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Exploring the relationship between online discourse and commitment in Twitter professional learning communities

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Abstract

Educators show great interest in participating in social-media communities, such as Twitter, to support their professional development and learning. The majority of the research into Twitter-based professional learning communities has investigated why educators choose to use Twitter for professional development and learning and what they actually do in these communities. However, few studies have examined why certain community members remain committed and others gradually drop out. To fill this gap in the research, this study investigated how some key features of online discourse influenced the continued participation of the members of a Twitter-based professional learning community. More than 600,000 tweets generated over six years under the hashtag #edchat were gathered. Online discourse was deconstructed to the cognitive dimension, the interactive dimension, and the social dimension. Text-mining methods were then used to automatically identify these dimensions in the tweets. Finally, survival analysis was used to quantify the influences of these dimensions on users' commitment time to the Twitter community. The implications of the results and findings are then discussed.

Keywords: online communities, professional learning, data mining, survival analysis, online discourse

Introduction

Social media platforms, such as Twitter, offer educators new ways to conceptualize learning and collaboration. Teachers, school administrators, university professors, and many others in the education world use Twitter to share news and resources, to converse online, to participate in education conferences, and to establish professional connections (Britt & Paulus, 2016; Carpenter & Krutka, 2014, 2015; Donelan, 2016). Educators' growing interest in participating in Twitter-based online communities for professional development and learning has prompted researchers to study such communities. The findings of this research suggest that Twitter plays an important role in engaging educators in informal, just-in-time professional learning (Britt & Paulus, 2016; Carpenter & Krutka, 2014, 2015; Donelan, 2016) and that teachers can enrich their educations by participating in online professional learning communities (Holmes, Preston, Shaw, & Buchanan, 2013).

Although the use of social media expands educator education beyond "one-size-fits-all, sit-and-get professional development" (Ross, Maninger, LaPrairie, & Sullivan, 2015), studies have shown that educators' participation in such communities is largely uneven. For example, a 2017 study by one of the authors (withhold for review) found that the online synchronous chat that occurred among the members of a Twitter community for educators was dominated by a group of active members. These active members not only generated a large volume of tweets but also interacted actively with other participants. About half of all members tweeted only once, however, and the majority of the members had limited connections with others. These results raised the question of whether the seemingly less-engaged members would continue to participate in online communities for professional development and learning.

Continued participation is essential, both to the members of a professional learning community and to the community as a whole. The benefits of remaining involved in such a community depend to a great extent on the information exchanged among its members. If a member does not remain part of the community, they are less likely to receive whatever the benefits offered by the community (Wang, Kraut, & Levine, 2012). Moreover, a community's members are its primary source of resources, and a larger community is likely to know more about a given topic than a smaller one is (Butler, 2001). For these reasons, it is important to understand the factors that influence educators' commitment to online professional learning communities and to encourage sustained participation in these communities at the individual and community levels.

This study examined the participation of users in the Twitter chats under the hashtag #edchat to determine how some key features of online discourse affect user participation. Because this was a longitudinal study and considered more than 600,000 tweets generated over the course of six years, qualitative methods (such as interviews) and content analysis would have been prohibitively difficult. Moreover, traditional quantitative methods, like sampling and questionnaires, usually have sparse temporal granularity (Qiu et al., 2011), which renders them unsuitable for investigating detailed temporal and continuous-participation issues related to a large online community. For these reasons, this study examined user participation holistically by employing data mining methods to process all the collected tweets. A survival analysis was then conducted to quantify the effects of different features of online discourse on users' decisions to stay in the community. The findings can help us to understand why certain members stay in a community longer than others do and, in turn, can aid in the design of support mechanisms that can better promote users' commitment and the overall sustainability of online professional learning communities.

Background

Theoretical Foundation for Online Discourse

Conversation is widely considered the driving force behind learning (Sharples, Taylor, & Vavoula, 2006), and conversation's role in learning has been studied extensively by educational theorists and researchers. The subject has been approached from three main perspectives. First, according to the cognitive perspective, having conversations with others allows learners to actively engage in cognitive activities such as questioning, interpreting, elaborating, or relating information to prior knowledge. These activities increase the likelihood that information will be understood and retained (Anderson & Biddle, 1975; Collins, Brown, & Larkin, 1980; Pressley, Wood, Woloshyn, & Martin, 1992). Second, social constructivists like Vygotsky have held the position that high-order functions develop out of language-based social interactions (Vygotsky, 1978). By communicating and interacting with others, individuals share and negotiate perspectives, modify their interpretations of the world in response to others' perspectives, and thereby improve their understanding of the world. Third, Lave and Wenger (1991) proposed the concept of the "community of practice", and emphasized the importance of social relationships through which learning takes place. According to Lave and Wenger (1991), learning is fundamentally a social process in which the members of a community engage in an ongoing process of negotiation, building their contribution to a larger enterprise (Wenger, 1998). These three perspectives highlight the importance of discourse in learning. A review of theoretical frameworks for analyzing online discourses suggests that there are three interrelated dimensions most critical to online discourse and learning, which reflect the three perspectives. The three dimensions are: the cognitive dimension, the interactive dimension, and the social dimension.

