Received: 4 May 2022 | Revised: 1 August 2022 | Accepted: 8 August 2022
DOI: 10.1002/lrh2.10337

RESEARCH REPORT

Learning Health Systems

Building local decision-making competencies during COVID-19: Accelerating the transition from learning healthcare systems to learning health communities

Rohit Ramaswamy[1] | Varun Ramaswamy[2] | Margaret Holly[3] | Sophia Bartels[4] | Paul Barach[5]

[1]Cincinnati Children's Hospital Medical Center, James M Anderson Center for Health Systems Excellence, Cincinnati, Ohio, USA
[2]Reach Labs, Emeryville, California, USA
[3]Department of Health Policy and Management, University of North Carolina at Chapel Hill Gillings School of Global Public Health, Chapel Hill, North Carolina, USA
[4]Department of Health Behavior, University of North Carolina at Chapel Hill Gillings School of Global Public Health, Chapel Hill, North Carolina, USA
[5]College of Population Health, Thomas Jefferson University, Philadelphia, Pennsylvania, USA

Correspondence
Rohit Ramaswamy, Cincinnati Children's Hospital Medical Center, James M Anderson Center for Health Systems Excellence, Cincinnati, OH 2518, USA.
Email: rohit.ramaswamy@cchmc.org

[Correction added on 28 September 2022, after first online publication: The title of the article was changed from "Transitioning from learning healthcare systems to learning health communities: Building decision-making competencies during COVID-19".]

Abstract

Introduction: The persisting and evolving COVID-19 pandemic has made apparent that no singular policy of mitigation at a regional, national or global level has achieved satisfactory and universally acceptable results. In the United States, carefully planned and executed pandemic policies have been neither effective nor popular and COVID-19 risk management decisions have been relegated to individual citizens and communities. In this paper, we argue that a more effective approach is to equip and strengthen community coalitions to become *local learning health communities* (LLHCs) that use data over time to make adaptive decisions that can optimize the equity and well-being in their communities.

Methods: We used data from the North Carolina (NC) county and zip code levels from May to August 2020 to demonstrate how a LLHC could use statistical process control (SPC) charts and simple statistical analysis to make local decisions about how to respond to COVID-19.

Results: We found many patterns of COVID-19 progression at the local (county and zip code) levels during the same time period within the state that were completely different from the aggregate NC state level data used for policy making.

Conclusions: Systematic approaches to learning from local data to support effective decisions have promise well beyond the current pandemic. These tools can help address other complex public health issues, and advance outcomes and equity. Building this capacity requires investment in data infrastructure and the strengthening of data competencies in community coalitions to better interpret data with limited need for advanced statistical expertise. Additional incentives that build trust, support data transparency, encourage truth-telling and promote meaningful teamwork are also critical. These must be carefully designed, contextually appropriate and multifaceted to motivate citizens to create and sustain an effective learning system that works for their communities.

KEYWORDS
adaptive decision-making, community learning system, community solutions, COVID-19

1 | INTRODUCTION

The COVID-19 pandemic was addressed with federal and state mandates in the United States.[1] When these localized mandates expired, before the rise of the Delta variant, there was little political appetite to reinstate them in spite of rising COVID-19 morbidity. As of May 2022 with the Omicron variant resulting in increased cases, mandates lifted when case counts were lower have not been revisited.[2] As many individuals in the United States celebrate freedom from restrictions, hundreds of people are still dying daily in the United States as of September 2022. Continuing concerns remain about the emergence of new variants and the possibility of a vaccine-resistant variant that could return society back to the early days of the pandemic.[3] Over the past two years, public fatigue, the unpredictable nature of the virus's mutation and spread, the pervasive misinformation from multiple sources, and contradictory public health messaging from experts have resulted in the reality where states and communities have little appetite for top-down measures.

As the pandemic has progressed, more and more decision-making responsibility has devolved to the county and municipality levels. The Center for Disease Control's (CDC) latest framework for monitoring and prevention (Figure 1) indicates the need for communities to apply local metrics and information about their risk factors (eg, congregate living locations, large gatherings, equity considerations, etc.) and optimize decisions that work best in their communities. Unfortunately, there is little guidance about how to implement this new framework and no evaluation tools to measure outcomes.

There are many examples of community coalitions leading effective COVID-19 responses and implementing real-time strategies as the pandemic progressed. These communities demonstrated that many coalitions have the intrinsic capability to learn and relearn, as they get better in managing uncertainty and responding to ongoing crises.[4] The Robert Wood Johnson Foundation Sentinel Community project[5] tracked the COVID-19 response in 9 out of its 29 communities and found that those that had established multi-sectoral collaborations between the government, non-profits and businesses sectors, that had a system for involving community members in decision-making and that had an operational equity plan were more effective at responding to the pandemic. However, even communities with these capabilities struggle with access to real-time data and to mobilize the knowledge and capacity to make rapid adaptive decisions. Most communities during the pandemic needed to make decisions using simple rules, to address political or social pressures. This resulted in decisions that were neither timely nor responsive. We argue in this paper that local authorities should recognize the need to prepare community leadership for future outbreaks, and consider using a dynamic risk management approach to making thoughtful, informed decisions about how best to protect their community without disruption of essential activities, social interaction and commerce.[6] There is an urgent need to create coalitions of diverse community stakeholders and to build their capacity to routinely use data to understand patterns of risk progression and vulnerability, and to identify local hotspots in their communities where immediate actions are required. Building capacity for these systems will enable communities to not only address the next phase of this pandemic but

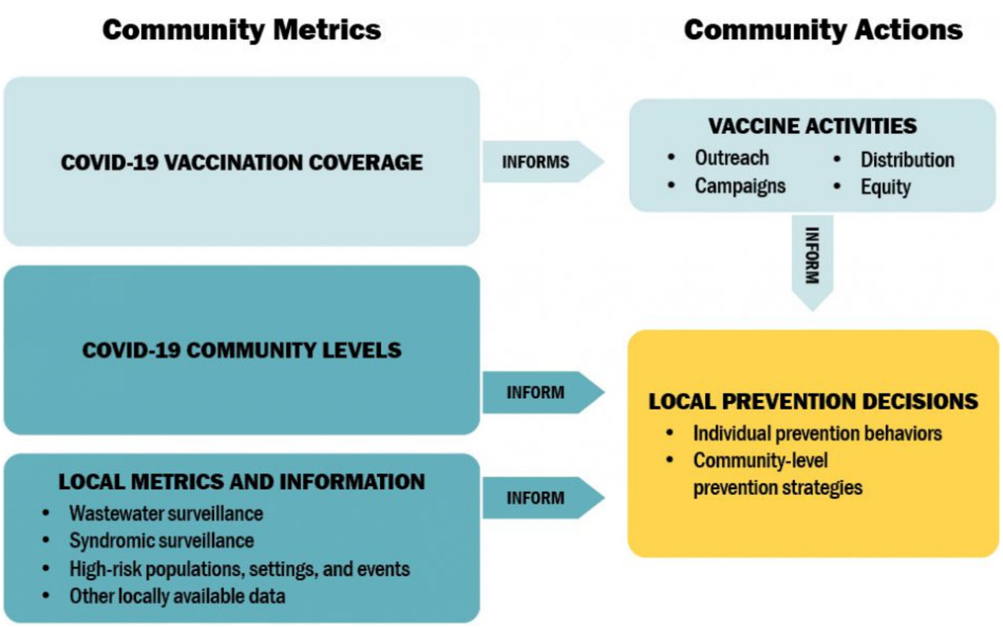

FIGURE 1 CDC guidelines for the use of community metrics for prevention decisions. https://www.cdc.gov/coronavirus/2019-ncov/science/science-briefs/indicators-monitoring-community-levels.html

also position them to better address other seemingly intractable public health challenges such as homelessness, mental health, racism, climate change, and addiction that affect the health and well-being of their community members. Joint decision making using data will go a long way toward developing and building the trust, respect and collaboration needed for policy coordination that ensures transparent and well-communicated decisions.

Healthcare has been successful in promoting a high-performance model that promotes the routine use of healthcare data to inform decision-making—the learning health system (LHS).[7] A LHS is defined as a system in which "science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the delivery process and new knowledge captured as an integral by-product of the delivery experience."[7] An effective LHS makes decisions informed by the most current and relevant scientific evidence and contextualizes it with local data.[8] Patients play a central role by cooperatively setting and shaping the LHS priorities for inquiry and action. Leaders actively solicit collaborations within and outside the health system and create incentives for advancing outcomes in the areas where improvement is perceived by the community to be most urgent.[8]

We propose an analogous decision making system at the community level that we call a *local learning health community* (LLHC). We define this community *as a multi-stakeholder partnership that uses the data infrastructure, analytical capability, culture, and incentives to routinely apply local data with the best available evidence to make decisions that improve the health, well-being, and equity outcomes for community members*. We apply a hypothetical example in which we show how a community can use routine and local COVID-19 per capita, case-count data to make effective decisions about mask mandates, business closures, or school attendance policies in a manner that facilitates compliance rather than polarization.

