

Balancing timeliness of reporting with increasing testing probability for epidemic data

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ABSTRACT

Reporting of epidemiological data requires coordinated action by numerous agencies, across a multitude of logistical steps. Using collated and reported information to inform direct interventions can be challenging due to associated delays. Mitigation can, however, occur indirectly through the public generation of concern, which facilitates adherence to protective behaviors. We utilized a coupled-dynamic multiplex network model with a communication- and disease-layer to examine how variation in reporting delay and testing probability are likely to impact adherence to protective behaviors, such as reducing physical contact. Individual concern mediated adherence and was informed by new- or active-case reporting, at the population- or community-level. Individuals received information from the communication layer: direct connections that were sick or adherent to protective behaviors increased their concern, but absence of illness eroded concern. Models revealed that the relative benefit of timely reporting and a high probability of testing was contingent on how much information was already obtained. With low rates of testing, increasing testing probability was of greater mitigating value. With high rates of testing, maximizing timeliness was of greater value. Population-level reporting provided advanced warning of disease risk from nearby communities; but we explore the relative costs and benefits of delays due to scale against the assumption that people may prioritize community-level information. Our findings emphasize the interaction of testing accuracy and reporting timeliness for the indirect mitigation of disease in a complex social system.

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1. Introduction

An ideal unconstrained response to an epidemic would have rapid reporting of positive test results, but such implementations are rarely logistically or practically feasible (Jajosky & Groseclose, 2004; Marinović et al., 2015). Facilitating rapid reporting has been argued to be of direct value only if improvement of outbreak control can be achieved (Marinović et al., 2015), but achieving timeliness for the direct mitigation of outbreaks via interrupting transmission is often impractical (Jajosky & Groseclose, 2004). This is even worse for rapidly spreading diseases, such as COVID-19 (Khachfe et al., 2020). Reporting is, additionally, complicated by considerable variation in the accuracy of data for infectious diseases (Doyle et al., 2002; Reed et al., 2015). Each step along the chain of testing (Larremore et al., 2021), surveillance, and reporting (Jajosky & Groseclose, 2004) potentially introduce inaccuracies and delays. Indeed, early surveillance of COVID-19 cases likely under-reported actual infections (Wu et al., 2020).

Delays in clinical screening of symptomatic cases have been argued to be less critical in preventing future direct transmission, because people can self-isolate at the onset of symptoms (Larremore et al., 2021). We emphasize, however, that delays are critical for avoiding disease transmission in a further, often underemphasized, context: the generation of public concern. Case counts contribute to the reporting of epidemiological information, which can generate concern regarding disease spread among the population being reported on and encourage the use of protective behaviors. Disease surveillance and subsequent reporting can thereby indirectly mitigate outbreaks by generating public awareness of disease transmission (Rubin et al., 2010; Steiger et al., 2021). Such concern can influence wider decision-making within communities, since people aware of increased risk may be more likely to adopt or adhere to protective behaviors that reduce their likelihood of acquiring or transmitting infection (Wise et al., 2020). For respiratory diseases, protective behaviors are typically the primary method of outbreak control amongst unvaccinated people (Leppin & Aro, 2009), especially if effective treatments are not widely available. Furthermore, the emergent use of protective behaviors can result in the construction of a new social norm (Bavel et al., 2020; Cialdini & Trost, 1998; McAlaney & McMahon, 2007), which may normalize behaviors that are more effective at mitigating a disease than in a norm-naïve public. Prior work has indicated that the promotion of concern, and the associated adherence to protective behaviors, is most effectively implemented during a behaviorally receptive phase (Silk et al., 2021). This phase signifies the period of time within which the normalization of protective behaviors can occur, without reassurance eroding their adoption prior to an epidemic peak. Thus, timeliness in reporting is a crucial factor in promoting concern, but may rely on the accuracy of the information reported.

Distributing epidemiological information often relies on coordinated action: reporting is contingent on collecting test data, collating and processing information at regional or national levels (Jajosky & Groseclose, 2004), and disseminating case reports – often via third-party media agencies. Dedicating resources and time to ensuring that only highly accurate information (i.e., information reflecting actual cases via a high testing probability of detecting infections) is provided could negatively impact the speed with which information is disseminated to the wider public. Similarly, the scale at which information is reported could influence the timeliness or accuracy of reporting, especially if limited resources are available to help overcome the challenges associated with coordination among multiple relevant agencies (e.g., integrating data from multiple states' health departments). The speed and accuracy of reporting, therefore, could be viewed as a trade-off, albeit one that may not always be intrinsic to the implementation of public policy. High performing agencies, as measured via outcomes, may be able to produce with both speed and accuracy; even so, underperforming agencies may still be restricted by a speed-accuracy trade-off (Wenger et al., 2008). Research on the timeliness of reporting is underrepresented (Jajosky & Groseclose, 2004; Marinović et al., 2015), but even if policy agencies are high performing as singular entities, the chain of events between multiple agencies (Jajosky & Groseclose, 2004) may be challenging to coordinate and perform with timeliness.

