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Key Points:

- The response of society to the COVID-19 pandemic was explored
- Socio-economic status had an inverted U-shaped relationship with infections during the COVID-19 pandemic
- SES affected infections mainly through action time, demographics, medical resources and vaccination

Supporting Information:

Supporting Information may be found in the online version of this article.

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The Inverted U-Shaped Relationship Between Socio-Economic Status and Infections During the COVID-19 Pandemic

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Abstract Although the World Health Organization has declared that the COVID-19 pandemic no longer qualifies as a global public health emergency, it still needs to explore the response of society to the COVID-19 pandemic. Socio-economic status (SES) was proven to be linearly associated with the COVID-19 pandemic, although this relationship may be more complex due to regional differences. In the study, we analyzed and revealed the effects and mechanisms of SES on infections among low, lower-middle, upper-middle and high SES group (LSG, LMSG, UMSG, and HSG, respectively). The results showed that the relationship between SES and infections was inverted U-shaped, especially in the first three phases. In Phase I, UMSG had the highest number of infections, with an average of 238.31/1M people (95%CI: 135.47–341.15/1M people). In Phases II and III, infections decreased insignificantly with increasing SES ($r = -0.01$, $p = 0.92$; $r = -0.11$, $p = 0.22$) and the highest number of infections were found in the LMSG. In Phase IV, SES was positively related to the number of infections ($r = 0.54$, $p < 0.001$). Furthermore, the nonlinear impact of multiple factors related to SES on the infections explains the complex relationships between SES and infections. SES affected infections mainly through medical resources, demographics and vaccination, and differed across the SES groups. Particularly, demographics could exert an impact on population mobility, subsequently influencing infections in LMSG, with an indirect effect of 0.01 ($p < 0.05$) in Phase II. This study argues for greater attention to countries with middle SES and the need for future targeted measures to cope with infectious diseases.

Plain Language Summary As the virulence of SARS-CoV-2 diminishes and vaccination coverage rises, countries around the world are gradually returning to normal development like the pre-COVID-19 period. However, the COVID-19 pandemic crisis of the past three years calls for thoughtful reflection, presenting us with experiences and lessons to learn from. Previous studies suggested that the infections were linearly associated with socio-economic status (SES). Nevertheless, SES was related with multiple factors (such as vaccination), leading to the complex relationship between infections and SES. Therefore, it still needs to analyze the impacts and mechanisms of SES on infections. Empirical results show the relationship between SES and infections was an inverted U-shape in the progress of the COVID-19 pandemic, and the infections in lower-middle and upper-middle SES countries was the highest in the first three phases. SES affected infections through multiple factors and the mechanisms differed across SES groups. This work emphasizes the need to be attentive to the further prevalence of infectious diseases in middle-SES countries and implementing the target measures in different SES countries in the future.

1. Introduction

The World Health Organization (WHO) announced the end of the public health emergency of international concern caused by the COVID-19 pandemic on 5 May 2023 (WHO, 2023c) and the COVID-19 pandemic seems appear to be at an end. However, within three years of the prevalence of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), the COVID-19 pandemic has had a tremendous impact on regional economy, industry development, and public psychology (Clemente-Suárez et al., 2021; Škare et al., 2021; Xiong et al., 2020). Although the health impact of the COVID-19 pandemic has declined (Wolter et al., 2022), the experiences and lessons learned from this pandemic needs to be analyzed and summarized to better cope with large-scale infectious diseases in the future.

Differences in the COVID-19 pandemic are existed in countries with different socio-economic levels. According to data reported by the WHO, the total number of cases in the high-income group was 424,314,108, which was 210 times that of the cases in the low-income group as of 9 August 2023 (WHO, 2022b). This is similar to the results of most previous studies, which suggested that owing to large population density, active social events, and other reasons, SARS-CoV-2 spread faster in high-income countries (Cao et al., 2021; Gangemi et al., 2020; Rafael et al., 2020). A study of global metropolises reported that the gross domestic product (GDP) per capita was positively correlated with the number of COVID-19 cases (Cao et al., 2021). On a national scale, SARS-CoV-2 had spread widely to high-income areas in Brazil (Rafael et al., 2020). However, due to insufficient medical resources and detection capacity, some researchers have been concerned regarding the spread of COVID-19 in low-income regions (Hawkins et al., 2020; Huyser et al., 2021; Oronce et al., 2020). In the United States, the COVID-19 pandemic in severely poor counties with low socio-economic status was more serious than that in communities with high socio-economic status (Hawkins et al., 2020), and the pandemic was more serious in areas with income inequality (Huyser et al., 2021; Oronce et al., 2020). Some studies have documented that the low infection rates in Africa were caused by insufficient detection capabilities (Addai & Ngwa, 2021).

The socio-economic level may change the human living environment, way of travel, living habits and available medical resources, further affecting the COVID-19 pandemic in a complex manner (Cao et al., 2021; Edgar & Gabriel, 2021; Pardhan & Drydakis, 2021). Many studies have analyzed the impact of non-pharmaceutical interventions (NPIs), vaccines, medical resources, population and other factors on the COVID-19 pandemic (Bai et al., 2020; Hsiang et al., 2020; Marziano et al., 2021; Sun et al., 2021), for example, the study indicated that vaccination rate had nonlinear impact on the infections of the COVID-19 pandemic (Sun et al., 2021). SES may indirectly affect infections through the abovementioned factors, which may result in the complex relationship between SES and infections. Furthermore, the path by which SES affects the COVID-19 pandemic remains unclear.

Therefore, the study aims to explore the complex relationship between SES and infections in the COVID-19 pandemic and analyze the differences among countries with different socio-economic levels. First, the study calculated SES of 128 countries from 22 January 2020 to 9 March 2023, and divided them into low, lower-middle, upper-middle and high SES groups (LSG, LMSG, UMSG, and HSG, respectively). We then divided the COVID-19 pandemic into four phases: first wave (Phase I), normalized management (Phase II), vaccination (Phase III), and reopening (Phase IV). Second, we reconstructed the infections caused by the COVID-19 pandemic and analyzed the relationship between infections and SES. Finally, we considered factors such as vaccination rate and change in population mobility, which are related to SES, and further analyzed the mechanisms of SES on the infections.

2. Data and Methods

2.1. Data

The daily cumulative number of reported cases and deaths from 1 January 2020 to 9 March 2023, were collected from Dong et al. (2020) in the Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE). Since 7 December 2022, China has canceled the publication of daily epidemic data, and we collected death data from the Chinese Center for Disease Control and Prevention (Chinese CDC) (Chinese Center for Disease Control and Prevention, 2023). As the data were scaled weekly, the average of the data was considered for daily number of deaths.

Weekly data on SARS-CoV-2 variant sequences, including B.1.1.7 (Alpha), B.1.351 (Beta), P.1 (Gamma), B.1.617.2 (Delta), and B.1.1.529 (Omicron), were collected from the Global Initiative of Sharing All Influenza Data (GISAID) (Elbe & Buckland-Merrett, 2017) until 9 March 2023. The weekly proportion of the variants was defined as the ratio of the number of mutant sequences to the total number of sequences.

Daily data on change in population movement from 4 February 2020 to 31 December 2021 and the rate of mask usage from 4 February 2020 to 9 March 2023 were obtained from Institute for Health Metrics and Evaluation (IHME) (IHME, 2022).

The vaccination data from 1 January 2020 to 9 March 2023, was obtained from the Our World in Data data set provided by Mathieu et al. (2021), including the vaccination rate (people fully vaccinated per hundred population). We assumed that the vaccination rate increased at a constant rate and interpolated missing daily data.

Furthermore, we considered the lag in infection due to vaccination. The protection provided by vaccines in preventing infections occurred 12 days after the first dose (Fernando P Polack, 2020). Thus, we set a lag of 12 days in the vaccination rate for the analysis.

