Universal Shelter-in-Place Versus Advanced Automated Contact Tracing and Targeted Isolation: A Case for 21st-Century Technologies for SARS-CoV-2 and Future Pandemics

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Abstract

Objective: To model and compare effect of digital contact tracing versus shelter-in-place on severe acute respiratory syndrome − coronavirus 2 (SARS-CoV-2) spread.

Methods: Using a classical epidemiologic framework and parameters estimated from literature published between February 1, 2020, and May 25, 2020, we modeled two non-pharmacologic interventions — shelter-in-place and digital contact tracing — to curb spread of SARS-CoV-2. For contact tracing, we assumed an advanced automated contact tracing (AACT) application that sends alerts to individuals advising self-isolation based on individual exposure profile. Model parameters included percentage population ordered to shelter-in-place, adoption rate of AACT, and percentage individuals who appropriately follow recommendations. Under influence of these variables, the number of individuals infected, exposed, and isolated were estimated.

Results: Without any intervention, a high rate of infection (>10 million) with early peak is predicted. Shelter-in-place results in rapid decline in infection rate at the expense of impacting a large population segment. The AACT model achieves reduction in infected and exposed individuals similar to shelter-in-place without impacting a large number of individuals. For example, a 50% AACT adoption rate mimics a shelter-in-place order for 40% of the population and results in a greater than 90% decrease in peak number of infections. However, as compared to shelter-in-place, with AACT significantly fewer individuals would be isolated.

Conclusion: Wide adoption of digital contact tracing can mitigate infection spread similar to universal shelter-in-place, but with considerably fewer individuals isolated.

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In the absence of a vaccine or cure, non-pharmacological interventions are critical to reducing spread of severe acute respiratory syndrome − coronavirus-2 (SARS-CoV-2). This is primarily accomplished through containment and isolation, such as the universal shelter-in-place order used in many cities and states across the United States.

The need for such orders is due to the exponential growth of cases that occur during an outbreak, which generally needs to be countered by a fast, coordinated, and widespread response. Transmission of SARS-CoV-2 during asymptomatic infectious periods further complicates this response.[1] Asymptomatic infected individuals may not see the need to self-isolate, and it is difficult for public health infrastructure to identify such cases and enforce isolation during this period.[2]

Contact tracing has the potential to limit spread of infectious diseases. This has been proven in epidemics such as SARS, bird flu, Middle East respiratory syndrome, and others.[3,4] Traditional contact tracing suffers from the problem of scalability as they are based on phone interviews and record keeping. On the other hand, current technologies permit constant tracking of individuals and locations via mobile phones, global positioning systems, WiFi, and Bluetooth. A system that leverages these technologies to track and record movement of individuals, and monitor proximity to others for potential exposure, can help overcome difficulties posed by manual contact tracing. Many app-based systems — for example, Private Kit: SafePaths,[5] Covid Symptom Tracker,[6] and the Apple/Google collaborative contact tracing venture[7] — are currently being tested. Such advanced automated contact tracing (AACT) systems, which could infer exposure risk and propagate warnings to people at risk, may help curb disease spread by facilitating targeted self-isolation rather than universal mandates such as shelter-in-place.

In this paper, we compare universal shelter-in-place with targeted self-isolation envisioned in AACT. With available data pertaining to SARS-CoV-2 we model strategies for the United States and estimate societal burden. Our work builds on a prior model.[8] Materials and source code are available at Github.[9]

METHODS

Our disease model is based on the susceptible, exposed, infected, recovered (SEIR) model assuming a constant susceptible population.[8,10,11] Using these data, two separate models were created — AACT and universal shelter-in-place. In both, computational methods were used to determine impact in terms of infected individuals and proportion of population impacted by isolation/quarantine orders. Modeling and study was performed based on data regarding the pandemic published between February 1, 2020, and May 25, 2020.

Initial Variables

For the model, we assumed the following: T_{inc} = incubation period (~5.1 days),[12] T_{lat} = latency period before development of symptoms (~ 11.5 days),[12] and basic $R_0 = 3.02$.[13] Preliminary death rate $\mu = 0.057$ (with case fatality ratio of 1.5018%, as estimated by recent global data).[14] Further details are summarized in Supplemental Material (available online at http://www.mayoclinicproceedings.org).

