What Makes or Breaks a Health Fundraising Campaign on Twitter?

Nugroho Dwi Prasetyo & Claudia Hauff
Web Information Systems
Delft University of Technology
Delft, the Netherlands

Dong Nguyen & Djoerd Hiemstra & Tijs van den Broek
University of Twente
Enschede, the Netherlands

Abstract

Health campaigns that aim to *raise awareness* and subsequently *raise funds* for research and treatment are commonplace. While many local campaigns exist, very few attract the attention of a global audience. One of those global campaigns is `Movember`, an annual campaign during the month of November, that is directed at men's health with a special focus on cancer. Health campaigns routinely use social media portals to capture people's attention. Recently, researchers began to consider to what extent social media is effective in raising the awareness of health campaigns. In this paper we focus on the second goal of such campaigns (fundraising), and investigate to what extent different campaign strategies influence people's *visitor* & *donation behaviour*. To that end, we analyze the 2013 `Movember` Twitter campaigns across four different countries, cross-correlating the awareness signals of Twitter users, with `Movember` visitors and donations raised through Twitter.

1 Introduction

The rise of social media portals — and thus access to vast amounts of user-generated data — has not gone unnoticed within the health care domain. Existing works have, among others, exploited social media data to track and predict the spread of diseases (Achrekar et al., 2011; Culotta, 2010; Chew and Eysenbach, 2010; Diaz-Aviles and Stewart, 2012), to analyse the effects of drug interactions (Segura-Bedmar et al., 2014), and to examine trends for cardiac arrest and resuscitation communication (Bosley et al., 2013).

Social media portals have also been employed to distribute health information on diseases and treatment options. In (Scanfeld et al., 2010; Vance et al., 2009), for instance, it has been shown that effective dissemination of such information can be achieved through Twitter and YouTube. At the same time though, Moorhead et al. (2013) argues that social health communication research is still in its infancy and large gaps in our understanding remain.

While the usage of social media for health campaigns is ever-growing, very few works have considered how *effective* these campaigns are in achieving their goals. While Thackeray et al. (2013) and Bravo and Hoffman-Goetz (2015) investigated the change of people's awareness during social media health campaigns, to our knowledge no research so far has considered the second goal of many health campaigns — raising funds for research and treatment.

In this paper, we contribute to closing this gap, (1) by conducting an awareness-based large-scale analysis *across several countries*, and (2) by investigating the extent to which a global social-media based health campaign is successful in terms of fund-raising. We investigate the particular use case of `Movember`, an annual health campaign conducted (amongst others) through social media channels that has two goals[1]: (1) to gather *"funding for the `Movember` Foundation's men's health programs"*, and, (2) to start *"conversations about men's health"*. In both cases, the main foci are on various types of cancer that typically occur in men and on men's mental health. `Movember` is a *world-wide* campaign that aims to raise funds through a number of social activities, chief among them the growing of a moustache in the month of November. Although a global event, the `Movember` campaigns are *localized*; each participating country runs its own campaign. In our analysis we focus on the four

[1]Source: `http://us.movember.com/en/about/vision-goals`

English-language local campaigns that yield the most donations via Twitter: the United States, the United Kingdom, Canada, and Australia[2]. Globally, `Movember` can be considered a success, as in 2013 alone (the year we investigate) funds in excess of 123 million *AU$* were raised world-wide[3].

In our work, among others, we investigate whether social media activities can explain the *financial* success of the campaign by correlating Twitter usage with `Movember` donations. We chose Twitter as our social media channel of choice, due to its popularity and ubiquitous nature in the English-speaking world. We investigate the differences and similarities between the `Movember` Twitter campaigns running in different countries, and analyze to what extent those factors can explain `Movember` fund-raising metrics. We thus aim to answer the following research question:

RQ: Which aspects of a Twitter campaign in the health domain have the largest impact on raising awareness and funding success?

2 Health Campaigns & Social Media

In this section we provide an overview of existing health campaign research across social media channels. Almost all research conducted in this area investigates the social media portal Twitter due to its popularity and widespread use. An overview of the employed data in past works is presented in Table 1.

