Professional Development in 140 Characters? Analyzing Twitter as a Professional Learning Platform for Science Teachers

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Abstract

This mixed-methods observational study analyzes Advanced Placement (AP) Biology teachers' engagement in microblogging for their professional development (PD). Data from three hashtag-based Twitter communities, #apbiochat, #apbioleaderacad, and #apbioleaderacademy (121 users; 2,253 tweets), are analyzed using methodological approaches including educational data mining, qualitative two-cycle content analysis, social network analysis, linear and logistic regression analyses, and hierarchical linear modeling. Results indicate that Twitter adheres to standards of high-quality PD and has the potential to complement more traditional PD activities. Notably, Twitter's non-hierarchical leadership affords shared content creation and distribution. Additionally, Twitter allows for different temporal participation patterns and supports the personalization of learning experiences aligned to teachers' needs and preferences. Furthermore, teachers frame their interactions on Twitter positively, thus, creating a supportive environment for professional learning that might reduce teachers' perceived isolation. Therefore, policy makers and school leaders should feel empowered to encourage teachers to use microblogging complementary to other PD activities.

Keywords: Microblogging, science education, professional development, virtual communities of practice, Advanced Placement

In times of accelerated technological advancements, traditional framings of images of teacher professional development (PD) stand to benefit from re-examination in new contexts.

These include opportunities that might extend or replace traditional face-to-face professional learning activities. The microblogging platform Twitter, which allows users to communicate with their followers through short messages, is an example of such an environment. Besides text information, tweets can also include images, videos, and links to other websites. As of June 30, 2016, Twitter attracted 313 million monthly active users who accumulated one billion unique visits per month to websites with embedded tweets (Twitter, Inc., 2017). Features that distinguish Twitter from other online communities are its usability (e.g., limited technology knowledge necessary), accessibility (e.g., support of mobile applications), personalization (e.g., unique information displayed to every user), low financial costs (e.g., no sign-up fees or other monetary costs), breadth and depth of available information (e.g., diverse user groups), limited time commitments for individual tweets (e.g., 140-character limit), and dynamic display of new information (e.g., real-time updates) (Carpenter, 2015; Carpenter & Krutka, 2014, 2015; Java, Song, Finin, & Tseng, 2007; Zhao & Rosson, 2009).

Educators have recognized the potential of Twitter as a useful tool for enhancing their professional life. For instance, practitioner-focused publications describe how Twitter can transform interactions with students, parents, and administrators (e.g., Kurtz, 2009; Porterfield & Carnes, 2011), change instructional practices (e.g., Domizi, 2013; Krutka & Milton, 2013), or – on an anecdotal level – contribute to professional learning (e.g., Boss, 2008; Trinkle, 2009). However, the scholarly literature base analyzing teachers' use of microblogging as a form of PD for K-12 teachers is limited. As of now, most research of microblogging as PD is descriptively illustrating usage patterns or perceived benefits such as availability of resources, encouragement to reflect on instructional practice, and relationships building with colleagues (e.g., Carpenter, 2015; Carpenter & Krutka, 2014, 2015; Carpenter, Tur, & Marín, 2016; Lord & Lomicka, 2014;

Mills, 2014; Risser, 2013; Wesely, 2013; Wright, 2010). However, empirical studies that analyze how teachers' participation in microblogging might complement more traditional PD or how microblogging fulfills characteristics of high-quality PD are underrepresented in the scholarly literature base.

Decades of systematic empirical research studies on the impacts of teacher PD identified several design elements that contribute to high-quality PD experiences such as practice orientation, focus on content knowledge, coherence with school and teaching contexts, collaboration and community building among colleagues, and intensity and continuation of professional learning (e.g., Darling-Hammond & Richardson, 2009; Darling-Hammond, Wei, Andree, Richardson, & Orphanos, 2009; Desimone, 2009; M. M. Kennedy, 2016). The potential to use new technologies for teacher PD led to several calls for empirical research to analyze the potential of online teacher learning (Borko, Jacobs, & Koellner, 2010; Dede, 2006; Dede, Ketelhut, Whitehouse, Breit, & McCloskey, 2008) and recent studies responded to these calls analyzing impacts of online PD on teachers' knowledge, classroom instruction, and student learning and achievement (Fishman et al., 2013; Kelly & Antonio, 2016; M. J. Kennedy, Rodgers, Romig, Lloyd, & Brownell, 2017; Macià & García, 2016). Similarly, this study responds to this call for research by exploring how Twitter complements more traditional forms of professional learning and whether Twitter adheres to characteristics described as important for high-quality PD experiences.

