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Review Paper

Comparative efficacy of respiratory personal protective equipment against viral respiratory infectious diseases in healthcare workers: a network meta-analysis

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A B S T R A C T

Objective: With the epidemic of coronavirus disease 2019 (COVID-19), the healthcare workers (HCWs) require proper respiratory personal protective equipment (rPPE) against viral respiratory infectious diseases (VRIDs). It is necessary to evaluate which type of mask and manner of wearing is the best suitable rPPE for preventing the VRID.
Study design: A Bayesian network meta-analysis was performed to comprehensively analyze the protective efficacy of various rPPE.
Methods: This network meta-analysis protocol was registered in an international prospective register of systematic reviews (CRD42020179489). Electronic databases were searched for cluster randomized control trials (RCTs) of comparing the effectiveness of rPPE and wearing manner in preventing HCWs from VRID. The primary outcome was the incidence of laboratory-confirmed viral respiratory infection reported as an odds ratio (OR) with the associated 95% credibility interval (CrI). The secondary outcome was the incidence of clinical respiratory illness (CRI) reported as an OR with the associated 95% CrI. Surface under the cumulative ranking curve analysis (SUCRA) provided a ranking of each rPPE according to the primary outcome and the secondary outcome as data supplement.
Results: Six studies encompassing 12,265 HCWs were included. In terms of the incidence of laboratory-confirmed viral respiratory infection, the continuous wearing of N95 respirators (network OR, 0.48; 95% CrI: 0.27 to 0.86; SUCRA score, 85.4) showed more effective than the control group. However, in terms of reducing the incidence of CRI, there was no rPPE showing superior protective effectiveness.
Conclusions: There are significant differences in preventive efficacy among current rPPE. Our result suggests that continuous wearing of N95 respirators on the whole shift can serve as the best preventive rPPE for HCWs from the VRID.

Introduction

Respiratory personal protective equipment (rPPE) is critical to reducing the risk of spreading respiratory pathogens in the current coronavirus disease 2019 (COVID-19) epidemic.[1] There are three main types of rPPE currently used among healthcare workers (HCWs): cloth mask, surgical mask, and N95 respirator. Cloth mask, although it has been replaced by the disposable surgical mask, is still used repeatedly in the area wherein the shortage of rPPE. The surgical mask has traditionally been used by HCWs to avoid hand-to-face contact and prevent respiratory droplet transmission, although it may not be reliable for preventing aerosol transmission.[2] The N95 respirator is designed to prevent HCWs from inhaling small airborne particles when treating patients with suspected viral respiratory infectious diseases (VRIDs).[3] In the epidemic of COVID-19, the N95 respirator is strongly recommended to use in HCWs from occupationally acquired infections through droplet or airborne spread.[1]

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Although N95 respirator has been thought to be superior to other masks (e.g. surgical mask) in preventing the COVID-19 and the other common VRIDs (adenoviruses, influenza, respiratory syncytial virus, metapneumovirus, parainfluenza virus, rhinovirus enterovirus, coronavirus, coronaviruses parainfluenza viruses, severe acute respiratory syndrome–associated coronavirus, adenoviruses and human bocavirus, coxsackie/echoviruses), the existing evidence is still controversial.[4,5] This may be due to that the diagnosis of VRIDs replies on laboratory tests based on nucleic acids or antibodies. It could be false negative results generated from nucleic acid and antibody based on lab tests. To minimize the risk of missing specific targets and increase the sensitivity, clinical respiratory illness (CRI) is an important supplemental method to diagnose VRIDs. We include the data from laboratory tests, as well as clinical presentations (coryza, fever [temperature >37.8°C], lymphadenopathy, tachypnea [respiratory rate >25/min]) and symptoms (arthralgias/myalgias/body aches, chills, cough, diarrhea, dyspnea, fatigue, headache, malaise, other gastrointestinal systems, sore throat, sputum production, sweats, vomiting/nausea),[6] in this network meta-analysis (NMA) to better evaluate and compare the protective effects of rPPE.

It is noteworthy that asymptomatic infections existed in many VRIDs. Therefore, the wearing manner is also important for HCWs who were facing the suspectable patient.[7–9] There are two types of wearing manners including continuous wearing and targeted wearing. Continuous wearing refers to wearing of the rPPE during the whole working shift, whereas targeted wearing refers to wearing it only on performing high-risk procedures (e.g. endotracheal intubation) or when in high-risk situations (e.g. entering an isolation room or barrier nursing of a patient).[10] The previous study also found out that different wearing manners affected the protective efficacy of rPPE.[10] Recently, Bartoszko et al.[5] provided a negative result in comparing surgical masks and N95 respirators in COVID-19 epidemics. However, the manner of wearing might take consideration in preventive efficacy in rPPE. Hence, we conducted this network meta-analysis to examine which type of mask and manner of wearing is the best suitable rPPE for preventing the VRID.

Methods

Study design

In this Bayesian network meta-analysis, we compared the efficacy of various rPPE in preventing VRIDs in HCWs.

Data sources and search strategy

This NMA protocol was registered in a prospective register of systematic reviews (CRD42020179489). This NMA was conducted following guidelines in the preferred reporting items for systematic reviews and meta-analyses report, the extension of network meta-analyses.[11] PubMed, the Cochrane Library, Web of Science, and EMBASE were searched by computer to collect cluster randomized control trials of comparing the effectiveness of rPPE and wearing manner in preventing HCWs from VRIDs. The retrieval time limit was from Jan 1, 1970, to Dec 31, 2019. Simultaneously, the research and related systematic evaluation references that have been included in the manual retrieval are conducted to supplement and obtain relevant literature. Through PubMed, the search strategy is determined, and the search is carried out with a combination of subject words and free words. English search terms include the randomized controll trials (RCT), mask, face mask, respirator trace effects, respirator masks, N95 respirator masks, virus, and so on.

Study selection and eligibility criteria

Inclusion criteria were cluster RCTs comparing the effectiveness of rPPE and wearing manner in preventing HCWs from VRIDs. The outcome includes the incidence of laboratory-confirmed viral respiratory infection and the incidence of CRI (Table 1). Exclusion criteria were non-RCT experiments; incomplete or repeated publication of relevant data; non-human studies; and reviews, study protocols, comments, case reports, and letters.

Data extraction and quality assessment

Two authors (X.Y. and X.W.) independently extracted relevant data parameters. In case of disagreement, the arbitration shall be conducted by the corresponding author. The following data extraction parameters were extracted: name of the primary author, country of study, number of HCWs, number of participants per arm, HCW age (mean or median and standard deviation [SD] or range, if available), the gender of HCWs, quality information included in the study, the efficiency of the incidence of laboratory-confirmed viral respiratory infection in the rPPE arm and control arm, the efficiency of the incidence of CRI in the rPPE arm and control arm.

The study quality was assessed by two authors (X.Y. and X.W.) according to Cochrane Collaboration's tool. It includes six aspects: sequence generation, allocation consideration, blinding, incomplete outcome data, no selective outcome reporting, other sources. RevMan software (v 5.3) was only used for the risk of bias summary. In case of disagreement, the arbitration will be conducted by the corresponding author.

Outcomes

The prespecified primary outcome was the incidence of laboratory-confirmed viral respiratory infection reported as an odds ratio (OR) value and 95% credibility interval (CrI). The OR value was calculated by taking the odds of laboratory-confirmed viral respiratory infection in a specific rPPE group and dividing this value by odds of the control. The prespecified secondary outcome was the incidence of CRI reported as an OR with the associated 95% CrI. The OR was calculated by taking the odds of CRI in a specific rPPE group and dividing this value by odds of the control. The protective effect of rPPE was defined as an OR (including the associated 95% CrI) falling under unity (1.0).

Statistical analysis

The Stata15 SE was used for network diagrams. ADDIS software (version1.16.8) was used for network meta-analysis; all analyses use a random model by default. Node-split analysis was used to test the consistency between direct and indirect comparisons. If the P value > 0.05, a consistency type was used; otherwise, an inconsistency type was used. If node-split analysis could not be applied, both type data were reported.[12] Potential scale reduction factor (PSRF) analysis was used to determine the model convergence; when the PSRF value was 1,[13] approximate convergence had been reached. Network OR value, and 95% CrIs were used as the effect magnitude, output ranks, and the surface under the cumulative ranking curve analysis (SCURA) value.

R software (version 3.6.1) was used for heterogeneity analysis and sensitivity analysis. According to the Cochrane handbook, Q-values less than the degree of freedom (DF), P values greater than 0.10, and I^2 values between 0% and 40% suggested no significant heterogeneity. If the Q-value was greater than the DF, the P value was less than 0.10, and the I^2 value was between 75% and 100%, the data were considered heterogeneous.[14] Sensitivity analysis was

Table 1
Characteristics of the included studies.

