

Healthcare system resilience and adaptability to pandemic disruptions in the United States

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Supplementary Information

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1 Supplementary Note 1: Quantification framework

1.1 Resilience definition

Resilience is a system property that measures system performance in response to disturbances. It is a multifaceted concept with over 70 definitions¹⁻⁴, and its interpretation varies when applied to different systems. After an extensive literature review spanning various systems, we have summarized the four major definitions in Table. S1. It includes two major extreme definitions. One defines resilience as the ability of a system to absorb and recover back to the expected level after sudden stress^{2,5}. Another defines resilience as the capacity of systems to adapt or transform in response to continued shocks⁶. The first one focuses on the system response to one disruption (static), which is more applicable to engineering systems and short-term policies to restore the system functions. The second focuses on system response across multiple disruptions (dynamical), which is more applicable to socio-technological systems and long-term policies. Despite the difference, promoting either recovery or adaptation and achieving a balance between them is necessary.

However, the adaptability of the system to disruptions has often been ignored across various systems, due to the absence of comprehensive long-term data collection and observed successive disruptions. For the healthcare system, a socio-technological system that has observed successive disruptions during pandemics, understanding its ability to absorb and recover from each disruption, and based on that to understand its adaptability to multiple disruptions are significant⁷⁻¹⁰.

1.2 Mathematical model

As summarized in the literature¹¹, several mathematical models exist to capture the temporal changes in system performance during disruptions and assess system resilience. However, many of these models primarily focus on modeling the recovery phases, often overlooking the dynamics of the disruption phase as well as the various combinations of disruption and recovery process. In this study, we opted to utilize the beta family equations, as detailed in¹²,

$$O(t) = P(t) - \alpha \frac{(\theta + \vartheta)^{\theta + \vartheta}}{\theta^\theta \vartheta_1^\vartheta} \left(\frac{t}{T}\right)^\theta \left(1 - \frac{t}{T}\right)^\vartheta \quad (\text{S1})$$

where α , θ , ϑ , and T respectively represent disruption amplitude, parameters for disruption and recovery, and disruption duration. Assuming that $P(t) = 2$, when we change the parameters α , θ , ϑ , and T within beta family equations (Fig. S1a), we observe that α governs the determination of negative peaks, representing disruption amplitude. In contrast, parameters θ ($\theta \in (0, 1)$) and ϑ ($\vartheta \in (0, 1)$) influence the shape of the curve during the disruption and recovery process but do not impact the disruption amplitude and duration. The model allows for separate manipulation of these parameters, providing flexibility in representing various disruption and recovery rates, whether slow or fast. In contrast, other equations, such as those from the hybrid family (Fig. S1b) and gamma family (Fig. S1c), can only model scenarios characterized by rapid disruptions and slow recoveries. Additionally, their parameters are compound, adding complexity to their interpretation and application.

While the mathematical equation represented by Eq.S1 effectively captures system dynamics for a single disruption, it proves inadequate for modeling scenarios involving multiple disruptions. To address this limitation, we generalized the mathematical model (see Eq.1).

2 Supplementary Note 2: Dataset

2.1 Dataset overview

To assess healthcare resilience, we primarily use Electronic Medical Records (EMR) datasets¹³, which allows us to examine temporal changes in the volume of patient visits to essential health services during pandemics. To explore the correlations between resilience with pandemic severity, physician shortages, and socioeconomic factors in states, we utilize the three datasets COVID-19 infection datasets¹⁴, Physician datasets¹⁵, and Social consensus datasets¹⁶. All datasets and their limitations are summarized in Table. S2 and yearly statistics of EMR data are summarized in Table. S3.

2.2 Essential services of concern

A resilient healthcare system should be able to deliver urgent services for COVID-19 patients during pandemics while also maintaining essential health services for other non-COVID-19 patients⁸. According to the literature^{17,18}, essential health services generally include maternal service, chronic disease care, diagnostic and laboratory services, vaccination, primary care,

emergency care, and other services. Within data availability constraints and excluding the impact of COVID-19 care, our study only considers maternal service and chronic disease care for a total of 23 diseases. Table. S4 presents details of the services considered, including their sub-types and corresponding ICD-10 codes.

3 Supplementary Note 3: Robustness test

For a fair assessment of healthcare resilience, we need appropriate predictive models $P(t)$ that can effectively capture the trends in patient visit volumes if COVID-19 didn't occur. With the growing adoption of certified Electronic Medical Records (EMR) technology in U.S. hospitals and increased accessibility to healthcare facilities due to the Affordable Care Act, there has been a noticeable rise in patient visit volumes in our datasets. To validate the results on the occurrence of the two disruptions and incorporate the adoption rate of EMR technology, we collected external datasets and conducted robustness tests using a range of predictive models.

3.1 Robustness test on successive disruptions with external datasets

Based on the National Health Interview Survey¹⁹ provided by the CDC (Extended Data Fig.2), we observed that both patient visits to physicians and emergency departments exhibited two disruptions. Additionally, based on the Quarterly Services Survey¹⁹ provided by the US Census Bureau (refer to Extended Data Fig.2c), the number of hospital discharges also showed evidence of two disruptions. Specifically, the first disruption was noted to occur between the first quarter of 2020 and the second/third quarter of 2021, with the second disruption commencing in the third/last quarter of 2021. The results from these external datasets validate the two disruptions from pandemics in our study and confirm their respective periods occurring around January 2020 to May 2021, followed by a second disruption from June 2021 to the end of 2022 in the manuscript.

3.2 Robustness test on controlling population

To exclude the influence of EMR adoption rates, we conduct a robustness test by controlling the population:

- **Model-0: Constant population.** To mitigate the influence of EMR adoption, we exclusively focus on the subset of the population that have active encounters during the pre-pandemic period in our dataset. Different from Model-1 to Model-4, this filtration yields the constant patient visit trend:

$$P(t) = \mathcal{V} \quad (\text{S2})$$

where $\mathcal{V}$ is the volume of the patient visits that were active during the pre-pandemic period.

