What Factors Matter for Engaging Others in an Educational Conversation on Twitter?

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Abstract: Educator-driven professional learning communities are increasingly developing and thriving on social media platforms such as Twitter. Even though these communities are large and popular, very little is understood about how their users interact with one another. This paper explores factors that explain why some tweets generate interaction (replies, retweets, likes, etc.), while others do not. Results show that several user-level factors predicted greater interaction, including more followers and a longer history on Twitter. At the tweet level, individual tweets received interaction on average when that tweet, for example, mentioned more users, and included fewer URLs. Furthermore, there were differences in interaction predicted by the topic of individual tweets, the time of day, and day of the week. The results of this study show that interactions with tweets using an educational hashtag like #miched is the result of many interwoven factors with implications for research and teacher education and professional development.

Introduction

Researchers recognize the importance of social organizations, from classroom communities of learners to teachers' professional learning networks. Increasingly, these communities are developing on social media sites such as Twitter, and, indeed, some of the largest educational communities in the world are thriving on Twitter (Britt & Paulus, 2016). These communities have sprung up via the use of a special convention for organizing topical conversations emerged – hashtags (words prefaced with a '#' character) topically organize communities and find them using specialized searches (e.g., #edchat, #siteconf, etc.).

As an education technology, Twitter affords community members some very simple actions: Members can post up to 140-character content (tweets), that can include images and links (Kaplan and Haenlein, 2011) and members can interact with one another by reading tweets, replying to tweets, retweeting (reposting another user's tweet), and favoriting tweets (similar to Facebook's "like" feature). Despite the simplicity of using and interacting on Twitter (using just 140 characters), Twitter has emerged as a powerful platform for creating large, public, democratic, largely unmoderated, and thriving communities (Rosenberg, Greenhalgh, Koehler, Hamilton, & Akcaoglu, 2016). Yet, very little research has been done that explores fundamental issues such as who participates in these communities and how members interact with one another. Understanding the interaction that occurs, and often times does not occur, is a particularly noteworthy issue that has not been the focus of past research.

Research has shown that community members on Twitter consider an imagined audience and tailor their tweeting and their interactions to better engage with such communities (Marwick & boyd, 2011; Veletsianos, & Shaw, 2017). Less understood is the conditions in which community members are successful in reaching and engaging the audience they imagine. For example, many tweets in such communities receive little attention – they generate no replies, no retweets, and are not liked (or what previously was "favorited"). Past research has also shown that the ability of a single tweet to engage and influence a community extends beyond any simple measure, such as how many followers the tweet maker has (Cha et al., 2011), and includes other factors such as the text of the tweet.

Purpose and Research Questions

In this paper, we seek to better understand what factors underlie the ability of a tweet to engage members of an educational community. In particular, we contextualize this study by examining the Twitter content of the #miched chat posted over one year. #miched, we believe, exemplifies the large, public, democratic, and thriving educational community that we are most interested in. Additionally, through prior research (e.g., Rosenberg et al., 2016; Rosenberg, Akcaoglu, Willet, Greenhalgh, & Koehler, 2017) we know that it is a community we are both familiar with and have collected a lot of data about.

In carrying out this work, we seek to address three main limitations of prior research in this field. *First*, while previous research has identified three factors (e.g., Cha et al. 2011) that lead to interaction (e.g., followers, retweets, and mentions), in this study we extend this work by consideration additional user-level factors (e.g., their overall follower and following counts) as well as factors specific to individual tweets (e.g., contains a URL or not, mentions other users or not, etc.). *Second*, we extend this work to studying an educational community whereas prior research has shown there to be high levels of engagement in general; thus, we are not selecting as a sample a random sample of tweets, but rather one in which there is evidence of community and in which there may be clear processes of engagement and influence at work. *Third*, our analyses employ a mixed effects or multilevel modeling methodology to appropriate model and honor the nested nature of this data. That is, individual tweets (level 1) are nested within users (level 2) – analyzing what leads to interaction has to properly disentangle tweet level factors (e.g., contains a URL or not) from user-level factors (e.g., number of followers the user has). In addition, we account for the day of the week and the hour of the day using random effects, meaning that tweets are cross-classified between hour of day and day of week, and with both nested within users. We believe this is the first study of this type to employ multi-levels to properly understand the hierarchical nature of this data.

Specifically, we wish to understand:

1) What user-level factors predict interaction with the audience within the #miched community?
2) What tweet-level factors predict interaction with the audience within the #miched community?

Answers to these questions will lead to a better understanding of how to increase interactions with tweets by educators interested in using Twitter. Some of this advice may be specific to the contents of a tweet (e.g., a tweet-level factor), while other advice might point to the importance of building an audience on Twitter (e.g., a user-level factor). Answers to these questions also has important theoretical implications for how educational communities foster engagement and methodological considerations about the complex, hierarchical nature of social media data.

