Feasibility of modelling to predict seasonal influenza like illnesses in Western Australia

Part 1: Exploratory review

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Key points

- Public hospitals experience increased demand during outbreaks of winter influenza.
- Surveillance systems directly confirm outbreaks of influenza and other respiratory viruses by notifications of virological testing and through sentinel reporting arrangements.
- Season to season variations in onset, severity and duration of influenza outbreaks occur each year.
- The use of indirect measures of levels of influenza infection generated by community concern about symptoms reliably and accurately identifies the onset of outbreaks of winter influenza.
- The level and seriousness of influenza like illness (ILI) each winter depends on a number of factors including immunity levels in the community, the arrival of new strains and the severity of winter conditions.
- Research which uses predictive methodologies involving direct and indirect measures of ILI has identified measures that predict outbreaks.
- A trial to determine the feasibility of using predictive and modelling software to model and forecast the impact of seasonal patterns of ILI on public hospitals would have utility in modelling the occurrence of other health conditions which also occur in a seasonal pattern.

Abbreviations and acronyms

ED	Emergency Department
GFT	Google Flu Trends
GP	General practitioner
NBER	National Bureau of Economic Research
ILI	Influenza like illnesses
CDC	Communicable Diseases Center
WA	Western Australia

Demonstration project: Prospects for modelling and predicting seasonal occurrences of influenza like illnesses in WA

1. Background

1.1 Introduction

This review was prepared in June 2013 and reflects the existence of software and methodologies that were available at that time. It has not been updated since it was written, which was to identify the feasibility for the use of off-the-shelf desktop applications to identify, predict and model the likely occurrence and impact of seasonal influenza like illnesses (ILLs) on the Western Australian health system.

The appreciation for the need to improve decision making in an efficient and timely manner has placed a growing premium on identifying mathematical and statistical methods that improve decision making whilst providing risk management. The early uptake of mathematical models to quantify risk and make reliable longer term decisions stemmed from a series of studies by the US National Bureau of Economic Research (NBER) in the late 1930s and early 1940s into a systematic process for making credit risk assessment for small business finance during the Great Depression.[1]

The principles of the NBER research over the following years and the increased capacity of automated data processing has enabled the development of software applications in areas like insurance, investment and finance to bring a high level of precision and certainty to predicting future events and manage risk.

More recently the use of these methodologies has been adopted in other areas. Examples include enabling a proactive compared to reactive approach to workplace safety[2], the prediction of extreme weather events, to reduce hospitalisation by identifying patients at high risk of readmission[3], to improve management of high care patients[4] and to predict future utilization of services of those with mental health conditions.[5]

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[1] Bumacov V & Ashta A. 'The conceptual framework of credit scoring from its origins to microfinance (draft)' 2011) <www.rug.nl/gsg/Research/.../Papers/new.10C.Bumacov.format.doc>.
[2] Schulz G, 'Don't investigate safety incidents - predict and prevent them.'(2012)June *EHS Today*.
[3] Avanade Health Care. 'Could predictive analytics help slash readmissions?' May 2012),ChronicConditionManagementDelivered.com, <http://www.chronicconditionmanagementdelivered.com/news/could-predictive-analytics-help-slash-readmissions/>; Caramenico A. 'Hospitals cut readmissions with predictive modeling' 30 April 2012),FierceHealthCare, <http://www.fiercehealthcare.com/story/hospitals-cut-readmissions-predictive-modeling/2012-04-30>; Minich-Pourshadi K, 'Predictive modeling options to cut preventable admissions.'(2012)15 *HealthLeaders Magazine*; ibid.
[4] Feder JL, 'Predictive modeling and team care for high-need patients at health care partners.'(2011)30 *Health Affairs*; Martin A; Macleod C & Naqvi SAR. 'The effectiveness of predictive modelling tools in identifying patients at high risk of using secondary care resources' 2011),Evidence Adoption Centre, National Health Service, <http://www.eac.cpft.nhs.uk/Download/Public/18632/1/PredictiveModellingToolsReviewSummary.pdf >; Rakovski CC Rosen AK; Fei W; Montez ME, Berlowitz DR & Lucove JC,, 'Identifying future high-healthcare users: Exploring the value of diagnostic and prior utilization information.'(2005)13 *Disease Management & Health Outcomes*.
[5] Reich L & Futterman R Kolbasovsky A, 'Predicting future hospital utilization for mental health conditions.'(2007)34 *Journal of Behavioral Health Services & Research*.

The increasing sophistications of these applications means predictive techniques are able to model complex scenarios, such as decision making about resources and develop timelines to plan for the management of casualties arising from events such as the release of biological, chemical or radiological substances affecting the community.[6]

At this time the concept of disaster management is not a primary objective for undertaking a project to demonstrate and evaluate the utility and functionality of predictive modelling software applications. However, if a real time effective and reliable methodology can be demonstrated which will predict outbreaks of influenza like illnesses (ILI) to support a process to manage demand on public hospital resources, it is likely this will also have a capability to measure and track other infectious diseases with biohazard capabilities.

It is clear that a growing range of areas have embraced the use of modelling and predictive analytical methodologies, which in turn has stimulated the development of sophisticated forecasting applications that can operate across a diverse range of areas, beyond the financial services area when these techniques had been established and developed.

1.2 Terminology

The term "predictive analytics" refers to analytical and forecasting techniques, decision making strategies and processes which extract and process data to make projections about the likely occurrence of future behaviours and/or events.

The term "predictive modelling" describes the relationships and specific circumstances which constituted the collection of information and assumptions that are used to model the outcomes for a specific scenario.

2. Infectious diseases as focus area

2.1 Introduction

Since the early 2000s there has been growing interest to develop improved methods to augment and enhance the traditional public health syndromic surveillance methods spurred by specific concerns about the threats of bio-terrorism. The possibility of catastrophic health related events causing large numbers of people to be exposed to direct harm, in addition to the disaster-like consequences from alarm and panic, is a tangible concern following incidents like the intentional release of anthrax spores in 2001 [7] and the 2004 outbreak of SARS in the United States.[8]

Awareness of the potential for large scale health events has also spurred development of data gathering and real time methods of analysis to establish an early warning capability that are able to detect onset of epidemics of infectious diseases and predict their impact on health systems.