Policy data were collected from the Oxford COVID-19 Government Response Tracker (Hale et al., 2021), from 1 January 2020 to 31 December 2022. The stringency index is the average of nine policy intensities (school closing, workplace closing, canceling public events, restrictions on gatherings, closing public transport, staying at home requirements, restrictions on internal movement, international travel controls, and public information campaigns) and has been used in several studies (Ge et al., 2022; Zuo et al., 2023) to investigate the effect of policy on the COVID-19 pandemic. Thus, we used the stringency index to characterize the policy intensity in countries. Countries have tended to relax policies such as canceling restrictions on international travel (reopening) due to fewer virulent mutant viruses and increased vaccination rates. We collected the national reopening time data from social media, but several countries did not disclose their reopening time on social media. Therefore, based on the previous study (Sun et al., 2024), we calculated the reopening time using the data set provided by Oxford COVID-19 Government Response Tracker (Hale et al., 2021). First, we compared the policy intensity before and after the reopening announced by the countries on social media. We found that some countries implemented certain policies after reopening. Therefore, the reopening date was considered the day on which four out of eight policies (except public information campaigns) were eliminated and were continued until 9 March 2023. For countries that announced the reopening time, we chose the earlier date as the country's reopening time to ensure that it could be captured more accurately. Specifically, if the date announced by the country was later than the date we calculated, it indicates that the country may have already relaxed measures before announcing the reopening, we thus choose the earlier date we calculated as the reopening date; if the date announced by the country is earlier than the date we calculated, we selected the date announced by the country as the country's reopening date to prevent the data delay.

The socio-economic data until 2021 are shown in Table S1 in Supporting Information S1 and were provided by the World Bank (2022a). The latest data on the share of urban population and share of population aged 15–64 years old until 2021 are available from the World Bank (2022c, 2022b). The data on population in different age groups in 2022 are from the United Nations Population Division (United Nations, 2022). The latest medical resources data up to 2022, including hospital beds per 10,000 people and medical doctors per 10,000 people, were obtained from the WHO (WHO, 2023b).

Meteorological data was downloaded from ERA5 hourly data set (Hersbach et al., 2023), including temperature, relative humidity and wind speed. We then processed the data into daily national average through ArcGIS 10.2.

2.2. Methods

We used the following methods to analyze the nonlinear relationship between SES and infections during the COVID-19 pandemic from the three dimensions and the research framework is illustrated in Figure 1. This study assumed that the differences in data within countries (at state, city or district level) are negligible compared to the differences between countries.

2.2.1. Defining Phases and Socio-Economic Groups

Defining phases: Based on the timing of the COVID-19 pandemic published by WHO (WHO, 2022a) and previous studies (Carter et al., 2021; Ge et al., 2021), we divided the COVID-19 pandemic from 22 January 2020 to 9 March 2023, into four phases. (a) The first phase was the first wave of the COVID-19 pandemic in 128 countries, which was identified based on the previous studies (Carter et al., 2021; Ge et al., 2021). We first smoothed the infections for 7 days to calculate the peaks and troughs of the infection series for each country. The trough points between the first and second peaks were the end-points of the first wave of the COVID-19 pandemic. We found that the daily average number of infections in January and February 2020 (early in the COVID-19 pandemic) was approximately 304 and the medium of daily number of infections was approximately 11. Meanwhile, since the first wave of the COVID-19 pandemic in most countries was caused by low-level community transmission of imported cases (Ge et al., 2021), if the first peak was >300, the beginning date of the first wave was when the infection was >0.05 of the first peak. Some countries had small outbreaks at the beginning, and when the peak was ≤ 300, the beginning date was when the daily number of infections was >10. Since the incubation period of the COVID-19 pandemic is up to 14 days (WHO, 2023a), we set the following

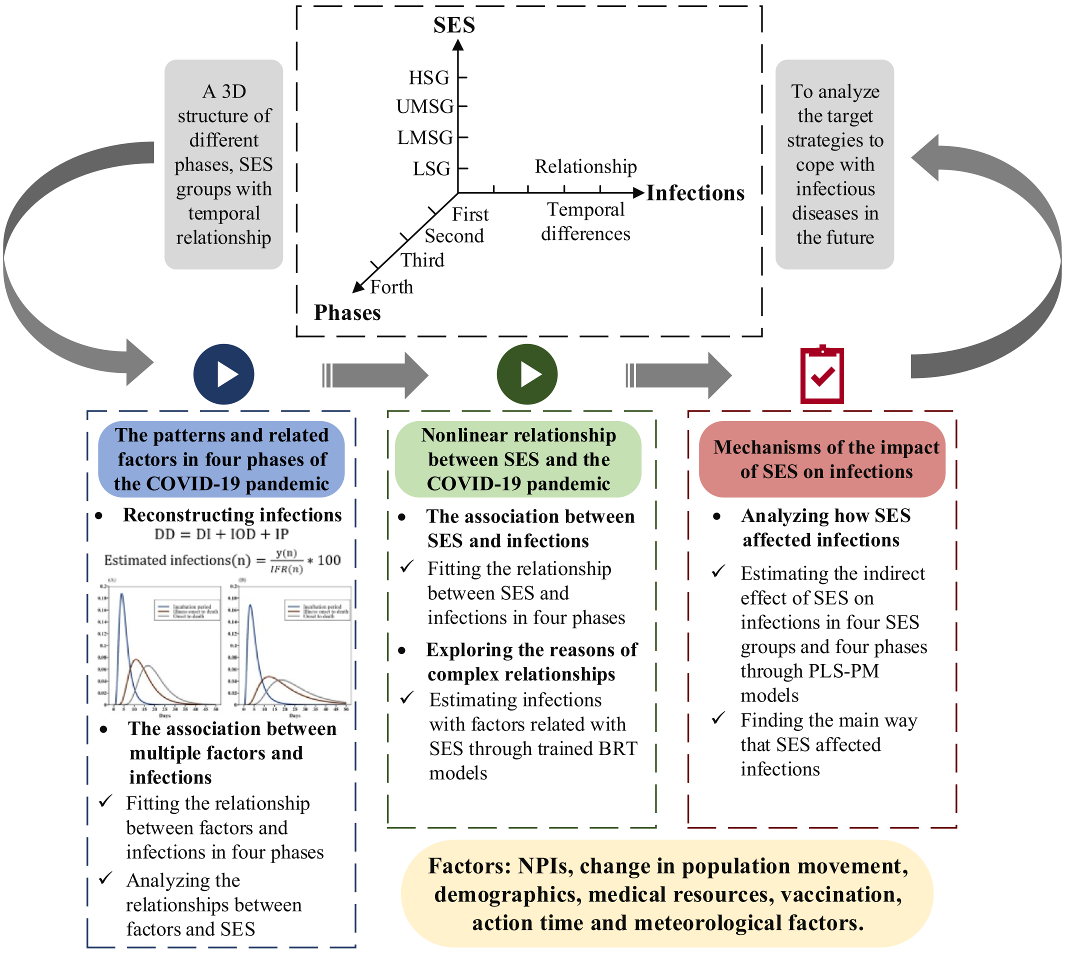

Figure 1. The research framework in the study.

restrictions on the process to obtain the distinct first wave of the COVID-19 pandemic: (A) The first peak should be >20; (B) Two neighboring peaks/toughs should be more than 28 days apart, and the neighboring peaks and troughs >14 days apart, using the highest/lowest value as the peak/tough points. (b) We used the start of vaccination as the point at which the second and third phases were delineated. It has been noted that vaccine data are subject to limitations, such as frequency of national updates and language translation, which lead to some contingencies in data (Mathieu et al., 2021). In order to avoid the contingencies, we used a 1% vaccination rate at the beginning of vaccination because 1% vaccination rate indicated that at least parts of people in the country has been vaccinated. The second phase was the time between the end of the first phase and the start of vaccination. (c) The reopening time was the time divided between the third and fourth phases. The third phase was the time between the start of vaccination and the start of reopening. (d) The fourth phase was the time between the start of reopening and 9 March 2023. The time spans of the phases in the 128 countries are listed in Table S2 in Supporting Information S1.