Conceptual Framework

This study is situated in the context of the redesign of the Advanced Placement (AP) examinations in the sciences. College Board, the provider of the AP program, redesigned the AP program to decrease its former emphasis of memorization while foregrounding deep content understanding, scientific inquiry, and reasoning (e.g., Magrogan, 2014; Yaron, 2014). Many of these changes are consistent with the Next Generation Science Standards (NGSS; NGSS Lead States, 2013). AP courses provide rigorous, college-level learning experiences for high-school students and the corresponding AP examinations are considered high-stakes as they relate to higher enrollment rates in four-year postsecondary institutions, increased college graduation rates, and higher college GPAs (Chajewski, Mattern, & Shaw, 2011; Hargrove, Godin, & Dodd, 2008; Mattern, Marini, & Shaw, 2013; Patterson, Packman, & Kobrin, 2011). Given the large-scale top-down curriculum changes and the high-stakes nature of the AP examinations, teachers are highly incentivized to engage in PD activities to improve their instruction which provides a great opportunity for research.

This observational mixed-methods study is guided by Bruns and Moes' (2013) framework that describes user interactions on Twitter with three cross-layered categories (i.e., micro-level: reply conversations, meso-level: follower-followee networks, macro-level: hashtagged exchanges) and Desimone's (2009) summary of decades of PD effectiveness research that identifies high-quality PD characteristics. In particular, this study focuses on Bruns and Moes' (2013) macro-level conversational practices and analyzes interactions in hashtag-based communities. Additionally, this study explores whether teachers' Twitter usage fulfills the 'collective participation' and 'duration' PD design characteristics that Desimone (2009) highlights as important for high-quality PD experiences.

Macro-Level User Interactions

Bruns and Moes' (2013) macro-level conversational practice relates to users' dissemination of content (i.e., tweets) to a broader audience by contributing to a hashtag-based conversations (i.e., #-sign preceding the name of conversation included in tweet). Such tweets are not restricted to users' follower-networks. Nonetheless, all macro-level interactions are also meso-level interaction (but not vice versa) as tweet are always distributed to users' follower networks. Similarly, macro-level user interactions can also include micro-level conversational practices as users may reply to tweets in the hashtag-based communities or mention other users (i.e., @-sign preceding the username included in tweet), which affords informal collaborations between users (Bruns & Moe, 2013; Honeycutt & Herring, 2009). In general, hashtags have conversational and social tagging functions that allow users to filter and promote content, foster conversations, and initiate and sustain collaborations with other users (Bruns & Moe, 2013; Huang, Thornton, & Efthimiadis, 2010).

Collective and Collaborative Professional Learning

Desimone (2009) defines the high-quality PD characteristics 'collective participation' as "[PD] participation of teachers from the same school, grade, or department. Such arrangements set up potential interaction and discourse, which can be a powerful form of teacher learning" (p. 184). This definition has geographic- and activity-related components. AP Biology teachers are often the only AP Biology teachers in their school which constrains collaborative engagement in PD targeted towards the AP Biology redesign with colleagues from their school. Therefore, meaningful collaborative interactions with other AP Biology teachers in virtual learning communities could overcome such geographical boundaries.

Twitter as a collaborative learning environment. Collective PD participation and collaboration in learning communities among educators can enhance teacher learning, knowledge gains, and changes to instructional practice (e.g., Garet, Porter, Desimone, Birman, & Yoon, 2001; Hadar & Brody, 2013; Penuel, Fishman, Yamaguchi, & Gallagher, 2007). Communities of practice are a prime example of such collaborative environments that facilitate learning situated in individuals' contexts (Lave, 1991; Wenger, 1998). Some researchers argue that participation on Twitter can enable learners to form virtual communities of practice and create social capital (Lord & Lomicka, 2014; Rehm & Notten, 2016; Wesely, 2013). Whether Twitter provides more informal, democratic, and bottom-up collaboration and learning compared to more traditional PD activities with more formal, hierarchical, and top-down information distribution structures is a focal question of this study.