Method

The data for this study is comprised of 37,291 original tweets collected from the #miched hashtag over the period of 9/1/2015 through 9/1/2016. These original tweets were sent from 1,766 unique users. The mean number of tweets for each participant was 21.12 (SD = 91.84). The data were collected using the TAGS tracker (Hawksey, 2015). In addition to the data collected through TAGS, we also used the statistical software and programming language *R* to access additional information about the tweets using the Twitter and the Twitter Application Programming Interface. We also carried out text analysis that automatically detected topics being discussed using the Linguistic Inquiry and Word Count software (Pennebaker, Boyd, Jordan, & Blackburn, 2015). Specifically, topics identified on the basis of cognitive process, social, work-related, positive, and negative words. Each tweet has a number of measures associated with it, including the level of interaction it generated and all of the tweet-level and user-level features in the analysis as described in *Table 1*.

Measure	Description	Mean	Std. Dev.
Interaction	On Twitter, users can interact in four different ways, including: reading a tweet, replying to a tweet, favoriting a tweet (similar to liking on Facebook), and retweeting the tweet. Three of these types of interaction are publically available through Twitter's API (application programmer interface), whereas one of them is not available (the number of users who read a tweet). Thus, in this paper, interaction is defined by the sum of all the likes, replies, and retweets the original tweet generated.	2.91	4.77
User-level			
Followers	The number of users who follow (subscribe) to the current user.	2,424.00	8,797.14
Following	The number of users the current user follows (subscribes to).	1,200.91	2,990.72
Year Created	Year the profile was created	2011.87	2.41
# of Tweets	Number of tweets made over the duration of the account.	9,982.52	38,971.08
# of Likes	Number of tweets liked over the duration of the account	2,570.12	6,947.23
Tweet-level			
# characters	Number of characters in the tweet (up to 140)	116.27	25.90
# links	Number of external links (URLs) in the tweet	0.50	0.51
# hashtags	Number of hashtags (e.g., #miched) references in the tweet	1.97	1.25
# mentions	Number of other uses mentioned in the tweet	0.61	0.97
Day	Day of the week (e.g., Thursday)	NA	NA
Hour	The hour of the day the tweet was posted represented as four-hour windows (e.g., 0-3, 4-7, 8-11, etc.)	NA	NA
Cognitive processing	Proportion of tweet text containing words such as think and know	0.06	0.70
Social	Proportion of tweet text words such as talk and friend	0.06	0.70
Work-related	Proportion of tweet text words such as job, major	0.06	0.60
Positive	Proportion of tweet text words such as love and nice	0.03	0.05
Negative	Proportion of tweet text words such as hurt and ugly	0.01	0.02

Table 1. Description of measures used for each tweet

It is worth noting that within the 1766 unique users, 26 of those users had over 100,000 tweets since the creation of their accounts. Such high-volume users represent a dilemma for this type of research. On one hand, these users may be considered outliers and data analysis could be conducted without these outliers. On the other hand, these high volume users account for much of the tweeting, retweeting, and interaction that happens in these spaces and may be considered central to understanding how interaction works in educational discourse. For the purposes of the present study we decided to include these high-volume users in our analyses. In future work, however, we will consider different ways of accounting for the heavy influence these users may have in data analysis.

To analyze the data, we used mixed effects, or multilevel models, also in R (R Core Team, 2017), using the lme4 package (Bates, Machler, Bolker, & Walker, 2015). These models included fixed effects for the user- and tweet-level variables in Table 1. They also included random effects for the user as well as the hour and weekday. We used two models, the first, a null model, with only the random effects, in order to determine what proportion of the variability in interactions can be attributed to each of the random effects, and second, a full model, with the fixed effects predictors added.

Results

The null model, with only the random effects, showed that substantial variability exists at the user level (ICC = .255, suggesting that 25.5% of the variability in interactions is associated with characteristics of users), with much less at the hour (ICC = .002), and weekday (ICC = .003) levels). Results from the mixed effects models suggest that user- and tweet-level variables impact the number of interactions with tweets.

Accordingly, we conducted a mixed effects (or Hierarchical Linear Model [HLM]) that tests both tweet level factors (e.g., number of characters) and user-level factors (e.g., year account created).