We present this paper to stimulate a discussion about the promise and challenges of building capacity and local competencies to better equip communities with an agile mindset, tools and data to optimize their health, well-being and equity during acute (e.g., pandemic), and chronic (e.g., homelessness) public health challenges.

2 | METHODS

2.1 | Setting

We imagine a county-level LLHC composed of stakeholders from schools, community organizations, health departments and hospitals. We assume that given the rapidly evolving nature of the pandemic, the LLHC members would convene routinely (eg, every two weeks) to review local data and assess this data in combination with relevant state and local variables. They would make decisions about the necessity and feasibility of strengthening or loosening COVID-19 related restrictions, providing just-in-time communications, or launching other community initiatives (e.g., centralized food pickup from restaurants) to balance safety needs and community well-being.

2.1.1 | Data requirements

We propose a dynamic risk management approach that regularly reviews data over time. To illustrate this approach, we use COVID-19 data from various counties in the State of North Carolina. We purposely extracted *six county-level per-capita case-count datasets of 28 days each* using data reported by the State of North Carolina from May 29 to August 20, 2020. Each dataset was selected to demonstrate a different pattern of local COVID-19 rate progression over time at the county level. We selected 28 days given the dynamic nature of the disease and because it seemed like a reasonable historical time frame suitable for review in bi-weekly LLHC meetings. We envisioned that the LLHC members would have access to a rolling 28-day sequence of data. We focused on the per-capita case counts because this data was easily available at the county level, and was the data used to determine county-level risks by the CDC until February 2022.[9] In practice, LLHCs will need to use a combination of other local data sources such as total case counts, deaths, number of hospitalizations, intensive care unit (ICU) bed occupancy, business closures or revenue, and community perceptions of well-being to make the best decisions about local risks in the community. We used one type of data just for illustration purposes.

2.1.2 | Data synthesis and analysis

Our data analysis approach is based on the assumption that the typical LLHC will not initially have sophisticated data analytics and visualization tools nor statistical expertise at their disposal and will need to make decisions using time plots, basic line-fitting techniques and other simple visual tools available in commercial spreadsheet software. However, this should neither be seen as an impediment to effective LLHC performance, nor as a prohibition on additional analysis. Up to a point, a more sophisticated data analytic capability can result in better information for decision-making, but in complex systems involving multiple stakeholders, the ability for advanced quantitative analysis does not necessarily lead to a deeper understanding of the dynamics of the system.[10]

Our goal is to show how LLHCs can generate collaborative insights from visual representation of data collected over time, recognizing that this data may be incomplete or inaccurate. Our approach draws on methods from the field of quality improvement that do this, with tools such as run charts or Statistical Process Control (SPC) charts. Run charts present process data in order to understand variation over time. Statistical Process Control (SPC) is defined as "*a branch of statistics that combines rigorous time series analysis methods with graphical presentation of data, often yielding insights into the data more quickly and in a way more understandable to lay decision-makers*."[11] SPC charts supplement run charts by using "3-sigma" limits. The formula for calculating these limits depends on the type of SPC chart, but overall, performance above and below these limits is likely to be the result of "special causes" not attributable to random variation.[12] The choice of SPC chart is determined by the type of data being analyzed. I-charts are used for individual measurements, X-bar- and

S-charts for average measurements of continuous data, P-charts for classification data, C- and U-charts for count and rate data. Ample guidance exists for selecting, constructing, and interpreting run and control charts in the literature, and these have been adapted for COVID-19 data.[13,14] Our examples of SPC charts are to demonstrate their feasibility by LLHCs to facilitate decision-making over time, but this paper is not a tutorial on the rigorous use of SPC methods. This is because these methods may not directly apply to COVID-19 spread that can alternate between periods of stability and exponential growth. In addition, daily data may not be available or accurate, or several days' statistics may be aggregated into a single day's totals. To account for these challenges, Perla et al[11] developed a "hybrid" control chart method that used a regression model to plot the center line for a SPC chart when COVID-19-related deaths were no longer stable over time, and adapted the traditional SPC rules to identify signals for non-random changes in the spread of the pandemic. Inkelas et al[15] and Parry et al[16] used this approach tools to demonstrate how SPC charts can provide valuable signals for the management and progression of the pandemic in Ireland and California. However, these studies involved applying a new and complex set of rules that have still not been widely tested and are likely to be overwhelming to most LLHC members. In our example, we maintain the combination of regression and SPC methods proposed by Perla but present a simpler, actionable approach. Specifically, our approach first recommends visual inspection of SPC chart data, and then suggests regression to explore potential special causes indicated by the charts even if the SPC rules are not met. While this may not represent a textbook application of SPC methods, we believe this approach is more responsive to real world data challenges and more useful for collaborative decision-making.

2.1.3 | Defining variables of interest

We assume that LLHCs are interested in using data to answer three basic questions about COVID-19 in their bi-weekly meetings:

1. How large and/or contagious is it?
2. How is it changing over time?
3. How is it distributed across relevant community strata (eg, geographic, socio-economic, demographic etc.)?

The following variables were used to provide the data to answer these questions:

Size: The size of the COVID-19 problem in the county is measured by the prevalence, defined as the average per-capita case count over the 28-day period and categorized as *low*, *moderate*, *substantial*, *and high* by adapting the original thresholds set by the CDC[9] as shown in Table 1. (Note, these CDC thresholds were changed in February 2022, but do not change our analytic approach.)

Change over time: Measured using three terms for common non-random patterns usually seen in SPC charts, though defined differently from standard SPC methods.

Trend: An upward or downward progression of per-capita case counts over the 28-day period detected through visual inspection by: (a) 7 consecutive points moving in the same direction OR (b) by fitting a regression line if the SPC rules are not met but the LLHC team feels that daily data is missing or inaccurate.

Spike: An unusual increase or decrease in the case count data in a particular day detected by a point outside the upper or lower control limits in a control chart.

Shift: A change in the mean per-capita case counts detected through visual inspection by: (a) 8 or more consecutive points on either side of the center line OR (b) by fitting a regression line if the SPC rules are not met but the LLHC team feels that daily data is missing or inaccurate.

Distribution: Measured by heterogeneity, which is the relative contribution of each zip code in a county to the total case counts on any given day. A small number of zip codes dominating the case counts over a period of time is *heterogeneous*, because there is variation in the way infection spreads within the county. High heterogeneity may indicate a localized super-spreader event or an outbreak within a high-risk long-term care living facility. Low heterogeneity may be a signal for community widespread illness. Clearly, these two scenarios have different implications for dynamic risk management and community control.

To explore patterns in the key variables described above, we plotted SPC charts of per-capita case counts using Laney's U-chart to account for over dispersion resulting from the large denominator (county population). We froze the centerline and upper and lower control limits after two weeks.

3 | RESULTS

3.1 | Sample scenarios and decisions

These examples represent different 28-day time periods and counties, and they are all patterns that actually occurred in North Carolina between the months of May and August 2020. This is neither an exhaustive list nor a list of the patterns that are the most important. Our intent is to demonstrate that the dynamics of a pandemic can

TABLE 1 Prevalence level definition of community transmission levels

Community transmission levels	Low transmission	Moderate transmission	Substantial transmission	High transmission
Total new cases per 100 000 persons in the past 28 days	0 to 9.99	10 to 49.99	50 to 99.99	≥100