Several of Twitter's design characteristics support perspectives that Twitter could afford such informal, democratic, and bottom-up learning. *First*, Twitter's peer-to-peer interaction structure reduces disconnects between learners and experts. Flat hierarchical communication structures might afford increases of informal collaborations and shared responsibilities for learning processes (Ardichvili, 2008; Kirschner & Lai, 2007). *Second*, Twitter's asynchronous following-followee structure and personalized display of tweets allows learners to personalize their experiences. In contrast to "one-size-fits-all" approach of some traditional PD activities, teachers on Twitter can interact with selected resources and participants based on their individual needs and contexts (Carpenter & Krutka, 2014, 2015; Zhao & Rosson, 2009). *Third*, Twitter removes potential participation barriers which affords collaborations of more diverse teacher populations. Twitter does not cost money to sign up, and is easily accessible via smart phones, thus reducing participation barriers by socioeconomic status (Pew Research Center, 2017). Also, Twitter learning communities can be accessed anywhere, anytime, and with any intensity reducing geographic and temporal participation barriers (Carpenter & Krutka, 2014; Ebner, Lienhardt, Rohs, & Meyer, 2010; Zhao & Rosson, 2009).

Twitter as a supportive learning environment. In the teaching profession, teachers frequently experience isolation, which does not only negatively impact teachers' well-being but also their teaching performance. In particular, beginning teachers are more likely to suffer from emotional stress and isolation if their school environment does not meet support needs (Moore & Chae, 2007). Supportive environments are important as emotions have profound influences on motivation, cognitive processes, decision making, and learning outcomes (e.g., Kim & Pekrun, 2014; Pekrun, Goetz, Titz, & Perry, 2002; Sansone & Thoman, 2005). However, such effects are bidirectional as learning accompanied with positive emotions relate to greater learning outcomes, whereas negative emotions negatively relate to learning outcomes (e.g., Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010; Zusho, Pintrich, & Coppola, 2003).

Research indicates that online communities have potential to provide positive and supportive learning environments that promote collaboration, foster the development of professional identities, and potentially reduce isolation (Dodor, Sira, & Hausafus, 2010; Hanuscin, Cheng, Rebello, Sinha, & Muslu, 2014; Hough, Smithey, & Evertson, 2004; Lieberman & Mace, 2010). While Twitter is often described as supportive, encouraging, and positive environment (Carpenter & Krutka, 2014, 2015; Wesely, 2013; Wright, 2010), Twitter use can also have adversary effects as the public nature of tweets, in accordance with the immediacy of a mostly anonymous participation culture, can evoke responses with extreme forms of disapproval or harsh commentary (Burbules, 2016; Mandavilli, 2011). Also, student-teacher relationships can be impacted if students view their teachers' social media interactions as inappropriate or unprofessional (DeGroot, Young, & VanSlette, 2015; Mazer, Murphy, & Simonds, 2007).

Temporal Aspects of PD Participation

Twitter provides a flexible platform for professional learning with respect to teachers' preferred temporal engagement patterns offering immediate feedback and personalized just-in-time information (Carpenter & Krutka, 2014; Ebner et al., 2010; Zhao & Rosson, 2009). Teachers can participate in any intensity and frequency as permanently publicly available information on Twitter allows for asynchronous learning. Both intensity (i.e., contact hours) and continuation (i.e., time span, frequency) of PD participation are integral factors for teacher learning (Darling-Hammond et al., 2009; Desimone, 2009; M. M. Kennedy, 2016). While duration thresholds are not specified, Desimone (2009) estimate of 20 hours contact time and Darling-Hammond and colleagues' (2009) estimate of 50 hours spread across 6-12 months provide some insights on lower PD duration thresholds to yield teacher knowledge and student performance gains.

Research Questions

This study explores how teachers' interactions and engagement on Twitter might complement more traditional forms of PD, as well as whether Twitter exhibits features Desimone (2009) relates to high-quality PD. The research questions (RQ) are as follows:

RQ1: Are participation structures in AP teacher Twitter communities organized similarly to more traditional, hierarchically organized professional learning activities?

a. Are AP Biology teachers who share content knowledge or resources on Twitter more or less likely to be influential in the corresponding Twitter communities?
b. Are AP Biology teachers who seek information or share resources on Twitter more or less likely to be central in the corresponding Twitter communities?
c. Are AP Biology teachers who organize teacher chats on Twitter more or less likely to have a higher ability to connect with other teachers in the corresponding Twitter communities?

