospheric particulate matter (PM), temperature, humidity and pollution may play an important role in SARS-CoV-2 differential distribution and transmission (Croft et al., 2020; Ficetola and Rubolini, 2021; Seif et al., 2021; Zhang et al., 2020). Meteorological conditions like temperature and humidity...
increase pollution peak and increase the virus survival.

PM can increase respiratory morbidity and mortality (Liu et al., 2019), especially in susceptible people and for this reason it may be associated to COVID-19 susceptibility. PM is composed by a wide range of anthropogenic and natural sources such as solid and liquid particles, with different size and chemical composition (organic and inorganic pollutants), including PM$_{2.5}$, PM$_{10}$ and NO$_2$.

The evidence for the association between air pollution and COVID-19 severity is getting stronger, suggesting that the potential chronic exposure to air pollution might increase the susceptibility to COVID-19; nevertheless, the potential association between PM$_{10}$ exposure and SARS-CoV-2 spreading remains unclear (Bontempi, 2020; Gao et al., 2021; Conticini et al., 2020; Copat et al., 2020; Veronesi et al., 2022; Zheng et al., 2021).

Several authors have addressed the impact on morbidity and lethality of infectious diseases concerning the epidemic component (disease that clusters in space and time) and the endemic component (sporadic infections that persist in space and over time). Surveillance and public health prevention authorities emphasize the importance of taking into account both the endemic and epidemic components of the disease when assessing the risk of transmission (Pelling, 2020; Hilton and Keeling, 2019; Riley, 2019).

As concerning statistical modelling, the infectious disease dynamics can be divided in endemic and epidemic components using individual-level surveillance data (Meyer and Held, 2014; Held et al., 2005; Paul et al., 2008). In the epidemic component, infected cases are directly linked to the previously observed cases, whereas in the endemic component, new infected cases are independent, not directly attributable to the epidemic process, and then they do not generate secondary cases.

The aim of this study is to assess the effect of residential exposure to atmospheric PM on SARS-CoV-2 infection and on the dynamics of disease spreading in Marche Region (Italy) during the first wave of the COVID-19 pandemic with a prediction model including both endemic and epidemic components.

2. Materials and methods

2.1. Population

This study included all individuals with first positive SARS-CoV-2 nasal/oropharyngeal swab test from February up to May 2020 that were residents or domiciled in Marche Region, central Italy. Reverse transcription-polymerase chain reaction (RT-PCR) method was used to detect the SARS-CoV-2 virus and all tests were recorded in a database by the Regional Health Service (RHS); other data collected were gender, age, domicile or residence address and employment. People living in Nursing Homes and Long-Term Care Facilities were included and identified through linkage with the Information System for the Territory Network.

A sensitivity analysis was performed to explore the impact of potential confounding due to pre-existing diseases (PED) and to evaluate the robustness of PM estimates. Linkage with administrative healthcare data, routinely collected by the RHS, allowed to collect information about pre-existing conditions within the previous 5-years from the first positive SARS-CoV-2 molecular test. Tumours (lymphoma, metastatic cancer, cancer without metastasis, malignancy medication), diabetes, hypertension and chronic diseases of the respiratory system (chronic pulmonary diseases, cystic fibrosis) were considered as comorbidities in this study and identified with the International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) encoding on primary and secondary diagnosis fields in hospital discharge records (HDR) and with drugs prescriptions reimbursed by the National Health System, coded according to the Anatomical Therapeutic Chemical (ATC) Classification, in agreement to criteria used to define a multsource comorbidity score from administrative data (Corrao et al., 2017).

All residential addresses were geocoded and socio-economic deprivation index, measured at census block level (Rosano et al., 2020), was attributed to each residence/domicile. Due to unavailable subject-level socioeconomic conditions in administrative database, area-level deprivation index is used as a proxy measure for individual socioeconomic status. The deprivation index was calculated as the sum of standardized indicators (low level of education, being unemployed, living in rent, living in crowded house, living in a single-parent family) and categorized into quintiles, from the least deprived to most deprived. Missing values of deprivation index in census block were replaced by the mean of the neighbour’s values.