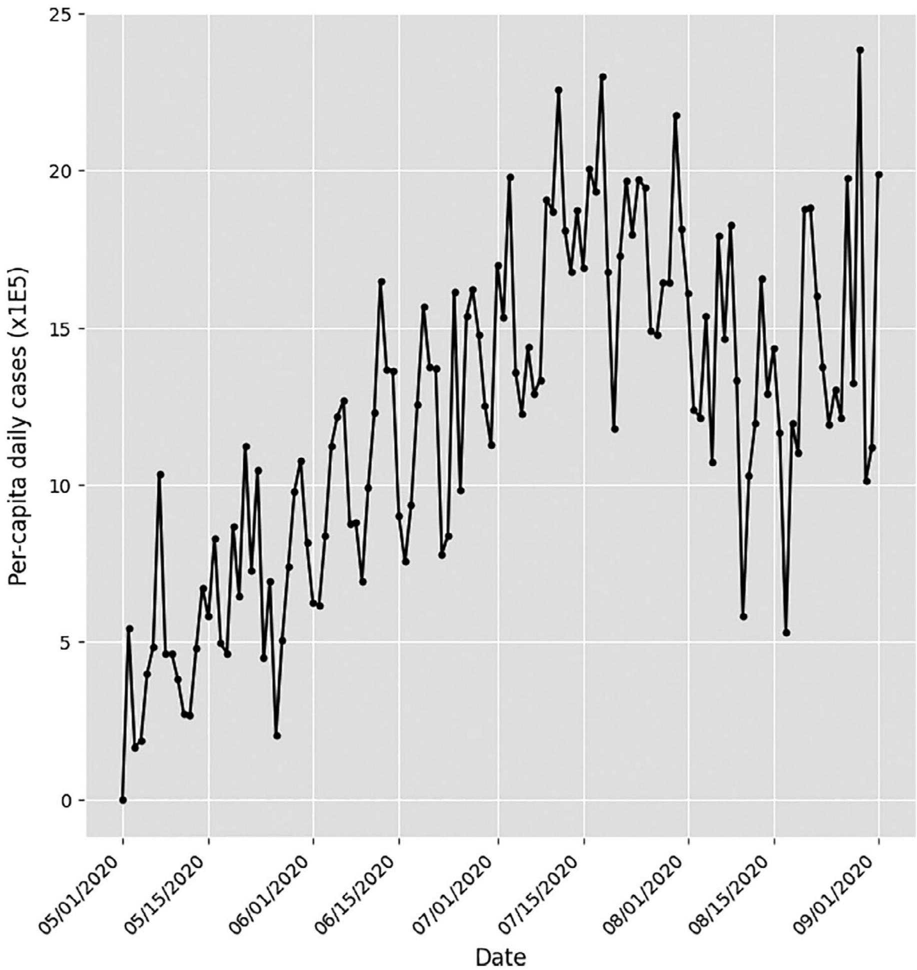

FIGURE 2 State aggregated COVID-19 cases per 100,000 inhabitants, May 1, 2020 to September 1, 2020

TABLE 2 County-level scenarios by data prevalence, trend, spike, shift and heterogeneity

Scenario	Prevalence	Trend	Spike	Shift	Heterogeneity	Figures
A1	High					Figure 3
A2	Low					Figure 4
B1	Substantial/High	Increasing				Figure 5
B2	Substantial/High	Decreasing				Figure 6
C1	Substantial/High		Multiple			Figure 7
C2	Substantial/High		Single			Figure 8
C1A	Substantial/High		Multiple		High	Figure 9
C2A	Substantial/High		Single		Low	Figure 10

vary significantly across counties and be quite different from aggregate state-level statistics. The state level data for this period is shown in Figure 2. Figures 3 to 10 show the county level scenarios that are summarized in Table 2.

3.1.1 | Scenarios A1 and A2: Stable progression at different levels of disease prevalence

These scenarios are demonstrated in the SPC charts in Figures 3 and 4. In these charts, none of the individual data points are outside the control limits nor is there an obvious trend or shift, indicating that the progression of the illness is stable. However, the prevalence is different, with County A1 showing a higher number of cases than County A2. The stable progression provides the opportunity for both counties to make planned decisions instead of having to urgently react in an ad hoc manner. For example, County A1 might communicate that current restrictions would remain in place until the case counts decrease to a certain level, but that no further restrictions are planned. County A2 might communicate a very different message and continue reducing restrictions unless the case counts increase beyond a certain

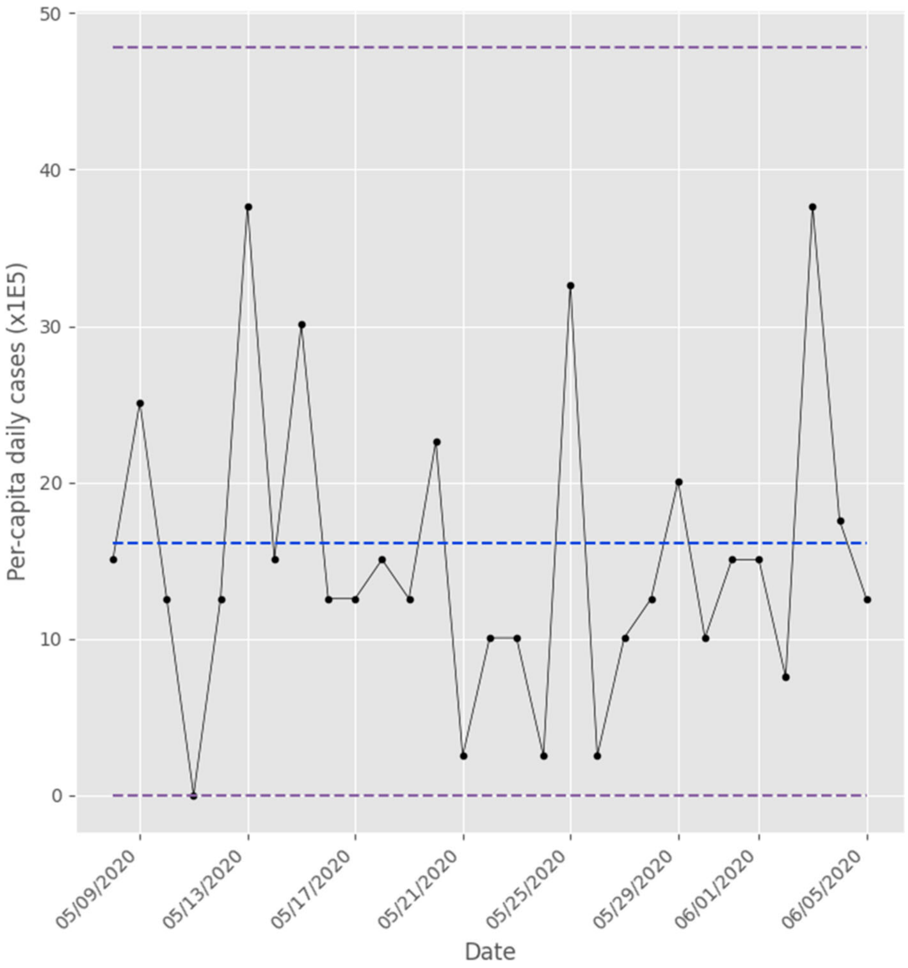

FIGURE 3 SPC chart of COVID-19 cases per 100,000 inhabitants. County A1, May 8, 2020 to June 5, 2020

level. Note that neither County A1 nor A2 would have reached a conclusion of stable progression by merely looking at the aggregate state-level data (Figure 2), which was trending up over the same 28-day period.

3.1.2 | Scenarios B1 and B2: Shifts and trends

Figures 5 and 6 demonstrate situations in two counties where the average prevalence is high but there are opposite trends, with cases increasing in County B1 and decreasing in County B2 over the same 28-day period. The SPC charts show evidence of special cause variation—specifically spikes and shifts. A regression line over this data (Figures 7 and 8) shows a statistically significant trend over the 28-day period. Augmenting analysis with the regression line provides LLHCs with a way of verifying patterns in the presence of inconsistent reporting of case counts. For example, a small change in the case counts reported on July 29th or July 31st in county B1 may result in the SPC rules for special cause variation not being met, but the regression line will still indicate a upward trend, which may be salient to the LLHC.

Unlike the previous scenarios, these are more dynamic situations that may require quick decision-making to mitigate or reinforce the data trends. For example, County B1 may immediately increase restrictions in an effort to limit further spread, while County B2, might deploy more effective messaging to encourage the community to continue compliance with present mask and distancing guidance and support the progress achieved to date.

3.1.3 | Scenarios C1 and C2: Spikes

Figures 9 and 10 show two scenarios with special cause variation in an otherwise stable process. County C1 has two instances of abnormal variation on May 18 and May 23 where the case counts are (respectively) 6.4- and 6.8-fold higher than the average. County C2 has a spike on May 20 and the case count is 4.4-fold higher than the average. These two spike patterns represent different processes of disease transmission that may be identified by looking at the data heterogeneity in Counties C1 and C2.

