



Measuring the Influence of Commercial Entities in the Twitter backchannels of medical conferences: The #MICEproject

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ABSTRACT

Twitter backchannels are increasingly popular at medical conferences. A variety of user groups, including healthcare providers and third party entities (e.g., pharmaceutical or medical device companies) use these backchannels to communicate with one another. These backchannels are unregulated and can allow third party commercial entities to exert an equal or greater amount of influence than healthcare providers. Third parties can use this influence to promote their products or services instead of sharing unbiased, evidence-based information. In the #MICEproject we quantified the influence that third party commercial entities had in 13 major medical conferences.

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INTRODUCTION

Medical conference organizers (CO) must strike a balance with commercial entities (a/k/a 3rd party commercial entities; e.g., pharmaceutical companies and device manufacturers). Third parties are needed to offset the cost of many national scientific meetings and provide valuable information about the latest developments in the field (1,2). Concurrently, COs must mitigate “detailing”: the process in which third parties have direct and unregulated access to conference attendees (learners) (3,4). COs have reached this balance in live conferences by: 1) not allowing third parties to select speakers at plenary and other sessions, 2) not allowing third parties to pass out literature in-and-around classrooms, and 3) restricting learner access to third parties to one geographic location (“exhibition hall”) and only during specific periods of time that do not conflict with other scientific sessions (2). Theoretically, these safety mechanisms allow a learner to experience a live medical conference without ever exposing him/herself to a third party.

This model has not been replicated in the increasingly popular Twitter backchannels (5,6). Backchannels are online social media streams (typically Twitter streams) that allow learners,

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COs, and third parties to share information with each other (5,6). Backchannels are considered an excellent way to enhance a live conference and an increasing number of medical conferences are incorporating them into their annual meetings (7-18). To date, medical conference backchannels are unregulated; this allows third parties direct access to learners that they cannot achieve at a live conference. Detailing on Twitter exposes learners to third parties and facilitates the transfer of biased information in an environment that does not have established safety mechanisms in place (1,3,4). Theoretically, third parties can exert a greater influence over learners through Twitter detailing.

In this investigation, we quantified the degree of influence that third parties have in the Twitter backchannels of thirteen prominent medical conferences from 2011-2013. We measured influence in three different ways. In the unregulated realm of Twitter backchannels, we hypothesized that third parties are as influential as any other group.

METHODS

Data Set

We identified five medical societies that promoted the Twitter backchannels of their respective annual meetings. These societies assigned a conference-specific hashtag for each backchannel and registered each with the Healthcare Hashtag Project (HHP; symplur.com). The HHP is an independent organization that archives, and makes available for research, tweets of various healthcare-related Twitter backchannels. The HHP is a comprehensive database of all tweets authored at a particular scientific conference. We queried the HHP database for all conference-specific tweets using the pre-assigned hashtags. Table 1 shows the thirteen conferences that were included in the data set. We collected a) date and time of tweet, b) Twitter username of the tweet author, c) content of the tweet, and d) Twitter username(s) of individuals/organizations mentioned within the body of a tweet (@mentions).

Table 1. Baseline Data.

Medical Society / Conference Organizer(s)	Conference Name	Dates	Hashtag	Healthcare Hashtag Project URL (shortened)	Tweets (No.)
American College of Cardiology*					8505
	2012	3/24/2012	#acc12	http://goo.gl/Os3f0C	2951
	Annual Meeting	3/27/2012			
	2013	3/9/2013 -	#acc13	http://goo.gl/nnwEPK	5554
	Annual Meeting	3/11/2013			
American Society of Nephrology					4299
	Kidney Week 2011	11/8/2011	#kidneywk11	http://goo.gl/m3UvNm	583
		11/13/2011			
	Kidney Week 2012	10/30/2012	#kidneywk12	http://goo.gl/ni5CC6	1137
		11/4/2012			
American Society of Clinical Oncology	Kidney Week 2013	11/5/2013	#kidneywk13	http://goo.gl/8vog3n	2579
		11/10/2013			
					31991

