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A Multi-Dimensional Evaluation Model for Epidemic Prevention Policies

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ABSTRACT

In recent years, governments of more than 200 countries and regions have enacted measures to control the spread of COVID-19. A precise and comprehensive evaluation of policy effect provides important grounds for policy-making. Since the whole world has entered the post-epidemic era, prevention policies are inclined to strike a trade-off between controlling confirmed/death cases and the economic rebound. Furthermore, with the increasing vaccination rate, vaccination has become a considerable factor in determining policy stringency. However, the existing approaches are still limited in efficiency due to the following reasons: (1) They are still confined to policies' containment effect on COVID-19, neglecting the impact of vaccination on policy effect and the impact of policies on economy; (2) While evaluating policy effect in different regions, most existing models lack robustness. To address these problems, we propose a multi-dimensional evaluation model for more effective assessment of epidemic prevention policies in post-epidemic era. The proposed model consists of two modules: (1) A multi-dimensional objective-programming module is raised to evaluate the policy effect comprehensively, where vaccination, policy stringency, economy indicators, confirmed cases, and reproductive rate are taken into account; (2) A vaccine-dependent parameter learning (VDPL) module based on Bayesian deep learning (BDL) models a vaccine-dependent parameter which indicates the relationship between vaccination and policy stringency. The module also strengthens the robustness of the proposed model with the help of BDL since BDL can adapt the data of different regions better through resampling the probability distribution of network weights. Finally, We evaluate our model on the data of the US. The results demonstrate that the proposed approach performs better in depicting the spread of COVID-19 under the influence of policy.

KEYWORDS

COVID-19; Bayesian deep learning (BDL); vaccine; optimal policies

COVID-19, a pandemic caused by the SARS-CoV-2 virus, has spread around the globe since 2020[1]. In order to tackle the outbreaks of COVID-19, the governments of almost every countries have adopted many kinds of measures to delay the spread of COVID-19[2]. For the sake of assessing policy effect and making adjustments promptly, a large amount of researches on COVID-19 policy effect evaluation have been conducted.

Early in 2020, COVID-19 policies are evaluated by means of constructing counterfactual, which is the prediction of confirmed cases or reproductive rate of COVID-19 in a given policy and time scenario[3]. Various methods[4, 5] ranging from difference equation to machine learning (ML) are applied to evaluate the effect of COVID-19 policies more accurately. With further researches, more detailed indicators like age, medical facilities, income, and so on are considered to study the relation between these indicators and the effect of policies[2]. In 2021, Center for Disease Control and Prevention (CDC) put forward the concept of vaccine-differentiated policies[6, 7], which means vaccinated people can access greater freedoms due to their vaccination status, and are subject to less stringent restrictions.

Though previous works have achieved initial success, there still exists some deficiencies. Firstly, the existing works fail to consider the impact of vaccination on policy effect and the impact of policies on economy. While entering the post-epidemic era, controlling the confirmed cases only seems to be short-sighted. More attention is supposed to be paid to the recovery of economy. The more people get vaccinated, the fewer people will be infected and the more labor force available. Hence, new factors like vaccination and adjustment of policies are required imminently. Secondly, the existing models have disadvantages of being subjective and in short of robustness. For example, the age-dependent parameter in the age-structured model[8] is determined on the basis of real statistics artificially rather than being inducted by algorithms. Most of the works[4–8] only discuss case study at the level of the whole country or just in a fixed region, which lacks in enough robustness while evaluating in different states.

To solve the challenges above, a multi-dimensional evaluation model is proposed in this article for more efficient assessment of epidemic policy effect. The whole model consists of a vaccine-dependent parameter learning (VDPL) module and an objective-programming module. Considering that the spread of COVID-19 is a complicated process, the VDPL module is designed based on the architecture of Bayesian deep learning (BDL) to learn a vaccine-dependent parameter in a more robust way. In the proposed BDL architecture, policy stringency is imported as the prior probability, and Monte Carlo (MC) dropout method is used to determine the relationship between vaccination and policy stringency. In addition, an objective-programming module is applied to give a more comprehensive evaluation of policy effect.

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The objective function is to minimize the confirmed cases, and the constraints are composed of economic indicators, policy stringency, vaccination, etc. The confirmed cases, reproductive rate, and policy stringency are linked with a velocity formula[9]. Hence, the optimized policies in post-epidemic era can be described quantitatively.

Through extensive experiments, the proposed model has successfully evaluated the policy effect. Furthermore, the common characters and particularity of each policy in each state are discussed in detail, which provides significant supplementary for policy-making in post-epidemic era. The main contributions of this paper are as follows:

(1) We take the impact of vaccine-differentiation into consideration in epidemic prevention policy effect evaluation for the first time, and a vaccine-dependent parameter is correspondingly designed to describe the impact, which optimizes the existing method of policy effect evaluation.

(2) We model the uncertainty of epidemic data through Bayesian deep learning and a variational$_{\text{estimator}}$ module is designed while coding, which improves the robustness of the proposed model.

(3) Economic indicators are considered as constraints of the objective-programming part of our model, which make the criteria of policy effect evaluation more comprehensive and reasonable in the post-epidemic era.

The rest of the paper is as follows. The related literature and current works about the topic are discussed in Section 1. Section 2 describes the whole model and introduces the principles in detail. In Section 3, the experimental results are displayed and detailed analyses are also performed. Finally, Section 4 concludes the whole passage and gives some inspirations for further researches.

1 Related Work

The topic of COVID-19 policies evaluation has harvested immense interest and spawned various literature. The methods and focus of current studies varied as research progresses.

Specifically, the approaches of studying COVID-19 policies' effect can be divided into 3 groups, that is traditional method, ML-based method, and other methods.

1.1 Traditional method

Traditional method includes difference equation[10], markov process, statistical inference, etc. These models have the advantage of: (1) The architecture is easy to understand and operate. (2) No demanding requirements for hardware like CPU or GPU. Vokó and Pitter[11] applied the method of interrupted time series analysis to discuss the effect of social distance measures on COVID-19 epidemics in Europe. Berry et al.[12] proposed a difference-in difference (DID) model to assess the effects of shelter-in-place policies. Bonacini et al.[3] used panel data model to fitting the trend of the spread of COVID-19 and analyzed the effect of lockdown measures in Italy. However, since there are fewer parameters used to describe the spread of COVID-19, the counterfactual predicted by traditional method was not accurate enough to give governments any effective guidelines. And therefore, ML-based method plays a more and more significant role in later work.