Several variables were considered in model development and summarized in Figure 1. Compartments included: S (susceptible individuals), E (exposed to infection, unclear symptomatic conditions, and potentially infectious), I (infected, confirmed symptomatic, and infectious), R (Recovered, immune from further infection), and D (death due to SARS-CoV-2). In AACT, an additional compartment Sq (traced contacts who are exposed and under self-isolation) was used whereas for shelter-in-place, the compartment Q (individuals isolated through universal enforcement measures) was used. The basic difference between the models is that isolation/quarantine is based solely on exposure history in AACT, whereas isolation orders apply to the entire population in universal shelter-in-place.

Advanced, Automated Contact Tracing Model

We assumed that through the AACT app (Figure 1, at left), it is possible to inform exposed (asymptomatic/noninfected) individuals of exposure risk. Once warned, they may self-isolate and prevent second-order spreading. Therefore, self-isolated contacts will depend on penetrance p of the AACT app in infected and exposed populations. The equations and details used to build the model are summarized in the Supplemental Material (available online at http://www.mayoclinicproceedings.org). Two key elements that fall into AACT include percentage of individuals adopting (ie, downloading) the app, and percentage who self-isolate in response to an exposure alert. Our model assumes that for the fraction of individuals who heed the warning, there is no transmission of SARS-CoV-2 from exposed individuals to other susceptible individuals.

Universal Shelter-in-Place Model

Measures that limit public gatherings or mandate full lockdown uniformly impact the susceptible population. They are successful

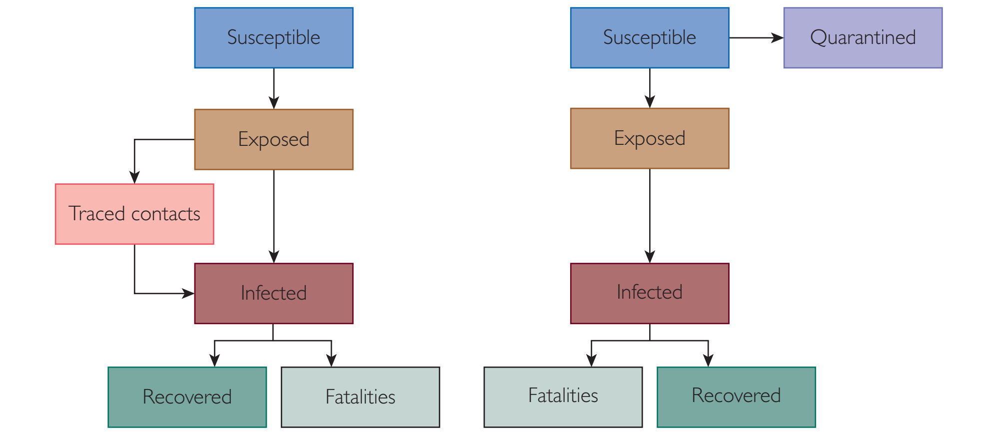

FIGURE 1. Overview of model transitions used to simulate advanced automated contact tracing based targeted isolation (left) and universal shelter-in-place (right).

in isolating a fraction of the population, with the unquarantined transitioning through exposure, infection, recovery, or death. Such measures, depending on duration of enforcement (assumed to be constant in our model), are independent of percentage of infected population or percentage exposed. The key variable considered is percentage of population that is under shelter-in-place orders. For example, if 100% of the population (including essential personnel) is ordered to stay at home, nobody will be allowed outside and disease transmission will be halted. In real life, percentages far below 100% would be expected. In the current model, we assume shelter-in-place measures will be released after 50 days (Figure 1, at right).

Software and Modeling

All models were created using R (version 3.6.1, 2019), and Tidyverse (2017) and Stats packages (https://cran.r-project.org). All graphs were created using R.

RESULTS

Both models agree with each other when adoption of digital contact tracing and universal shelter-in-place mandate are close to zero (ie, p=0 and g=0, where p is adoption rate of AACT and g is percentage population ordered to shelter-in-place) (Figure 2). Without any control measures, our models suggest a high rate of SARS-CoV-2 infection (Table).

Both shelter-in-place and AACT achieve reductions in number of infected cases (Table). For example, with 20% adoption and 100% compliance, AACT would lower peak number of infected individuals by 49% and cumulative deaths by 23%. Enforcing shelter-in-place measures for 30% of the population would almost completely halt SARS-CoV-2 spread. However, such a measure would quarantine, at peak, more than 71 million people as opposed to isolating approximately 12 million in AACT to achieve similar reduction. As can be seen in Figures 2E and 2F, the main difference between the models is in societal burden imposed in terms of number of individuals expected to be quarantined or isolated.

