

Monitoring Discussion of Vaccine Adverse Events in the Media: Opportunities from the Vaccine Sentimeter

**Guido Powell, Kate Zinszer, Jahnavi Dhananjay, Chi Bahk,
Lawrence Madoff, John Brownstein, Sabine Bergler, David Buckeridge**

McGill Clinical & Health Informatics, Department of Epidemiology and Biostatistics,
Faculty of Medicine, McGill University, 1140 Pine Ave. W., Montreal, Canada, H3A 1A3, 514-934-1934 ext. 32999
guido.powell@mail.mcgill.ca, kate.zinszer@mail.mcgill.ca, j_dhanan@encs.concordia.ca, chi@epimedico.com,
lmadoff@promedmail.org, john.brownstein@childrens.harvard.edu, bergler@cse.concordia.ca, david.buckeridge@mcgill.ca

Abstract

As doubts about vaccine safety threaten adequate coverage across the world, surveillance of online media, a widespread source of information about vaccines, can prove useful in many regards. The Vaccine Sentimeter, an extension of HealthMap, was established for the purpose of monitoring online vaccine discussion in news, blogs, and other websites. The development of the tool involved extensive manual annotation of media content, such as the sentiment or category of discussion in the report. Given its relevance to vaccine confidence and public health, the current paper describes in detail the annotated discussion of adverse event following immunization (AEFI). The goal of the current project is to automate the detection of AEFI reports in the media. Future steps in this automation process are proposed.

1. Introduction

Despite the proven effectiveness and safety of licensed vaccines, many people continue to have concerns about vaccination. These concerns are often disproportionate to the actual risks of vaccines. For example, up to 52% of 1,015 Americans surveyed in 2015 were “unsure” of whether vaccines cause autism, with a small but significant 6% of the sample believing in this association (Newport 2015). In Canada, 41% of a sample of 27,382 internet users believed the H1N1 vaccine to be unsafe, while 35% were ambivalent about its safety (Seeman, Ingm and Rizzo 2010). Such uncertainty about vaccine safety is intensified by exposure to media with negative sentiment about vaccines or unbalanced portrayals of vaccine risk (Dixon and Clark 2013; Betsch et al. 2011). This uncertainty can translate directly into decreased vaccine coverage (Larson et al. 2011).

With an increasing number of individuals relying on online media as a source of health information, misrepresentations of vaccine risks published online now have a greater reach than ever. A common source of controversial and unsubstantiated claims about vaccines is the “anti-vaccine” movement, whose members often publish in blogs or popular alternative medicine websites (Betsch and Sachse 2012). However, traditional news websites may also present incorrect or unbalanced information about the safety and effectiveness of vaccines (Bodemer et al. 2012). Monitoring of vaccine discussions in different types of online media can therefore improve our understanding of vaccine hesitancy or refusal.

The Vaccine Sentimeter is a global surveillance tool of online media discussion about vaccines, derived from HealthMap, a more general monitoring tool of media content about diseases. It grew out of the Vaccine Confidence Project, an earlier collaboration between the Program for Monitoring Emerging Diseases (ProMED) and the London School of Hygiene and Tropical Medicine. The Vaccine Sentimeter describes in each identified report a specific vaccine, the sentiment (positive, neutral, or negative), and the topics discussed (according to a typology). An important category is “adverse events following immunization” (AEFI). Along with a few other categories, reports about serious AEFI were flagged as high priority reports and forwarded to health ministries and officials at institutions such as the WHO and UNICEF (Larson et al. 2013). The Vaccine Sentimeter thereby provides various public health agencies with real-time information on public concerns about vaccines, allowing them to identify emerging patterns, which may help to direct immunization communication and programming.

The Vaccine Sentimeter, however, relied to a large extent on manual classification of reports by a team of analysts (described further in Methods section). While the application continues to filter for vaccine-relevant reports from HealthMap, along with its automatically populated fields (e.g., date and location), the more demanding manual classification of categories, vaccine, and sentiment ended in October 2014. Yet the number of reports (22,293) classified since the start of the project offers a unique opportunity to develop new classification algorithms using a large, manually validated dataset. This paper describes a subset of these data, specifically reports that discuss AEFI, and describes our planned research to automate this classification.