3.1.4 | Scenarios C1A and C2A: Heterogeneity

Figures 11 and 12 demonstrate the heterogeneity of the spike for Counties C1 and C2. These can be simply assessed by tabulating case counts by zip

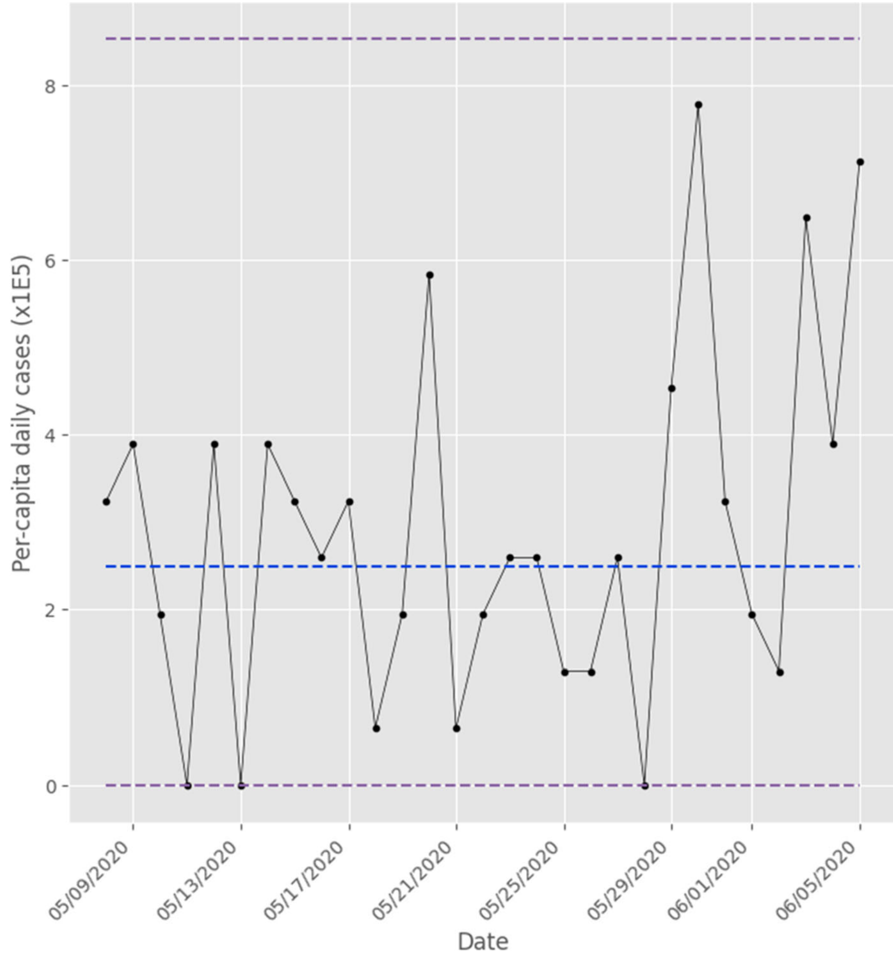

FIGURE 4 SPC chart of COVID-19 cases per 100,000 inhabitants. County A2, May 8, 2020 to June 5, 2020

code to determine if particular zip codes contribute disproportionately to the spike. These are shown in Tables 3 and 4. Funnel plots[17] can be used for a more sophisticated analysis. The limits in these plots are calculated in the same way as those in the U-chart, and data points outside the limits can be attributed to special causes. Figure 11 demonstrates this for the spike on the 23rd of May for County C1. The solid lines are the 3-sigma limits. Figure 11 is an example of *heterogeneous* disease transmission with one zip code (zip code 9), the most populous zip code making a significant contribution to case rates. The funnel plot in Figure 12 for County C2, by contrast, shows a *homogeneous* transmission, which cannot be primarily localized to a small number of zip codes within the county. Based on this data, County C1 may investigate super spreader events in zip code 9, while County C2 may choose to impose broad restrictions in the county since it is more difficult to pinpoint the exact source of the infection spike.

4 | DISCUSSION

Our North Carolina example is intended to demonstrate how regularly monitored COVID-19 patterns over time could provide a model for a learning health system through action that is predicated on incorporating dynamic information to support effective local decision-making and accrued wisdom. However, most counties are still a long way from having this capacity, even if the data is available. LLHCs need to have the *data infrastructure*, the *analytical capability*, *culture*, and *incentives* to be effective *by actively exploring and testing changes, collecting data to see if the changes are working, and thereby learning what does and does not work in that community*. We discuss these needs and the challenges in each of these areas as a call to action to strengthen community capacity.

4.1 | Creating a data infrastructure

LLHCs cannot be effective without timely and accurate access to local data. Throughout the pandemic, even daily case count data has not been universally available, information related to pandemic prevalence.[18] Other indicators of the impact of COVID-19 useful to LLHCs, such as business closings or local unemployment, are not routinely collected at a resolution level that allows for a reliable assessment of the local impacts of the pandemic.

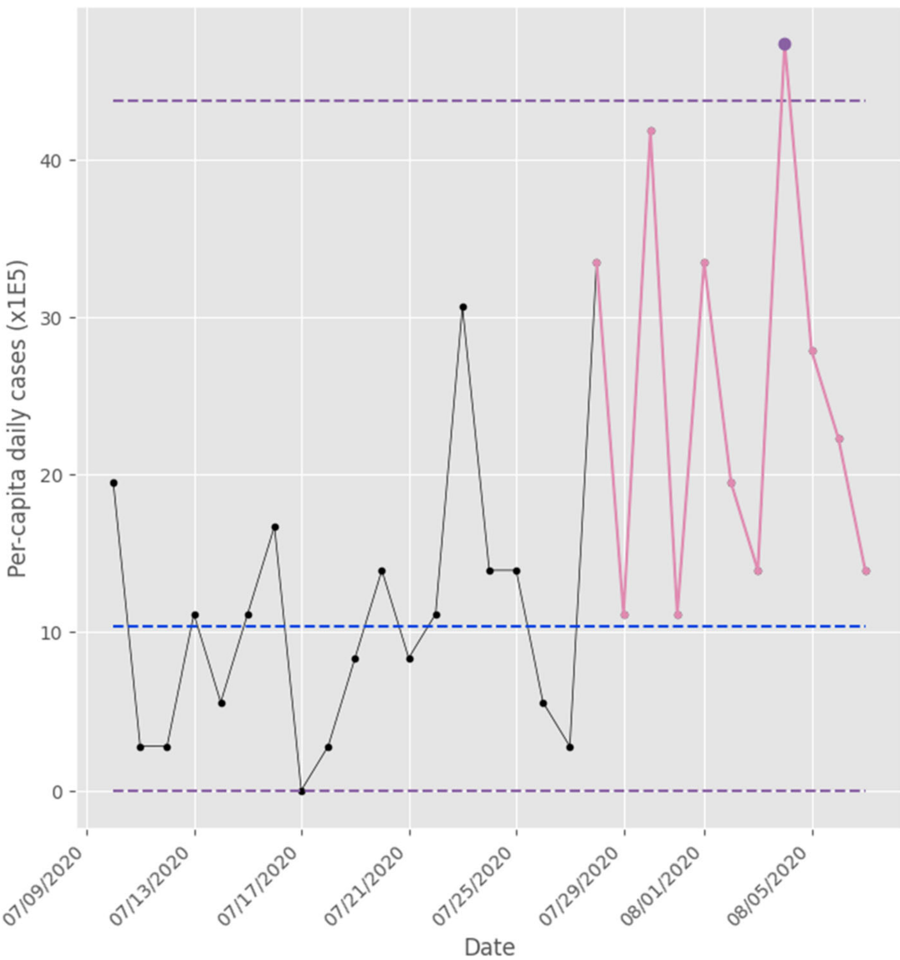

FIGURE 5 SPC chart of COVID-19 cases per 100,000 inhabitants. County B1, July 10, 2020 to August 7, 2020

The need for timely and relevant "bottom-up" data from multiple sources at the right level of granularity, shared in a transparent and truthful manner to support decision-making and action[19] has been acknowledged by public health leaders well before the pandemic.[20] However, there are few reported instances of data availability to support systematic and sustained learning system activities, other than a few academic research and demonstration projects. For example, the Community Learning Data-Driven Discovery process (CLD3), supported by Virginia Tech and the University of Iowa, collaborated with community leaders to extract, analyze, and present data in near real time to answer locally relevant questions about what was working and what was not in containing COVID-19.[20] This learning-through-action process brought together four different types of data: (a) designed (for research purposes); (b) administrative (routine data about local social and economic activities); (c) opportunity (eg, cell phone or GPS data); and (d) procedural (eg, court rulings or local policies) to provide a dynamically rich and multifaceted picture of the community's daily life. Another example was the integration of the emergency 911 call incidence data with EMS health records and their GPS data to better understand county-level patterns of 911 usage in Arlington County, Virginia.[20] These examples represent the kind of routine data access that is needed for daily and ongoing learning, course corrections and sustained improvement in the community's well-being.[21]

4.2 | Combining local data with established evidence

Collecting reliable, accurate and granular data and constructing visual representations are necessary but not sufficient over time for effective decision-making. The charts at the county level provide real-time information on the local progress of the pandemic. This data must be used in combination with state, national, and global data on case counts; the best available scientific evidence for understanding disease spread mechanisms and the effectiveness, and failure, of disease mitigation procedures to support dynamic decision-making about implementation and de-implementation strategies as local conditions change.[22] One example of community use of local data to identify vulnerable populations to target community outreach is the non-profit Parkland

