Causal explanations, error rates, and human judgment biases missing from the COVID-19 narrative and statistics

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Abstract

A person is labelled as having COVID-19 infection either from a positive PCR-based diagnostic test, or by a health professional's assessment of the clinical picture in a process described by some as *symptom screening*. There is considerable fragility in the resulting data as both of these methods are susceptible to human biases in judgment and decision-making. In this article we show the value of a casual representation that maps out the relations between observed and inferred evidence of contamination, in order to expose what is lacking and what is needed to reduce the uncertainty in classifying an individual as infected with COVID-19.

Introduction

Absolute transparency is necessary when messages are given to the public during events like the current SARS-CoV-2 coronavirus disease (COVID-19) epidemic. Skewed media reporting at the outset of the H1N1 'swine flu' epidemic, and the tendency to exaggerate likelihood and severity of contamination, was believed to have created the erroneous impression that most people infected with the virus would die (Wheaton et al, 2012). As with swine flu, many reports are comparing COVID-19 to the 1918 Spanish Flu epidemic. When statistics are communicated at press conferences or in the media, it is very important that their limitations are explained and any relevance to the individual or population are properly delineated.

Due primarily to the novelty of COVID-19, current guidance on laboratory testing from the World Health Organisation (WHO) has been based in part on interim guidance releases written in 2011 and 2018 for completely different disease outbreaks (Sohrabi et al, 2020; WHO, 2020). More than 200 different molecular assays (WHO, 2020b) and multiple gene targets (WHO, 2020c) have been identified, yet there is currently no 'gold standard' test for COVID-19. Nor is there a freely available *polymerase chain reaction* (PCR) PCR-based COVID-19 test (subject to an acceptable quality control and quality assurance scheme, for instance, endorsed by Public Health England) to

identify with perfect accuracy if a person has an active COVID-19 infection. Hence, irrespective of the diagnostic assay, it is always wrong to assume that people 'diagnosed with COVID-19' must have the virus, or even that people who through PCR 'test negative' do not, even in some cases after repeat testing. An unknown number of rapid diagnostic tests have become available but, as some health officials are finding, many are not diagnostically sound and validation and reliability issues create an unbelievably high number of dangerous false negatives (Kahn, 2020; Odubanjo, 2020; Osborne, 2020). For example, it is claimed that when a swab is taken from a symptomatic person there is a 45-70% chance that no active virus is taken and so a false negative is likely to result (Krumholz, 2020; Ye et al, 2020). Many test negative only to undergo repeat testing and later test positive for the disease (Hendrie, 2020; Krumholz, 2020). For all of these reasons, some clinicians are warning those with symptoms in the face of a negative test result to assume that they have the disease (Krumholz, 2020; Ober, 2020).

While it is claimed that false positive results from formal testing procedures are low, it is clear that limitations in test availability mean the true rate of community penetration of COVID-19 may never be known, and many who are assumed to be 'positive' have not actually been formally tested (Kumar et al, 2020; Meltzer, 2020). Multiple informal assessment methods can be used to determine if a patient is 'COVID-19 positive'. Symptom screening was proposed for use at international borders, but in light of limited test availability it has extended into common healthcare practice and was used to diagnose 22% of suspected cases of COVID-19 in China alone (Phelan et al, 2020; Wu et al, 2020). Since COVID-19 virus particles are shed while the patient is asymptomatic, symptom screening misses more than half of all infected persons (Gostnic et al, 2020; Phelan et al, 2020). The primary indirect method for diagnosis appears to be screening the person for at least two flu-like symptoms and a history of contact with a previously diagnosed person, even if that person was similarly diagnosed by symptom screening absent of formal testing. Some of the signs and symptoms being screened for include: (1) nasal congestion, runny nose and sore throat; (2) fever; (3) persistent dry cough; (4) pneumonia-like chest with (a) crackles or (b) obvious infiltration on chest radiography; (5) tiredness that does not abate on sleeping; (6) myalgia (muscle pain) and joint pain; (7) headache; and in severe cases (8) difficulty breathing and/or hypoxia (Sohrabi et al, 2020; Ye et al, 2020). The problem with this as a method of assessment is that most other colds, influenzas and seasonal infections, and even early lung cancer, can produce two or more of these symptoms. Hence, such screening assessments are likely to contribute to high false positive rates of diagnosis for COVID-19.