This advantages of these methodologies has been demonstrated in a large and growing body of research, including areas such as predicting epidemics of respiratory illnesses caused by ILI, which due to their seasonal pattern, can result in extreme and unmanageable demands on public hospital systems and health providers.

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[6] John Hopkins Office of Critical Event Preparedness and Response. 'Electronic mass casualty assessement & planning scenarios (EMCAPS)',CEPAR, John Hopkins University, <http://www.hopkins-cepar.org/EMCAPS/EMCAPS.html>.
[7] The importance in the US given to this area can be gauged from the investment in the Biosurveillance Common Operation System, to provide comprehensive integrated biosurveillance situational awareness: http://itlaw.wikia.com/wiki/Biosurveillance_Common_Operating_Network.
[8] Kman NE & Bachman DJ, 'Biosurveillance: a review and update.'(2012)*Advances in Preventive Medicine*.

Research in a number of other public health areas has also demonstrated the effectiveness of predictive analytical techniques to improve the detection of the earliest stages of other infectious illnesses like cholera,[9] Lyme disease[10] and[11] Ross River virus (in Australia)[12] so as to prevent large numbers of presentations of symptomatic people who would otherwise overwhelm emergency departments if they became infected.[13]

It has been recognised that as '(t)raditional public health surveillance for specific conditions is unlikely to identify a disease outbreak'[14], it is important to have a reliable capacity to develop the capacity for an early warning system to predict the occurrence of ILI. Brillman et al (2005) have identified an important limitation with reliance on the established approach to monitor ILI, as well as other infectious diseases.

> ' Many 'drop-in' surveillance systems have been hampered by a lack of knowledge of baseline activity. Other systems have used short-term moving averages of the recent past to predict current usage, but this does not provide optimal performance when day-of-the-week or seasonal effects are smoothed away by averaging.'[15]

It should be reiterated these shortcomings do not do not mean the traditional surveillance systems, which involve the use of direct measures of ILI from virological and clinical data and from sentinel systems should be discounted. Examples of the latter include ILI calls received by telephone services such as Health Direct and web search engine ILI related queries, such as Google Flu Trends (GFT).

Whilst GFT may not contain the demographic details obtained from practitioner generated sources, because of the sheer volume of information, it has an important capability for identifying near real time changes in levels of experience and concern about a spectrum of ILI symptoms at an aggregate level as well as for localised areas. This means that the value of

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[9] Bowman D. 'Twitter use forecasted cholera outbreak' 12 January 2012),FierceHealthIT, <www.fiercehealthit.com/story/twitter-use-forecasted-cholera-outbreak/2012-01>; Chunara R; Andrews JR & Brownstein JS, 'Social and news media enable estimation of epidemiological patterns early in the 2010 Haitian cholera outbreak.'(2012)86(1) *American Journal of Tropical Medicine and Hygiene*.

[10] Seifter A; Schwarzwalder A; Geis K & Aucott J, 'The utility of Google trends for epidemiological research: Lyme disease as an example.'(2010)4(2) *Geospatial Health*.

[11] Chunara R; Andrews JR & Brownstein JS, 'Social and news media enable estimation of epidemiological patterns early in the 2010 Haitian cholera outbreak.'

[12] Gatton ML; Kelly-Hope LA; Kay BH & Ryan PA, 'Spatial-temporal analysis of Ross River virus disease patterns in Queensland, Australia.'(2004)71(5) *American Journal of Tropical Medicine and Hygiene*; Watkins RE; Eagleson S; Veeneddaal B; Wright G & Plant AJ, 'Applying cusum-based methods for the detection of outbreaks of Ross River virus disease in Western Australia.'(2008)8 *BMC Medical Informatics and Decision Making*.

[13] Brillman JC; Burr T; Forslund D; Joyce E; Picard R & Umland E, 'Modeling emergency department visit patterns for infectious disease complaints: results and application to disease surveillance.'(2005)5(4) *BMC Medical Informatics and Decision Making*; Dugas AF; Hsieh YH; Levin SR; Pines JM; Mareiniss DP; Mohareb A; Gaydos CA; Perl TM & Rothman RE, 'Google Flu Trends: correlation with emergency department influenza rates and crowding metrics.'(2012)54 *Clinical Infectious Diseases*; Perry AG; Moore KM; Levesque LE; Pickett WL & Korenberg MJ, 'A comparison of methods for forecasting emergency department visits for respiratory illness using telehealth Ontario calls.'(2010)101(6) *Canadian Journal of Public Health*; Reis BY & Mandl KD, 'Time series modeling for syndromic surveillance.'(2003)3(2) *BMC Medical Informatics and Decision Making*; Van Dijk A; McGuiness D; Rolland E & Moore KM, 'Can Telehealth Ontario respiratory call volume be used as a proxy for emergency department respiratory visit surveillance by public health?'(2008)10(1) *Canadian Journal of Emergency Medicine*.

[14] Brillman JC; Burr T; Forslund D; Joyce E; Picard R & Umland E, 'Modeling emergency department visit patterns for infectious disease complaints: results and application to disease surveillance.'

[15] Ibid.

emerging indirect measures, such as GFT and text searches of social media data generated by Twitter, is to complement, not supplant, the established surveillance systems.

> 'Harnessing the collective intelligence of millions of users, Google web search logs can provide one of the most timely, broad-reaching influenza monitoring systems available today. Whereas traditional systems require 1-2 weeks to gather and process surveillance data, our estimates are current each day. As with other syndromic surveillance systems, the data are most useful as a means to spur further investigation and collection of direct measures of disease activity.'[16]

2.2 Measuring ILI

The limitations of traditional public health systems to readily identify the onset stage, the period of latency when there are relatively small numbers of cases that have ILI symptoms, which could spread and infect much larger numbers of people, has stimulated research into new areas to mine large volumes of data generated by social media and web searches.