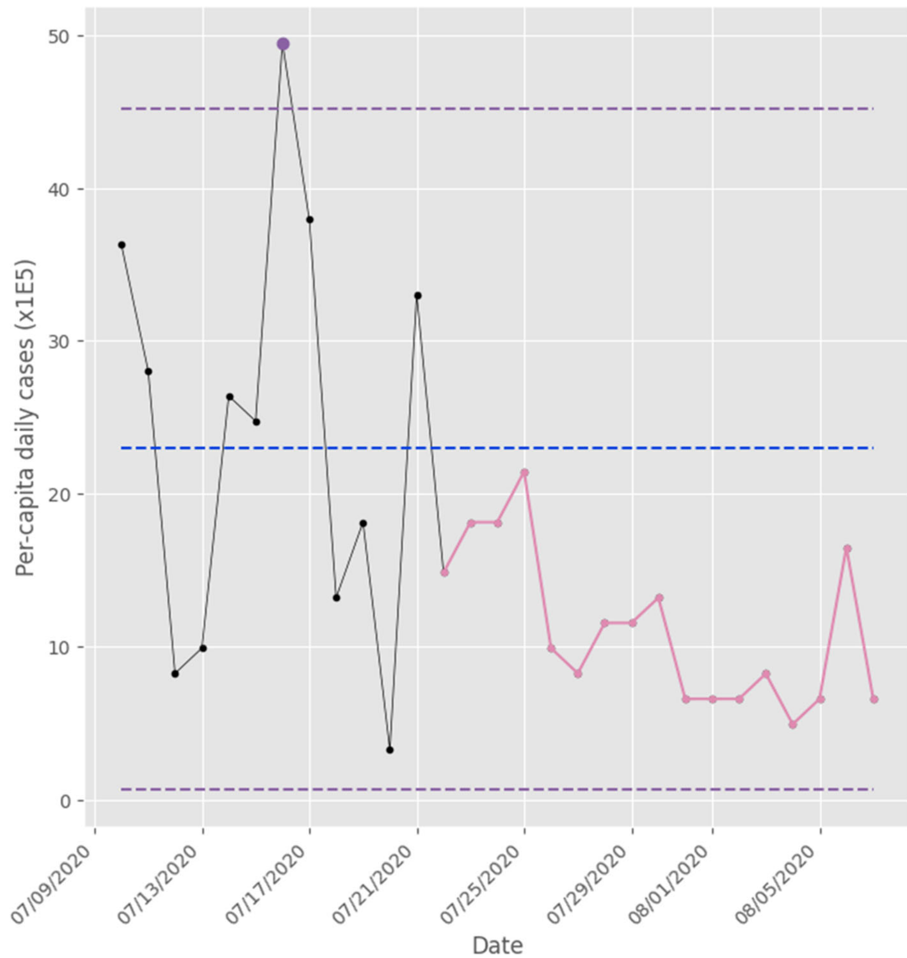

FIGURE 6 SPC chart of COVID-19 cases per 100,000 inhabitants. County B2, July 10, 2020 to August 7, 2020

Center for Clinical Innovation (PCCI) in Dallas, Texas. PCCI has led the creation of the Dallas Connected Community of Care (CCC) that brings together health systems, social service agencies and over a hundred community organizations to improve the well-being of Dallas residents. During COVID-19, PCCI used the CCC infrastructure to build geo-coded heat maps to identify neighborhood-level COVID-19 case hotspots that informed local decisions and the future location of new testing sites.[23]

Unfortunately, this type of a learning system in action has not been how most communities have made decisions in the United States during the pandemic. Mostly, public policies have been unidirectional and top-down, specifying when restrictions could be relaxed but providing little to no actionable guidance on when additional restrictions might be necessary despite further waves of infections with emerging variants. For example, the state of North Carolina embarked on a cumbersome multi-phase process of easing restrictions after the initial lockdown in March 2020 that created stress and uncertainty as the result of multiple postponements. When most restrictions were lifted in May 2021, the state had roughly 1000 daily cases. In January 2022, there were about 20 000 daily cases, but guidance on restrictions had not changed and was not reinstated.

4.3 | Creating a supportive culture of learning

The culture of a learning healthcare system has been described by the National Academy of Sciences as one that emphasizes leadership support, learning norms through actions, trust and collaboration.[24] These elements are also relevant to a LLHC that is more likely to be a coalition or alliance (identified as individuals with different interests working together to achieve a common goal) rather than a formal organization. Research on organizational culture and climate in community coalitions has demonstrated that a constructive culture for collaboration depends on coalition members having supportive relationships with mutual concerns for one another, the ability to resolve conflicts constructively and encourage one another.[25] At the same time, success depends on individual citizens' perceptions and abilities to freely participate in supporting and achieving the coalition's common goals.

Building a supportive learning culture within a LLHC requires coalition members to clearly demonstrate that they can make adaptive decisions that collectively represent the interests of the entire community even though each individual decision may not be optimal for every community stakeholder. This is essential given

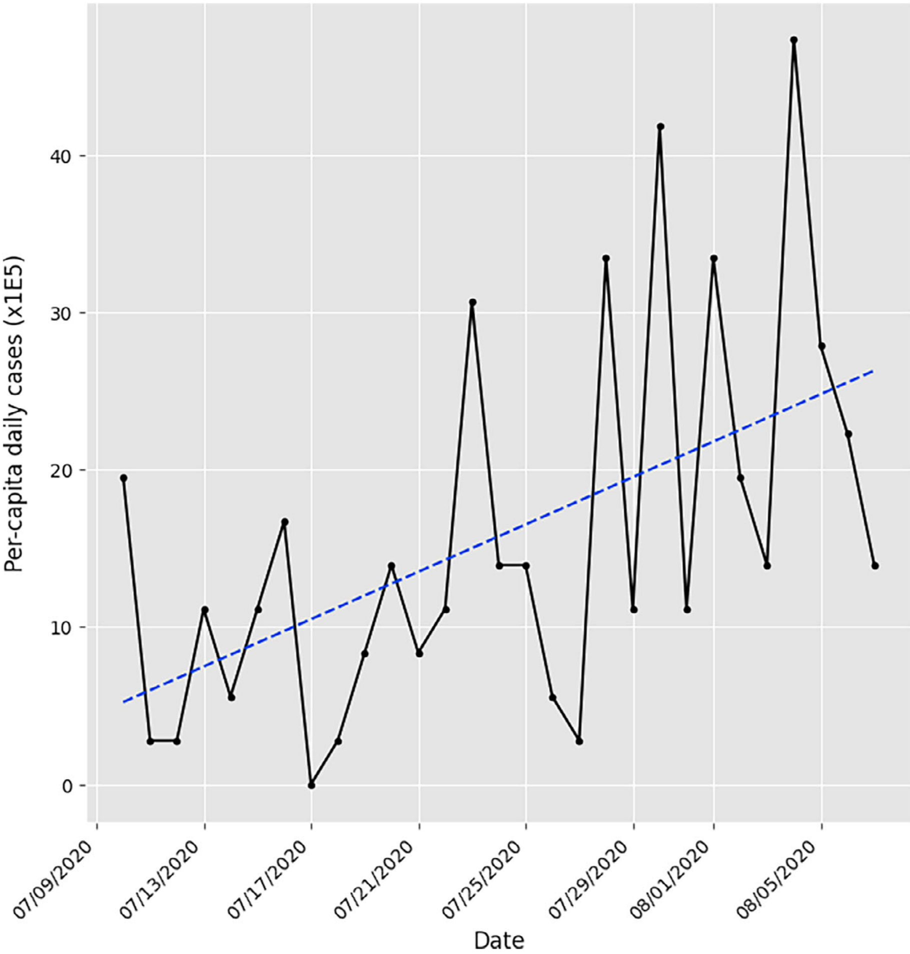

FIGURE 7 COVID-19 cases per 100,000 inhabitants with regression line. County B1, July 10, 2020 to August 7, 2020

the wide diversity of interests and priorities among large groups of stakeholders. The LLHC must be transparent about how it is learning and making decisions from the review of the data, and be confident enough about its internal cohesion to allow all stakeholders to see the data patterns in near real-time upon which decisions are made. This radical transparency is needed to build trust and combat misinformation.