Study ID	Country	Study size	Sex (male/female)	Age (years)	(Allocated numbers in arms)	Laboratory-confirmed viral respiratory infection	Clinical respiratory illness
Loeb[18] 2008-09	Canada	446	26/420	36.15 ± 10.59	Targeted wearing of surgical mask (225) vs targeted wearing of N95 respirator masks (221)	Parainfluenza, influenza viruses A and B, respiratory syncytial virus, metapneumovirus, rhinovirus enterovirus, coronavirus	Body temperature 38 °C or greater; new or worsening cough; shortness of breath
MacIntyre[16] 2008-09	China	1922	N/A	N/A	Continuous wearing of N95 respirator masks (949) vs continuous wearing of surgical masks (492) vs control (481)	Adenoviruses, human metapneumovirus, coronaviruses, parainfluenza viruses, influenza viruses A and B, respiratory syncytial viruses A and B, or rhinovirus A/B	N/A
MacIntyre[17] 2008-09	China	1441	142/1299	33.63 ± 9.56	Continuous wearing of surgical mask (492) vs continuous wearing of N95 respirator masks (949)	Adenoviruses, human metapneumovirus, coronavirus, parainfluenza viruses 1, 2 and 3, influenza viruses A and B, respiratory syncytial virus A and B, rhinovirus A/B and coronavirus	At least two respiratory symptoms (cough, sneezing, runny nose, shortness of breath, sore throat) or one respiratory symptom and one systemic symptom (including fever, headache, and lethargy).
MacIntyre[10] 2009-10	China	1669	243/1426	33.1 ± 9.61	Continuous wearing of surgical masks (572) vs targeted wearing of N95 respirator masks (516) vs continuous wearing of N95 respirator masks (581)	Adenoviruses, human metapneumovirus, coronaviruses parainfluenza viruses, influenza viruses A and B, respiratory syncytial viruses A and B, or rhinoviruses A/B	At least two respiratory symptoms (cough, sneezing, runny nose, shortness of breath, sore throat); one respiratory symptom and one systemic symptom (including fever, headache, and lethargy).
MacIntyre[15] 2011	Vietnam	1607	357/1250	35.65 ± 10.39	Continuous wearing of surgical masks (580) vs continuous wearing cloth masks (569) vs control (458)	Respiratory syncytial virus (RSV) A and B, human metapneumovirus (hMPV), influenza A and B, parainfluenza viruses, influenza C, rhinoviruses, severe acute respiratory syndrome (SARS)–associated coronavirus, adenoviruses and human bocavirus (hBoV)	At least two respiratory symptoms (cough, sneezing, runny nose, shortness of breath, sore throat); one respiratory symptom and one systemic symptom (including fever, headache, and lethargy).
Radonovich[6] 2011-15	America	5180	798/4382	43 ± 11.55	Targeted wearing of N95 respirator masks (2512) vs targeted wearing of surgical masks (2668)	Coxsackie/echoviruses, coronavirus, human metapneumovirus, human rhinovirus, influenza A and B, parainfluenza virus, respiratory syncytial virus	At least 1 sign or 2 symptoms listed, representing a change from baseline. Sign: coryza, fever (temperature >37.8 °C), lymphadenopathy, tachypnea (respiratory rate >25/min); Symptoms: arthralgias/myalgias/body aches, chills, cough, diarrhea, dyspnea, fatigue, headache, malaise, other gastrointestinal systems, sore throat, sputum production, sweats, vomiting/nausea

conducted by changing the random model to the fixed model; if the results show no significant change, the sensitivity was low, and the results are relatively stable and reliable. No publication bias analysis was conducted in this NMA as only 10 studies were included.[14]

Results

Characteristics of the included studies

The search produced 745 citations, and 21 eligible articles were retrieved in full text. Six cluster RCTs were included after screening (Fig. 1).[6,10,15–18] In total, 12,265 HCWs were analyzed with a network meta-analysis, including 3 two-arm studies and 3 three-arm studies (Table 1). In the included literature, we studied five kinds of interventions and one control group. The average age of the HCWs was 38.66 ± 11.65 years (10,343 HCWs, five articles included, one article not reported[16]), and the sex ratio was 0.18 (10,343 HCWs, 1,566 men, 8,777 women, five articles included, one article not reported[16]).

Risk of bias and quality of evidence assessment

The research included in this study used RevMan software (version 5.3) for the risk of bias summary (Fig. 2). All of them were

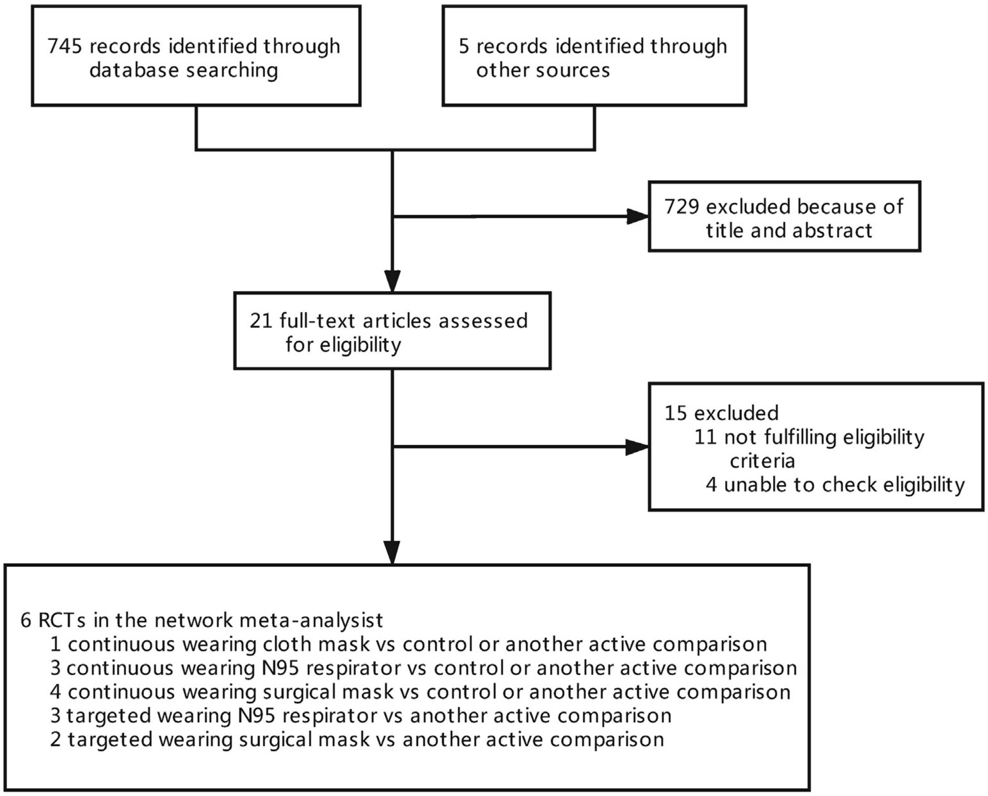

Fig. 1. PRISMA process. PRISMA, preferred reporting items for systematic reviews and meta-analyses.

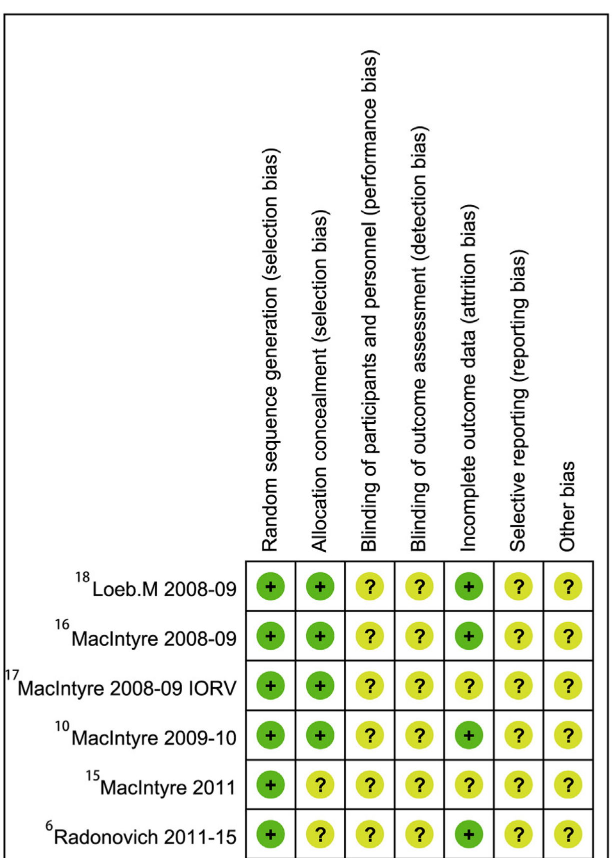

Fig. 2. Risk of bias summary. IORV, without control arm.

designed as cluster randomized controlled studies. All studies used random allocation concealment. Two studies were reported as double blinded.[6,18]

The incidence network meta-analysis for the laboratory-confirmed viral respiratory infection.

