Adaptability Reveals the Healthcare Resilience to Pandemics

By: Dimitri Lopez, Lu Zhong, Sen Pei, and Jianxi Gao

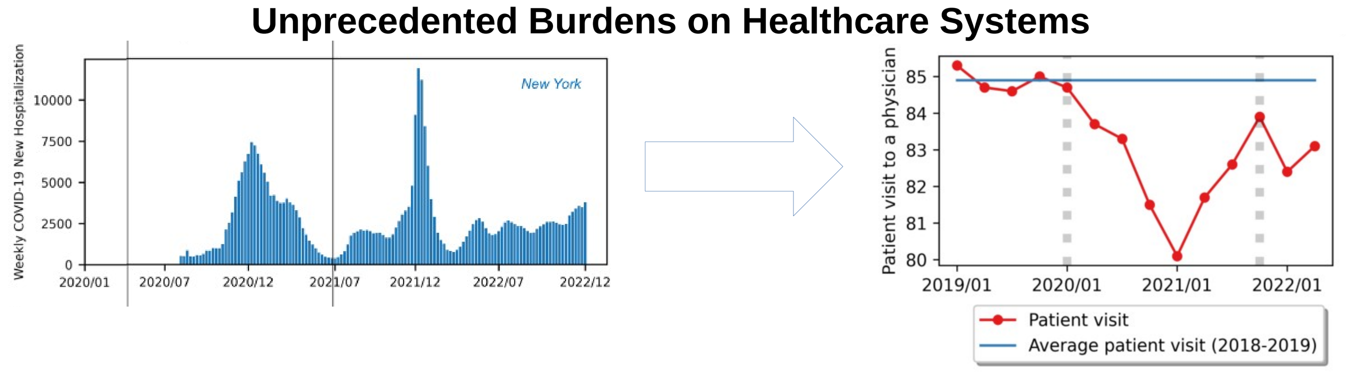
Academic Paper Under Review for Nature Medicine

Abstract

Enhancing the resilience of healthcare systems in the face of successive disruptions has become increasingly important, particularly in light of the COVID-19 pandemic. Currently resilience is defined as the system's capacity to absorb, recover from, and adapt to disruptions. However, despite more than 50 years of research in this field, empirical evidence and mathematical tools to quantify adaptive capability - the ability to learn from previous disruptions to enhance system future performance - remains lacking. We propose a quantification framework for measuring system resilience and adaptability and then apply it to billions of electronic medical records (EMR) across United States. Our analyses reveals that healthcare systems went through two significant successive disruptions, showed substantial adaptabilty but only moderate levels of resilience. Furthermore, Black and Hispanic groups consistently endured severe disruptions and were less resilient than White and Asian groups. We find that physician abundance is the key characteristic for determining healthcare system responses. Our results offer vital guidance in designing resilient and sustainable health systems to prepare for future successive disruptions, such as climate change, environmental pollution, and pandemics.

Introduction

Unprecedented Burdens on Healthcare Systems



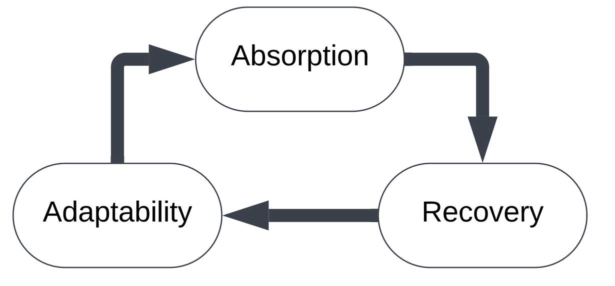
Essential healthcare services were disrupted.

For Example: 9.4 million cancer treatments and screenings were delayed or canceled...

What is the Resilience and Adaptability of Healthcare Systems?

Resilience

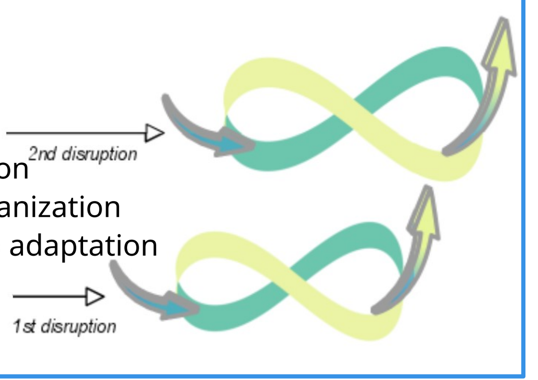
How much a system can absorb?
How much a system can recover?
How well can a system adapt?