	Impact on Interactions		
Variables	β	SE	*p*
Intercept	1.09	0.21	< .001
Year Account Created	-0.11	.03	.002
1,000 Followers	0.07	0.01	< .001
1,000 Following	-.01	0.04	.763
1,000 Previous Tweets	0.00	0.00	.274
1,000 Likes	0.05	0.01	.002
Number of Mentions	0.20	0.03	.917
Number of URLs	-1.40	0.06	< .001
Number of Hashtags	0.12	0.02	< .001
10 Text Characters	0.18	0.01	< .001
Cognitive Processing Words	-0.06	0.03	.013
Social Words	-0.05	0.02	.030
Work-related Words	-0.04	0.02	.106
Positive Words	-0.04	0.02	.076
Negative Words	0.10	0.02	< .001

Table 2. Findings of Mixed Effects Model for Predicting Number of Interactions

As shown in Table 2, at the user level the number of users followed, the number of followers, and the number of likes all lead to statistically significant more interaction. For example, following 1,000 more Twitter users (than the mean user in the sample) is associated with 0.325 more interactions (likes, retweets, or replies) on average for each of that users' tweets. This suggests that overall the network that users have (following and followers) and their overall activity level (likes), have impacts for how specific tweets to #miched garner interaction. Additionally, the year the account is created, which was centered to have a mean of 0, has a negative relationship with interactions: Thus, having had an account for a shorter period of time is associated with less interactions with tweets.

At the tweet level, number of URLs (fewer is better), number of characters (more is better), number of hashtags (more is better), time of day, day of the week, and topic of the tweet all lead to statistically significant differences in interaction. Please note that time of day, day of week, and topic factors were included in the analyses, but omitted from Table 2 for purposes of brevity. Specifically, each additional URL (than in the mean tweet for the tweets in the sample) is associated with 1.331 fewer interactions, hashtag with 0.134 more interactions, mention with 0.21 interactions, 10 additional text characters with 0.173 interactions.

Tweets sent very early in the morning (5:00 am - 6:00 am) and late in the evening (7:00 pm - 8:00 pm) are associated with more interactions, while tweets on Saturday and Sunday are associated with more interactions than those sent during the week, though there are slightly more interactions with tweets sent on Monday and Friday. Tweets on the weekend receive just around .075 more interactions than tweets sent during the week, possibly due to these tweets being viewed more during non-work hours. Some of the spike late in the evening (and the decrease in even later, at 9:00 pm) is likely due in part to the prevalence of weekly chats using #miched; after high levels of interaction (with tweets being associated with around 0.10 more interactions), there are fewer interactions with tweets sent after the conclusion of the chat). A figure representing these findings will be included in the presentation and full paper.

Results from the LIWC analysis showed that cognitive processing and social words were both negatively associated with interactions; these values are proportions and can be interpreted on the basis of the relationship between a one-percent increase in words associated with each category, such as cognitive processing and social, and an additional interaction. Negative words were associated with more interactions.

Discussion

The results of this study show that having an impact (through interactions) on an educational hashtag like #miched is a result of many interwoven factors. First and foremost, a user's history on Twitter has a big part in interpreting how individual tweets are interacted with. That is educators interested in interacting on Twitter should pay attention to developing their presence and networks on Twitter by developing a base of followers as well as a network of other users to follow. Furthermore, interacting with these other users (via likes, for example) also matters, most likely because this interaction further develops the network and community between users, as does being on Twitter for a longer duration.

Second, results also show that paying attention to what goes into a tweet matters as well. Educators should pay attention to developing longer tweets (up to 140 characters), that tap into other conversations (i.e., include additional hashtags). Findings related to the specific topics included in tweets suggests that negative words are associated with more interactions: although less than 1% of the words in tweets contained negative words, and so this finding may require further analysis in order to be substantiated, this suggests that tweets that are critical may be the subject of greater interactions, while using words that suggest cognitive processing or social topics is associated with tweets that receive fewer interactions. These findings related to text analysis—though carried out simply on the basis of what words were included in tweets, and not their order or intended meaning (as could be determined through in-depth qualitative analysis)—suggest that incisive tweets that perhaps elicit a strong response from other users may be interacted with more than those that, for example, use careful wording and complete sentences.

Conclusion

We sought to address three gaps in past research in this paper on what factors matter for engaging others in an educational conversation on Twitter. Using data associated with a state-wide educational hashtag associated with Michigan, #miched, first, we sought identify factors at the user-level and the tweet-level, and how they relate to interactions. We found that factors at both levels were important, meaning that a user's Twitter network as well as what and how they tweet are both important. Second, we sought to make this research relevant to educational communities (whereas prior research has often taken a marketing approach). In doing so, found we were able to model the factors that matter to educators in educational communities. Third, the mixed effects or multilevel modeling strategy that allowed us to account for both user and time-related factors in a methodological approach novel to this type of educational research with Twitter.

These results demonstrate that interactions with tweets using an educational hashtag like #miched is a result of many, interwoven factors. There is no one factor associated with increased numbers of interactions, but rather are factors related to who is sending the tweet and what is in it. These results, then, suggest that newcomers to Twitter (such as pre-service teachers or in-service teachers new to the platform) who may not see their tweets receiving many interactions should follow other users as soon as possible, and to try including fewer URLs, but, perhaps, more hashtags. Future research could build on this work through exploring different samples and characteristics of tweets, as well as other methodological approaches, such as holistic approaches that examine what characteristics of tweets or tweeters commonly group together, and interactive, network-analytic approaches that examine how users influence one another.

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