Both adoption of AACT (ie, how many people downloaded the application), and percentage of people who heed the advice of the application (ie, self-isolate when a warning is issued) are critical to success of digital contact tracing. For example, if 100% of users respond to an exposure alert by self-isolating, lower adoption rates would be sufficient; conversely, lower response rates to alerts require a higher adoption rate in the general population. Figure 3A and the Supplemental Video (available online at http://www.mayoclinicproceedings.org) summarize this tradeoff for different

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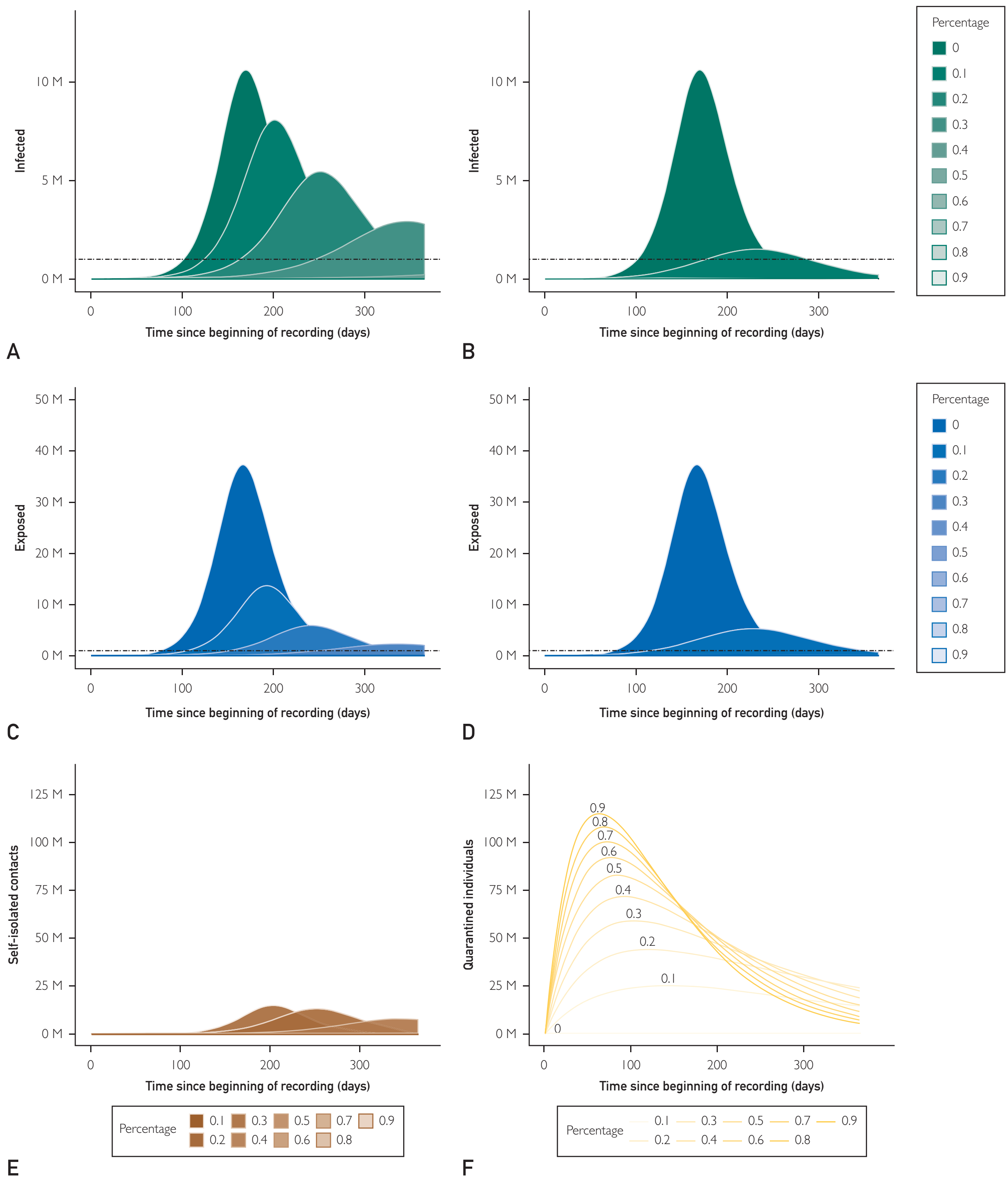

FIGURE 2. Comparison of impact of advanced automated contact tracing (left) and shelter-in-place (right) in terms of number infected (A vs B), exposed (C vs D), and size of impacted population (E vs F). Dashed lines show maximum intensive care unit capacity for the United States.