Adaptive Cycle

Characterized by the following recurrent process:

- Growth
- Disruption
- Self Organization
- Leads to adaptation



Current research lacks quantitative tools measuring adaptability. We hope to remedy this

Methodology

Data

Data access provided by the COVID-19 Research Database

A data collection platform with more than 60 million patient records a year

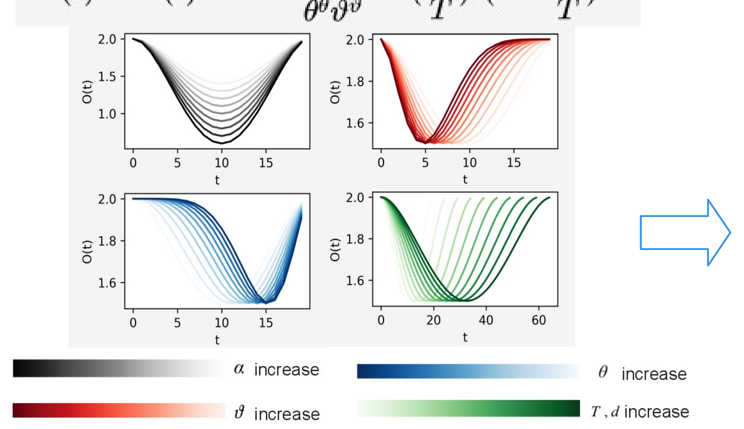
We then analyze how patient visits for different services and populations were affected by the pandemic

Quantification Framework

We fit our beta function to detected disruptions and measuring how long it takes for a system to return to expected values.