Thackeray et al. (2013) analyzed the impact of the *Breast Cancer Awareness* month (an international campaign held annually in October) on Twitter users. They focused on engagement metrics and found that tweets discussing breast cancer issues spiked dramatically in the beginning of October but quickly taper off. In terms of topical aspects, organizations and celebrities posted more often than individuals about fundraisers, early detection and diagnoses, while individuals focused more on wearing pink[4]. Similarly, a topic analysis was conducted by Bravo and Hoffman-Goetz (2015) on the 2013 Canadian `Movember` campaign. The authors categorized 4,222 sampled tweets related to the campaign into four different categories (health information, campaign, participation and opinion). Due to the small number of identified health information tweets in the sample (the main signal of increasing awareness), the authors concluded that the goal of raising awareness has not been met.

(Lovejoy et al., 2012) investigated how non-profit organizations *use* Twitter by analyzing more than 70 different organizations, including 19 health care organizations, along various basic aspects including the number of followers, tweets, retweets, etc. Importantly, the authors found that most organizations use Twitter as a one-way communication channel instead of making full use of its potential and multi-way communication. Smitko (2012) developed two theories, of how non-profit organizations can build and strengthen their relationships with donors on Twitter: the *Social Network Theory* (SNT) and the *Social-Judgement Theory* (SJT). According to SNT, organizations need to strengthen their network of trust by engaging more with their followers while in SJT, organizations need to tailor the content of their tweets to match the interest of their followers. Due to the small-scale nature of the empirical analysis (based on 300 tweets), we consider it an open question to what extent those theories hold.

While to our knowledge, no existing work has considered the financial success of health campaigns, we note that Sylvester et al. (2014) studied the relationship between social media activities (on Twitter and news streams) and donations to a large non-profit organization during hurricane Irene, a tropical cyclone that hit the US in 2011. A spatial analysis revealed that donors living in states affected by Irene donated more than donors in non-affected states.

To summarize, past works have shown that (i) various types of social media users behave differently during health campaigns (celebrities vs. individuals vs. organizations), and (ii) sufficient content related to health campaigns is created on Twitter. What we are largely lacking is an analysis of the impact these social media health campaigns have on fund-raising.

3 Tweets & Donations of **`Movember`**

One important goal of our work is to establish whether we can *explain* donations the local `Movember` campaigns received through Twitter[5].

[2] Note that these four countries are also in the overall top-five countries in terms of donations.

[3] Source: `http://us.movember.com/about/annual-report`

[4] A pink ribbon is the symbol of the campaign.

[5] Defined as donations received from users that clicked on a donation link on Twitter.

Article	Campaign/Event	Data	Processing	Main Result(s)
(Bravo and Hoffman-Goetz, 2015)	- Movember - Nov. 2013 - Canada	22.3K tweets containing #Movember and located in Canada (user-profile based)	Content analysis	Tweets discussing health topics are significantly outnumbered by tweets discussing non-health topics.
(Sylvester et al., 2014)	- Hurricane Irene - Aug./Sep/ 2011 - United States	- 22K geotagged tweets containing keywords related to Irene - 10K mobile donations - 28K Web donations	Spatial and temporal analysis	- The number of tweets correlate positively with the number of Web donations. - Mobile donations are mostly caused by the relief agency's text message solicitation - Users directly affected by the hurricane display greater social media activity and donate more often
(Thackeray et al., 2013)	- Breast Cancer Awareness - Sep.-Dec. 2012 - N/A	1.3M tweets containing breast cancer related keywords	Content analysis	- Tweets spiked dramatically the first few days of the campaign. - Organizations & celebrities emphasized fund-raisers, early detection, and diagnoses; individuals focused on wearing pink.
(Lovejoy et al., 2012)	- 73 non-profit organizations - Nov.-Dec. 2009 - United States	4.6K tweets posted by organizations	User categorization	Organizations use Twitter mostly as one-way communication channel
(Smitko, 2012)	- 2 health care non-profit & 1 for-profit organizations - 12 hours on Feb. 8, 2011 - Canada	300 tweets either posted by the organizations or mentioning them	Content analysis	Categorized the style of communication into two types: Social Network Theory and Social Judgment Theory

Table 1: Overview of data sets employed in previous work.