1.2 ML-based method

ML-based method applies neural networks (NN) like artificial neural network (ANN)[13], gate recurrent unit (GRU), long-short-time-memory (LSTM), etc. to predict the confirmed cases at given policies. Ghamizi et al.[14] combined susceptible-infected-recovered (SIR) model with Deep Neural Network (DNN), and epidemiological model's parameters were learnt by DNN. Genetic algorithm was also applied to search for optimal exit strategies. Arora et al.[15] compared 3 types of LSTM's variants, that is deep LSTM (DLSTM), cached LSTM (CLSTM), and bidirectional LSTM (BiLSTM) to predict the positive cases in India. Luo et al.[16] combined LSTM with XGBoost algorithm to determine the optimal non-pharmacological interventions. Tayarani-Najaran[17] integrated 9 kinds of ML-based models including K-nearest neighbor (KNN), probabilistic neural networks (PNN), feedforward neural networks (FNN), etc. to search for the optimal epidemic prevention policies.

Recent studies focus on producing more precise results. In the early stage of research, what experts discussed was the types of polices, the duration, the starting time, etc. Sun et al.[18] quantified the effect of public activity intervention policies in 145 countries and found that earlier implementation and longer duration were able to reduce the infections of COVID-19. Subsequently, detailed indicators like policy stringency, age, vaccine, etc. were taken into account. Grundel et al.[19] and Canabarro et al.[20] determined age-dependent social-distancing policies with the assistance of a model predictive control framework. Chen et al.[21] discussed the vaccine allocation problem based on the structural properties of individuals' underlying social contact network. Li et al.[22] investigated how policy stringency affect the spread of COVID-19 pandemic and provided cases study on the US, the UK, Italy, and Turkey.

1.3 BDL-based method

Considering the spread of COVID-19 is a complicated process, which is a result of collective effect of virus, prevention policies, economy, etc. BDL has been demonstrated to perform well in estimating the uncertainties in the spread of COVID-19. BDL was a principled probabilistic framework that integrate deep learning with probabilistic graphical models (PGM), which had two seamlessly integrated components: a perception component for understanding the task's component (e.g., text, image, etc.) and a task-specific component for describing the probabilistic relationship among different variables[23, 24]. Normally, deep learning was adept at perception tasks while PGM specialized in probabilistic reasoning tasks. BDL took the advantage of the two models, and therefore, it works effectively in assessing uncertainty of a complicated tasks and avoiding over-fitting. This method has been applied in the researches of COVID-19 prediction. Cabras[25] applied BDL in estimating COVID-19 evolution in Spain, and a comparison between LSTM and BDL was also discussed in this paper.

Our approach combines the characteristics and superiority of BDL and objective-programming, which leads to a multi-view evaluation of COVID-19 policies and proposes the optimal one in vaccine-differentiated scenario.

2 Method

The architecture of our model is shown in Fig. 1, which is composed of 2 main modules. The COVID-19 confirmed cases data, vaccine-differentiated data, and policy stringency data are adopted as the input of our model. A VDPL module applies BDL architecture to determine the parameter, which will be used in the next module. Following this, an objective-programming module sets the objective function as minimizing confirmed cases. Some hard constraints like Gross Domestic Product (GDP), unemployment rate, etc. are taken into consideration to give a

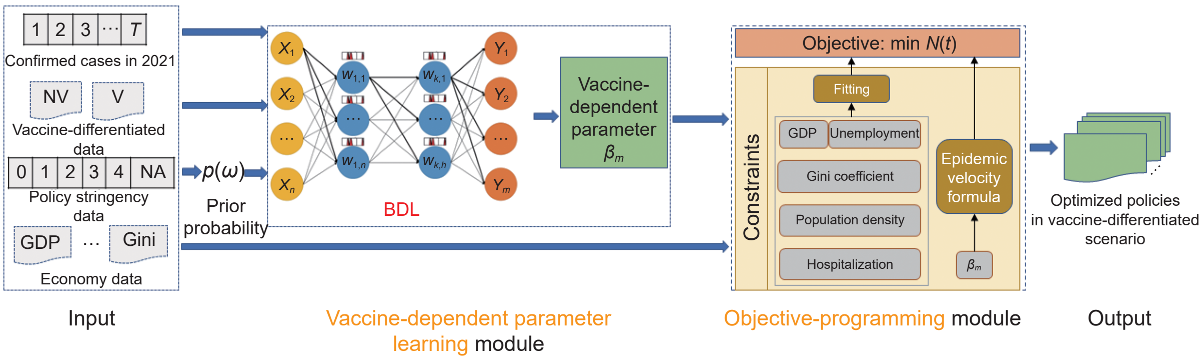


Fig. 1 Achitecture of our model. NV is short for non-vaccinated, V is short for vaccinated, and NA is short for not available.

more comprehensive evaluation of policy effect and suggestions on policy-making. And epidemic velocity formula is used to bridge the parameter and confirmed cases. In this section, we firstly introduce the basis theories of BDL and the VDPL module in Section 2.1. Furthermore, a complete description of the objective-programming part is shown in Section 2.2.

2.1 VDPL module

According to existing researches[20], policy stringency can be affected by many factors like vaccination, environment, population, etc. The relationship between vaccination and policy stringency can be interfered by other uncertainties. Moreover, the vaccine-differentiated data have the characteristic of sparsity and volatility since the vaccination policy is changing in different regions all the time. Therefore, a VDPL module based on BDL is applied to learning the vaccine-dependent parameter.

2.1.1 Basic framework of BDL

Before introducing the framework of BDL, let us have a brief retrospect of the Bayes' formula in probability theory[23].

$$p(z|x) = \frac{p(x,z)}{p(x)} = \frac{p(x|z)p(z)}{p(x)} \tag{1}$$

where $p(z|x)$ is referred to as the posterior, $p(x,z)$ is the joint probability, $p(x|z)$ is the likelihood probability, $p(z)$ is the prior probability, and $p(x)$ is called evidence. Considering total probability formula, that is:

$$p(x) = \int p(x|z)p(z)\mathrm{d}z \tag{2}$$

Equation (1) can be represented in the following form:

$$p(z|x) = \frac{p(x|z)p(z)}{\int p(x|z)p(z)\mathrm{d}z} \tag{3}$$

Based on Bayes' formula and relative theories, PGM especially directed PGM is proposed and applied to describe random variables and relationships among them[24]. A brief example of PGM for BDL is shown in Fig. 2, where the red part on the left is

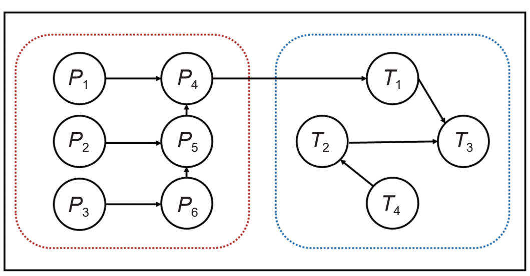


Fig. 2 Brief example of PGM for BDL.

the perception component and the blue part on the right indicates the task-specific component.