2. Methods

Data Collection

The Vaccine Sentimeter obtained reports through the HealthMap automated media monitoring system (Freifeld et al. 2008). HealthMap acquired health reports through aggregators such as Google News, Google Blog Search, and Moreover Public Health (health-related rich site summary [RSS] news feeds). The reports acquired by HealthMap consisted mainly of online news articles, blog posts, government reports, and webpages discussing health (including vaccines). The Vaccine Sentimeter adapted the HealthMap system to retrieve reports related to vaccines, vaccination programs, and vaccine-preventable diseases (excluding articles on animal vaccines), using search criteria (e.g., “intitle:vaccine OR intitle:influenza OR intitle:pertussis”). Though the Vaccine Sentimeter’s complete collection contains international reports published as early as April 2010 and written in over 18 languages, the current analysis was limited to English-language reports, published between June 2012 and October 2014. Public access to the Vaccine Sentimeter’s content is available for online browsing through a web application (vaccinesentimeter.org) or by correspondence with info@epimedico.com. Funding for development of the Vaccine Sentimeter was supported by Sanofi-Pasteur. Current analyses are supported by the Canadian Immunization Research Network.

Sentimeter Classification

Vaccine-related HealthMap reports were extracted and classified every hour using manual and automated methods. HealthMap’s automated classifications assigned a title, date, source, URL, plain text content, location (city, state, and/or country), and disease to each report using a text processing algorithm (Freifeld et al. 2008). Public health professionals from ProMED served as analysts to

review and modify the automatically assigned classifications on a daily basis. With a standardized coding guide and periodic quality assessments to ensure consistency, the analysts manually classified the reports according to vaccine-preventable disease, vaccine type, vaccine manufacturer, the type of source (news or blog/other), and provided a one-line summary of each report. The analysts also classified the reports according to 55 categories based on the report’s content. These categories were identified by an advisory group of experts as important factors contributing to past breakdowns in public vaccine confidence. The 55 categories were further grouped into 7 broader categories: Vaccine Safety (e.g., all categories of AEFI, additives, contamination, tampering); Vaccine Development and Research (e.g., new products); Contextual Factors (e.g., disease burden, high profile individuals); Beliefs, Awareness, Perception (e.g., risk/benefit, motives, conspiracy theory); Recommendations (e.g., policy recommendations, recommendations by healthcare worker); Impacts (e.g., outbreaks, vaccine refusals, vaccine suspension); and Vaccine Delivery Program (e.g., vaccine effectiveness, strategy, cost). All classifications of AEFI were based on its definition as “any untoward medical occurrence that follows immunization and which does not necessarily have a causal relation with the usage of the vaccine” from the Council for International Organizations of Medical Sciences and WHO working group on vaccine pharmacovigilance. Analysts also classified reports according to sentiment (positive, negative, or neutral/unclear), based on the report’s likely effect on vaccine confidence after reading. Negative sentiment was assigned to reports indicating concerns about vaccines or concerns that may negatively affect vaccine programs (AEFI, vaccine suspension, etc.). Positive or neutral/unclear sentiment was assigned to any report without such indicators of concern about vaccines or programs, such as articles announcing new vaccination campaigns (Larson et al. 2013).

Automated Classification of AEFI

We plan to develop methods to automate the classification of AEFI discussion in reports. This category of report was selected among other options (i.e., sentiment, vaccine, other categories) for initial automation steps given its public health importance. To develop a classification algorithm, we will first partition the reports into a training set based on 65% of English-language reports discussing any AEFI. We will reserve 15% of the reports for algorithm validation, and 20% of the reports as a test set. We will then adapt a pipeline designed for sentiment analysis (Ozdemir and Bergler 2015) to classify reports according to the presence or absence of AEFI. A set of

term lists obtained from health-related sources will be used instead of sentiment lexica. These lists will include terms from the Vaccine Adverse Event Reporting System (VAERS; Singleton et al. 1999), the FDA Adverse Event Reporting System (FAERS; Kessler 1993), the Unified Medical Language System (UMLS) Meta-thesaurus (Bodenreider 2004), and the Consumer Health Vocabulary (CHV; Zeng-Treitler et al. 2008). Tags from the different term lists and other characteristics of the reports (e.g., linguistic features, negation) will be used as features in a support vector machine (SVM) or other supervised learning method. The classification pipeline will be iteratively refined using the validation set before final evaluation of our method using the test set. We will compare the final performance of our algorithms to those of classifiers developed for detecting discussion of drug adverse events in social media, such as Twitter and patient support forums (Sarker and Gonzalez 2015)

3. Results

Results presented here are restricted to descriptions of the dataset for which automated classification is currently being developed. Table 1 presents the distribution of each type of AEFI (2,016 total reports). The sum of frequencies is greater than the total number of reports as the reports may discuss more than one type of AEFI. Other non-AEFI categories were also discussed in most (79%) of the AEFI reports. The two most common vaccines discussed for each type of AEFI are presented in the last column of the table.