Not only are there challenges in providing timely and accurate information, but there may also be critical differences in the impact of the data contingent on the scale of its collection and dissemination. This is important as delays might be more impactful for community-level reporting, because an epidemic can spread more rapidly within a community before reporting provides an indication of the current high epidemiological risk. In population-level reporting, adjacent communities currently without local infections could gain a greater benefit via reporting of infections at a wider scale, despite longer delays before receiving information. People, however, may respond more readily to within-community information, than to information about people outside of their community (Dudo et al., 2007; Griffin et al., 1995).

Here we examined how variation in the timeliness of reporting and probability of testing may influence the generation of concern and subsequent adherence to protective behaviors, when confronted with an outbreak. We built on a previously published simulation-based dynamic multiplex network model (Silk et al., 2021, 2022) that coupled a disease network layer with a communication network layer. We included a population of 2000 individuals, distributed among three age categories and ten communities. The two layers were dependent, such that individuals gained concern with: growing awareness of local infections, growing social construction of adherence, and heightened reported case numbers. Case numbers were reported either as a daily number of new-cases or as the total number of active-cases, and also either at the population- or community-level, with varied timeliness and probabilities of testing. Although included as a single parameter, the probability of symptomatic testing encapsulates any step between the onset of symptoms and a case being identified as positive by a reporting agency. As such, this parameter is multifactorial, and representative of: test availability, probability of false negatives, motivation to get tested or probability of intervention via testing, and correctly collating positive test results.

2. Methods

2.1. Original model

We built upon a model detailed elsewhere that relied on dynamic multiplex disease and communication layers (**Supplementary Methods**) (Silk et al., 2021, 2022). A diagram for the general progression of the model is included in Fig. 1. The disease model included seven epidemiological compartments: susceptible (S), exposed (E), pre-symptomatic (I1), symptomatic (I2), hospitalized (I3), recovered (R), and dead (D), informed by disease progression documented at the early stage of the COVID-19 pandemic (Silk et al., 2022). Network layers were constructed with an assumed population of 2000, comprised of three age-groups: children (24%), younger adults (63%), and older adults (13%). We generated random Erdős-Renyi graphs parameterized with overall homophily: a) absent in both layers, b) present in the communication layer, or c) present in both layers. Then, we introduced 10 communities rewired to attain relative modularities (Sah et al., 2017) of: 0.4 in both layers; 0.6 in both layers; or 0.4 in the communication layer, but 0.6 in the disease layer. Finally, we joined age-group layers with parent-