Diagnostic Bias and COVID-19

As demonstrated in Figure 1, the correct causal model for any data on people who are 'COVID-19 positive' must incorporate the measurement idiom (Fenton & Neil, 2018) which takes account of the accuracy of the various assessment methods and their potential to produce *false positives* and *false*

negatives. Specifically, the less accurate the assessment method the lower the probability that a person assessed as COVID-19 positive or negative really does or does not actually have COVID-19.

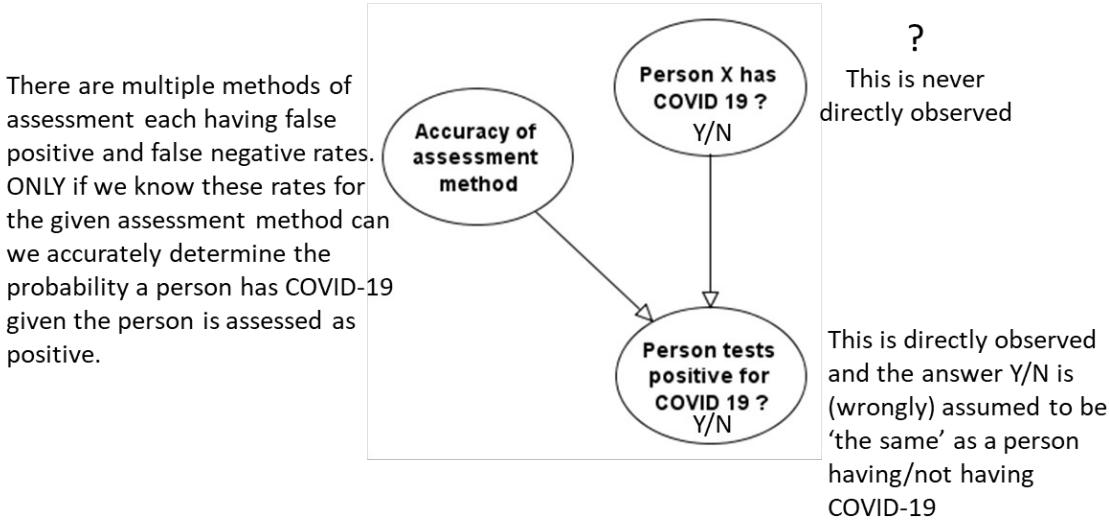

Figure 1: Being assessed COVID-19 positive/negative does not necessarily mean person does/does not have COVID-19

As discussed in (Fenton, Osman M, Neil, & McLachlan, 2020) the absence of systematic random testing creates a problem in interpreting the observed data on confirmed COVID-19 cases and deaths. Even where some tests are being performed, the significant numbers of validation and reliability problems being reported suggests quality assurance (QA) and quality control (QC) issues exist in both the development of testing protocols and assays, and the manufacture of test kits being used. As such, only a highly selective set of people have truly been 'assessed'. These are typically people who have severe symptoms and are almost always being considered for or already have been hospitalised. If the person has had close contact with somebody previously assessed as 'COVID-19 positive' then this increases their individual chance of being 'assessed', which introduces a major problem of diagnostic bias.

One key problem created by poor quality data and the way it tends to be reported is that it enables business to capitalise on the fear and confusion with claims that untested and unregistered products will be effective at protecting the public against viruses like COVID-19: it is not surprising that regulators are working hard to reduce the uncertainty and create new rules and public warnings to combat such misinformation (AHA, 2020; Tchetvertakov, 2020; TGA, 2020; TGA, 2020b).