A total of six cluster RCTs were included in this NMA. There were 3 two-arm studies and 3 three-arm studies. A total of six nodes were included in this NMA, with each node representing a different rPPE and a wearing manner; the analysis results are shown in Fig. 3. The size of each node represents the included number of HCWs for the intervention. The width of each line represents the number of direct comparisons between interventions (Fig. 3A). The most studied interventions were continuous wearing of surgical masks (4 RCTs) and continuous wearing of N95 respirators (3 RCTs).

In the NMA, node splitting analysis shows *P*-value is 0.96 (Table 2), so we used the consistency type to analyze data. After 100,000 simulation iterations, the PSRF value is 1, indicating that approximate convergence has been reached. Pooled network OR values indicate that continuous wearing of N95 respirators (network OR, 0.48; 95% CrI: 0.27 to 0.86) showed significant superiority over the control group (Fig. 3C). Forest plot of the network meta-analysis comparing differences of the efficacy of each rPPE class against the control group (Fig. 3B). SUCRA analysis provided a ranking of each rPPE and a wearing manner according to its efficacy in reducing the incidence of laboratory-confirmed viral respiratory infection (Fig. 3C). The top-ranked rPPE was the continuous wearing of N95 respirators (SUCRA score, 85.4; Fig. 3C).

Heterogeneity analysis shows no significant heterogeneity (Q-value = 1.32 < 4 (DF), *P*-value = 0.86, I^2-value = 0%) (Fig. 3B). The

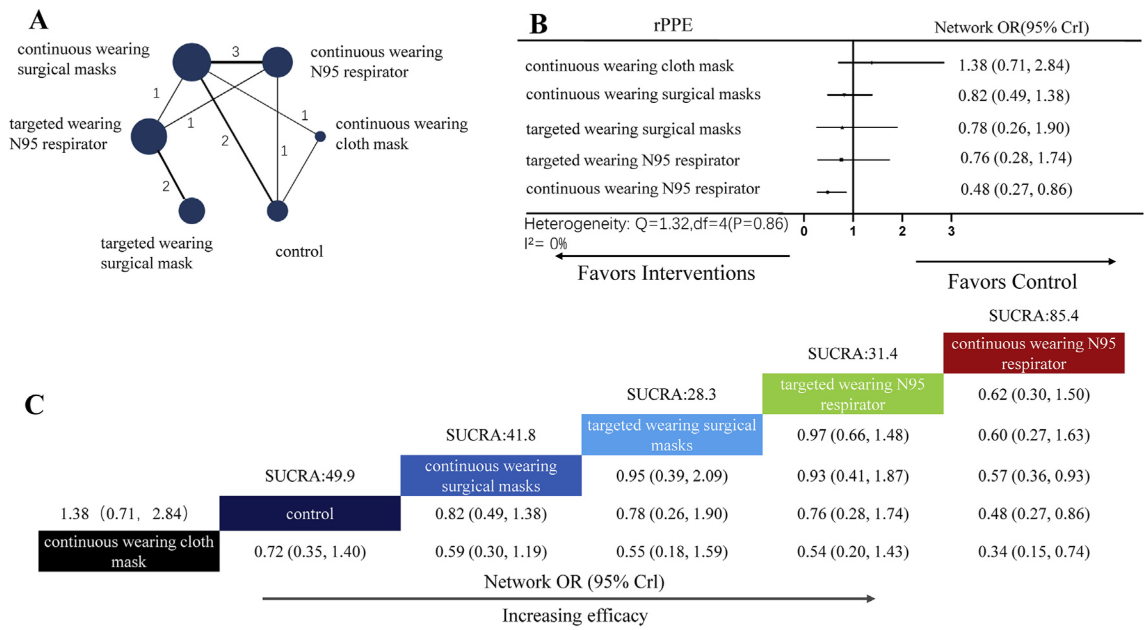

Fig. 3. Network meta-analysis for laboratory-confirmed viral respiratory infection. (A) The network plot shows a comparison of the incidence of the laboratory-confirmed viral respiratory infection between nodes (blue circles). Each node represents a unique rPPE and wearing manner or control; the size of each node represents the included HCWs for the intervention. The width of each line represents the number of direct comparisons between interventions. The connecting line noted the number of trial-level comparisons between the two nodes. (B) The forest plot of the network meta-analysis comparing the VRID of each rPPE group against the control group. (C) Schematic detailing the most efficacious rPPE class in terms of reducing laboratory-confirmed viral respiratory infection according to the surface under the cumulative ranking curve analysis (SUCRA). HCWs, healthcare workers; OR, odds ratio; CrI, credibility interval; rPPE, respiratory personal protective equipment; VRID, viral respiratory infectious disease. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

Table 2
Node splitting analysis for incidence of laboratory-confirmed viral respiratory infection.

Name	Direct effect	Indirect effect	Overall	*P*-Value
Continuous wearing of N95 respirator, control	0.76 (0.01, 1.60)	0.72 (−0.26, 1.77)	0.74 (0.16, 1.31)	0.96

sensitivity analysis was conducted, and results showed that there is no significant change in fixed models (Supplementary Fig. 1A and B). Hence, the sensitivity was low, and the results were stable.

The incidence network meta-analysis for CRI

A total of five cluster RCTs were included in this NMA. There were 3 two-arm studies and 3 three-arm studies. A total of six nodes were included in the efficiency of the incidence of CRI network meta-analysis, with each node representing a different rPPE and a wearing manner; the analysis results are shown in Fig. 4. The size of each node represents the included HCWs for the intervention. The width of each line represents the number of direct comparisons between interventions (Fig. 4A). The most studied interventions were continuous wearing of surgical masks (3 RCTs) and targeted wearing of N95 respirators (3 RCTs). In the NMA, because the node splitting analysis can not run, we provide both consistency type and inconsistency type data (Supplementary Fig. 2A and B). Pooled network OR values indicate that no intervention was significantly superior over the control group (Fig. 4C). Forest plot of the network meta-analysis comparing differences of CRI of each rPPE class against control group (Fig. 4B). SUCRA analysis provided a ranking of each rPPE and wearing manner according to its incidence of CRI (Fig. 4C). Although all classes were equivalent to controls, the top-ranked rPPE was the continuous wearing of N95 respirators (SUCRA score, 79.5; Fig. 4C).

Heterogeneity analysis shows no significant heterogeneity (Q-value = 0.73 < 2 (DF), *P*-value = 0.69, I^2-value = 0%) (Fig. 4B). The sensitivity analysis was conducted, and the results showed that the 95% CrI has a significant change in fixed and random models (Supplementary Fig. 2C and D). Hence, the sensitivity was high, and the results were unstable.

Discussion

COVID-19 is predominantly transmitted by contact or droplet. Airborne transmission may occur if the patient had respiratory symptoms such as coughing or HCWs performing high-risk procedures such as incubation.[19] Preventing VRID transmission by rPPE is highly recommended. But current guidelines for the use of rPPE in HCWs in the hospital setting are based on limited evidence-based studies.[20] In this NMA of 6 RCTs consisting of 11,828 HCWs, we compared the protective effect of three types of rPPE. In addition, we focused on the wearing manner for further assessment. Results of NMA showed that continuous wearing of N95 respirators on the whole shift may have better protection against VRIDs, whereas there is no significant difference in the CRI.