As depicted in Extended Data Fig.1, non-COVID-19 patient visits encounter two disruptions, coinciding with the trends shown in Extended Data Fig.2. The system did not achieve full recovery during the second disruption and remained unrecovered by the end of 2022. The control of a subset of the constant population demonstrates greater resilience $r = 0.73$ compared to alternative methods, and adaptability $\rho = 0.42$. However, pre-selecting a constant population tends to favor individuals residing in higher socioeconomic areas who can readily adopt EMR technology. Thus, we also explore alternative models.

3.3 Robustness test on predictive models

To accommodate the nonstationary trend of patient visits in our dataset due to increasing EMR adoption rates, we collected the yearly EMR adoption rates $\kappa(t)$ in the US from the American Hospital Association (AHA) Annual Survey/Health IT Supplement²⁰. See in Fig. S2, the national adoption rate increased from 0.960 to 0.963 up to 2019 but experienced a decline of 0.937 in 2020 (the pandemic period). For example, New York State witnessed an increase in the adoption rate during the pandemic, while Oklahoma experienced a decrease in the adoption rate during the pandemic period. To factor the influence of AHA EMR adoption rate $\kappa(t)$ on our results, we include state-by-state $\kappa(t)$ within our predictive model.

However, the EMR adoption rates from the general survey cannot well present the Healthjump dataset we used in collecting EMRs. The Healthjump datasets contain the National Provider Identifier (NPI) for physicians and state locations, covering 99.9% of patient encounters. Figure S3 illustrates the monthly number of physicians $\mathcal{P}_v(t)$ adopting EMR technology across states from 2017 to 2022. Notably, New York exhibits a more significant increase in the adoption of EMR technology among physicians compared to Oklahoma. The values also fluctuate

during the pandemic period. To account for the impact of EMR adoption by physicians, we utilize $\mathcal{P}_v(t)$ to estimate expected patient visits during the pandemic period in each state, as follows,

- **Model-1: Estimation model with physician adoption EMR rate.** The Healthjump dataset includes the National Provider Identifier for physicians and their state locations. Fig. S3 shows the number of physicians $\mathcal{P}_v(t)$ adopting EMR technology across states from 2017 to 2022. By leveraging this information alongside state populations, we can estimate anticipated patient visits during the pandemic period. Mathematically,

$$P(t) = \mathcal{P}_v(t)\sigma N \quad (\text{S3})$$

where $\mathcal{P}_v(t)$ is the number of physicians that adopted EMR technology in the state. N is the state population, and σ is the state Physician-to-Population Ratio, adjusted by monthly visits frequency in the pre-pandemic period.

- **Model-2: Generalized logistic model.** Acknowledging the fact that EMR adoption rates in our dataset follow the laws of innovation adoption²¹, which suggests that adoption will eventually saturate to encompass all populations and facilities, we utilize the generalized logistic function to estimate anticipated patient visits during the pandemic period,

$$P(t) = \kappa(t) \frac{K}{1 + e^{-(\beta t + \beta_0)}} \quad (\text{S4})$$

where K represents the maximal capacity of data volume, β controls the collection rates of the data vendor, β_0 is determined when the data is half collected. The term $\frac{K}{1 + e^{-(\beta t + \beta_0)}}$ describes the adoption rate of dataset vendor healthjump and $\kappa(t)$ is the general EMR adoption rate in the state, sourced from AHA.

- **Model-3: Simple exponential smoothing model.** Given the nonstationarity of the data, we adopt the time-series SES model to forecast the trend,

$$P(t) = \kappa(t)[\hat{P}(t + h|t)] \quad (\text{S5})$$

where $[\hat{P}(t + h|t)]$ is the forecast in our dataset using weighted average, where weights decrease exponentially as observations in further past. $\kappa(t)$ is the general EMR adoption rate in the state, sourced from AHA.

- **Model-4: Exponential smoothing model with seasonality.** We use the Holt-Winter’s seasonal method to capture the seasonality in the trend of patient visits,

$$P(t) = \kappa(t)[\hat{P}(t + h|t)] \quad (\text{S6})$$

where $[\hat{P}(t + h|t)]$ is the weighted average in our dataset between seasonally adjusted observation and nonseasonal forecast. $\kappa(t)$ is the general EMR adoption rate in the state, sourced from AHA.

Extended Data Fig.1 shows the trends of patient visits generated by the proposed predictive models. With the national volume of patient visits as an example, all models capture two disruptions: the first disruption spans from January 2020 to around May 2021, and the second disruption begins in June 2021, with no recovery observed by the end of 2022. Model-1 (Extended Data Fig. 1a) shows fluctuations in predicted patient visits due to the unstable and seasonal impact of physician EMR adoption $\mathcal{P}_v(t)$ during the pandemic, resulting in resilience ($r = 0.79$) and adaptability ($\rho = 0.27$). Model-2 exhibits a decaying increase in patient visits ($r_{\text{model-2}} = 0.63$, $\rho_{\text{model-2}} = 0.30$). Both Model-3 and Model-4, the time-series models, demonstrate a nonlinear escalation of patient visits. However, Model-4, which incorporates seasonal impact, displays a more reasonable increase ($r_{\text{model-3}} = 0.44$, $\rho_{\text{model-3}} = 0.53$ and $r_{\text{model-4}} = 0.61$, $\rho_{\text{model-4}} = 0.63$).