We are thus conducting an exploratory analysis on two distinct data sources:

Twitter Corpus Tw_{Mov}: **All** tweets[6] published during the month of November 2013 that contain the keyword *Movember* — 1,113,534 tweets in total, posted by 688,488 unique Twitter users across the world. Twenty-one local `Movember` campaign accounts are active, such as `@MovemberUK`, `@MovemberAUS` and `@MovemberCA`. To enable a country-by-country analysis, we estimated the country each tweet was sent from, according to the machine learning approach described by Van der Veen et al. (2015), which labeled all tweets in our data set and achieves a country-level accuracy of 82%. In total, tweets from 125 different countries were found. The distribution of the tweets can be seen at Figure 1, normalized with respect to each country's population, to allow a comparison across countries. It is evident, that the `Movember` campaign is most popular in North America, Australia and Europe. Most activity (relative to the population) is generated by Twitter users in the UK, followed by those in Canada.

Movember donations : Our 2013 donation data is restricted to those donations the individual national `Movember` campaigns received through Twitter. Overall, in 2013, 357,400 *AU$* were donated through Twitter, spread over 21 national campaigns (though donations were received from 179 countries in total). Thus, only 2.9% of all 2013 donations were received through Twitter. This is a limiting factor to our work, but at the same time allows to be certain that all of our donors were exposed to Twitter activities related to `Movember`. The donation data has a single day resolution with all of the following information being available for each individual national campaign website: (1) the number of visitors, (2) the number of returning visitors, (3)-(4) the number of financial transactions from new and returning visitors, and, (5)-(6) the number of total revenue generated from new and returning visitors. Note that this data does not contain information identifying individual users, it is an aggregate — per day — of all user activities on each `Movember` campaign website. For the four most active national campaigns, the donations are listed in Table 3.

[6]Twitter provided access to their firehose for this study.

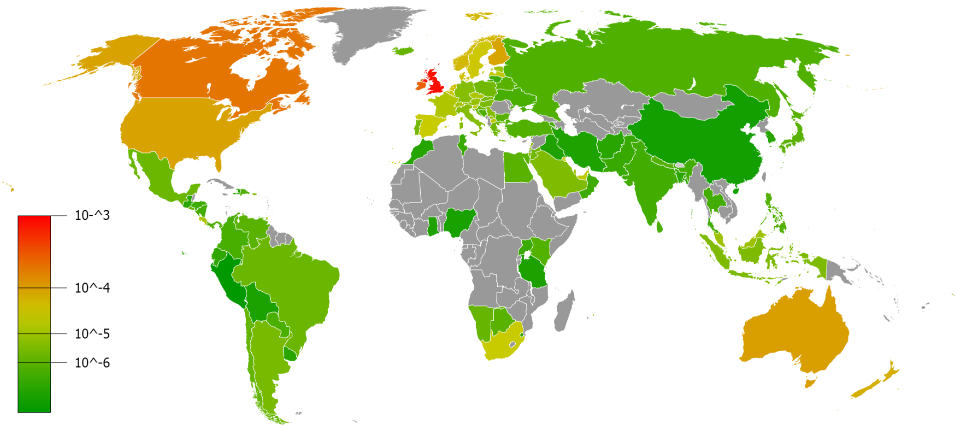


Figure 1: Geo-spatial distribution of all tweets in Tw_{Mov}. We normalized the number of tweets originating in each country by the country's population.

As already indicated, `Movember` is a social event, members of the campaign are called *Mo Bros* (men) and *Mo Sistas* (women). Every member can register on the `Movember` website and collect donations through that site (localized per country). *Mo Bros* & *Mo Sistas* can join to form teams and fund-raise together. While growing a moustache is the most common activity, *Mo Bros*/*Mo Sistas* can also use alternative social activities for fund-raising. At the end of the one-month campaign cycle, the teams and individuals raising the most donations within their country receive awards and prices.

3.1 Research Hypotheses

Based on our research question, we developed three research hypotheses:

- **H1:** The more well-known Twitter users (celebrities and organizations) support a `Movember` campaign, the more funds the campaign will raise.
- **H2:** `Movember` campaigns that emphasize the social and fun aspect of the campaign, *engage* the users better and thus will raise more funds.
- **H3:** `Movember` campaigns that focus on health topics, raise more *awareness* to the campaign and thus will raise more funds.