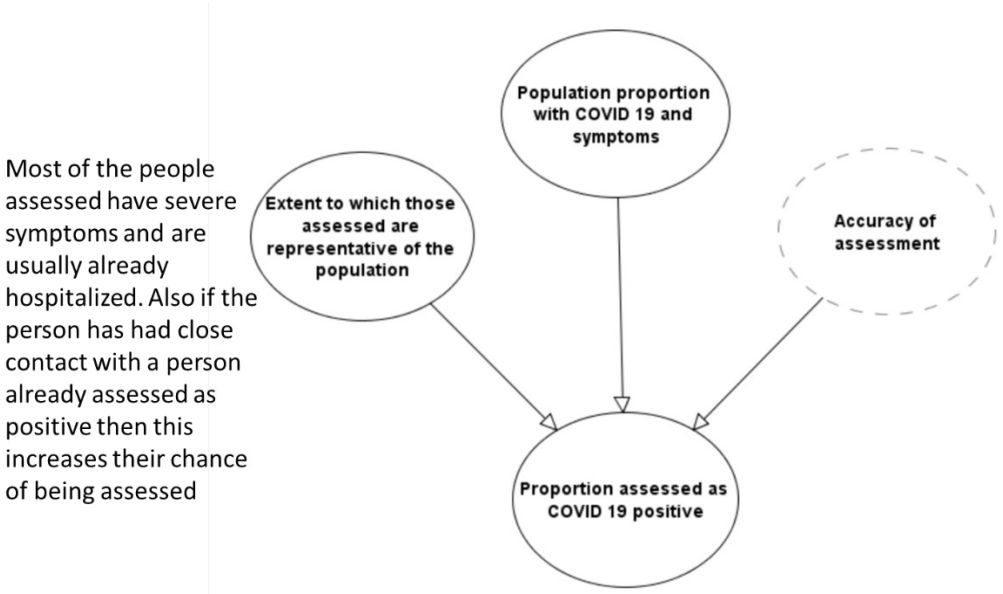

Figure 2: Proportion of people assessed COVID-19 positive tells us little about the true population proportion with COVID-19

Biases in decision-making

Multiple potential biases also seem to play a much higher role in the decision making and assessment process than has generally considered by Oke & Heneghan (2020). For instance: before a person is given a formal COVID-19 test, health professionals make their own judgement about whether the person is likely to have COVID-19, as was already discussed above. This also involves their personal judgement about the severity of symptoms and importantly, whether the person has been in close contact with somebody believed to have COVID-19. Taken together with their perception of the risk associated with underlying medical conditions, they decide whether to hospitalise that person. The judgement about whether to hospitalise the person is especially critical since hospitalization currently appears to be a *necessary* condition for getting a formal test. Hence, the decision to hospitalize a patient amounts to an informal 'positive' assessment and diagnosis made without any formal testing for COVID-19. The fact that the decision is influenced by whether the person has been in close contact with somebody believed to have COVID-19 is especially problematic. The core point is that, without a reliable antibody test to COVID-19, we do not know how many of those 'believed to have had COVID-19' really had it. Even if formal PCR-based testing for active infection was perfectly accurate currently it is taking several days to produce a result; and people who have been tested but are awaiting the result are very likely to be included in those 'believed to have COVID-19' when the decision to hospitalise a person who has been in close contact with them. Even though many will eventually go on to test negative. However, that is too late for the bias 'snowball' to have set in, resulting in many people who may not need to be, being hospitalised and tested for COVID-19.

