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Author/s:

Barr, IG;Cheng, AC

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Barr Ian (Orcid ID: 0000-0002-7351-418X)

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COMMENTARY

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The difficulties of predicting the timing, size and severity of influenza seasons

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Every year in temperate climates, influenza epidemics arise. What drives these epidemics and what determines their size and severity is a complex interaction the outcomes of which are somewhat stochastic, making it difficult to predict the upcoming season. This makes pre-planning to take preventative measures such as encouraging vaccination, stockpiling of antivirals, having sufficient hospital beds extremely difficult. An important determinant for how each season in each country plays out is dependent on what kind of influenza viruses actually circulate. Influenza viruses can be separated into 4 types A, B, C, D, (2 of which cause most human disease; influenza A and B), 18 subtypes (just for influenza A, only 2 of which cause most human infections A(H1N1) and A(H3N2)) and two lineages (only for B viruses; B/Victoria and B/Yamagata). So in fact up to four different influenza viruses can and often do, co-circulate in any one country concurrently, although often one virus type or subtype usually predominates for an extended period of time. Depending on which virus predominates also determines the most susceptible age groups. For example if an influenza A(H3) virus circulates widely it usually affects all age groups in contrast to and influenza H1 which mainly affects children and adults and less so the elderly. This simple difference also influences the severity of the season, with A(H3) having a higher mortality in seasons when it predominates, as it infects more elderly people, who have more comorbidities and are more prone to have secondary bacterial infections that can lead to pneumonia and hospitalization or death, as seen in Australia and the USA in 2017-8.^{1,2}

Modern surveillance systems provide a much broader range of indicators than simply recording the number of influenza positive laboratory cases. Surveillance systems assessing transmissibility examine influenza-like illness in community surveys and presentation rates to sentinel general practices. Severity is assessed by the number of hospital admissions and the proportion of hospital admissions requiring admission to intensive care. Impact is a more elusive quantity to measure, but potential metrics include the number of nursing home and healthcare facility outbreaks, the proportion of hospital beds and intensive care beds occupied by patients with influenza, or the need to invoke contingency plans, such as cancellation of elective surgery. The challenge is to be able to

collate this information in real time or ultimately, before the season even begins. Even with enhanced surveillance practices, already adopted in many countries, all of these systems collect data after the season has begun, which is not ideal. Predicting when the influenza season will start, which influenza type or subtype that will predominate each year and what intensity/severity it will have has proved to be a much more problematic task even for temperate countries with a clear influenza seasonality. This is due to the complexity of factors that are in play in such as, what viruses circulated previously and currently, prior infection and vaccination history, virus evolution and antigenic drift, climatic factors such as temperature, humidity and UV levels, population density, travel patterns along with a myriad of other factors.

Identifying the “start” of the season is easier and is usually determined by a predetermined threshold being exceeded, such as the U.S. Outpatient Influenza-like Illness Surveillance Network (ILINet) where a background threshold of 2.2% of cases due to influenza-like illness (ILI) has been set.² Different thresholds and measures are used in other countries but with all of these the degree of forewarning and usefulness they provide is limited.

Seasonal intensity, longevity, peak date and severity predictions are even more difficult to forecast. An alternative approach using “Big Data” to estimate influenza activity earlier/better was developed by Google with a proprietary algorithm known as “Google Flu Trends”³. However, over subsequent years, it became evident that the predictive capacity of this model was limited⁴ and that use of web-user information alone was insufficient and would have been better combined with traditional surveillance information.⁵ In general, mathematical models based on known transmission dynamics have been somewhat hamstrung by a lack of understanding of the drivers of seasonality, and these have generally performed better when fitted to past data but less well prospectively.⁶

More recently, modellers have been enlisted by the US CDC to tackle this problem. In 2013 they launched their “Predict the Influenza Season Challenge,” a contest which encourages participants to use the data from CDC’s routine flu surveillance systems and social media data (e.g., Twitter, internet search data, web surveys, etc.) to predict the timing, peak, and intensity of influenza seasons. The conclusion from the early results was that “further efforts are needed to improve forecast accuracy so that policy makers can reliably use these predictions” These efforts are ongoing and the results can be viewed online.⁷

So, rather than trying to predict what will happen in the following weeks and months at any point of the season, our systems for the time being at least, would be better off monitoring the current situation in near real time and responding appropriately. A key learning from the 2009 influenza pandemic was the understanding that we need flexible public health responses for influenza that would apply in “bad” seasonal years as well as pandemic years. Similar work is required for health services and primary care services to develop contingency plans for different influenza scenarios that are in many ways similar to emergency management plans for any type of event. In the meantime, influenza epidemics will continue to surprise us and challenge our responses for many years to come until we have better vaccines and drugs to combat the disease and better ways to measure and forecast its ongoing impact on mankind.

Ian G Barr¹, PhD and Allen C Cheng², MB BS, FRACP, MPH, MBiostat, PhD,

¹World Health Organization (WHO) Collaborating Centre for Reference and Research on Influenza, VIDRL, Peter Doherty Institute and Department of Microbiology and Immunology, University of Melbourne, Melbourne, VIC, Australia.

²School of Public Health and Preventive Medicine, Monash University; Infection Prevention and Healthcare Epidemiology Unit, Alfred Health, Melbourne, VIC, Australia.

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