TABLE. Estimated Disease Burden (Measured in Number of People Infected and Number of Fatalities at Pandemic Peak) and Societal Burden of Implementing Isolation (Measured in Number of People Affected)[a]

AACT				Universal shelter-in-place			
% Adoption of AACT system	Peak infected (in thousands)	Peak deaths	Peak self-quarantined (in thousands)	% Population under enforcement	Peak infected (in thousands)	Peak deaths	Quarantined (in thousands)
0	10,623	91,384	0	0	10,623	91,384	0
10	8070	83,324	14,948	10	1522	25,276	25,218
20	5450	70,118	13,248	20	38	675	44,058
30	2919	33,472	7899	30	8	113	59,056
40	214	2150	620	40	5	45	71,635
50	5	123	12	50	5	25	82,480
60	5	30	11	60	5	17	92,004
70	5	16	11	70	5	12	100,485
80	5	11	11	80	5	10	108,120
90	5	8	11	90	5	8	115,050

[a]AACT = advanced automated contact tracing.

adoption rates and user response rates over the course of the pandemic. Figure 3B offers a graphic of the percentage of the population impacted at peak as a function of the application adoption rate and user response rate.

DISCUSSION

SARS-CoV-2 is a global pandemic with variable approaches implemented to address its spread. Past experience with Spanish flu, SARS, and Middle East respiratory syndrome shows that interventions that limit contact, increase social distance, and reduce exposure risk are essential to "flattening the curve." Governments around the world have instituted isolation measures such as shelter-in-place or stay-at-home to achieve these goals.

However, universal isolation measures disrupt the fabric of society by hindering social interactions, limiting support for people with disabilities, and exacerbating mental health challenges. On the economic front, such measures decrease productivity, disrupt supply chains, and unsettle financial markets. In fact, recent invocation of "aegrescit medendo" in the US political discourse refers to the pain and suffering associated with these measures.

Contact tracing is routinely used for controlling infectious diseases.[15] Stochastic mathematical models, and past experience in the swine flu pandemic of 2009 and Ebola outbreak of 2014, have shown contact tracing can reduce R_0 by as much as 90%.[15] Preliminary studies have shown that, accounting for heterogeneity of social interactions, it may be sufficient to trace 36 contacts per infected person to reduce R_0 for SARS-CoV-2 from 3.11 to 0.21.[16]

Contact tracing is not novel, but the exponential nature of the ever-enlarging tree of exposures makes conventional manual contact tracing cumbersome.[17] Especially in later stages of an epidemic, an automated or semi-automated solution is required to be scalable — a solution that we have dubbed AACT. In this paper we compared universal containment against AACT, a version of automated contact tracing that is able to recursively enumerate all persons who came into contact with an infected person. AACT envisions a system that can instantaneously trace individuals in the exposure network of an index case, and issue warnings to everyone in this network.

AACT coupled with targeted self-isolation has several advantages over universal containment measures. The obvious advantage is society can still function with a select number of individuals in isolation. This approach also attempts to halt disease spread at the earliest time point after identification of infected

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individuals. AACT enables first- or second-order exposures to isolate and limit further disease spread even when not showing symptoms. Therefore, it enables remedies that may work in the pre-symptomatic stage. From the point of view of public health officials, AACT may provide an early estimate of exposure risk and disease burden that the health care system will face. Such information can be used to increase readiness. It may also facilitate patient surveillance and streamline flow and distribution through the health care system. Finally, with the envisioned pandemic control system, AACT and targeted isolation can be quickly deployed at first signs of an outbreak with the goal of limiting disease spread without resorting to measures such as shelter-in-place.

Our models show that with targeted digital contact tracing it is feasible to reduce disease spread while impacting fewer individuals. Success of AACT hinges not only on user adoption, but also on users' willingness to abide by recommendations. If individuals do not universally respond to alerts by self-isolating, impact of AACT on disease spread would be minimal. Similarly, at lower adoption rates, exposures could not be tracked, thus undercutting benefits. AACT would be most successful with universal adoption and universal response. Nonetheless, we have shown even at modest adoption and response rates, it is feasible to significantly mitigate disease spread while limiting number of individuals isolated.

