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Data-driven COVID-19 policy is more effective than a one-size-fits-all approach

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The latest COVID-19 guidelines from the Centers for Disease Control and Prevention (CDC) discount the best data sources and rely too heavily on outdated, one-size-fits-all decision rules. Instead, the CDC should recommend data-driven guidelines, which are more accurate, adaptable, transparent about implicit tradeoffs, and tailored to the relevant context.

The Centers for Disease Control and Prevention (CDC) recently updated its COVID-19 guidelines in a stated effort to reduce unnecessary quarantine and disruption to daily life.[1] These are important goals because everyone is weary of the ongoing pandemic. However, in trying to achieve these aims, the CDC discounts the best data sources and relies too heavily on outdated, one-size-fits-all guidance. This risks leading the US to accept an unnecessarily and unsustainably high level of COVID-19 transmission, together with the disruption from illness, growing disability rates, and accumulating deaths that entail. We should implement a more sophisticated approach.

The CDC should use data-driven guidelines that are up-to-date with the current scientific evidence, harness the best available data for decision-making, and offer a more tailored approach to managing the pandemic. Put simply, data-driven guidelines are more accurate, more adaptable to changing conditions, and more transparent about implicit tradeoffs than the fixed decision rules used in the current guidelines. A data-driven approach enables health officials and the general public to judiciously balance tradeoffs to slow transmission while also reducing economic and social costs.

Admittedly, no data source is perfect. But when it comes to the three key pieces of information needed to make decisions about COVID-19 precautions, the CDC should encourage the use of high-quality data rather than favoring simple but often inadequate decision rules: (1) the CDC should recommend rapid antigen tests to determine the length of isolation rather than relying on symptoms or duration of infection,[2] (2) the CDC should consider the full spectrum of potential health impacts of COVID-19 infection including mild illness and disability due to long COVID-19 rather than focusing narrowly on acute cases,[3] and (3) the CDC should

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recommend precautions based on wastewater monitoring and routine surveillance testing in addition to basing them on CDC Community Levels, which are poorly predictive of both acute cases and transmission risk.[4]

Advantages of rapid antigen tests over symptom-based decision rules

Rapid antigen tests remain the most accurate and reliable tool available to determine when someone is infectious and guide decisions around the duration of isolation. They enable a tailored approach by providing data to warrant isolation only as long as someone remains infectious, thereby reducing disruption both from further COVID-19 transmission and from unnecessary isolation. Pilarowski et al. (2021) found that the Binax-CoV2 rapid antigen tests have a sensitivity of 93.3% and specificity of 99.9% compared to PCR testing.[2] The CDC's own website notes that rapid antigen tests have "comparable sensitivity to laboratory-based NAATs when viral load in the specimen is high and the person is likely to be most contagious."[5] The sensitivity and specificity of rapid antigen tests are even higher for serial testing when two or more tests are administered 24–48 h apart.[6] Rapid antigen tests are easy to administer and widely available, though the cost may be prohibitively high for many.

A data-driven approach would recommend rapid antigen testing as the best option for determining the duration of isolation while also providing symptom- or duration-based guidance for when rapid antigen tests are unavailable. This is consistent with the principle that those who are infectious should be isolating when possible to slow transmission and not engaging in daily life.

By contrast, the sensitivity and specificity of CDC's symptom-based guidance are lower because symptoms are poorly correlated with infectiousness.[2] Additionally, fixed decision rules such as a one-size-fits-all 5-day isolation guideline can quickly and unpredictably become outdated. For example, there is evidence that the duration of infectiousness is longer for the Omicron variant than for the Delta variant. One recent study found that approximately half of Omicron cases had a duration of infectiousness of 8 days or longer from symptom onset.[7] Simulation studies suggest that focusing on people with symptoms is unlikely to be sufficient to control ongoing spread.[8]

Though the CDC provides sound guidance for how to use serial rapid antigen testing to end required masking for people with COVID–19, it stops short of recommending rapid antigen testing over the 5-day isolation rule, even when tests are available.[9] This framing contradicts the scientific rationale for isolation and may also undermine confidence in the usefulness of rapid antigen tests. This is a step backwards given the current evidence. A data-forward approach would encourage the use of rapid antigen tests when available, which builds an understanding of their strengths and limitations while stimulating demand for them.

Advantages of considering the full spectrum of health outcomes of COVID-19 infection

The CDC should consider the full spectrum of health effects from COVID-19 infection rather than considering only "medically significant illness," which leads to short-sighted and biased decision making.[1] A continued focus on severe illness, hospitalization, and death is warranted. But the CDC should also consider the health costs of mild illness that include not only discomfort and disruption during the acute stage but also a risk of developing post-COVID-19 condition, commonly known as long COVID, which is defined as having symptoms that last for at least 2 months following a probable or confirmed SARS-CoV-2 infection.[10]

A growing body of evidence demonstrates that the health burden of long COVID is substantial, even following a mild initial infection, though the precise prevalence remains unclear. For example, a study of users of the Veterans Health Administration (VHA) found long COVID prevalence to be 4.1% among non-hospitalized cases relative to a control group with no known COVID-19 infection and 15.8% among hospitalized cases,[11] whereas a recent systematic review and meta-analysis found the prevalence of post-COVID-19 condition to be 54% of hospitalized cases and 34% of non-hospitalized cases.[10] Long COVID sufferers may experience a degree of disability that inhibits their employability and/or engagement in daily activities. CDC guidelines that do not fully take this serious health risk into account will lead to far worse population health outcomes.