The variables in the red rectangle in Fig. 2 is named as perception variable Ω_{p}, the blue ones are task-specific variables Ω_{t}, and another type of variable is hinge variable Ω_{h} which associates perception component with task-specific component. In our BDL architecture, perception variables are composed of the weights and neurons in the probabilistic formulation of the deep learning network, which means all quantities (e.g., weights, neurons, bias, etc.) are displayed as probability distributions rather than point estimates in BDL, just like the network architecture in BDL module shown in Fig. 1.

Getting back to the Bayes' formula, prior probability distributions have close associations with model parameters and are applied to describe their relationships to the data. With the aid of probability theory, uncertainties in these data can be inferred. By transforming the prior probability distributions (determined before training) into posterior distributions (defined after observing data), features and parameters of the observed data (e.g., confirmed cases) can be learnt.

2.1.2 Method of training BDL

In Section 2.1.1, we have an understanding that BDL can be applied by sampling the distribution of weight and bias, which contributes to making the results more robust. However, a critical problem is how to train the network in BDL.

The key issue of solving this problem is uncertainty (e.g., aleatory uncertainty, epistemic uncertainty, and ontological uncertainty) estimation. Some variables need to be defined. We denote by W the weight and bias of our network, by $X = x_1, x_2, \ldots, x_n, n \in \mathbb{Z}$ the input of network (e.g., confirmed cases and vaccine-differentiated data), and by $Y = y_1, y_2, \ldots, y_n, n \in \mathbb{Z}$ the actual data (e.g., policy stringency). Our goal is to minimize the loss between prediction and actual policy stringency values $\ell(y_i, \widehat{y}_i, i \in \mathbb{Z})$. $\widehat{y}_i, i \in \mathbb{Z}$ means the predicted stringency value and $\ell(\cdot)$ is the loss function. And therefore, Eq. (3) can be written as

$$p(W|X,Y) = \frac{p(Y|X,W)p(W)}{\int p(Y|X,W)p(W)\mathrm{d}W} \tag{4}$$

Generally speaking, the prior probability $p(W)$ is initially defined as the distribution of the policy stringency in our model, and the likelihood probability $p(Y|X,W)$ is a function of W. Assuming that X and Y are given, the posterior probability distribution of weight $p(W|X,Y)$ can be determined easily. However, our goal is to calculate the probability distribution of W, which means the denominator of Eq. (4) need to be solved. It is a barrier that $p(Y|X)$ can not be solved analytically and some approximation techniques are required like: (1) Approximating the integral with Markov chain Monte Carlo (MCMC); (2) Using black-box variational inference; and (3) Using MC dropout sampling. Because the COVID-19 data and policy data are so large that make our network complex, and dropout is superior to preventing over-fitting. In our experiments, we adapt a BLiTZ module to build the BDL network.

When we assume that $P(\omega)$ is set as probability density function (pdf). As the prior distribution of weights, $Q(\omega|\theta)$ is the posterior empirical distribution pdf of sampling weights. By combining the derivation with Kullback–Leibler divergence, that is:

$$D_{\mathrm{KL}}\ (p(z|x)\ ||q(z|x)) = \sum p(z|x)\ \log(p(z|x))/(q(z|x)\ ) \tag{5}$$

We can find that for each sample, complexity cost can be expressed as

$$C_n(\omega(n),\theta) = \log Q(\omega(n),\theta) - \log P(\omega(n)) \tag{6}$$

Finally, the loss function of the NTH weight sample is

$$L_n(\omega(n),\theta) = C_n(\omega(n),\theta) - P_n(\omega(n),\theta) \tag{7}$$

By doing so, we ensure that while optimizing computational complexity, the differences between our model and its predictions will be reduced. Therefore, the variational$_{\text{estimator}}$ module is built into the BLiTZ framework to do this. Bayesian neural networks are typically optimized by sampling losses from the same batch several times before, which is to compensate for the randomness of the weights while avoiding optimizing them on losses affected by outliers. Given the input, output, criterion, and sample$_{\text{nbr}}$, BLiTZ calculates the sample$_{\text{nbr}}$ loss and its mean during the iteration, and finally returns the sum of the complexity loss and fitting loss.

In this way, the weight and bias of the network are sampled in a more accurate way, and therefore the uncertainty of network and prediction of output can be estimated more robustly.

2.2 Objective-programming module

In order to provide policymakers with more useful and proper suggestions on policy making, an objective-programming module is formulated. Thus we can explore the optimized measures that satisfy our requirement of both controlling confirmed cases and economy recovery. Before we present the specific formula, some parameters that are selected as constraints are introduced.

The criterion we opt for these constraint parameters is that they should have direct or obvious relationship with not only the spread of COVID-19 but also the economy. Population density, hospitalization, unemployment rate, Gini coefficients, and GDP are selected.

2.2.1 Population density

According to the report published by CDC[26], COVID-19 transmission occurs when people breathe air contaminated by droplets and small airborne particles containing the virus. Therefore, a positive correlation between infection rate and population density can be confirmed. The more crowded the population is, the higher the chance of infection will be. Moreover, denser population can bring more labor force that will directly contribute to the economic resurgence.

2.2.2 Population density

Hospitalization gives a rough estimation of the capacity of the hospital to receive patients with severe symptoms. if the number of patients with severe symptoms exceeds the limit of hospitalization, it will cause serious problems in society. Hence, keep the number of confirmed cases under control can be estimated by hospitalization. Furthermore, countries or regions with good economic conditions are more likely to conduct more investment on the construction of medical infrastructure like hospital.

2.2.3 Unemployment rate

The definition of unemployment rate is the percentage of people above a specified age (usually 15) not being in paid employment or self-employment but currently available for work during the reference period[27]. Since the outbreak of COVID-19, it has been reported that many infectious people were fired by the company and became unemployed. To some degree, unemployment rate can reflect the development of economy.

