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## Supplement Article

# International, national and local trends in the spread of COVID-19: a geographic view of COVID-19 spread and the role to be played by coproduction

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## Abstract

**Background:** COVID-19, a respiratory disease caused by the SARS-CoV-2 virus, emerged in 2019 and led to a worldwide pandemic in 2020. The COVID-19 pandemic has been a massive natural experiment in the formation of mitigation strategies to prevent cases and to provide effective healthcare for those afflicted. Regional differences in the impact of the pandemic on morbidity and mortality have been driven by political and regional differences in the coproduction of public health and social policy. We explored the United States (US) experience of COVID-19 for trends and correlations with other nations and also at the national, regional, state and local levels.
**Objective:** To identify geographic and temporal trends in the spread of COVID-19 in the United States.
**Methods:** Population data on COVID-19 cases and mortality were acquired on a daily basis from multiple publicly available databases, including the New York Times and Johns Hopkins University. At each geographic level (national, state and county), geographic entities' reported cases were evaluated for correlations using linear least-squares methods to identify patterns of correlation in the cases independent of scale. We evaluated for two specific characteristics: (i) the nature of the curvature of the line linking across percentile scores, ranging from concave to convex and (ii) the area under this curve, indicating how effectively a selected region (nation, state and county) is linked to its entire containing unit (world, country and state). We used this approach to identify three distinct COVID behavior phenotypes, each of which consisted of a number of states in the USA.
**Results:** We found that COVID activity in the USA follows a unique trend compared to other countries and that within the USA during the first year of the pandemic, three initial COVID phenotypes emerged: (i) the metropolitan outbreak (early outbreak phenotype); (ii) the regional outbreak (summer peak phenotype) and (iii) trans-regional outbreak (fall/winter peak phenotype), which, taken in sum, represent the overall USA national trend. Each phenotype has specific behavioral characteristics and is composed of a cluster of different states experiencing different conditions.

**Conclusion:** Our findings suggest a new opportunity for public health strategy in the pandemic, namely to apply targeted public health approaches to address the specific needs of each phenotype. In the future, we should create databases that capture key health and hardship data elements at the smallest geographic level possible and use these to track trends, predict the future and apply targeted coproduction approaches to more effectively and efficiently safeguard population health, economic vitality and social well-being.

## Introduction

COVID-19 has wrought havoc on health and the economy—on people's lives and their livelihoods on a global scale [1]. A principal challenge of the pandemic has been engaging diverse stakeholders in the effective coproduction of public health interventions to minimize COVID-19 incidence and case fatality rates and to pursue strategies ranging from eradication to 'flattening the curve' to manageably achieving herd immunity [2]. These challenges have been felt, as the pandemic has spread to every continent in the world. As people anticipate having new vaccines to prevent new cases of COVID-19 in 2021, the lessons of the successes and failures of public health, the body politic and regular citizens to manage the pandemic form a template upon which to build policies in anticipation of future challenges, whether they arise from infectious disease, environmental challenges or other threats.

The pandemic has been a massive natural experiment in the formation of mitigation strategies to prevent cases and to provide effective healthcare for those afflicted [3, 4]. COVID-19 transmission mitigation has existed at the nexus of government policy, clinical guidance and individual behavior. The trajectory of the pandemic has largely been shaped by the natural forces of the novel coronavirus, human attempts to minimize the damage through public health non-pharmaceutical interventions [5, 6], clinical and pharmaceutical interventions, policy proclamations regarding schools [7], businesses, travel, social distancing and choices and actions taken by individuals. Coproduction of care can include a situation where clinical care plays a supporting role for care that is administered by a service user or family at home [8]. During the pandemic, many people purchased inexpensive pulse oximeters and used these to monitor their oxygen saturation. Clinical guidelines now recommend that service users with pulse oximeters at home and mild COVID-19 be instructed to monitor for oxygen saturation measurements below 95% and return to the clinic if these occur [9]. This is an example of coproduction of care. COVID-19 transmission mitigation is coproduced: guidance provided clinically or through public health channels is implemented by individuals for their own benefit and, often, for the benefit of friends or family members at risk.