Considering variations in healthcare systems and patient service needs across different states, all the models are trained state-by-state, service-by-service, and population-by-population. Fig. S4 presents the results of all essential services and patient groups using the proposed predictive models. Across all models, the healthcare system exhibits at least two disruptions: an initial disruption characterized by significant amplitude but short duration, followed by a second disruption with smaller amplitude but requiring a longer duration for recovery (Fig. S4a-b). Comparisons of the results consistently reveal that chronic disease treatment shows more prominent resilience gaps compared to maternal care, as depicted in Fig. S4c and d. The relative resilience gaps among patient groups remain consistent, as illustrated in Fig. S4e and f.

Due to the limitations inherent in using (AHA) EMR adoption rate data beyond 2021, we selected model 1 for our manuscript.

3.4 Robustness test on disruption criteria

To identify significant disruptions, we established two criteria to exclude disruptions that fail to meet requirements: (1) those lasting smaller than T months, and (2) those with a performance loss ratio less than A . We conducted sensitivity tests by varying the criteria, considering $T = 3$ or $T = 6$ and $A = 1\%$, $A = 5\%$, and $A = 10\%$. Using Model-1 as the example, as depicted in Fig. S5, increasing the criteria for disruption duration T had minimal impact on the first disruption but facilitated the capture of a longer second disruption. These changes resulted in a smaller disruption rate during the second disruption and higher adaptability, with no observed changes in resilience. Furthermore, increasing the performance loss ratio A had no effect on disruption duration and resilience. However, larger values of A tend to overlook small disruptions and instead focus on capturing disruptions with significant losses. This often leads to a more severe second disruption and lower adaptability.

4 Supplementary Note 4: Empirical results

4.1 State resilience index and adaptability index

Figure S6 shows that states with higher adaptability indeed tend to have higher resilience. However, their correlation is not significant with a Pearson correlation coefficient of 0.24 ($P=0.09$). In a system facing numerous disruptions, such as encountering ten, adaptability would indeed be the primary dimension of system resilience. However, in our study where the healthcare system only faces two disruptions, the other two dimensions—the ability to absorb disruptions and recover from them—still play crucial roles in determining system resilience.

4.2 State resilience index and social vulnerability index

As indicated in Extended Data Fig.3, the resilience index of the states exhibits an inverse correlation with their respective social vulnerability index with a Pearson coefficient of -0.38 ($p=0.001$). This inverse correlation implies that states that are better equipped to respond to and recover from various challenges, such as natural disasters, economic fluctuations, and social disruptions, tend to be more resilient.

4.3 Resilience of essential sub-disease

Figure S7 depicts the resilience index and adaptability index for each disruption for specific subtypes of chronic disease care and maternal care. Services related to asthma, COPD, cancer, diabetes, and hypertension demonstrate higher resilience compared to heart disease and prenatal care. It's noteworthy that only COPD and prenatal services exhibit a negative adaptability index, while other services demonstrate positive adaptive characteristics. The reason lies in more acute and specialized care required for heart disease and prenatal care during critical periods. Disruptions in these areas of care make rapid recovery more challenging.

4.4 Resilience of dialysis service

While testing essential health services for patients is effective for assessing the healthcare system's ability to sustain basic functions, assessing services for patients requiring long-term, uninterrupted treatment during the pandemic provides a more robust measure of healthcare resilience. For this purpose, we conducted an analysis focusing on patients in need of dialysis services (ICD-codes N18.6, Z99.2, Z91.15), which necessitates multiple weekly sessions. Extended Data Fig.4 illustrates the temporal trend of patient visits for dialysis services. Similar to conclusions drawn for other essential services, two disruptions are observed, but the period differs, with the first occurring from December 2019 to March 2022, and the second beginning in April 2022 with no recovery. For dialysis services, the system demonstrates higher resilience $r = 0.89$. Because of the limited availability of data on dialysis at the state level, we are unable to conduct state-by-state analysis.

4.5 Resilience measure with surpassing

As shown in Extended Data Fig. 1, which is marked in the grey area, there is a scenario where observed patient visits exceed predicted numbers, leading to a resilience index r' surpassing the original index r . This could be attributed to various factors, including increased demand, improved access to healthcare, a better-equipped healthcare system, and potential inaccuracies in predictive estimations. In Fig. S8, we compare the resilience of states considering surpass (r') with those without (r). The analysis reveals consistent trends, yet the inclusion of surpassing elements yields higher resilience values.