Beta Equation

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

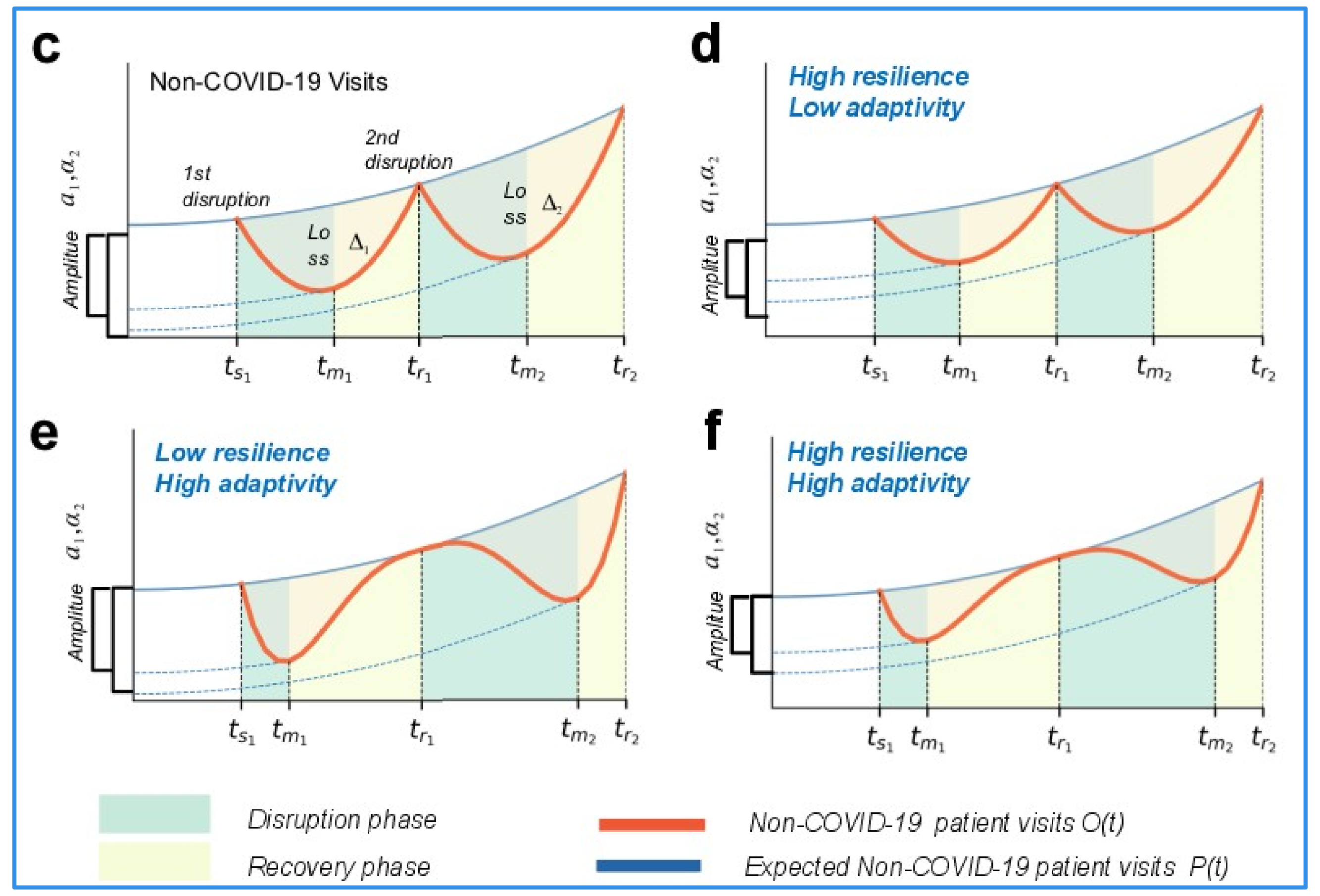


α - Disruption amplitude
ϑ - Recovery rate
Θ - Disruption rate
T - Duration

Expected Patient Visits: P(t)

Based on prepandemic trends

$$O(t) = \begin{cases} P(t); & 0 \le t < t_{s_1} \\ P(t) - \alpha_1\frac{(\theta_1+\vartheta_1)^{\theta_1+\vartheta_1}}{\theta_1^{\theta_1}\vartheta_1^{\vartheta_1}}\left(\frac{t}{T_1}\right)^{\theta_1}\left(1-\frac{t}{T_1}\right)^{\vartheta_1}; & t_{s_1} \le t < t_{r_1} \\ P(t) - \alpha_2\frac{(\theta_2+\vartheta_2)^{\theta_2+\vartheta_2}}{\theta_2^{\theta_2}\vartheta_2^{\vartheta_2}}\left(\frac{t}{T_2}\right)^{\theta_2}\left(1-\frac{t}{T_2}\right)^{\vartheta_2}; & t_{s_2} \le t < t_{r_2} \\ \dots & \\ P(t); & t > t_{r_n} \end{cases}$$