Appropriate rPPE use is critical to decreasing the infectious risk for HCWs. However, previous RCTs showed inconsistent results in different rPPE.[21,22] Our finding supports that the N95 respirator is superior to the surgical mask and the cloth mask. Furthermore, continuous wearing showed an increasingly protective effect against VRIDs. In the medical setting such as in the emergency medicine department, patients with VRIDs are not able to be screened or confirmed by serological tests or medical imagining. HCWs who are exposed to such an environment will face a higher

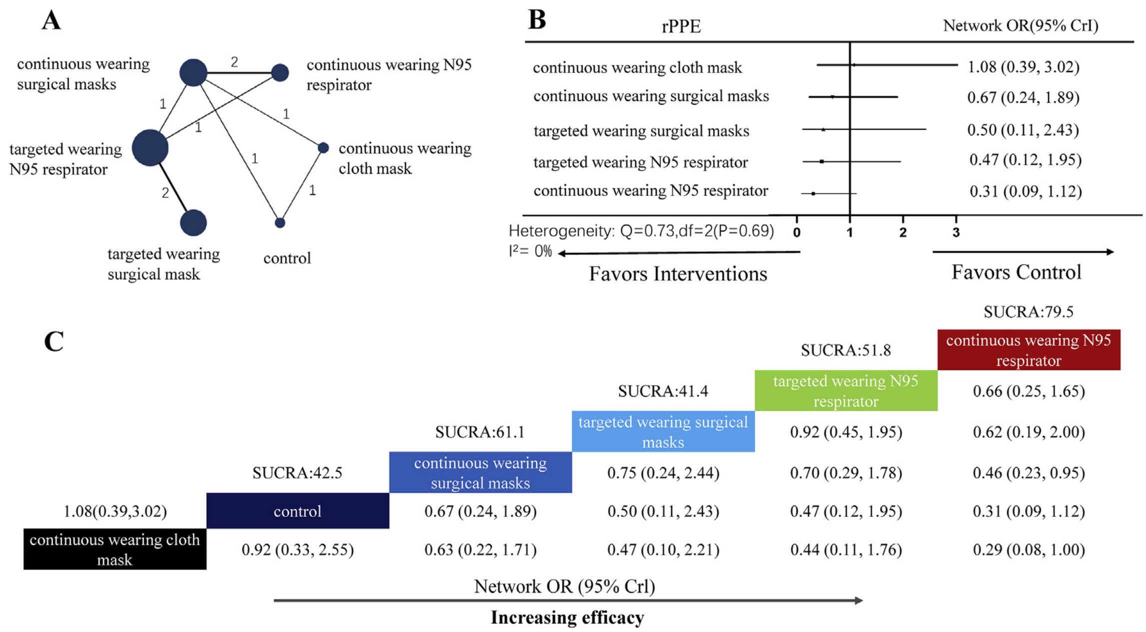

Fig. 4. Network meta-analysis for clinical respiratory illness. (A) Network plot showing comparisons of the incidence of clinical respiratory illness between nodes (blue circles), each representing a unique rPPE and wearing manner or control; the size of each node represents the included HCWs for the intervention. The width of each line represents the number of direct comparisons between interventions. The connecting line noted the number of trial-level comparisons between the two nodes. (B) Forest plot of the network meta-analysis comparing the CRI of each rPPE group against the control group. (C) Schematic detailing the most efficacious rPPE classes in terms of reducing CRI according to the surface under the cumulative ranking curve analysis (SUCRA). HCWs, healthcare workers; OR, odds ratio; Crl, credibility interval; rPPE, respiratory personal protective equipment; CRI, clinical respiratory illness. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

risk of VRIDs. In the COVID-19 epidemic, asymptomatic carriers had been proved to be contagious,[8] which also became a potential risk for HCWs. Hence, the continuous wearing of the N95 respirator during the whole shift might provide more consistent and reliable protection for HCWs.

The unexpected result is that the targeted wearing of surgical masks showed better efficacy than the continuous wearing of it. It could be prolonged and continuously wearing time leads to moist condensation to the inner layer of mask which decrease filtration rate and its efficacy.[23] Reusable cloth mask, which is widely used in the underserved area, showed only marginal protection against VRIDs. Lack of proper guidelines and equipment to decontaminate reusable cloth mask could contribute to this because the airborne pathogen can survive on the mask surface for days. Besides, the cloth mask showed lower filtration capacity than disposable masks.[24]

The sensitivity analysis of the incidence of CRI is unstable (Supplementary Fig. 2). Therefore, we assumed there is no rPPE superior to the control group in preventing VRIDs (Fig. 3C). We speculated that factors that drive other biases are difficult to quantify. Therefore, our finding of the aforementioned rPPE in preventing VRID by the incidence of CRI should be cautiously interpreted.

There are some other limitations to our analysis. Firstly, the consistency evaluation for the protective efficacy of rPPE may vary in different studies. Different medical settings might have different risks of infection. For example, HCWs in emergency settings are more susceptible to VRIDs due to the crowded environment comparing with a well-controlled surgical/operation setting. To better evaluate the protection level of rPPE, it is preferred to evaluate rPPE under the same working environment and treating similar patient groups. Secondly, there is a limited quantity of studies that focus on rPPE have been published during this COVID-19 epidemic. Therefore, the reliability of selection in this study is relatively lacking. The network meta-analysis for the incidence of CRI failed to pass the sensitivity analysis. Some unknown biases may exist. Therefore, the results should be dealt with some cautions. Thirdly, as no other studies could be found based on the inclusion criteria, the retrieval time was set from 1970 in search strategy. Finally, our results were largely based on previous studies about other VRIDs such as influenza. Although the World Health Organization has recommended using N95 respirators to prevent COVID-19 in HCWs, our results should be interpreted with caution. More COVID-19 RCTs need to be performed to further support our results.

Conclusion

This NMA showed that continuous wearing of N95 respirators on the whole shift may have the best protection against VRIDs. Surgical mask, on the contrary, needs to be replaced frequently for better efficacy. In terms of cloth mask, although it is still being used, it only provides marginal protection against VRIDs. Further analysis should include more RCTs during this COVID-19 epidemic.

Author statements

Ethical approval

Ethical approval was not required for this study.

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Competing interests

The authors have no conflicts of interest to disclose.

Author contributions

C.H. conceptualization (lead) and in writing, reviewing, and editing the manuscript (equal).; X.Y contributed in writing methodology of the study (lead); software (lead); formal analysis (lead); and writing, reviewing, and editing the manuscript (equal). X.W. writing the original draft (lead) and writing, reviewing, and editing the manuscript (equal). S.X. contributed in writing, reviewing, and editing the manuscript (equal).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.puhe.2020.11.004.

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Original Research

Early mandated social distancing is a strong predictor of reduction in peak daily new COVID-19 cases

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Mandated social distancing
Quarantine

ABSTRACT

Objectives: Mandated social distancing has been applied globally to reduce the spread of coronavirus disease 2019 (COVID-19). However, the beneficial effects of this community-based intervention have not been proven or quantified for the COVID-19 pandemic.
Study design: This is a regional population-level observational study.
Methods: Using publicly available data, we examined the effect of timing of mandated social distancing on the rate of COVID-19 cases in 119 geographic regions, derived from 41 states within the United States and 78 other countries. The highest number of new COVID-19 cases per day recorded within a geographic unit was the primary outcome. The total number of COVID-19 cases in regions where case numbers had reached the tail end of the outbreak was an exploratory outcome.
Results: We found that the highest number of new COVID-19 cases per day per million persons was significantly associated with the total number of COVID-19 cases per million persons on the day before mandated social distancing ($\beta = 0.66$, $P < 0.0001$). These findings suggest that if mandated social distancing is not initiated until the number of existing COVID-19 cases has doubled, the eventual peak would result in 58% more COVID-19 cases per day. Subgroup analysis on those regions where the highest number of new COVID-19 cases per day has peaked showed increase in β values to 0.85 ($P < 0.0001$). The total number of cases during the outbreak in a region was strongly predicted by the total number of COVID-19 cases on the day before mandated social distancing ($\beta = 0.97$, $P < 0.0001$).
Conclusions: Initiating mandated social distancing when the numbers of COVID-19 cases are low within a region significantly reduces the number of new daily COVID-19 cases and perhaps also reduces the total number of cases in the region.

Introduction

Quarantine and isolation are standard procedures to avoid transmission of infectious disease from infected to non-infected persons and have been used in numerous epidemics.[1] Social distancing is another method for reducing frequency of contact between people to decrease the risk of disease transmission. Social distancing has been used in both influenza and coronavirus disease 2019 (COVID-19) pandemics (caused by severe acute respiratory syndrome coronavirus 2 [SARS-CoV-2]). Social distancing can be voluntary at the individual level or mandated at a community level by governing authorities.

Mandated social distancing comprises of a combination of travel restrictions, closure of non-essential group meeting venues (e.g., restaurants, schools, shops) and steps to avoid close contact at essential meeting venues (e.g., hospitals, food supply, pharmacies). Mandated social distancing is also referred to as 'societal lockdown' and will have a variable impact on the spread of disease depending on the mode of disease transmission and ability to identify and isolate persons infected with the disease.[2] Critical analysis of mandated social distancing in 17 cities in the United States during the 1918 pandemic (caused by H1N1 influenza A virus) found that cities with mandated social distancing at an early phase of the

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epidemic had peak death rates 50% lower than in those cities that did not implement such early interventions.[3] Although results from the 1918 pandemic, influenza pandemics and severe acute respiratory syndrome have been used to justify mandated social distancing in various parts of the world, limited analysis of the effect of mandated social distancing on the COVID-19 pandemic is available. The value of mandated social distancing requires a critical assessment for each pandemic because of inadvertent adverse psychological and health consequences on individuals[4,5] and financial effects on society.[6] We examined the effect of timing of mandated social distancing on the rate of COVID-19 cases in 119 geographic regions, derived from 41 states within the United States and 78 other countries.

