Analyzing Perceived Risk of Flu Vaccine on Twitter

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Abstract. To improve influenza vaccination rates, public health officials must understand potential factors in an individual's decision to get a flu shot. Evidence suggests that an individual's perception of risks related to infection and to vaccination may be influential, though surveys assessing these can be costly and slow. This paper triangulates data from multiple sources to study perceived risk in the context of flu vaccination. We create machine learning classifiers for relevant information on Twitter and statistically analyze discussions of perceived risk. We then compare Twitter discussions to data from a survey on perceived risk, showing how these data sources agree qualitatively. Future work will quantitatively examine these perceptions and potential misperceptions of risk.

Keywords: risk, flu, vaccine, classifier, Twitter, survey

1 Introduction

Annual vaccination remains among the best tools to prevent seasonal influenza, but the Centers for Disease Control and Prevention (CDC) indicates coverage falls short [4, 17, 35]. To improve vaccination rates, it is crucial for public health officials to understand the factors that influence an individual's decision to vaccinate.

Public health experts agree that vaccination behavior is complex [25]. However, evidence suggests that an individual's perception of risks related to infection and vaccination may be highly influential [1]. While traditional surveys can assess these attitudes, they are expensive, time-consuming, and fraught with measurement challenges [2].

The novel contribution of this paper lies in triangulating data from multiple sources to analyze perceived risk in the context of flu vaccination. Specifically, we construct machine learning (ML) classifiers to identify Twitter messages relevant to such perceptions of risk, then compare results to survey data. The following sections motivate identifying perceived risk and data sources; detail ML methods; analyze messages and compare to survey data; and discuss implications, limitations, and future work.

2 Literature Review

Contracting influenza poses significant risks. Though most cases are mild, influenza consistently ranks among the top ten causes of death annually [21]. Immunization is one of the best ways to avoid illness; CDC estimates that in the 2015-16 flu season, immunization averted nearly 7 million cases of disease [5]. The flu vaccine is not entirely without risks, as mild side effects may occur (e.g., muscle soreness or slight fever) [4]. Severe side effects are rare, but include Guillain-Barre Syndrome; the flu vaccine cannot cause the flu [4].

How an individual perceives risk significantly impacts their health behaviors. Research supports that increased perception of disease risk is a significant predictor of influenza immunization [26, 12, 18, 37]. A systematic review of flu vaccine research showed that low perceived risk of disease corresponded to lower rates of vaccine uptake [31]. It also found that perceived risk of vaccine side effects was associated with lower rates of uptake [31]. Qualitative research showed that factors affecting flu shot decisions include perceived low risk of disease, bad reactions, and the misperception that the flu shot causes the flu [22, 26].

Social media are a promising tool for understanding perceptions of risks related to flu and vaccines. While analyzing them introduces complexity, it overcomes issues in survey work, as it observes individuals' real-time spontaneous assessments of risk. Previous studies have combined ML with social media to explore discussion of the flu [e.g., 8, 32], and vaccine behavior [19]. Researchers may also validate these methods using known and reliable data. For example, Huang et al. [19] correlated tweets indicating intention and receipt of flu vaccines with CDC data, showing Twitter data were a reliable indicator of national vaccine uptake. For similar results related to perceived risk, one needs to be able to identify relevant messages.

3 Methods - Classifiers and Survey

We construct our classifier system in two steps. We first classify if a tweet is about the flu or about the flu shot (hereafter, 'topical'). Then if it is, we classify if it is relevant to perceived risks of the flu and the flu shot (hereafter: 'relevant'). We detail data collection, annotation, training, and evaluation for both topical and relevant classifiers. We then detail how we compare with survey data.

3.1 Data Collection

We gather filtered Twitter data streams from 8/2011-7/2017 using Healthtweets.org, "a research platform for sharing the latest developments in mining health trends from Twitter and other social media sites" [10]. For the topical classifier, we filter by the following keywords: 'influenza', 'flu', 'adenovirus', 'h1n1', 'h3n2', 'h5n1', 'ah1n1', 'shot', 'shots', 'immunize', 'immunized', 'immunization'. For the relevance classifier, we first filter using 269 health-related keywords [10]. Examples include: nasal, congestion, woken, ribs, swollen, viral, physical. We then randomly select 204 million tweets and apply our topical classifiers to prune alternate meanings. For example, 'shot' may refer to 'flu shot' or 'basketball shot'. We hope to find more relevant examples by increasing the likelihood that the posts are first topical.

3.2 Mechanical Turk Annotations

We annotate data using Amazon Mechanical Turk[1] (MT). In the topical annotations, we ask if the tweet is about the flu (y/n), and if it is about the flu vaccine (y/n). A tweet can be about both. We follow best practices[2] of asking simple questions, providing examples, and leveraging repetition with 10 tweets per task (HIT). Our topical annotations yielded 9990 messages, of which 8873 were about_flu, 1201 about_fluShot.

In the relevant annotations, we prioritized increasing validity and simplification. We compared workers' results to known, gold, results, including 241 gold tweets in our HITs labeled by the author with expertise in this area. Three random gold tweets were randomly included in each HIT's ten. If a worker achieved less than 75% accuracy on gold data, we dropped his labels. We simplified by asking two questions of one type. For each of the flu and flu shot, we ask only if the tweet discusses high risk, low risk, or does not discuss risk at all. We conducted a pilot study with 1000 tweets. After examining results including gold accuracies, we concluded that workers could annotate well, so we annotated more data. We combined high and low risk results across both flu and flu shot into a general 'relevance' class for a binary classifier. A relevant message is either about risk of the flu, about risk of the flu shot, or both. A non-relevant message is not about risk of the flu or risk of the flu shot. We obtained 1081 relevant tweets, and randomly sampled 1081 non-relevant tweets from the 23272 annotated.