Regional differences in the impact of the pandemic on morbidity and mortality have been driven by political and regional differences in the coproduction of public health—to save people's lives—and the coproduction of social policy—to save the economy and general well-being [10]. To begin to understand these issues and the potential to leverage the coproduction of disease prevention and treatment policies and practices, we explored the US experience of COVID-19 for trends and correlations with other nations and also at the national, regional, state and local levels of activity. Geographically correlated outbreak parameters can identify contact patterns associated with travel or commerce and also regions of similar policy, public health and personal behaviors.

## Methods

Data on COVID-19 cases and mortality were downloaded on a daily basis from the GitHub repositories maintained by Johns Hopkins [11] and the New York Times [12]. The Johns Hopkins data were used for national case totals, while the New York Times database was used for US state and county data. International data were limited to the 100 nations with the most cases.

The data were downloaded to a computer workstation (Apple Mac Pro, 2020) and the data formatting was aligned using data processing script (Perl 5). At each geographic level (national, state and county), each pair of geographic entities' reported cases each day were evaluated for correlation using the method of linear least squares to identify patterns of correlation in the cases independent of scale. This yielded, at each level, a matrix of correlation coefficients where the value in the $i$th row of the $j$th column corresponded to the correlation coefficient between the $i$th and $j$th region (nation, state and county), with the main diagonal 1.0 indicating the perfect correlation between a region and itself (see Appendix).

To evaluate interregional correlations, each region was scored for its percentile ranks of correlation coefficients. For the national data, the 85th percentile correlation coefficient represented the 85th highest of the 100 international correlations, for US states the 65th percentile correlation was the average of the 32nd and 33rd highest interstate correlations, and for (e.g.) North Carolina, the 15th percentile correlation among the counties was the 15th highest intercounty correlation among that state's 100 counties.

The patterns of correlations emerged as indicators of the nature of an outbreak, with two specific metrics identified: (i) the nature of the curvature of the line linking across the percentile scores, ranging from concave (low correlations broadly across comparators but increasing correlations at the higher percentiles, rising sharply at the 95th and 99th percentile); and (ii) the area under this curve, indicating how effectively a selected region (nation, state and county) is linked to its entire containing unit (world, country and state). For example, if every county's reported cases in a state were perfectly correlated with every other county, this would produce a *convex* relationship with the area under the curve equal to 1.0. If a county had a completely isolated outbreak—for example, cases spreading across a prison—this would result in a completely *concave* curve (correlation would be zero everywhere except for a 100% correlation between the county and itself) and the area under the curve would be zero.