Discourses that participants have when generating and sharing ideas and positions belong to the cognitive dimension (Benbunan-Fich, Hiltz, & Harasim, 2005; Henri, 1992). They typically include self-reflection, brainstorming, generating information, and so on. A few frameworks capture the cognitive dimension of online discourse that is critical to learning. For example, Henri (1992) argued that cognitive behaviors like clarification, inference, judgment, and strategizing are evidence that learning is taking place. Building upon the work of Henri (1992) and others, Newman, Johnson, Cochrane, and Webb (1995) identified particular kinds of critical-thinking processes—such as justification and critical assessment—as crucial to learning.

Discourses that participants have when they are engaged in the mutual construction of shared knowledge and understanding belong to the interactive dimension (Benbunan-Fich et al., 2005; Henri, 1992). They typically include showing agreement and disagreement, relating multiple ideas to one another, building upon previously mentioned ideas, and so on. One of the most popular frameworks that describe the interactive dimension of online discourse, Gunawardena et al.'s (1997) interaction analysis model identifies five stages in the co-construction of knowledge: (a) the "sharing/comparing of information;" (b) the "discovery and exploration of dissonance or inconsistency among ideas, concepts or statements;" (c) the "negotiation of meaning/co-construction of knowledge;" (d) the "testing and modification of proposed synthesis or co-construction;" and (f) "agreement statement(s)/application of newly constructed meaning" (p. 414). Similarly, Pena-Shaff and Nicholls (2004) developed an instrument that includes 11 categories—such as "question," "reply," "clarification," and "reflection"—that capture the interactive process of constructing knowledge via online discussion.

Discourses that belong to the social dimension of online, discussion-based collaborative learning does not involve generating and developing content-related ideas. Instead, it focuses on behaviors like facilitating, community building, showing support, and socializing. Though community building is not immediately related to learning, it contributes to the learning process. Henri (1992) argued that the social dimension is important because it encourages participation and the development of social cohesion and a sense of belonging. Garrison Anderson and Archer (2000) emphasized the importance of social presence in their Community of Inquiry (CoI) model, in which "social presence" is defined as "the ability of participants in the Community of Inquiry to project their personal characteristics into the community, thereby presenting themselves to the other participants as 'real people'" (p. 89). They argued that "socio-emotional interaction and support are important and sometimes essential in realizing meaningful and worthwhile educational outcomes" (p.95) and that social presence contributes directly to the success of an educational endeavor.

The majority of the frameworks mentioned above were developed by analyzing discussions in online, formal educational settings in which learners developed their understanding of course content or completed collaborative learning tasks. Few studies have examined learning via informal online communities, though some studies have attempted to examine the purposes or interaction types of tweets in Twitter-based online communities (Author, 2017; Greenhalgh & Koehler, 2017). Since the three above-mentioned dimensions are considered essential for learning, whether and how tweets featuring each of these dimensions impact users' commitment to Twitter-based online communities is a subject worthy of investigation. The findings of this study will improve our understanding of how best to promote educators' use of social media for professional development.

Twitter for Educators' Professional Development and Learning

The majority of the research on this topic thus far has sought to identify why educators choose to use Twitter for professional learning and development. For example, Wesely (2013) adopted a qualitative, netnographic approach in investigating the twitter community of a group of world-language teachers and found that the teachers believed that participating in their online professional community allowed them to connect, share resources, and produce deep learning that changed their teaching practices. Carpenter and Krutka (2014, 2015) surveyed 494 educators about their use of Twitter for professional purposes and found that they used Twitter to chat, to network, to collaborate with others, to communicate with parents and students, and to share resources. Using Twitter helped the teachers to combat a sense isolation, to get connected with others who shared similar philosophies and interests, and to learn from a diversity of opinions and perspectives. The teachers also suggested that the professional learning communities they had developed through Twitter had helped them to improve their teaching practices (Carpenter & Krutka, 2016). Similarly, Rodesiler and Page (2015) examined the participation of secondary English educators in Twitter, blogs, and a few other social networking sites. They found that the educators participated in online activities for the following reasons: (a) to relieve a sense of isolation, (b) to establish a social network, (c) to shape their thinking or their practice, (d) to hone their digital writing skills, (e) to generate professional opportunities, and (f) to improve their ability to support their students.

A group of researchers recently went further, determining what educators do in Twitter-based professional learning communities. Using methods such as social-network analysis and content analysis, Greenhalgh and Koehler (2017) examined users' participation patterns and tweets. They observed a 28-day-long, just-in-time professional learning event on Twitter and found that the teachers used a hashtag, #educattentats, to effectively discuss how to converse with their students about recent terrorist attacks. Author (2017) examined the content of a one-hour synchronous chat with the hashtag #edchat and concluded that the conversation had the characteristics of successful professional development suggested by Moon, Passmore, Reiser, and Michaels (2014): it was embedded in the subject matter, involved active sense making and problem solving, and was connected to issues related to the teachers' own practice.

Although Twitter offers potential opportunities for professional development and learning, its potential may not yet be fully realized. Researchers have determined that participation in these communities is uneven. Greenhalgh and Koehler (2017) found that of 3,598 participants, less than

11% posted original tweets; the rest only retweeted or “liked” posts. Macià and García (2017) examined a few Twitter communities for teachers and noticed that while most participants were “connected to less than 80 nodes,” small numbers of participants acted as hubs and were connected to a majority of members (p. 117). This kind of unequal participation raises the question of whether users whose participation is limited still benefit from membership in such communities. Additionally, according to Garet and colleagues (2001), the duration of a professional development activity is important: a sustained professional development activity is more likely to have an impact than a shorter one is. However, few studies have examined educators’ long-term participation in Twitter-based professional learning communities, and even fewer have attempted to identify factors that impact the duration of educators’ participation. Veletsianos (2017) argued that future research would be needed to investigate how and why users’ participation changes over time and that such an investigation could “generate knowledge that helps researchers understand how to sustain participation in social media contexts and professional development endeavors” (p.291).