3.3 Training Procedures

We use a Twitter-specific tokenizer [15, 24] and restrict vocabulary to the 10,000 most frequent types. Classifiers operate over tweets[3]. We train tweet-level multinomial logistic regression classifiers in Python by comparing many classifiers' performance by macro-averaged F-score using four-fold cross-validation, sweeping over feature sets. We try sum and mean of GloVe word embeddings trained on Twitter[4] [28], with widths none (no GloVe), 20, 50, 100, and 200. We try token n-grams of none, unigram, bigram, or both. The topical classifiers used a 60-40 train-test split; the relevance model, 80-20.

3.4 Model Results

The best about_flu topical classifier had an F-score of 0.48 on test data, with GloVe width of 100 and unigrams and bigrams, but it successfully identifies held-out positive

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[1] www.mturk.com
[2] http://mturkpublic.s3.amazonaws.com/docs/MTURK_BP.pdf
[3] This simplifies applying the classifier because additional content such as user profiles and timelines are unnecessary.
[4] http://nlp.stanford.edu/data/glove.twitter.27B.zip

examples 98% of the time, negative examples 38% of the time.[5] The best about_fluShot had an F-score of 0.87 on held-out data, with GloVe width of 50, using unigram and bigrams. Held-out negative examples were identified 99% of the time, positive examples 77% of the time. The best relevance classifier achieved macro-F1 of 0.8780 on test data, using unigrams and bigrams and a GloVe embedding width of 50. This classifier correctly predicted 83% of not relevant tweets, and 92% of relevant tweets.

3.5 Survey Data

We validate classifier results by comparing to data from a 2015 survey of American adults' attitudes on flu and flu vaccination [25]. It focused on four measures: perceived susceptibility to flu, perceived severity of flu, perceived likelihood of flu vaccine side effects, and perceived severity of flu vaccine side effects. These were measured with Likert scales from 'no risk' through varying degrees of risk. We dichotomize this data to mirror our system's output: relevant to perceived risk, or not. The relevant category is the union of all respondents who answered above 'no risk' for any measure.

4 Results - Perceived Risk Analysis

4.1 Twitter Analysis

We ran our topical and relevance classifiers over all messages in the first day of every month, noting only positive examples. Counting output of the three classifiers yields how many messages are about the flu (1098084) and about the flu shot (540996), and within each group, how many are relevant to perceived risk (173809 and 23005, resp.). The proportion of relevant messages about the flu (16%) is significantly larger than the proportion of relevant messages about the flu shot (4%; $c^2(1) = 45967$, $p < 0.001$).

4.2 Survey Results and Qualitative Comparison to Twitter

Most of the 1640 survey respondents perceived risks of flu: 68% perceived some susceptibility to flu, and 76% reported that flu could be at least slightly severe. Fewer perceived risks of flu vaccine: 58% perceived some likelihood of side effects, and 50% reported that side effects could be at least slightly severe. These numbers are much higher than those from Twitter; the self-reporting on Twitter might contain other information than perceived risk, but the survey explicitly asked about risk. Both data sources paint the same picture: that people are concerned with risks of the flu, that people are also concerned with risks of the flu shot, but less so than for risks of the flu.

[5] Insufficient examples not about_flu might have caused this low F-score.

5 Discussion

Twitter provides a new lens for studying perceived risk. Our results suggest that in both survey and Twitter data, a significant portion of adults perceive at least some risk of flu. While the proportion of adults who perceive risk of vaccine side effects is less than that which perceive some risk of flu in both data, it is still concerningly high. For most patients, risks of flu outweigh risks of side effects, reflecting that most side effects of flu are mild and resolve without medical intervention [5]. More messages discuss perceived risk of flu than perceived risk of flu vaccine, reflecting that influenza poses a greater threat than a vaccine side effect [4]. That 4% of relevant discussion involves flu shot risks is concerning for public health. However, this 4% proportion, along with the 16% for flu risk, can provide insight into how the public perceives risk in this context.

5.1 Limitations and Future Work

Survey data often include demographic information, as e.g., age, race, and gender have a substantial effect on perception of risks [14, 23]. Tools that identify demographics in Twitter data [e.g. 8, 20] might show who on Twitter is discussing perceived risk [11]. Using these would enable more granular comparisons, and better match and understand survey results that include breakdowns by ethnicity [25].

Classifier improvements might distinguish between low- and high-risk side effects. 50% of survey respondents reported some risk of side effects, but we cannot yet compare with social media. Improvements would show how individuals discuss mild side effects (e.g., sore arm) or severe ones (e.g., serious allergic reaction). These could be validated against surveys [25] as in previous work [19], and against web surveys of social media users [e.g., 34]. Future work could examine how people might self-report different risks, and whether self-report or traditional surveying offers more insight here.

6 Conclusion

To our knowledge, this is the first comparison of surveys with social media for perceived risk. We classified perceived risk of influenza and its vaccine on Twitter. Tweets showed qualitative agreement with survey data. Perceived risks of the flu are more prevalent than those of flu shot, but in both data sources, there is still a significant amount of concern about the flu shot. The overall frequencies are lower on social media for various reasons, and although misperceptions of risk may exist, more fine-grained risk information is yet unknown on social media. Future work will investigate these factors as we tune these different lenses into perceived risk in this public health context.

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