Dividing into socio-economic groups: World Bank classified countries by income level based on gross national income (GNI) per capita (World Bank, 2023) and the socio-demographic index (SDI) was calculated based on a combination of GDP per capita, average education level, and fertility (Network, 2020). However, the classification by the World Bank or the IHME does not provide a good representation of health and education levels, and the SDI was updated only up to 2019. Therefore, to comprehensively represent the health environment, education, and economic development, we used principal component analysis (PCA) to classify the 128 countries into different socio-economic groups using the 18 indicators obtained above (Table S2 in Supporting Information S1). PCA was performed in R 3.6.3 and standardized to the national SES of 128 countries [0,1] through four steps: standardization, calculation of the correlation coefficient matrix, calculation of eigenvalues and eigenvectors, and calculation of composite scores. The results of PCA showed that the cumulative contribution of the first seven principal components was closing to 90%; therefore, we selected the first seven principal components to calculate the final scores. We used the socio-economic indicators for 2020 and 2021 for our research, and the results were similar; therefore, the average of the two was chosen. We divided the 128 countries into four SES groups: low SES (LSG, SES < 0.1), lower-middle SES (LMSG, $0.1 \leq$ SES < 0.2), upper-middle SES (UMSG, $0.2 \leq$ SES < 0.4) and high SES (HSG, SES ≥ 0.4). The four SES groups (from low to high) comprised 34, 41, 29 and 24 countries, respectively. The spatial distribution is shown in Figure S1 in Supporting Information S1.

2.2.2. Estimating the Real Infections

Owing to the limited detection and reporting discrepancies in countries, we reconstructed the daily infection data by referring to previous studies (García-García et al., 2021; Mena et al., 2021). This method is based on the principle that the death date (DD) can be derived from the infection date (DI), time from illness to death (IOD), and incubation period (IP). The equation is as follows.

$$\mathrm{DD} = \mathrm{DI} + \mathrm{IOD} + \mathrm{IP} \tag{1}$$

Therefore, DI can be estimated if DD, IOD, and IP are known. IOD and IP are consistent with the log-normal distribution, with a mean of 14.5 days and a median of 13.2 days in X_{IOD}, and a mean of 5.6 days and a median of 5 days in X_{IP} (Linton et al., 2020). Although the distribution of the infection-to-death period ($X_{IP + IOD}$) does not conform to any probability distribution, we can calculate the probability density (PDF) of X_{IP} and X_{IOD} to estimate the PDF of $X_{IP + IOD}$.

$$f(t) = \int_{-\infty}^{+\infty} \mathrm{IP}(t_0 - t) \cdot \mathrm{IOD}(t)\, dt \tag{2}$$

where $f(t)$ is the PDF of $X_{IP + IOD}$; IP(t) and IOD(t) are the PDF of X_{IP} and X_{IOD}, respectively; t_0 is the number of days from infection. The distributions of $f(t)$, IP(t), and IOD(t) are shown in Figure S2 in Supporting Information S1. In addition to the above distributions of X_{IP} and X_{IOD}, we also considered the right truncation as a sensitivity analysis, with a mean of 20.2 days and a median of 17.1 days in X_{IOD} and a mean of 5.6 days and a median of 4.6 days in X_{IP} (Linton et al., 2020).

The infection at time t_0 can be estimated by considering the time series of death data ($d(t)$) and the probability of death t days after infection.

$$y(t_0) = \int_{t_0}^{+\infty} f(t - t_0) \cdot d(t)\, dt \tag{3}$$

Meanwhile, since the time series are discrete, the equation is as followed.

$$y(n_0) = \sum_{n=n_0}^{+\infty} F(n - n_0) \cdot d(n) \tag{4}$$

where,

$$F(n) = \int_{n}^{n+1} f(t)\, dt \tag{5}$$

If the infection fatality rate (IFR) is known, real infections can be estimated using the following formula.

$$\text{Estimated infections}(n) = \frac{\mathrm{y(n)}}{\mathrm{IFR}(n)} \times 100 \tag{6}$$

Thus, the focus is on estimating the accurate IFR in countries. This study estimated the pre-vaccination IFR in 128 countries on 15 April 2020, 15 July 2020, 15 October 2020 and 1 January 2021 (COVID-19 Forecasting

Team, 2022). Our study used this data set with the assumption that the IFR was a uniformly changed variable on 15 April 2020, 15 July 2020, 15 October 2020 and 1 January 2021, thus interpolating to the daily data. In addition, the severity of Omicron infection was lower than that of previous SARS-CoV-2 variants (Wolter et al., 2022). The pre-vaccination IFR may lead to inaccurate estimates. Thus, we divided the stages of infection into Omicron pre-dominance and post-dominance with different IFR. We then calculated the percentage of Omicron sequences based on GISAID data and determined that when the percentage reached ≥80%, the Omicron variant was considered dominant. The Shanghai study (Chen et al., 2022) was conducted after the dominance of the Omicron variant and age-adjusted IFRs were calculated based on the age structure. The IFRs used in this study are shown in Figure S3 in Supporting Information S1. Finally, owing to the problem in reporting the number of deaths, the daily estimated cases may be less than the daily real cases. We then processed the data using Gaussian kernel smoothing (see Text S1 in Supporting Information S1 for further details). The validation is presented in Supporting Information S1 (Text S2).

2.2.3. Booster Regression Trees (BRT)

The BRT is a fitted statistical model that can explain nonlinear relationships between variables (Elith et al., 2008). To verify the reasons for the nonlinear relationship between SES and infections, we constructed the BRT models to analyze the nonlinear impact of multiple factors on infection rate using the "gbm" package and BRT function (Elith et al., 2008) in R 3.6.3. The factors included mask usage, change in population mobility, share of urban population, proportion of people aged 15–64 years old, hospital beds per 10,000 people, medical doctors per 10,000 people, vaccination rate, action time. In addition, previous studies have found the relationship between meteorological factors and the COVID-19 pandemic (Choi et al., 2021; Prata et al., 2020; Wu et al., 2020). For example, the study in Brazil showed that the relationship between air temperature and the number of confirmed cases was linearly negative (Prata et al., 2020). Therefore, we selected air temperature, relative humidity and wind speed as control variables into BRT model to ensure simulating the real situation of the COVID-19 pandemic.

In BRT models, 80% of the data were selected for construction and 20% of the data were used for validation. The nature of the error structure was set to "Gaussian" and the tree complexity was 10. The root mean square error (RMSE) and Pearson's correlation between the observations and fitted values of the training and testing data were calculated to explain the fitting effect of the model (Table S3 in Supporting Information S1). Furthermore, BRT can be used to obtain the response curve of each variable to the infection rate. The horizontal coordinate represents the change in the predictor variable, and the vertical coordinate represents the marginal effect of the variable on the infection rate. Furthermore, we placed all factors related to SES into the trained models, and the other factors were set to the average of 128 countries to calculate the infections for each country. We then analyzed the relationship between the estimated infections and SES to explain the reasons for the nonlinear relationship between SES and infections.

2.2.4. Partial Least-Squares Path Mode (PLS-PM)

PLS-PM was constructed to explain the mechanisms of SES on the COVID-19 pandemic. PLS-PM models have been successfully used in previous studies (Wei et al., 2023; Zhao et al., 2022), such as those in ecology, and have been shown to be useful for analyzing complex relationships between the modules of variables. In this paper, we utilized the "plspm" package in R 3.6.3 to construct the model (Sanchez, 2013).

We categorized all the factors that may affect the infection rate into eight groups: SES, NPI, mobility, demographics, medical resources, vaccination, action time, and meteorological factors. Meteorological factors were also included as control variables. The eight groups of latent variables used to construct the models and the factors included in the models are listed in Table 1. We further chose the explicit variables that best reflected the latent variables through the response indicator loadings. The goodness-of-fit (GOF) can evaluate the merits of the model, and band resampling (for 1,000 times) can explain the significance of each path of the model (Sanchez, 2013). We considered all latent variables in the initial models but included the latent variables for which the path coefficient could pass through the significance test ($p < 0.05$).