Methodological Foundation for Twitter Professional learning communities

Many studies into professional learning communities on Twitter have employed traditional methods of social science and examined limited numbers of tweets and subjects (Greenhalgh & Koehler, 2017). Because of the scale of this study, we used large-scale text mining to examine how online discourse influenced user retention. Text mining automatically finds and extracts interesting information from unstructured texts (Feldman, 1995) by employing methods borrowed from information retrieval, machine learning, data mining, and computational linguistics. In contrast to the traditional mining of structured databases or XML files, text mining can process unstructured or semi-structured textual sources, such as emails.

Methods of text mining include information extraction, topic tracking, text summarization, classification, clustering, and concept linkage (Gupta & Lehal, 2009).[1] In text classification, a piece of text (e.g. a tweet) is assigned to one or more categories. The process of text classification usually begins with the development of training data, in which human coders manually code a sample of texts. Next, to build and test a text classification model, the labeled data is fed into a supervised machine-learning algorithm so that the built model can learn human insight. Finally, the machine-learning model is applied to the remaining texts, assigning these texts to the appropriate categories.

Though few studies have used text classification to examine the professional development and learning in Twitter communities, this method has been widely used in other Twitter-related contexts. Aphinyanaphongs et al. (2016) used text classification to automatically process 228,145 tweets from 5,435 users, categorizing the users as “smokers” and “non-smokers.” Pla and Hurtado (2014) used text classification to identify the political leanings of the authors of 68,000 tweets. Irani, Webb, Pu, and Li (2010) used text classification to examine 1.3 million tweets to identify

[1] This section will explain and review text classification. For information on other methods, see Berry (2004).

the popular topics for media research on Twitter. This study builds on previously established methods and applications to automatically identify the different dimensions of a Twitter discourse.

Research Questions

Based on the literature review, research is needed to uncover educators' long-term participation patterns in Twitter-based professional learning communities and identify discourse features that impact the duration of educators' participation. Given the enormous quantity of tweets in the communities, we first had to design an efficient and reliable way to recognize the Twitter discourse features and then examined the influence of the features on members' commitment. Therefore two research questions (RQs) were proposed:

RQ1: How do we automatically detect the different discourse features in a Twitter professional learning community?

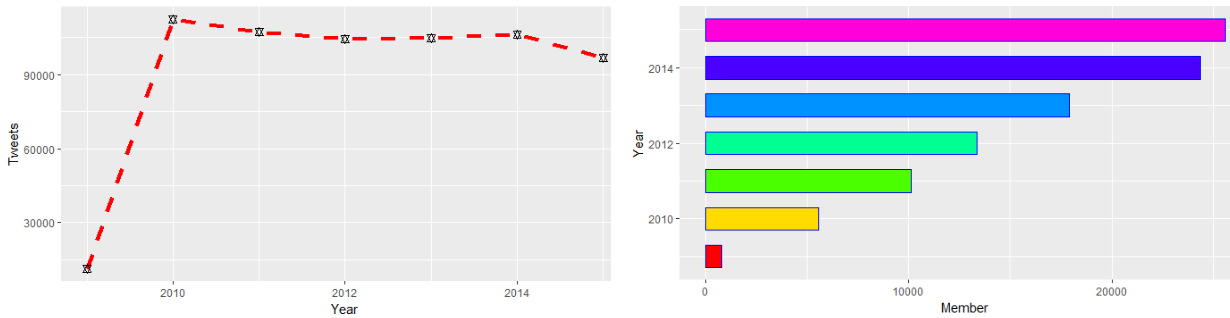
RQ2: How does the exposure to the tweets featuring cognitive dimension, interactive dimension and social dimension impact the participants' duration of a Twitter professional learning community?

We proposed a data mining workflow to automatically identify the different discourse features in tweets under the hashtag #edchat and then applied survival analysis to investigate the impact of exposing different discourse features on educators' participation duration of the Twitter community.

Methodology

Research Data and Context

The dataset used in this study was a large, Twitter-based professional learning community for teachers, #edchat. #edchat started in 2009 and has been consistently identified by a number of websites as one of the most popular hashtags in education. One of its most important elements is its weekly synchronous chat, in which members from all over the world discuss a selected topic. More specifically, #edchat hosts two synchronous chats every Tuesday, one at 12 PM NYC (5 PM UK) and one at 7 PM NYC (12 AM UK). Each chat begins when the facilitator posts the topic. After that, the participants join discussion on the topic. To examine the community members' survival, we retrieved all the tweets in the chats from 2009 to 2015. In total, 644,914 tweets were initially retrieved. After removing the irrelevant tweets at the end of each chat, 643,347 tweets from 72,342 unique users were used for the longitudinal analysis. Figure 1(a) gives an overview of the number of tweets generated each year, and Figure 1(b) provides information on the number of users who remained active in the community during that time.