4.4 | Building data-driven decision-making competencies

Building the science and the data infrastructures, and developing a collaborative and trusted organizational environment, are critical foundational steps in growing and sustaining a learning community culture. Ensuring that the individuals responsible for review of the data and decision-making have the skills, wisdom and confidence to do so is a key requirement. The statistical process control tools presented in this paper require contextual knowledge and judgment, and without mentored training can lead to "speculation, intuition, subjective assessments or the application of inappropriate statistical approaches."[11] Quality improvement training offered in healthcare settings,[26] with additional training on using these skills in a coalition or network settings are essential. The Robert Wood Johnson Foundation-funded SCALE project[27] and the Carnegie Foundation's Networked Improvement Communities are two excellent examples.[28]

4.5 | Incentivizing ongoing engagement

Creating an effective LLHC is challenging as there are intrinsic tensions between the need to include a diverse set of decision-makers, and the resultant heterogeneity in perspectives, local politics, priorities and loyalties. Even if individual representatives from different groups create a respectful and trusting organizational culture amongst themselves, they may be reluctant to lend their support to controversial group decisions if they feel that these could be viewed unfavorably (e.g., such as with imposing lockdowns) by their constituents or the media. To address this, one of the explicit goals of LLHCs should be to build trust broadly within the community about the importance of collective use of data to bring about change.[29] Enhancing the visual presentations of data described in this paper with storytelling approaches can help explain what the data means in context, and gain support and trust for decisions made from the data.[30]

Balancing individual considerations (eg, emotional needs) as well as the community and the environmental context in which people live

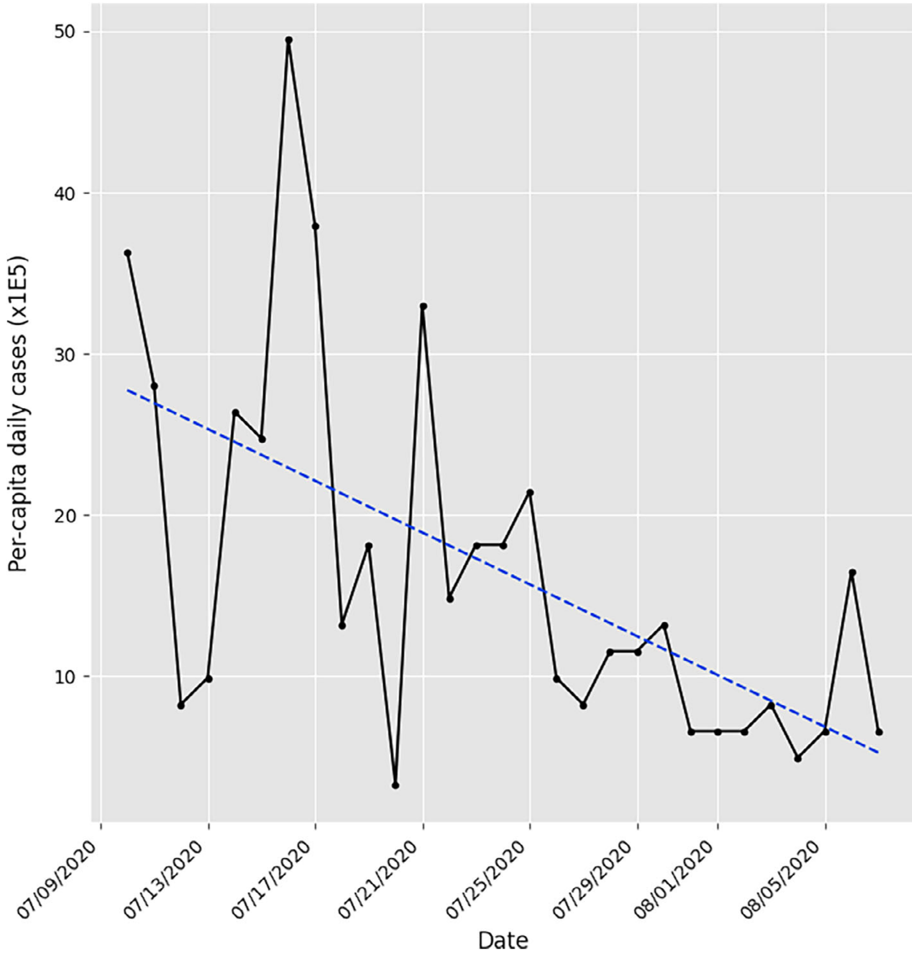

FIGURE 8 COVID-19 cases per 100,000 inhabitants with regression line. County B2, July 10, 2020 to August 7, 2020

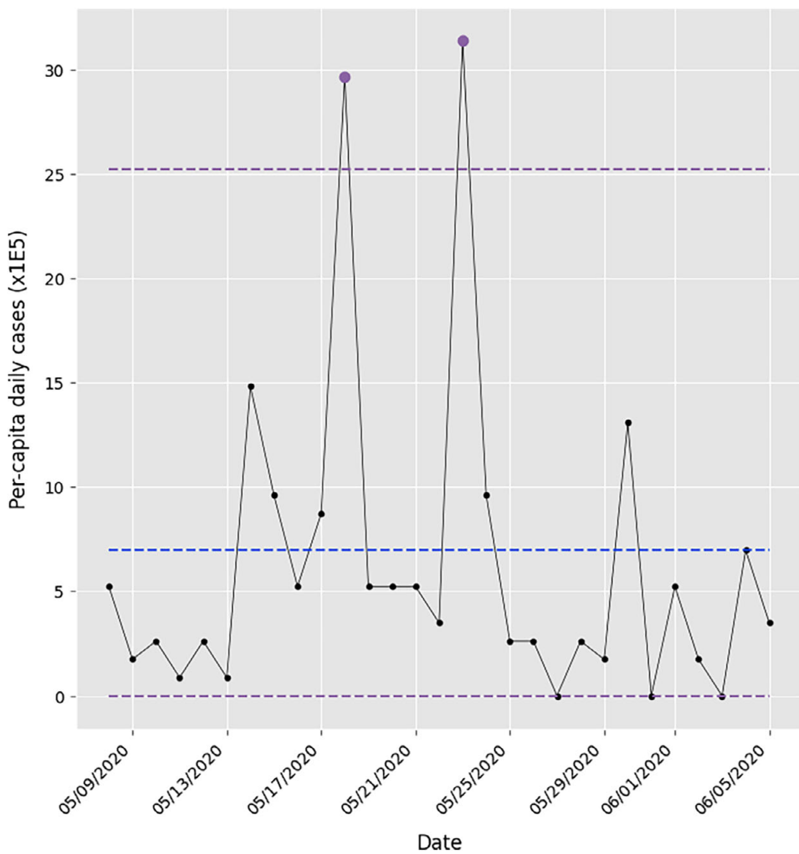

FIGURE 9 SPC chart of COVID-19 cases per 100,000 inhabitants. County C1, May 8, 2020 to June 5, 2020

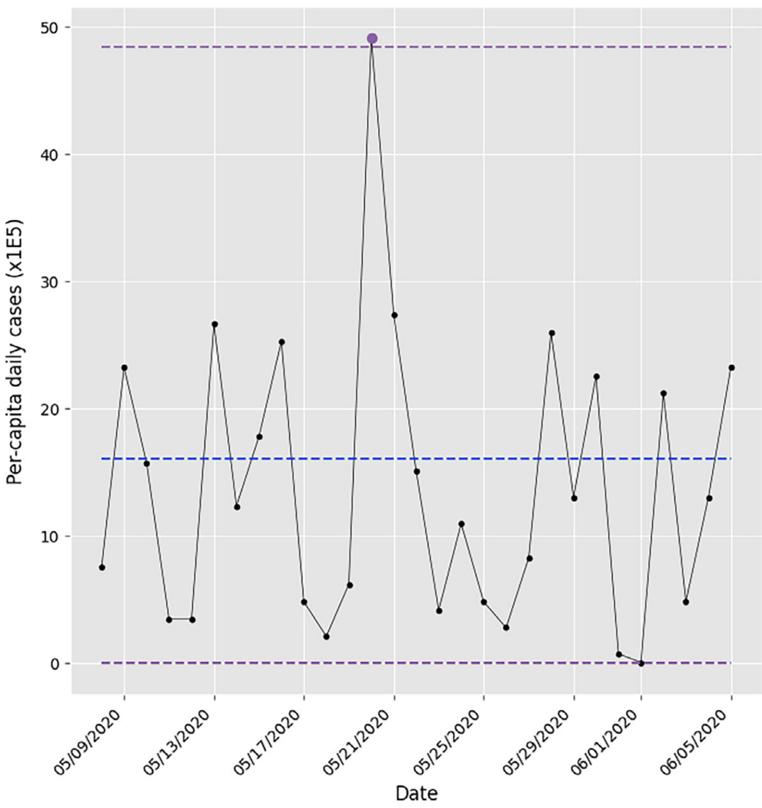

FIGURE 10 SPC chart of COVID-19 cases per 100,000 inhabitants. County C2, May 8, 2020 to June 5, 2020

TABLE 3 COVID-19 cases per 100,000 inhabitants by zip code. County C1, May 23, 2020

ZIP code	Cases per 100k population	County population
1	0	328
2	0	2274
3	0	2384
4	0	905
5	0	7474
6	0	25 868
7	0	0
8	30	28 926
9	70	38 009
10	0	8427

TABLE 4 COVID-19 cases per 100,000 inhabitants by zip code. County C2, May 20, 2020

Zip code	Cases per 100k population	County population
1	9	10 738
2	3	3224
3	7	38 517
4	0	14 944
5	0	15 170
6	0	2241
7	13	7085
8	0	15 254
9	0	155
10	23	13 036
11	0	7713
12	0	12 414
13	16	6068

is key. The incentives to motivate participation may need to focus on solutions targeted to individual members or their constituents. Studies about the motivations for participation in coalitions[31-33] indicate that opportunities for individual empowerment such as influence, recognition and advancing personal agendas are likely to be motivators for participation, and that the most active participants are those for whom the personal benefits to participate outweigh the social costs.[34] At the same time, for LLHCs to be effective, it is important to understand who in the community is suffering, struggling or thriving[35] so that decision-makers can develop a response that focuses on the well-being of the most vulnerable. These tensions reinforce our conclusion that here are no simple solutions to incentivize community decision-makers to engage in a LLHC framework. Incentives need to be carefully designed, contextually appropriate and multifaceted to motivate the formation and sustainment of a learning community system. Equity and justice considerations should be primary considerations for membership in the LLHC. Principles drawn from Design Justice[36] can provide guidance on how to design and communicate incentives to ensure that those most affected are willing and able to participate in the decision-making process.