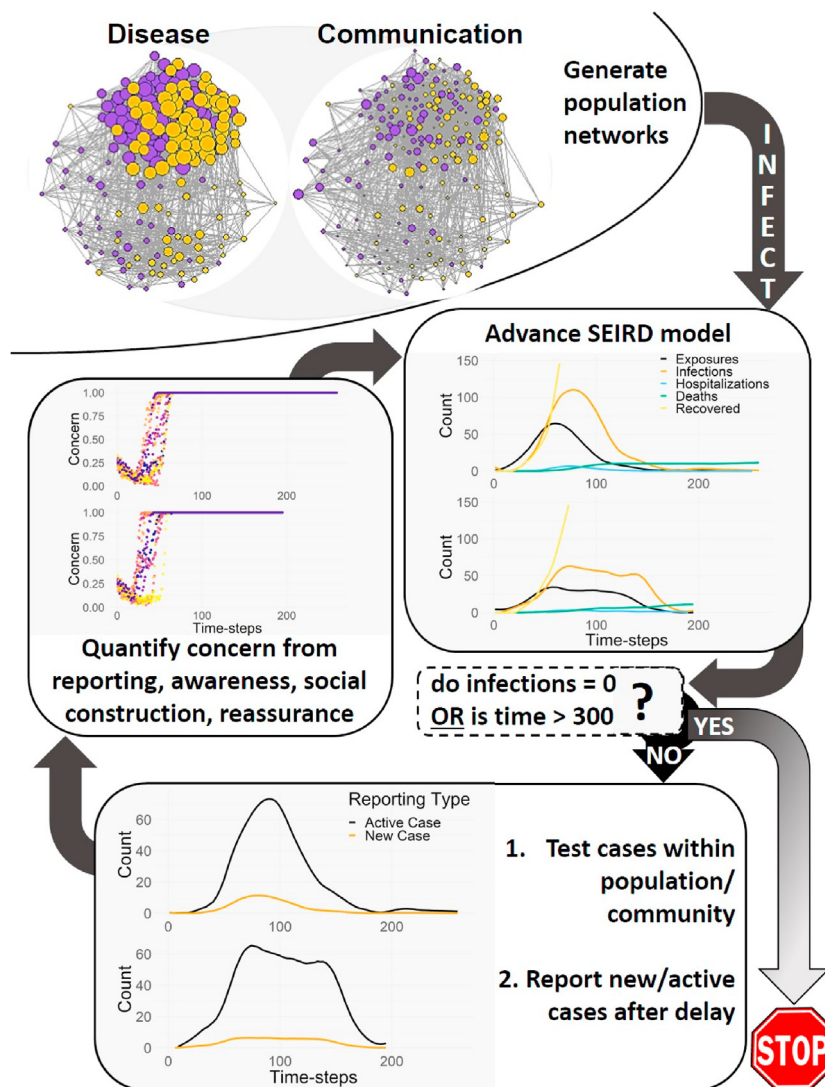


Fig. 1. Diagram of the general model progression. Model starts in the partial ovoid at the top, with the generation of the population structures from one of nine network structures for each layer. Here, the inset visualizes just one of the 10 communities, but with a denser disease layer. After initial infection, the model's central loop is set in motion, proceeding, here, in a clockwise direction until there are no more infections or until 300 time steps are reached. For each of the insets, we provided example images spanning the duration of two runs with community reporting to emphasize the influence of mitigation; the upper insets have a negligible strength of response (0.001) with a 0.25 probability of testing, and long delay (7); the lower insets have a moderate strength of response (0.02) with a 0.75 probability of testing, and no delay (1). Note that each color in the concern plots represent one of the ten communities – in this instance concern is not markedly eroded by reassurance.

child connections and Poisson-drawn younger-older adult connections. Thus, we ended up with 9 networks with 3 homophily x 3 modularity layer combinations (**Supplementary 1**). As the model progressed, individuals could become adherent to protective behavior, included as a reversible state of social distancing: individuals cut 50% of their connections in the disease layer, but retained their connections in the communication layer. Adherence was determined by a Bernoulli draw of the concern parameter, which, for each adult individual, was dynamically informed via: ‘reporting’ (below), awareness, social construction, and reassurance. Social construction elevated concern as the proportion of adherent direct connections increased, awareness elevated concern as the number of symptomatic connections increased, while reassurance reduced concern when none of the direct connections were infected (**Table 1**).

2.2. Reporting of cases

The ‘Reporting’ function aggregated, at every time-step (equivalent to a day), total active-cases or new-cases since the previous time-step. Cases were contingent on a ‘daily’ probability of testing parameter for symptomatic infections (**Table 1**), with asymptomatic testing modeled as a result of a product function (0.20) of the symptomatic testing probability. Positive cases were aggregated and reported at either of two scales: within each of the ten communities of 200 individuals (community-level) or within the total of 2000 individuals in the population (population-level). Case numbers were multiplied by the strength of response parameter – which, for population-level reporting, was also divided by the number of communities (assuming people would correct for different population sizes reported). Concern informed adherence via a Bernoulli draw: e.g., if concern increased from 0.000 to 0.400 between two time-steps, this would result in change of probability for becoming adherent from 0.500 to 0.599. We included delay as a timeliness modifier for the aggregation of case numbers, such that higher values resulted in a greater lag in time-steps between actual and reported cases. Thus, delay simulated latency between positively identified cases and their dissemination to the public via reporting. Values used in this paper are presented in **Table 1**.

2.3. Running the model

We used R3.6.3 (R Core Team, 2019) for modelling, the code is shared on GitHub (https://github.com/matthewsilk/CoupledDynamics3_reporter) and in the **Supplementary**. We ran 241,920 runs with various parameter combinations (**Table 1**). The model was initiated with 5 infected individuals, and a starting concern of 0.20. We started each simulation with five infections and ran each simulation for 300 time-steps or until there were no possible infections, whichever came first. Performance of different parameter combinations were compared by their relative effectiveness at flattening the curve, via: (a) reduced maximum infection peaks, and (b) later infection peaks.

3. Results

3.1. Overall effects of delay and probability of testing

Both delays in reporting and shifts in the probability of testing generally were found to be important in altering the height of the epidemic peak (**Fig. 2**; **Fig. 3**). Relative to a delay of 1 day, a delay of 7 days required doubling the strength of response to

Table 1
Model parameters and values.

Parameters:	Number of Values:	Included Values	Relative Categories for Results:
Awareness	1 value	0.1	
Social Construction	1 value	0.1	
Type of Reporting	2 values	Total Active-Cases, New-Cases	
Level of Reporting	2 values	Population, Community	
Reassurance	2 values	−0.075, −0.025	Strong (−0.075) Weak (−0.025)
Network Structure	9 types	3 types of modularity x 3 types of homophily	
Replications	20 replications	1–20	
Reporting Delay	3 values	1, 4, 7 days (time-steps)	
Daily Probability for Diagnosis of Symptomatic	7 values	0.02, 0.05, 0.10, 0.25, 0.50, 0.75, 1.00	Low (≤ 0.05) Moderate (0.10) High (≥ 0.25)
Reporting Response Strengths	8 values	0.001, 0.005, 0.010, 0.025, 0.05, 0.1, 0.2, 0.5	Negligible (0.001) Low (0.005–0.05) Moderate (0.1–0.2) High (0.5)
Total number of runs: (product of value combinations)		241,920	