2.2.5. Robustness Testing

Since this study was country-based to analyze the relationship between SES and infections in the COVID-19 pandemic, it might erase the differences at the subnational scale (state, city or district). To improve the

Table 1
The Latent and Initially Explicit Variables in PLS-PM Models

Latent variable	Initially explicit variable
SES	SES
NPI	Stringency index
	Mask usage
Mobility	Change in population movement
Demographics	Share of urban population
	Share of people aged 15–64 years old
Medical resources	Hospital beds per 10,000 people
	Medical doctors per 10,000 people
Vaccination	Vaccination rate
Action Time	Action time (the time between the first case and the date when implementing containment policies)
Meteorological factors	Temperature
	Relative humidity
	Wind speed

robustness, we selected the United States, China, India and Ethiopia in four different SES groups at the subnational scale to analyze the relationship between SES and infections in the COVID-19 pandemic. The details about the robustness testing are shown in Supporting Information S1 (Text S3).

3. Results

3.1. The Patterns and Related Factors in Four Phases of the COVID-19 Pandemic

Figures 2a–2d show the reported and estimated data over time in the four SES groups, and the fluctuations between reported and estimated infections are similar. The estimated infections with or without right-truncation were also similar (Figure S4 in Supporting Information S1). The validation of estimating infections shown in Supporting Information S1 (Text S2) indicated the reliability of estimating real infections. The infections in the four SES groups showed a slow increasing trend, and a peak was observed after the dominance of the Delta and Omicron variants (Figure S5 in Supporting Information S1). There are also spatial and temporal differences during the COVID-19 pandemic on a global scale. In Phase I, most countries had an infection rate of <10%, and countries in South America had higher infection rates (Figure 2e). In Phase II, the infection rate was higher in the Americas, southern Africa, and parts of Europe (Figure 2f). After vaccination (Phase III), a rapid increase in the infection rate was observed in countries of the Americas, Europe, and southern African due to the spread of Delta and Omicron variants (Figure 2g). After reopening (Phase IV), the infection rate decreased in some countries, and countries with high infection rates were in Europe, the Americas, and Australia (Figure 2h).

In order to further explore the reasons for temporal and spatial differences in the COVID-19 pandemic in different countries, we analyzed the nonlinear impact of factors on the infections by using BRT models (Figures S6–S9 in Supporting Information S1) in the four phases. In Phase I, mask usage had the key impact on the changes in infections and the importance was approximately 23.17%. Proportion of people aged 15–64 years old and mask usage were also critical to changes in infections in Phase II. In Phase III and IV, vaccination was important in changing in infections, with a contribution of approximately 19.46% and 43.90%, respectively. The nonlinear effect of these factors on infections resulted in temporal and spatial variation in the COVID-19 pandemic.

Furthermore, we observed the relationships between SES and these factors related with infections in the COVID-19 pandemic (Figure S10 in Supporting Information S1). Most factors are positively related with SES, such as share of urban population ($r = 0.64$, $p < 0.001$). The change in population mobility was negatively associated with SES ($r = -0.44$, $p < 0.001$). However, the relationship between mask usage and SES was insignificant ($r = -0.08$, $p = 0.37$). Because of the nonlinear effect of factors on infections in the COVID-19 pandemic, which in turn were related to SES, the analysis on the relationship between SES and infections is needed.

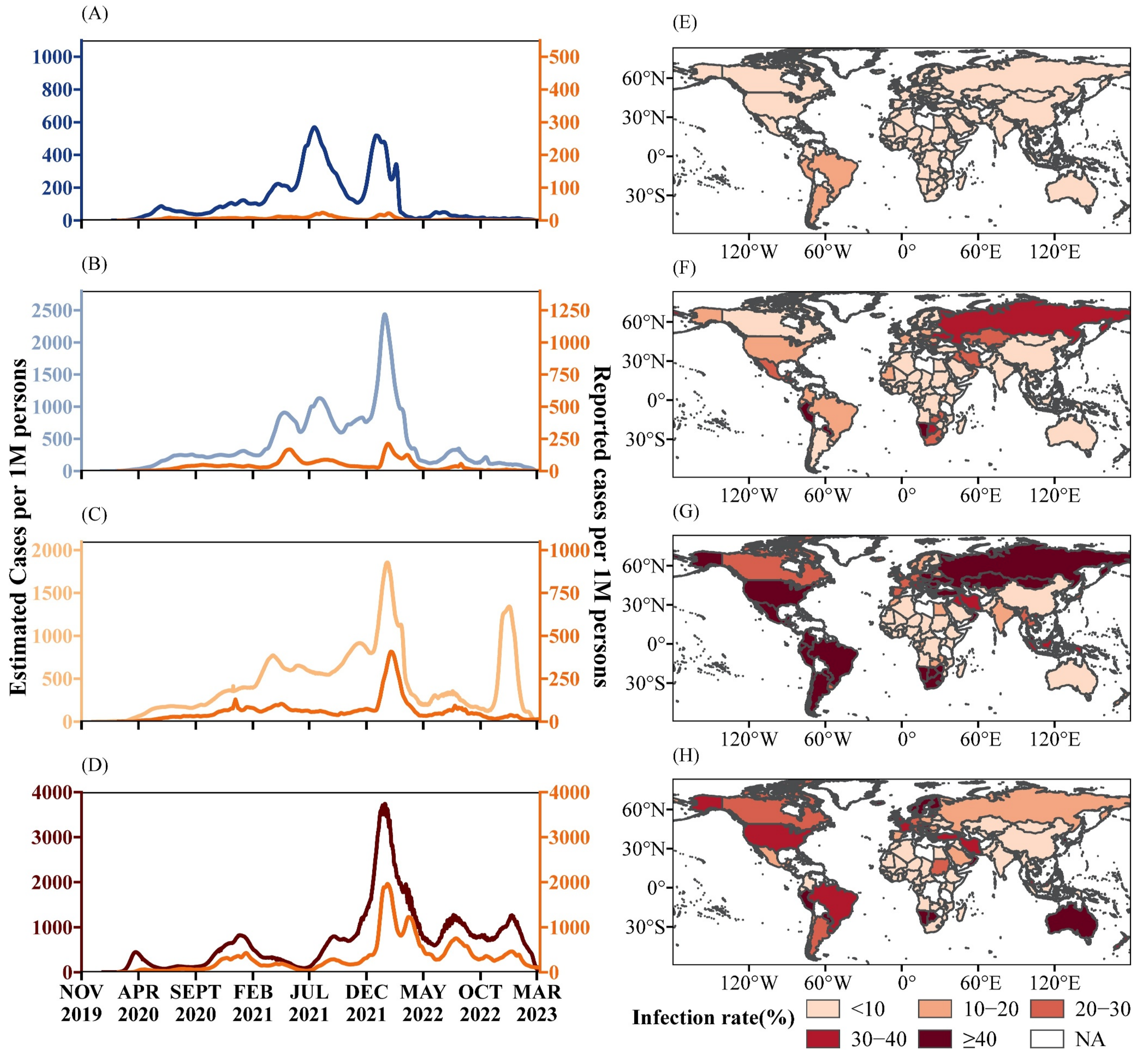

Figure 2. The estimated cases in four SES groups and across 128 countries in four phases as of 9 March 2023. The orange line is the sequence of reported cases. Panels (a)–(d) indicate the estimated cases in LSG, LMSG, UMSG, and HSG, respectively. Panels (e)–(h) show the spatial distribution across 128 countries in Phase I to IV.