(a). The number of tweets over time (b). The number of users over time

Figure 1. Descriptive statistics for the #edchat community

Online Discourse Dimension Automatic Detection for RQ1

Most research into social interaction and communication via educational media has been conducted by hand-coding the content of a relatively small number of tweets (Barak, Watted, & Haick, 2016). Such qualitative techniques are impractical, or would have at least demanded an enormous amount of effort in coding the more than half million tweets. To overcome this methodological challenge, text classification models were constructed to automatically identify the online discourse dimension of each tweet. Building and validating the text classification models occurs in three steps according to Figure 2. First, human coders generally categorize a small random sample of posts into different online discourse dimensions. Their judgments are then used as the ground truth or training data. Then, the coded tweets are transformed into a set of features that are ready to be inputted into machine-learning algorithms. Finally, the text classification model is trained and validated by applying various algorithms to the feature sets so that it can automatically identify the discourse dimensions for the rest of the tweets.

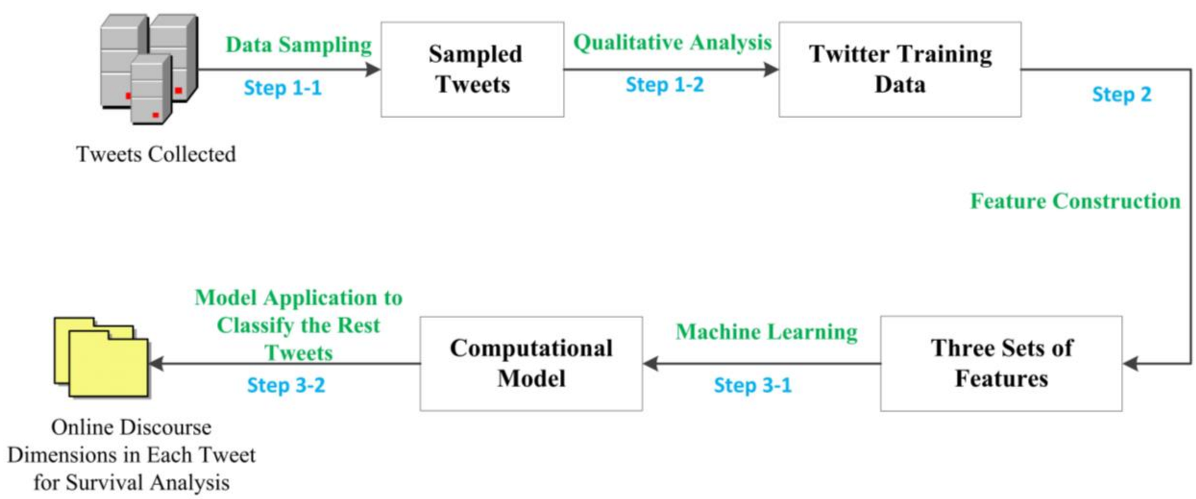


Figure 2. Online Discourse Dimension Automatic Detection Method

In the first step, to create the training dataset, 2500 tweets were first randomly sampled from the entire dataset as in Step 1-1. Qualitative analysis was used to develop the training data in the Step 1-2. Specifically, 500 of the tweets were used to develop the coding scheme. One of the researchers in the author team and a senior graduate student developed the coding scheme by combining top-down and bottom-up procedures (Chi, 1997). During the top-down procedure, a preliminary set of codes was generated for each dimension based on the existing studies detailed in the literature review. During the bottom-up process, an open-coded approach to analysis was adopted (Corbin & Strauss, 2008). The tweets were examined one by one to create an initial set of codes, and reassessments and revisions were made through constant comparison until additional analyses provided no new information or insights (Strauss & Corbin, 1998). The codes that emerged were then compared to the preliminary set of codes developed in the top-down process to develop the final coding scheme (see Table 1). During the process, when a difference of opinion or ambiguity arose, the researcher and the graduate student worked together to discuss and resolve the issue. Then 400 tweets were coded independently by the researcher and the graduate student. To assess the inter-rater reliability of their coding, a Cohen's Kappa was computed and reached .87, revealing a high level of agreement between the coders. Last, the researcher on the author team and the senior graduate student each coded 800 posts on their own to serve as the training data. Table 1 shows the Tweet coding examples.

Table 1. Tweet Coding Example and Explanation

Dimensions	Descriptions	Tweet Examples
Cognitive Dimension	Tweets that state personal ideas or opinions or share personal experiences in a general way. Also, tweets that initiate conversation on a new topic, typically by asking a question (to the general audience).	• "Since learning takes place in places in addition to the classroom seat time is a far less accurate measure." #Edchat • "How do we get educators to critically analyze something that comfort zones preclude them from using?"
Interactive Dimension	Tweets that express agreement. Also tweets that build upon an existing comment by asking or responding to a question, providing an example, making an argument, or offering a complementary or alternative view.	• "ok... @User_ky aren't other and more important things also measurable with ease? Why aren't they?" • "@drdouggreen @HanaTicha Couldn't agree more. But Internet is still not a 100% reliable resource. Kids still need guidance." #edchat@DerekRhodenizer • "@jpsteltz @mattwallaert Exactly! Ts need to feel #blendedlearning is something they can DO! Let's

		bring Ts into convo about BL #edchat”
Social Dimension	Tweets for socializing, greeting, or being courteous. Also, tweets that express appreciation or establish rapport.	• “Thanks to our #edchat moderators today @ShiftParadigm & @blairteach and Thanks to all of those who participated in our Chat.” • “Well: I have to go: Stds in 8 min and they are making videos. great chatting with you all.”