2.2.4 Gini coefficient

Gini coefficient is a measure of statistical dispersion intended to represent the income inequality or the consumption inequality within a nation or a social group[28]. Many researches have revealed the inequality problem in medical resources allocation like vaccine, mask, etc. For the sake of providing optimized policies in a fairer way, Gini coefficient is under consideration.

2.2.5 GDP

GDP is the final result of the production activities of all resident units in a country (or region) within a certain period of time[29], which can reflect the condition of economic rebound in the most apparent way. The last 3 years have witnessed a sharp decline in GDP of all countries or regions around the globe. One of the most significant goals of economic recovery is to stimulate the increase of GDP.

Here, we can give a complete description of our objective-programming module:

$$\min N(t) \tag{8}$$

$$\begin{aligned} \text{s.t., } \log\ R(t) &= N(t) + \beta_m \log R(t-1) + \epsilon(t), \\ R(t) &\in (0,1), \\ \beta_m &\in [0,4], (\beta_m \in \mathbb{Z}), \\ W(t) &= \Gamma(N(t), \phi_i), \\ \phi_i &\in [0, \phi_i^{\max}] \end{aligned} \tag{9}$$

where $N(t)$ refers to the number of confirmed cases. Our goal is to minimize the value of $N(t)$, which is also the traditional standard of policy effect evaluation. In order to establish the association with $N(t)$ and β_m learnt by BDL, epidemic velocity formula in Formula (9)[9] is applied. $R(t)$ stands for the reproductive rate of COVID-19, which is a common-used parameter. It is generally believed that the reproductive rate $R(t)$ is the result which historical reproductive rate $R(t-1)$ and new infections $N(t)$ affect together. The effect of policy stringency has a direct impact on historical reproductive rate $R(t-1)$. $\epsilon(t)$ is a perturbation term to depict potential noise. According to researches home and abroad, $R(t)$ is less than 1 when the spread of COVID-19 is well controlled, while $R(t)$ is larger than 1 when COVID-19 tends to spread continuously. For the purpose of controlling COVID-19, the range of $R(t)$ is set between 0 and 1.

The range of β_m is given by the reports published by the Oxford COVID-19 Government Response Tracker (OXCGRT)[7], and the specific definition is shown in Table 1. The larger the number is,

Table 1 Policies and stringency definition.

Policy	Stringency definition				
	Stringency=0	Stringency=1	Stringency=2	Stringency=3	Stringency=4
School closing	No measures	Recommend closing or all schools open with alterations resulting in significant differences compared to non-COVID-19 operations	Require closing (only some levels or categories, e.g., just high school, or just public schools)	Require closing all levels	—
Public event cancel	No measures	Recommend cancelling	Require cancelling	—	—
Stay-at-home requirement	No measures	Recommend not leaving house	Require not leaving house with exceptions for daily exercise, grocery shopping, and "essential" trips	Require not leaving house with minimal exceptions (e.g., allowed to leave once a week, or only one person can leave at a time, etc.)	—
Restriction on gatherings	No measures	Restrictions on very large gatherings (the limit is above 1000 people)	Restrictions on gatherings between 101−1000 people	Restrictions on gatherings between 11−100 people	Restrictions on gatherings of 10 people or less

the stricter the policy implementation will be. The specific relationship between confirmed cases and economic indicators will be fitted in our experiment and $\Gamma(\cdot)$ denotes the mapping function. The value of ϕ_i is also constrained by the real situation. For example, the capacity of a hospital can be calculated by the value of ICU occupancy, and therefore, we can constrain the confirmed cases through the mapping function between confirmed cases and $\phi_{\text{hospitaliztion}}$ to prevent healthcare system from collapsing.

3 Experiment

In this section, we back up our model with concrete examples and a detailed case study in the US is investigated. COVID-19 confirmed cases data from the Center for Systems Science and Engineering (CSSE) in John Hopkins University (JHU), policy-related data form OXCGRT, and economy data form World Bank and World Economy Organization (WEO) are used in our experiment.

In July 2021, OXCGRT upgraded their datasets to track the differentiated policies to the vaccinated and non-vaccinated people[8], which brings us great convenience to study the effect of COVID-19 policies in a vaccine-differentiated scenario. All the data before "2020-12-31" are set as training set and the data ranging from "2021-01-01" to "2021-06-30" are set as testing set. Firstly, four types of policies including school closing, public event cancel, stay-at-home requirements, and restrictions on gatherings are taken into account since they involve education, work, public events, and household that help us to put forward more comprehensive suggestions. Secondly, in order to make our final suggestions more general, fine-grained case studies in eight states (e.g., New York, Massachusetts, California, Kentucky, North Dakota, Wyoming, Florida, and Texas) all over the US are conducted.

3.1 Effectiveness of vaccine-differentiated policies

Figure 3 shows the prediction of confirmed cases after applying vaccine-differentiated policies in eight states in the US in the first two quarters in 2021. Three types of differentiation ratio including 75%, 50%, and 25% are under estimation.

According to the results in Fig. 3, it is obvious that vaccine-differentiated policies are effective in controlling the infection of COVID-19. For instance, the confirmed cases are predicted to decline by at least 0.5% in California, which means at least 0.3 million people can prevent from being infected. Similarly, the confirmed cases will decrease by at least 0.2% in Florida, 0.05% in New York, 0.03% in Kentucky, and so on.

However, vaccine-differentiated policies do not perform well in all the states in the US. We can easily find that the prediction cases are almost overlapped with the real data in Wyoming or even higher than the actual confirmed cases in North Dakota. As far as we are concerned, these situations have close relations with the economic state of the region. It is reported that states with better developments of economy are tend to be equipped with more adequate medical resources like vaccines, which play a vital role in immunity. The inequality of medical resources can be regarded as the major cause of the difference in the effectiveness of same policies.

Moreover, on the basis of our prediction, there is a trend that the higher the vaccine-differentiation rate is, the fewer the confirmed cases are. The cases in Florida, New York, Kentucky, and North Dakota have demonstrated it. However, there are still some exceptions like Texas. After searching for related reports and studies in Texas, we attribute it to the lack of vaccination initiative by Texas' government. It is reported that there is no state or local COVID-19 immunization requirements, and even no government entity in Texas can mandate the COVID-19 vaccine according to Governor Abbott's Executive Order GA-39 in Texas[30].

3.2 Evaluation of different policies

In Section 3.1, we have investigated that vaccine-differentiated policy is effective. Therefore, in this section, we will conduct further discussion about how vaccine-differentiated policy can make contributions to economy resurgence and other factors that may make a difference.