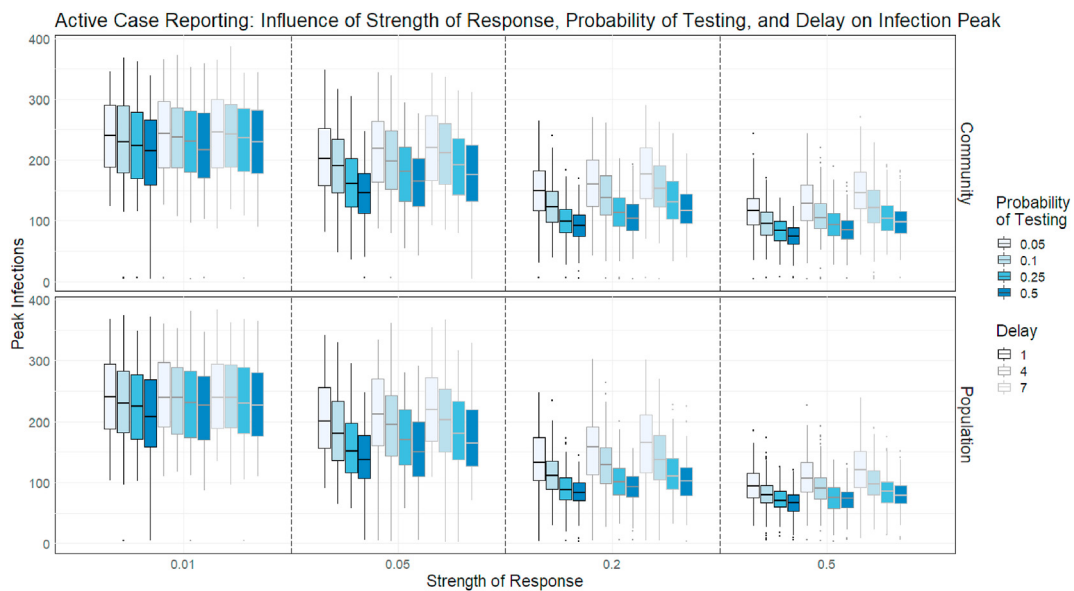


Fig. 2. Delay versus accuracy of testing, for active-case reporting. For each of the above plots, the x-axis corresponds to four bins for strength of response (Effect = 0.01, 0.05, 0.20, 0.50), while the y-axis shows variation in infection peaks. The boxes vary according to probability of testing (grouped by shading – see legend) and delay in reporting (grouped by outline: dark = 1, intermediate = 4, light = 7). Both plots are fixed with strong reassurance (-0.075). The top plot shows active-case reporting at the population-level, while the bottom plot shows active-case reporting at the community-level. Each of the boxes is representative of 360 runs.



Fig. 3. Delay versus accuracy of testing, for new-case reporting. For each of the above plots, the x-axis corresponds to four bins for strength of response (Effect = 0.05, 0.20, 0.50), while the y-axis shows variation in infection peaks. The boxes vary according to probability of testing (grouped by shading – see legend) and delay in reporting (grouped by outline: dark = 1, intermediate = 4, light = 7). Both plots are fixed with strong reassurance (-0.075). The top plot shows new-case reporting at the population-level, while the bottom plot shows new-case reporting at the community-level. Each of the boxes is representative of 360 runs.

gain equivalent effectiveness at mitigating the infection peak. At a low strength of response, any delay in active-case reporting had a deleterious effect on the epidemic peak. When we increased to a moderate strength of response, however, any aggregated latency continued to exacerbate the epidemic peak. Consequently, if a population was not receptive to the dissemination of information (i.e., low strength of response), then very rapid reporting of active-cases was of disproportionate importance – while more receptive populations (i.e., high strength of response) benefited from any gain in timeliness. A

similar, albeit weaker, relationship was observed for new-case reporting. Delay had no interaction with network structure, but epidemic peaks and the effectiveness of protective behaviors did (**Supplementary 1**).

When the probability of testing was low, then increasing the probability of testing was more effective at mitigating the infection peak, relative to reducing delay (**Fig. 2**; **Fig. 3**). Irrespective of the strength of response, even small changes at low probabilities of testing (e.g., from 0.05 to 0.10) offset the benefit gained by reducing delay. As the strength of response increased, then the relative benefit of a higher probability of testing also increased. Once the probability of testing was already high (>0.25), however, then the benefits of increasing it were greatly diminished (i.e., decreased marginal return) and prioritizing rapid reporting was of a greater relative benefit (**Fig. 4**; **Supplementary 2**). After a probability of testing of 0.25 has been achieved, then decreases in delay (delay = 4) provide an equivalent or greater benefit than increasing probability of testing to 0.50. Maximally decreasing delay (delay = 1) provides a greater benefit than any further increases to the probability of testing.