There is an impressive body of research which has analysed social media communications, such as GFT data (based on counts of specific flu-related terms recorded by Google searches)[17] and identified terms and phrases contained in Tweets defined as being flu related.[18]

The use of data obtained from Google search terms and Twitter has identified that a more nuanced approach is desirable in understanding of the meaning of public health data gathered by these methods. For instance, data concerning the relative risk of ILI may be constructed from responses on perceptions by the wider community based on the opinions and experience of other, which in effect can amplify the relative risk of ILI.

> 'Public health agencies do not act in a void, but rather are part of a larger feedback loop that includes both the media and the public. The social amplification of risk framework postulates that psychological, social, cultural, and institutional factors interact with emergency events

[16] Ginsberg J; Mohebbi MH; Patel RS; Brammer L; Smolinski MS & Brilliant L, 'Detecting influenza epidemics using search engine query data.'(2009)457 *Nature*, 1014.

[17] Bowman D. 'Google Flu Trends a good warning system for EDs' 10 January 2012),FierceHealthIT, <www.fiercehealthit.com/node/14846/>; 'Hopkins researchers find "Google Flu Trends" a powerful early warning system for emergency departments' 10 January 2012),FierceHealthIT, <http://www.fiercehealthit.com/node/14842/>; Dugas AF; Hsieh YH; Levin SR; Pines JM; Mareiniss DP; Mohareb A; Gaydos CA; Perl TM & Rothman RE, 'Google Flu Trends: correlation with emergency department influenza rates and crowding metrics; Fahad Pervaiz et al., 'FluBreaks: Early epidemic detection from Google Flu Trends.'(2012)14 *Journal of Medical Internet Research*; Seifter A; Schwarzwalder A; Geis K & Aucott J, 'The utility of Google trends for epidemiological research: Lyme disease as an example; Shiga D, 'When the world catches flu, Google sneezes.'(11 November 2008).

[18] Aramaki E; Maskawa S & Morita M. 'Twitter catches the flu: detecting influenza epidemics using Twitter' *Proceedings of 2011 Conference on empirical methods in natural language processing, Edinburgh, 27-31 July 2011*2011),Association for Computational Linguistics, <http://www.aclweb.org/anthology-new/D/D11/D11-1145.pdf>; Bowman D. 'Twitter helps to predict flu trends in New York' 1 August 2012),FierceHealthIT, <www.fiercehealthit.com/story/twitter-helps-predict-flu-trends-new-york/2012-0...>; 'Twitter use forecasted cholera outbreak'; Freeman K. 'Twitter revealed epidemic two weeks before health officials [study]' 10 January 2012),Mashable.com, <mashable.com/2012/01/10/twitter-epidemic-choler-haiti/>; Kessler S. 'How Twitter tracks the spread of disease in real time' 19 October 2011),Mashable.com, <http://mashable.com/2011/10/19/twitter-track-h1n1/>; Robert Wood Johnson Foundation. 'The use of Twitter to track levels of disease activity and public concern in the U.S. during the A H1N1 pandemic' 4 May 2011) <www.rwjf.org/pr/product.jsp?id=72370>; Signori A; Segre AM & Polgreen PM, 'The use of Twitter to track levels of disease activity and public concern in the US during the influenza A H1N1 pandemic.'(2011)6(5) *PLoS one*; University of Iowa Computational Epidemiology Group. 'Using Twitter to predict H1N1 influenza activity',University of Iowa Computational Epidemiology Group, <http://compepi.cs.uiowa.edu/>.

and thereby intensify or attenuate risk perceptions. Traditionally, print media, TV and radio are the major transmitters of information from public health agencies to the public and play a large role in risk intensification and attenuation. However, during the most recent public health emergency, 2009 H1N1, respondents cited the internet as their most frequently used source of information on the pandemic.'[19]

In the words of Eysenbach, whilst internet data has extraordinary potential to undertake syndromic surveillance, as social media data may distort the risk as it can also measure "epidemics of fear", it is necessary to control for this when analysing this source of data. [20]

An example of this phenomenon is demonstrated in a study of the H1N1 ('swine flu') epidemic which considered social media data at different stages of the epidemic during 2009, based on analysis of keywords contained in large volumes of Twitter data.[21]

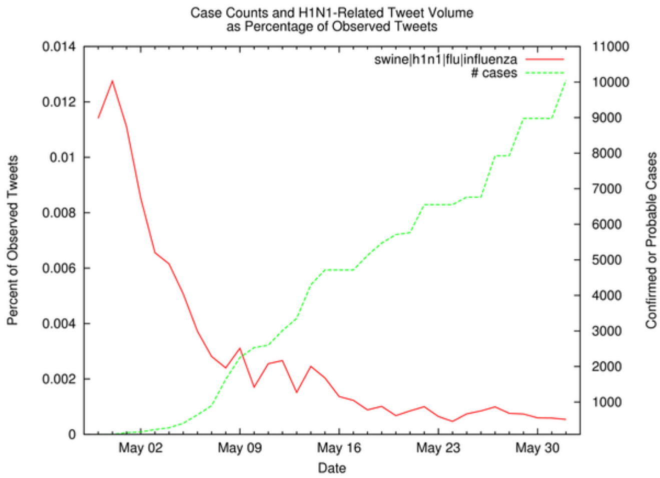

Figure 1: Counts of confirmed or probable H1N1 cases and % of H1N1 related Tweet volume of all Tweets.

Figure 1 which has been adapted from Signorini, Segre and Polgreen's study, shows at the beginning of May 2009 there was a marked peak in the volume of tweets and thereafter the proportion of H1N1 tweets steadily declined.

However, compared to the peak in H1N1 tweets, the increase in the number of confirmed cases over the course of the month supports the proposition the literal epidemic of public alarm about the seriousness had attenuated, even though the virus was becoming more prevalent.

The phenomenon of this peak in early May was not supported by a corresponding increase in confirmed virological test data at this time. This has been described as "fear week" in the swine flu outbreak and has been correlated with a public announcement by the Communicable Diseases Center (CDC) on 26 April 2009 of a public health emergency and by an announcement

[19] Chew C & Eysenbach G. 'Pandemics in the age of Twitter: content analysis of tweets during the H1N1 outbreak' 5(11)(2010),PLoS One, <http://www.plosone.org/article/info%3Adoi%2F10.1371%2Fjournal.pone.0014118>.