RQ2: Do AP teacher Twitter communities provide a positive, supportive environment for teachers engaging in professional learning activities?

a. Do topics AP Biology teachers discuss in the Twitter communities exhibit mostly positive, negative, or neither positive nor negative sentiments?
b. Do AP Biology teachers engage (i.e., like and retweet) more with positive, negative, or neither positive nor negative tweets in the Twitter communities?

RQ3: Do teachers' temporal Twitter usage patterns in AP teacher Twitter communities complement more traditional forms of professional learning activities?

a. What are AP Biology teachers' participation patterns in the Twitter communities regarding frequency and lifespan of participation?
b. What tweet content, tweet sentiment, tweet characteristics, and community participation characteristics are associated with AP Biology teachers' lifespan of participation in the Twitter communities?

In particular, 'collective participation' is explored by analyzing hierarchical participation structures (RQ1) and affective support structures (RQ2). "Duration" is examined by analyzing temporal participation patterns (RQ3).

Methodology

Data Sources and Sample

This observational study analyzes public data from three purposefully selected hashtag-based AP Biology Twitter teacher communities (*#apbiochat*, *#apbioleaderacademy*, *#apbioleaderacad*). This study adheres to ethical standards to protect users' privacy, despite all data being publicly available, by following ethical guidelines for social media research (Bruckman, 2006; Moreno, Goniu, Moreno, & Diekema, 2013). For instance, instead of verbatim quotations of tweets which might lead to an identification of teachers' true identities, synthetic tweets with identical content and sentiment are generated to illustrate relevant concepts. This is similar to practices of generating synthetic data sets that protect user's privacy in large-scale quantitative analyses (e.g., Abowd & Lane, 2004; Reiter, 2002). These synthetic tweets are only used for illustrative purposes and not for any analyses.

AP teacher communities are selected because the top-down, national AP science reform incentives teachers to engage in PD to align their classroom instruction to the new curriculum. The first redesigned AP Biology exam was administered in 2013 compared to AP Chemistry and AP Physics in 2014 and 2015, respectively. Thus, Biology communities afford the longest observational period for science teacher learning on Twitter. Hashtag-based communities are chosen to analyze macro-level user interactions (Bruns & Moe, 2013). The *#apbiochat* community is selected because teachers reported frequent engagement in this Twitter community on web-based surveys connected to a large-scale longitudinal research project examining this curriculum reform (e.g., Fischer et al., 2016, 2018; Frumin et al., 2018). The *#apbioleaderacademy* and *#apbioleaderacad* communities are selected because of their affiliation with the NABT/BSCS AP Biology Leadership Academy, an intense two-year long PD program that includes week-long face-to-face workshops, conference participations, and online support throughout the program.

The full public tweet history from the beginning of each hashtag until June 14, 2016 (four weeks after the 2016 AP Biology examination) is retrieved and cleaned using Twitter's search function, the Twitter API, the R package twitteR, and custom Python scripts. Additionally, Python scripts collect biographical information and descriptive Twitter usage data. In total, the three online communities contain 2,276 tweets from 135 users. Users not identifiable as teachers, school administrators, or representatives from professional organizations are removed reducing the data set to 121 users (93 teachers) posting 2,253 tweets (2,040 tweets authored by teachers). The research questions are answered exclusively with teacher data. However, variables that describe teachers' relational positions in the communities also utilize data from school administrators and representatives from professional organizations.

Measures

Qualitative tweet measures. On the tweet-level, qualitative coding approaches are applied to describe tweet content and tweet sentiment. The unit of analysis is a single tweet. The initial coding schema uses an exploratory two-cycle coding strategy applying descriptive coding (first cycle) and subcoding (second cycle) (Miles, Huberman, & Saldana, 2014). After multiple iterative improvements of the inductively developed coding guidelines, a final list of codes was chosen and treated as the deductive coding framework. Tweets were recoded based on this final list of codes. Following Lombard, Snyder-Duch, and Bracken (2002), the reliability of the coding scheme was evaluated through three additional external coders who independently coded an identical subset of 225 randomly selected tweets (more than 10% of the full sample) after a face-to-face training session. Interrater reliability of the coding schema (88.8 mean percentage agreement, average Cohen's κ rating of 0.73) meets benchmarks of "substantial" agreement (Landis & Koch, 1977, p. 165).

Tweet content is coded based on seven categories related to AP learning and teaching, (a) sharing AP Biology content knowledge, (b) sharing resources, (c) seeking information, (d) organizing PD on Twitter, (e) mentioning curricular elements, (f) sharing information about laboratory investigations, and (g) assessments. Each tweet is either classified as exhibiting the characteristics of a category ('1') or not ('0'). Tweets can exhibit any number of categories simultaneously (Table). Notably, teachers' tweets most frequently shared resources (14.6%), sought information (12.3%), and related to assessments (9.2%).

