RESEARCH ARTICLE

Influenza Altmetric Attention Score and its association with the influenza season in USA [version 1; peer review: awaiting peer review]

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Abstract

Background: Altmetrics measure the impact of journal articles by tracking social media, Wikipedia, public policy documents, blogs, and mainstream news activity, after which an overall Altmetric attention score (AAS) is calculated for every journal article. In this study, we aim to assess the AAS for influenza related articles and its relation to the influenza season in USA.

Methods: This study used the openly available Altmetric data from Altmetric.com. First, we retrieved all influenza-related articles using an advanced PubMed search query, then we inputted the resulted query into Altmetric explorer. We then calculated the average AAS for each month during the years 2012-2018.

Results: A total of 24,964 PubMed documents were extracted, among them, 12,395 documents had at least one attention. We found a significant difference in mean AAS between February and each of January and March (p< 0.001, mean difference of 117.4 and 460.7, respectively). We found a significant difference between June and each of May and July (p< 0.001, mean difference of 1221.4 and 162.7, respectively). We also found a significant difference between October and each of September and November (p< 0.001, mean difference of 88.8 and 154.8, respectively).

Conclusion: We observed a seasonal trend in the attention toward influenza-related research, with three annual peaks that correlated with the beginning, peak, and end of influenza seasons in USA, according to Centers for Disease Control and Prevention (CDC) data.

Keywords

Influenza, Altmetric, Detection, Vaccine, CDC, Infection
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Introduction
In the last few years, a new way to measure the attention brought by journal articles, termed altmetrics (a shortening of “alternative metrics” or “article-level metrics”), was adopted. It was also considered an “alternative” to the conventional citation-based measures. Altmetrics measure the impact and attention of an individual article. Altmetrics are increasingly recognized tools with an aim to measure the real-time influence of an academic article. Altmetrics measure the impact of journal articles by tracking social media, Wikipedia, public policy documents, blogs and mainstream news activity, after which an overall Altmetric attention score (AAS) is calculated for every journal article. Altmetrics have been used to measure the impact of articles on a disease, or even the impact of article on a whole field.

Each country has its own influenza detection center; the U.S has the Centers for Disease Control and Prevention (CDC), Europe has the European Influenza Surveillance Scheme (EISS), and Japan has the Infectious Disease Surveillance Center (IDSC). These surveillance systems mainly depend on the collection of numerous indicators, including clinical symptoms, virology laboratory results, hospital admissions and mortality statistics, resulting in a several-week lag in data reporting. The problem of influenza detection and prediction can be tracked back to Serfling’s work in 1963 in epidemiology, which tried to find a threshold for influenza breakout. Since then, various approaches have been proposed for flu detection and prediction in multiple situations. In an attempt to provide earlier influenza detection, the literature provided several examples of ‘syndromic approaches’ to anticipating or forecasting influenza-like illness (ILI), where various new methods are proposed each year, ranging from telephone triage service to observing the amount of over-the-counter drug sales. A previous project by Google in cooperation with the CDC was able to track in a population based on influenza-related web form queries on the Google search engine. This approach has paved the way for many new approaches designed using the same concept of using search engines for flu detection. In this study, we aim to assess the AAS for influenza related articles and its relation to the influenza season in USA. Moreover, we will assess the top articles and journals publishing about influenza in terms of attention they brought.

Methods

Search strategy
This study used the openly available Altmetric data by Altmetric.com. Accordingly, this study was exempted from institutional board review IRB approval. We conducted the search on June, 5th 2019. To retrieve all articles indexed in PubMed related to influenza, we used MeSH database to extract influenza-related terms, and the following were identified:

- Influenza
- Influenza in Humans

We then searched PubMed database in the following steps:

1- All influenza entry terms mentioned above were used as “MeSH terms”.
2- Language: English.
3- Publication type: Journal articles.
4- Search period: from 1/1/2000 to 31/12/2018.

The following query resulted:

```
((((((Grippe[MeSH Terms]) OR Human Flu[MeSH Terms]) OR Influenza[MeSH Terms])) OR Influenza in Humans[MeSH Terms]) AND “english”[Language]) AND (“2000/01/01”[Date - Publication] : “2018/12/31”[Date - Publication])) AND “journal article”[Publication Type]
```

Altmetric data

We inputted the resulted search query into Altmetric Explorer, a web-based platform that enables users to browse and report all attention data for every piece of scholarly content.