2.2. Environmental data

Long-term exposure to outdoor fine PM air pollution of ≤10 μm diameter (PM$_{10}$) concentrations (μg/m$^3$), Temperature (°C) and Relative Humidity (%) were estimated at 10 km$^2$ grid cells of Marche Region; subjects were assigned to their respectively pollution and meteorological variables of grid cell containing their residential addresses, so model-estimated exposure to PM10 is being used as surrogate for individual exposure. PM$_{10}$ concentrations was estimated as average of daily concentrations on 2010–2019 years at 10 km$^2$ spatial grid, recorded at the 15 stations of Regional Air Quality Monitoring Networks located across Marche (not all stations had full 10 years of data available). Daily temperature and relative humidity from 113 monitoring stations were provided by the Regional Civil Protection Service for February–May 2020 period. Mean daily value of long-term exposure to outdoor PM$_{10}$ concentrations, daily temperature, and relative humidity for each 10-km$^2$ grid cell were assigned using the following method:

- case 1: grid cell not containing any monitoring station. Nearest neighbour search (NNS): the data are from the closest station, measuring distance from the centre of the cell;
- case 2: cell containing one monitoring station. The data are from the said station;
- case 3: cell containing two or more monitoring stations. Mathematical average: the data are the average of the data available from all the aforementioned stations.

2.3. Statistical analysis

Descriptive statistics for socio-demographic characteristics of the study subjects (absolute and relative frequency) were calculated; based on grid cells estimates, population-weighted average and interquartile range (IQR) at regional level were estimated for environmental and meteorological covariates.

Continuous monitoring of individuals with SARS-CoV-2 infection across Marche Region from February up to May 2020, provided a sample function of a self-exciting spatio-temporal point process. The endemic-epidemic spatio-temporal point process regression model was used to identify individuals and contextual factors that influenced SARS-CoV-2 spreading and CODIV-19 rate (Meyer et al. 2012, 2017; Meyer and Held, 2014).

The infection rate $\lambda(s,t)$ at a specific location $s$ and time point $t$, given all past infections, was additionally decomposed into endemic and epidemic component:

$$\lambda(s,t) = \nu_0(s) + \sum_{j(t)} \eta f(s-s_j)g(t-t_j)$$

where:

- $s$ was the geocoded residence address of each individual, $t$ is the time of infection; $[s][t]$ was the spatio-temporal index referred to the 10kmx10km grid cell covering residence address $s$, during the day $t$;
was a log-linear predictor of endemic component and included exogenous factors such as pollutant and climatic covariates, lockdown and day of the week;
• \( \eta_i \) was a log-linear predictor of epidemic component and included event-specific characteristics, that were gender, age, pre-existing diseases, employment, deprivation index, residence type, exposure to long-term PM\(_{10}\), climatic covariates and lockdown. \( f_i(s, t) \) was the set of past events that, for each infection \( j_i \), triggered secondary events during its infectious period and within its spatial interaction radius.

Linear trend in epidemic risk across deprivation quintiles was assessed using categories as a continuous variable. The effect of temperature and humidity was evaluated at the previous 14 days (average lag 1–14) to account for the incubation period reported by WHO (WHO, 2020b).

The endemic component considered the grid cell population as population at risk of infection (offset). The population in each grid cell was estimated on the basis on municipalities population data in 2019, using area weighted interpolation, overlapping municipalities and 10 km\(^2\) cell grid layers to maintain the spatial compatibility of environmental covariates. The total Marche population in 2019 was 1,427,525 and was obtained from the National Institute of Statistics (http://demo.istat.it/).

The epidemic component described the disease transmission from a primary case-patient to its secondary cases (direct person-to-person contact). Each primary case exerted its effect within an infectious period of 14 days and a spatial radius of 200 km, assuming a decay of the infection force as the spatial and temporal distance from it increased. It was modelled with exponential functions \( f \) and \( g \) in the formula; hence, the effect of covariates estimated the risk of a primary case to generate a secondary case.

Dummy variables were created to account for national lockdown, extended to all Italian regions on March 11, 2020, and to take into account the decrease in the number of COVID-19 swab test carried out during Sundays.

Rate ratios (RR) and 95% Wald confidence intervals (CI) for endemic and epidemic factors were calculated.

A two-tailed \( P \) values<0.05 were considered statistically significant; analyses were performed using R Studio Software (Version April 1, 2016). The spatio-temporal analyses were carried out using R package “surveillance” (Meyer et al., 2017).

3. Results

The number of subjects with first positive SARS-CoV-2 swab test was 6638 from February to May 2020. They all had complete information on residential address, except for deprivation index that was not available for 105 individuals. For each subject, missing data were replaced with the average of adjacent block census deprivation index.

Absolute and relative frequencies of gender, age, socio-economic deprivation index, healthcare workers, nursing homes and long-term care facilities were reported in Table 1.

The 46% of subjects was aged \( \geq 65 \) years, 53% were female, 19% were healthcare workers and 7% lived into a residential nursing homes or long-term care facilities.