Methods

Daily cumulative COVID-19 case numbers for individual regions (countries and individual states within the United States) from January 22, 2020, are publicly available.[7,8] The start dates of mandated social distancing for different regions have been compiled and are also available.[9] For this analysis, only regions that had data for both mandated social distancing start dates and daily cumulative case volumes for COVID-19 were included. For the United States, data were available for each state, thus allowing a detailed analysis. In countries other than the United States, we used national mandated social distancing start dates and national COVID-19 case volumes. For France, Denmark, the Netherlands and the United Kingdon, overseas regions were not included in the calculation of national case volumes.

New COVID-19 cases per day were calculated from cumulative daily case volumes up to April 25, 2020. The period of observation in this study was limited up to April 25, 2020, because after this date, relaxation of mandated social distancing occurred in various geographical units, thus confounding the results. We used 2019 population estimates for states in the United States and other countries to calculate daily new and cumulative total COVID-19 case volumes per million persons residing within the region.[10,11] For further analysis, data were smoothed using a moving average to remove daily fluctuations in reported COVID-19 cases. Smoothed data were plotted over raw data for all geographical regions to ensure that they were representative of the raw data (see Appendix A in the supplementary material). China was excluded from the current analysis as the curve was visually different from other regions and the aforementioned methodology could not be reliably applied.

We used the total number of COVID-19 cases per million on the day before mandated social distancing was implemented as the independent variable and predictor for the analysis. The peak of the smoothed curve was used to determine the highest number of new COVID-19 cases per day (expressed in per million persons) and was used as the dependent variable. Owing to the skewness in both the dependent and independent variables, log transformation was applied. To determine if the number of daily new cases had plateaued or was still increasing, linear regression for the previous 13 days was used. The previous 13 days was selected after visually checking the trend for all geographic regions and repeating linear regression for various intervals, ranging from 5 to 13 days. The linear positive trend for the previous 13 days (April 12–25) correlated best with visual interpretation of an upward trend.

Log-transformed values of the highest number of new COVID-19 cases per day per million population and the total number of COVID-19 cases on the day before mandated social distancing were used for all regression analyses. Linear regression analysis was used to predict the highest number of new COVID-19 cases per day using the total number of COVID-19 cases on the day before mandated social distancing as the predictor (model A). Additional analysis of this association was performed after adjustment for the day mandated social distancing started in the course of the COVID-19 pandemic (calculated as the number of days since January 22, 2020), log-transformed population of the geographic region and proportion of persons living in urban areas (model B).[12,13] We use adjusted R-squared (R^2) to calculate how much of the correlation was determined by the addition of independent variables.

The analyses were repeated after classifying the geographic regions into those where the daily new COVID-19 case volume had plateaued and those where COVID-19 cases were still increasing.

Using Internet searches, individual elements of mandated social distancing were manually abstracted for each of the geographical regions included in the analyses (see Appendix B in the supplementary material), and additional analyses were performed after adjusting for these elements.

For regions where the average (over the last 5 days) daily new case volume had trended down to less than 20% of the peak daily new case volume (considered here as reaching the tail end of the epidemic), linear regression analysis was performed to predict the overall number of new COVID-19 cases per million from the total number of COVID-19 cases per million persons on the day before mandated social distancing after log transformation of both variables.

Results

Initiation dates of mandated social distancing were available for 85 countries and 42 US states. Daily COVID-19 case volume data were available for 183 countries and all 52 US states. Both mandated social distancing starting dates and daily COVID-19 case data were available for 78 countries and 41 states. After excluding three regions where the date of the peak number of daily new cases was either before (Israel and Maine) or on the start day of mandated social distancing (Eritrea), the number of days from the start date of mandated social distancing to the peak in daily new COVID-19 cases ranged from 1 to 45 days (Fig. 1).

Mandated social distancing start dates within individual states of the United States ranged from March 17 to April 3, 2020, and for other countries ranged from March 9 to April 15, 2020. The total number of COVID-19 cases ranged from 0 to 1571 cases per million persons on the day before the start date of mandated social distancing (Fig. 2). The highest number of new COVID-19 cases per day ranged from 0.10 to 503 per million persons (Fig. 3). There was a clear trend towards the association between the total number of COVID-19 cases on the start date of mandated social distancing and the highest number of new COVID-19 cases per day when plotted on a logarithmic scale using a scatter plot (Fig. 4).

The results of the linear regression analyses with different models are reported in Table 1. In model A, the highest number of new COVID-19 cases per day was significantly associated with the total number of COVID-19 cases on the day before mandated social distancing ($\beta = 0.66$, $P < 0.0001$). Model B showed improvements in the adjusted R^2 values from 0.59 to 0.72, but no change was observed in terms of β values for the total number of COVID-19 cases on the day before mandated social distancing. Subgroup analyses on those regions where the daily new COVID-19 cases had already peaked showed increase in β values for the total number of COVID-19 cases on the day before mandated social distancing to 0.85 for both the unadjusted and adjusted models ($P < 0.0001$).

Similar results from analyses for states within the United States are reported in Table 2. There was a less clear association between the highest number of new COVID-19 cases per day and the total number of COVID-19 cases on the day before mandated social distancing ($\beta = 0.3$, $P < 0.001$) in the unadjusted model, but a

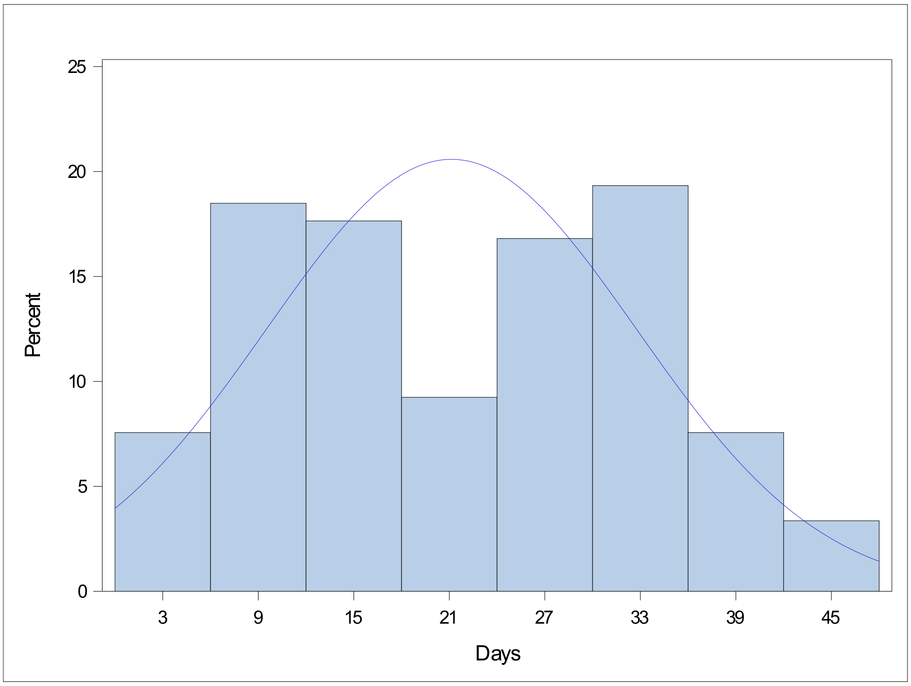

Fig. 1. Interval (in days) between the date of mandated social distancing and reaching the highest number of new COVID-19 cases per day. COVID-19, coronavirus disease 2019.