3.2. Reporting scale

Irrespective of delay, reporting at the population-level outperformed community-level reporting (**Fig. 2**; **Fig. 3**; **Supplementary 3**). The impact of timing of local outbreaks within the span of the population-level epidemic was found to depend on interactions between the testing probabilities, the strength of response, and the strength of reassurance (**Supplementary 4**; **5**). To further explore the interaction of reporting scale with the other parameters, we compared rapid community-level reporting to population-level reporting at either an equivalent- or halved-strength of response (**Fig. 5**). With equivalence in the strength of response, population-level reporting outperformed community-level reporting when both had shorter delays. If, however, we assumed an increased delay in population-level reporting, then rapid community-level reporting was more effective, but only when reassurance was strong resulting in the erosion of adherence without other input (**Fig. 5a**; **5b**). If we assumed a stronger strength of response for rapid community-level reporting, then *only* the combined scenario of strong reassurance, rapid reporting, and low probability of testing resulted in more effective community-level reporting (**Fig. 5a**). If these criteria were not fulfilled, then population-level reporting was nearly as effective (**Fig. 5b**; **5c**; **5d**), even with the reduced strength of response. These results emphasize the overall effectiveness of population-reporting, except in any social communities that are exceptionally receptive to within-community reporting.

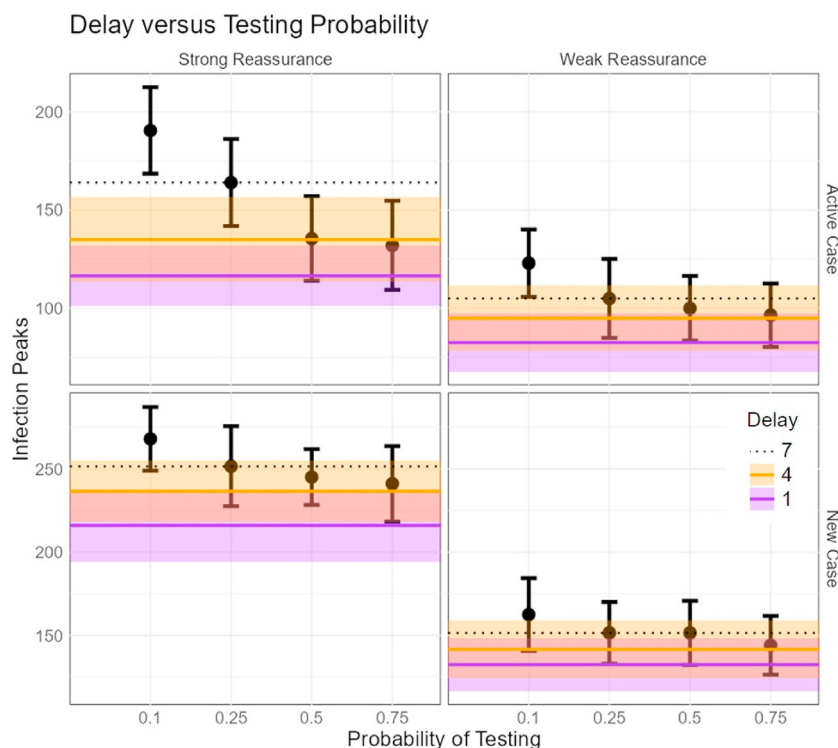


Fig. 4. Comparing the advantage of increasing delay versus a greater investment in increasing daily probability of testing. The x-axis partitions probability of testing shown with plotted points (median) and whiskers (IQR) representing the infection peak (y-axis) for each testing probability, uniformly assuming a delay of 7. The dotted horizontal line extends the median of a 0.25 daily probability of testing, with a delay of 7. Below this, we have added solid horizontal lines (median) with shading (IQR) to show the delay of 4 (in orange) and a delay of 1 (in purple), fixed at a probability of testing of 0.25. Panels are divided along reporting type in rows (top: active case, bottom: new case), while the columns are divided by reassurance (left: strong, right: weak). These results are fixed with a strength of response of 0.2 and limited to community-level results (see **Supplementary 2** for population-level results).