Summary statistics of ambient air pollution and meteorological data at regional level were showed in Table 2. Mean PM\(_{10}\) concentration for the years 2010–2019 was 24.0 \( \mu g/ m^3 \) (IQR 17.5–30.1) and was below the Italian regulation annual limit of 40 \( \mu g/ m^3 \); however, it exceeded the WHO guideline value of 20 \( \mu g/ m^3 \) (WHO, 2006) and the new limit of 15 \( \mu g/ m^3 \), recently updated (WHO, 2021).

Parameter estimates, confidence intervals and \( P \) values of regression model were presented in Table 3 for the epidemic component, including environmental and individual covariates, and in Table 4 for the endemic component, where only spatio-temporal exogenous covariates were considered.

10-years PM\(_{10}\) exposure was associated with an increased risk of new endemic infectious (RR 1.14, 95% CI 1.04–1.24), as well as lockdown period (RR 2.29, 95% CI 1.96–2.66).

The severity of infection was associated with male gender and older age. Living in a nursing homes/long-term care facility, a long-term exposure to PM\(_{10}\) concentrations and the worsening of the socioeconomic deprivation class increased the risk of secondary infection, whereas lockdown and high temperature reduced the transmission risk (RR 0.96, 95% CI 0.94–0.97). Temperature also reduced the risk of

### Table 1

| Covariate | Category | \( n \) (%) |
|-----------|----------|-------------|
| Gender    | Female   | 3511 (52.9%) |
|           | Male     | 3127 (47.1%) |
| Age       | 0–44     | 1309 (19.7%) |
|           | 45–64    | 2292 (34.5%) |
|           | 65–79    | 1405 (21.2%) |
|           | 80+      | 1632 (24.6%) |
| DI        | 1 (Least deprived) | 1228 (18.5%) |
|           | 2        | 1450 (21.8%) |
|           | 3        | 1436 (21.6%) |
|           | 4        | 1255 (18.9%) |
|           | 5 (Most deprived) | 1269 (19.1%) |
| Employment| Other    | 5407 (81.5%) |
|           | Healthcare | 1231 (18.5%) |
| Residence | Home     | 6169 (92.9%) |
|           | NH/LTCF  | 469 (7.1%)  |

Note: DI, Deprivation Index. NH/LTCF, Nursing Homes and Long-Term Care Facilities.

### Table 2

| Covariate | Mean (Interquartile Range) |
|-----------|---------------------------|
| PM\(_{10}\) (\( \mu g/ m^3 \)) | 24.0 (17.5, 30.1) |
| Average Temperature (\( ^\circ C \)) | 12.6 (9.3, 16.4) |
| Relative Humidity (%) | 68.4 (57.7, 79.1) |

### Table 3

| Covariates | RR (95% CI) | \( P \) value |
|------------|-------------|---------------|
| PM\(_{10}\) (\( \mu g/ m^3 \)) | 1.15 (1.08, 1.22) | <0.0001 |
| Temperature (\( ^\circ C \) · Lag 1–14) | 0.96 (0.94, 0.97) | <0.0001 |
| Relative Humidity (% · Lag 1–14) | 1.00 (1.00, 1.01) | 0.0543 |
| Lockdown No | Reference | |
| Male | 1.16 (1.06, 1.26) | 0.0007 |
| Temperature (\( ^\circ C \) · Lag 1–14) | 1.25 (1.10, 1.42) | 0.0005 |
| Relative Humidity (% · Lag 1–14) | 1.48 (1.30, 1.70) | <0.0001 |
| DI | 1.69 (1.48, 1.93) | <0.0001 |
| Employment Other | Reference | |
| Temperature (\( ^\circ C \) · Lag 1–14) | 1.05 (1.03, 1.08) | 0.0001 |
| Relative Humidity (% · Lag 1–14) | 1.03 (0.92, 1.16) | 0.6272 |
| Residence NH/LTCF | Reference | |
| Temperature (\( ^\circ C \) · Lag 1–14) | 1.2 (1.04, 1.38) | 0.0112 |

Note: Rate Ratio per 10 \( \mu g/ m^3 \) increment in PM\(_{10}\). RR, Rate Ratio. CI, Confidence Interval. DI, Deprivation Index. NH/LTCF, Nursing Homes and Long-Term Care Facilities.
Two-component Spatio-Temporal Point Process Regression Model.