[TABLE 1 ABOUT HERE]

Tweets classified as *sharing AP Biology content knowledge* provide content information relevant for AP Biology, common content knowledge, misconceptions, use of biological language, and recommendations for content knowledge resources. Tweets classified as *sharing resources* provide information on accessing additional resources or on their use. Tweets classified as *seeking information* ask questions or request resources related to student learning, instructional enactments, curricular standards, and assessments. Tweets classified as *organizing PD on Twitter* include selections of Twitter chat topics, scheduling of Twitter chats, reminders of upcoming Twitter chats, recruitment, and confirming absence or participation in upcoming Twitter chats. In particular, tweets do not exhibit this characteristic if Twitter is used to organize face-to-face meetings. Tweets classified as *curricular elements* include references to other state or national curricula, the AP lab manual, practice exams, conceptual flow graphics, standards-based grading, free- and open-response questions, and AP curriculum framework elements. Tweets classified as *laboratory investigations* include descriptions of experiments, equipment and supplies, and lab reports. Tweets classified as *assessments* include information about AP examinations, test preparations, and summative and formative assessments strategies. Table illustrates each category with exemplary tweets.

[TABLE 2 ABOUT HERE]

Tweet sentiment coding follows an emotion coding approach (Miles et al., 2014) and classifies tweets as *more positive*, *more negative*, and *not exclusively positive or negative*

(Table 3). The unit of analysis is a single tweet. Each tweet is assigned one sentiment category and one only. Tweet sentiment evaluations also account for tone, emoticons, hashtags, sarcasm, and irony. Tweet sentiments classified as *more positive* include expressions of joy, excitement, liking, motivation, inspiration, and thankfulness. Tweet sentiments classified as *more negative* include expressions of being overwhelmed, struggle, anxiety, and admittance of mistakes. Tweet sentiments classified as *not exclusively positive or negative* include tweets that exhibit neutral, neither positive nor negative sentiment, or both positive and negative sentiments. Table 4 illustrates these categories with exemplary tweets.

[TABLE 3 ABOUT HERE]

[TABLE 4 ABOUT HERE]

Quantitative tweet measures. Quantitative tweet information include the number of retweets and likes a tweet received, the number of mentions, hashtags, and links incorporated in a tweet, teachers' lifespan of community participation (number of days between first and last tweet), and frequency of teachers' engagement in the communities (total number of tweets divided by lifespan) (Table 5).

[TABLE 5 ABOUT HERE]

Inferential social network measures. Relational positions of teachers in the selected Twitter communities are examined analyzing Bruns and Moes' (2013) micro-level conversational practice of "mentioning" (i.e. including the "@"-sign in their tweet). Social network analysis (SNA) measures are computed to analyze the hierarchical structures of teachers within the communities. The literature base that uses SNA to analyze social ties among educators has grown in recent years (Atteberry & Bryk, 2010; Coburn, Russell, Kaufman, & Stein, 2012; Penuel & Riel, 2007). The “mentions network” is comprised of all interactions of users mentioning another in the selected communities. Data from school administrators and representatives of professional organizations is included for computing these SNA variables to avoid misrepresentations of teachers’ relational positions in the communities. However, the research questions are explored solely using teacher data.

Social network diagrams of the mentions network use the ForceAtlas2 algorithm of the open-source software Gephi (Jacomy, Venturini, Heymann, & Bastian, 2014). Visualizations are centered and zoomed-in on the largest connected network to increase readability. Nodes, the circles, represent users in the mentions network. Node sizes reflect users’ in-degree (i.e., number of users mentioning the user). Edges, the line between two nodes, represent that user A (source node) mentions user B (target node). Clockwise-curved edges illustrate that the source node mentions the target node, and vice versa. Tweets not mentioning other users are treated as self-referential (source identical to target). Edge thickness represents the number of mentions between two users. Edge colors are identical to source node colors. Such visualizations provide insights on the relative importance of users based on their positioning in the network. For instance, teachers mostly mention other teachers and rarely representatives from professional organizations, who hold generally less prominent roles in the communities (Figure 1). This supports the subsequent teacher-level subgroup analyses.