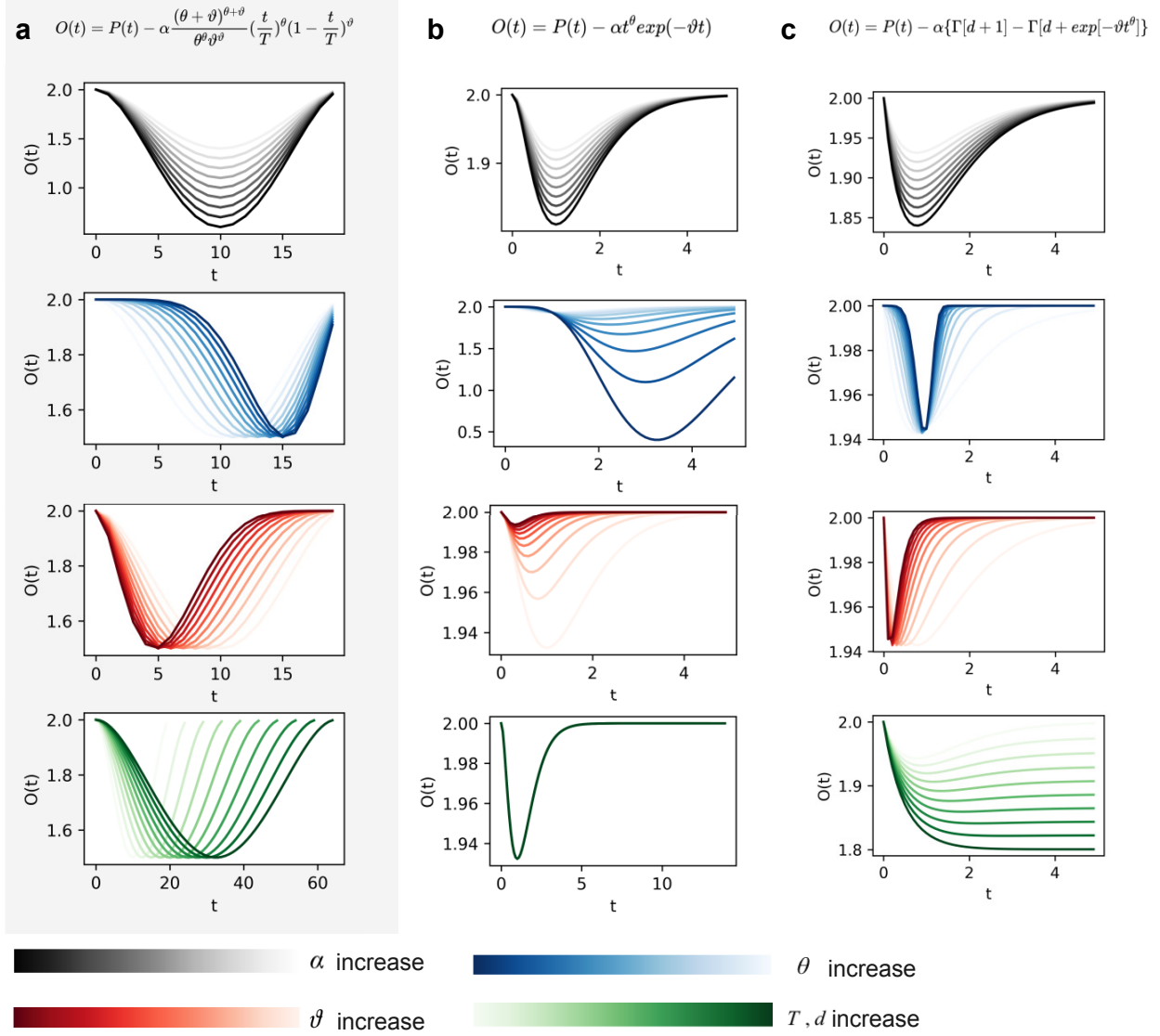


Figure S1: **The comparison between mathematical equations $O(t)$ to describe resilience curve.** Assuming $P(t)=2$. **(a)** Beta family equations. **(b)** Hybrid family equations. **(c)** Gamma family equations. The beta family equations (utilized in this study) offer the advantage of individually characterizing disruption amplitude (α), disruption rate (θ), recovery rate (ϑ), and time (T), enabling the combination of both slow and fast disruption and recovery rates. However, the other alternative equations primarily focus on the recovery process, emphasizing rapid disruption and slow recovery.

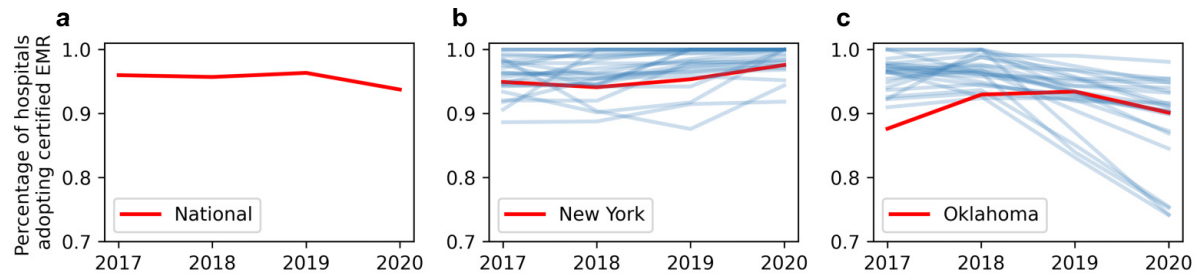


Figure S2: **Percentage of hospitals adopting certified EMR from 2017 to 2020 across the US states.** Source data: American Hospital Association (AHA) Annual Survey/Health IT Supplement. **(a)** National adoption rate. **(b)** States where the adoption rate increase in 2020. **(c)** States where the adoption rate decrease in 2020. Adoption rates in New York state and Oklahoma state are highlighted in red.

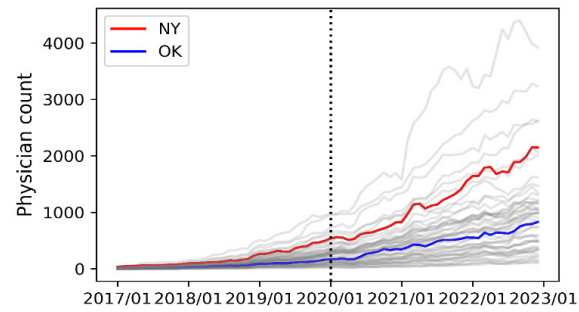


Figure S3: **Counts of physicians adopting EMR technology in US states within Healthjump Dataset.** Counts of physicians in New York state and Oklahoma state are highlighted.