[20] Eysenbach G. 'Infodemiology: tracking flu-related searches on the web for syndromic suveillance' *Paper presented at AMIA 2006 Symposium*2006) <http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1839505/pdf/AMIA2006_0244.pdf>.

[21] Signori A; Segre AM & Polgreen PM, 'The use of Twitter to track levels of disease activity and public concern in the US during the influenza A H1N1 pandemic.'

on 25 April 2009 by the Director General of the World Health Organisation there was a public health emergency of international concern.[22]

> 'However, fear week reflected more than simply public fear of influenza, because ED patient volumes increased by 7.0% across the United States during that week, with a 19% increase in pediatric ED visits and a 1% increase in adult ED visits compared with baseline. This increase is comparable to the increase seen with the actual influenza surge in June 2009, measured by the same mechanism, with a 6.6% overall increase in ED visits.'[23]

As a result of this and other research there has been a growing sophistication in analysing social media data, by using techniques like text mining that combine direct surveillance methodologies (eg sentinel networks GP data) with event techniques which require analysis of large volumes of unstructured data. A feature of the latter is that as it is dynamically changing, this poses challenges in its use.

> 'Whilst dictionary-based search techniques certainly have their role to play, text mining usually goes far beyond key word searching used by traditional search engines to find needles in the proverbial haystack. Rather the task can be characterised as a race to find a needle with a particular colour, weight and length. Uncovering documents on the topic of malaria for example, is no guarantee that the information contained in them is relevant to discovering a new epidemic. What is needed is to condense the facts contained in the document into a fixed format, an event frame, that embodies all aspects of interest to the expert.'[24]

It is useful to consider some of the advantages of using tweets compared to web search query data like GFT, as Twitter has grown in popularity over recent years and engaged the interest of researchers.

An advantage of Twitter data is that includes additional contextual information that is not available from a list of key search terms garnered from web search queries. This contextual information includes metadata like time of day, the date and geographical coordinates which can identify location and movement, as well as additional text in the body of the tweet which may infer health status by use of ILI related words, such as temperature, wellbeing and responses to medication.

Increasingly sophisticated applications have been developed to mine the geolocation data associated with tweets, such as Carmen, which by assembling location and user profile information, is able to track the onset and spread of influenza outbreaks.[25]

Another advantage of Twitter data is that use of a tweet does not raise privacy concerns as the text string has been broadcast to the whole world, whereas if fine grained search query data is used it will raises privacy issues as search queries could be linked to an individual if a search history or multiple search history is compiled.

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[22] Centers for Disease Control and Prevention. 'The 2009 H1N1 pandemic: summary highlights, April 2009 - April 2010' 16 June 2010) <www.cdc.gov/h1n1/cdcresponse.htm>.

[23] Dugas AF; Hsieh YH; Levin SR; Pines JM; Mareiniss DP; Mohareb A; Gaydos CA; Perl TM & Rothman RE, 'Google Flu Trends: correlation with emergency department influenza rates and crowding metrics.' 467.

[24] Collier N, 'Uncovering text mining: a survey of current work on web-based epidemic intelligence.'(2012)7(7) *Global Public Health*, , 732.

[25] Dredze M; Paul MJ; Bergsma S & Tran H. 'Carmen: a Twitter geolocation system with application to public health' *AAAI workshop on expanding the boundaries of health informatics using AI*2013),John Hopkins University, <http://www.cs.jhu.edu/~mdredze/publications/aaai13_geo.pdf>.

An American study of a sample of 2.5 million geotagged Twitter messages, which is an example of the extended range of possibilities from Twitter based research, found even though for every one health related tweet there was 1,000 unrelated tweets, that it could confirm individuals had an increased likelihood of contracting ILI through being co-located with infected individuals.

The assumption in this and other research is that

> 'self reported symptoms are the most reliable signal in detecting if a tweet is relevant to an outbreak or not. This is because people often do not know what their true problem is until diagnosed by an expert, but they can readily write about how they feel.'[26]

The twenty most significant positively related ILI related terms from this research were - 'sick, headache, flu, fever, feel, cough, feeling, coughing, throat, cold, home, still, bed, better, being, being sick, stomach, and my, infection and morning'.

Another example of research which identified a set of weighted markers in tweets which were used to validate Twitter data against direct ILI surveillance data is contained in Table 1.[27]

Table 1: List of ranked stemmed markers

muscl	throat	symptom	home	short	fever	feel	pandem
like	nose	consid	condit	onlin	earli	ach	increas
appetit	check	sens	mention	pregnant	tired	flu	stage
read	suddenli	breath	servic	small	carefulli	case	far
unwel	pleas	cough	runni	exist	import	sore	pandem
child	immun	loss	member	headach	weaken	unusu	increas
work	phone	recognis	wors	unsur	nation	spread	stage
follow	swine	peopl	diseas	cancer	famili	vomit	far
season	sick	number	diarrhoea	stai	similar	ill	
page	dai	mild	high	concern	temperatur	thermomet	

It has been pointed out in spite of concerns of the generalisability of analysis of tweets, as Twitter users are not representative of the general population, nevertheless

> 'Twitter data can also be used as a proxy measure of the effectiveness of public health messaging or public health campaigns. Our ability to detect trends and confirm observations from traditional surveillance approaches make this new form of surveillance a promising area of research at the interface between computer science, epidemiology, and medicine.'[28]

[26] Sadilek A; Kautz H & Silenzio V. 'Modeling spread of disease from social interactions' (paper presented at the Sixth International AAAI Conference on Weblogs and Social Media, 2012)Association for the Advancement of Artificial Intelligence, 326.
[27] Lampos V & Cristianini N. 'Tracking the flu pandemic by monitoring the social web' (paper presented at the 2nd IAPR workshop on cognitive information processing, 2010).
[28] Signori A; Segre AM & Polgreen PM, 'The use of Twitter to track levels of disease activity and public concern in the US during the influenza A H1N1 pandemic.' 9.