Correlations were found to change over time. In order to address these changes, the course of the virus was divided at 1 August 2020, with the period from 23 January 2020 (the first day of public reporting of cases) through 31 July (spring) as the initial period and 1 August through 26 December describing the second period (fall). At each level, relationships were evaluated for the overall time period and separately for the spring and fall outbreaks.
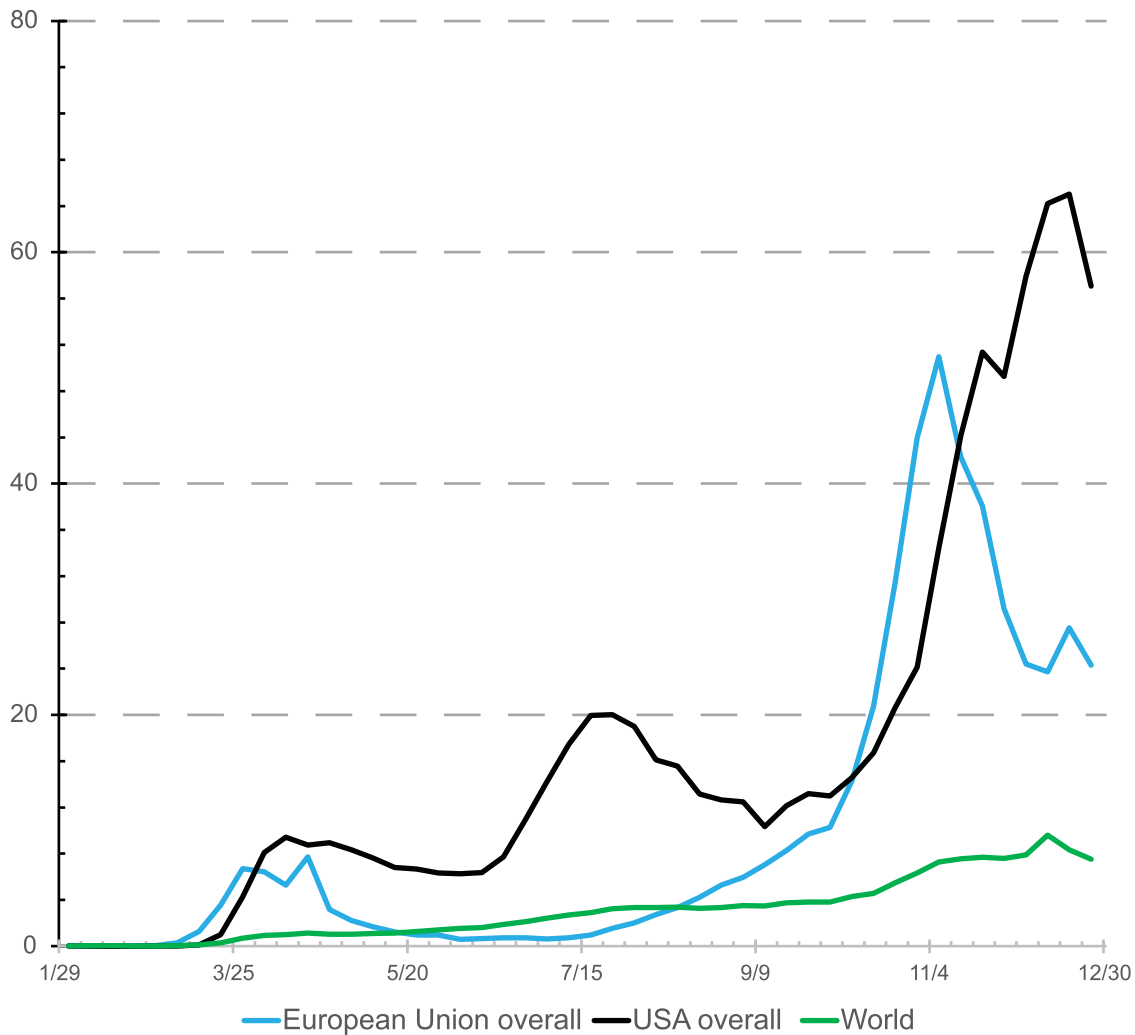
**Figure 1** COVID-19 cases per 100 000 population in the USA and the European Union.

## Results

The patterns of reported infections are characterized by a frightening outbreak in the spring followed by a larger and broader outbreak in the fall (Figure 1). While history of new cases nationally shows spring, summer and winter peaks, an evaluation at the state level shows that this manifested as early metropolitan outbreaks in March and April, subsequent broader outbreaks occurring in different regions in June and July, and a late fall outbreak that crossed the nation from October through January. Either a spring or summer peak occurred depending on the region, while only in a few cases (e.g. Louisiana) did a region experience more than one significant outbreak before the fall. Regionally a two-peak pattern was typical, with the separation between the April case declines and June case growth representing a period of effective national mitigation.

The USA has been the case leader throughout the majority of the pandemic; however, its case rates have not been widely disparate from other nations. This is not because of cross-border cases—the closest correlating nations span the world and are characterized by a failure to control virus transmission before the summer. The US experience of a three-peak distribution is unparalleled internationally.