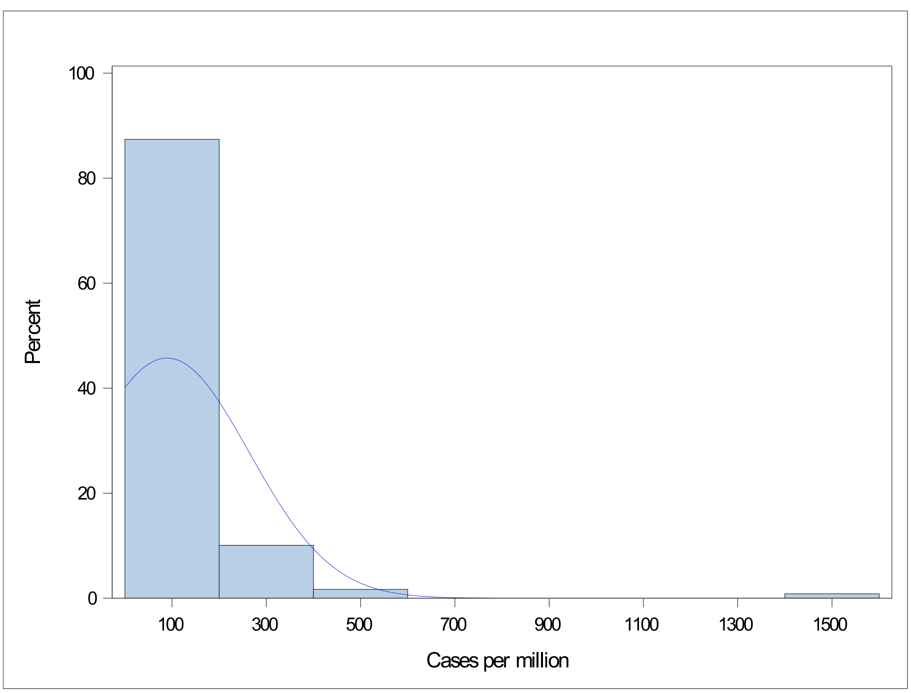

Fig. 2. Distribution of the total number of COVID-19 cases (per million population) on the day before initiation of mandated social distancing. COVID-19, coronavirus disease 2019.

stronger association was observed in the adjusted model ($\beta = 0.72$, $P < 0.0001$). In a model adjusted for only the day of mandated social distancing (not shown in the table), the association between the highest number of new COVID-19 cases per day and total number of COVID-19 cases on the day before mandated social distancing was strong ($\beta = 0.78$, $P < 0.0001$). Daily COVID-19 case volume plateaued in only 13 US states. Both the unadjusted (model A) and adjusted (model B) association between the highest number of new COVID-19 cases per day and the total number of COVID-19 cases on the day before mandated social distancing was stronger in US states where the number of new cases had plateaued compared with states where the number of new COVID-19 cases per day had not plateaued (Table 2).

Internationally, there was a strong association between the highest number of new COVID-19 cases per day and the total number of COVID-19 cases on the day before mandated social

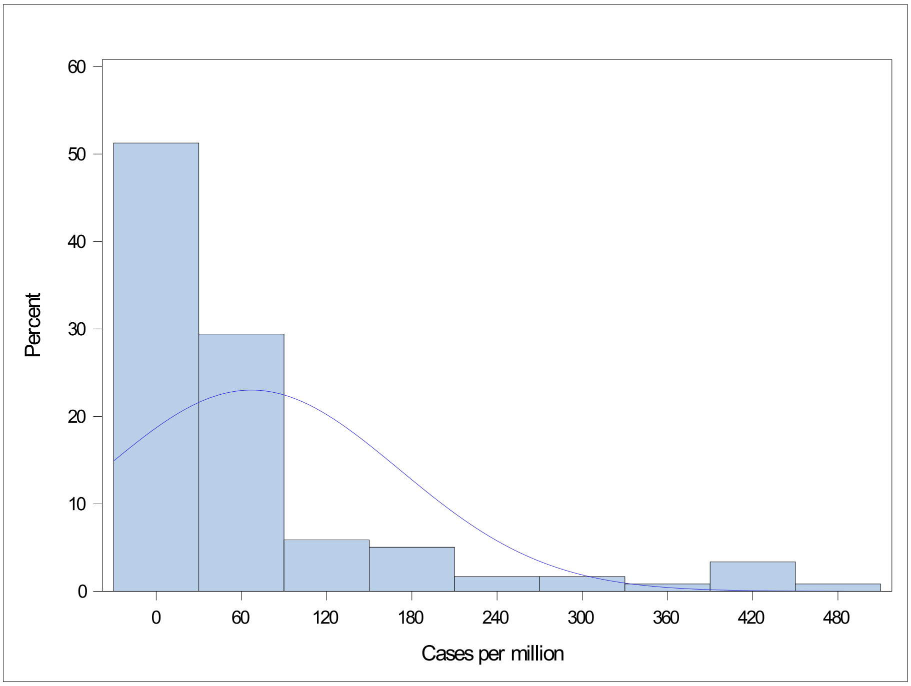

Fig. 3. Distribution of the highest number of new COVID-19 cases per day (per million population). COVID-19, coronavirus disease 2019.

distancing both in the unadjusted and adjusted models (Table 3). This association was stronger for countries where the number of new COVID-19 cases per day had already plateaued ($\beta = 0.88$, $P < 0.0001$).

Addition of individual elements of mandated social distancing (e.g., closure of educational institutes, public transport, restaurants and other shops) did not affect the association between the highest number of new COVID-19 cases per day and the total number of COVID-19 cases on the day before mandated social distancing. Visually, Australia appeared to have plateaued; however, based on a positive trend over the last 13 days of regression, it was classified as not plateaued. The analysis of plateaued regions was repeated after manual addition of Australia, and no change in the aforementioned results was noticed.

For 17 regions (including three states within the United States), the daily new case volume reduced to less than 20% of the peak daily new case volume. The log-transformed total number of cases was strongly predicted by the total number of COVID-19 cases on the day before mandated social distancing (adjusted $R^2 = 0.87$, $F = 112$, $\beta = 0.97$, $P < 0.0001$).

Discussion

This study confirmed the benefit and provided a quantitative estimate of the value of mandated social distancing. The findings suggest that if mandated social distancing is not initiated until after the number of existing COVID-19 cases has doubled, there would be an eventual peak with 60% more COVID-19 cases per day. This investigation found that initiation of mandated social distancing when the number of existing COVID-19 cases had doubled would result in an eventual peak with 58% more COVID-19 cases (using β of 0. 66). If mandated social distancing is started when 100 persons are infected with COVID-19 and the subsequent highest number of cases is 1000 persons, initiating mandated social distancing when 200 persons are infected would increase the peak number of cases to 1580 persons. New York provides an example where mandated social distancing was initiated on day 61 when there were 10,356 cases. As per our analysis, if mandated social distancing was initiated on day 50 (142 cases), then the maximum number of cases per day would have been reduced by a factor of 16 (31 per million compared with 500 per million persons).

This study also identified what is considered a ‘spillover’ effect. There was a blunting of the quantitative value of mandated social distancing in states within the United States when mandated social distancing was initiated later in the course of the pandemic. It is suggested that this blunting of the effect was confounded by earlier mandated social distancing in the surrounding states, which resulted in mitigating the effect by reducing inflow of infected patients with COVID-19. This effect was not seen between countries, where boundaries between countries may serve to insulate by restricting travel into the country. There are no restrictions in movement between states in the United States, thus enhancing this spillover effect.

Ferguson et al.[1] estimated that combining school and workplace closure with area quarantine and antiviral prophylaxis can result in 90% containment of infection (assuming the infection has a basic reproduction number [R0] = 1.9) and when containment was initiated with less than 200 detected cases. The model was based on the spread of H5N1, a highly pathogenic avian influenza in wild and domestic poultry in Southeast Asia. Longini et al.[14] modelled the avian influenza A (subtype H5N1) outbreaks in Southeast Asia. They reported that the local household quarantine was effective in containing the epidemic if R0 ≤2.1, but is not as effective at an R0 value of 2.4. However, a combination of 80% antiviral prophylaxis plus quarantine was effective at an R0 as high as 2.4, and adding previous vaccination makes antiviral prophylaxis plus quarantine even more effective. Both analyses mentioned that one of the reasons limiting the beneficial effect of mandated social distancing is the continued contact between households and neighbourhoods during social distancing, which may offset the benefit with highly infectious agents. Ferguson et al.[1] assumed in their model that household and random contact rates increase by