4. Discussion

were consistent with the main model that did not include PED. CoV-2 infection and all effect estimated and their statistical inference pre-existing disease were associated with the risk of transmitting SARS-CoV-2. This result may indicate the transition of SARS-CoV-2 from epidemic to endemic virus. Some people continued to work, becoming positive to SARS-CoV-2. This might suggest that PM could act as a carrier for virus, mainly during high polluted days; however, as concerning the other epidemic model components, it is important to underline that the risk of transmitting SARS-CoV-2 infection was found to increase as socio-economic deprivation rises. People with high socio-economic deprivation had less chance to work from home, as distancing policy recommended by Italian Government in March, due to elemental/manual occupations (Cetrulo et al., 2020), and less chance to safely self-isolate or self-quarantine owing to overcrowded housing conditions and lack of space.

endemic infection (RR 0.88, 95% CI 0.87–0.89) (Tables 3–4).

Regarding sensitivity analysis, no statistically significant effects for pre-existing disease were associated with the risk of transmitting SARS-CoV-2 infection and all effect estimated and their statistical inference were consistent with the main model that did not include PED.

4. Discussion

The results of this study show an important increment of RR for exposure to increased levels of PM10 both in endemic and epidemic models. The endemic component is correlated with RR of becoming positive to SARS-CoV-2, while the epidemic component of the model is correlated to RR of virus secondary transmission. As concerning endemic component, increased exposure to PM10 may increase risk of becoming positive to SARS-CoV-2. This might suggest that PM could act as a carrier for virus, mainly during high polluted days; however, because of rapid dilution effect in the outdoor air, the interaction between a fine particle and virus-laden aerosols is less likely to occur.

The plausible hypothesis for this result may be due to a chronic exposure to pollutants that can compromise upper airways and lung function (Havet al., 2020; Berend, 2016). Lung immunity particularly may be compromised due to exposure to air pollution (Glencross et al., 2020). This impairment could also increase RR of the epidemic component since a less efficient immunity system could increase virus replication and transmission. We found results in agreement with the conclusion of an Italian study with individual-level data on long-term exposure to air pollution and COVID-19 (Veronesi et al., 2022); due to different statistical approach of the two studies, the accordance refers to the endemic part, that is association between exposure to PM10 and the incidence of COVID-19 infection.

Regarding temperature, we point out a negative association with disease risk in endemic and also in a lower degree in epidemic component. Warm temperature and dry condition may impact on the efficiency of respiratory droplet transmission affecting the stability of virus particles and causing a rapid viral inactivation (Raines et al., 2021; Lowen and Steel, 2014). A systematic review shows that warmer climates are less likely to spread the virus, despite a low level of evidence due to a poor identification of confounding variables (Mecenas et al., 2020). As concerning the other epidemic model components, it is important to underline that the risk of transmitting SARS-CoV-2 infection was found to increase as socio-economic deprivation rises. People with high socio-economic deprivation had less chance to work from home, as distancing policy recommended by Italian Government in March, due to elemental/manual occupations (Cetrulo et al., 2020), and less chance to safely self-isolate or self-quarantine owing to overcrowded housing conditions and lack of space.

Age also leads to an interesting increase of the RR in the epidemic component: it’s well known that a crucial component of aging is a set of functional and structural alterations of the immune system that can manifest as a decreased ability to fight infection (Sadighi Akha, 2018). Regarding the increased RR for people residing in nursing/long-term care facilities, the secondary infection is higher than home residents’ one because many subjects shared same rooms and care givers in those same residential care structures that, especially during first wave of COVID-19 pandemic, were totally unprepared to face SARS-CoV-2 transmission. Moreover, subjects in nursing/long-term care structures have pre-existing diseases or particular health conditions favouring SARS-CoV-2 infection and transmission.

About healthcare employment, the evidence of no association with the risk of transmitting SARS-CoV-2 infection can be due to an active surveillance program consisting of performing daily employee health checks to find out the infection before the symptom onset and hence reducing coronavirus’ spreading risk.

A final consideration about the endemic component concerns the lockdown that seems to act as an amplifying factor of RR of becoming positive to SARS-CoV-2. This result may indicate the transition of SARS-CoV-2 from epidemic to endemic virus. Some people continued to work, especially those employed in selected fields (energy and food distribution).

On the other hand, lockdown in epidemic component shows a congruent effect since in this case the RR is referred to virus transmission to secondary cases; hence, the presence of lockdown breaks this trend, lowering virus spreading.

To our knowledge, our study is the first to combine together several elements previously distinctly used in literature. These elements are the two-step model with the endemic/epidemic components, combined with the deprivation index as a proxy of indoor pollution exposure together with SARS-CoV-2 infection exposure values. Moreover, we adjusted results coming from this complex relationship with values of temperature, humidity, and presence of important comorbidities in our subjects to strength consistency of our results.

