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Estimating influenza vaccine effectiveness using data routinely available in electronic primary care records

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ABSTRACT

Background: To support timely, annual estimation of influenza vaccine effectiveness (VE), we explored the use of automated data extraction from general practice records to estimate VE over four consecutive southern hemisphere influenza seasons.
Methods: A software tool installed at 130 practices in Western Australia identified all outpatients tested for influenza by polymerase-chain-reaction (PCR) during annual influenza seasons occurring 2012–2015. Laboratory test results were collated with any existing record of influenza vaccine administered in the same year; limited patient demographic and clinical information was also collected. A case test-negative control analysis compared the odds of seasonal influenza vaccination between patients positive or negative for influenza by PCR with VE = 1 − the odds ratio.
Results: A total of 7270 influenza PCR test results were identified of which 1907 (26.2%) were positive; 9.4% of patients with a positive result had received contemporaneous influenza vaccination ≥14 days prior to specimen collection, compared to 17.9% of those with a negative result. Overall VE was 52% (95% CI, 43–60%); annual VE estimates ranged from 46% (95% CI, 22–63%) in 2012 to 60% (95% CI, 41–73%) in 2014.
Conclusion: Electronic records routinely maintained by general practice provide a promising opportunity for estimating annual influenza VE in a timely and resource-efficient manner.

1. Introduction

Seasonal influenza is a potentially life-threatening respiratory illness affecting 5–15% of the population during annual epidemics [1]. In Australia, yearly vaccination is recommended for persons at increased risk of influenza-associated complications, including older adults, young children and individuals with certain medical conditions, such as coronary artery disease, asthma, diabetes, and impaired immunity. Unlike other vaccines, the antigenic composition of seasonal influenza vaccine is altered frequently in an effort to match continual changes in circulating wild-type influenza virus epitopes as a result of genetic drift [2]. As a consequence, ongoing, accurate post-licensure measurements of influenza vaccine effectiveness (VE) are important for assessing the impact of seasonal influenza vaccination programs over time. In addition, implementing large-scale influenza vaccination programs every year is resource intensive and contemporary estimates of seasonal influenza VE are necessary to in order to assess the costs and benefits of this intervention [3].

At present, seasonal influenza VE estimates are often based on recurring studies of data collected by sentinel surveillance systems in hospital or primary care settings [4]. Limitations to these systems can include relatively small numbers of participants resulting in VE estimates with wide-confidence intervals and delayed availability of the data [5]. Pooling of data from separate systems has been one proposed method for overcoming small numbers and improving the precision of VE estimates; however, issues of heterogeneity across VE assessment systems remain [6].

Electronic Health Records (eHR) have been widely adopted globally and show promise for informing public health surveillance and research [7]. We describe a system to estimate seasonal influenza VE among outpatients using a software tool to extract existing data from eHRs at general practices in Australia.

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2. Materials & methods

The Canning Tool is a software program used by many general practices in Australia to extract and compile data from eHR in order to measure key indicators of practice performance [8]. In 2012, the Department of Health Western Australia (WA Health) collaborated with the developers of the Canning Tool to create an additional module to extract for influenza test results and to collate a given patient's results with the presence or absence of a seasonal influenza vaccination administered in the same year, as documented in the patient record. In Australia, laboratory-confirmed influenza is a nationally notifiable condition, and general practitioners routinely collect and submit specimens for influenza testing by polymerase chain reaction (PCR) at local laboratories [9]. In light of this, the system was designed to extract influenza PCR testing results. General practices were eligible to participate in this evaluation if they were using practice management software that was compatible with the Canning Tool module, including Best Practice, Medical Director V3, MedTech, PracSoft, or Practix. A total of 130 practices with the Canning Tool across Western Australia provided access to their eHRs during 2012–2015. Extraction of non-identifiable patient data occurred between November and December of each year, i.e. shortly after cessation of the southern hemisphere influenza season, except for the data from 2012 which was extracted in 2013.

Additional information extracted with the patients' influenza vaccination and PCR testing results included patient age at the time of respiratory specimen collection, date of influenza vaccination, vaccine brand, and predefined medical conditions, including diabetes, chronic heart disease, chronic obstructive pulmonary disorder, asthma, and pregnancy. For this study, patients were defined as vaccinated if the extraction tool identified an influenza vaccine administered in the same year as the specimen tested for influenza and the vaccination date was ≥14 days prior to the date of the specimen collection. Patients with no influenza vaccination recorded for the same calendar year prior to specimen collection were classified as unvaccinated in the analysis of VE for that year. Test results for persons vaccinated <14 days prior to the date of specimen collection were excluded. Annual data extraction from eHRs for the purpose of estimating VE was approved by the WA Health Human Research Ethics Committee (RA#2013.58).