Within the USA, the spring period exhibited two different patterns: the metropolitan outbreak, where the disease spread along lines of contact in high travel, high contact regions (e.g. New York), and the regional diffuse outbreak pattern, where cases were well correlated regionally. In the state correlation graphs (Figure 2A), Florida and Louisiana both represent the latter pattern: outbreaks correlated across state lines. At the county level (Figure 2B), the data link back to the state graph in the case of New York City, where the metropolitan outbreak reached suburban regions of New Jersey and Connecticut and linked metro regions as far away as Chicago, but counties in New York's upstate region were unaffected. Similarly, Palm Beach county parallels the Florida curve, showing broad correlations across the region. However, the county graph shows the split between an urban-type outbreak in Orleans Parish in the spring that contrasts with Louisiana's overall regional-type outbreak at the state level.

Note that the fall shows significant changes, as New York state's correlations move from a metropolitan outbreak in the spring to a regional one in the fall and Orleans Parish and New York City both align with their state at the county level. Using these archetypes, the entire US outbreak can be described with high accuracy (Figure 3).
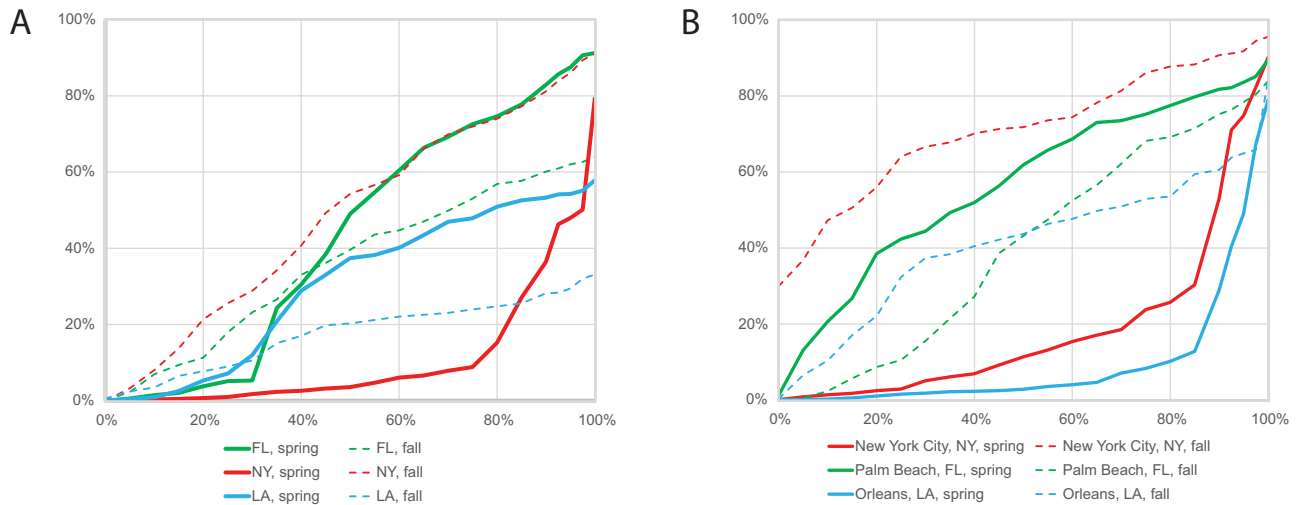
**Figure 2** State groupings of three distinct COVID-19 behavior patterns.
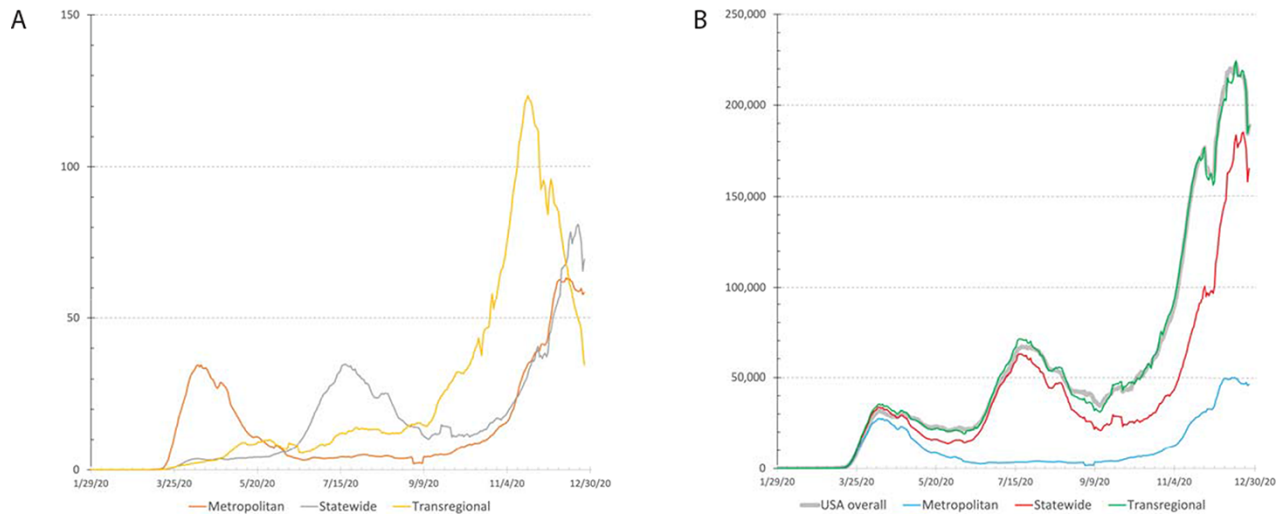