Users generated ideas, co-constructed ideas, and socialized with others on Twitter in different ways and different languages. To capture these different strategies and cues, the second step identified three kinds of features: linguistic features, LIWC features, and regular repression features as in Step 2. Examples of these features are shown in Table 2. Linguistic features captured the general diversity of the members’ language and included word counts, question marks, and numbers of adjectives. LIWC features were extracted using the Linguistic Inquiry and Word Count (LIWC) library (Pennebaker et al., 2015), which goes beyond simply counting words or punctuation marks. LIWC features were used to determine the degree to which members in the community used different linguistic categories (e.g. tense and grammar) and topical constructs (e.g. “time” and “biological”). For instance, the use of “we” (and “us” and “ours”) is often associated with the social and with feelings of companionship. In addition, while developing the training data, the researchers frequently summarized different rules that could differentiate different types of interactions. We applied regular expression to capture these features, which are named “regular expression features.” For instance, when a tweet contains an @ and a question mark, it is more likely to be a cognitive-dimension tweet. However, if a tweet contains both an @ and “agree,” and later on a “but,” it is generally an interactive-dimension tweet.

In the third step, four kinds of supervised machine-learning algorithms were employed to improve the performance of the text classification model: Naïve Bayes, Logistic Regression, Support Vector Machines (SVM), and Decision Tree as in Step 3-1. The details of these algorithms can be found in Kotsiantis (2007). A 10-fold cross validation was used to evaluate the predictive success of each algorithm. Classical metrics, precision, and recall were used to show the actual performance. After we built the text classification model, it will be applied to automatically classify the rest of the tweets into different online discourse dimensions as in Step 3-2. These tweets with automatically identified online discourse dimensions will be further used for survival analysis explained in the next section.

Table 2. Feature Sets

Linguistic Features (LF) Word counts, words per sentence, question marks, parts of speech
LIWC Features (LIWC) Pronoun: I, we, you, she, they Tense: auxiliary verb, past, present, future Topic: time, cognitive, biological
Regular Expression Features (Regex) Cognitive dimension: no @ + yes/no question mark Interactive dimension: @, agree, but Social dimension: Thank you @

Survival Analysis for RQ2

We used survival analysis to examine how the exposure to tweets with different online discourse dimensions influenced the tendency of a user to continue participating in the community. Survival analysis is able to estimate the truncated nature of time-series data in a less biased way than are standard regression models (Yang et al., 2011). In particular, Hazard Ratio can be used to explain the impact of an independent variable on the probability of a user's dropping out. Parametric regression survival analysis was used with the Weibull distribution of the survival times. This is a generally appropriate method of survival modeling.

Twitter does not record information about which tweets people read, only information about who tweets. To estimate the amount of each online discourse dimension the users were exposed to, we assumed that they read all of the tweets generated during the synchronous chats in which they participated that week. This assumption likely led to an underestimation of the discourse dimensions that individuals were exposed to because individuals can gain information by reading tweets without posting. For this reason, our analysis probably underestimates the influence of online discourse on users' duration of participation in the community. Since the synchronous chats took place weekly, we discretized the time by week. The timestamp of a user's first tweet determined the date on which they started participating in the community, and the date of their last tweet marked the end of their participation.

Dependent Variable

Dropout: A user was considered to have left the community when they failed to tweet within 3 months of their last tweet. Users who posted only once was not considered for the analysis. Since users whose last tweets were generated less than three months before the end of the data collection period could still have been participating, these users were treated as right censored in the survival analysis.

Control Variables

Tweet Number (Tweet): Because people who tweeted more often may have been different from those who tweeted less often, we calculated the average number of tweets that each user posted in a week. This was computed by dividing the total number of tweets that a user contributed by the number of weeks they participated.

Retweet Number (Retweet): For similar reasons, people who retweeted more often may have been different from those who retweeted less often. For this reason, the average number of retweets each user contributed in a week was also computed. This was calculated by dividing the total number of retweets generated by the user by the number of weeks they participated in the synchronous chat.

Independent Variables

Tweet Count Exposure (TweetExp): We estimated the total number of tweets a user was exposed to by assuming that they read all of the tweets in the synchronous sessions to which they contributed. This variable represented the total number of tweets generated during a week in which a user tweeted.

Cognitive Dimension Tweets Exposure (CDTExp): This variable represented the average number of cognitive-dimension tweets a user was exposed to in a week. It was computed by calculating the total number of cognitive-dimension tweets generated during a week in which the user tweeted and dividing this value by the total number of tweets the user was exposed to that week.

Interactive Dimension Tweets Exposure (IDTExp): This variable represented the average number of interactive-dimension tweets a user was exposed to in a week. It was computed by calculating the total number of interactive-dimension tweets generated during a week in which the user tweeted and dividing this value by the total number of tweets the user was exposed to that week.

Social Dimension Tweets Exposure (SDTExp): This variable represented the average number of social-dimension tweets a user was exposed to in a week. It was computed by calculating the total number of social-dimension tweets generated during a week in which the user tweeted and dividing this value by the total number of tweets the user was exposed to that week.

Before the survival analysis was conducted, all of the control and independent variables were standardized with a mean of zero and standard deviation of one. This allowed us to predict the change in the probability of a user dropping out of the community for each unit increase in these variables.