2.1. Statistical analysis

Only testing results associated with specimens collected during influenza season were included in the analysis. The start of the influenza season was defined as the first of two consecutive weeks where the percent of routine tests positive for influenza virus exceeded the annual mean. The end of the season was defined as the second consecutive week where the percent positive was below the annual mean. Multiple influenza testing results for the same patient with a date of specimen collection <14 days apart were considered part of a single episode of influenza-like illness. For patients with multiple test results <14 days apart, where one was positive, we included only the positive result in the analysis. For patients with multiple negative test results, the first negative result was included. VE was calculated using the test-negative case control design (TND) [4,10]. Test positive cases were defined as patients with a laboratory test result positive for influenza; test negative controls were defined as patients with a laboratory test negative for influenza. VE was estimated by comparing the odds ratio (OR) of vaccination in test negative cases and controls. VE was defined as 1-OR. Multivariate logistic regression models were used to control for age, the presence of an underlying medical condition (yes/no), and the week of specimen collection.

Additional analyses were used to explore the potential influence of variation in general practitioner clinical testing behavior. In separate models, we used logistic regression with generalized estimating equations to account for unknown potential clustering of outcomes by general practitioner. These models also adjusted for age, presence of an underlying medical condition and week of specimen collection and VE was estimated similarly.

Because providers who test less frequently may do so in a non-systematic manner and introduce bias to VE estimates (i.e., test unvaccinated patients for influenza more frequently than vaccinated patients), we performed a supplemental analysis which considered the frequency of influenza testing ordered by general practitioners. General practitioners who submitted <5 specimens per year (lowest 50th percentile) were classified as providers who "sporadically test for influenza," those who submitted 5–19 specimens per year (50-95th percentile) were classified as providers who "regularly test for influenza," and those who submitted ≥20 specimens (top 5th percentile) were classified as providers who "frequently test for influenza." Because practice size is likely to be smaller in rural and remote parts of the state resulting in infrequent testing, we restricted these supplemental analyses to practices in the Perth metropolitan area. Patient characteristics were compared by influenza testing group using chi-square statistics and we estimated VE while adjusting for influenza testing frequency as a potential confounder.

3. Results

One-hundred-and-thirty general practices with 777 general practitioners contributed testing and vaccination data during the four-year study period, of which 101 (78%) were in the Perth metropolitan area, where approximately 2 million (77%) of Western Australia's 2.6 million people reside. The median size of participating practices was 4781 active patients (IQR 2670–6709 patients).

A total of 7579 influenza PCR test results were extracted from general practice eHRs for specimens collected during the four annual influenza seasons occurring between 2012 and 2015 (Fig. 1). After removing 86 (1.1%) duplicate test results, 181 (2.4%) patients with missing demographic information and 42 (0.6%) laboratory test encounters where the patient had been vaccinated within <14 days prior to specimen collection, 7270 records were available for estimation of VE (1498 from 2012, 1140 from 2013; 1982 from 2014; and 2650 from 2015).

Demographic characteristics of the patients are shown in Table 1. The majority were 18–64 years of age (55.1%) and one-in-five (20.3%) had a predefined underlying medical condition recorded in their health record. The most frequently identified medical condition was asthma (13.5%) followed by chronic heart disease (2.5%), chronic obstructive pulmonary disease (1.7%) and pregnancy (1.2%). A total of 1,139 (15.7%) of the 7,270 patients had documentation of receiving an influenza vaccine in the same year as, and ≥14 days prior to, the date they had a respiratory specimen tested for influenza. The age distribution of patients, the proportion of patients who were vaccinated, and the proportion of patients with a medical condition recorded was similar in each year of the study (Table 1).

In aggregate, 1907 (26.2%) of the 7270 specimens tested were positive for influenza; the eHR contained typing, and where applicable, subtyping information for almost all (99%) of positive results (Fig. 2). The positive PCR results included 316 influenza A/H1N1 detections, 838 influenza A/H3N2 detections, and 759 influenza B detections (Fig. 2). Twenty-three co-infections with different types/sub-types were identified.