3. Study of influenza like illnesses

3.1 Why study ILI?

As pointed out in a recent opinion piece by Dr Jennifer McKimm-Breschkin, it is important when talking about influenza, to differentiate between the type A and B group of viruses, each of which are able to cause serious infections, whereas the type C group are considered as responsible for mild infections. [29]

The term ‘pandemic’ is used to describe how a strain of influenza virus can rapidly spread because humans have not been exposed and therefore they do not possess immunity to the virus. As type B strains do not circulate in animal populations, particular concern can arise with the emergence of type A strains which have infected populations of birds and pigs and able to also infect humans.

As different seasonal strains of type A and B influenza are described by specific types of haemagglutinin (H) and neuraminidase (N) which are attached to them, it is helpful to note that there are 17 different types of haemagglutinin, which are numbered from H1 to H17 and nine different types of neuraminidase, which are numbered from N1 to N9.

This means that a particular virus will have one type of H and one type of N. For example, H1N1 or ‘Swine flu” refers to the 2009 flu outbreak.

Research has also been conducted to identify the feasibility of using other form of non-traditional data to develop real time syndromic surveillance systems, such as of whether the use of telephone health line information can predict ED attendances related to respiratory illnesses.[30]

A study in Ontario based on some 650 days of ED and Ontario Telehealth data, for the period June 2004 to March 2006, which covered the 2004/2005 winter flu season, found the 32 distinct named respiratory illness syndromes distinguished in the Telehealth system which ‘correlated with ED visits at the provincial level up to two weeks in advance.’[31]

The impact of ILI respiratory illness on EDs indicates data should identify new forms which may be masked by how data is coded or analysed, such as noted in the study at the University Hospital in Albuquerque, that found ‘the number of respiratory complaints fell with time while the number of fever complaints rose, (which) may reflect the relative mildness of recent influenza seasons.’[32]

3.2 Recent history in WA

The impact of seasonal outbreaks of influenza like illnesses and other infectious illnesses, such as SARS[33] in 2003 and H1N1 in 2009 in Western Australia (WA) and elsewhere has been well

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[29] McKimm-Breschkin J. 'H1N1, H5N1, H7N9? What on earth does it all mean' 4 June 2013),The Conversation, <https://theconversation.com/h1n1-h5n1-h7n9-what-on-earth-does-it-all-mean-14815>.

[30] Van Dijk A; McGuiness D; Rolland E & Moore KM, 'Can Telehealth Ontario respiratory call volume be used as a proxy for emergency department respiratory visit surveillance by public health?'.

[31] Perry AG; Moore KM; Levesque LE; Pickett WL & Korenberg MJ, 'A comparison of methods for forecasting emergency department visits for respiratory illness using telehealth Ontario calls.'

[32] Brillman JC; Burr T; Forslund D; Joyce E; Picard R & Umland E, 'Modeling emergency department visit patterns for infectious disease complaints: results and application to disease surveillance.' 12.

[33] Severe acute respiratory syndrome (SARS) is caused by a member of the coronavirus family, which is believed to have spread from small mammals to humans in China in 2003: http://www.ncbi.nlm.nih.gov/pubmedhealth/PMH0004460/

documented.[34] It is instructive to revisit some of the coverage in the press concerning flu outbreaks to illustrate the profound impact this has had in recent years and to highlight some of the perceptions of causal factors, like the role of cold weather and movement of already infected people from interstate and overseas to WA.

In early May 2009 The West Australian newspaper reported that swine flu (H1N1) had been responsible for five deaths in the US, it had been detected in 14 countries and was spreading in a further five countries:

> 'In little more than a week, world health authorities have tracked the emergence of swine flu, formally known as H1N1, from a few cases in Texas and California to the brink of the first influenza pandemic since 1968.'[35]

By 4 August 2009 swine flu had become a major local concern, with a newspaper report of more than 2,000 cases had been diagnosed. This report included a quote from the Health Minister that there had been a 11 percent increase in presentations at emergency departments in WA.

> 'He said that WA hospitals were well prepared to handle a predicted rise in patient demand despite warnings today by the Australian Medical Association that hospitals were near 'meltdown".'[36]

It was noted in an article on 23 September 2009 that there had been 24 deaths linked to swine flue in WA over winter, and that there had been more than 170 deaths across Australia.[37]

In the following year the first case of hospitalisation in Perth due to swine flu was reported in March 2010. A newspaper report about this case included an observation by Associate Professor Paul Kelly, from the National Centre for Epidemiology and Population Health, that 'We need to be alert to the fact that each week tens of thousands of people come into our country from the northern hemisphere which has just gone through its latest influenza season.'[38]

In a newspaper article on 5 August 2010 it was stated two West Australians had died from swine flu and also that in the previous year (ie 2009) a total of 27 West Australians had died due to the H1N1 pandemic.[39] A report in the following month, on 21 September 2010, reported a total of four West Australians had died from swine flu in the previous six weeks.[40] The fifth death for the year 2010, described in a lengthy newspaper article as involving a "healthy dad" of 53, was reported the following day.[41]

The commencement of 2011 season, which was attributed in part to a "cold snap" in a report on 13 July, noted at the same time two years earlier that:

> 'The Health Department's monitoring of GPs has revealed a higher number of winter illnesses. Doctors are reporting an influx of people with colds, flu and other respiratory illnesses at GP surgeries and hospital emergency departments. Apart from flu, other germs on the rise include para-influenza and respiratory synctial viruses, which can lead to respiratory infections such as bronchitis, and rhinoviruses which cause the common cold.'[42]

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[34] Kman NE & Bachman DJ, 'Biosurveillance: a review and update; ibid.
[35] The West Australian, 'Swine flu reaches 14 nations, *The West Australian* 2 May 2009.
[36] Perth Now, 'Perth boy, 12, dies after swine flu diagnosis, *PerthNow.com.au* 4 August 2009.
[37] O'Leary C, 'Swine flu vaccine for WA, *The West Australian* 23 September 2009.
[38] 'New swine flu case in Perth, *The West Australian* 24 March 2010.
[39] 'Two deaths in WA from swine flu, *The West Australian* 5 August 2010.
[40] 'Swine flu kills four in six weeks, *The West Australian* 21 September 2010.
[41] Pownall A, 'Swine flu claims life of health dad, *The West Australian* 22 September 2010.
[42] O'Leary C, 'Cold snap see rise in flu bugs, *The West Australian* 13 July 2011.