Due to the space constraints, here we take the results of Massachusetts, New York, and North Dakota as examples. Obviously, vaccine-differentiated policies stimulate the recovery of economy. We can conclude some common characters. Firstly, the implementation of vaccine-differentiated policies in public event cancel policy is the most effective way to improve the economy rebound among the four measures. It is because public event has a tight and direct association with economy. Secondly, gathering restrictions policy can hardly make contributions to economic development even though vaccine-differentiated policies are put into effect, which is caused by consumption restrictions. Thirdly, the results in Figs. 4–6 are consistent with the results in Fig. 3. The better the economic state is, the more vaccine resources they have, and the higher vaccination rate they can obtain. Therefore, vaccine-differentiated policies can perform in a more effective way in these states.

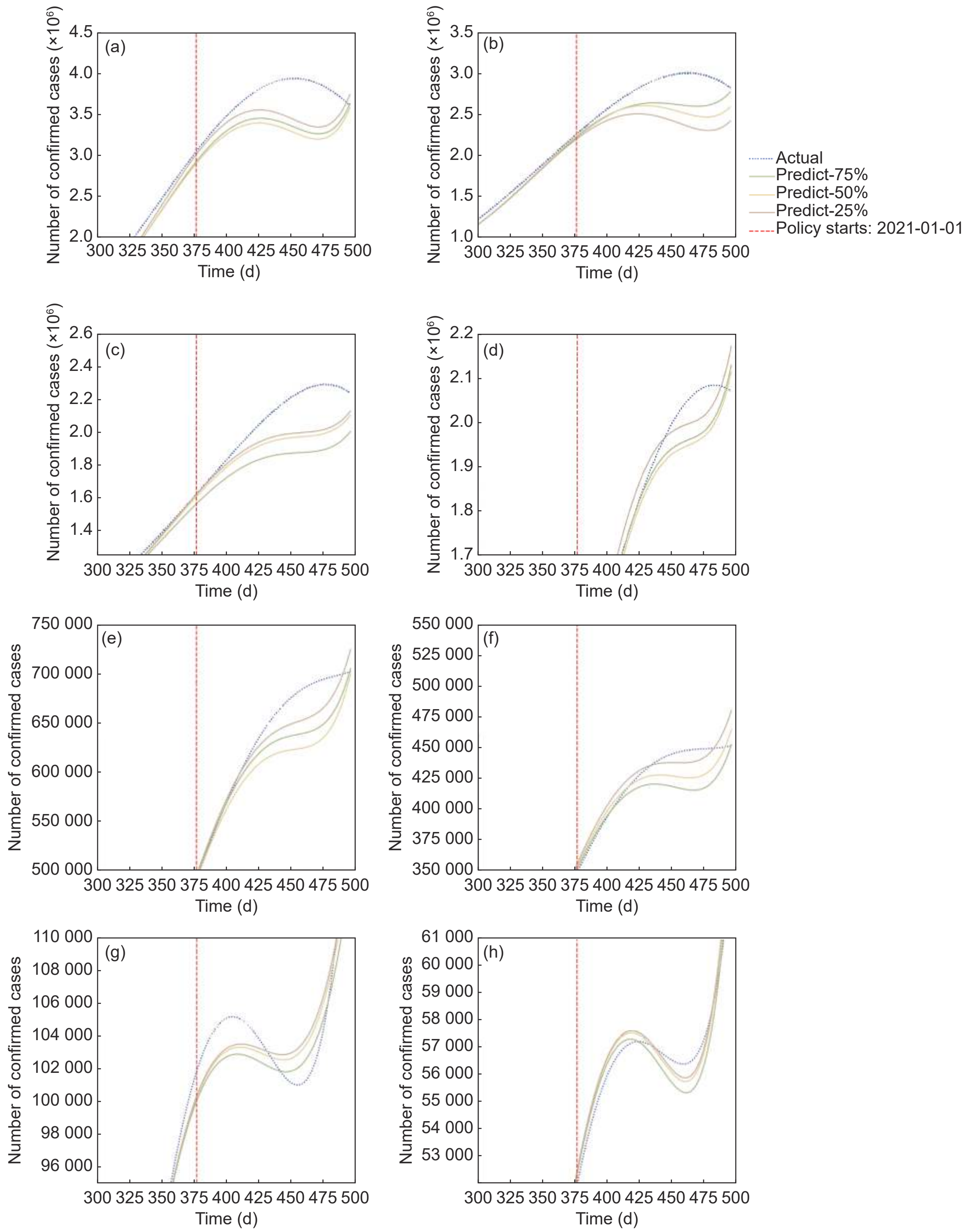
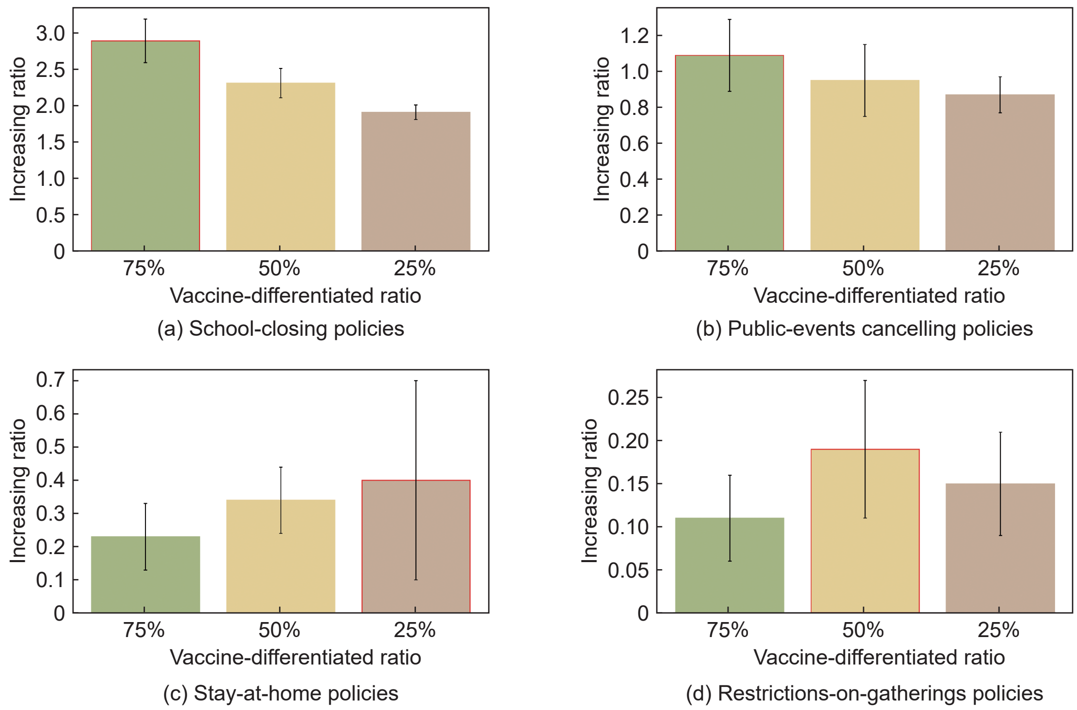