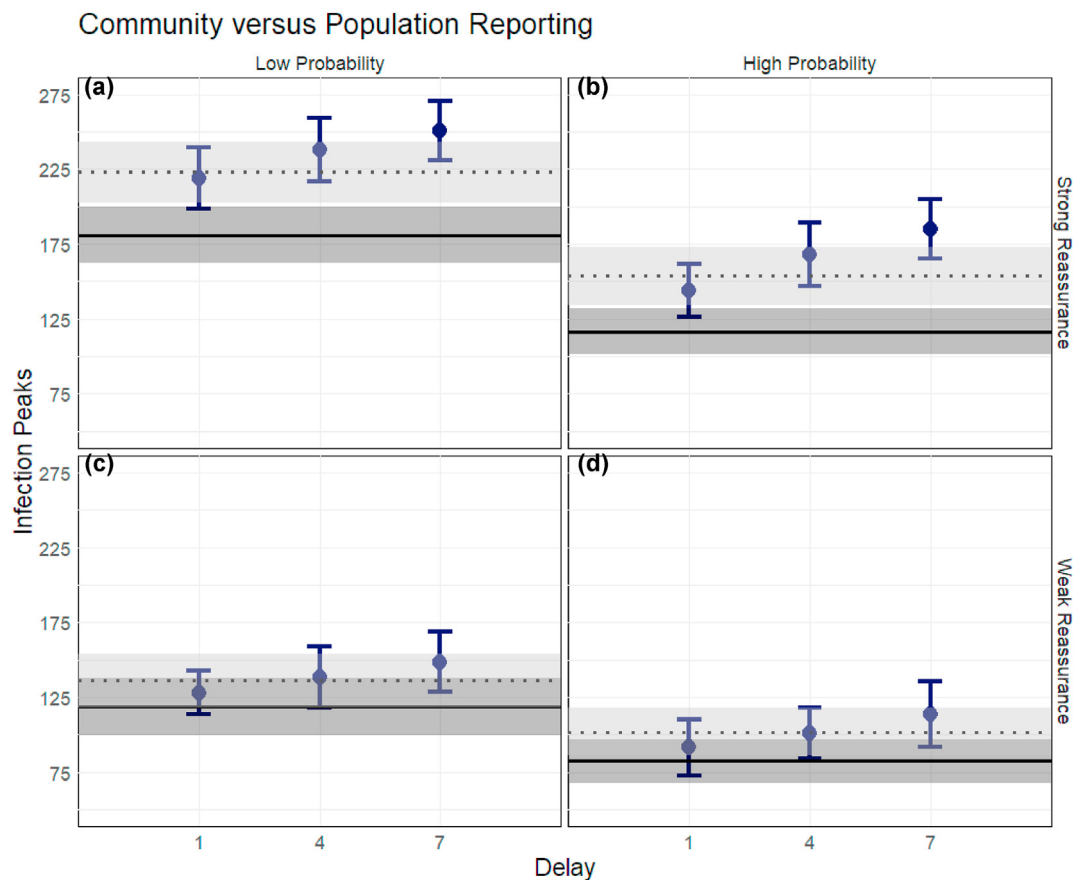


Fig. 5. Comparing community-versus population-level active-case reporting. Community-level results are presented as horizontal lines (median) with shading (IQR), fixed at a delay of 1 with equivalent (0.10, dotted line) or double the strength of response (0.20, solid line) relative to population-level reporting (point [median] and whiskers [IQR], strength of response 0.10). The x-axis partitions population-level delay as a factor, while the y-axis shows population infection peaks. Panels are divided along rows by strength of reassurance (top: strong, bottom: weak), while the columns are divided by testing probability (left: 0.05, right: 0.25).

4. Discussion

4.1. Reporting timeliness and testing probability

Overall, the minimization of delays in reporting is of great importance to the success with which non-pharmaceutical interventions can interrupt ongoing outbreaks. This is especially true if individual responses are predominantly driven by the information received from reporting. If testing accuracy is low, then concern is most effectively generated by facilitating accurate reporting, e.g., via promotion of or availability of testing. When testing rates are already high and accurate, however, then prioritizing the rapid dissemination of reports has a greater benefit. The precise timing of this shift in priorities would be a factor of when access to testing has saturated the system, such that there is a high probability – summative of willingness, accuracy, and availability – of someone undergoing testing when they are symptomatic. This is evident in our model: given a high systemic probability of testing per time-step (e.g., 0.25) across the mean length of a symptomatic period (10 days), then there is a high average probability of a symptomatic person testing positive (= 94.37%). Importantly, people that are unresponsive to reporting may still react strongly to local awareness of infections (Taha et al., 2013) or be influenced through the construction of social norms by more adherent direct connections (Christakis & Fowler, 2013; Dickie et al., 2018). Thus, reporting can have indirect effects through responsive individuals which cascade to less receptive individuals, as included in our model.

4.2. Direct and indirect benefits of testing

Much of our rationale for this study has focused on the indirect benefits of epidemic mitigation through the process of generating concern via reports of case numbers to the general population. There are, however, various pathways through which testing can flatten the epidemic curve. For instance, obtaining positive test results earlier in a person's infection period

can result in a more rapid isolation prior to subsequent spread and also can contribute to awareness of the epidemic. The promoted utility of active screening tests (Larremore et al., 2021; Paltiel et al., 2020; Service, 2020) is in concordance with this concept; screening tests are affordable and rapid, thus capable of higher rates of information acquisition while also facilitating timeliness (Larremore et al., 2021). Screen testing extends the period of cumulative probability testing, since people can be positive before the onset of symptoms, even despite lower per-test probabilities of positive results (Larremore et al., 2021; Paltiel et al., 2020; Service, 2020). Thus, screen testing has multiple benefits: (a) isolating people earlier to reduce transmission, (b) increasing local awareness of the disease via direct social communication, and (c) contributing, earlier, to case reporting, which subsequently promotes protective behaviors. Indeed the first widespread implementation of screening seems to provide affirming evidence that these programs are feasible (Rosella et al., 2022). Furthermore, such testing regimes are often part of multifaceted initiatives to reduce epidemic peaks, e.g., test-trace-and-isolate policies.