3.2. Nonlinear Relationship Between SES and the COVID-19 Pandemic

There was a nonlinear relationship between SES and infections in different phases. Figure 3a shows the nonlinear relationship between SES and infections, but the relationship is likely to be positive ($r = 0.20$, $p = 0.02$). The daily average number of infections in UMSG was the highest in Phase I (Figure 3b) (238.31/1M people [95%CI: 135.47–341.15/1M people]), followed by HSG (146.39/1M people [95%CI: 94.85–197.93/1M people]). The relationship between SES and infections was inverted U-shaped in Phases II and III (Figures 3c and 3e). The highest daily average number of infections was observed in LMSG, with an average of 738.37/1M people (95% CI: 522.33–954.40/1M people) and 2,141.12/1M people (95%CI: 1,450.49–2,831.75/1M people) in Phase II and III, respectively (Figures 3d and 3f). Figure 3g shows a significant positive relationship between SES and infections in Phase IV. The highest daily average number of infections was in HSG, with an average of 975.16/1M persons (95%CI: 798.31–1,152.01/1M persons) (Figure 3h). In order to exclude the effect on the results due to

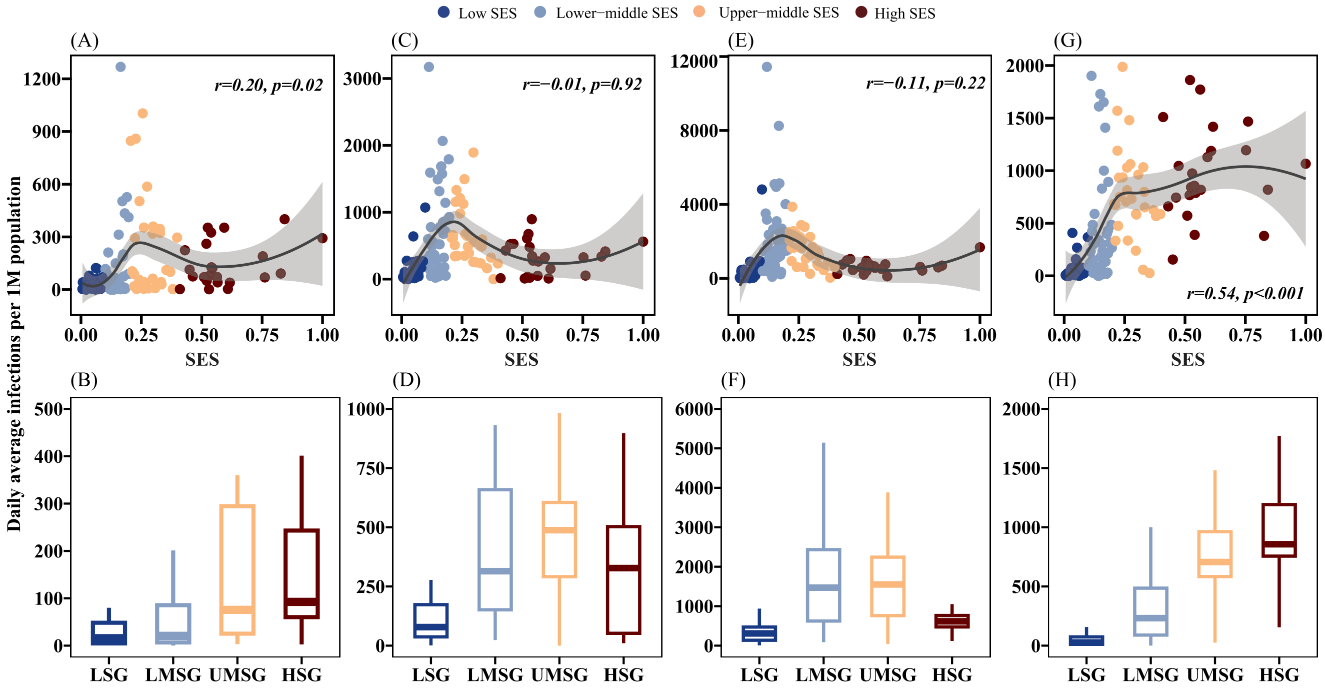

Figure 3. The relationship between SES and infections of the COVID-19 pandemic in the four phases. The vertical coordination is the daily average infections per 1 million people (the proportion of daily number of estimated cases and total population). Panels (a) and (b) are in Phase I. Panels (c) and (d) are in Phase II. Panels (e) and (f) are in Phase III. Panels (g) and (h) are in Phase IV. The gray solid lines were fitted using loess method and the shade region indicates 95% regression confidence interval.

intra-country differences on the state level, we conducted robustness testing (see Supporting Information S1 for details). We first analyzed the relationship between SES and infections with countries with different SES (the United States, China, India and Ethiopia), and found that the relationships within four countries were almost linear. The relationships in India (within LMSG) were positive and the relationships in the United States were negative in Phase II and III. It confirmed the inverted U-shaped relationships between SES and infections on the global scale. Furthermore, we analyzed the relationships between SES and infections by combining subnational data. We also found the relationships between SES and infections were the inverted U-shaped, which confirmed the robustness of the results in the study.

We found that multiple factors, such as vaccination, had the nonlinear impact on the infections of the COVID-19 pandemic, while SES was associated with these factors. Therefore, to confirm that multiple factors resulted in a nonlinear relationship between SES and infections, we calculated the number of infections in 128 countries with factors related to SES using trained BRT models (Figure 4). The fitted number of infections were similar to those shown in Figure 3, which explains the nonlinear relationship between SES and infections. The fitted number of infections were positively related to SES ($r = 0.25$, $p < 0.05$) and the highest infection rate was in UMSG, with an average of 81.89/1M people (95%CI: 61.95–101.84/1M people) in Phase I (Figures 4a and 4b). SES had an insignificant negative correlation with infections ($r = 0.00$, $p = 0.96$), and the highest number of infections were in the LMSG (Figures 4c and 4d), which is the same with as that shown in Figures 3c and 3d. The estimated infections had a negative correlation with SES ($r = -0.22$, $p < 0.05$), and the highest infection rate was in the LMSG, with an average of 1,666.36/1M people (95%CI: 1,180.05–2,152.67/1M people) in Phase III (Figures 4e and 4f). SES was positively correlated with the estimated number of infections ($r = 0.64$, $p < 0.001$), and the highest number of infections were in the HSG (Figures 4g and 4h), which is similar to that observed in Figures 3g and 3h.

3.3. Mechanisms of the Impact of SES on Infections

In the LSG, SES affected the infection rate mainly through medical resources and demographics (Figures 5a–5d). Medical resources were the main path that SES affected infection rate in the first three stages (Figures 5a–5c),