Fig. 3 Confirmed cases prediction after applying vaccine-differentiated policies in (a) California, (b) Texas, (c) Florida, (d) New York, (e) Massachusetts, (f) Kentucky, (g) North Dakota, and (h) Wyoming in the US in the first two quarters in 2021. The vaccine-differentiated condition is 75% vaccination (green), 50% vaccination (yellow), and 25% (brown). The actual confirmed cases are shown in a solid line (blue). Time axis corresponds to the days since the first outbreak of COVID-19.

However, there are still some diversities in different states. Firstly, different types of policies have various contributions to the economy. For instance, implementation of vaccine-differentiated policies in school closing has achieved great success in our prediction. That is because there are plenty of universities and colleges in Massachusetts like Harvard University and Massachusetts' Institution of Technology, and there are many students and scholars from all over the world. Vaccine-differentiated policies in school closing means travel restrictions on students could be relaxed and the economy will be resuscitated gradually. Unlike Massachusetts, public event cancel policy outstands in New York since New York is a cosmopolitan city, and



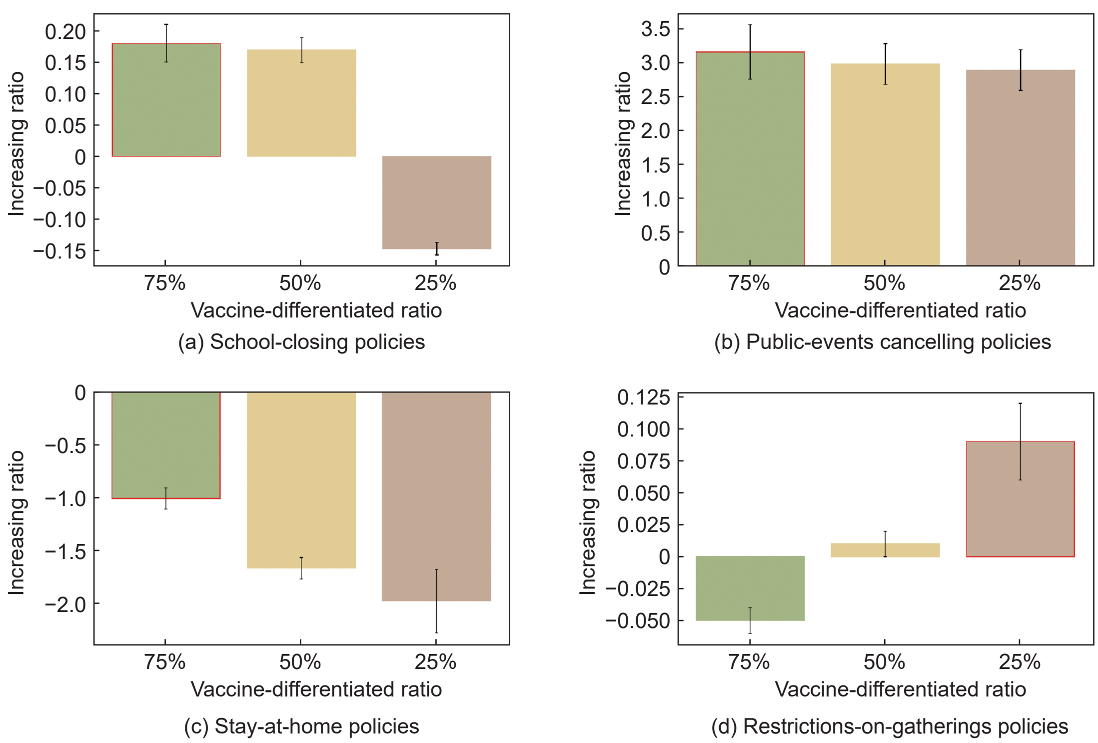
(a) School-closing policies

(b) Public-events cancelling policies

(c) Stay-at-home policies

(d) Restrictions-on-gatherings policies

Fig. 4 Predictive increasing ratio of GDP in Massachusetts after applying different vaccine-differentiated policies.



(a) School-closing policies

(b) Public-events cancelling policies

(c) Stay-at-home policies

(d) Restrictions-on-gatherings policies

Fig. 5 Predictive increasing ratio of GDP in New York after applying different vaccine-differentiated policies.

business issues are active there. Secondly, vaccine-differentiated policies does not perform well in North Dakota in comparison with that in New York and Massachusetts, which owes it to the economic underdevelopment in North Dakota, and it is similar to the circumstances in Texas.

According to the concept of vaccine-differentiated, different vaccination rate correspond to various policy stringency. Generally speaking, the higher the vaccination rate is, the lower the policy stringency will be. For instance, vaccination rate of 75% corresponds to policy stringency of 0 or 1, and vaccination rate of 25% or even lower corresponds to policy stringency of 3 or 4. We highlight the most effective policy stringency in Fig. 7 with red edge. On the whole, more accommodative policies are recommended in the post-epidemic era. Moreover, we appeal to allocate more medical resources like vaccine, mask, etc. to economically underdeveloped areas. It will improve the overall effect of policy.