Test-trace-and-isolate policies have been suggested to be effective when implemented with rapid testing regimes (Kretzschmar et al., 2020), but the success of such regimes are, in part, benefited by self-isolation after positive testing. Here we assumed symptomatic individuals would self-isolate. In reality, evidence from the United Kingdom suggests that only 46% of symptomatic people self-isolated most of the time (Fok, 2021). Even with comparable isolation rates (50%), however, test-trace-and isolate policies have the potential to greatly mitigate outbreaks (Panovska-Griffiths et al., 2020), though that mitigation is contingent on high rates of testing and tracing (Panovska-Griffiths et al., 2020). Once such capacity limits are exceeded, however, disease control via test-trace-and-isolate policies becomes less tenable (Contreras et al., 2021). These policies can be effectively implemented with the aforementioned screening, which can permit identification of and tracing from pre-symptomatic and asymptomatic cases (Rosella et al., 2022). Systematic testing and a robust infrastructure for contact tracing, however, become central mechanisms that need to be either institutionalized or socially normalized.

4.3. Interaction of testing with other processes

Testing could interact with other concern-generating processes. For example, testing itself could become a constructed practice (Witzel et al., 2017) and the act of testing may (Rolfe & Burton, 2013; Witzel et al., 2017), or may not (Rolfe & Burton, 2013), provide a modicum of reassurance – potentially contingent on self-perceived risk (Rolfe & Burton, 2013). False-positive tests, too, could have the unintended impact of increasing concern disproportionately to the actual risk. Such a circumstance is likely to be worse when prevalence is low (Healy et al., 2021). False-positives, however, are likely to only comprise 0.8–4.0% of positive results (Surkova et al., 2020). Therefore, increases in false-positives can covary with actual disease risk when there is a higher abundance of true-positives, although this does not mean that false-positives are trivial (Surkova et al., 2020). Survey-based or internet trend sampling (e.g., Rubin et al., 2010; Steiger et al., 2021) could be combined with epidemic data to provide real-time measures of the dynamics modeled here. Our model, however, can represent a diversity of real-world systems, as socio-cultural dynamics may impede or enhance awareness, reassurance, and social norms.

We also acknowledge that there are a variety of considerations that might intervene with timely reporting or access to testing. For instance, many demographics have sub-par or nonexistent access to the internet (Bartikowski et al., 2018; Ryan & Lewis, 2017), which potentially impedes the effectiveness or timeliness of reporting (Bartikowski et al., 2018; Ryan & Lewis, 2017) and self-testing (Catania et al., 2021). Self-testing has been proposed as a viable method of identifying infections and tracing exposures (Catania et al., 2021), but, even with access to free tests, some people are unwilling to utilize tests (Thunström et al., 2021). Unwilling people may represent a large minority (e.g., 31%) (Thunström et al., 2021) that may also be unresponsive to reporting (Grossman et al., 2020) until outbreaks have progressed beyond a behaviorally receptive phase (Silk et al., 2021).

4.4. Synthesizing scale, delay, and testing

Scale is an important component of reporting, as the logistics involved in coordinating reporting could impact its rapidity or accuracy. For instance, collating cases from a larger area may cause a delay in the dissemination of information. Coordinating testing across broad regions in the same country or across state and district boundaries introduces challenges that may not apply to smaller scale (e.g., community-level) reporting (Jajosky & Groseclose, 2004). Sub-regions may differ, however, in their ability to rapidly collect and disseminate information (Brookmeyer & Liao, 1990). Decision-making for reporting likely needs to be contextually informed via the testing and reporting infrastructure, the epidemiological metrics of the relevant pathogen, and the cultural-historical context of the relevant communities.

In our model, where accurate testing and rapid communication is possible, population-level reporting can be more effective than community-level, primarily because population-level reporting acts as an early warning system for later-hit communities. In regions where access to healthcare providers or centralized healthcare systems is limited, however, community-led reporting systems could facilitate relatively rapid (Karimuribo et al., 2017) or accurate reporting, compared to population-level coordinated initiatives. Even for nations where a central healthcare system has been implemented (e.g., the National Notifiable Diseases Surveillance System [Chorba et al., 1990]), timely reporting may be impeded by a variety of political, social, or healthcare hurdles (Whelan, 2020a; 2020b). In such instances, relatively rapid community-level reporting (Field et al., 2021) could be more effective at flattening the epidemic curve rather than releasing numbers from an untimely or uncoordinated population-level system. The severity of the delay, however, remains relevant, as population-level reporting

was equally effective (with weak reassurance) or almost as effective (strong reassurance) with only moderate delays, compared to rapid community-level reporting.