Recovery Rate

$$u_i = \frac{1}{\theta_i T_i}$$

Disruption Rate

$$v_i = \frac{1}{\vartheta_i T_i}$$

Adaptability

$$\rho = \frac{-[u_{i+1}-u_i]}{\max(u_{i+1},u_i)}$$

Resilience

$$r = 1 - \frac{\int_{t_s}^{t_r}[P(t)-O(t)]dt}{\int_{t_s}^{t_r}[P(t)]dt}$$

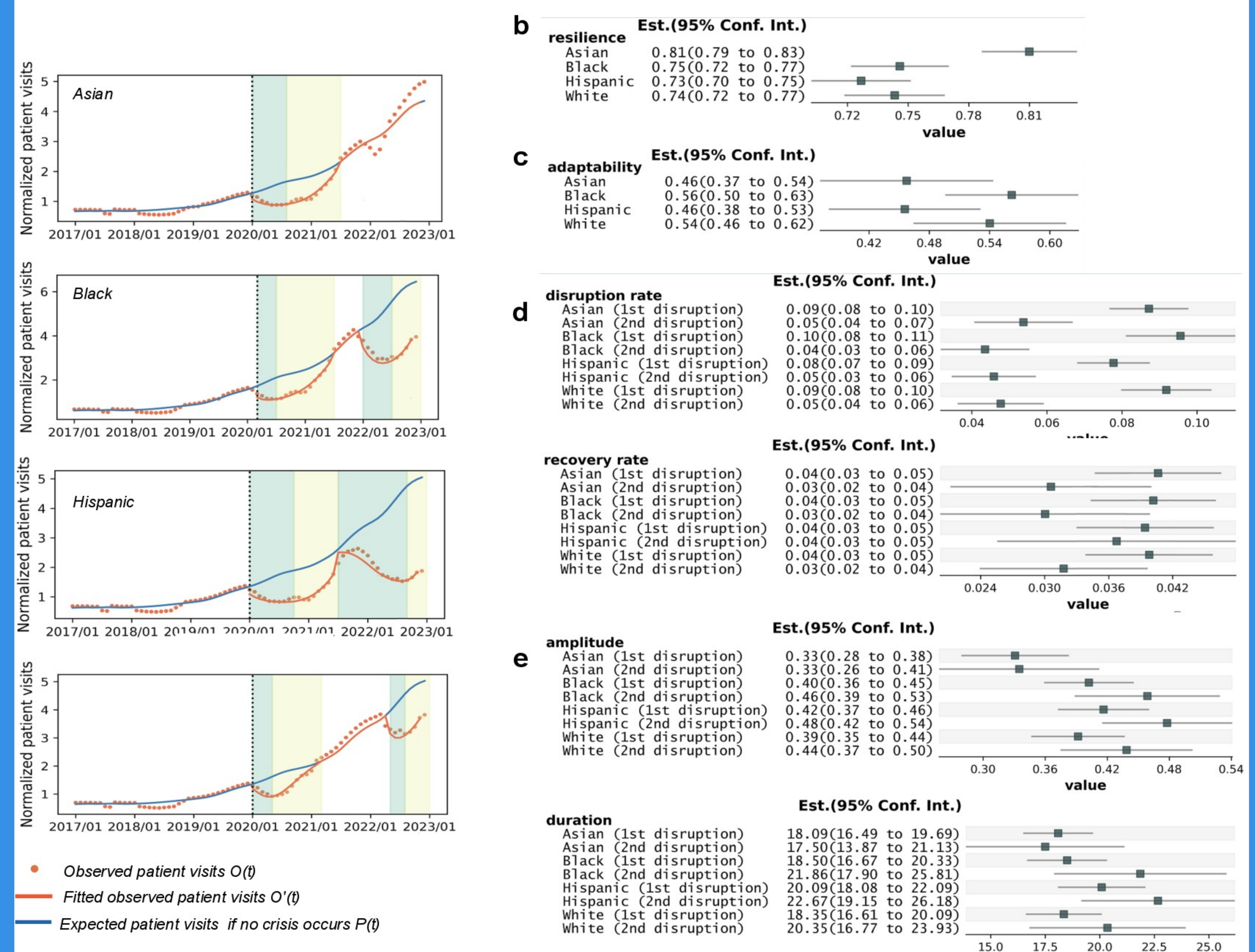
Applied to millions of patient records across states, services and racial groups.

Results

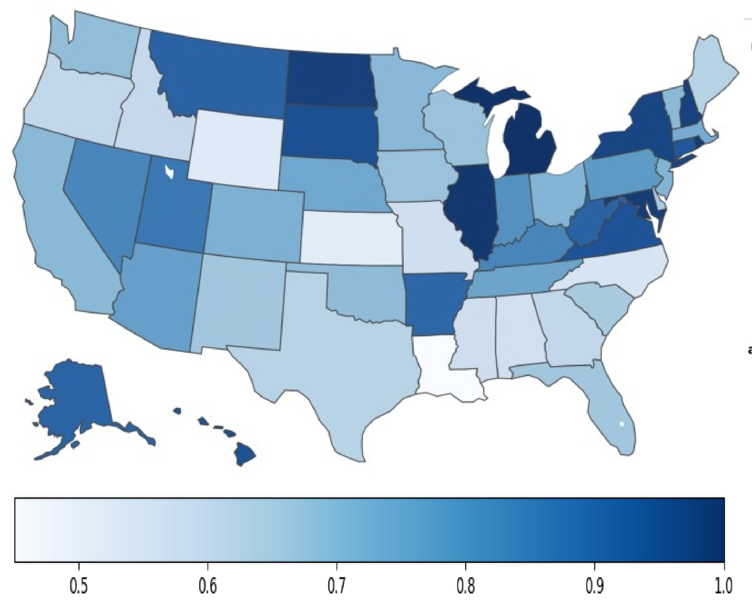
Table 1. Successive disruptions on healthcare system from 2020 to 2022. We classify the healthcare system as 'Not recovered' if the observed non-COVID-19 patient visits keep less than 90% of the expected counts.