In a real-world context, several countries have started introducing AACT to help reopen societies and mitigate continued disease spread. Data from Singapore suggested that digital contact tracing carries higher sensitivity and specificity for identifying contacts than traditional approaches.[18] The data on the efficacy of these measures, however, is limited and requires rigorous analysis before conclusions from models can be made. Thus, recommendations have been proposed to achieve this and hopefully will result in more rigorous analysis.[19] The need for real-world context is especially important given that several factors, including technological literacy, infrastructure, governmental regulations, user adoption based

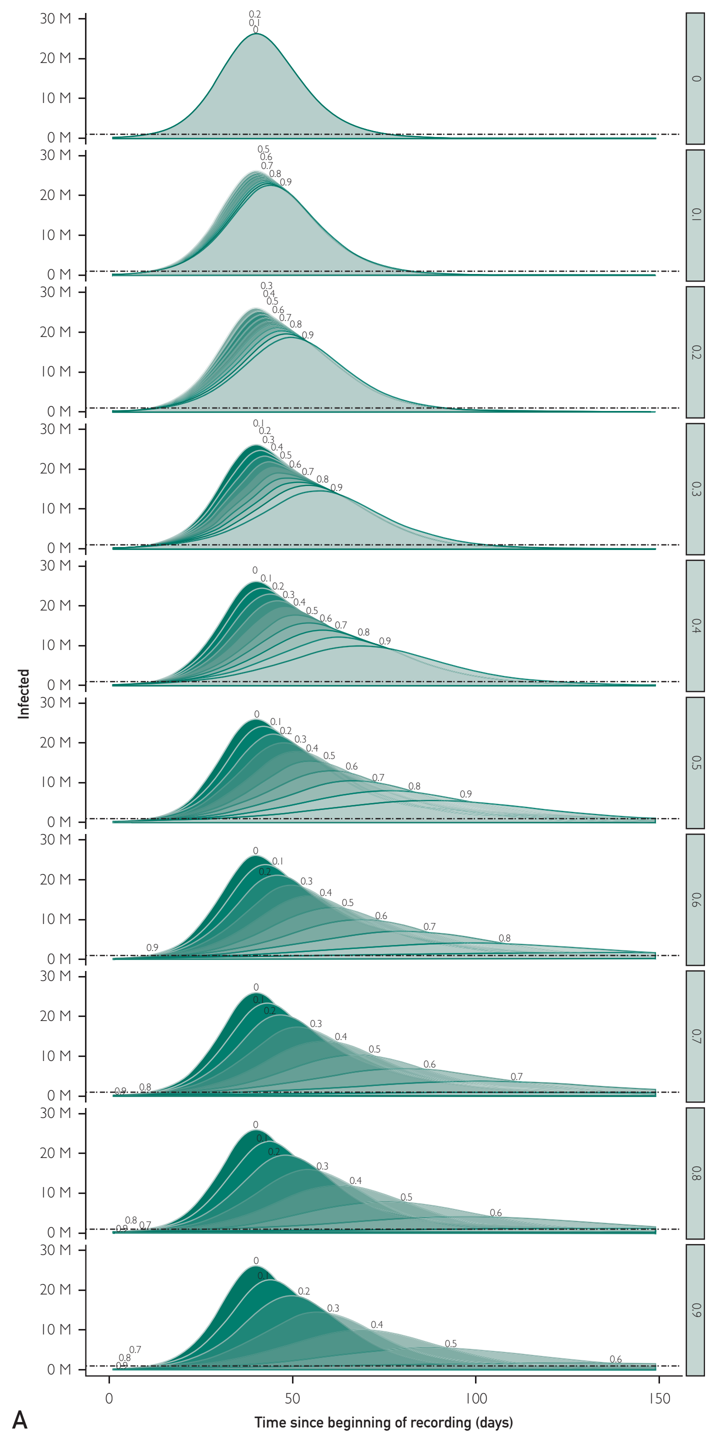

FIGURE 3. Variation in number of impacted individuals over time as a function of (A) percent adoption of AACT and (B) percentage who self-isolate in response to alerts. A, Curves for different levels of adoption and response rates over the course of the pandemic. In this figure, the right panel summarizes response rates, and inset numbers are adoption rates. B, Graphic of the number of individuals expected to be isolated at difference adoption and response rates.