Altmetric.com is one of the providers of altmetrics and was found to have the best coverage of blog posts, news, and tweets. It pulls data from:

- Social media (e.g. Twitter and Facebook).
- Traditional media (e.g. The Guardian and New York Times).
- Blogs for individuals and organizations (e.g. Cancer Research UK).
- Online reference managers (e.g. Mendeley and CiteULike).

The AAS is a quantitative measure of the quality and quantity of attention an output has received, it provides an indicator of the amount of attention a research has received. It weights the amount of attention received by each source based on an algorithm. Data can be filtered and presented for countries and in specific time periods. We filtered influenza mentions for the USA as a country, to correlate with influenza frequency detected by the CDC, then we measured the AAS for each month in the period from 2012 to 2018, we then calculated the average AAS for each month.

Statistical analysis

We used SPSS version 21.0 (Chicago, USA) in our analysis. We used mean (± standard deviation) to describe continuous variables (e.g. AAS). We used count (frequency) to describe other

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nominal variables (e.g. countries). We performed one-way ANOVA followed by Tukey's post-hoc test to analyze the difference in the mean AAS score between each month, we presented the results in mean difference with 95% confidence interval (CI). All underlying assumptions were met, unless otherwise indicated. We adopted a p-value of 0.05 as the significance threshold.

Results
A total of 24,964 PubMed documents were extracted. Among them, 12,395 documents had at least one Altmetric point. The total number of mentions for the included documents was 185,744, of which 152,899 were from social media, 20,499 were from news and blogs, 10,608 were from policy and patents, 1,309 were from other sources and 479 were from academic sources. The USA contributed to 28,001 (20.4%) of the total mentions, followed by UK 12,007 (8.8%), and Japan 8,684 (6.3%).

We observed regular monthly mentions of the research output only after January 2012, thus we only included mentions from January 2012 and on. We filtered the search for US mentions only. We collected US mentions of influenza related articles in each month in the years from 2012 to 2018, and we then calculated the average AAS score for each month. This is shown in Table 1.

On one-way ANOVA, we found a significant difference between the months (p< 0.001). Following post-hoc analysis, we found a significant difference in mean AAS between February and each of January (p< 0.001, mean difference of 117.4 with 95% CI: 89.7 to 145.2) and March (p< 0.001, mean difference of 460.7 with 95% CI: 430.2 to 491.1). We also found a significant difference between June and each of May (p< 0.001, mean difference of 1221.4 with 95% CI: 87.0 to 155.8) and July (p< 0.001, mean difference of 162.7 with 95% CI: 126.1 to 199.2). We also found a significant difference between October and each of September (p< 0.001, mean difference of 88.8 with 95% CI: 59.6 to 118.0) and November (p< 0.001, mean difference of 154.8 with 95% CI: 125.8 to 183.9). As shown in Figure 1, there are three peaks for the AAS; the highest is

Table 1. Average US mentions of influenza-related articles each month in the years 2012 to 2018.

<table>
<thead>
<tr>
<th>Month</th>
<th>Mean</th>
<th>Total mentions</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>January</td>
<td>959.0805</td>
<td>4274</td>
<td>626.92688</td>
</tr>
<tr>
<td>February</td>
<td>1076.5216</td>
<td>4331</td>
<td>614.63388</td>
</tr>
<tr>
<td>March</td>
<td>615.8514</td>
<td>3056</td>
<td>276.20525</td>
</tr>
<tr>
<td>April</td>
<td>593.2094</td>
<td>3037</td>
<td>288.99383</td>
</tr>
<tr>
<td>May</td>
<td>464.7877</td>
<td>2930</td>
<td>196.47219</td>
</tr>
<tr>
<td>June</td>
<td>586.1891</td>
<td>2930</td>
<td>346.54126</td>
</tr>
<tr>
<td>July</td>
<td>423.5106</td>
<td>2162</td>
<td>196.47219</td>
</tr>
<tr>
<td>August</td>
<td>408.3328</td>
<td>2368</td>
<td>141.68444</td>
</tr>
<tr>
<td>September</td>
<td>742.6760</td>
<td>3611</td>
<td>441.88501</td>
</tr>
<tr>
<td>October</td>
<td>831.4399</td>
<td>4237</td>
<td>441.88501</td>
</tr>
<tr>
<td>November</td>
<td>676.6112</td>
<td>3668</td>
<td>253.31778</td>
</tr>
<tr>
<td>December</td>
<td>693.9009</td>
<td>3623</td>
<td>369.53838</td>
</tr>
<tr>
<td>Total</td>
<td>712.6055</td>
<td>39991</td>
<td>441.73627</td>
</tr>
</tbody>
</table>