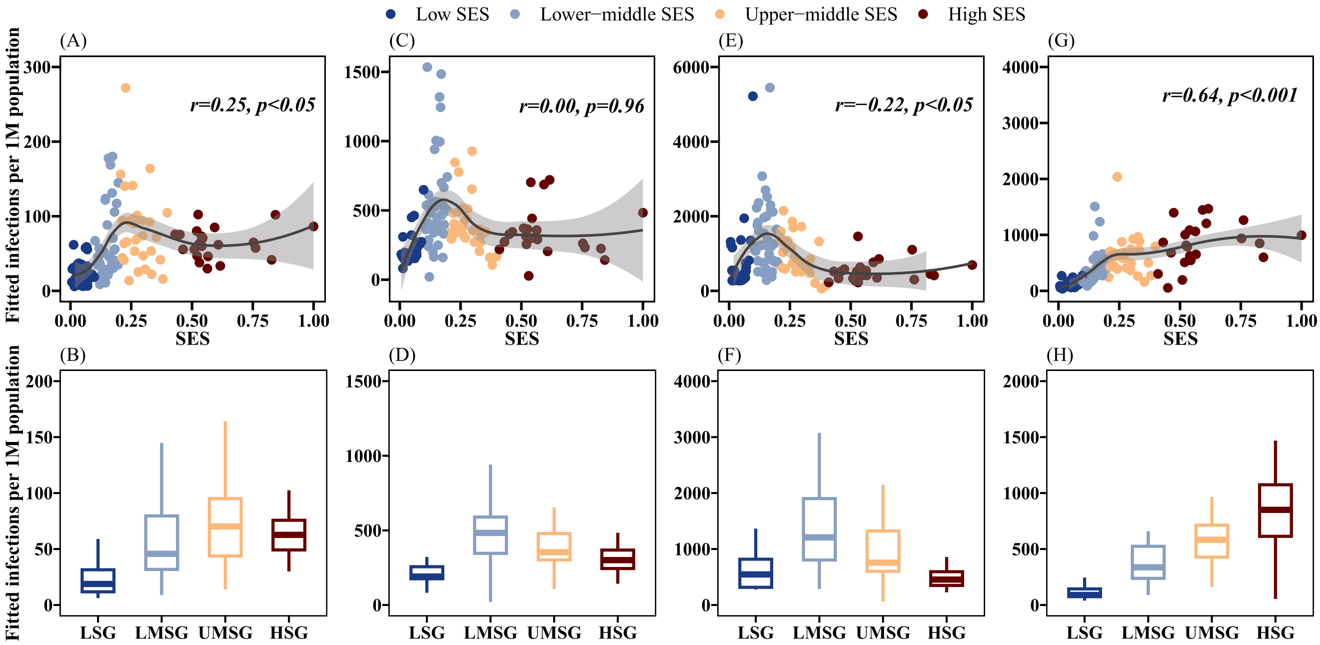

Figure 4. The relationships between SES and fitted infections by BRT models in the four phases. We included the factors (such as vaccination rate) related to SES and set other factors (such as temperature) as the average of all countries into trained BRT models. Panels (a) and (b) are in Phase I. Panels (c) and (d) are in Phase II. Panels (e) and (f) are in Phase III. Panels (g) and (h) are in Phase IV. The gray solid lines were fitted using loess method and the shade region indicates 95% regression confidence interval.

with the proportion to the total effect of approximately 79.70%, 64.03% and 67.10%, respectively. The main path in Phase IV was "SES-Demographics-Infection rate" and the path effect was approximately 0.09 ($p < 0.05$). In addition, LSG has the advantage of quickly responding to the COVID-19 pandemic and the path effect of "SES-Action Time- Infection rate" was approximately −0.05 ($p < 0.05$) (Figure 5a), which is how SES primarily affects infection rate. SES could also affect infection rate through vaccination. The path effect of "SES-Vaccination-Infection rate" in Phase III was approximately −0.04 ($p < 0.05$). SES also could directly or indirectly affect population mobility through NPI and demographics, but the absolute effects were limited (<0.01).

The mechanisms that SES affected infection rate in LMSG were similar to LSG (Figures 5e–5h). SES affected the infection rate mainly through demographics in Phase I, II, and IV, with the proportion to the total effect of approximately 66.88%, 45.42%, and 64.60%, respectively. The main path in Phase III was "SES-Medical Resources-Infection rate" and the proportions to total effects was approximately 87.38%. However, increasing medical resources could not reduce infection rate (Figures 5f and 5g), which is similar to LSG. Compared with LSG, demographics could increase infections by increasing population mobility and the path effect of "SES-Demographics-Mobility- Infection rate" was approximately 0.01 ($p < 0.05$) in Phase II.

SES mainly affected medical resources and vaccination rates, further affecting the infection rate in UMSG (Figures 6a–6d). SES affected the infection rate mainly through medical resources in the first three phases, with a proportion to total effect of approximately 55.26%, 69.96%, and 38.02%, respectively. Meanwhile, medical resources played an important role in reducing infection rate in UMSG. In Phase IV, "SES-Vaccination-Infection rate" was the main path that SES affected infection rate, with an indirect effect of approximately −0.07 ($p < 0.05$). However, vaccination could not reduce infection rate in Phase III, with a path coefficient of 0.01 ($p < 0.05$). In addition, vaccination could affect NPI and further affect infection rate, and the indirect effect of "SES-Vaccination-NPI-Infection rate" was approximately 0.01 ($p < 0.05$) in Phase III.

SES affected the infection rate through multiple mechanisms in the HSG (Figures 6e–6h). In Phase I, SES affected infection rate mainly through action time, with an indirect effect of approximately 0.06 ($p < 0.05$). In Phase II, the main path was "SES-Medical Resources-Infection rate," with the proportion of path effect to the total effect of approximately 75.69%, but the effect was positive (0.03 [$p < 0.05$]). In Phase III, SES affected infection rate mainly through NPI, with an indirect effect of approximately −0.06 ($p < 0.05$). In addition, vaccination could

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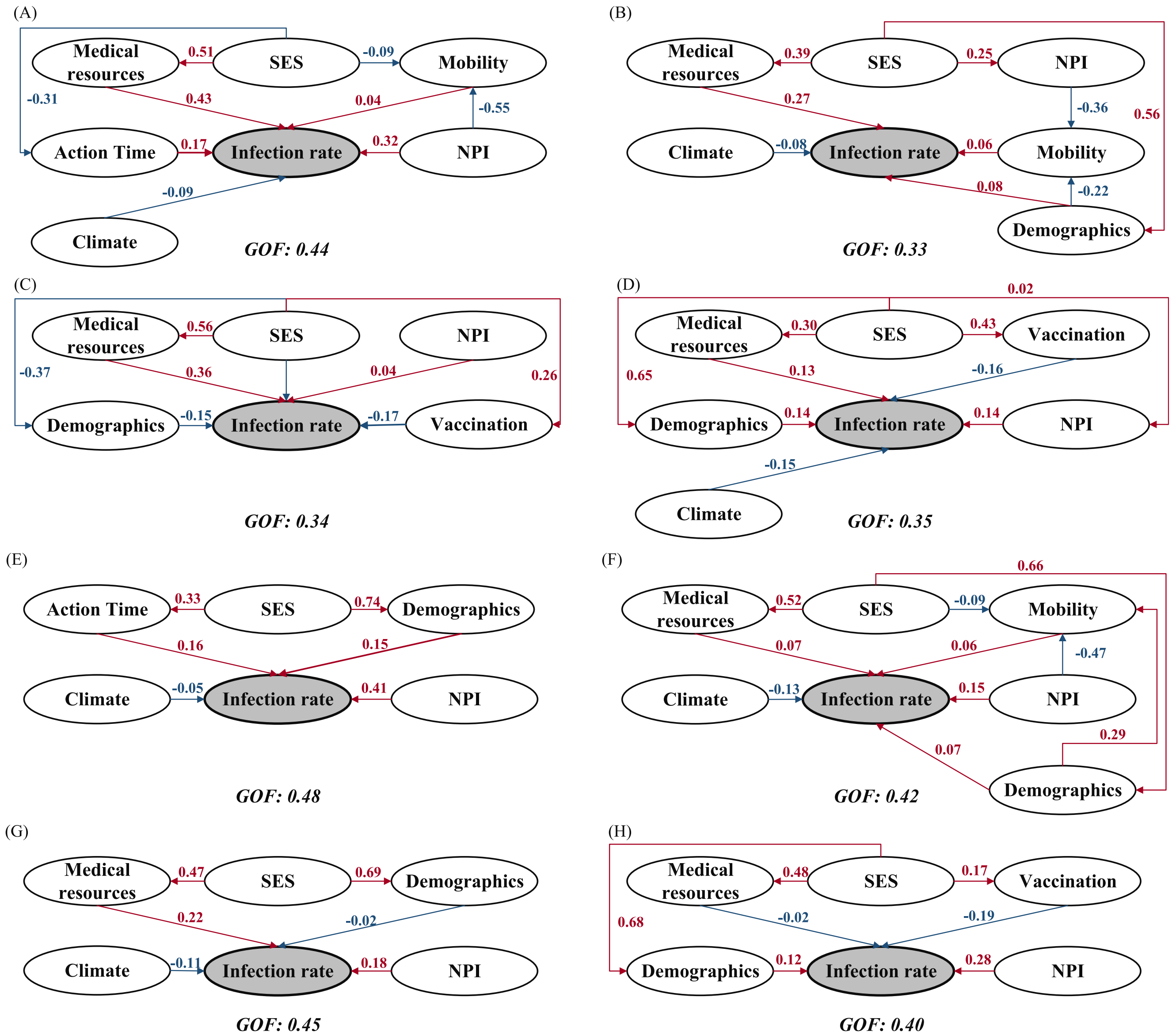