The first press report of the 2012 flu season was on 20 June 2012, which reported a surge of attendances at emergency departments over the past few days, to about 1,700 patients per day.[43] Dr David Mountain was also quoted in the same article as saying that:

> 'there was little spare capacity and he did not know how hospitals would cope, particularly with flu season picking up early. "Hospitals in the Eastern States are under the pump and we're usually a bit behind them time-wise, and I can see hospitals here falling further and further behind in meeting the four-hour rule targets," he said.'

3.3 Impact on emergency departments

The context outlined above indicates the development of an early warning system would have important benefits for the community in general as well as for emergency departments of public hospitals, especially Princess Margaret Hospital for Children and those with units which have a paediatric unit.

The complications from influenza may pose a heightened risk to those with pre-existing medical conditions such as chronic lung disease and acute respiratory diseases as well as being a risk to some groups in the community, particularly young children and the elderly.[44]

Therefore, identification of the outcomes from monitoring and predicting the impact of ILI respiratory illnesses should include other health care use indicators involving use of the hospital system such as occupancy rates, waiting times and utilisation of EDs. A systemic approach is consistent with the view that increased rates of winter time ILI require that hospitals adopt a number of strategies,

> 'such as temporarily increasing staffing levels during influenza seasons, enhancing hospital discharge services or increasing home care services so that patients who no longer need acute care can be discharged (to) …help minimize the impact of influenza-associated respiratory illnesses on the health care system and potential hospital and emergency overcrowding.'[45]

It should be noted that whilst minimum average daily temperature is a key variable in a study of the feasibility of modelling and predicting ILI in WA, additional meteorological data such as maximum daily average temperature and precipitation should be included as other health conditions are associated with seasonal weather patterns.

The Victorian Heat Health Information Surveillance System (HHISS) was established in 2009 to determine the health impacts of extreme heat during summer. The rationale for establishing this system was that vulnerable groups in the population, such as elderly people, are more susceptible to extreme heat events. A study of the 2009/2010 and 2010/2011 surveillance periods in the Melbourne metropolitan area determined that

> 'people aged 65 years and over were four times more likely to present to a hospital emergency department in Melbourne with a heat-related condition than people from any other age group. People born in Australia were 1.6 times more likely, and people living alone in a private residence were 1.5 times more likely to present to a hospital emergency

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[43] 'Flu bites in WA, *The West Australian* 20 June 2012.
[44] Menec VH; Black C; MacWilliam L & Aoki FY, 'The impact of influenza-associated respiratory ilnesses on hospitalisation, physician visits, emergency room visits and mortality.'(2003)94(1) *Canadian Journal of Public Health*.
[45] Ibid., 63.

> department with a heat-related condition than people born overseas and people living in other types of accommodation or living arrangements, respectively.'[46]

3.4 Rationale for study

In addition to being able to identify particular time periods when ILI can represents increased risk for at-risk-groups in the community such as children and the elderly, a forecasting and analytic tool has other advantages in relation to the wider health system. This includes underpinning and supplementing other public health efforts to deliver credible health messages concerning ILI and produce changes in health seeking behaviour by attending a GP and information to enable early identification of symptoms.

As pointed out earlier, an advantage in utilising indirect surveillance data from GFT and Twitter text searches, is that even though there may be

> 'inherent limitations of Internet-based surveillance tools, which by definition, may identify the public perceptions of the threat of influenza as a signal and as actual symptoms or cases … because the increase in GFT correlates with an increase in ED patient volumes, there remains practical use of the system for surge capacity planning for EDs.'[47]

3.5 Forecasting software

The purpose of the study was to trial forecasting software to determine the relative merits of the selected forecasting applications to:

- identify their suitability to monitor and anticipate the impact of outbreaks of ILI,
- inform decision making to launch preventative measures, and
- improve allocation of scarce resources of the public health system..

The study involved an evaluation of the capability of a number of the dedicated forecasting applications listed in Appendix 1. This will involve a study based on a dataset compiled from a range of time series data which measure both proximal and outcome aspects of outbreaks of ILI.

The selection of specific dedicated forecasting software will be determined by a number of considerations, such as reviews of testing conducted by others, availability of the software as either a low cost, time limited (ie trial) or limited functionally version and limitations due to operating systems. It is anticipated that testing and experience gained from use of a number of these packages would assist in the evaluation and comparison of the forecasting capability of more expensive statistical packages.

The software in the dedicated forecasting group contained in Appendix 1 reflects that though some applications in this group may not possess additional statistical capabilities, they are typically characterised as providing a spectrum of essential forecasting functions such as Box-Jenkins calculations, exponential smoothing, regression and non-linear trend analysis.

Furthermore, whilst these applications may not necessarily provide a confidence interval or perform a factor analysis, they may possess features like ARIMA interventions, econometric and transfer models, not available in statistical software packages.

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[46] Health Intelligence Unit.The population health impacts of heat.Melbourne, VIC, Prevention and Population Health Branch Health Intelligence Unit, Victorian Department of Health, 2011,2; ibid.
[47] Dugas AF; Hsieh YH; Levin SR; Pines JM; Mareiniss DP; Mohareb A; Gaydos CA; Perl TM & Rothman RE, 'Google Flu Trends: correlation with emergency department influenza rates and crowding metrics.' 468.

3.6 Data sources

3.6.1 Public health surveillance data

There are a number of well-established national (operated by the Department of Health and Ageing in conjunction with the Commonwealth Biosurveillance Group) and state based systems (operated under the aegis of the Communicable Disease Control Division). These have operated over a number of years and form the backbone of a critical public health function to monitor outbreaks of infectious illnesses at both the State and national level.

Some of the national systems consist of data from State and Territory operated system through collaborative cost sharing arrangements (eg the National Health Call Centre Network which 'trades' as Healthdirect Australia).[48] Given these surveillance systems have operated for some time, it is important to acknowledge this data is in a sense fortuitously available, even though it is collected for a different purpose, ie to underpin public health surveillance.

A consideration for the selection of key data sources is that it covers at least the past four years, it should have already been published, it is readily obtainable from providers and that it is available at least at a weekly level. However, as a number of the time series data is available over a longer period, wherever possible data has been included covering the period from 2006 to 30 September 2012, ie a maximum of 350 weekly data points, to strengthen the predictive reliability of the analyses.