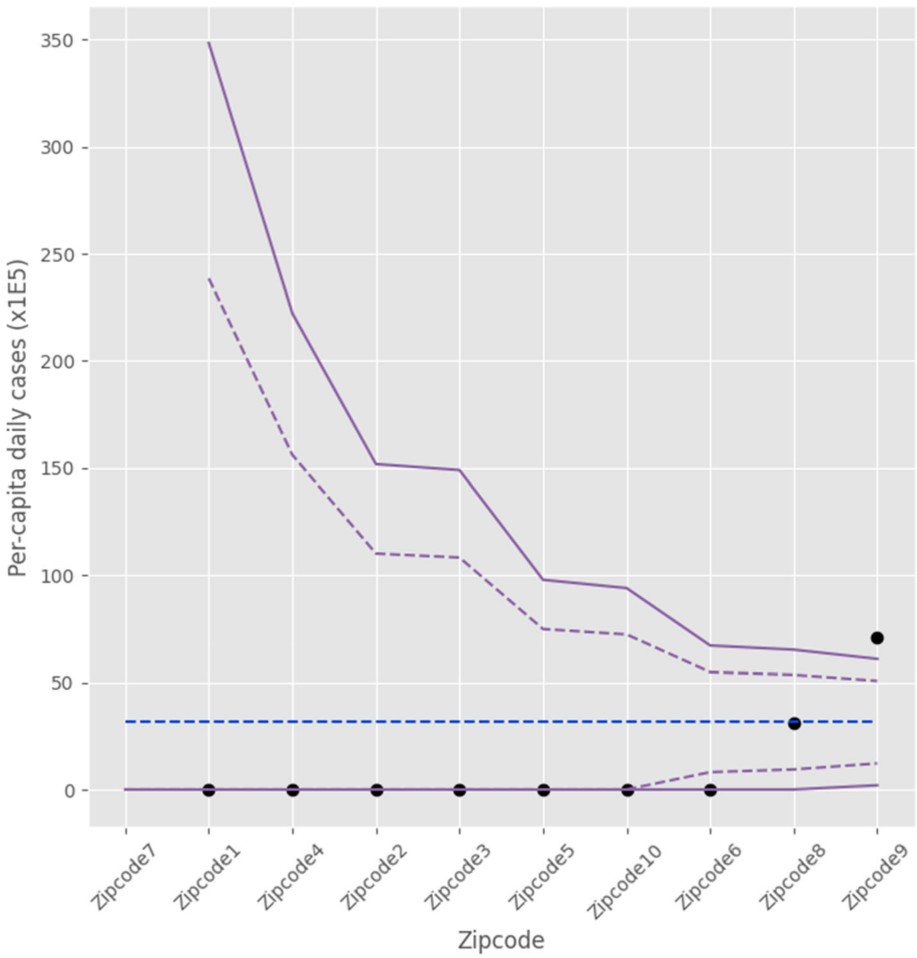

FIGURE 11 Funnel Plot, County C1, May 23, 2020. The solid lines are 3-sigma limits

4.6 | Limitations of our model

The study has several limitations and must be interpreted in the context of its exploratory design. First, we used one type of data (case counts) during one phase of the pandemic (early, when it was still progressing) to demonstrate the misalignment between state and local data. It is quite possible that other data more directly linked to outcomes (e.g., hospitalizations or deaths), or collected during a different time (e.g., after vaccinations were available) or in a different state (e.g., more urban) could have demonstrated that decisions taken by the state were also applicable locally. Second, we selected data from 2020 because this was the year when there were few safeguards against the pandemic, and when a reliable risk management approach was most critical and most politically challenging. Other studies have demonstrated variation in outcomes during this period in other geographies and contexts (eg, variation in deaths across zip codes in New York City and across hospitals), reinforcing our argument for the importance of local adaptive decision-making.[37,38] Replicating our example in other settings and other time frames would add to the strength of our findings and recommendations. Third, the data patterns we highlighted and the potential actions were speculations and it is very possible that community groups might prioritize other patterns and take other actions. Fourth, a participatory co-design approach with community stakeholders would be needed to extend our hypothetical example into practice. Finally, our study reflects the context and distinct constraints of the impact of COVID-19 on decision making in U.S. communities, which might differ from other countries' community systems and limit its generalizability.

5 | CONCLUSIONS AND FUTURE PERSPECTIVES

We applied data from the early days of the COVID-19 pandemic in North Carolina to illustrate that there was significant heterogeneity in the manner that the pandemic manifested itself at the local level during state mandates. The macro-level decisions (eg, made by the state government) using aggregate data did not reflect the situation at the micro-county level. There is an increasing recognition as the pandemic has progressed that local decision-making is the only effective way to manage the uncertainty and disease spread and its health system impacts.

Effective strategies are needed to build new local competencies. Most reported community responses have been unsystematic, highly

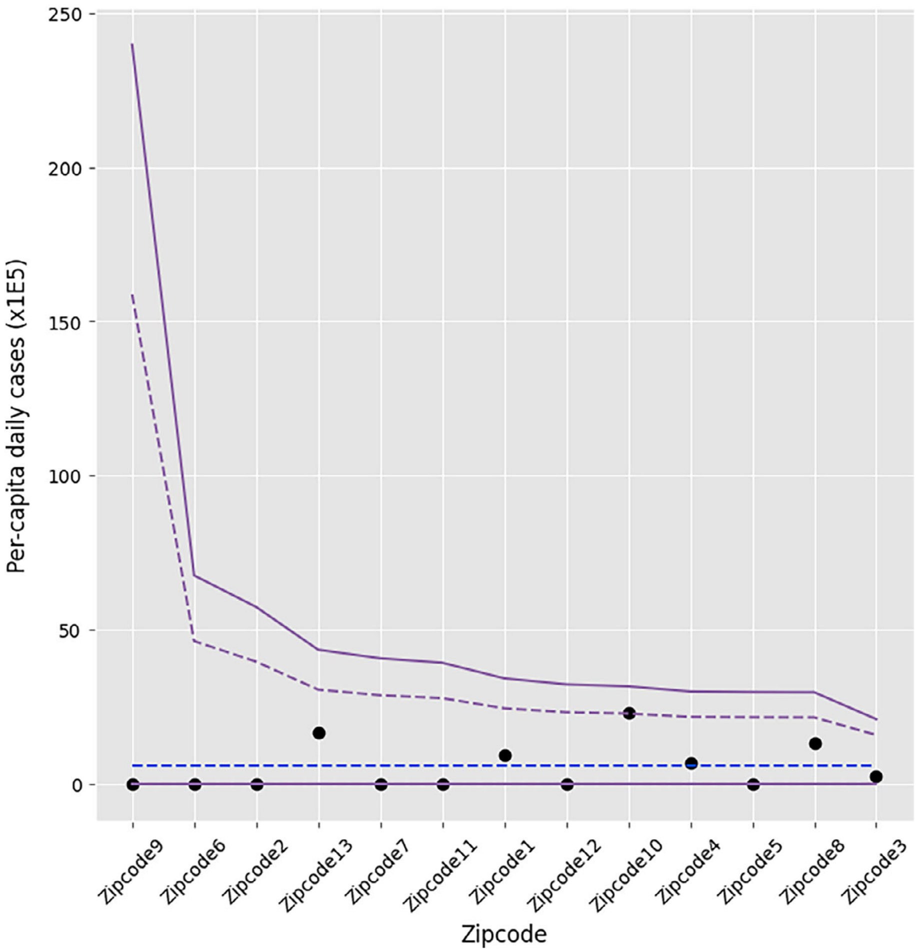

FIGURE 12 Funnel Plot, County C2, May 20, 2020. The solid lines are 3-sigma limits

variable and arbitrary (see, for example, Lochmiller describing the varied responses of five rural school superintendents in the same state).[39] Trust in public health officials and the information they provide is greatly eroded which is essential for the public uptake of preventative strategies to reduce the transmission of COVID-19. This alarming lack of community preparedness has greatly diminished trust in public officials, and is already having deleterious effects with the emergence of more dangerous variants as well as other health care emergencies.[40,41]