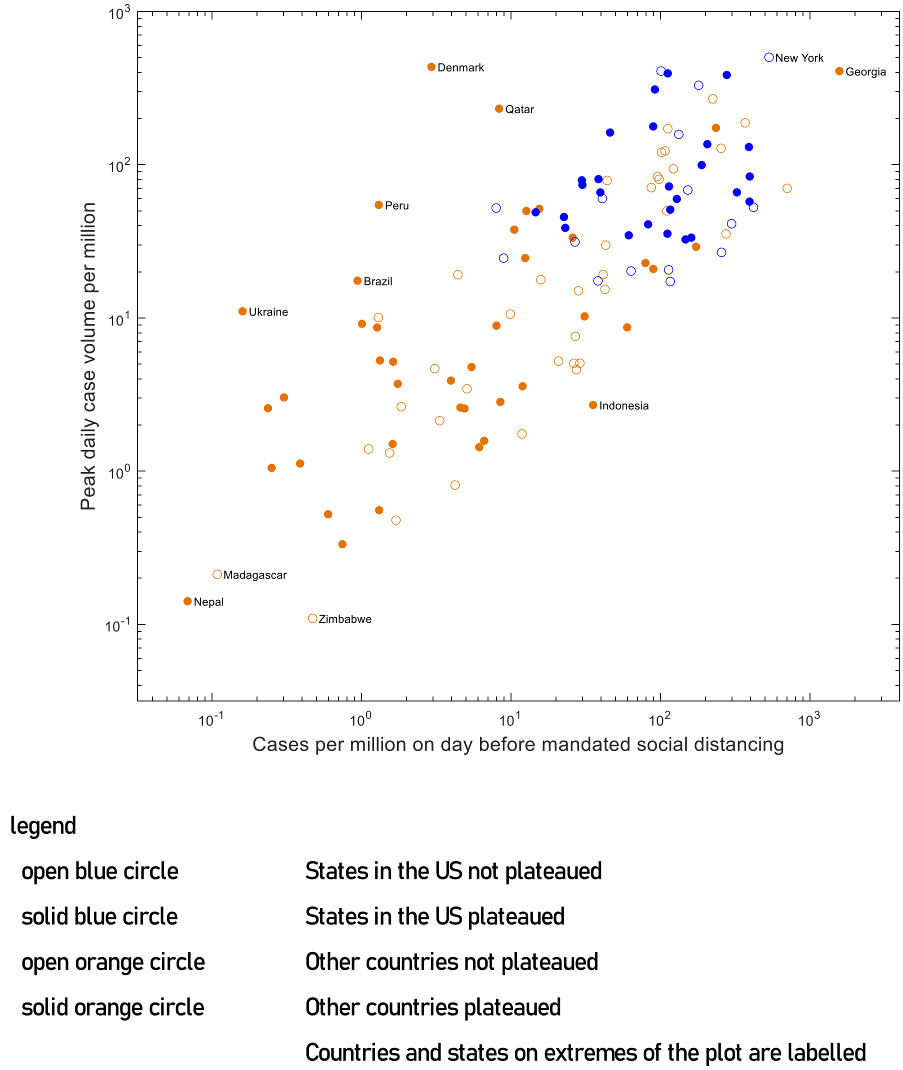

Fig. 4. Relationship between the total number of COVID-19 cases on the day before mandated social distancing initiated and the highest number of new COVID-19 cases per day on the logarithmic scale. COVID-19, coronavirus disease 2019.

100% and 50%, respectively, for individuals no longer able to attend school or work. Previous models have been based on the H1N1 epidemiological experience. The R0 for H1N1 influenza has ranged between 1.25 in Canada,[15] 1.682 in China,[16] 1.96 in New Zealand,[17] 1.6 in Mexico,[18] and 1.7 in the United States.[19] One of the surprising findings is that the benefit of mandated social distancing in the COVID-19 pandemic has been seen, despite the high infectivity of SARS-CoV-2. The R0 of the SARS-CoV-2 infection was originally estimated between 2.2 and 2.7.[20–25] More recent data suggest that the R0 of SARS-CoV-2 infection may be as high at 5.7.[20] The R0 of SARS-CoV-2 is higher than the threshold of 2.4 estimated by Longini et al.[14] and 1.8 for new viral strains estimated by Ferguson et al.,[1] meaning that a higher R0 will result in loss of benefit of mandated social distancing.

There may be other reasons to explain the beneficial effect of mandated social distancing in the COVID-19 pandemic. Ridenhour et al.[26] indicated the importance of the role of transmission rate, recovery rate and size of the population in the overall speed of the epidemic, independent of R0. Tang et al.[16] emphasised the role of asymptomatic patients and those who are in the prodromal period without symptoms in the spread of H1N1 influenza in the province of Shaanxi. The beneficial effect of mandated social distancing may also be related to a relatively long prodromal period and high proportion of asymptomatic SARS-CoV-2–infected patients. The time between transmission and symptoms ranges between 2 and 14 days for SARS-CoV-2.[27] Data on 468 COVID-19 transmission events reported in mainland China outside of Hubei Province showed that 59 (12.6%) of the 468 patients developed symptoms before the potential source developed symptoms, suggesting that transmission occurred in the prodromal period.[28]

There have been small case studies highlighting that COVID-19 can be acquired from patients who are and will remain asymptomatic.[29–31] The estimated proportion of asymptomatic COVID-19 was 17.9% based on screening of travellers on board a cruise ship[32] and 30.8% from data of Japanese citizens evacuated from Wuhan.[33] However, the viral loads in the upper respiratory specimens appeared to be similar in symptomatic and asymptomatic persons.[34] It is possible that the beneficial effect of mandated social distancing may be related to reducing contact between asymptomatic individuals infected with SARS-CoV-2. Another unique aspect of SARS-CoV-2 is its ability to persist on various surfaces and thus be transmitted by indirect contact from

Table 1
Results of the regression analysis predicting the highest number of new COVID-19 cases per day.[a,b]

Statistic	All regions		Plateaued		Not plateaued	
Total	119		51		68	
States within the United States	41		15		26	
Other countries	78		36		42	
	Model A	Model B	Model A	Model B	Model A	Model B
F	171.9	77.5	132.1	55.1	79.4	42.6
Adjusted R^2	0.59	0.72	0.72	0.81	0.54	0.71
Constant	10.1 (0.56)	15.1 (1.65)	11.8 (0.78)	19.3 (2.15)	9.6 (0.76)	15.2 (2.56)
Log (cumulative case volume per million on the day before mandated social distancing)	0.66** (0.05)	0.66** (0.05)	0.85** (0.07)	0.85** (0.07)	0.59** (0.07)	0.61** (0.09)
Log (population of the region)		−0.06 (0.07)		−0.08 (0.08)		−0.12 (0.11)
Day of mandated social distancing (from January 22, 2020)		−0.09** (0.02)		−0.1** (0.02)		−0.08** (0.02)
Percentage of the urban population in the region		0.02* (0.006)		0.001* (0.008)		0.02* (0.009)

COVID-19, coronavirus disease 2019.
*$P < 0.01$, **$P < 0.001$.
[a] Standard errors are reported in parentheses.
[b] Model A = unadjusted; model B = adjusted for the day mandated social distancing started in the course of the COVID-19 pandemic (calculated as the number of days since January 22, 2020), for log-transformed population of geographic region and for proportion of persons living in urban areas.

high-touch surfaces.[35,36] SARS-CoV-2 can persist on plastic, stainless steel, copper and cardboard, and viable virus has been detected for up to 72 h after application on these surfaces. The longest viability was on stainless steel and plastic; the estimated median half-life of SARS-CoV-2 is approximately 5.6 h on stainless steel and 6.8 h on plastic. Therefore, the mandated social distancing is likely to reduce contamination and transmission from high-touch surfaces within society.

One of the limitations of the current model is the variability in policies pertaining to mandated social distancing and compliance to the policies in various geographic regions. Mandated social distancing has several facets, which include special precautions on travel on public transit, ride-shares or taxis; only operating essential businesses, such as grocery stores, gas stations and banks; closure of non-essential businesses; using drive-thru, kerbside pickup or delivery services; prohibiting events and gatherings of more than 10 people; maintaining distance (approximately 6 feet or 2 m) from others when possible; avoid eating or drinking at restaurants, bars or food courts; closing of schools and non-essential factories and workplaces and limiting the number of patrons at retail shops. Compliance with mandated social distancing is an important factor in determining success of the intervention.[1] There is also variability in exposure risk reduction within a given population as each individual does not have the same chance of coming in contact with others.[26] There appears to be a difference exposure risk according to age of the individuals[37] and population structure such as the number of households, workplaces, schools and community groups.[38] Differences in age and population structure between geographic regions may also confound the results.

There is also a confounding effect of case identification and isolation, and robustness of testing for asymptomatic individuals, which may vary in different geographic units in the current analysis. The Centers for Disease Control and Prevention (CDC) concluded that the degree to which COVID-19 cases might go undetected or unreported varies in geographic regions because testing practices differ widely and might contribute significantly to the observed variations.[39,40] For example, the state of New York (excluding New York City) reported administering 4.9 tests per 1000 population, which was higher than the national average of 1.6 (CDC, unpublished data, March 25, 2020). The confounding effect of contact tracing and isolation was not analysed in the present study. There was variability between geographic regions in implementation of contact tracing and isolation. Contact tracing and isolation was also affected by the number of COVID-19 cases within a geographic region and may not be possible if the number of new cases exceeds a certain threshold owing to limitations in resources. The socio-economic status and location (urban versus rural) also influence access to health care and thus case identification and may alter the differences between various geographic regions.

The variability in the highest number of new cases per day that was not explained in the statistical models of the present study is likely due to variability in mandating social distancing in different regions. Although most of the organisations were closed during mandated social distancing, certain businesses, such as meat- and poultry-processing facilities, were recognised as critical for infrastructure and permitted to continue work with precautions. Outbreaks in such places resulted in increasing numbers of new cases per day that are not explained by the current model.[41,42] It is also noted that in some regions (excluded from the analysis), the highest number of new cases per day plateaued before mandated social distancing. This suggests that there may be other mechanisms that can reduce the number of new cases in certain regions.