	2011 Annual Meeting	6/3/2011 - 6/7/2011	#asco11	http://goo.gl/GX3svS	7531
	2012 Annual Meeting	6/1/2012 - 6/5/2012	#asco12	http://goo.gl/Hlky9X	9555
	2013 Annual Meeting	5/31/2013 - 6/4/2013	#asco13	http://goo.gl/IOS4pf	14905
American Gastroenterological Association and American Society for Gastrointestinal Endoscopy and American Association for the Study of Liver Diseases and The Society for the Surgery of the Alimentary Tract					5123
	Digestive Disease Week 2011	5/7/2011 - 5/10/2011	#ddw11	http://goo.gl/xpwZpY	1199
	Digestive Disease Week 2012	5/19/2012 -	#ddw12	http://goo.gl/fgM3di	1720
	Digestive Disease Week 2013	5/22/2012 5/18/2013 -	#ddw13	http://goo.gl/QmL66C	2204
American Academy of Dermatology*					1241
	2012 Annual Meeting	3/16/2012 -	#aad12	http://goo.gl/ZrcGOj	585
	2013 Annual Meeting	3/20/2012 3/1/2013 - 3/5/2013	#aad13	http://goo.gl/BeCl23	656

*Conference Twitter backchannel for the 2011 meeting was not registered with the HHS & unavailable for analysis

Categorization of Account Holders

In order to quantify the influence that third parties exert in Twitter backchannels, we categorized every tweet author/account holder mentioned within the body of a tweet (@mentions) into one of four categories: a) healthcare provider (HCP), b) third party commercial entity (third party), c) unclear identity, and d) none of the above. Table 2 defines each category and provides a representative example. We used each account holder's Twitter profile to ascertain under which category that account should be. Categorization was done from January to April 2014. We did not perform additional Internet searches (e.g., Facebook or Google search) of accounts categorized as "unclear". None of the investigators contacted any of the account holders, in any venue, to determine their identity.

To ensure inter-rater reliability when categorizing Twitter account holders, we performed a

Light's kappa statistic on a different set of previously published Twitter data (19). The Light's kappa score was 0.72.

Table 2. User categories and examples.

Category	Definition	Representative Example	Twitter Profile
Healthcare Provider	Individual or organization whose primary purpose is to disseminate medical information or provide clinical care for patients	@nephondemand	Tejas Desai, MD. Creator of Nephrology On-Demand & Kidney Konnection & Nephrology Fellowship Director @ ECU. I conduct research in social media & medicine & program iOS Apps
3rd Party Commercial Entity	Organization or individual representing an organization whose primary purpose is to provide a product or service to medical professionals and/or patients	@mmsholdings	MMS Holdings Inc. MMS Holdings Inc. is a global niche pharmaceutical service organization that focuses on regulatory submission support for the pharma and biotech industries.
None of the Above	Individuals or organizations that are unrelated to healthcare or the purpose of the scientific meeting	@RdgTerminalMkt	The Reading Terminal Market - Since 1893
Unclear Identity	Individual or organizations whose Twitter profile was vague or empty	@KhaliqWhy	Khaliq. Seeking Knowledge

Measuring Influence of Account Holders

We assessed Twitter influence by three different methods. In the first method, we measured the number of distinct account holders per category that authored at least one tweet in one of the 13 conferences analyzed. We defined a high Twitter influence as that category with the largest number of account holders.

In the second method, we measured the total number of tweets authored by account holders in each category. We calculated the tweet:author ratio by dividing the number of tweets composed by the total number of authors within a particular category. We ascribed the greatest Twitter influence to that category with the highest ratio.