H2 and **H3** are competing hypotheses, as prior works have not offered conclusive evidence to emphasize one direction (health vs. social) over another.

3.2 From Hypotheses to Measurements

Having presented the research hypotheses that guide our work, we now describe how to empirically measure to what extent they hold.

To examine **H1** we require a definition for what constitutes a well-known Twitter user (a "celebrity"). We start with the definition posed by Thackeray et al. (2013), according to which celebrities have more than $f_{USA} = 100,000$ followers and are verified by Twitter. As this definition was derived for tweets originating in the United States, we normalize $f_{Country}$ according to the country's population and remove the requirement of being verified . Specifically, for the remaining three countries we employ the following cutoffs: $f_{Canada} = 11,000$, $f_{UK} = 20,000$, and $f_{Australia} = 7,000$.

To investigate the impact of health (related) organizations on Twitter, we define *health organizations* as those Twitter accounts with more than $5,000$ followers and at least one of the following keywords in their Twitter profile (borrowed from (Thackeray et al., 2013)): {*cancer, health, pharmacy, pharmaceutical, campaign, government, firm, company, companies, news, group, society, committee, volunteer, we, official, marketing, promotions and forum*).}. The overlap between both types of users is .

3.2.1 Manual Annotation Efforts

Hypotheses **H2** and **H3** require a content analysis of the Twitter messages. For this purpose, one of the authors manually annotated 2,000 randomly drawn English-language tweets (with 500 tweets each drawn from the UK, Canada, the United States and Australia) from Tw_{Mov} into several categories, inspired by the work of (Bravo and Hoffman-Goetz, 2015). We distinguish five main categories: *health*, *campaign*, *participation*, *so-*

cial and *other*, with each one (except *other*) containing between two and three sub-categories (e.g. *health* tweets are further categorized as *cancer*, *general* and *mental*). Overall, we distinguish 12 different categories/sub-categories. Tweets can belong to multiple categories or sub-categories; tweets that are not found to belong to any of the first four categories are classified as *other*. An overview of the categories and the resulting annotations (including exampl tweets) is shown in Table 2. Across all countries, we find the social aspect to be the most pronounced in our sample — 51% of the sampled tweets are categorized as such. Less than 5% of the tweets mention health issues and even more strikingly, the second pillar of `Movember`'s campaign (mental health) is almost completely absent in our sample. These results are in line with (Bravo and Hoffman-Goetz, 2015)'s findings, where cancer-related tweets were found in only 0.6% of the sample.

3.2.2 Automatic Classification

Due to the small number of manually annotated tweets in the individual sub-categories, we decided to automatically classify all tweets of Tw_{Mov} according to the most opposing ends of the spectrum: *heatlh* vs. *social*. This was done separately per country. Concretely, we aim to classify each tweet into one of four categories: (1) *health*, (2) *social*, (3) *health & social* or (4) *other*. In order to add robustness to the classifier, we use the insights gained during the manual annotation process to enlarge our training set by automatically selecting additional positive training tweets. For the *health* classifier, tweets containing one of the following key phrases were used: {*prostate, testicular, cancer, mental, health*}. Similarly, for the *social* classifier, we relied on tweets containing at least one of: {*gala, party, event, contest, competition, stach, handlebar, facial hair, shave, instagram, twitter.*photo.*} as positive training data. Recall, that all tweets in our corpus contain the term *Movember* by definition, thus ensuring topicality. Overall, in this manner we collected $406,709$ tweets as training data across all countries, consisting of $120,601$ *health* tweets and $286,108$ *social* tweets. A total of $35,489$ tweets were identified as being both *social* and *health*-related. The detailed breakdown of positive training data per country is shown in Table 5. These simple rules have thus allowed us to categorize 36.5% of all tweets in Tw_{Mov}; the remaining 63.5% of tweets are categorized according to our classifier output.

In order to build an effective classifier, we also require sets of negative training examples. We randomly drew the same amount of tweets (120 thousands of non-health and 286 thousands of non-social) tweets from Tw_{Mov} to function as negative examples for both the *health* and *social* classifiers. . We performed basic data cleaning steps, removing stopwords (which in this case includes the term "Movember") and employing stemming. As classification algorithm we selected Naive Bayes with terms as features[7]. We trained two classifiers per country: *health* and *social*; we classified the tweets in Tw_{Mov} to zero, one or both categories depending on the confidence threshold of the individual classifier (a tweet classified with confidence ≥ 0.5 is assigned to the classifier's category).