There were certain analyses that could not be performed for all the regions included in the present study as the pandemic is

Table 2
Results of the regression analysis predicting the highest number of new COVID-19 cases per day—states in the United States.[a,b]

Statistic	All regions		Plateaued		Not-plateaued	
States within the United States	n=41		n=15		n=26	
	Model A	Model B	Model A	Model B	Model A	Model B
F	5.5	8.8	3.2	10.8	1.5	4.5
Adjusted R^2	0.1	0.44	0.13	0.74	0.02	0.36
Constant	7.1 (1.2)	20 (4.01)	7.9 (2.18)	17.1 (5.15)	6.1 (1.41)	16.9 (5.85)
Log (cumulative case volume per million on the day before mandated social distancing)	0.3** (0.13)	0.72** (0.15)	0.41** (0.23)	0.7** (0.17)	0.18** (0.15)	0.52** (0.24)
Log (population of the region)		0.01 (0.12)		0.5 (0.19)		−0.26 (0.13)
Day of mandated social distancing (from January 22, 2020)		−0.15** (0.04)		−0.2** (0.04)		−0.08** (0.06)
Percentage of the urban population in the region		0.009* (0.009)		−0.016* (0.013)		0.023* (0.012)

COVID-19, coronavirus disease 2019.
*$P < 0.05$. *$P < 0.01$. **$P < 0.001$.
[a] Standard errors are reported in parentheses.
[b] Model A = unadjusted; model B = adjusted for the day mandated social distancing started in the course of the COVID-19 pandemic (calculated as the number of days since January 22, 2020), for log-transformed population of geographic region and for proportion of persons living in urban areas.

Table 3
Results of the regression analysis predicting the highest number of new COVID-19 cases per day—other countries.[a,b]

Statistic	All regions		Plateaued		Not-plateaued	
Total	n=78		n=36		n=42	
	Model A	Model B	Model A	Model B	Model A	Model B
F	87.6	42.9	129.5	58.3	23.5	14.3
Adjusted R^2	0.53	0.69	0.79	0.87	0.35	0.57
Constant	9.6 (0.8)	12.8 (2.05)	12.1 (0.86)	18.4 (2.16)	8.3 (1.32)	12.3 (3.68)
Log (cumulative case volume per million on the day before mandated social distancing)	0.63** (0.07)	0.6** (0.06)	0.88** (0.08)	0.83** (0.07)	0.51** (0.1)	0.55** (0.12)
Log (population of the region)		0.02 (0.09)		−0.06 (0.08)		−0.02 (0.15)
Day of mandated social distancing (from January 22, 2020)		−0.09** (0.02)		−0.1** (0.02)		−0.08** (0.03)
Percentage of the urban population in region		0.02* (0.008)		0* (0.009)		0.025* (0.011)

COVID-19, coronavirus disease 2019.
*$P < 0.05$. *$P < 0.01$. ***$P < 0.001$.
[a] Standard errors are reported in parentheses.
[b] Model A = unadjusted; model B = adjusted for the day mandated social distancing started in the course of the COVID-19 pandemic (calculated as the number of days since 22 January, 2020), for log-transformed population of geographic region and for proportion of persons living in urban areas.

ongoing, with changing numbers of COVID-19 cases. In subgroup analysis, it was clear that the relationship was strongest when the highest number of new cases per day had reached its peak. Some regions were still in the period wherein the number of new cases per day is continuing to increase. It is also important to note that the total number of COVID-19 cases in a region can only be determined after the pandemic subsides. In total, only 17 regions in the current analysis were thought to be at the tail end of the pandemic (i.e., where daily new cases had reached less than 20% of the highest number of new cases per day observed). There was a clear relationship between the total number of cases before the start date of mandated social distancing and overall total number of cases in the region, indicating that early mandated social distancing also reduced the total number of COVID-19–infected individuals over time.

Future studies should focus on identifying the effectiveness of individual components of mandated social distancing to determine the most effective model for prevention of COVID-19. Another issue is the re-emergence of COVID-19 (termed as the 'second wave') with relaxation of the mandated social distancing policy. Estimation of the impact of relaxation of the mandated social distancing policy is confounded by a staged and heterogenous set of policies, which make it difficult to identify a distinct effect. However, the differences in relaxation policies between regions may be correlated with regional re-emergence of COVID-19 to identify the most effective strategy for relaxation and termination of mandated social distancing.

Conclusions

The value of mandated social distancing in reducing the spread of COVID-19 has been questioned at multiple levels owing to widespread inadvertent effects on individuals' well-being and the financial consequences on society. This study demonstrates that initiating mandated social distancing when smaller numbers of COVID-19 cases are present will reduce the highest number of new cases per day and perhaps even the overall total number of COVID-19 cases in the region, highlighting the importance of this community-based intervention.

Author statements

Ethical approval

Not required.

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Competing interests

None declared.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.puhe.2020.10.015.

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Letter to the Editor

Online ‘anti-vax’ campaigns and COVID-19: censorship is not the solution

Vaccine scepticism has existed since the advent of the technology itself. However, the mass uptake of social media is blamed for the significant traction recently gained by the ‘anti-vax’ movement. A recent report found that 400 anti-vax social media accounts contain 58 million followers based primarily in the US, UK, Canada and Australia.[1] Misinformation campaigns such as these have contributed to the decline in routine childhood vaccination uptake,[2] infection outbreaks stripping numerous European countries of their ‘measles-free’ status[3] and the World Health Organization naming vaccine hesitancy as a top ten threat to global public health.[4]

The international spread of SARS-CoV-2 has focussed the attention of anti-vax campaigners on the development of vaccines against COVID-19.[5] Since the start of the pandemic, the largest anti-vax social media accounts have gained more than 7. 8 million followers, an increase of 19% since 2019.[1] This has triggered the UK government and social media platforms to agree a package of measures to reduce online vaccine disinformation, including the labelling of posts marked as untrue by third party fact checkers.[6] However, as vaccine trials report encouraging results,[7,8] there have been calls to introduce emergency laws that impose financial and criminal penalties on social media platforms that do not remove vaccine misinformation or fail to close down anti-vax campaign groups.[9] Whilst tackling widespread vaccine misinformation is of vital importance, laws of this nature should not be implemented for three main reasons.

Firstly, many people have legitimate concerns around the safety and efficacy of COVID-19 vaccines due to factors including the speed of their development, the underrepresentation of ethnic minority groups in clinical trials[10] and the unknown longevity of their immunological effects. The public must feel freely able to voice these concerns, raise challenging questions and expect transparent replies from trusted institutions. An unintended effect of shutting down anti-vax groups may be to silence those with legitimate questions for fear of shame or ridicule and lead them to harbour greater suspicion of public health authorities and sympathise with anti-vax rhetoric.

Secondly, such emergency laws would enforce censorship and deplatforming and threaten the democratic cornerstone of freedom of speech. All ideas – even the bad ones – must be allowed a public airing, and their qualities debated in the marketplace of ideas. It is through this process that institutions foster influence, respect and public trust, by presenting empirical evidence, reasoned arguments and a scientific method based on critical thinking. Conversely, widespread deplatforming of anti-vax campaigners is unlikely to dissuade those sympathetic to these messages but rather reinforce their strongly held beliefs about vaccine conspiracies while deepening their mistrust of public health authorities. In addition, removing the social media stages of anti-vax campaigners is likely to drive them underground to adopt alternative stages that are more difficult to identify, monitor and respond to with public health messaging. The lack of evidence to support censorship as a reliable means of producing desirable health behaviour change should deter against the deployment of this strategy.

Thirdly, the features of an ‘anti-vax campaign’ are themselves undetermined and, depending on the breadth of the definition imposed, may include both the mere voicing of concern for vaccine safety and the intentional distribution of dangerous falsities. Governments will be without the substantial resources required to identify all online anti-vax campaigns and thus will be forced to handover decision-making powers to social media platforms themselves. This is unlikely to be an optimal strategy for the delivery of public health messaging and risks triggering dangerous normative shifts in the ability of social media platforms to control what the public is and is not able to see.

The anti-vax movement poses a huge threat to global public health, particularly in the era of COVID-19. However, censorship and deplatforming are unlikely to improve this situation but may unintentionally exacerbate it. Instead, governments should recommit to providing clear, consistent, regular, frequent and accessible public health messaging that is highly visible to the public and transparent about what is, and is not, known to the scientific community. Attention should be drawn to the plethora of benefits enjoyed by humanity to date as a consequence of global mass vaccination programmes and contrasted with the recent setbacks and harms caused by prominent campaigns of anti-vax misinformation. In this manner, public trust in vaccination programmes, medical professionals and public health institutions will be reinstated at the time it is needed most.

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