Beyond the infrastructure, community composition may inform the most effective scale of reporting: how do people structure their own perception of risk? If information from a wider area is less impactful, then providing rapid local information is key. Identification of communities resistant to the generation of concern or adherence to protective behaviors becomes paramount for the prioritization of testing and rapid reporting. For instance, communities have been identified that underestimate the risk of COVID-19 – e.g., out of socioeconomic necessity or social norms – and are unable or unwilling to undergo frequent testing (Ali *et al.*, 2020; Grossman *et al.*, 2020; Thunström *et al.*, 2021). People that perceive little to no risk of contracting or incubating a respiratory disease might be unwilling to undergo testing (Catania *et al.*, 2021; Thunström *et al.*, 2021). A community comprised of such people (Grossman *et al.*, 2020; Thunström *et al.*, 2021) potentially creates a negative feedback whereby low testing results in low case counts for reporting, which allows reassurance to erode concern and impedes the perception of risk. Communities with perceptions of low-risk may perceive population-level reporting as more distant or sensationalist (Dudo *et al.*, 2007; Griffin *et al.*, 1995) (e.g., a low population-level strength of response for reporting) – even if actual reporting is equally sensationalist at both levels (Jerit *et al.*, 2019). In such circumstances, self-reported community-level reporting (Karimuribo *et al.*, 2017) may be more trusted, relative to government- or media-lead reporting, which may be prone to distrust (Freimuth *et al.*, 2014).

4.5. Limitations and future directions

Coupled behavioral-epidemiological models are an important tool for examining the complexity of real-world systems based on established principals of social psychology, behavior, and risk aversion. Even so, numerous plausible scenarios or the exclusion of additional variables of interest can alter some of the outcomes, just as in a real-world system. Thus, there are limitations to our model, some of which have already been discussed elsewhere (Silk *et al.*, 2021):

Importantly, we have treated the probability of testing and the timeliness of reporting as static processes, but both of these processes can change over time. For example, in examining case reports from an Ebola outbreak, Tariq *et al.* (2019) documented a general increase in the timeliness of reporting over time. They emphasize, however, that this trend may not be temporally uniform, and is contingent on other events (e.g., conflict). This introduces the reality that non-disease-related events can derail reporting efforts and provide a false sense of reassurance even if actual disease risk has not changed.

We excluded screening tests, which can result in the detection of infections prior to early spread (Larremore *et al.*, 2021; Paltiel *et al.*, 2020; Service, 2020). While we did include asymptomatic testing, we acknowledge that, as previously discussed, screening tests could detect pre-symptomatics or asymptomatics at higher rates, which facilitate intervention and contribute to disease awareness. Inclusion of screening tests might have a strong mitigating effect, though this might be contingent on whether an increased abundance of asymptomatic cases or widespread dissemination of low test-to-case ratios erode fear of disease burden.

Finally, we did not include habituation or information avoidance effects; for instance, the usage of television news spiked in Germany following a COVID-19 peak, but this usage subsequently waned over time (Dan & Brosius, 2021). The peak in usage was posited to reflect information-seeking, another axis of variation that we did not explicitly include. Individuals might vary in how they seek or value disease-related information due to, for instance, personality or numeric comprehension (Liu *et al.*, 2021; Wright *et al.*, 2009). As such, particular individuals may be more susceptible to, for example, reporting, and could act as social hubs who exert change through other concern-generating processes, e.g., construction of social norms.

5. Conclusions

Both the accuracy of testing and timeliness are significant contributing factors to the generation of concern via reporting while additionally accounting for the role of local social processes. We presented a coupled-dynamic multiplex network model to examine such a system. Our results indicate, when populations are less receptive to the generation of concern via reporting, rapidity is of greater importance. Relative to expediting the timeliness of reporting, increasing the probability of testing was generally more effective for generating concern and, therefore, facilitating social distancing during a behaviorally receptive phase (Silk *et al.*, 2021). This relationship was not uniformly expressed, however, as lowering delay became more effective once the probability of testing – summative of willingness, accuracy, and availability – was sufficiently high. Therefore, in a system where information acquisition is low, priority should be given to attaining more accurate information via testing; but, in a system where information is already high, then priority should be given to the rapid dissemination of case reporting.

We also examined the effectiveness of population- and community-level reporting if we assumed differentially expressed burdens – such as decreased timeliness or effectiveness of reporting. With delays, population-level reporting can be outperformed by more rapid community-level reporting, despite population-level reporting providing an advanced warning of imminent disease risk. This outperformance was more pronounced when we assumed a response bias towards more local information, but was contingent on how quickly people are assumed to be reassured. Overall, these results emphasize the importance of including consideration of the indirect effectiveness of rapid reporting and accurate testing to promote public disease awareness and adoption of protective behaviors.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.idm.2022.04.001>.

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