Figure 1. Average Altmetric Attention Score (AAS) for each month from years 2012 to 2018. There are three peaks for the AAS; the highest is observed in February with a mean AAS of 1076.5 (±614.6), the second peak is in October with a mean AAS of 831.4 (±441.9), and the third is in June with a mean AAS of 586.2 (±271.1).
observed in February with a mean AAS of 1076.5 (±614.6), the second peak is in October with a mean AAS of 831.4 (±441.9), and the third is in June with a mean AAS of 586.2 (±271.1).

The journals publishing articles with highest AAS scores were PLOS ONE with a total AAS of 872 for 979 research outputs, followed by Vaccine with 842 for 1015 research outputs, and Influenza & Other Respiratory Viruses with 465 for 465 research outputs. Table 2 shows the top 10 journals in terms of AAS for influenza-related research.

The top research article in terms of AAS is entitled “Infectious virus in exhaled breath of symptomatic seasonal influenza cases from a college community” published in “Proceedings of the National Academy of Sciences of the United States of America” in January 2018, with an AAS of 2927. Table 3 shows the top 10 research outputs discussing influenza by AAS.

**Discussion**

The research on influenza attracted considerable attention, as measured by the AAS, with the USA the source of the greatest attention. For influenza research from the USA, we observed three peaks for the AAS. The highest peak is observed in February, with a mean AAS of 1076.5 (±614.6), which corresponds to the peak of influenza season as reported by CDC; the second peak is in October with a mean AAS of 831.4 (±441.9), which corresponds to the beginning of the influenza vaccination season; and the third is in June with a mean AAS of 586.2 (±271.1), which corresponds to the end of the influenza season.

Previous studies have used several analytic methods to correlate with influenza season. One of the first studies that brought significant public attention was the one that based its influenza surveillance on Google search engine query data⁹, in a study co-authored by Google Inc. and CDC researchers. The idea behind this surveillance system was detecting health-seeking behavior in the form of queries to online search engine, where this system managed to estimate weekly influenza activity with only a one-day lag from the CDC actual data. Other studies that used similar estimation techniques followed, where a study by Dugas et al. correlated queries to Google search engine with ILI cases reported by emergency departments¹³. This approach of estimating influenza infection trends based on search engine query was also found to be accurate in other countries, for instance, Europe¹⁴, China¹⁵, and South Korea¹⁶. Other authors also used the Yahoo search engine query to yield similar estimations¹⁷. Several studies also used Twitter massages and tweets to detect trends that may correlate with ILI trends as detected by CDC¹¹,¹⁸–²¹. Other studies used text