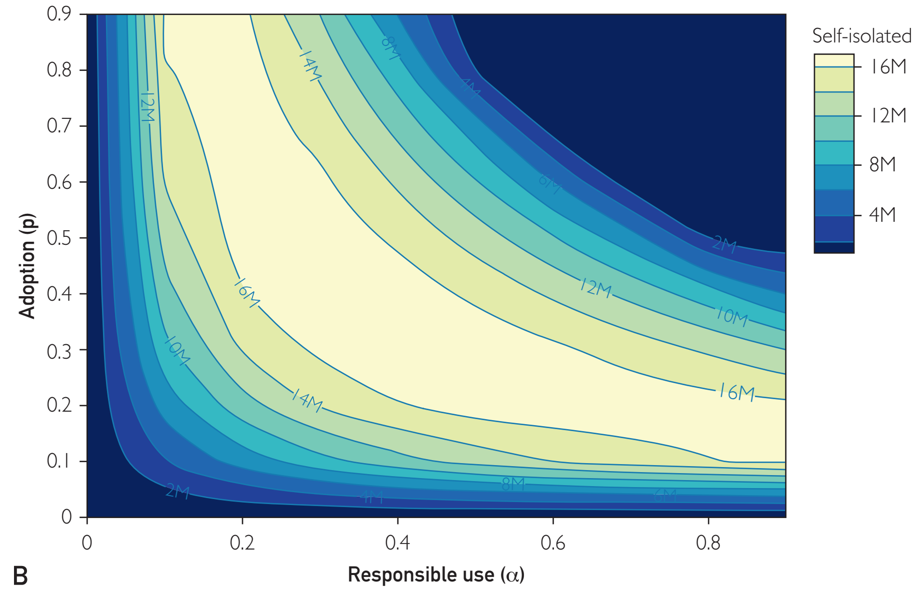

FIGURE 3. continued

on culture, and factors such as regional population flow may impact efficacy. For example, likelihood of broad user adoption and compliance would likely be lower in the absence of governmental support, depending on the population. Furthermore, populations with high frequency of exchange with surrounding countries, states, or regions in which AACT is not used may overcome any value of AACT. Additionally, without appropriate infrastructure (wireless systems to transmit data, centralized databases that can aggregate data, etc), the viability of AACT would be limited.

Study Limitations

There are several limitations to our models. First, we initialized our models with fixed parameters; in reality, parameters have been dynamic and evolved as the pandemic progressed. However, the intent of this paper was to compare strategies for mitigating disease spread assuming a common disease model. It is fair to assume comparative outcome of AACT and universal stay-at-home would be similar regardless of their initialization. Second, success of AACT may depend on type of technology used. For example, global positioning systems have lower location accuracy than Bluetooth or WiFi. Thus, systems that predict exposure based on proximity between an infected individual and an app user would be more accurate (and thus impact fewer people) when technology has higher location accuracy. Also, we assumed adoption of AACT is uniformly distributed throughout the population. Diffuse uptake evenly throughout a society would be expected to have more benefit than uptake in dense pockets. Finally, our modeling does not account for transmission from exposed individuals to other susceptible individuals (eg, household members) between the time of exposure and the time they self-quarantine. Such third-order exposures were not accounted for by the model and thus skew the data in favor of AACT. However, with comprehensive use, near real-time results, and application of self-quarantine rules to household exposures, such deviations could be reduced.

CONCLUSION

Contact tracing can mitigate disease spread through a curated approach of identifying and isolating exposed individuals, as opposed to shelter-in-place orders. Applications that can be implemented through available smart phones and other devices may offer an opportunity to facilitate contact tracing and alert individuals to self-isolate after exposure. These efforts afford the ability to mitigate disease spread in similar rates to universal shelter-in-place when adopted at sufficient rates, assuming a high percentage of users respond to exposure alerts issued by the system.

SUPPLEMENTAL ONLINE MATERIAL

Supplemental material can be found online at http://www.mayoclinicproceedings.org. Supplemental material attached to journal articles has not been edited, and the authors take responsibility for the accuracy of all data.

Abbreviations and Acronyms: **AACT** = advanced automated contact tracing; **CoV** = coronavirus; **SARS** = severe acute respiratory syndrome

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Potential Competing Interests: Dr Raskar is the founder of a non-profit to facilitate digital contact tracing. The other authors report no potential competing interests.

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