4 Results

To determine the influence on donations as well as *potential* donations, we correlate (using Pearson's correlation coefficient r) the Twitter-based metrics (e.g. number of tweets) with the donation and visitor data from the `Movember` data set on a day-by-day basis.

4.1 Hypothesis H1

To investigate **H1**, we correlate the number of `Movember` tweets by well-known Twitter users on a given day with the donations/visitors to the `Movember` campaign website on a per-country basis. The results are shown in Table 4. While the visitors correlate to a significant degree with several tweet-based measures for the United Kingdom and Australia, we do not observe significant correlations for visitors in Canada or the US. Organizations have a similar impact to Twitter celebrities (normalized by country) in terms of drawing visitors to the `Movember` website . Contrary to our intuition, we do not observe any significant correlations between daily donations and Twitter activities.

4.2 Hypotheses H2 & H3

In Table 5 we present the impact social and health topics have on `Movember` donations and visitors. The results are similar to the previous ex-

[7]We employed the WEKA toolkit: `http://www.cs.waikato.ac.nz/ml/weka/`

	Canada	United States	United Kingdom	Australia
health:cancer	21	16	18	20
blah di blah				
health:general	41	88	45	40
health:mental	3	2	0	1
%health overall	xx%	xx%	xx%	xx%
campaign:value	41	69	71	36
campaign:news	25	18	13	14
campaign:status	28	46	58	24
%campaign overall	xx%	xx%	xx%	xx%
participation:support	127	155	96	82
participation:report	20	32	27	14
%participation overall	xx%	xx%	xx%	xx%
social:moustaches	182	202	202	217
social:service/goods	31	13	30	30
social:events	38	35	19	14
%social overall	xx%	xx%	xx%	xx%
other	91	77	118	76

Table 2: Overview of the manual annotation results. For each country, 500 tweets are sampled and categorized.

	Donation (AU$[8])	Transactions	Users/Visitors	Population
Canada	91,741	2,054	43,720	35 M
United States	79,828	1,847	76,257	321 M
United Kingdom	75,124	4,397	95,867	65 M
Norway	25,034	74	2,707	5 M
Australia	13,170	583	11,194	24 M
in total	284,897	8,955	229,745	—

Table 3: Overview of the 2013 `Movember` campaign donations received by the top-5 campaigns through Twitter. The final column lists each country's population (in millions).

periment: we observe significant correlations only with `Movember` visitor data; Australia & United Kingdom exhibit moderate to strong correlations while for Canada & the US the correlations are weak to non-significant. Considering the influence of health vs. social we find that social tweets exhibit a stronger correlation with visitor data than health tweets across all countries — this in fact is the only experiment where statistically significant results are observed across all four countries (for $p < 0.05$).

4.3 Further Analyses

In Figure 2 we visually correlate the visitors/donations with the number of health/social tweets in the form of scatter plots. While the visitor data shows few outliers and has a clear linear trend, the donation plot is evidently non-linear without a clear pattern emerging.

5 Conclusions

In this paper, we set out to investigate the impact of different social media strategies on a health campaign's ability to raise awareness and attract funds. We investigated the specific use case of `Movember`, a recurring global campaign which enjoys widespread popularity in a considerable number of countries. We focused our analyses on the four most active English-language countries of the `Movember` campaign.