**Figure 3** Correlations among geographic phenotypes.

The outbreak patterns of New York, New Jersey, Pennsylvania and Massachusetts describe the shape of the early US outbreak through the metropolitan pattern. The experience of Texas, California, Florida and Nevada represents state-wide regional outbreaks and their patterns model the July peak. The national-style trans-regional outbreak characterized by the pattern of cases in Wisconsin, South Dakota and Minnesota representing the Midwest-led fall outbreak covers the case growth in September and October, and then, the other states experience growth as well in November and December. A linear combination of these three models correlates with the overall US cases with $R^2 = 0.999$.

## Discussion

In this section, we summarize our findings, describe strengths and limitations of our research, discuss implications for the future and offer concluding remarks.

## Statement of principal findings

Our results suggest that COVID activity in the USA follows a unique trend compared to other countries and that within the USA, and during the first year of the pandemic, three initial COVID phenotypes emerged: (i) the 'metropolitan outbreak' (early outbreak phenotype); (ii) the 'regional outbreak' (summer 2020 peak phenotype) and (iii) 'trans-regional outbreak' (fall/winter 2020 peak phenotype), which, taken in sum, represent the overall US national trend precisely. Each phenotype has specific behavioral characteristics; this suggests the use of targeted public health approaches specific to each phenotype. Finally, over time, we observed that the three phenotypes begin to converge toward a singular steady-state pattern of endemic spread.

Early cases in the USA appeared in regions of high contact rates and high travel, typically large cities, and diffused into regions of lower contact rates and lower travel. This regional divide also largely represented the divide in a highly partisan political climate. The 'three-peak' dynamic in the USA represents the failure of early

**Box 1** COVID phenotypes

| COVID Activity Phenotype | Geographic Examples | Behavioral Characteristics | Correlation Trajectory Features | Public Health Policy Considerations |
|---|---|---|---|---|
| Metropolitan outbreak | NY, NJ, PA, MA | *Event-driven:* Early outbreaks with hidden spread constrained to high population density city areas with high contact rates. | Concave shape with initial steep peak, low area under the curve (AUC). | Early mitigation efforts targeting metropolitan epicenters. |
| Regional outbreak | TX, CA, FL, NV | *Event driven:* Summer peak outbreaks without specific city epicenters, regional spread constrained within state borders. | Flat line shape, high AUC. | Enhanced public health interventions and enforcement at state level. |
| Trans-regional outbreak | WI, ND, SD | *Event-driven:* Fall and early winter peak outbreaks in midwestern states including rural outbreaks crossing state borders due to failure of borders and travel limitations and failure of national prevention messaging. | Convex shape flattens to the right demonstrating correlated regions. | Coordinated and aligned public health efforts at regional level crossing state lines. |
| Steady state endemic expansion | National | *Stochastic:* Winter expansion. Endemic disease spreading shifts from event-driven to stochastic pattern of spread. | Broad non-causal correlations, previous event-driven phenotypes begin to regress to an overall national mean. | Vaccination, prevention efforts at national level. |

mitigation, as regions hit during the first wave of infection largely complied with public health guidance after early lockdowns were lifted and regions minimally impacted in the first wave did not. The net effect of this is that through 2020, no region truly experienced a three-peak outbreak, the first two national peaks were regionally isolated.