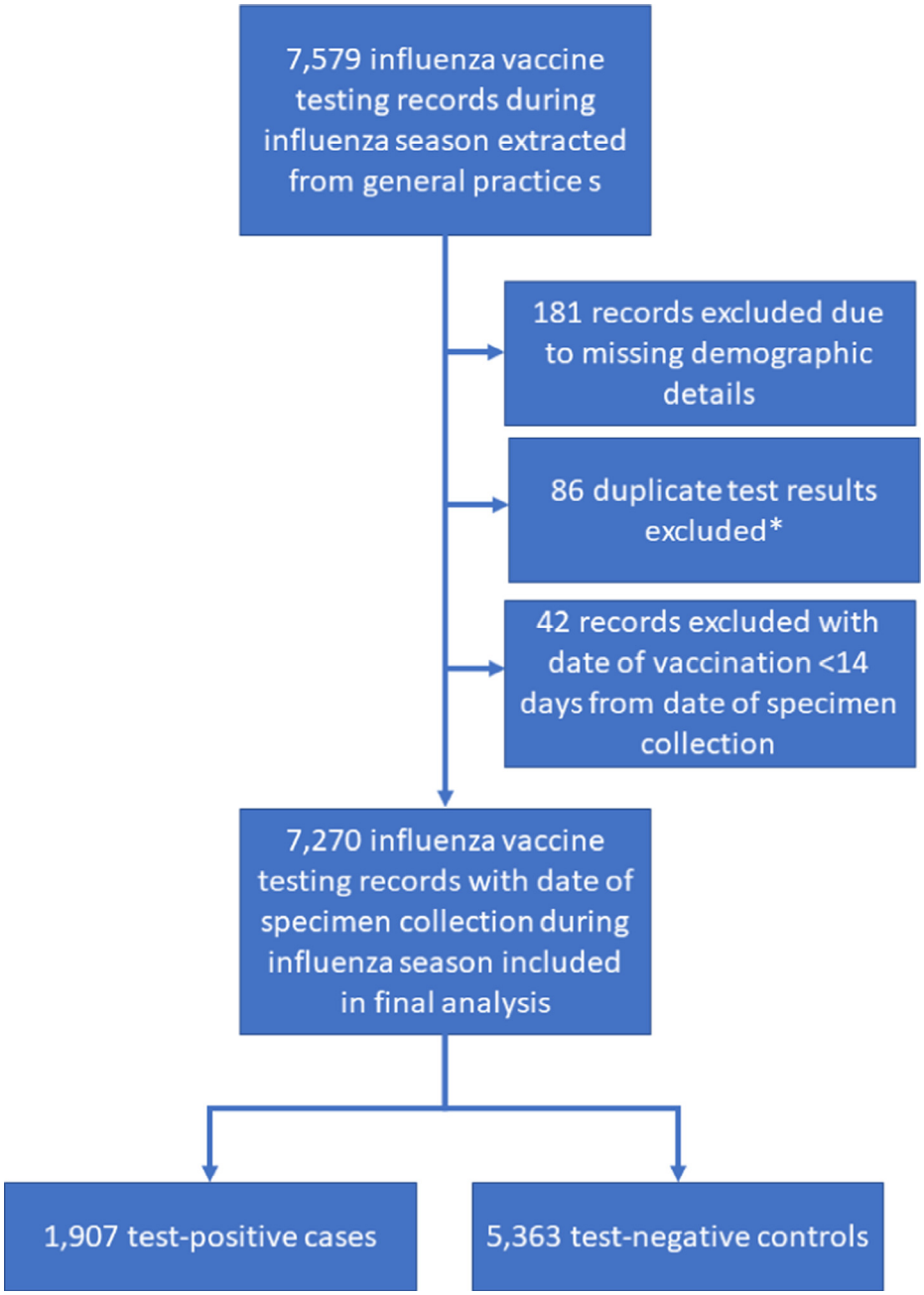

Fig. 1. Selection of influenza testing results from electronic health records from 130 general practices used to measure seasonal influenza vaccine effectiveness – Western Australia, 2012–2015. *Duplicate test results were defined as those with a date of specimen collection <14 days apart.

Over the four influenza seasons occurring between 2012 and 2015, 9.4% (180/1907) of test-positive cases and 17.9% (959/5363) test-negative controls had received a contemporaneous seasonal influenza vaccination; the overall VE (adjusted for age, underlying medical condition, and week of specimen collection) was 53% (95% CI: 44–61%). Annual adjusted VE, all-subtypes combined, were statistically greater than zero for all study years and ranged from 46% (95% CI: 22–63%) in 2012 to 60% (95% CI: 41–73%) in 2014 (Table 2). Annual VE point estimates for influenza B were generally higher, ranging from 58% (95% CI 17–79%) in 2013 to 76% (95% CI: 27–91%) in 2014. In 2013, VE against influenza A/H3N2 was 58% (95% CI: 17–79%) but in all other years the point estimate was low, and the 95% confidence interval included zero. In 2014, there were 238 detections of influenza A/H1N1 and VE against this subtype was 59% (95% CI: 32–76%); in other years, relatively few A/H1N1 viruses were detected (range 9–47), which limited our ability to estimate VE due to sparse data. In general, VE estimates dervied from clustered models were similar to models which assumed independence of outcomes, falling within five percentage points of our original VE estimates (Table 2).