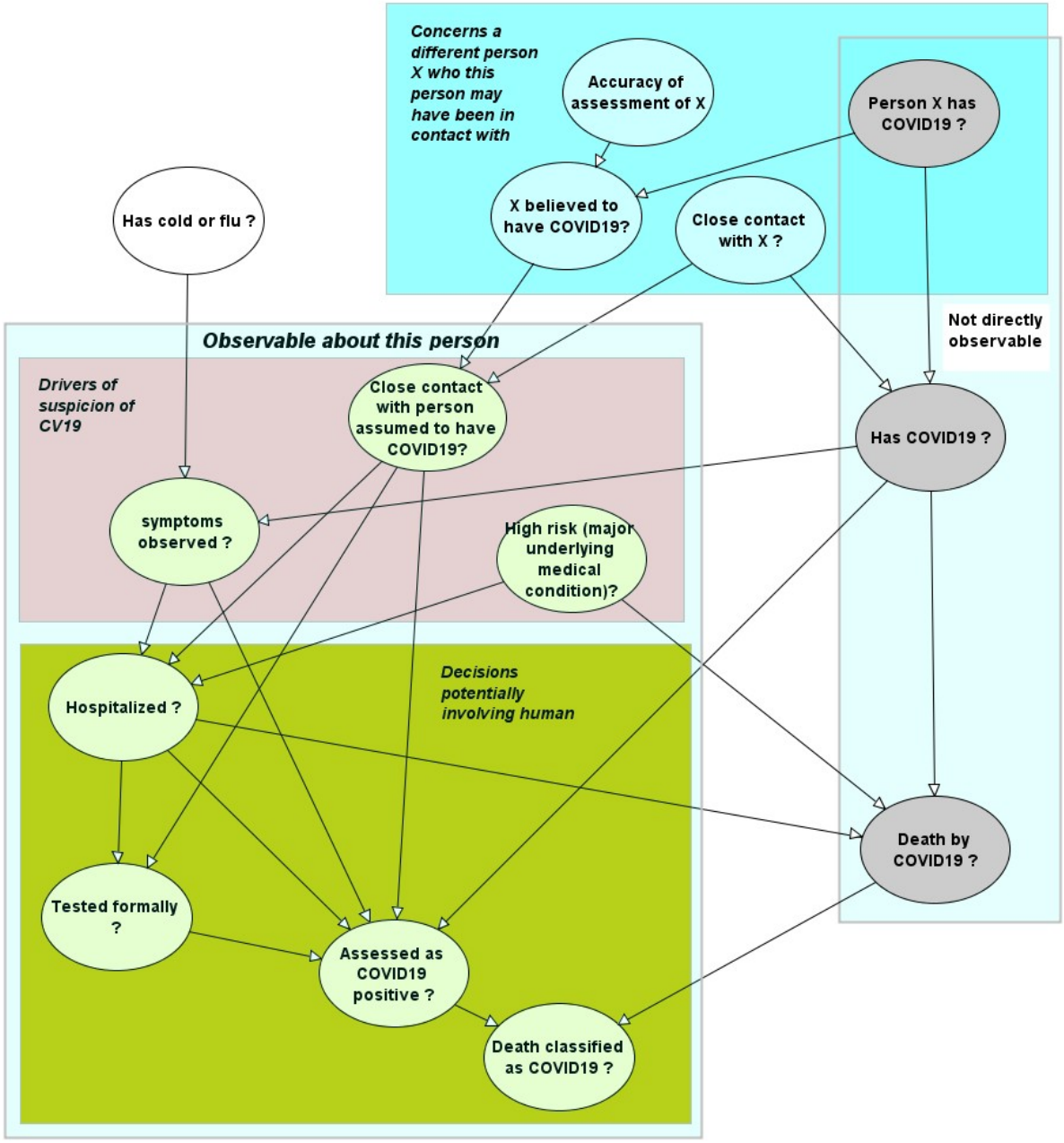

Figure 3: Causal structure leading to a person being potentially assessed COVID-19 positive

Once the person who is unwell is admitted to hospital, health professionals also often make 'definitive assessments' of COVID-19 before results of PCR based COVID-19 testing are known. In high stake situations such as these we are likely to find examples of experts displaying what is known as the *uncertainty paradox* (Van Asselt & Vos, 2008). Here, experts can include scientists, practitioners and policy makers: they are making assessments around evidence, which is inherently uncertain and unreliable on which highly consequential decisions need to be made. However, despite this they will show *uncertainty intolerance* by focusing on communicating certitude in the evidence. This inevitably impacts the type of decisions that are made based upon the evidence as it is communicated. '*This would be akin to a prosecutor asking an eye-witness to give evidence about a*

crime and how unsure they are that they witnessed the crime, and then reframing the evidence in terms of surety that the crime was committed, thus leading to biased jury decisions'. (Osman, Heath, & Lofstedt, 2017, p. 135).

The Public Health England case definition for in-patient admission (13th March 2020) to hospital (where a hospital practitioner has decided that admission to hospital is required with an expectation that the patient will need to stay at least one night) is that the patient must have either/or:

1. clinical or radiological evidence of pneumonia
2. acute respiratory distress syndrome
3. influenza like illness (fever ≥37.8°C and at least one of the following respiratory symptoms, which must be of acute onset: persistent cough (with or without sputum), hoarseness, nasal discharge or congestion, shortness of breath, sore throat, wheezing, sneezing

However, whilst the assessment may increase the probability of making a diagnosis of COVID-19, other primary conditions cannot be ruled out and as a result the published figures related to COVID-19 are being biased as a result (Goldstein & Burstyn, 2020).

A comprehensive causal model of the process for arriving at a COVID-19 assessment is shown in Figure 3. Suppose that the overall false positive rate for all types of assessment is higher than the false negative rate and that no 'new' assessment methods are introduced. Then, because of the role that *being in close contact with a person believed to be COVID-19 positive* has in the decision-making process, it is inevitable that the overall false positive rate will continue to exponentially increase. This is because out of the false positives there will be some new people wrongly diagnosed positive simply because they were in close contact with those others.

Bias in Classification

There is also an issue about the classification of COVID-19 deaths. We know that the *precautionary principle* is likely to be employed instead of, for example, a cost-benefit analysis. Both of these have their disadvantages (Clark, 2010), but the former has been discussed at length concerning its susceptibility to cognitive biases (Sunstein, 2005). Extreme employment of a precautionary principle by scientists, practitioners and policy makers will mean that scientific evidence, along with assessment of risk, will be heavily focused on mitigating the costs *at all costs*, and placing weight on worst case scenario at the expense of exploring any possible risky alternatives that could produce benefits in the long run. This is morally justified (Van Bavel et al, 2020) and certainly Gov.Uk polling of the UK public show exceptionally high support for lock down measures (YouGov, 2020), but is nonetheless biased by definition (Clarke, 2010; Sunstein, 2005). This may go some way to explaining issues in the way that COVID-19 deaths are classified.