By far, autism is the most discussed AEFI in media reports about vaccines, notably in media about the measles/mumps/rubella (MMR) vaccine. The fact that this discussion persists despite widespread refutation of any causal association reflects different attitudes depending on the type of media. News reports tend to also discuss outbreaks (50%) and vaccine refusals (34%) with little negative sentiment about vaccines (14%), while blogs and other websites primarily discuss conspiracy theories (30%) and additives (20%), with a high proportion of reports having negative sentiment (58%). Reports discussing various AEFI also frequently discuss vaccines for human papillomavirus (HPV; 19%) and influenza (14%). Though discussion of adverse events is perhaps more likely for such vaccines given their more recent development, the especially high percentage of negative sentiment for both HPV (54%) and Influenza (39%) suggest online media in general portray these vaccines as more dangerous than the evidence suggests.

Table 2 presents the distribution of the top 12 other categories discussed in AEFI reports. The last column

presents the ratio of the percentage of AEFI reports over the percentage of non-AEFI reports for each category. This ratio indicates how much more likely a category is to be identified in reports that discuss AEFI than in all other vaccine reports. Such an indicator may be useful for training the automated classification of AEFI reports, since it highlights categories of discussion that are more specific to AEFI reports. Examples of such categories are additives (ratio of 21.1), strategy - investigations (ratio 14.2), and beliefs - conspiracy theories (ratio of 6.7). The type of language used in such reports may inform the choice of features to supplement the NLP process.

Table 1 Distribution of AEFI Category Annotations

Adverse Event	Frequency (%)	2 most relevant vaccines (%)
Autism	876 (43.5)	Vaccines in general(56), MMR(50)
General	497 (24.7)	HPV(43), Vaccines in general (29)
Death	300 (14.9)	HPV(30), Pentavalent(19)
Neurological damage	113 (5.6)	HPV(36), Vaccines in general (30)
Fertility	107 (5.3)	Polio(59), HPV(33)
Narcolepsy	95 (4.7)	Influenza(98), MMR(4)
Seizures	92 (4.6)	HPV(37), MMR(30)
Mild	90 (4.5)	HPV(37), Influenza(26)
Immune system	76 (3.8)	HPV(65), Vaccines in general (20)
Vaccine Derived Poliovirus	63 (3.1)	Polio(86), Influenza(18)
Paralysis	57 (2.8)	HPV(39), Influenza(30)
Fever	47 (2.3)	MMR(32), Influenza(28)
HIV/Aids	7 (0.3)	Polio(86), MMR(14)
Miscarriage	4 (0.2)	HPV(75), Influenza(25)
Category co-occurring with AEFI	1593 (79)	Vaccines in general(34), MMR(30)
Total AEFI reports	2016	Vaccines in general(31), MMR(27)

Outcomes of Classification

Results of classification algorithm will be assessed using measures of sensitivity, specificity, and area under the receiver operating characteristic curve. We will also

compare the performance of the classification with and without linguistic features to assess the individual contribution of different methods.

Table 2 Additional Categories Discussed in AEFI Reports

Other categories annotated in AEFI reports (top 12)	Frequency (%)	% of AEFI / % of non-AEFI
Risk/Benefit	342 (21.5)	4.5
Vaccine Refusals	306 (19.2)	3.6
Additives	290 (18.2)	21.1
Outbreaks	282 (17.7)	0.9
Research	198 (12.4)	1.1
Beliefs - Conspiracy theory	192 (12.1)	6.7
High Profile Individual	171 (10.7)	5.2
Disease Burden	120 (7.5)	0.5
Strategy - Investigation	119 (7.5)	14.2
Motives - Business	101 (6.3)	4.7
Beliefs - Religious	87 (5.5)	1.8
Low Vaccination Coverage	87 (5.5)	1.1
Other	892 (44.2)	-