Results

Online Discourse Dimension Automatic Detection Results for RQ1

Using different features and various algorithms, text classification models were constructed to automatically identify different kinds of online discourse among the twitter community. Table 3 shows the performance results for the machine-learning models. Logistic regression performed consistently better than did the other three algorithms. The comprehensive comparison revealed that logistic regression demonstrates the best performance when using regular expression features (69.8% for precision and 60.29% for recall rate). According to the review literature (Dalal & Zaveri, 2011; Khan et al., 2010), its predictive performance is comparable to those of other machine-learning models built in similar social-media contexts.

Table 3. Text Classification Model Results

	Naïve Bayes		Logistic Regression		SVM		Decision Tree	
	P	R	P	R	P	R	P	R
LF	8.15%	10.33%	18.95%	12.42%	13.05%	11.75%	13.59%	11.76%
LIWC	4.65%	11.88%	13.21%	13.47%	18.98%	14.27%	10.29%	10.27%
Regex	52.41%	43.68%	69.80%	60.29%	56.75%	23.23%	63.60%	62.85%
LF + LIWC	5.42%	13.95%	12.43%	12.54%	32.18%	17.93%	15.55%	17.33%
Regex + LIWC	59.60%	37.49%	65.01%	60.56%	44.52%	18.29%	57.30%	58.98%

P: precision, R: Recall

This text classification model was applied to the remaining tweets in the community. Table 4 shows the descriptive statistics for the related variables for the different online discourse dimensions among the twitter community. The statistics for the two controlled variables of the survival modeling in the next section were also reported.

Table 4. Descriptive Statistics for the Variables in the Survival Analysis

	Mean	Median	SD	Min	Max
Tweet	23.44	4.00	188.23	2.00	15425
Retweet	7.19	2.00	63.48	0	6345
TweetExp	2335.99	2356.27	324.26	732.50	3647
CDTExp	649.30	376.53	594.54	71.50	3323
IDTExp	638.23	641.42	241.13	0	1597.5
SDTExp	1044.30	1103.50	412.95	0	2508

Survival analysis results for RQ2

To quantify the influences of different online discourse dimensions in the twitter community on user attrition, a survival analysis was conducted while controlling for the effects of the average number of tweets and the average number of retweets posted by the user. To demonstrate the influences of the predicting variables on the probability of an individual dropping out, the effects were quantified using the hazard ratio. Since all of the predicting variables were standardized, the hazard rate could predict the change in the probability of a user leaving the community generated by each unit increase in these variables. Table 5 and Figure 3 show the results of the survival analysis.

Model 1 shows the influences of the control variables of average tweet number, average retweet number, and average tweet exposure. The hazard ratio for average tweet (Tweet) was 0.933, revealing that individuals who contributed one standard deviation more tweets than the mean were 7% (100*(1-.0.933)) more likely to survive than users with lower numbers of average tweets. The hazard ratio for average retweet (Retweet) was 0.893, indicating that users who retweeted one standard deviation more than the average were 11% more likely to stay engaged in the community. Similarly, the hazard ratio for average tweet exposure (TweetExp) shows that the survival rate is 15% higher for individuals who saw one standard deviation more tweets than the average.

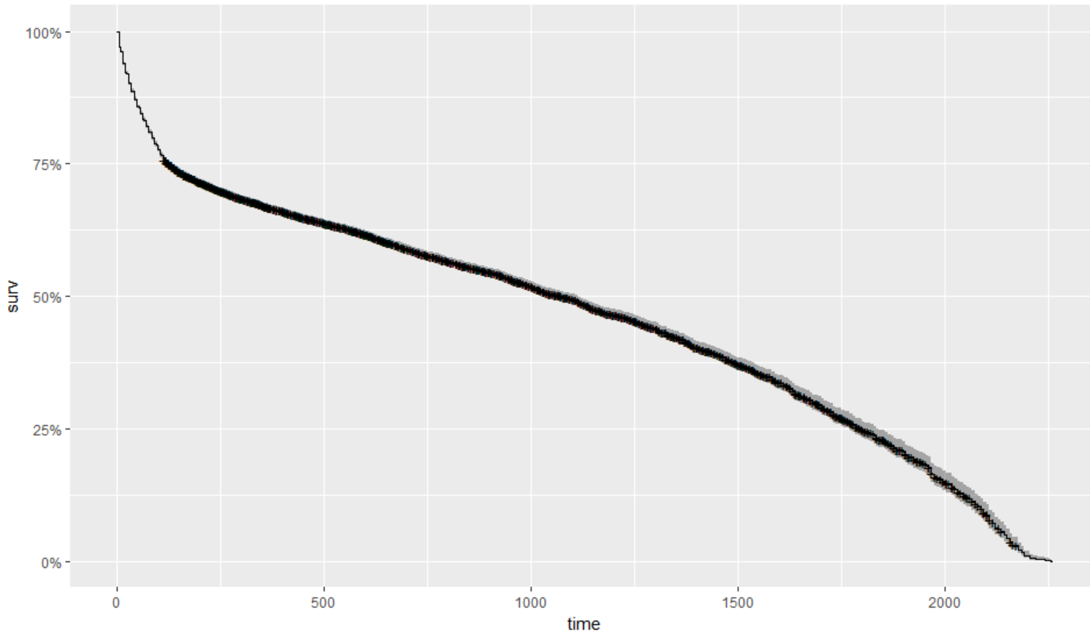
Table 5. Survival Analysis Results

	Model 1		Model 2		Model 3	
	Hazard Ratio	*p*	Hazard Ratio	*p*	Hazard Ratio	*p*
Tweet	0.933**	.002	0.949**	.005	0.956*	.011
Retweet	0.893**	.001	0.935*	.025	0.951	.071
TweetExp	0.850***	.000	1.227***	.000	1.408***	.000
CDTExp			0.547***	.000	0.469***	.000
IDTExp			0.545***	.000	0.573***	.000
SDTExp			1.136***	.000	1.115***	.000
TweetExp × CDTExp					1.355***	.000
TweetExp × IDTExp					1.095***	.000
TweetExp × SDTExp					1.031	.053