For example, currently in the UK a person assessed as COVID-19 positive who dies is classified as a COVID-19 death, even when an existing comorbidity cause is stated on the death certificate. In contrast, there are other countries where patients with comorbidities whose death is certainly hastened by being COVID-19 positive are *not* being classified as COVID-19 deaths, but rather by their underlying base diagnosis: for example, dementia, Alzheimer's or coronary heart disease. Hence, the interpretation of reported death rates as *defined* by health professionals are subject to, potentially rapid, changing reporting policies which may be political (depending on whether a government seeks to inflate or deflate the death figures). This means that we do not know what proportion of people dying primarily from some other cause also has COVID-19 (if the virus is as widespread as we are being told then soon everyone who dies will 'die with COVID-19').

Reducing gaps in the knowledge

There are many recent papers indicating that the error rates, even for formal testing, are high (Goldstein & Burstyn, 2020). Moreover, there is empirical evidence that the false positive rate from PCR testing could be 1-in-10 (Goldstein & Burstyn, 2020), and even higher for people assessed positive on the basis of *having symptoms + close contact with person previously assessed as COVID-19 positive*. In order to properly parameterise the causal model in Figure 3 we naturally need to know more about the error rates of various testing methods. But, perhaps more importantly, we really need to know more about the types of people getting hospitalised and tested and how many people who don't get hospitalised or tested but claim to have symptoms are (a) reporting them; and (b) being rejected for hospitalisation and/or testing. We also need to know more about impact of close contact, including: what is the probability that a person in close contact with somebody with COVID-19 will get COVID-19. Of course, almost none of the above would be needed if there had been a policy of random testing in a set of diverse locations. We might even have found that by now 95% of the population in most areas has or has had the virus and that it is therefore far less deadly than anybody thought.

What is also extremely important but absent from the above causal models and discussion is that currently they do not include the impact of different potential interventions because that requires a more complex population model with several dynamic time slices. Note that Figure 2 is a population model whereas Figure 3 is for an individual. This is partly addressed in (Fenton et al., 2020). Related to this point is that, from the behavioural literature, we can point to several factors which also need to be considered in the model to contextualise public response to State interventions, along with public responses that may inform State interventions. For instance, for pandemic influenza evidence shows that people who escape infection during an initial wave get careless, based on the assumption that they could be 'immune'. This leads to less precautionary behaviour, for example with respect to adherence to social distancing and hand washing. This in turn impacts a resurgent second or even third wave of the virus (Leppin, & Aro, 2009). Additionally, when there are significant threats to their freedom

(Brehm & Brehm, 2013) there is a heightened sensitivity to inequities, and if there is evidence of this locally or publicly then this will impact the extent to which people are willing to continue to comply with social distancing and other socially cooperative behaviours. We know changes in community behaviour following State intervention such as creation of rules limiting the gathering of people in groups of no more than 50 versus gathering of people in groups of no more than 2 will vary by severity, and vary in the length of time that they are implemented: i.e. 30 days vs. 3 months. Past studies on behavioural responses to pandemics tells us that factors such as sensitivity to inequalities of opportunity, beliefs about personal immunity leading to distortions of perceived risk, and reactance to actual as well as perceived threats to personal agency and control (Osman, 2014) play a causal role in understanding behavioural change.

Conclusion

The COVID-19 pandemic is, along with other previously experienced pandemics, a situation that carries enormously high stakes for any data being relied upon to formulate decisions. The data that we refer to in this article is gathered from tests of active COVID-19 infection and through indirect methods. The decisions from it will invariably include how to communicate to the public the likelihood and severity of infection along with rates of recovery and rates of death, as well as whether to, and what mitigation measures should be implemented when, and for how long, along with how best to reduce the supply-demand gap in critically needed resources.

The heavy burden that data carries during these times also means that it is incumbent on those handling it to show some epistemic humility, and in so doing, exposing where uncertainties and inaccuracies lie. High stakes conditions such as these means a considerable susceptibility to biases in all aspects of data handling: measurement, collection, analysis, inferencing, and decision-making. Thus, when data are available, we aim to show where identifying the fragility of the data might be helpful by taking a causal approach. The approach offers a much-needed structure to map out the situation in a principled way so that it can be updated as the quality of the data handling improves.

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