Metrics to be included in the study are concerned with a number of well-established systems which specifically record occurrences of ILI events as well as other measures outlined in Appendix 2, including:

- respiratory viral presentations at emergency departments (recorded by EDSS)
- influenza notifications (recorded by the Department of Health)
- influenza positive tests (recorded by PathWest QE II)

Additional data will be included in relation to:

- Google Flu Trends
- social media data (eg Twitter)
- Australian Bureau of Meteorology maximum temperature
- HealthDirect Australia flu related data

The analysis will include stratification of a number of the above data series, such as a breakdown of ED presentations by metropolitan hospital and for maximum average temperature involving a number of interstate jurisdictions, to demonstrate the predictive capability of packages.

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[48] It is understood that WA contributes about $5 million to the running cost of HealthDirect Australia, with the Commonwealth providing about 40% of its total costs with the balance shared between the participating jurisdictions. HealthDirect Australia handles about 250,000 calls per annum.

4. Appendices

4.1 Appendix 1: Forecasting applications

List of (a) dedicated forecasting software applications, (b) general statistical analysis products which include a forecasting function and (c) other software, which can undertake limited forecasting by working as an Excel add on.

4.1.1 Forecast Pro XE

Forecast Pro XE
http://www.forecastpro.com/

This software package is potentially suitable for the purpose of conducting a trial of an off the shelf PC based product.

A single license of Forecast Pro XE would cost US $1,295 and a 2-license bundle would cost US $2,190.[49] This includes physical media on CD (preferred) and 12 months of maintenance and support.

There are three editions of Forecast Pro—ForecastPro Unlimited, Forecast Pro TRAC and Forecast Pro XE.

Which edition is right for you, depends on a number of factors including how many items you need to forecast, which forecasting techniques you need to use, how you manage forecast adjustments, and whether or not you need to work with others to establish the final forecast.

Forecast Pro Unlimited and Forecast Pro TRAC provide the foundation for creating a sustainable, well-documented forecasting process. The company recommends purchase of Forecast Pro Unlimited and Forecast Pro TRAC if you:

- forecast more than 100 items on a routine basis; and/or
- collaborate with others to create the final forecast; and/or
- make judgmental forecast adjustments that need to be documented.

> 'Although Forecast Pro XE uses the same underlying forecasting methodologies found in Forecast ProUnlimited and Forecast Pro TRAC, it is a very different solution. Forecast Pro XE is a desktop analysis tool designed for use by individuals who are forecasting less than 100 items and whose primary goal is to generate accurate statistically based forecasts (as opposed to manipulating the forecasts after they are generated). It is the only version of Forecast Pro that includes dynamic regression modeling and it also provides more detailed custom modeling options and diagnostic displays than other versions of ForecastPro.'[50]

In relation to the hardware requirements for running Forecast Pro, the company's website states the following:[51]

> 'Forecast Pro is fully compatible with all the latest Microsoft Windows operating systems, including Windows2000, XP, Vista, and Windows 7 operating systems.
>
> Forecast Pro ships with both 32-bit and 64-bit versions that run under all current Windows platforms. Forecast Pro requires a minimum of 512 MB of RAM and 30 MB of hard disk space.

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[49] http://www.forecastpro.com/products/overview/productpricing.htm
[50] http://www.forecastpro.com/products/overview/which.htm
[51] http://www.forecastpro.com/products/faq/index.htm

With such modest hardware requirements, Forecast Pro can run on virtually any Windows-based computer.'

As a downloadable trial/demonstration of Forecast Pro is not available, consideration of the product has been based on viewing online videos that the company provides to demonstrate product features, other promotional material on the company website and information on other sites in the nature of introductory materials and user forums.

4.1.2 Other applications

OpenForecast
http://www.stevengould.org/software/openforecast/index.html

Smart Forecasts
http://www.smartcorp.com/smartforecasts.asp

Vanguard Forecast Server –
http://www.vanguardsw.com/products/forecast-server/

Analytica -
http://www.lumina.com/

Autobox 6.0 -
http://www.autobox.com/cms/

Forecast X Wizard -
http://www.forecastxperttoolkit.com/sales_forecasting_software.shtml

iData
http://www.idataresolutions.com/

Logility Voyager Solutions
http://www.logility.com/

PEER Forecaster
http://www.peerforecaster.com/

PSI Planner
http://www.psiplanner.com/

Decision Tools Suite 6
http://www.palisade.com/decisiontools_suite/

Lavastorm (Analytics platform & Desktop)
http://www.lavastorm.com/

Smoothie (Demand Works)
http://www.demandworks.com/products.html

IBM SPSS Modeller

SAS Forecasting

Oracle Business Intelligence Foundation Suite

Minitab 16
http://www.minitab.com/en-AU/default.aspx

Zoomlar
http://zoomlar.com/

Autobox
http://www.autobox.com/cms/

NCSS 8
http://www.ncss.com/index.htm

Oracle Crystal Ball Suite
http://www.oracle.com/technetwork/middleware/crystalball/overview/index.html

Statgraphics
http://www.statlets.com/

Systat
http://www.systat.com/

Stata 12
http://stata.com/

4.2 Appendix 2: Surveillance and early warning systems

4.2.1 National surveillance systems

National Notifiable Diseases Surveillance System
The National Notifiable Diseases Surveillance System[52] (NNDSS) was established in 1990 under the auspices of the Communicable Disease Network Australia. Its purpose is to coordinate the national surveillance on an agreed list of communicable diseases or disease groups in Australia and has published annual reports since 1991.