A consideration of the overall health burden of COVID-19 is necessary for optimal decision-making. Health policy generally uses the quality-adjusted life year (QALY) to inform decision making because it is designed to capture the full burden of potential health effects, from the least serious to the most serious.[12] The burden of COVID-19 morbidity may seem trivial but it adds up: one study estimated that at least 18% of the health burden of COVID-19 comes from morbidity rather than mortality.[3] Focusing on mortality to the exclusion of morbidity provides a skewed perception of the health costs of COVID-19, which results in worse decision making.

It is undeniably part of the CDC's mission to consider the full spectrum of health effects. For example, the CDC currently provides guidance on managing minor morbidity from seasonal allergies and asthma.[13] Yet the CDC COVID-19 guidance remains rooted in the early stages of the pandemic when the immediate focus was on avoiding overwhelming hospital systems and the risks of long COVID were not yet apparent.[1] The latest CDC guidance appears to minimize the burden of mild illness and the risk of long COVID. A more forward-looking, data-driven mindset would recognize the need to stem the rise in long-term disability that may strain health care systems well into the future.

Advantages of wastewater monitoring and routine surveillance to track transmission rates

The CDC should recommend precautions based on wastewater monitoring and routine surveillance testing data in addition to CDC Community Levels.[14] Wastewater monitoring and routine surveillance rapid antigen testing provide the most reliable and accurate data for tracking transmission rates in real-time. These two tools are currently broadly available though they require continued investment to be universally accessible. Wastewater monitoring is the optimal data source because it has near universal population coverage, does not require behavior changes to collect samples, provides real-time data, and is easily understood by the general population (unlike, for example, test positivity). Routine surveillance rapid antigen testing—regularly rapid antigen testing a small sample of the population—can help with early detection of local outbreaks. Any risk of unnecessary disruption from false positives can be virtually eliminated via serial testing.[2]

By contrast, the CDC overlooks both wastewater monitoring and routine surveillance testing data in favor of its COVID-19 Community Levels index to inform the implementation of precautions to slow transmission.[14] There are three shortcomings to this approach. First, Community Levels are designed to prevent "medically significant illness" and minimize the burden on the healthcare system, rather than reducing the risk of transmission, which is the relevant metric for avoiding infection, disruption due to illness, and/or the risk of long COVID.[4] Second, Community Levels are not even a strong predictor of medically significant illness: the CDC reports that they only predict 30% of the variation in county death rates.[4] Third, Community Levels are a lagging indicator because they have only three levels (low, medium and high) and cover a large geographic area. Local transmission rates must therefore rise substantially to trigger a change in Community Levels, leading to missed opportunities for timely action.

Wastewater monitoring data is excluded from the calculation of COVID-19 Community Levels because it does not have nationwide coverage.[4] Again, this is a serious limitation of one-size-fits-all metrics that necessitate defaulting to the lowest common denominator rather than tailoring guidelines to local data. Including wastewater monitoring data where possible would not only leverage this valuable source of information but also encourage greater investment in nationwide coverage.

Put simply, the CDC's Community Levels are a poor predictor of both transmission and the health burden of COVID-19. They focus on a limited objective, exclude high-quality data sources, and mask early warning signs of surges. We have data and tools to do better.

Key advantages of data-driven guidelines over fixed decision rules

A shift toward data-driven guidelines represents a step forward for the CDC that will provide broad benefits not only for the management of the ongoing pandemic but also for other areas of public health policy.

First, data-driven guidelines lead to superior outcomes overall because they balance costs and benefits better than fixed decision rules. This helps ensure that the recommended actions are tailored directly to the relevant context. Relying on high-quality data improves the predictability of the outcomes, which builds trust in both the guidance and the underlying science. For example, relying on rapid antigen tests rather than a 5-day isolation rule will reduce the likelihood of onward transmission while also limiting unnecessary isolation.

Second, data-driven guidelines adapt to new situations better than fixed rules. They rely directly on the relevant data rather than a proxy and are therefore more likely to remain valid when conditions change. This also means data-driven guidelines are forward-looking and do not need to be updated as often. For example, relying on rapid antigen tests rather than a five-day rule remains effective even when the correlation between symptoms and infectiousness shifts due to new variants or changes in vaccination coverage.

Third, data-driven guidelines are transparent in that they use scientific principles to draw a direct link between recommended actions and the circumstances that call for them. This stands in contrast to fixed rules that are based on unknown tradeoffs. Data-driven guidelines are therefore easier to explain and justify to the general public compared to fixed decision rules that can seem arbitrary. For example, relying on rapid antigen tests links isolation directly to the likelihood of infectiousness, whereas a 5-day rule is based on implicit assumptions. The transparency of data-driven approaches also helps insulate the CDC from undue political interference.

Fourth, data-driven approaches educate the public about the underlying science and empower everyone to apply data-driven tools to all areas of pandemic decision-making. For example, encouraging the use of rapid antigen tests rather than a 5-day rule for isolation improves the public's understanding of the strengths and limitations of rapid antigen tests, which enables their use more broadly.

We face a lot of uncertainty about the future: take-up of boosters is slow and new variants risk evading existing immunity.[15] In this environment, one-size-fits-all guidance can quickly and unpredictably become outdated, leading to an unnecessarily and unacceptably high level of COVID-19 transmission and disruption. The CDC's latest guidelines, with their narrow focus, reliance on lower-quality data, and use of fixed decision rules, represent a retreat from the reality that we have the tools to implement a more sophisticated approach to managing the pandemic.

It's time for the CDC to adapt for the next phase of the pandemic. Shifting the focus toward evidence-based, data-driven guidelines is the best strategy for adjusting in real-time to a constantly changing pandemic landscape. A data-driven approach to public health policy is not only more effective in addressing current challenges, but also more forward-looking. It leverages the best available tools while investing in them to prepare us for the challenges ahead.

DECLARATION OF INTERESTS

The author has no interests to declare.

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