The patterns we observed represent the early evolution of the COVID pandemic viewed through a different lens than that provided by standard epidemiological monitoring approaches. The early metropolitan outbreaks demonstrated unmitigated transmission. The later state-wide (regional) outbreaks represented the coordinated lifting of state-wide restrictions, resulting in renewed transmission state wide. The fall national outbreak may be related to a decline in national prevention messaging, with the virus ultimately reaching lower contact rate areas and lower travel states never truly impacted by the pandemic previously. This demonstrated a pattern of trans-regional expansion, followed by exponential growth.

This 'phenotyping' approach may have practical applications for targeting appropriate public health mitigation strategies. In 'metropolitan outbreak' states (see Box 1), such as New York, New Jersey and Massachusetts, early and intensive local efforts targeting outbreak epicenters might be preferable to state-wide mitigation efforts. In 'trans-regional outbreak' states, such as Wisconsin, North Dakota and South Dakota, coordinated public health efforts crossing state borders might be preferable to state-level approaches. Conversely, in 'regional outbreak' states, such as Texas, California and Florida, state-level approaches might be most effective.

### Strengths and limitations

Although we attempted to use the most accurate, up to date, longitudinal, publicly available international, national and regional data on COVID-19 incidence and mortality and to apply appropriate analysis methods and statistical techniques, this research has several notable limitations. First, the accuracy and the timeliness of COVID-19 case rates and case fatality rates are not always valid or reliable. Our explanations of COVID-19 trends and correlations are limited by the accuracy of the underlying data. Second, we have elected to focus our data analysis attention on a narrow slice—COVID-19 cases and mortality—of the pandemic's rapidly evolving legacy that can be partially illuminated with a wider array of qualitative and quantitative data. Third, although our modeling results do align well with overall national trends modeled by others, our efforts to make sense out of the first phase of the pandemic using explanatory analytic methods does not guarantee the accuracy of predictions about future outcomes based on past performance data.

### Implications for policy, practice and research

Our results have implications for the future with respect to several critical topics that are addressed next. We believe that thoughtful adoption of coproduction principles and methods advanced by Elinor Ostrom (10) and others—by local, regional and national leaders—has the potential to improve pandemic mitigation strategies that aim to protect both human lives while minimizing the deleterious effects on people's livelihoods and on social well-being [13]. In particular, the ability to identify behavioral phenotypes of COVID activity and link these to specific geographic regions may make it possible to more effectively and efficiently target appropriate public health interventions to specific areas, a 'hot spotters' concept [14] that has been described previously for applications in cost control, in studying variation in healthcare utilization [15] and using data-informed learning health system approaches to improve healthcare outcomes [16].

*Principles and methods*

First, we need principles and methods to guide intelligent, effective, context-specific coproduction of policies, plans and actions to successfully minimize the negative impacts of the pandemic. We offer a few core principles to encourage a 'good start' at leveraging coproduction to effectively address the pandemic.

1. Complex adaptive systems (CASs): The course of COVID-19 in any region appears to be determined by the interplay of multiple factors including the disease agent, the hosts' characteristics and behaviors, the physical and social environment, both therapeutic treatments and non-therapeutic treatments to prevent and treat COVID-19, as well as chance events. This suggests multiple CASs of disease causation, spread and mitigation [17]. Our analysis suggests that especially in the initial outbreak phases of the pandemic three distinct CASs may have existed, each with its own specific behavioral phenotype, and each with different potential mitigation strategies.

