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Appendix: Content Summaries of Selected Best Papers for the 2017 IMIA Yearbook, Section 'Public Health and Epidemiology Informatics'

Kite J, Foley BC, Grunseit AC, Freeman B

Please Like Me: Facebook and Public Health Communication

PLoS One 2016;11(9)

This study aimed at reviewing the use of Facebook by Australian public health organisations to identify features of posting activity that are associated with user engagement, which authors define as likes, shares, or comments. Authors selected 20 eligible pages relevant to selected public health issues through a systematic search and coded 360-days of posts for each page. The health issues were: smoking, healthy diet, physical activity/sedentariness, overweight/obesity, alcohol, sexual health, illicit drug use, skin cancer, aboriginal health. Posts were coded by: post type (photo, text only, game, poll/quiz, app, link, event, or video), communication technique employed (informative, call-to-action, instructive, positive emotive appeal, fear appeal, testimonial, humor), and use of marketing elements (e.g., branding, use of mascots, etc.). Negative binomial regressions were used to assess associations between post characteristics (post type, communication technique, and marketing elements as categorical independent variables), and user engagement (respectively, number of likes, shares, and comments as the outcome variables). The results showed that video posts produced the greatest amount of user engagement, although an analysis of a subset of the data suggested that this might be a reflection of the Facebook algorithm, which governs what is and is not shown in user newsfeeds and appears to prefer videos over other post types. Posts that featured a positive emotional appeal or provided factual information attracted higher levels of user engagement, while conventional marketing elements, such as sponsorships and the use of persons of authority, generally discouraged user engagement, with the exception of posts that included a celebrity or a sportsperson. Further research could assist in understanding whether engagement with public health-related pages on Facebook actually leads to the achievement of public health goals. This study has shown that in order to increase the chances of achieving public health goals, content providers must encourage engagement and adapt to the Facebook algorithm in order to maximize message exposure, while also ensuring that the content is of high quality.

Sharpe JD, Hopkins RS, Cook RL, Striley CW

Evaluating Google, Twitter, and Wikipedia as Tools for Influenza Surveillance Using Bayesian Change Point Analysis: A Comparative Analysis

JMIR Public Health Surveill 2016 20;2(2)

Traditional influenza surveillance relies on the reports provided by health care providers of influenza-like illness (ILI) syndromes. It primarily captures individuals who seek medical care and misses those who do not interact with the health care system, and this surveillance method is limited by relatively dated technology and by delays of up to one to two weeks between the occurrence of the illness event and the dissemination of surveillance information. Syndromic surveillance includes the use of novel data sources such as emergency department records and prescription sales to enhance traditional surveillance systems. Recently, nontraditional data sources, particularly Web-based, have been applied to public health surveillance, as there is a growing number of people who search, post, and tweet about their illnesses before seeking medical care. This so coined 'digital epidemiology' can be less expensive, timelier, and can expand detection by increasing the range of health events that can be detected. Existing research has shown some promise of using data from Google, Twitter, and Wikipedia to complement traditional surveillance for ILI, but none compared the three of them. The objective of this study is to comparatively analyze Google Flu Trends , Twitter, and Wikipedia by examining which best corresponds with Centers for Disease Control and Prevention

(CDC) ILI data. It was hypothesized that Wikipedia will best correspond with CDC ILI data as a previous research found it to be least influenced by high media coverage as compared with Google and Twitter. Publicly available, deidentified data were collected from the CDC, Google Flu Trends, HealthTweets, and Wikipedia for the 2012-2015 influenza seasons. Bayesian change point analysis was used to detect seasonal changes, or change points, in each of the data sources. Change points in Google, Twitter, and Wikipedia that occurred during the exact week, the preceding week, or the week after the CDC's change points were compared with the CDC data as the gold standard. All analyses were conducted using the R package "bcp" version 4.0.0 in RStudio. In addition, sensitivity and positive predictive values (PPV) were calculated for Google Flu Trends, Twitter, and Wikipedia. During the 2012-2015 influenza seasons, a high sensitivity of 92% and a PPV of 85% were found for Google Flu Trends. A low sensitivity of 50% and a low PPV of 43% were found for Twitter. Wikipedia had the lowest sensitivity of 33% and lowest PPV of 40%. Limitations: 1) Bayesian change point analysis assumes time series data are distributed normally, which may not be the case with public health surveillance data, 2) for the analysis of Wikipedia views, only the "Influenza" article was used for analysis, excluding other articles on influenza medications and influenza strains. The authors assumed that all the views of the English-language Wikipedia "Influenza" article were done by US users when some may have come from users in other English-speaking countries where the influenza season is very different, 3) the Google Flu Trends data were fitted to match CDC data, 4) data duplication could be an issue with each data source used in this study, 5) Internet users are younger than the general U.S. population. Of the three Web-based sources, Google had the best combination of sensitivity and PPV in detecting Bayesian change points in influenza-related data streams. Findings demonstrated that change points in Google Flu Trends, Twitter, and Wikipedia data occasionally aligned well with change points captured in CDC ILI data, yet these sources did not detect all changes in CDC data and should be further studied and developed.

Tran A, Trevennec C, Lutwama J, Sserugga J, Gély M, Pittiglio C, Pinto J, Chevalier V

Development and Assessment of a Geographic Knowledge-Based Model for Mapping Suitable Areas for Rift Valley Fever Transmission in Eastern Africa

PLoS Negl Trop Dis 2016;10(9)

Rift Valley fever (RVF), a mosquito-borne disease affecting ruminants and humans, is one of the most important viral zoonoses in Africa. The RVF virus (RVFV) is transmitted from ruminant to ruminant by mosquitoes. Different climatic, environmental, and socio-economic factors may impact the transmission of the virus. The objective of the present study was to develop a geographic knowledge-based method to map the areas suitable for RVF amplification and RVF spread in four East African countries, namely, Kenya, Tanzania, Uganda, (three countries which have been historically affected by RVF), and Ethiopia (where the disease has never been reported but which shares borders with infected countries), and to assess the predictive accuracy of the model using livestock outbreak data from Kenya and Tanzania. Risk factors and their relative importance regarding RVF amplification and spread were identified from a literature review. The data were imported into a geographic information system (GIS) and processed to produce standardized spatial risk factor layers, namely a mosquito index (suitability for RVF mosquito vectors), sheep density, goat density, cattle density, proximity to markets, road density, railways density, proximity to water bodies, proximity to wildlife national parks. A numerical weight was calculated for each risk factor using an analytical hierarchy process. The corresponding geographic data were collected, standardized, and combined based on a weighted linear combination to produce maps of the suitability for RVF transmission. The accuracy of the resulting maps was assessed using RVF outbreak locations in livestock reported in Kenya and Tanzania between 1998 and 2012 and the ROC curve analysis. Results confirmed the capacity of the geographic information system-based multi-criteria evaluation method to synthesize available scientific knowledge and to accurately map (AUC = 0.786; 95% CI [0.730–0.842]) the spatial heterogeneity of RVF suitability in East Africa. Some areas may be at-risk without having experienced outbreaks in past years. The identification of these areas is essential for implementing risk-based surveillance and reducing the impact of RVF human and animal outbreaks in the coming years (until 2016, Uganda and Ethiopia remained free from outbreaks, but these two countries are highly vulnerable to the disease). This approach provides users with a straightforward update of the maps according to data availability and contributes to the further development of scientific knowledge.