On average, general practitioners submitted five specimens for influenza testing each year (mean: 5.4; median: 2; IQR: 1, 4.7; range: 1, 168). One in six specimens (17.3%; n = 918) were taken by a general practitioner who "sporadically tested" for influenza, 41.6% (n = 2207) were taken by a general practitioner who "regularly tested" for influenza, and 44.5% (n = 2364) were taken by a general practitioner who "frequently tested" for influenza during the influenza season (Table 3). General practitioners who frequently tested for infuenza more commonly tested children <18 years of age compared to practitioners who tested less

Table 1
Characteristics of patients with seasonal influenza virus testing results extracted from general practice – Western Australia, 2012–2015.

	Total n (col %)	2012 n (col %)	2013 n (col %)	2014 n (col %)	2015 n (col %)
Total number	7270	1498	1140	1982	2650
Age group					
<5 years	1139 (15.7)	209 (13.9)	230 (20.2)	319 (16.1)	381 (14.4)
5–17 years	1378 (18.9)	330 (22.0)	214 (18.8)	345 (17.4)	489 (18.5)
18–64 years	4005 (55.1)	825 (55.1)	577 (50.6)	1112 (56.1)	1491 (56.3)
≥65 years	748 (10.3)	134 (8.9)	119 (10.4)	206 (10.4)	289 (10.9)
Medical condition					
Any condition	1475 (20.3)	309 (20.6)	226 (19.8)	360 (18.2)	580 (21.9)
Asthma	983 (13.5)	227 (15.1)	146 (12.8)	233 (11.8)	377 (14.2)
Chronic lung disease	121 (1.7)	22 (1.5)	12 (1.1)	37 (1.9)	50 (1.9)
Chronic heart disease	66 (2.5)	33 (2.2)	30 (2.6)	38 (1.9)	66 (2.5)
Diabetes	338 (4.7)	60 (4.0)	51 (4.5)	83 (4.2)	144 (5.4)
Pregnant	84 (1.2)	10 (0.7)	14 (1.2)	22 (1.1)	38 (1.4)
Vaccination status[a]					
Yes	1139 (15.7)	195 (13.0)	188 (16.5)	320 (16.1)	436 (16.5)
No	6131 (84.3)	1303 (87.0)	952 (83.5)	1662 (83.9)	2214 (83.5)
Influenza test result[b]					
Positive	1907 (26.2)	592 (39.5)	213 (18.7)	420 (21.2)	682 (25.7)
A/H1N1	316 (4.3)	9 (0.6)	47 (4.1)	233 (11.7)	27 (1.0)
A/H3N2	838 (11.5)	340 (22.7)	133 (11.7)	117 (5.9)	248 (9.4)
A/Unsubtyped	17 (0.2)	1 (0.1)	1 (0.1)	15 (0.7)	0 (0)
B	759 (10.4)	248 (16.6)	32 (2.8)	72 (3.6)	407 (15.3)
Negative	5363 (73.8)	906 (60.5)	927 (81.3)	1562 (78.8)	1968 (74.3)

[a] Record of seasonal influenza vaccine ≥14 days prior to clinical testing for influenza.
[b] Test results are not mutually exclusive; 23 detections were co-infections.

frequently ($P < 0.001$). There were no differences in the vaccination status ($P = 0.96$) or chronic medical conditions of patients by influenza testing frequency ($P = 0.91$). We observed little variation in VE estimates after factoring for frequency of influenza testing (Tables 2 and 4).

4. Discussion

We describe a 'proof-of-concept' system which extracts vaccination and laboratory test data from eHR in general practices to estimate seasonal influenza vaccine effectiveness. Using this system, we estimated influenza VE over four consecutive influenza seasons in Western Australia and found overall VE ranged between 46 and 60% each year during 2012–2015. In three of the four years of our study, VE estimates from this system fell within 3–4 percentage points of figures published for Australia during the same time period [11]. Specifically in 2012, our eHR data extraction system found that the vaccine was 46% effective and published estimates from Western Australia reported the vaccine was 49% effective [11]. In 2013, the eHR system estimated VE to be 57% and published figures from Australia found it was 60% effective [6]. In 2015, the eHR derived VE was estimated to be 50% and published estimates indicated the vaccine was 54% effective [12]. In 2014, however, our eHR system estimated VE to be 60% and published estimates indicated it was 44%, although the 95% confidence interval for our estimate (41–73%) overlaps with those for the published estimate (31–55%) [6]. The general consistency of our results with those derived through other mechanisms suggests data extraction from eHR at general practices may be useful for estimating influenza VE.