We propose an innovative organizational structure, the LLHC modeled after a Learning Health System, as a mechanism to bring together a coalition of diverse stakeholders to be trained, trusted and incentivized to effectively apply local data to make timely and responsive decisions that are best suited for their community. We have demonstrated that if data on key variables of interest are reliably available, the systematic review of data collected over time is feasible for county-level decision-makers to make cogent and entrusting decisions on their own, and that the analysis can be accomplished using commonly available software. These learned competencies go well beyond just COVID-19 progression and management, and are critical for addressing the many complex public health problems that our communities face.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

ORCID

Rohit Ramaswamy https://orcid.org/0000-0003-3410-4441

REFERENCES

1. NCSL. State Action on Coronavirus (COVID-19). https://www.ncsl.org/research/health/state-action-on-coronavirus-covid-19.aspx. Published 2022. Accessed March 25, 2022.
2. USA Today. Hawaii will become last state in nation to drop its mask mandate on March 26. Published March 8, 2022. Accessed April 13, 2022.
3. WHO. Statement on Omicron sublineage BA.2. https://www.who.int/news/item/22-02-2022-statement-on-omicron-sublineage-ba.2. Published 2022. Accessed April 13, 2022.
4. Michener L, Aguilar-Gaxiola S, Alberti PM, et al. Engaging with communities - lessons (re)learned from COVID-19. *Prev Chronic Dis*. 2020;17:E65.
5. Robert Wood Johnson Foundation. https://www.rwjf.org/en/library/interactives/covid-19-community-response--emerging-themes-across-sentinel-communities.html
6. Friedberg MK, Barach P. A dynamic risk management approach to reduce harm in hypertrophic cardiomyopathy. *Prog Pediatr Cardiol*. 2018;49:12-17.
7. Roundtable on Value & Science-Driven Health Care. *The Roundtable*. Washington, DC: Institute of Medicine; 2012.

8. AHRQ. About Learning Health Systems. https://www.ahrq.gov/learning-health-systems/about.html. Published 2019. Accessed March 25, 2022.
9. CDC. COVID-19 Community Levels. https://www.cdc.gov/coronavirus/2019-ncov/science/community-levels.html. Published 2022. Accessed March 25, 2022.
10. Greenhalgh T, Papoutsi C. Studying complexity in health services research: desperately seeking an overdue paradigm shift. *BMC Med*. 2018;16(1):95.
11. Perla RJ, Provost SM, Parry GJ, Little K, Provost LP. Understanding variation in reported COVID-19 deaths with a novel Shewhart chart application. *Int J Qual Health Care*. 2021;33(1):mzaa069.
12. Provost LP, Murray S. *The Health Care Data Guide: Learning from Data for Improvement*. 2nd ed. Hoboken, NJ: John Wiley & Sons; 2022.
13. Benneyan JC, Lloyd RC, Plsek PE. Statistical process control as a tool for research and healthcare improvement. *Qual Saf Health Care*. 2003;12(6):458.
14. Lloyd R. Understanding variation with Shewhart charts. *Quality Health Care: A Guide to Developing and Using Indicators*. 2nd ed. Burlington, MA: Jones & Bartlett Learning; 2019.
15. Inkelas M, Blair C, Furukawa D, et al. Using control charts to understand community variation in COVID-19. *PLoS One*. 2021;16(4):e0248500.
16. Parry G, Provost LP, Provost SM, Little K, Perla RJ. A hybrid Shewhart chart for visualizing and learning from epidemic data. *Int J Qual Health Care*. 2021;33(4).
17. Sterne JAC, Sutton AJ, Ioannidis JPA, et al. Recommendations for examining and interpreting funnel plot asymmetry in meta-analyses of randomised controlled trials. *BMJ*. 2011;343:d4002. doi:10.1136/bmj.d400
18. Bauer W. *Here's why Nebraska isn't Showing up on National COVID Case Maps*. Nebraska Public Media; 2021.
19. DeSalvo KB, Wang YC, Harris A, Auerbach J, Koo D, O'Carroll P. Public health 3.0: a call to action for public health to meet the challenges of the 21st century. *Prev Chronic Dis*. 2017;14:E78.
20. Keller S, Lancaster V, Shipp S. Building capacity for data-driven governance: creating a new Foundation for Democracy. *Stat Public Policy*. 2017;4(1):1-11.
21. Cech TG, Spaulding TJ, Cazier JA. Data competence maturity: developing data-driven decision making. *J Res Innov Teach Learn*. 2018;11(2):139-158.
22. Walsh-Bailey C, Tsai E, Tabak RG, et al. A scoping review of de-implementation frameworks and models. *Implement Sci*. 2021;16(1):100.
23. Kosel KC, Nash DB. *Connected Communities of Care in Times of Crisis*. NEJM Catalyst; 2020. https://catalyst.nejm.org
24. Medicine Io. *The Learning Healthcare System: Workshop Summary*. Washington, DC: The National Academies Press; 2007.
25. Wichinsky L, Thomlison B, Pennell J. Exploring organizational culture and climate in community coalitions. *Community Dev*. 2012;43(2):133-146.
26. Worsley C, Webb S, Vaux E. Training healthcare professionals in quality improvement. *Future Hosp J*. 2016;3(3):207-210.
27. Reid A, Abraczinskas M, Scott V, et al. Using collaborative coalition processes to advance community health, well-being, and equity: a multiple–case study analysis from a National Community Transformation Initiative. *Health Educ Behav*. 2019;46(1_suppl):100S-109S.
28. Networked Improvement Community Design Learning Lab. Carnegie Foundation. https://www.carnegiefoundation.org/engage-with-us/professional-learning-opportunities/learning-lab/. Accessed April 14, 2022.
29. Cranston J. Relational trust: The glue that binds a professional learning community. *Alberta J Educ Res*. 2011;57(1):59-72.
30. Muneoka S, Browne C. Social work in action: Hā Kūpuna: telling stories of challenge and resilience through data. *Hawaii J Health Soc Welf*. 2019;78(10):324-325.
31. Wells R, Ward AJ, Feinberg M, Alexander JA. What motivates people to participate more in community-based coalitions? *Am J Community Psychol*. 2008;42(1–2):94-104.
32. Lasker RD, Weiss ES. Broadening participation in community problem solving: a multidisciplinary model to support collaborative practice and research. *J Urban Health*. 2003;80(1):14-47. discussion 48–60.
33. Prestby JE, Wandersman A. An empirical exploration of a framework of organizational viability: maintaining block organizations. *J Appl Behav Sci*. 1985;21(3):287-305.
34. Prestby JE, Wandersman A, Florin P, Rich RC, Chavis D. *Benefits, costs, incentive management and participation in voluntary organizations: a means to understanding and promoting empowerment*. New York, NY: Plenum Publishing Corporation; 1990:117-149.
35. Riley C, Herrin J, Lam V, et al. Trends and geographical variation in population thriving, struggling and suffering across the USA, 2008–2017: a retrospective repeated cross-sectional study. *BMJ Open*. 2021;11(7):e043375. doi:10.1136/bmjopen-2020-043375
36. Costanza-Chock S. *Design Justice: Community-Led Practices to Build the Worlds we Need*. Cambridge, MA: MIT Press; 2020.
37. Lieberman-Cribbin W, Alpert N, Flores R, Taioli E. A risk index for COVID-19 severity is associated with COVID-19 mortality in New York City. *BMC Public Health*. 2021;21(1):1452.
38. Churpek MM, Gupta S, Spicer AB, et al. Hospital-level variation in death for critically ill patients with COVID-19. *Am J Respir Crit Care Med*. 2021;204(403–411):403-411.
39. Lochmiller CR. Rural Superintendents' responses to COVID-19: navigating local control during a public health crisis. *Front Edu*. 2021;6.
40. Henderson J, Ward PR, Tonkin E, et al. Developing and maintaining public trust during and post-COVID-19: can we apply a model developed for responding to food scares? *Front Public Health*. 2020;8:369.
41. Pollard MS, Davis LM. *Decline in Trust in the Centers for Disease Control and Prevention during the COVID-19 Pandemic*. Santa Monica, CA: RAND Corporation; 2021.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Ramaswamy R, Ramaswamy V, Holly M, Bartels S, Barach P. Building local decision-making competencies during COVID-19: Accelerating the transition from learning healthcare systems to learning health communities. *Learn Health Sys*. 2022;e10337. doi:10.1002/lrh2.10337