Figure 5. The results of PLS-PM models in LSG and LMSG in the four phases. The blue line is the negative relationship between factors and the red line is the positive relationship between factors. The path coefficient in the panel is significant ($p < 0.05$). Panels (a)–(d) indicate Phase I, Phase II, Phase III, and Phase IV, respectively, for LSG. Panels (e)–(h) indicate Phase I, Phase II, Phase III, and Phase IV, respectively, for LMSG. GOF: goodness-of-fit.

affect population mobility and further affect infection rate, but the absolute effect was limited (<0.01). After reopening, the main path was "SES-NPI-Infection rate" and the effect is approximately −0.11 ($p < 0.05$). However, owing to the negative impact of SES on vaccination, the indirect effect of "SES-Vaccination-Infection rate" was approximately 0.03 ($p < 0.05$) after reopening. This finding indicated that the vaccination rate did not increase with the increasing SES.

4. Discussion and Conclusions

This study systematically analyzed the impact and mechanisms of SES on the COVID-19 pandemic and found an inverted U-shaped relationship between SES and infections during the COVID-19 pandemic, which provides new insights for future research. The lessons learned from the COVID-19 pandemic are beneficial for future responses to the occurrence of new infectious diseases.

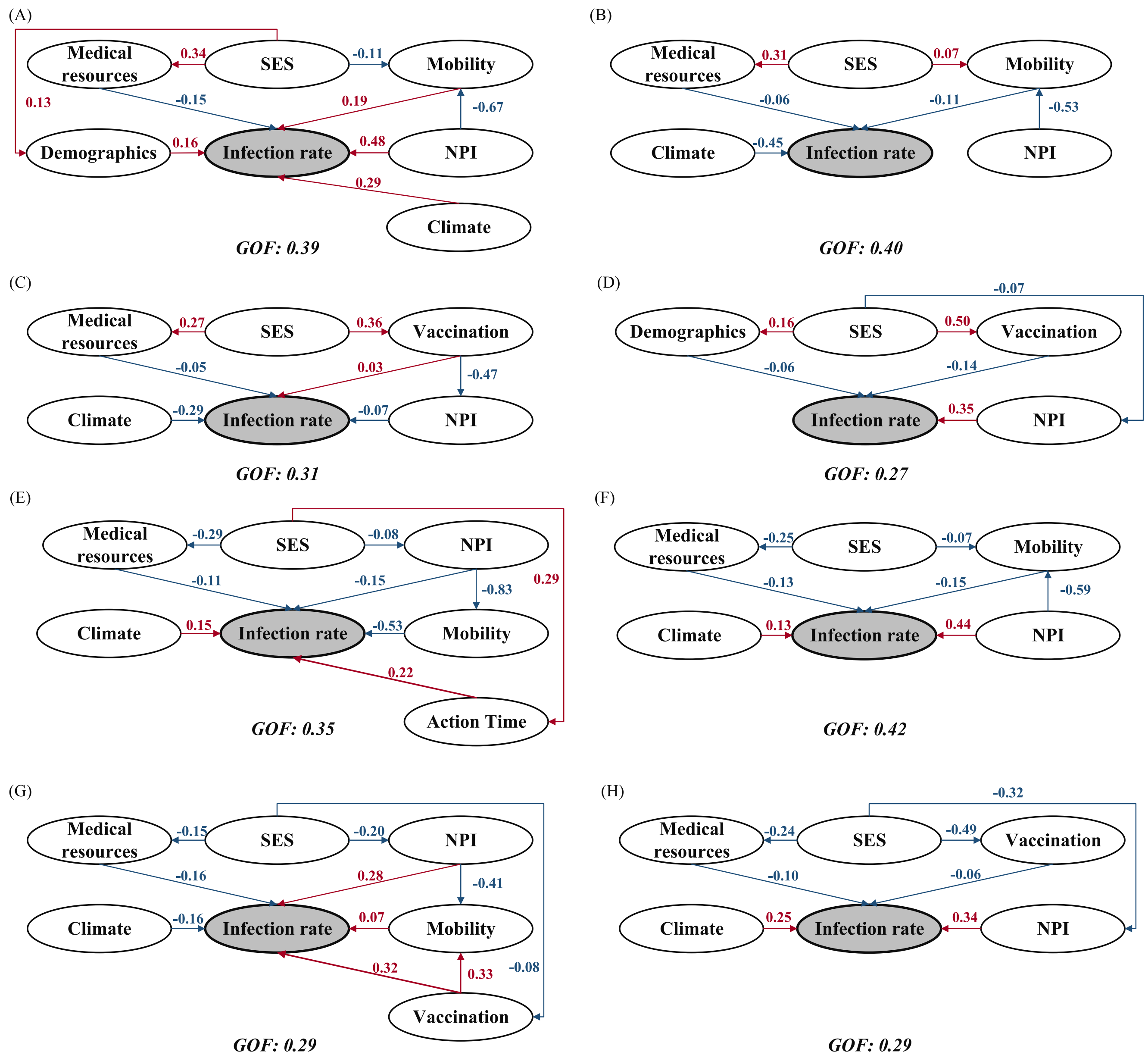

Figure 6. The results of PLS-PM models for UMSG and HSG in the four phases. The blue line is the negative relationship between factors and the red line is the positive relationship between factors. The path coefficient in the panel is significant ($p < 0.05$). Panels (a)–(d) show Phase I, Phase II, Phase III, and Phase IV, respectively, for UMSG. Panels (e)–(h) indicate Phase I, Phase II, Phase III, and Phase IV, respectively, for HSG. GOF: goodness-of-fit.

Previous studies have analyzed the impact of SES on the COVID-19 pandemic on a regional scale (Edgar & Gabriel, 2021; Hawkins et al., 2020; Pardhan & Drydakis, 2021); but, this study provides a new insights on a global scale. Compared to studies in low- and high-income countries (Bayati, 2021; Donde et al., 2021), we combined health environment, education and economic development and found an inverted U-shaped relationship between SES and infections, especially in Phase II and III, revealing an unfavorable situation in middle-SES countries. Middle-income countries are also threatened by other infectious diseases (Shao & Williamson, 2012; Tao et al., 2022). Human immunodeficiency virus type 1 (HIV-1) is spreading the fastest in low- to middle-income countries, because of factors such as poor socio-economic conditions and lack of medical resources (Shao & Williamson, 2012). Despite the differences in socioeconomic classification in other studies, this indicates that the risk of infectious diseases in countries with middle socio-economic levels cannot be ignored. In addition, SES had a positive association with infections of the COVID-19 pandemic after reopening, which indicated that HSG has faced spreading risk of SARS-CoV-2 with increasing population mobility.

This study further explains the reasons for the inverted U-shaped relationship between SES and infections using BRT models. These findings suggest that the nonlinear impact of demographics, population responses and vaccination related to SES results in a complex association between SES and infections. Although the estimated number of infections from the BRT models (Figure 4) were somewhat different from the actual infections (Figure 3), the relationship between SES and infections was consistent, indicating that factors associated with SES contribute to the nonlinear relationship between SES and infections. In addition, the study indicated that the COVID-19 pandemic had a negative impact on the economy (Clemente-Suárez et al., 2021), adding some uncertainty to the complex relationship; however, our primary perspective is on the impact of SES on the infections. Previous study suggested that low- and middle-income countries has faced challenges in non-communicable diseases (Remais et al., 2013). Combined with the study, more attention needs to be paid to diseases in middle SES countries.