A potential criticism of using pre-existing data obtained as part of routine clinical practice stems from concerns regarding the reliability of the information contained in the practice management software. For example, it is possible that patients who are tested by their general practitioner for influenza might have been vaccinated at a different general practice, or a pharmacy, or in the workplace, and this information would not be available through the eHR held by the practice that ordered the test. To assess this, in a separate study, we compared vaccination status extracted from patients' eHRs to their self-reported vaccination status. We observed 84% agreement between vaccination status obtained from eHRs agreed and self-reported vaccination status [13]. Studies in the US and Canada also suggest that influenza vaccination information contained in eHRs correlates well with other data sources [14–16]. These studies have generally found that the positive predictive value of an influenza vaccination record in an eHR is quite high, but the negative predictive value is imperfect, nearing 80%; therefore, we can assume some vaccinated individuals may be misclassified as unvaccinated if we rely on eHR [15,16]. While misclassification of exposure (vaccination) can result in an underestimation of VE, of greater concern is misclassification of the outcome (influenza diagnosis), which has been demonstrated to bias VE estimates in a test-negative design [17,18]. In our eHR system, we relied on PCR influenza testing, which is highly sensitive and specific, performed on patient specimens collected by their doctor in an attempt to diagnose their clinically compatible illness [19]. Therefore, we believe our system is highly reliable with regard to outcome measurement, but is more prone to exposure misclassification. Because there is no reason to think misclassification of vaccination status would occur differentially between the cases and controls, we hypothesise that any potential exposure misclassification may bias VE estimates toward the null.

Other potential limitations of our system arise from patient data that were not collected. We were unable to collect information on presenting symptoms and the date of symptom onset prior to specimen collection in our analysis because this information is not readily accessible in the eHR. Such information is essential for assessing whether individuals meet a pre-defined case definition. Since this information was unavailable in the current system, our study includes all individuals tested for influenza by PCR rather than individuals with pre-defined acute symptoms, and the inclusion of participants may have been influenced by clinician's decisions to test for influence which can introduce bias to VE estimates [4,20].