3.3 Robustness of model

In previous work, case studies are almost conducted at the level of

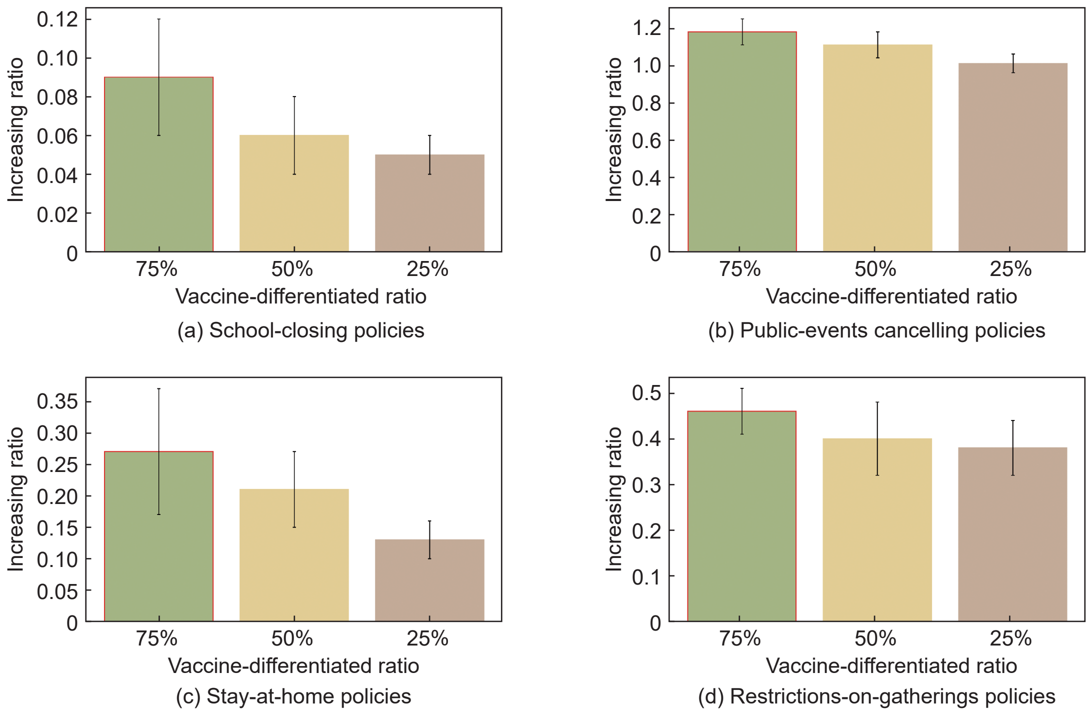


Fig. 6 Predictive increasing ratio of GDP in North Dakota after applying different vaccine-differentiated policies.

a country or just in a fixed area. Thus the models are more likely to perform well in a fixed region only. The robustness of model can not be guaranteed in researches of other regions. In order to demonstrate that our model has improved the robustness of results in comparison with existing work, we draw a boxplot of the mean absolute percentage error (MAPE) value of our experiments in eight states. A comparison with the robustness of LSTM model is also shown in Fig. 7. Generally speaking, the more centralized the data, the higher the robustness of the model. According to Fig. 7, we can conclude that the MAPE data of Florida, New York, California, and Wyoming are centralized, the difference among data is less than 0.1. Moreover, except Kentucky, the difference among data is less than 0.2 in the rest of the three states. Compared with the results of LSTM model, the MAPE value are more likely to be centralized in all 8 states. And the MAPE value in our model are much smaller than that of LSTM. Therefore, we can conclude that our model performs well in the accuracy and robustness of results.

3.4 Performance comparison

In existing works of policy effect evaluation, most of the results are compared with real observed data. Generally speaking, as long as the prediction results are lower than the real data, the model can be regarded as effective. However, if the prediction performance of the model is not accurate, it can hardly give the proper suggestions on policy-making. Hence, there is a lack of comparing the predictive performance of different policy effect evaluation model. According to the related work, various models ranging from traditional method of difference and fitting to ML-based approaches are applied in policy effect evaluation. The core idea of this subject is to construct counterfactual based on prediction model. Therefore, to make our results more convincing, we compared our model with some classic prediction model like ANN, LSTM, and LSTM+Transformer. The confirmed cases data from JHU ranging from "2020-01-22" to "2021-12-31" are regarded as the input of all the models. The data before "2021-11-30" are set as training data while the rest are set as test data to be predicted. The evaluation metrics we used for performance comparison are MAPE and R^2, which can be defined as

$$\text{MAPE}=\frac{1}{N}\sum_{t=1}^{N}\left|\frac{F^t-A^t}{A^t}\right| \tag{10}$$

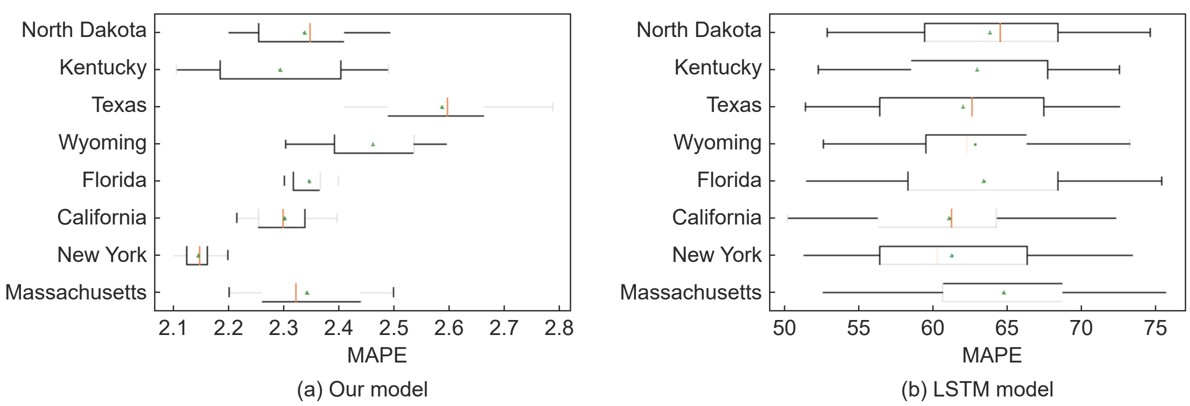


Fig. 7 MAPE value of our model and LSTM model in eight states in the US.

$$R^2 = 1 - \frac{R_{ss}}{T_{ss}} \tag{11}$$

where R_{ss} is the sum of squares of residuals and T_{ss} is the total sum of squares. F^t and A^t are the predicted results and actual data of confirmed cases, respectively. The performance index of each model is shown in Fig. 8 and Table 2.