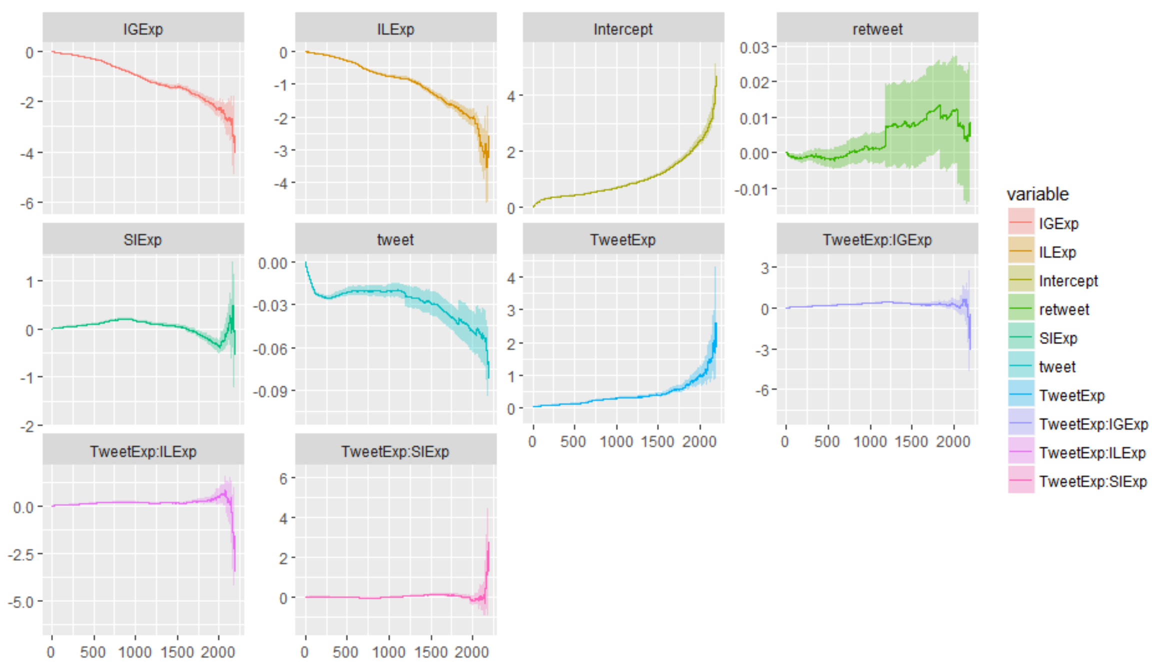
*: $p < 0.05$, **: $p < 0.01$, ***: $p < 0.001$

Model 2 reports the impacts of different online discourse dimensions on user survival when average tweet number, average retweet number, and total tweet exposure are controlled for. Exposure to tweets in all three dimensions—the cognitive dimension (CDTExp), the interactive dimension (IDTExp), and the social dimension (SDTExp)—affected the survival rate, albeit in different ways. Those who were exposed to tweets containing an average of one standard deviation more cognitive-dimension tweets were 46.3% more likely to remain in the twitter community. Users who were exposed to an average of one standard deviation more interactive-dimension tweets were 46.5% more likely to stay in the community. In contrast, those who were exposed to an average of one standard deviation more social-dimension tweets were 13.6% more likely to drop out of the community. In short, additional exposure to cognitive- and interactive-dimension tweets was related to staying in the community, and exposure to additional social-dimension tweets was associated with leaving.

Model 3 explores the interaction effects between the number of tweets users were exposed to and the average amount of online discourse interactions in these tweets (TweetExp × CDTExp, TweetExp × IDTExp, TweetExp × SDTExp). Users who were exposed to one standard deviation more tweets containing one standard deviation more IDTExp interactions were 11.5% (100% * [1 – 1.408*0.469*1.355]) more likely to remain in the community than members were exposed to an average number of tweets with an average number of CDTExp interactions. Similarly, members who were exposed to one standard deviation more tweets containing one standard deviation more IDTExp interactions were 12.7% more likely to stay in the community. In contrast, whether members were exposed to average tweets containing more SDTExp interactions did not affect their survival because TweetExp × SDTExp had no significant effect. Figure 3(a) shows the mean survival with all of the predicating variables. Figure 3(b) shows the mean survival with each predicating variable independently.



(a) Overall survival effect



(b) Independent variable effect on survival

Figure 3. Overall and independent effect on members' survival

Discussion

Participating in online communities for professional development and learning can benefit educators in numerous ways. However, educators cannot benefit from a community if they leave it. In this paper, we quantified the effects of different dimensions of online discourse on the user retention of a Twitter professional learning community. Specifically, we designed an accurate text classification model to automatically detect the cognitive, interactive, and social dimensions of an online discourse. We then used the survival analysis to examine the relationships between the different dimensions of the online discourse and its users' commitment time. The results revealed that different dimensions of online discourse have different impacts on users' commitment time.