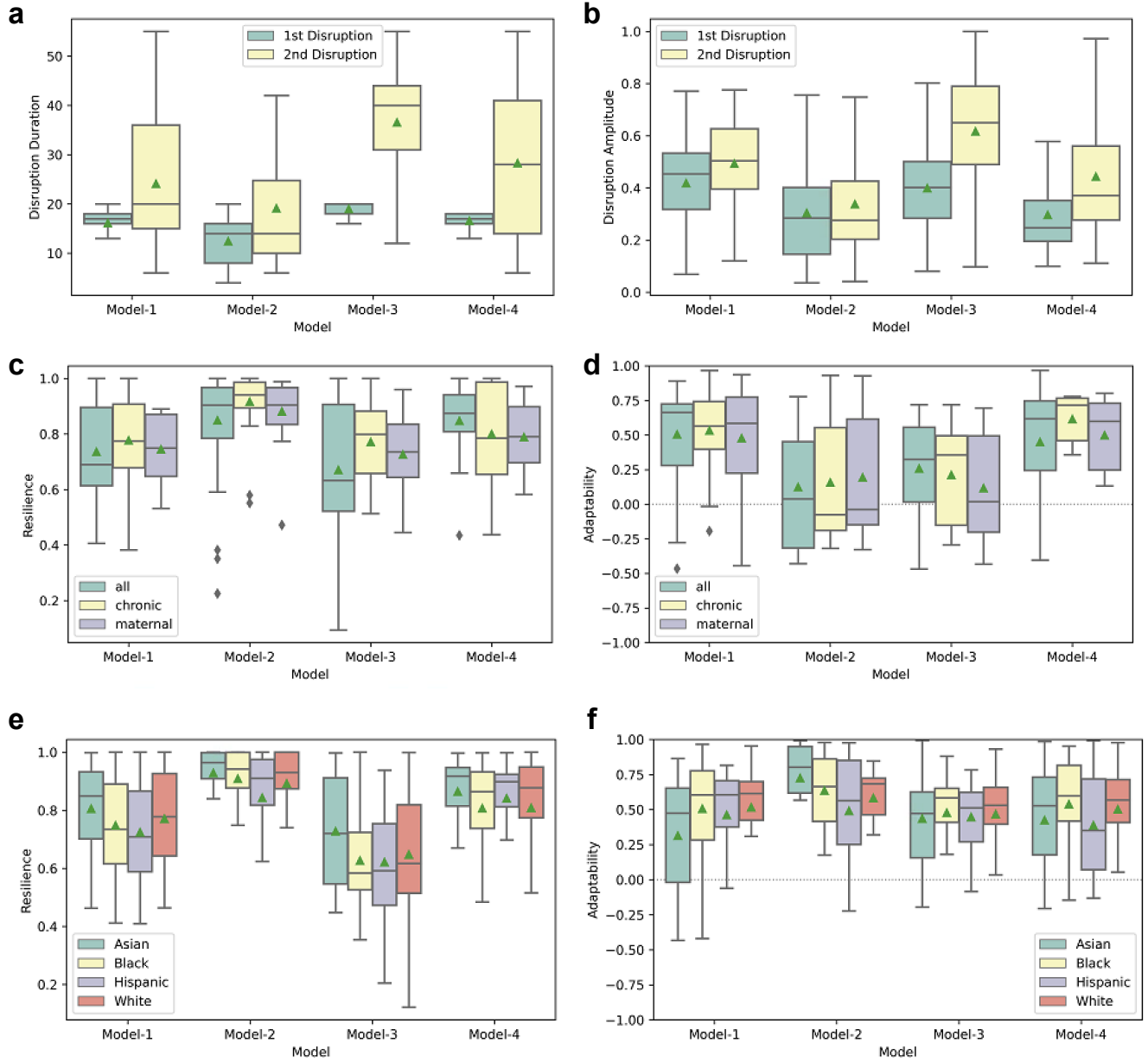


Figure S4: **Comparison between predictive models $P(t)$ for different services and populations in different states.** (a) Disruption duration. (b) Disruption amplitude. (c) Resilience for services. (d) Adaptability for services. (e) Resilience for races. (f) Adaptability for races. These boxplots illustrate the distribution of data using its five-number summary—minimum, first quartile, median, third quartile, and maximum. Triangles indicate the mean.