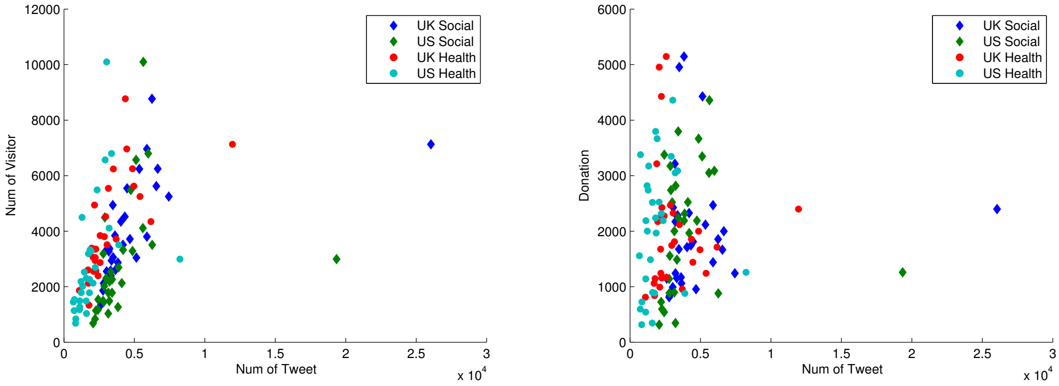
	Canada	United States	United Kingdom	Australia
Total number (#) of tweets	81,614	298,720	565,503	24,558
#Organizational tweets	17,535	50,131	78,174	5,222
#Tweets by well-known Twitter users	179	1,445	662	39
$f_{Country}$ normalized	2,056	1,445	6,167	2,158
#Tweets by well-known Twitter users				
$r_{donations}$	-0.02	0.13	0.35	0.30
$r_{visitors}$	0.13	0.23	0.36	0.37
$f_{Country}$ normalized				
$r_{donations}$	-0.05	0.13	0.19	0.56
$r_{visitors}$	0.22	0.23	0.58	0.68
#Organizational tweets				
$r_{donations}$	-0.04	0.10	0.14	0.47
$r_{visitors}$	0.27	0.33	0.56	0.77

Table 4: The top four rows show the number of different types of Tw_{Mov} tweets across the month of November 2013. In subsequent rows, we correlate the number of daily donations and daily visitors to each country's `Movember` website with the number of daily tweets. The threshold for statistical significance (for $N = 30$ days) is $r = 0.37$ ($p < 0.05$) or $r = 0.47$ ($p < 0.01$) respectively.

	Canada	United States	United Kingdom	Australia
Num of English Tweet	78,382	287,479	515,605	24,189
$r_{donations}$	-0.09	0.05	0.09	0.32
$r_{visitors}$	0.24	0.30	0.56	0.80
Health tweets (List of Words)	9,741	41,770	64,361	4,699
Health tweets (List of Words and ML)	13,776	58,846	96,674	5,007
Cross validation result	0.91	0.90	0.91	0.94
Social tweets (List of Words)	27,300	118,396	134,907	5,505
Social tweets (List of Words and ML)	28,064	125,062	148,957	13,936
Cross validation result	0.80	0.83	0.82	0.70
Health tweets				
$r_{donations}$	-0.08	0.06	0.07	0.31
$r_{visitors}$	0.22	0.30	0.54	0.75
Social tweets				
$r_{donations}$	-0.12	0.10	-0.02	0.08
$r_{visitors}$	0.37	0.43	0.67	0.83

Table 5: Tweet categorization result by using several search terms and combination with Machine Learning Classification. The result are then compared with donation and visitor data from `Movember` data. The threshold for statistical significance (for $N = 30$ days) is $r = 0.37$ ($p < 0.05$) or $r = 0.47$ ($p < 0.01$) respectively.

Our findings partially corroborate previous findings on raising awareness (especially (Bravo and Hoffman-Goetz, 2015)), while expanding on them across several dimensions, most importantly the number of countries investigated and the size of the investigated social media sample. We find that across all investigated countries the Twitter users mostly focus on the social aspect of the `Movember` campaign, with relatively few tweets focusing on the health aspect of `Movember`. Ad-



(a) Visitors

(b) Donations

Figure 2: Scatter plots of the daily number of health / social tweets and the daily number of visitors / donations shown exemplary for the United Kingdom and the US.

ditionally, those users that do mention health-related issues, often use generic statements, instead of focusing on the two specific health issues that `Movember` aims to address (cancer and mental health). Surprisingly, the mental health aspect of `Movember` is virtually not discussed at all in any of the investigated countries.