### Table 2

<table>
<thead>
<tr>
<th>Journal</th>
<th>Output</th>
<th>AAS</th>
</tr>
</thead>
<tbody>
<tr>
<td>PLoS ONE</td>
<td>979</td>
<td>872</td>
</tr>
<tr>
<td>Vaccine</td>
<td>1015</td>
<td>842</td>
</tr>
<tr>
<td>Influenza &amp; Other Respiratory Viruses</td>
<td>507</td>
<td>465</td>
</tr>
<tr>
<td>Journal of Infectious Diseases</td>
<td>348</td>
<td>323</td>
</tr>
<tr>
<td>Journal of Virology</td>
<td>350</td>
<td>306</td>
</tr>
<tr>
<td>Emerging Infectious Diseases</td>
<td>324</td>
<td>282</td>
</tr>
<tr>
<td>Clinical Infectious Diseases</td>
<td>291</td>
<td>253</td>
</tr>
<tr>
<td>BMC Infectious Diseases</td>
<td>272</td>
<td>245</td>
</tr>
<tr>
<td>BMC Public Health</td>
<td>178</td>
<td>151</td>
</tr>
<tr>
<td>Human vaccines immunotherapeutics</td>
<td>171</td>
<td>148</td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th>Title</th>
<th>AAS</th>
<th>Journal</th>
<th>Publication date</th>
<th>Citations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Infectious virus in exhaled breath of symptomatic seasonal influenza cases from a college community</td>
<td>2927</td>
<td>Proceedings of the National Academy of Sciences of the United States of America</td>
<td>January 2018</td>
<td>24</td>
</tr>
<tr>
<td>Chasing Seasonal Influenza — The Need for a Universal Influenza Vaccine</td>
<td>2478</td>
<td>New England Journal of Medicine</td>
<td>January 2018</td>
<td>46</td>
</tr>
<tr>
<td>Acute Myocardial Infarction after Laboratory-Confirmed Influenza Infection</td>
<td>2075</td>
<td>New England Journal of Medicine</td>
<td>January 2018</td>
<td>74</td>
</tr>
<tr>
<td>Influenza Vaccine Effectiveness Against Pediatric Deaths: 2010–2014</td>
<td>1889</td>
<td>Pediatrics</td>
<td>April 2017</td>
<td>41</td>
</tr>
<tr>
<td>Deposition of respiratory virus pathogens on frequently touched surfaces at airports</td>
<td>1696</td>
<td>BMC Infectious Diseases</td>
<td>August 2018</td>
<td>2</td>
</tr>
<tr>
<td>The Japanese Experience with Vaccinating Schoolchildren against Influenza</td>
<td>1686</td>
<td>New England Journal of Medicine</td>
<td>March 2001</td>
<td>611</td>
</tr>
<tr>
<td>1918 Influenza: the Mother of All Pandemics</td>
<td>1391</td>
<td>Emerging Infectious Diseases</td>
<td>January 2006</td>
<td>770</td>
</tr>
<tr>
<td>Prevention and Control of Seasonal Influenza with Vaccines</td>
<td>1347</td>
<td>MMWR Recommendations &amp; Reports</td>
<td>August 2016</td>
<td>240</td>
</tr>
<tr>
<td>The biggest pandemic risk? Viral misinformation</td>
<td>1346</td>
<td>Nature</td>
<td>October 2018</td>
<td>4</td>
</tr>
</tbody>
</table>
mining to extract influenza-related blogs from several web and social media sources. In another approach, several authors used Wikipedia access logs to achieve accurate, real time estimation of influenza cases. In a study by Santillana et al., the authors combined data from search engines, social media and hospital visits to estimate influenza activity in USA.

During our literature review, we found around 49 articles discussing the use of websites to detect influenza in USA (Figure 2). Using search engines as a source of data (e.g. Google and Yahoo) has limited the data provided, compared to micro-blogging websites (e.g. twitter), which contain more semi-structured metadata enabling a more detailed statistical analysis (e.g. cities, gender, age). Several papers proposed different models for detecting flu using Twitter-based methods. Ritterman et al. showed that twitter can improve the accuracy of market forecasting by detecting early external events like H1N1, followed by another study which used twitter, multiple regression, and document filtering to detect relationship between tweets and national data statistics. In another study, Broniatowski et al. created a new supervised classification model that separates tweets indicating influenza infection from those indicating influenza awareness or concern.

In general, the interest in publishing about influenza has increased in the recent years, with USA being the top country in terms of influenza research production. From the overall influenza research output, influenza vaccine was one of the main topics researched and Journal of Virology and Vaccine journal published the highest number of research articles since 1900. We also found that PLOS ONE was the top journal in terms of AAS followed by Vaccine.

Some limitations to the present study need to be taken into account. The search queries in these models are not exclusively submitted by users experiencing influenza-like symptoms, thus the correlations observed might be only meaningful across large populations. In addition, despite strong historical correlations, these systems remain susceptible to false alerts caused by a sudden increase in ILI-related queries. An unusual event, such as a drug recall for a popular cold or flu remedy, announcing a new flu strain, etc., could cause such a false alert. Disease mentions sometimes depend on social events, which might not be related to disease spread, like holding a conference about flu pandemic. Another limitation to using web-based tools is coverage. Additionally, much of the world is currently excluded from the current systems, which can only process English-language tweets.

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Figure 2. Article discussing the use of websites to detect influenza in USA.
We observed a seasonal trend in the attention toward influenza-related research, with three annual peaks that correlated with the beginning, peak, and end of influenza seasons in USA, according to CDC data. We believe that analyzing the attention of influenza related research may aid in detecting influenza season’s peaks, which may be a useful tool in areas with limited on-site detection centers.

**Data availability**

**Underlying data**

Harvard Dataverse: Altmetric Attention Score for influenza publications in USA. https://doi.org/10.7910/DVN/XCQ8WO.

**References**

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