2. Coproduction of plans and actions: This complex, adaptive system that drives the spread and management of the pandemic, calls for education, communication and cooperative actions among diverse groups for the purpose of coproducing sound mitigation plans and actions that are both tailored to a specific geographic area—with its local customs, attitudes, beliefs and social patterns—as well as informed by scientific knowledge [18, 19]. Geographic targeting has been used in many public health and health policy applications, perhaps most notably in work on geographic variation and the work of the Dartmouth Atlas [20–22]. The identification of distinct COVID behavioral phenotypes illustrated by our findings suggests that 'geo-phenotypic targeting' of pandemic activity may be possible and that this information could better enable intelligent coproduction of effective public health action. The approach and type of public health interventions undertaken could be matched to phenotype—in some cases beginning in small, targeted tests and then scaled, and others requiring a more immediate larger scale response. These 'phenotype-specific' approaches may present a promising and meaningful area for future development, application and study.

3. Science-informed policies and actions: Effective policies and plans that aim to mitigate negative effects of the pandemic on health, economic and social well-being should be guided by relevant science including biomedical sciences (e.g. epidemiology, virology and pulmonology), social sciences (e.g. sociology, psychology and anthropology) and healthcare delivery science (e.g. program design, improvement and implementation, change management, dissemination of innovations, program evaluation including outcomes and value measurement) [13, 23]. Our results suggest that applicable scientific perspectives will also need to be aligned with, and targeted to, the specific phenotypic context of the region and populations of interest, a principle commonly employed in modern systems improvement approaches as present in coproduction theory [13, 24].

4. Data and information: We will need data and information to track the overall lived experience of the pandemic, including disease burden and societal hardship. To do this, we must simultaneously study multiple trends including health outcomes, economic indicators and social hardship metrics. This trend data will be needed to inform data-based decisions tailored to local conditions that are ideally coproduced among different stakeholders such as public health and medical experts, regional leaders (representing political, economic, educational and social welfare interests) and regular citizens (with diverse backgrounds)

to track the impact of these policies, plans and actions on future outcomes associated with COVID-19 [24, 25]. Effective data analytic and visualization techniques, coupled with such an approach, could provide timely and effective descriptive information to public health leaders seeking to take intelligent action. Big Data methods enabling predictive analytics techniques could also be developed and applied.

5. Regional learning systems: Healthcare systems, supported by distributed data systems, must be designed and developed to be agile 'learning systems' that reflect the insights and interests of multiple stakeholders in a region and to take into account and balance competing interests in dealing with the pandemic. These regional learning systems might seek to deploy strategies, policies and actions that can work in a specific geographic area to protect population health, to promote economic vitality and to minimize social hardship [26]. Learning health systems also have the potential to demonstrate the benefit of employing coproduced services aimed at achieving these ends using different service structures and approaches [27].

## Conclusion

We believe that it is prudent and helpful to look back at the first phase of the COVID-19 pandemic to analyze phenotypic trends and to identify activity patterns that can inform future attempts to decrease the harm and hardship caused by the current and future epidemics. We suggest that in the future, we should create databases that capture key data elements at the smallest geographic level possible and use these data elements to track trends, to predict the future and to apply targeted coproduction principles and methods to more effectively and efficiently safeguard population health, economic vitality and social well-being. A better understanding of transmission dynamics may be valuable in informing approaches to the coproduction of transmission mitigation. New approaches should include a better understanding of populations at risk, specific strategies targeting outbreak prevention and outbreak mitigation, and more effective communication about the need for and goals of co-production interventions. Analysis of efforts to manage the COVID-19 pandemic across domains suggests the need for a cross-domain vision, linking and coordinating healthcare, public health, and policy approaches based on evidence. Such an approach could optimize health outcomes as well as economic and social well-being.

## Contributorship

The authors' contribution is as follows: P.S. and B.J.O. are responsible for conceptualization, writing/review/editing and data curation/analysis and E.C.N., G.K. and S.K. are responsible for conceptualization, writing/review/editing.

## Ethics and other permissions

None declared.

## Data availability statement

The data are publicly available, and the sources are listed in the paper references. All the analysis techniques are standard algorithms as described.

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