In the third method, we measured influence by calculating the PageRank of any account holder that was mentioned (@mentions) in the body of a tweet. Originally developed by Page, Brin, Motwani and Winograd, the PageRank is a link-based algorithm and considered by Williams, Baldwin, and Rubel to be the best measure of social media influence (20-23). As described by Abdullah, in the PageRank "a link from a page to another page is understood as a recommendation and the status of the recommender is important" (24). A webpage, to which many others are linked, is considered an influential webpage and is given a high PageRank (20,24). Its PageRank increases even more when the linking webpages are influential as well (i.e., have their own high PageRanks) (20,24-26). Similarly, a Twitter account that is mentioned (@mentions) many times and/or mentioned by other influential Twitter accounts will, itself, appropriately receive a high PageRank (28). Indeed a number of investigators, including Abdullah, Kwak et al and Bakshy et al, have successfully adopted the PageRank to accurately measure Twitter influence using @mentions (23,24,27-30). The PageRank of @mentions is

also known as the “Influence Index” and is used by the independent research firm Twitalyzer to measure one’s Twitter influence (31). It is also the preferred method of measuring influence by Evan Williams, co-founder of Twitter (31).

Privacy Considerations for Account Holders

The tweets collected from the HHP contained identifying information or links to such information. The same identifying information is freely available to the general public through the Library of Congress (32,33). Twitter’s Terms and Conditions warn account holders of the public nature of tweets, specifically, “what you say on Twitter may be viewed all around the world instantly” (12). Perhaps because such identifying information is freely accessible, prior investigators have not requested approval from their local institutional review boards (13,23,24,27-30). Currently there are no expectations for researchers to gain approval from any external agency (government, Twitter, or others) to research Twitter data (34). In many investigations, including our own, researchers have adopted the “distance principle”, explained by Buchanan et al (35). Given that our investigation was an observation of data in the public space and did not involve direct interaction with any account holder, the “distance principle”, along with the precedent set forth by previous investigators, supported our belief that external committee review was unwarranted (34-37).

Nevertheless, the identifying information within each tweet was as critical to our investigation as our ethical use of it. Therefore, we designed our methods in accordance with the United States Department of Homeland Security’s 2012 Menlo Report – a guide for investigators performing “communication technology research” (38). We also designed our methods to conform to the British Psychological Society’s guidelines for “Internet-mediated research” (39). Finally, we complied with the six ethics guidelines recommended by Rivers and Lewis when analyzing “big data” (34). Our adherence to these strict and established guidelines satisfied our professional sense of duty to maintain the privacy of the account holders whose Twitter activities comprised our data set.

Statistical Considerations

We calculated frequencies per category for: 1) number of Twitter accounts that authored tweets, 2) number of Twitter accounts that were mentioned within a tweet, 3) number of tweets composed. We performed chi-square tests to compare these data using JMP Pro version 10.0.0. We calculated PageRank using the NodeXL plugin (<https://nodexl.codeplex.com>) for Microsoft Excel 2013. Median and interquartile ranges for the PageRank were calculated and compared using the Kruskal-Wallis test. Each group needed to have at least 8671 @mentions in order to have achieved an 80% power to detect a 0.2 difference in PageRank. In order to mitigate any future concern about the lack of reproducibility of our results, we 1) did not perform subgroup analyses of Twitter influence by conference and 2) followed recent guidelines that make “classical hypothesis testing more congruent with evidence thresholds for Bayesian tests” (40). As a result, the significance level was set at $p < 0.005$ (40).

This investigation conforms to STROBE guidelines for observational research and SAMPL guidelines for statistical reporting (41,42).

RESULTS

Baseline Data

We collected 51159 tweets, authored by 8778 Twitter account holders, in 13 conferences, sponsored by 5 medical societies, from 2011 to 2013 (Table 1). Our data set represents 94.6% of tweets and 78.1% of authors in the HHP. The remaining data was either lost during the extraction process from the HHP or could not be parsed correctly by the software we used. The largest number of tweets and authors was in the 2013 American Society of Clinical Oncology’s

annual meeting (15120 and 3156, respectively).

Twitter Influence by Number of Authors

Nearly 61% of the authors had a Twitter profile that identified them (Table 3). In this group, there were 2173 (25%) healthcare providers and 1575 (18%) third party entities ($p < 0.0001$). The largest group of authors could not be identified (3412; 39%; $p < 0.0001$).