According to Table 2, our model have the best performance followed by LSTM, LSTM+Transformer, and ANN, which can demonstrate that all the results discussed in our paper above are reliable and can provide proper and dependable guidance for

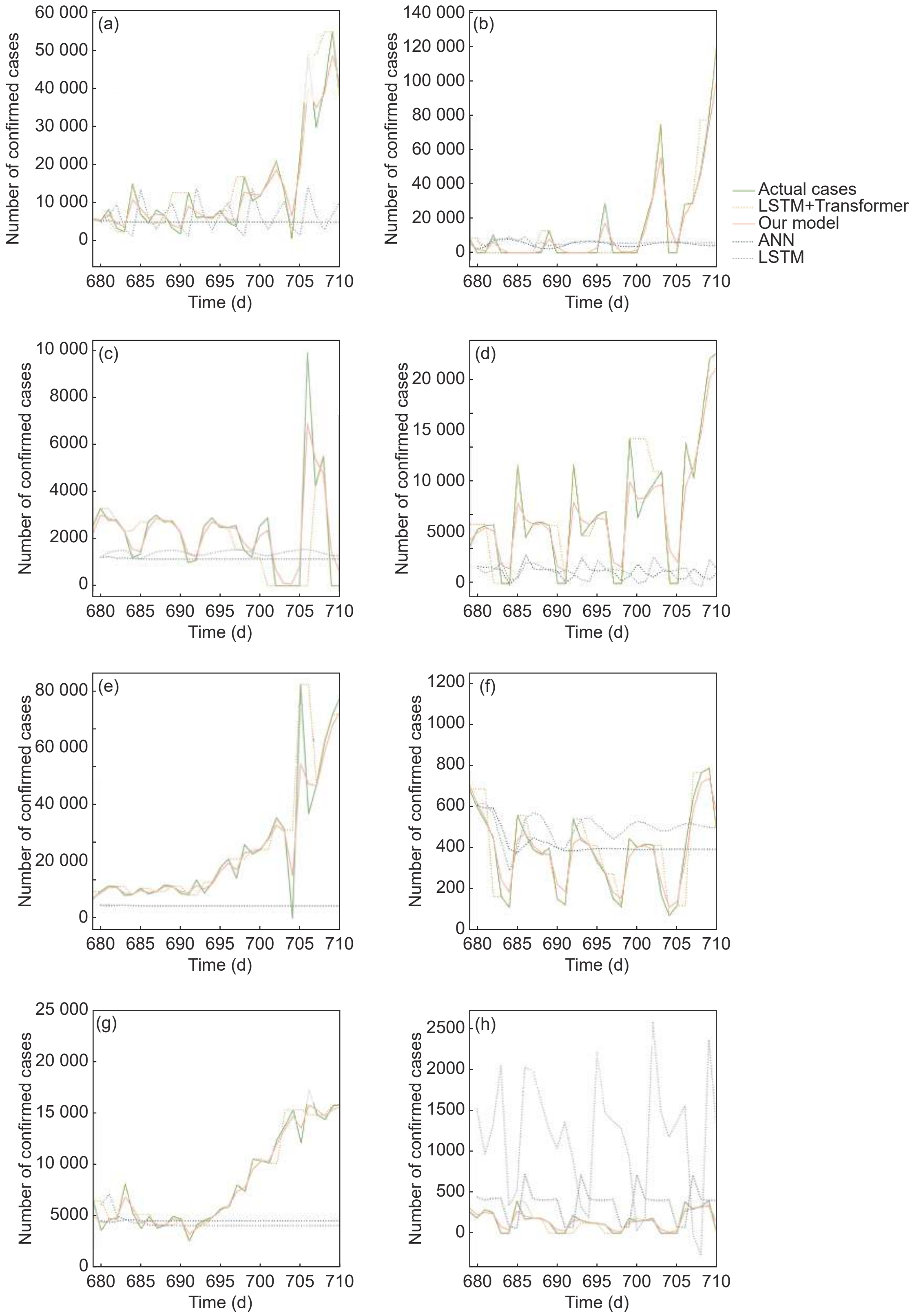


Fig. 8 Prediction performance comparison among LSTM, ANN, LSTM+Transformer, and our model in 2021 in (a) California, (b) Florida, (c) Kentucky, (d) Massachusetts, (e) New York, (f) North Dakota, (g) Texas, and (h) Wyoming.

Table 2 Model performance comparison.

State	Index	LSTM	ANN	LSTM+Transformer	Our model
California	MAPE	101.78	74.71	23.69	2.12
	R^2	−0.31	−0.43	0.68	0.98
Florida	MAPE	85.34	59.38	36.77	4.03
	R^2	−0.11	−0.14	0.74	0.85
Kentucky	MAPE	86.25	65.27	29.78	3.26
	R^2	−0.17	−0.33	0.88	0.95
Massachusetts	MAPE	79.32	40.98	24.66	3.33
	R^2	−0.97	−1.01	0.79	0.94
New York	MAPE	79.44	76.45	13.87	3.15
	R^2	−0.83	−0.83	0.81	0.96
North Dakota	MAPE	69.83	32.87	31.25	3.28
	R^2	−0.17	−0.04	0.90	0.97
Texas	MAPE	58.99	37.39	19.96	3.11
	R^2	−0.91	−0.71	0.86	0.95
Wyoming	MAPE	64.31	57.63	14.99	2.34
	R^2	−7.94	−5.21	0.91	0.98

policy-makers. In the future, considering most of the people have gotten vaccination and are immune to COVID-19, the stringency and form of anti-epidemic policies need adjusting timely.

4 Conclusion and Outlook

In this paper, we discuss the effectiveness of vaccine-differentiated policies and gave a more comprehensive policy evaluation that satisfied the requirements of both controlling confirmed cases and stimulate economic resurgence. An extending model that combines a VDPL module and objective-programming module has been put forward and put into application. The results have revealed some important conclusions. Firstly, vaccine-differentiated policies have been proven to be effective in both controlling and improving economy. Secondly, different types of vaccine-differentiated policies make contributions to economy recovery to varying degrees. Thirdly, responses to vaccine-differentiated policies vary in different states, and it depends on the condition of economic development to a large extent. Finally, a novel comparison mode in the subject of policy effect evaluation is proposed in our paper. The predictive performance of different models is compared, which leads to further verification of the accuracy of our model and the rationality of our results.

Even though our model has been demonstrated to perform well in the case study in the US, there are still a few limitations. For example, considering the complexity of model, only five indicators related to economy and COVID-19 are taken into account. More indicators involving geographical or climate indexes can be analyzed in further study. Another limitation is that we only compare our model with some typical ones like LSTM, ANN, and so on. Even if we come up with a novel thinking of policy effect evaluation, more discussion remains to be extended.

While entering the post-epidemic era, previous researches on policy effect evaluation are outdated, and the standard of assessment needs adjusting. A new set of opportunities and challenges has emerged. Apart from the state of economy rebound that we have discussed in this paper, other scenarios like medical resource allocation, infrastructure construction, social psychology, etc. are worth studying.

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