The following history of the surveillance of notifiable diseases is from the Department of Health Ageing website.[53]

> "National compilations of notifiable diseases have been published intermittently in a number of publications since 1917. The National Notifiable Diseases Surveillance System (NNDSS) was established in 1990 under the auspices of the Communicable Diseases Network Australia (CDNA).
>
> Sixty-five communicable diseases agreed upon nationally are reported to NNDSS, although not all 65 are notifiable in each jurisdiction. Data are sent electronically from states and territories daily or several times a week. The system is complemented by other surveillance systems, which provide information on various diseases, including four that are not reported to NNDSS (AIDS, HIV, and the classical and variant forms of Creutzfeldt-Jakob disease).
>
> The NNDSS core dataset includes data fields for a unique record reference number; notifying state or territory; disease code; age; sex; Indigenous status; postcode of residence; date of onset of the disease; death, date of report to the state or territory health department and outbreak reference (to identify cases linked to an outbreak). Where relevant, information on

[52] http://www.health.gov.au/internet/main/publishing.nsf/content/cda-surveil-nndss-nndssintro.htm
[53] http://www.health.gov.au/internet/main/publishing.nsf/Content/cda-surveil-surv_sys.htm#nndss

the species, serogroups/subtypes and phage types of organisms isolated, and on the vaccination status of the case is collected. Data quality is monitored by DoHA and the National Surveillance Committee (NSC) and there is a continual process of improving the national consistency of communicable disease surveillance.

While not included in the core national dataset, enhanced surveillance information for some diseases (hepatitis B [newly acquired], hepatitis C [newly acquired], invasive pneumococcal disease and tuberculosis) is obtained from states and territories."

The NNDSS consists of –

- laboratory confirmed cases.
- general practitioner consultations for influenza-like illness
- emergency department presentations for influenza-like illness
- call centre calls related to influenza-like illness
- community level surveys
- sentinel laboratory test results

Australian influenza surveillance report
Published by: Department of Health and Ageing

National Health Call Centre Network
http://www.health.gov.au/internet/main/publishing.nsf/Content/national-health-call-centre-network-team-overview

The creation of a National Health Call Centre Network (NHCCN) was the result of decision announced in February 2006 by the Council of Australian Governments. The NHCCN commenced delivering services in July 2007 under a single national name, Healthdirect Australia. It operates as a national phone number (1800 022 222).

Services are currently being delivered to the Australian Capital Territory, Northern Territory, South Australia, Western Australia, New South Wales and Tasmania. The service is staffed by registered nurses, supported by electronic decision support software and algorithms, to provide safe and effective health triage, information and advice to callers. It has an online capability and the capacity to support add-on services and to assist in health threats and emergency situations.

The Australian Government and the governments of the Australian Capital Territory, New South Wales, Northern Territory, South Australia, Tasmania and Western Australia have established National Health Call Centre Network Ltd (the Company). It is a private company limited by shares, which is responsible for contracting with service providers for the call centre's services and managing the Network's operations.

Queensland and Victoria have signalled an intent to join, but are yet to commit formally to the Network.[54]

FluTracking
http://www.flutracking.net/index.html

An online health surveillance to detect and monitor influenza epidemics in Australia through obtained from a weekly online survey. It is a project of the University of Newcastle, the Hunter New England Area Health Service and the Hunter Medical Research Institute.

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[54] Adapted from http://www.health.gov.au/internet/main/publishing.nsf/Content/national-health-call-centre-network-team-overview

Influenza complications alert network (FluCAN)
Sentinel hospital surveillance system

Sentinel general practice surveillance
https://www.victorianflusurveillance.com.au/

This is surveillance system is based on data obtained from two GP schemes – the Australian Sentinel Practices Research Network (ASPREN) and a Victorian infectious disease reference laboratory (VIDRL) which operates in metropolitan and rural GP sentinel sites in Victoria.

The ASPREN scheme has sentinel by GPs in NSW, NT, SA, ACT, VIC, QLD, TAS and WA, who report on ILI presentations throughout the year. Website:
https://www.dmac.adelaide.edu.au/aspren/
The (VIDRL) which operates in metropolitan and rural GP sentinel sites in Victoria and obtains data between May and October each year.

4.2.2 State data systems

Virus watch report
http://www.public.health.wa.gov.au/3/487/2/virus_watch_homepage.pm

Virus watch is published weekly by the Communicable Disease Control Directorate of the Health Department of WA. Its purpose is to provide summarised sentinel data obtained from general practice and hospital emergency departments concerned with a number of communicable diseases, including presentations involving influenza-like illness.

In addition to general practice data obtained by the Sentinel Practitioners Network of WA (SPNWA), the virus watch report includes emergency department presentations recorded by the Emergency Department Information System (EDIS), results from viral laboratory data analysed by PathWest from the QE II Medical Centre and Princess Margaret Hospital and notifications data sent to the Communicable Disease Control Directorate from all laboratories in WA.

Prior to June 2009 the data contained in Virus watch was published in Virus News and Emergency Department Sentinel Surveillance News.

Sentinel practitioners network of WA
http://www.public.health.wa.gov.au/3/493/2/sentinel_practitioners_network_of_western_australi.pm

This system is intended to collect information about vaccine preventable viruses, such as varicella, influenza and rotavirus, involving GPs located in metropolitan, country, rural and remote areas, who submit weekly data to the Australian Sentinel Practices Research Network, of the number of patients seen with and tested for influenza-like illnesses, gastroenteritis, chickenpox and shingles.

Princess Margaret Hospital respiratory pathogen report
Website: http://www.public.health.wa.gov.au/3/494/2/pmh_respiratory_pathogen_reports.pm

This weekly report is compiled by the Department of Virology at PathWest and has been published since July 2007.

Health Direct

This service was established by the Department of Health in 1999 and was operated as a State level service until it joined Health Direct Australia in July 2007.

Data is available from 2002 is largely for monthly counts of activity, with weekly data available from about 2006, with a daily feed provided to the State from the NHCCN system from July 2007.

4.3 Other data systems

WHO Collaborating Centre for Reference & Research on Influenza
The function of the WHOCC is to provide international influenza surveillance
Website: http://www.who.int/wer/2012/wer8724/en/

Bureau of Meteorology
Rainfall and temperature records –
http://www.bom.gov.au/climate/extreme/records.shtml

Climate data online –
http://www.bom.gov.au/climate/data/
http://www.bom.gov.au/jsp/ncc/cdio/weatherData/av?p_display_type=dailyZippedDataFile&p_stn_num=009225&p_c=-17202479&p_nccObsCode=122&p_startYear=2012

4.4 Appendix 3: List of figures Maximum average

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