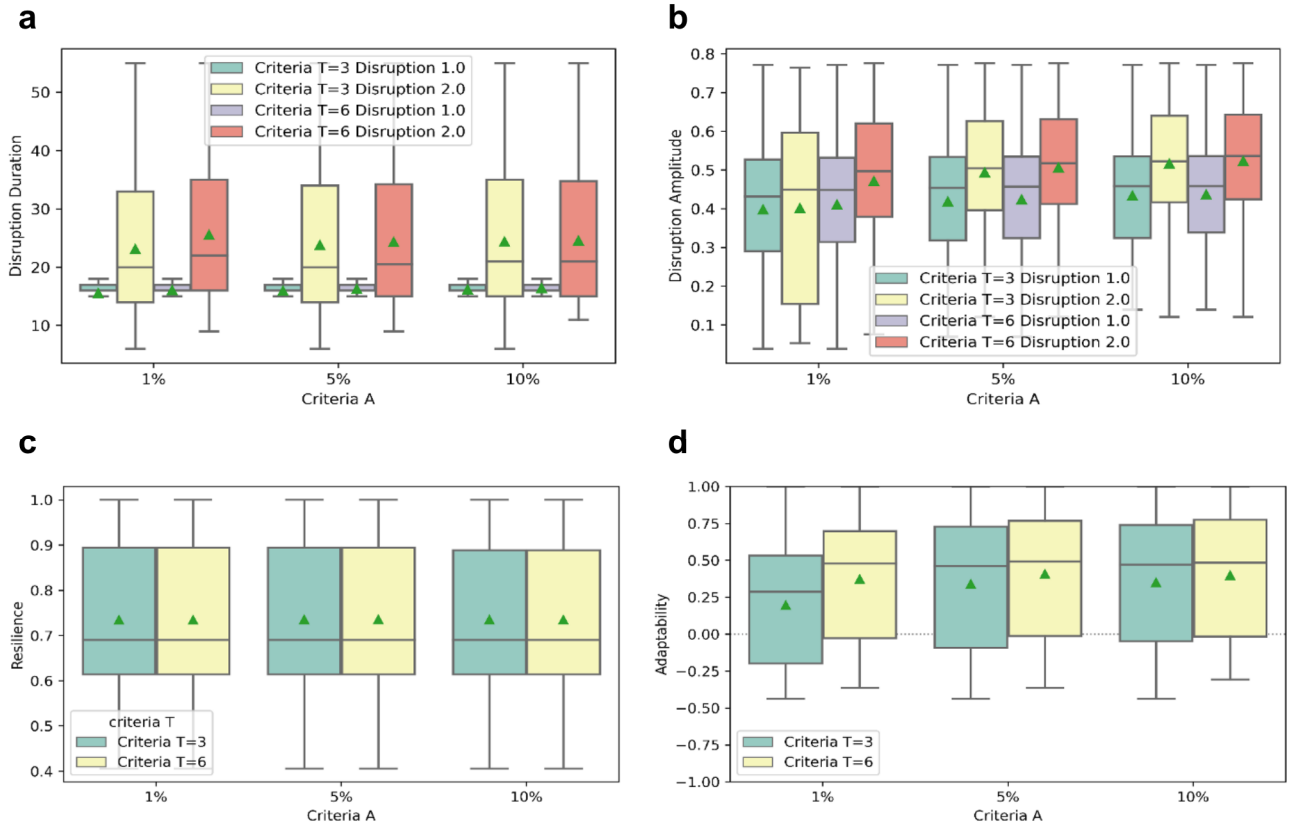


Figure S5: **Comparison on disruption criteria.** Using Model-1 as the example for all services. **(a)** Disruption duration. **(b)** Disruption amplitude. **(c)** Resilience for all services. **(d)** Adaptability for all services. These boxplots illustrate the distribution of data using its five-number summary—minimum, first quartile, median, third quartile, and maximum. Triangles indicate the mean.

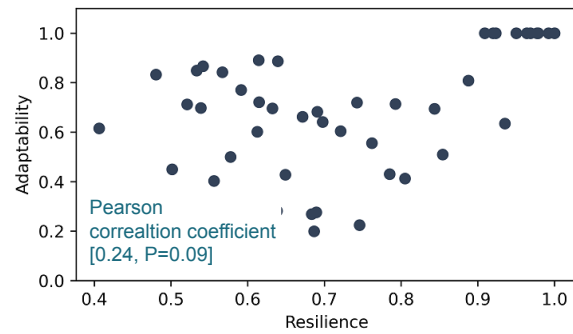


Figure S6: **Adaptability index versus resilience index of states.** The correlation significance is determined by a two-sided test and indicated by a P-value.

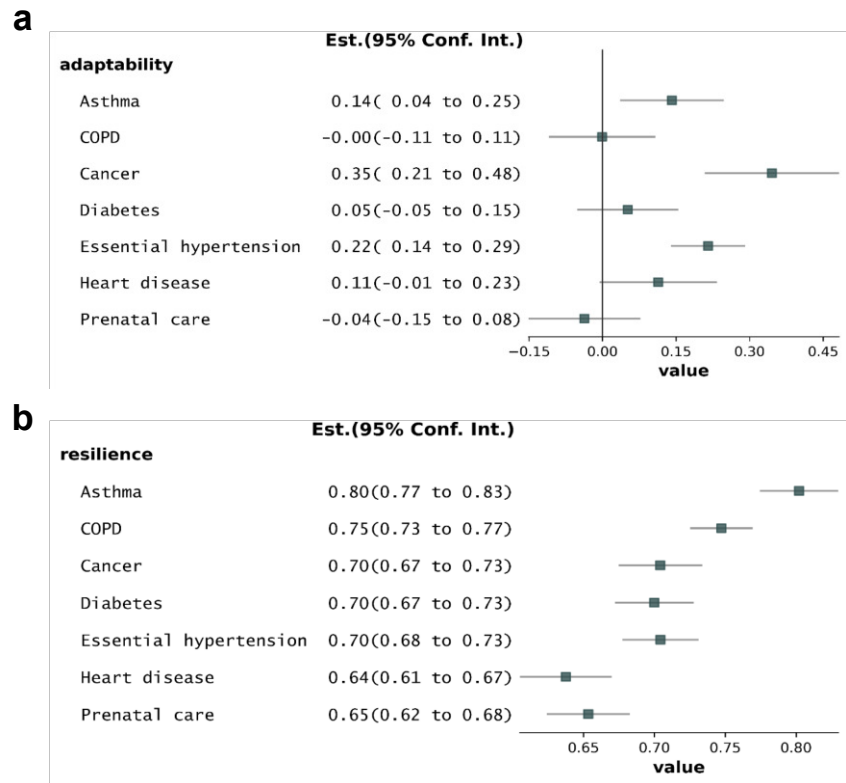


Figure S7: **Resilience and adaptability of essential services.**The adaptability and resilience indices and parameters across all states are expressed by the average and lower and upper limits of the 95% confidence level.