Twitter Influence by Tweet:Author Ratio

Despite being the greatest number of authors, those with unclear identities did not compose the greatest number of tweets (Table 3). The tweet:author ratio for unidentified Twitter account holders was only 3.7. Healthcare providers composed 19503 tweets and had a tweet:author ratio greater than that of third party entities (8.98 versus 6.93 tweets per author; $p < 0.0001$).

Twitter Influence by PageRank of @mentions

In our data set, a total of 3316 Twitter accounts were mentioned a total of 39997 times (Table 3). Healthcare providers were mentioned nearly 46% of the time, while third party commercial entities were mentioned less than 20% of the time. The sum total of @mentions in the healthcare provider and third party categories was 26175: 1.5 times greater than the 17341 @mentions needed to achieve 80% power. The median PageRank for healthcare providers was the highest amongst the four categories. However, there was no statistical difference between it and the median PageRank for third party commercial entities (0.797 versus 0.761, respectively; $p = 0.175$).

Table 3. Measures of Twitter Influence.

Measure of Influence	Third Party Commercial Entity	Healthcare Provider	None of the Above	Unclear Identity
Total Authors	1575	2173	1617	3413
Total Tweets	10916	19503	8105	12635
Tweets:Author Ratio	6.931	8.975	5.012	3.702
Unique @mentions	683	864	772	997
Total @mentions	7834	18341	8011	5811
PageRank				
10th Percentile	0.313	0.316	0.304	0.297
25th Percentile	0.425	0.441	0.405	0.401
Median	0.761	0.797	0.677	0.591
75th Percentile	1.391	1.546	1.124	1.005
90th Percentile	3.103	3.089	2.158	1.921

DISCUSSION

Third Party Influence

Third party commercial entities had a statistically similar PageRank as healthcare providers (0.761 versus 0.797, respectively) despite having significantly fewer authors (1575 versus 2173, respectively) and significantly less Twitter activity (6.931 versus 8.975 tweets/author, respectively). This suggests that third parties are equally influential in the Twitter backchannels of scientific meetings as healthcare providers; a parity that is difficult to achieve in live conferences. Admittedly, there are no investigations that measure third party influence at live conferences. Perhaps the lack of data is due to conference organizers' financial reliance on third parties to sponsor their conferences. In 2009, third parties gave close to \$850 million dollars of sponsorships to various medical conferences (1). In 2011, 75% of conference organizers received third party financial support (2). Third parties provide printed and digital

conference materials, travel grants, and meals gratis. This financial dependence may preclude any scientific study of third party influence at live conferences. Nevertheless, conference organizers mitigate third party influence by geographically isolating third parties, curtailing their “hours of operation”, and independently selecting topics and speakers for the conference agenda (2).

Conference organizers do not depend on the financial support of third parties to maintain active Twitter backchannels. Creating and registering a conference-specific hashtag and generating messages on Twitter are free. Yet not one of the eight conference organizers (in any of the 13 conferences studied) implemented any safeguards to limit third party “detailing” (3). As a former third party representative, Ahari outlined eight forms of detailing used by third parties to influence individuals (3). All eight can be easily adapted to work in Twitter backchannels. Indeed any message from a third party is more likely to place a favorable bias on that party’s product/service than unprejudiced evidence-based medicine (1).

Jalali, Wood, and others have suggested that conference organizers learn how their respective Twitter backchannels are being used/misused in order to curtail the influence that third parties have within them (16,28,43). Our study is the first to elucidate this use/misuse by various groups. Second, more must be done to establish guidelines for third party activities in Twitter backchannels. There are plenty of well-intentioned recommendations on the use of Twitter by healthcare providers and conference organizers (17,44). There are no comparable recommendations for third parties or their interactions with HCPs/COs (45). Both the Pew Charitable Trusts and American Medical Student Association discuss how COs can mitigate conflicts of interest (COI), but neither offer specific guidelines in managing COIs within social media streams (1,46,47). Therefore, the investigators of this study recommend the following activities to bring the medical community closer to such guidelines:

- *Conference organizers should publicly state in their Twitter backchannel that third party entities should declare themselves as such in their respective Twitter profiles (33)*
- *Conference organizers should insist that third parties compose tweets that disseminate scientific facts and not solicitations for products/services*
- *If third parties wish to solicit for a product/service, they should include an additional hashtag in the body of their tweet (e.g., #ad) to allow participants within the backchannel to filter out such tweets*
- *Conference organizers should encourage third parties to restrict their Twitter activity to coincide with their live “hours of operation”*
- *Conference organizers should task independent individuals/groups to annually measure the PageRanks for each Twitter account mentioned (@mentions) within their conference-specific hashtag*
- *Conference organizers should target third party accounts with abnormally high PageRanks for further education about best-practices within their respective Twitter backchannel*

These recommendations would align third party activities in Twitter backchannels with their activities at live conferences. We believe they are reasonable: neither burdensome to conference organizers nor offensive to third party commercial entities. Compliance can be measured yearly through PageRank assessments, as performed in this investigation, with targeted re-education to those third parties that require additional assistance.

PageRank versus other measures of Twitter influence

The PageRank of @mentions has been used by a number of Twitter researchers and is considered the closest estimation of Twitter influence (21-23,27,29,30). Indeed even commercial research firms, such as SEOmoz and Twitalyzer, use the PageRank of @mentions

to measure Twitter influence for their clients (31,48). As Bray and Peters have indicated, mentioning someone in one's tweet represents a major commitment to that person (48). The more a person is mentioned, the more they effect the conversation and the greater the influence they exert (28,31,48).

A common misperception is that the number of followers or impressions (which equals the product of the number of followers and tweets composed) is an accurate measure influence. Any metric that uses the number of followers and/or tweets often results in false calculations of influence (49). Bots can artificially inflate the number of tweets composed, causing the impressions to be misleadingly elevated. Moreover, the number of followers or impressions excludes any interaction between participants. Perhaps for these reasons impressions and the number of followers are considered "vanity" metrics: easy to calculate but of little value in measuring one's Twitter influence (48).

Twitter researchers do not perform content analyses to measure influence (23). Neither this investigation nor the studies referenced analyzed tweet content to measure influence. Cha et al has mathematically analyzed various metrics to measure Twitter influence and concluded that the PageRank of @mentions was one of the best ways to do so (29).

Unclear Identities on Twitter

There were 3413 Twitter accounts that could not be identified because their Twitter profiles were vague or empty. These accounts generated only 24.7% of the total tweets analyzed. We consciously avoided using alternative methods to identify these accounts. In accordance with recommendations by Farnan and McKee, we assumed that account holders with vague profiles wanted to remain anonymous (36,50). To respect these wishes, we did not contact any author or perform additional Internet searches to ascertain their identities (34,35).

Strengths

Perhaps the greatest strength of this investigation is its breadth (13 conferences sponsored by 8 medical societies) and depth (51159 tweets). Chaudhry et al conducted an analysis of 12644 tweets from 2 conferences sponsored by one medical society while Jalali et al analyzed 10937 tweets from 4 conferences sponsored by as many medical societies. (13,51). We measured Twitter influence by calculating the PageRank of @mentions – the recommended metric by a number of researchers, commercial research firms, and the co-founder of Twitter (21-23,27,29-31,48). We conformed to three well-established sets of guidelines for conducting Internet-based research and respected the privacy of those users who wanted to remain anonymous (1,34-36,38,50). Finally, and to the best of our ability we have reported our findings in accordance with two sets of research-reporting guidelines (41,42).

CONCLUSION

Third party commercial entities exert an equal influence as healthcare providers in the Twitter backchannels of medical conferences. Without safety mechanisms in place, Twitter backchannels can devolve into a venue for the spread of biased information rather than evidence-based medical knowledge, as that seen at lives conference. Continuing to measure the influence that third parties exert can help conference organizers develop reasonable guidelines for Twitter backchannel activity.

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