4. Discussion

The current paper reports progress on plans to automate the detection of AEFI discussion in online media. Our dataset contains extensive manual annotation beyond classification of AEFI. Descriptive analyses of the Vaccine Sentimeter reports reveals patterns in media discussion about AEFI that can help our future automation of classification. A limitation in the dataset worth noting is the ambiguity of certain directives guiding annotations. In addition, beside periodic quality assurance, no statistic of inter-rater reliability was tested during the annotation process. Despite these limitations, the Vaccine Sentimeter reports offer many opportunities for additional automation, from more detailed classification of categories and vaccines to sentiment analysis. Developing methods to automate the detection and classification of vaccine discussion in the media, should make the Vaccine Sentimeter more efficient and sustainable, thereby securing and extending its use by public health institutions.

References

- Newport, F. 2015. In US, Percentage Saying Vaccines are Vital Dips Slightly. Gallup. Available at: <http://www.gallup.com/poll/181844/percentage-saying-vaccines-vital-dips-slightly.aspx> [Accessed 20 Oct 2015]
- Seeman, N., Ing, A., & Rizo, C. 2010. Assessing and responding in real time to online anti-vaccine sentiment during a flu pandemic. *Healthc Q* 13(Spec No): 8-15
- Dixon, G., & Clarke, C. 2013. Heightening uncertainty around certain science media coverage, false balance and the autism-vaccine controversy. *Science Communication* 35(3): 358- 82.
- Betsch, C., Ulshöfer, C., Renkewitz, F., & Betsch, T. 2011. The influence of narrative v. statistical information on perceiving vaccination risks. *Medical Decision Making* 31(5): 742-753.
- Larson, H. J., Cooper, L. Z., Eskola, J., Katz, S. L., & Ratzan, S. 2011. Addressing the vaccine confidence gap. *The Lancet* 378(9790): 526-535.
- Betsch, C., & Sachse, K. 2012. Dr. Jekyll or Mr. Hyde? How the internet influences vaccination decisions: recent evidence and tentative guidelines for online vaccine communication. *Vaccine* 30(25): 3723-3726.
- Bodemer, N., Müller, S. M., Okan, Y., Garcia-Retamero, R., & Neumeyer-Gromen, A. 2012. Do the media provide transparent health information? A cross-cultural comparison of public information about the HPV vaccine. *Vaccine* 30(25): 3747-3756.
- Larson, H. J., Smith, D. M., Paterson, P., Cumming, M., Eckersberger, E., Freifeld, C. C. & Madoff, L. C. 2013. Measuring vaccine confidence: analysis of data obtained by a media surveillance system used to analyse public concerns about vaccines. *The Lancet Infectious Diseases* 13(7): 606-613.
- Freifeld, C. C., Mandl, K. D., Reis, B. Y., & Brownstein, J. S. 2008. HealthMap: global infectious disease monitoring through automated classification and visualization of Internet media reports. *Journal of the American Medical Informatics Association* 15(2): 150-157.
- Ozdemir, C., & Bergler, S. CLaC-SentiPipe: SemEval2015 Subtasks 10 B, E, and Task 11. 2015. *Proceedings of the 9th International Workshop on Semantic Evaluation 2015*: 479–485
- Singleton, J.A., Lloyd, J.C., Mootrey, G.T., et al. 1999. An overview of the vaccine adverse event reporting system (VAERS) as a surveillance system. *Vaccine* 17: 2908-17
- Kessler, D.A. 1993. Introducing MEDWatch. A new approach to reporting medication and device adverse effects and product problems. *JAMA* 269: 2765-8.
- Bodenreider, O. 2004. The unified medical language system (UMLS): integrating biomedical terminology. *Nucleic acids research* 32 (suppl 1): D267-D270.
- Zeng-Treitler, Q., Goryachev, S., Tse, T., Keselman, A., & Boxwala, A. 2008. Estimating consumer familiarity with health terminology: a context-based approach. *Journal of the American Medical Informatics Association* 15(3): 349-356.
- Sarker, A., & Gonzalez, G. 2015. Portable automatic text classification for adverse drug reaction detection via multi-corpus training. *Journal of biomedical informatics* 53: 196-207.