This study indicated that low socio-economic regions would implement containment measures earlier than the other regions (Walker et al., 2020). The quick response to the COVID-19 pandemic explains the low infection rate in LSG. However, medical resources and demographics add some uncertainty to the response of LSG to the COVID-19 pandemic. After a wave of the COVID-19 pandemic (Phase II–IV), demographics could increase the infections. Previous study indicated that the number of cases of the COVID-19 pandemic was high in large share of urban population (Ramírez-Aldana et al., 2020). This indicates demographics can still play a catalytic role in the spread of COVID-19, although the share of urban population and people aged 15–64 years was relatively low in the LSG. The study has also raised concerns about controlling the COVID-19 pandemic in low-income countries because of resource shortages (McMahon et al., 2020) and the study in Ethiopia suggested that governments should increase the supply of masks (Amhare et al., 2022). The average rate of hospital beds and the density of medical doctors in the HSG were approximately 5.56 and 16.62 times that of the LSG, respectively. Low medical coverage makes it almost impossible to reduce the number of infections in LSG. Although the LSG had the lowest infection rate during the COVID-19 pandemic in all the stages, the rapid spread of Ebola in low-income countries illustrated their great infectious disease risks (Ghazanfar et al., 2015). Increasing stock of medical resources and international cooperation are important for LSG to cope with infectious diseases in the future.

Early studies used change in population mobility to characterize the effects of restrictive policies and confirmed a negative relationship between SES and population movement (Chand et al., 2021; Liu et al., 2021). People in poor areas have to go out for work, which can increase population movement (Chand et al., 2021). These results are similar to those of our study. We further found that demographics could increase population movement and further increased the infections in the LMSG during Phases II. Previous study indicated that contact patterns and mobility of young people would increase the transmission risks of COVID-19 (Scala et al., 2020). It suggested that LMSG needs to pay attention to the implementation of restrictive measures across different age groups and regions. After vaccination, the population response was less effective in reducing the infection rate, but the individual protection leads to a negative effect of demographics on infection rate. Similar to the LSG, medical resources also had a limited impact on reducing the infection rate in the first three phases. The insufficient medical resources of LMSG have also raised concerns among the researchers (Khadka et al., 2020). Compared to the LSG, the LMSG may face greater infectious disease pressure. Therefore, the LMSG should enhance the responsiveness of the health system and focus on the restrictive effect of strict measures on population mobility.

A previous study showed that upper-middle-income countries faced higher attack rates (Hassan et al., 2020) and had the second highest number of deaths during the COVID-19 pandemic (Chowdhury et al., 2020). Our study also suggests the need to focus on the COVID-19 pandemic in the UMSG. Similar to the LMSG, the increased intensity of personal protection and NPIs explain the limited impact of demographics on the infection rate in UMSG. Taking quick action could reduce the number of COVID-19 cases (Bai et al., 2020). However, different to other SES groups, action time had limited impact on infection rate in Phase I. This explains the highest infection rate in the UMSG during Phase I. In addition, the increase in the vaccination rate could decrease the intensity of NPIs in Phase III, which is similar to the relationship between the policy stringency index and vaccination in the European study by Ge et al. (2022). There is a need to avoid the rapid increase in population movement when vaccination rates have not yet reached the immune barrier. After reopening, vaccination was the main factor that reduced the infection rate, which is similar to the global study (Sun et al., 2024). However, medical resources could not reduce the infection rate owing to the sudden increase in infections. Therefore, the UMSG needs to improve monitoring of infectious diseases and provide a quick response to reduce the spread of viruses in the future.

Previous studies indicated that high-income regions have advantages in terms of medical resources and vaccinations (Burki, 2021; Mena et al., 2021). Compared to lower-income groups, vaccination stockpile is adequate in high-income countries (Asundi et al., 2021). However, we found that SES negatively correlated with vaccination rates in inner HSG. It indicated that the higher SES countries did not provide more financial support for vaccines, resulting in a lower vaccination rate in countries with higher SES. The vaccination rates in UMSG and HSG were close (Figure S11d in Supporting Information S1), which also indicated HSG might not have taken advantage of the socio-economy to increase the vaccine coverage. In addition, hesitancy to vaccine might also slow the increase in vaccine coverage (Aw et al., 2021). These may result in the fact that vaccination rate did not increase with the increase in SES in inner HSG. In addition, vaccination could increase the population mobility in Phase III. It suggests that people tend to reduce personal protection against COVID-19 with the increasing in vaccination rate, which is similar with the results in previous study (Ge et al., 2022). Meanwhile, medical resources in HSG were similar to those of vaccines. SES increased the infections through medical resources because SES had a negative impact in medical resources in Phase I and II in inner HSG. After vaccination, the effect of medical resources in reducing infections decreased, which is similar to UMSG. The study in China indicated that the increased in infections have burdened the health system after reopening (Hon et al., 2023). It could result in insufficient medical resources to reduce number of infections, explain the reduced effect of medical resources in reducing infections in the study. Furthermore, the HSG faced more risks in increasing infections of the COVID-19 pandemic after reopening. It suggests that large-scale social activities in HSG may lead to an increase in the number of infections in the absence of restrictions, which is similar with the result in previous study (Gangemi et al., 2020). Therefore, the HSG should utilize its socioeconomic advantage to increase vaccination coverage and medical resources and enhance monitoring to prevent the rapid spread of infectious diseases in the future.

Although we found a nonlinear relationship between SES and infections and further analyzed its mechanisms, this study has some limitations. First, we considered two stages (before and after the dominance of Omicron) to estimate the IFR and improve the accuracy of the reconstructed sequence. However, the actual IFRs are difficult to obtain for 128 countries, leading to uncertainty in the nationally reconstructed infection rate series. Second, owing to data limitations, we did not consider the impact of changes in population movement in Phase IV. Although we considered multiple factors, there may still be some factors that were not included in the models, such as possible differences in exposure patterns between populations, which may also have an impact on the infection rate. Finally, we analyzed the relationships between SES and infections in the COVID-19 pandemic at the global scale. Although we selected data in the United States, China, India and Ethiopia to improve the robustness of the results, it would be necessary to have more data that could reveal their relations at more and smaller scale (city, district and community).

In conclusion, the inverted U-shaped relationship between SES and infections during the COVID-19 pandemic provides new insights for researches on infectious diseases, highlighting the need to focus on infectious diseases in middle-SES countries. The lessons learned from the past three years of the COVID-19 pandemic are beneficial for countries with different SES to cope with future infectious diseases. First, the relationship between SES and infections was inverted U-shaped in the early stage of the COVID-19 pandemic. The average number of infections in middle SES countries was the highest in the first three phases, indicating that governments should pay attention to infectious diseases in middle SES countries. Second, SES was related with multiple factors, and these factors had nonlinear effect on the infections, which explains the inverted U-shaped relationship between SES and the COVID-19 pandemic. Finally, SES affected infections through multiple pathways and they were different among the four SES groups. In the future, countries should increase medical resource reserves and improve the response capacity of the health system to cope with infectious diseases. In the event of a similar pandemic in the future, these experiences provide a scientific basis for policy-makers and a reference for countries of different SES to respond appropriately.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All data used in the study are publicly available. The epidemiological data about daily cumulative case and death are accessed from Dong et al. (2020), and the death data in China are accessed from the website (Chinese Center for Disease Control and Prevention, 2023). The data on SARS-CoV-2 variant sequences were collected from the Global Initiative of Sharing All Influenza Data (GISAID): Elbe and Buckland-Merrett (2017). The data about changes in population movement and the rate of mask usage were obtained from Institute for Health Metrics and Evaluation (IHME) (2022). The policy data were collected from the Oxford COVID-19 Government Response Tracker: Hale et al. (2021). The data about socio-economic indicators, the share of urban population and share of population aged 15–64 years old were provided by the World Bank (2022a, 2022c, 2022b). The data on population in different age groups are from the United Nations (2022). The medical resources data were obtained from the WHO (2023b). Meteorological data was downloaded from ERA5 hourly data set: Hersbach et al. (2023).

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