A possible weakness in this study is related to exposure: pollution data are retrieved at spatial resolution of 10 km × 10 km and based on a limited number of fixed monitoring stations. This introduces some amount of the exposure measurement error that weakens the statistical power of detecting significant effects, increasing the width of confidence

| Covariates | RR (95% CI) | P-value |
|------------|-------------|---------|
| PM10 (µg/m³) | 1.14 (1.04, 1.24) | 0.0035 |
| Temperature (°C - Lag 1–14) | 0.88 (0.87, 0.89) | <0.0001 |
| Relative Humidity (%) - Lag 1–14 | 1.02 (1.02, 1.03) | <0.0001 |
| Lockdown | Yes | 2.29 (1.96, 2.66) | <0.0001 |

Note: Rate Ratio per 10 µg/m³ increment in PM10, RR, Rate Ratio, CI, Confidence Interval.

Nevertheless, recent studies (Maleki et al., 2021; Marr et al., 2019) pointed out how at values of RH approximately around 64% or less, smallest droplets may remain suspended for more than 3 h and there is an increased efficiency deposition in head airways at 90% and 100% of relative humidity. Our results may be in agreement with this, since our RH mean value is 68.4% with an interquartile range from 57.7% to 79.1%, representing this an ideal range of humidity both for increasing suspension of droplets for more than 3 h and then promoting possible airborne transmission and both increased efficiency of viral depositing in upper airways at highest levels of this range. Indeed, our results agree to what have been found by a multicenter England study where highest RR for a SARS-CoV-2 positive test was between 50% and 70% of relative humidity with a peak at 61.1% (Nottmeyer and Sera, 2021). Another systematic review (Noorimolagh et al., 2021a, b) reports how on inanimate surfaces, the relationship of coronaviruses survival with RH is quite complex showing higher chance of survival at value of RH >60% and again our results may be in accordance with this because the more virus survival on surface the more possibility of infectious by contact.

Regarding sensitivity analysis, no statistically significant effects for pre-existing disease were associated with the risk of transmitting SARS-CoV-2 infection and all effect estimated and their statistical inference were consistent with the main model that did not include PED.

**Table 4**

Note: Rate Ratio per 10 µg/m³ increment in PM10, RR, Rate Ratio, CI, Confidence Interval.
Another limit is the possible misclassification error of individual exposure to PM$_{10}$ assessed on subjects’ residential address at the date of the first SARS-CoV-2 positive swab; it is calculated assuming that particular matter concentrations are homogenous in each cell of the 10 km$^2$ grid and that in the previous 10 years the subject has lived always in the same residential address.

In conclusion, these results show an important increment of RR for exposure to increased levels of long-term exposure to PM$_{10}$ both in endemic (RR 1.14, 95% CI 1.04–1.24) and epidemic (RR 1.15, 95% CI 1.08–1.22) components of the study model. Aging and worsening socioeconomic deprivation increase RR in the epidemic component. Lockdown seems to increase RR of becoming positive to SARS-CoV-2 as concerning endemic but, on the other hand, it reduces virus spreading in epidemic component because in this case the RR is referred to new secondary cases generation. Increased ambient temperature was associated with a reduction of both endemic and epidemic infectious.

In the context of communicable diseases, characterized by the spread through close contact with an infected person, the epidemic-endemic modelling for individual data take into consideration the explicit dependence between infected subjects. We therefore believe that the approach used in this study may be suitable for better identifying the risk factors with a greater impact on trigger or prevent spreading of endemic and epidemic COVID-19 disease, after controlling for spatial and temporal correlation between cases.

In summary, our results suggest that air pollution increases the risk of COVID-19 disease spreads, therefore targeted interventions are necessary to improve air quality in most polluted areas to minimize the burden of endemic and epidemic COVID-19 disease and to reduce unequal distribution of health risk arising from a differential air pollution exposure, bringing out that air pollution is not only an environmental problem but an important issue of public health, as remarked by the European Union in the Integrated Approach to Sustainable Development in the 2030 Agenda. Concerning priority actions, we suggest to improve a proper ventilation system in the indoor environment, especially in hospitals and crowded places (Noorimotlagh et al., 2021a, b; Vosoughi et al., 2021), to consider as stations of air quality monitoring network the areas with higher air pollution, where deprived populations are more likely to live, to increase the green space within 300 m from residences of communities of lower socio-economic status (EEA, 2022) and to implement the Inequalities Register, as announced by the European Commission (EU 2021), to map trends, disparities and inequalities for pollution-related diseases.

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Credit author statement

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