Specifically, the results revealed that the more tweets in the cognitive and interactive dimensions that the members were exposed to, the lower was their risk of dropping out. Furthermore, tweets in the interactive dimension had slightly stronger influences than did tweets in the cognitive dimension. This might suggest that the educators who participated in the Twitter community valued tweets that focused on generating and co-constructing ideas. This conclusion aligns with those of other researchers. Carpenter and Krutka (2015) found that educators considered participating in weekly chats to be beneficial because doing so made them reflect on their own practices, search out new ideas, and question and react to other people's ideas. According to Rodesiler (2015), Twitter chats help educators to engage in collaborative problem-solving, which generates "new knowledge through a shared endeavor" (Rodesiler, 2015, p. 37). Large numbers of cognitive and interactive tweets in a given chat indicated that the participants actively contributed to the collaborative problem-solving process. Such process allows participants to gain new knowledge and skills that could be applied to their classrooms (Booth & Kellogg, 2014). This positive experience may have encouraged them to continue participating in the Twitter community.

The results also showed that exposure to social tweets was negatively associated with user commitment. Though this result seems counter-intuitive, there are a few possible explanations. First, synchronous chats in Twitter communities are typically characterized by the "rapid flow of information" (Britt & Paulus, 2016, p. 56). When a chat generates three or four tweets every second, it might overwhelm some participants (Britt & Paulus, 2016). When a chat has a high percentage of social tweets, moreover, its participants may have to exert extra effort to identify the tweets that are relevant and important. The resulting cognitive overload might discourage some of them from continuing to participate. Another possible explanation concerns the types or quality of the social tweets in this study. When we reviewed the tweets, we found that the majority of the social tweets were greetings and courtesy tweets. Few provided rich socio-emotional support, perhaps because of the pace of communication or the 140-character limit for each tweet. The lack of quality social tweets might partially explain the negative association between social tweets and user commitment.

These findings have significant implications for the building of online communities for professional learning. Even though the machine-learning model was built to understand the discourse in a particular Twitter community, it can be modified to support active interventions. For example, if a Twitter community offers a limited number of cognitive and interactive tweets, but numerous social tweets, its moderator or an automatic agent could find ways to promote more cognitive and interactive discussion. We could also use our mechanism to construct a prediction model that could identify users at risk of dropping out. Targeted support could then be delivered to these users before they stopped participating in the community.

This study also has major methodological implications. Previous studies into online professional learning communities mainly tested relatively small amounts of data using traditional social-science methods, including surveys, interviews, and content analyses, (Britt & Paulus, 2016; Macià & García, 2017; Rodesiler & Pace, 2015). These methods of data collection and analysis tend not only to be time consuming, but also to suffer from the sparse time granularity (Qiu et all, 2011). This study demonstrated that carefully designed data-mining techniques can produce insights automatically that would otherwise be difficult to obtain. The method employed in this study was automatic and required almost no human effort. Moreover, the method applied was not coming out of blue but based on methods employed by previous researchers (Aphinyanaphongs et al., 2016; Pla & Hurtado, 2014). Future studies into Twitter-based professional learning communities and other social-science topics can consider going beyond traditional qualitative and quantitative methods by performing large-scale data analytics.

An important limitation of this study is that even though we considered longitudinal effects, the results are correlational. While the results are consistent with the assumption that online discourse can impact users' commitment time, they could also be explained by preexisting user differences. Experiments with additional controls could more clearly determine the impact of online discourse on communities' member retention. Another limitation of this study is that we only focused on users who had tweeted more than once. We may have overlooked "lurkers," users who participate only by reading the discussion. Finally, this study investigated just one Twitter community. The results should be applied with caution to other online communities.

Future work could pursue several directions. First, although the findings revealed that different dimensions influenced user retention differently, why this was the case is unclear. Future studies could administer surveys and conduct interviews with the users to determine why users choose to stay or leave an online community. Second, to generalize our findings, we could apply our methodology to additional online communities both within and outside of Twitter. Third, we could examine the extent to which online discourse ultimately influences participants' professional growth; promoting continuous participation in online professional learning communities is merely the first step.

Conclusion

There is a growing interest in participating in social-media communities, such as Twitter, to support educators' professional development and learning. While most of the studies have focused on why educators want to use Twitter for professional learning and what they actually do in these communities, this study attempted to understand a more fundamental question: why do certain users remain committed and others gradually dropout in a Twitter professional learning community? This study approached the community commitment problem from the online discourse perspective. Given the large number of tweets and users, we developed an accurate computational model to automatically recognize the cognitive, interactive, and social dimensions of the Twitter online discourse and further employed the survival analysis to quantify the effect of different online discourse on users' commitment time. Such quantified understanding and results can help us develop concrete support mechanisms to help maintain community members' continued participation. Such understanding and further support will influence the sustainability of the community and in turn the entire success of a Twitter professional learning community. After all, without a certain amount of committed users, it won't be called a community, not to mention satisfying its purpose for professional development. Methodologically, it can inspire future researchers of online communities and general social science topics to go beyond traditional qualitative and quantitative methods by conducting large-scale data analytics. Finally, in this study, a coding scheme was developed to capture the three dimensions of discourse that are essential for learning. The coding scheme may serve as a framework for analyzing discourse-based learning that occurs in other informal learning settings, particularly, Twitter-based learning communities.

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