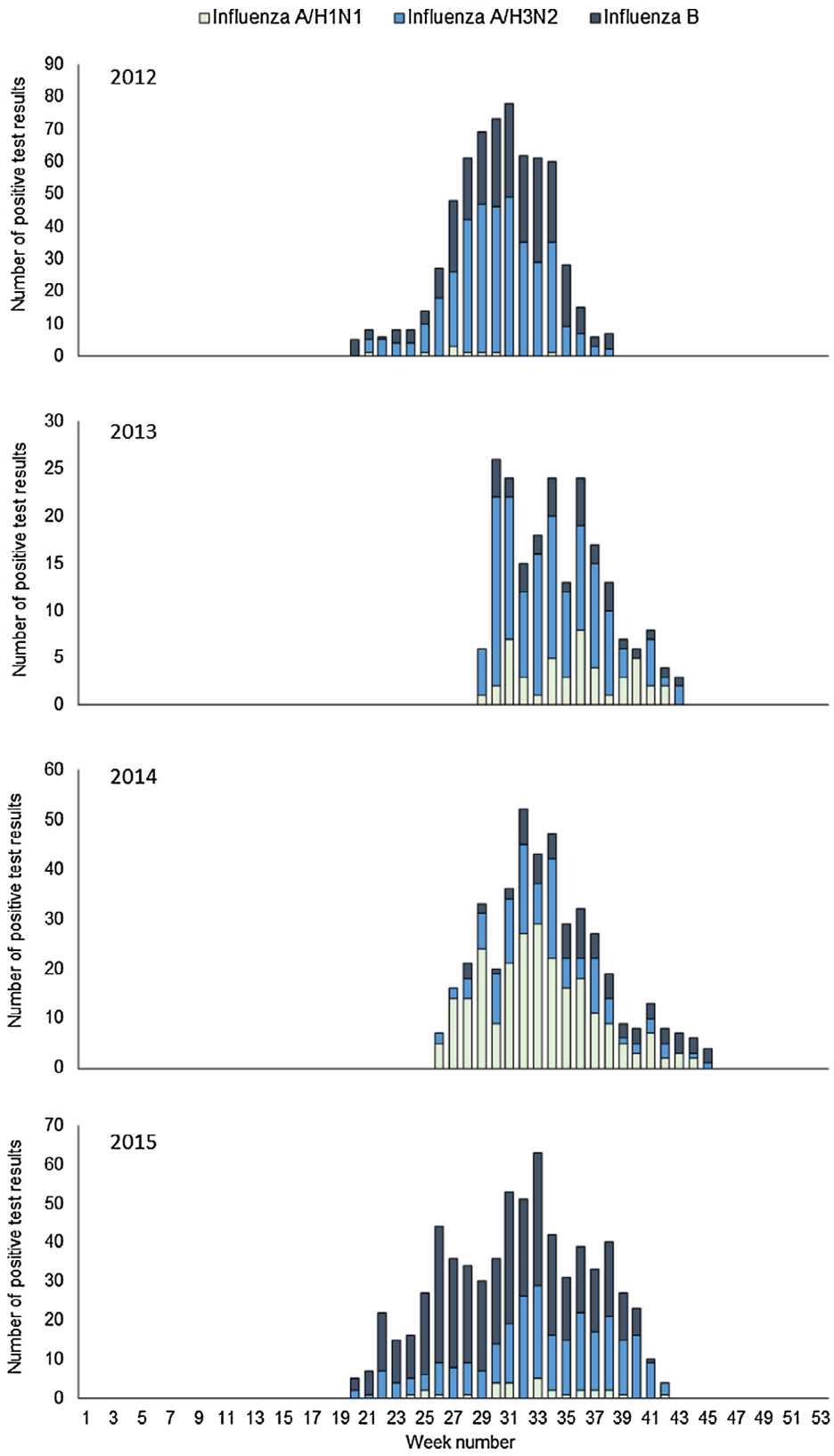

Fig. 2. Seasonal influenza virus reverse transcriptase polymerase chain reaction test results extracted from general practice records – by day of specimen collection Western Australia, 2012–2015.

Despite this, we did not observe variation in vaccination status or the presence of chronic medical conditions by influenza testing frequency, and our supplemental analyses showed similar VE estimates when attempting to factor for indicators of influenza testing behavior. Furthermore, even though we observed significant variation in non-influenza respiratory respiratory virus detections

Table 2
Seasonal influenza vaccine effectiveness as estimated by electronic general practice records – Western Australia, 2012–2015.

Year, Virus Type/ Subtype	Vaccinated test-positive cases n (%)	Vaccinated test-negative controls n (%)	VE (95% CI) – Model I[a]	VE (95% CI) – Model II[b]	VE (95% CI) – Model III[c]
2012–2015					
Any influenza	180 (9.4)	959 (17.9)	53 (44, 61)	53 (44, 62)	52 (40, 61)
A/H1N1	28 (8.8)		55 (32, 71)	56 (36, 70)	56 (28, 79)
A/H3N2	107 (12.8)		38 (21, 51)	38 (19, 52)	37 (17, 52)
B	46 (6.1)		68 (55, 77)	69 (58, 78)	66 (51, 77)
2012					
Any influenza	56 (9.5)	139 (15.3)	46 (22, 63)	48 (26, 63)	50 (23, 67)
A/H1N1	1 (11.1)		ISD[d]	ISD[d]	ISD[d]
A/H3N2	41 (12.1)		37 (4, 59)	40 (11, 59)	43 (7, 65)
B	14 (5.7)		65 (35, 81)	67 (41, 82)	67 (33, 83)
2013					
Any influenza	18 (8.5)	170 (18.3)	57 (26, 75)	52 (25, 69)	61 (29, 78)
A/H1N1	4 (8.5)		ISD[c]	ISD[d]	ISD[d]
A/H3N2	11 (8.3)		58 (17, 79)	49 (21, 67)	60 (19, 80)
B	3 (9.4)		ISD[d]	ISD[d]	ISD[d]
2014					
Any influenza	37 (8.8)	283 (18.1)	60 (41, 73)	61 (47, 70)	60 (35, 75)
A/H1N1	19 (8.1)		59 (32, 76)	63 (43, 75)	58 (21, 77)
A/H3N2	14 (12.0)		44 (−5, 70)	46 (15, 66)	45 (−18, 75)
B	5 (6.9)		76 (37, 91)	74 (34, 90)	74 (19, 92)
2015					
Any influenza	69 (10.1)	367 (18.7)	50 (32, 64)	49 (30, 63)	43 (18, 60)
A/H1N1	4 (13.8)		ISD[d]	ISD[d]	ISD[d]
A/H3N2	41 (16.5)		22 (−17, 48)	20 (−36, 53)	1 (−58, 38)
B	24 (5.9)		68 (49, 80)	68 (53, 78)	62 (36, 78)