Percentage	Disruptions			Not recovered (1st disruption)	Not recovered (2nd disruption)	States
	Once	Twice	>=Triple			
All	10.2%	89.8%	0%	48.9%	87.8%	49
Chronic Disease Treatment	6.6%	86.6%	6.6%	56.6%	93.5%	30
Maternal Service	0%	100%	0%	88.8%	94.4%	18
Asian	0%	100%	0%	42.4%	90.1%	33
Black	0%	100%	0%	44.1%	94.1%	34
Hispanic	2.5%	94.8%	2.5%	35.9%	87.1%	39
White	2.1%	97.8%	0%	59.5%	87.2%	47

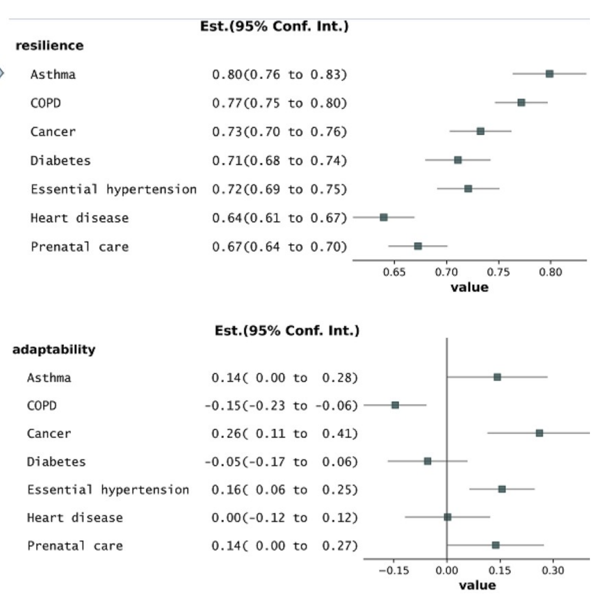
Analysis of Racial Groups



Resilience



Analysis of Services



Conclusion

Correlation Analysis

Table 2. Pearson correlation coefficients assessing the relationships between system adaptivity/resilience and pandemic severity, physician shortages, and socioeconomic factors in U.S. states. Significant correlations, indicated by a P-value less than the threshold of 0.05, are highlighted.

	COVID-19 cases	Physician per 100,000	Poverty percentile	Unemployment percentile	Uninsurance percentile	Age≥ 65 percentile	Age≤ 17 percentile	Minority percentile
Adaptivity index	0.24 (p=0.092)	**0.24 (p=0.018)**	**-0.325 (p=0.022)**	-0.176 (p=0.224)	**-0.327 (p=0.021)**	0.039 (p=0.785)	-0.132 (p=0.365)	-0.057 (p=0.697)
Resilience index	0.75 (p=0.60)	**0.34 (p=0.012)**	**-0.32 (p=0.019)**	-0.17 (p=0.220)	**-0.42 (p=0.002)**	0.13 (p=0.378)	-0.38 (p=0.086)	-0.18 (p=0.21)
Amplitude α (1st disruption)	0.17 (p=0.255)	**-0.35 (p=0.013)**	-0.013 (p=0.96)	-0.28 (p=0.076)	**0.28 (p=0.046)**	-0.090 (p=0.536)	**0.32 (p=0.028)**	-0.131 (p=0.369)
Amplitude α (2nd disruption)	0.164 (p=0.287)	**-0.25 (p=0.019)**	-0.001 (p=0.926)	-0.259 (p=0.089)	0.275 (p=0.070)	-0.080 (p=0.604)	**0.298 (p=0.049)**	-0.139 (p=0.365)

Major Take Aways

- 90% of states faced two consecutive disruptions.
- Secondary disruption tend to be longer and larger, with a lower disruption rate. This is a sign of good adaptability
- 50% of states didn't recover from the first disruption
- 87.8% states didn't recover from the second disruption

- Michigan and New York have the highest resilience scores
- Wyoming and Louisiana have the lowest resilience scores and negative adaptability indices.
- Asian populations demonstrated the highest levels of resilience, followed by White, Black and Hispanic groups having the least resilience.
- 86.6% of chronic disease treatment services and 100% of maternal services experienced two disruptions.
- Maternal care had lower resilience and more severe disruptions.

- Positive correlation between states' resilience index and physician abundance (0.34, P=0.012)
- Resilience has negative correlations with local poverty (-0.32 P=0.019) and unemployment (-0.42 P=0.002).
- Resilience indices are negatively correlated with state SVI (-0.46 P=0.001)
- Physician workforce abundance is key for healthcare resilience and adaptivity
- States with low physician abundance, high poverty, and unemployment are less resilient and less adaptive
- New resilience and adaptivity indices address limitations of existing indices

Acknowledgements

A big thank you to my coauthor Lu Zhong as well as my advisor Jianxi Gao for supporting this project at every step along the way. This project would never have worked out without their help. Thank you to Sen Pei as well for taking time to interpret results, providing a healthcare perspective, and editing the paper.

This project was funded by the COVID-19 Research Accelerator Grants (Bill & Melinda Gates Foundation)