The main focus of our work aimed to explore the impact of social media strategies on fundraising. To this end, we analysed the relationship between `Movember` website visitor & donation data and Twitter activities. We found significant correlations between `Movember` visitors (our potential donors) and the Movember-related activities of well-known Twitter users. We also found clear evidence that social tweets have a higher impact on visitors than health tweets. While the observed correlations were moderate to strong for the United Kingdom and Australia, we only found weak to non-significant correlations for Canada and the United States. Across all countries, we did not find significant correlations between donations and Twitter activities.

The last two statements form our roadmap for future work: we will investigate on a more fine-grained and semantic level in what aspects the Twitter-based `Movember` activities differ between Australia/UK and Canada/US. We will also consider a temporal analyses of the donation/visitor data, comparing trends across several years of Movember donation data and Twitter activities.

Acknowledgments

This research was funded in part by the 3TU Federation and the Dutch national project COMMIT. We are grateful to Twitter and Movember for providing the data.

References

Harshavardhan Achrekar, Avinash Gandhe, Ross Lazarus, Ssu-Hsin Yu, and Benyuan Liu. 2011. Predicting flu trends using twitter data. In *Computer Communications Workshops (INFOCOM WKSHPS), 2011 IEEE Conference on*, pages 702–707. IEEE.

Justin C Bosley, Nina W Zhao, Shawndra Hill, Frances S Shofer, David A Asch, Lance B Becker, and Raina M Merchant. 2013. Decoding twitter: Surveillance and trends for cardiac arrest and resuscitation communication. *Resuscitation*, 84(2):206–212.

Caroline A Bravo and Laurie Hoffman-Goetz. 2015. Tweeting about prostate and testicular cancers: Do twitter conversations and the 2013 movember canada campaign objectives align? *Journal of Cancer Education*, pages 1–8.

Cynthia Chew and Gunther Eysenbach. 2010. Pandemics in the age of twitter: content analysis of tweets during the 2009 h1n1 outbreak. *PloS one*, 5(11):e14118.

Aron Culotta. 2010. Towards detecting influenza epidemics by analyzing twitter messages. In *Proceedings of the first workshop on social media analytics*, pages 115–122. ACM.

Ernesto Diaz-Aviles and Avaré Stewart. 2012. Tracking twitter for epidemic intelligence: case study: Ehec/hus outbreak in germany, 2011. In *Proceedings of the 4th Annual ACM Web Science Conference*, pages 82–85. ACM.

Kristen Lovejoy, Richard D Waters, and Gregory D Saxton. 2012. Engaging stakeholders through twitter: How nonprofit organizations are getting more out of 140 characters or less. *Public Relations Review*, 38(2):313–318.

S Anne Moorhead, Diane E Hazlett, Laura Harrison, Jennifer K Carroll, Anthea Irwin, and Ciska Hoving. 2013. A new dimension of health care: systematic review of the uses, benefits, and limitations of social media for health communication. *Journal of medical Internet research*, 15(4).

Daniel Scanfeld, Vanessa Scanfeld, and Elaine L Larson. 2010. Dissemination of health information through social networks: Twitter and antibiotics. *American journal of infection control*, 38(3):182–188.

Isabel Segura-Bedmar, Ricardo Revert, and Paloma Martínez. 2014. Detecting drugs and adverse events from spanish health social media streams. In *Proceedings of the 5th International Workshop on Health Text Mining and Information Analysis (Louhi)@ EACL*, pages 106–115.

Kate Smitko. 2012. Donor engagement through twitter. *Public Relations Review*, 38(4):633–635.

Jared Sylvester, John Healey, Chen Wang, and William M Rand. 2014. Space, time, and hurricanes: Investigating the spatiotemporal relationship among social media use, donations, and disasters. *Robert H. Smith School Research Paper No. RHS*, 2441314.

Rosemary Thackeray, Scott H Burton, Christophe Giraud-Carrier, Stephen Rollins, and Catherine R Draper. 2013. Using twitter for breast cancer prevention: an analysis of breast cancer awareness month. *BMC cancer*, 13(1):508.

Han Van der Veen, Djoerd Hiemstra, Tijs van den Broek, Michel Ehrenhard, and Ariana Need. 2015. Determine the user country of a tweet. Manuscript submitted for publication.

Karl Vance, William Howe, and Robert P Dellavalle. 2009. Social internet sites as a source of public health information. *Dermatologic clinics*, 27(2):133–136.