[a] Vaccine effectiveness (VE) and corresponding 95% confidence intervals (CIs) as estimated by multivariate logistic regression controlling for age group (<5, 5–17, 18–64, ≥65), the presence of an underlying medical condition (yes/no), week of specimen collection (Model I).
[b] VE and corresponding 95% confidence intervals (CIs) as estimated by generalized estimating equation for logistic regression allowing for clustering of outcomes by general practitioner and controlling for age group (<5, 5–17, 18–64, ≥65), the presence of an underlying medical condition (yes/no), week of specimen collection (Model II).
[c] VE and corresponding 95% confidence intervals (CIs) as estimated by multivariate logistic regression controlling for age group (<5, 5–17, 18–64, ≥65), the presence of an underlying medical condition (yes/no), week of specimen collection, and frequency the clinician tested for influenza (sporadically/regularly/frequently) (Model III).
[d] Insufficient data; confidence intervals ≥100 in width.

Table 3
Characteristics of patients with seasonal influenza virus testing results extracted from general practice, by provider's frequency of influenza testing – Perth, Western Australia, 2012–2015.

Characteristic		Influenza testing frequency of general practitioner[a]			
	All general practitioners (n = 5309) n (%)	General practitioners who sporadically test for influenza (n = 918) n (%)	General practitioners who regularly test for influenza (n = 2207) n (%)	General practitioners who frequently test for influenza (n = 2364) n (%)	Chi-square p-value
Patient's age group					<0.001
<5 years	859 (16.2)	131 (14.3)	284 (14.0)	444 (18.8)	
5–17 years	993 (18.7)	129 (14.1)	356 (17.6)	508 (21.5)	
18–64	2948 (55.5)	559 (60.9)	1180 (58.2)	1209 (51.1)	
≥65	509 (9.6)	99 (10.8)	207 (10.2)	203 (8.6)	
Presence of chronic medical condition[b]	1031 (19.4)	174 (18.9)	393 (19.4)	464 (19.6)	0.91
Vaccinated against influenza[c]	817 (15.4)	144 (15.7)	310 (15.3)	363 (15.4)	0.96
Any influenza virus detected	1461 (27.5)	273 (29.7)	548 (27.0)	640 (27.1)	0.25
Influenza A/H1N1	230 (5.6)	56 (8.0)	62 (4.0)	112 (6.1)	<0.001
Influenza A/H3N2	660 (14.6)	129 (16.7)	249 (14.4)	282 (14.1)	0.21
Influenza B	579 (13.1)	86 (11.8)	233 (13.6)	260 (13.1)	0.46
Non-influenza respiratory virus detected	764 (14.4)	122 (13.3)	251 (12.4)	391 (16.5)	<0.001

[a] General practitioners were categorized as "sporadically testing" for influenza if they had <5 influenza tests per season, "regularly testing for influenza" if they had 5–19 influenza tests per season, and "frequently testing for influenza" if they had ≥20 influenza tests per season.
[b] Chronic medical conditions included chronic heart disease, chronic lung disease, asthma, diabetes, and pregnancy.
[c] Patient had a record of seasonal influenza vaccine ≥14 days prior to clinical testing for influenza.

by influenza testing frequency, suggesting it may introduce confounding bias [21], estimates which adjusted for this were similar to our original VE estimates. Regardless, future investigations into the use of eHRs for VE estimation should aim to identify additional clinical information available in patient eHRs which could be used to develop a reliable case definition.

Table 4
Seasonal influenza vaccine effectiveness as estimated by electronic general practice records, by provider's frequency of influenza testing – Perth, Western Australia, 2012–2015.

Influenza virus Type/Subtype		Vaccine effectiveness, by influenza testing frequency[a]		
	All general practitioners (n = 5309)	General practitioners sporadically testing for influenza (n = 918)	General practitioners regularly testing for influenza (n = 2207)	General practitioners frequently testing for influenza (n = 2364)
	VE (95% CI)[b]	VE (95% CI[b]	VE (95% CI)[b]	VE (95% CI)[b]
Any influenza (2012–2015)	52 (40, 61)	50 (18, 70)	46 (25, 62)	58 (41, 70)
A/H1N1	56 (27, 73)	ISD[c]	ISD[c]	68 (28, 86)
A/H3N2	37 (17, 52)	32 (−29, 64)	30 (−8, 54)	46 (18, 65)
B	67 (51, 77)	75 (30, 91)	69 (42, 83)	62 (36, 78)