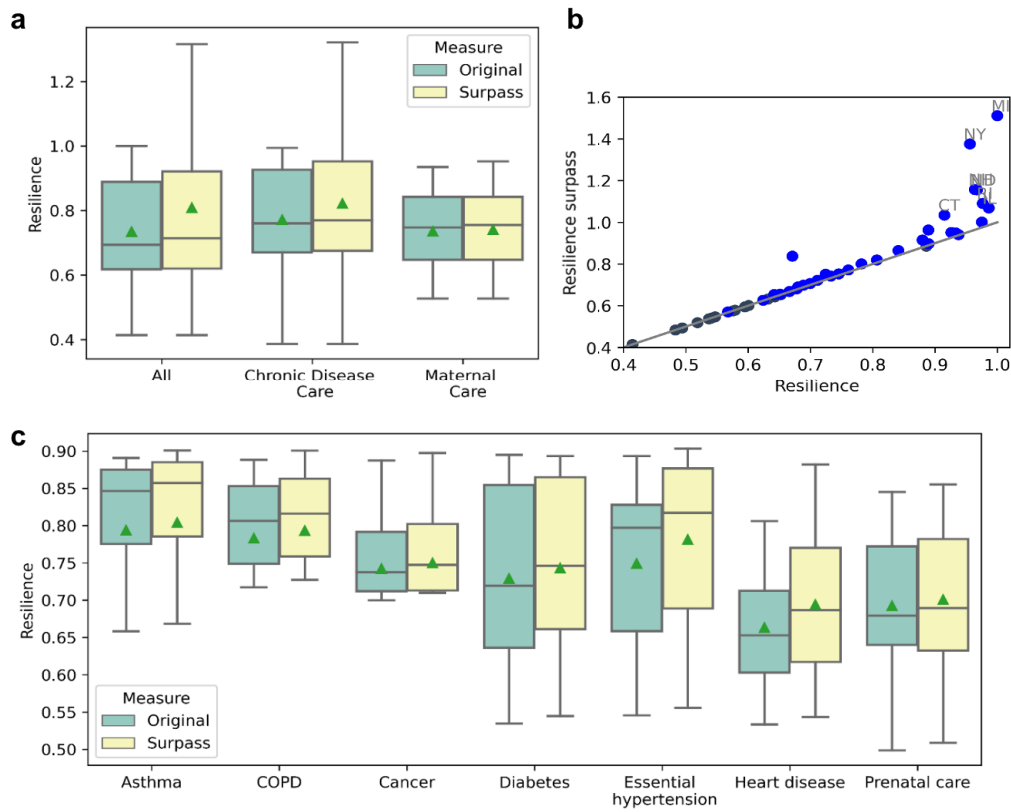


Figure S8: **Comparison of the resilience of states without and with considering surpass.** (a) Comparison across services. (b) Comparison of each state's resilience without and considering surpass. (c) Comparison across sub-services. These boxplots illustrate the distribution of data using its five-number summary—minimum, first quartile, median, third quartile, and maximum. Triangles indicate the mean.

Table S1: The multifaceted definitions of resilience.

	Definition	Explanation	Measure	Applicable to systems	Disaster
Static	Absorb	the ability of the absorb damages from disruptions	disruption rate	Engineering systems ^{2,12} (e.g., power systems, communication system, water system, robotics system), Social-technological system ²² , Ecology system ^{3,6,23}	Single disruption
	Recovery	the ability of the system to recover (bounce back) to normal level	recovery rate		
Dynamical	Adaptability	the ability of the system to customize itself to adapt and prevent damages from future disruptions rate	adaptability index	Social-technological system ²² (e.g, healthcare system, business system, social system), Ecology system ^{3,6,23} (e.g., human–environment systems),	Multiple successive disruptions
Future research: microscopic aspect		the ability of interconnected systems to sustain the functions despite street	–	Interconnected systems ^{3,4}	All

Table S2: Summary of datasets.

Dataset	Period	Data Source	Data Detail	Data Limitation
Electronic Medical Records (EMR) datasets	1995-2022	Healthjump	Include 33 million patients and 1 million healthcare providers with records from as far back as 1995; Collected from 70,000 hospitals and clinics and more than 1500 healthcare organizations; Patient Charts 83,899,214; 86.5% of Encounters by Office; 99.9% of Encounters with National Provider Identifier.	1) Biased sampling toward states having more facilities implemented the Electronic Health Records (EHR) systems 2) Missing attributes (such as ICD-10 code, demographic attributes) in data.
COVID-19 infection datasets	2019-2022	Johns Hopkins Coronavirus Resource Center	Delivers daily updates on COVID-19 confirmed cases, hospitalizations, deaths, and vaccine data across U.S. counties and states.	–
Physician datasets	2019	2019 State Physician Workforce Data	Offers state-specific detailed statistics on active physicians, including physician-to-population ratios, the percentage who are female, age distribution, and school type.	–
Social Consensus Dataset	2019	CDC Social Vulnerability Index	Offer the percentile of social factors in each region (census tracts, subdivisions of counties), encompassing unemployment rates, racial and ethnic minority status, and disability rates. These factors are further categorized into four related themes.	–

Table S3: Yearly statistics of patient visits in the Healthjump data.

		2017	2018	2019	2020	2021	2022
ALL		49,636k	69,534k	149,302k	181,060k	341,249k	795,156k
Services	With ICD code	2,117k	2,181k	3,563k	3,879k	8,323k	11,021k
Services	Chronic Illness Treatment	84k	78k	113k	108k	203k	613k
Services	Maternal and newborn	20k	18k	27k	35k	53k	74k
Race	Asian	212k	217k	358k	435k	857k	1244k
Race	Black	1,997k	2,013k	3,731k	4,278k	7,408k	1,079k
Race	Hispanic	1,951k	2,070k	3,577k	3,668k	7,010k	6,538k
Race	White	11,135k	11,115k	18,759k	22,559k	38,991k	51,926k