[a] General practitioners were categorized as "sporadically testing" for influenza if they had <5 influenza tests per season, "regularly testing for influenza" if they had 5–19 influenza tests per season, and "frequently testing for influenza" if they had ≥20 influenza tests.
[b] Vaccine effectiveness (VE) and corresponding 95% confidence intervals (CI) as estimated by multivariate logistic regression controlling for age group, the presence of an underlying medical condition (yes/no) and week of specimen collection, where VE = 1 − OR.
[c] Insufficient data; cells n < 5 or confidence intervals with width ≥100.

Other information which was not available to us included influenza B lineage. Although almost all patients had influenza type and subtype information extracted, estimating VE by B lineages was not possible because this data was not available through the eHR. Finally, the current version of our programming did not extract information on gender or ethnicity, although there is capacity to collect this going forward.

Despite the potential limitations, using data contained in eHRs to obtain annual estimates of influenza VE offers several advantages. First, the data required are already being collected as part of routine clinical care. This means that the data can be compiled at minimal expense compared to systems in which involve dedicated study personnel and procedures, and the sample size can be increased with relatively few additional resources. Many countries, including Australia, currently rely on labour-intensive data collection through general practice sentinel surveillance systems to estimate influenza VE each year [6,12,22–26]. Western Australia also operated a purpose-built sentinel physician influenza surveillance system for many years, and in our experience, the all-inclusive cost was approximately AUD 200,000 per annum (covering staffing, laboratory testing, practice reimbursement, and system maintenance). In contrast, the system we describe here cost AUD 80,000 to build and compile four years of data, i.e. approximately AUD 20,000 each year. The annual cost of the eHR-based VE surveillance system could be reduced even further because, for this proof-of-concept, the extraction of eHR data was performed manually, albeit remotely, for the 130 participating practices. Automated data collection is technically feasible and would significantly reduce the staffing costs involved.

Second, because using pre-existing clinical data in eHRs is less expensive, this approach facilitates gathering information on a greater number of participants each year. Large sample sizes are generally required in order to obtain annual VE estimates with meaningful confidence intervals, particularly when the estimates are broken down by individual virus type and sub-type. Previously when we analyse data collected via our State's sentinel practice network, we frequently found that the VE confidence intervals were wide and crossed the null, as there were too few data. As demonstrated here, the eHR extraction approach enabled us to derive overall VE estimates that were statistically greater than zero for each year studied, often by type and/or subtype.

Third, the eHR data extraction approach we describe is scalable and could be readily expanded to include persons tested for influenza illness throughout Australia. While there are many proprietary clinical practice management software programs in use in Australia, a random survey of general practices across the country in 2014 found that just two of the programs were used by 80% of general practices [27]. The Canning Tool program we used for this report extracted data from both of these systems and three others. Given that the number of laboratories in Australia performing influenza PCR testing for patient care is finite, and that laboratories communicate electronic data using established formats, developing a large practice-based system to measure influenza VE using data extraction appears within reach. Given the potential benefits, it is not surprising that researchers in Europe and Central America have been exploring use of routinely collected clinical data to obtain more timely estimates influenza VE [28–30]. A nationally-representative system in Australia, where many practices contribute data, should permit more rapid calculation of robust VE estimates that would be helpful in guiding clinical practice. It would also represent a major contribution to an informed response to the threat of influenza in the Southern Hemisphere.

5. Conclusions

Given that the continual mutation of circulating wild-type influenza viruses frequently requires changes in the antigenic composition of seasonal influenza vaccines, ongoing monitoring of influenza VE is needed. Timely estimates can be used provide an early indication of how well the vaccine is protecting the population and inform decisions about whether additional public health measures, such as more widespread use of antivirals, are indicated [31]. Establishing and refining systems which can produce valid, timely estimates of influenza VE during annual influenza epidemics should be a key component of preparing for pandemic influenza. While additional research verifying the validity of this approach is needed, results from our proof-of-concept assessment suggest extracting existing clinical information from eHR in general practices is a feasible, resource-efficient, way to estimate VE and yields results similar to those obtained through traditional provider-based surveillance systems.

Author declaration

The authors have no potential conflicts of interest to disclose.

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Author contributions

AR, RG, LEB, and PVE each contributed to the design of the data extraction tool. AR and RB managed the recruitment of participating practices. AR led all data analyses and wrote the first draft of the manuscript. All authors contributed extensively to the writing of the manuscript.

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