Services	Disease	Sub-disease	ICD-10 code
Chronic Disease Care	Alzheimer's disease	Alzheimer's disease	G30
	Asthma	Asthma	J45 - J46
	Atherosclerosis	Atherosclerosis	I70
	Cancer	Malignant neoplasms of lip, oral cavity and pharynx; Malignant neoplasm of esophagus; Malignant neoplasm of stomach; Malignant neoplasms of colon, rectum and anus; Malignant neoplasms of liver intrahepatic bile ducts; Malignant neoplasm of pancreas; Malignant neoplasm of larynx; Malignant neoplasms of trachea, bronchus and lung; Malignant melanoma of skin; Malignant neoplasm of breast; Malignant neoplasm of cervix uteri; Malignant neoplasms of corpus uteri and uterus, part unspecified; Malignant neoplasm of ovary; Malignant neoplasm of prostate; Malignant neoplasms of kidney and renal pelvis; Malignant neoplasm of bladder; Malignant neoplasms of meninges, brain and other parts of central nervous system; Hodgkin's disease; Non-Hodgkin's lymphoma; Leukemia; Multiple myeloma and immunoproliferative neoplasms; Other unspecified malignant neoplasms of lymphoid, hematopoietic & related tissue; All other and unspecified malignant neoplasms	C00-C97
	Stroke (cerebrovascular diseases)	Stroke (cerebrovascular diseases)	I60 - I69
	Chronic liver disease	Cirrhosis & Alcoholic liver disease; Other chronic liver disease and cirrhosis	K70, K73 - K74
	Chronic Obstructive Pulmonary Disease (COPD) excluding Asthma	Bronchitis, chronic and unspecified; Emphysema; Other chronic lower respiratory diseases	J40 - J47
	Diabetes	Diabetes	E10-E14
	Essential hypertension	Essential hypertension	I10, I12, I15
	Heart disease	Acute rheumatic fever and chronic rheumatic heart diseases; Hypertensive heart disease; Hypertensive heart and renal disease; Acute myocardial infarction; Other acute ischemic heart diseases; Atherosclerotic cardiovascular disease, so described; All other forms of chronic ischemic heart disease; Acute and subacute endocarditis; Diseases of the pericardium and acute myocarditis; Heart failure; All other forms of heart disease.	I00 - I09, I11, I13, I20 - I51
Maternal Care	Kidney disease (nephritis, nephrotic syndrome and nephrosis)	Acute nephritic / nephrotic syndrome; Chronic / unspecified nephritis and renal sclerosis; Renal failure; Other disorders of kidney	N00 - N07, N17 - N19, N25 - N27
	Other cardiovascular/circulatory conditions	Aortic aneurysm and dissection; Other diseases of arteries, arterioles and capillaries; Other disorders of circulatory system;	I71 - I78, I80 - I99
	Prenatal care	Prenatal care	Z34
	Postnatal care	Postnatal care	Z39
	Family planning	Family planning	Z31
	Pregnancy with abortive outcome	Ectopic pregnant; Hydatidiform mole; Other abnormal products of conception; Spontaneous abortion; Complications following (induced) termination of pregnancy; Failed attempted termination of pregnancy; Complications following ectopic and molar pregnancy	O00-O08
	Edema, proteinuria and hypertensive disorders in pregnancy, childbirth and the puerperium	Pre-existing hypertension complicating pregnancy, childbirth and the puerperium; Pre-existing hypertension with pre-eclampsia; Gestational [pregnancy-induced] edema and proteinuria without hypertension; Gestational [pregnancy-induced] hypertension without significant proteinuria; Pre-eclampsia; Eclampsia; Unspecified maternal hypertension	O10-O16

Other maternal disorders predominantly related to pregnancy	Hemorrhage in early pregnancy;Excessive vomiting in pregnancy;Venous complications and hemorrhoids in pregnancy; Infections of genitourinary tract in pregnancy; Diabetes mellitus in pregnancy, childbirth, and the puerperium; Malnutrition in pregnancy, childbirth and the puerperium; Maternal care for other conditions predominantly related to pregnancy; Abnormal findings on antenatal screening of mother; Complications of anesthesia during pregnancy	O20-O29
Maternal care related to the fetus and amniotic cavity and possible delivery problems	Multiple gestation; Complications specific to multiple gestation; Maternal care for malpresentation of fetus; Maternal care for disproportion; Maternal care for abnormality of pelvic organs; Maternal care for known or suspected fetal abnormality and damage; Maternal care for other fetal problems; Polyhydramnios; Other disorders of amniotic fluid and membranes; Premature rupture of membranes; Placental disorders;Placenta previa; Premature separation of placenta [abruptio placenta]; Antepartum hemorrhage, not elsewhere classified; False labor;Late pregnancy	O30-O48
Complications of labour and delivery	Preterm labor; Failed induction of labor; Abnormalities of forces of labor; Long labor; Obstructed labor due to malposition and malpresentation of fetus; Obstructed labor due to maternal pelvic abnormality; Other obstructed labor; Labor and delivery complicated by intrapartum hemorrhage, not elsewhere classified; Labor and delivery complicated by abnormality of fetal acid-base balance; Labor and delivery complicated by umbilical cord complications; Perineal laceration during delivery; Other obstetric trauma; Postpartum hemorrhage; Retained placenta and membranes, without hemorrhage; Complications of anesthesia during labor and delivery; Other complications of labor and delivery, not elsewhere classified; Abnormality in fetal heart rate and rhythm complicating labor and delivery	O60-O75
Delivery	Encounter for full-term uncomplicated delivery; Encounter for cesarean delivery without indication	O80-O84
Complications predominantly related to the puerperium	Puerperal sepsis; Other puerperal infections; Venous complications and hemorrhoids in the puerperium; Obstetric embolism; Complications of anesthesia during the puerperium; Complications of the puerperium, not elsewhere classified; Infections of breast associated with pregnancy, the puerperium and lactation; Other disorders of breast and disorders of lactation associated with pregnancy and the puerperium	O85-O92
Other obstetric conditions, not elsewhere classified	Sequelae of complication of pregnancy, childbirth, and the puerperium; Maternal infectious and parasitic diseases classifiable elsewhere but complicating pregnancy, childbirth and the puerperium; Other maternal diseases classifiable elsewhere but complicating pregnancy, childbirth and the puerperium; Maternal malignant neoplasms, traumatic injuries and abuse classifiable elsewhere but complicating pregnancy, childbirth and the puerperium	O94-O99

Table S4: Services of concern, along with their sub-types and corresponding ICD-10 codes.

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