[FIGURE 1 ABOUT HERE]

The SNA measures eigenvector centrality, closeness centrality, and betweenness centrality are computed to understand the hierarchies within collaboration and information flows patterns (e.g., Knoke & Yang, 2008; Scott, 2013). *Eigenvector centrality* describes teachers’ influence in the communities. This measure account for users' own connectedness and the connectedness of their neighbors. For instance, teachers with high eigenvector centrality could be interpreted to have more 'prestige' in the communities. Others might more likely follow guidance from such 'high-prestige' teachers. *Closeness centrality* describes teachers' connectedness in the communities. This measure represents the inverse of the sum of the shortest paths between the user and all other users in the network. For instance, teachers with high centrality might more efficiently distribute information to other teachers. *Betweenness centrality* describes teachers' "broker ability" to connect more distant subnetworks in the communities. This measure describes how often a user is part of the shortest path between two other users. For instance, teachers with high broker ability might encourage participation in larger networks.

Teachers are classified in four groups for each SNA measure based on numerical thresholds values in correspondence with the social network diagrams (eigenvector centrality: no importance (<0.001), low importance (0.001-0.150), medium importance (0.150-0.375), high importance (0.375-1.000; closeness centrality: no centrality (<0.001 and outside largest connected network), low centrality (0.001-0.350), medium centrality (0.350-0.425), and high centrality (>0.425); betweenness centrality: no broker ability (<0.1), low broker ability (0.1-30), medium broker ability (30-300), and high broker ability (>300)) (Table 6). For instance, nodes outside of the largest connected network are assigned to the "no centrality" closeness centrality group.

[TABLE 6 ABOUT HERE]

Analytical Methodologies

The *first research question* uses teacher-level proportional odds ordered logistic regression models with robust standard errors to analyze teachers' engagement patterns in the selected communities (e.g., Harrell, 2015). Dependent variables include ordinal variables that describe teachers belonging to teachers' influence (eigenvector centrality), centrality (closeness centrality), and broker ability (betweenness centrality) groups. Independent variables include the percentages of tweets in which teachers share AP Biology content knowledge (RQ1.a), share resources (RQ1.a, RQ1.b), seek information (RQ1.b), and organize PD on Twitter (RQ1.c). Covariates describe tweet content and teachers' community participation (Table 7).

The *second research question* uses contingency tables to illustrate tweet sentiment distributions across the different topics teachers discussed in the communities. Also, two-level fixed-effects hierarchical linear models (HLM) with Hubert-White sandwich estimators as robust standard errors analyze associations of tweet sentiment with tweet engagement (e.g., Raudenbusch & Bryk, 2002). Multi-level modeling is necessary because tweets (level 1) are nested within teachers (level 2). The dependent variable describes the sum of the number of retweets and likes a tweets receives. Independent variables describe tweet sentiment. Covariates describe tweet content, tweet characteristics, and teachers' community participation (Table 8).

[TABLE 7 ABOUT HERE]

[TABLE 8 ABOUT HERE]

The *third research question* uses descriptive analyses and teacher-level ordinary least squares (OLS) multiple regression analysis with Hubert-White sandwich estimators as robust standard errors (Montgomery, Peck, & Vining, 2012) to explore temporal participation patterns. The dependent variable describes teachers' lifespan of participation in the online communities. Independent variables describe tweet content, tweet sentiment, quantitative tweet characteristics, and community participation characteristics (Table 8).

Assumptions of the modeling approaches are tested. For instance, teachers are uniquely distributed across teacher groups and observations are independent from each other. Variance inflation factors confirm the absence of multicollinearity. Also, additional assumptions of the proportional odds logistic regression models are tested. For instance, the analytical sample includes more than 10 observations for each independent variable. Sensitivity analyses confirm stability of significance levels for changes in the threshold values for the teacher group assignments. Likelihood-ratio tests and AIC and BIC goodness-of-fit indices that compare proportional odds models to generalized ordered logistic regression models do not reject the parallel regression assumption. Furthermore, additional assumptions of OLS regression and (when appropriate) HLM models are tested. For instance, DFBETAs indicate that mean standard errors for all independent variables can be approximated as zero. Ramsey RESET tests indicate that residuals are not correlated with omitted independent variables. Leverage versus residual-squared plots indicate absence of influential cases. However, Breusch-Pagan/Cook-Weisberg tests and residual versus predictor plots identify homoscedasticity problems for some independent variables in OLS regression and HLM models. Similarly, univariate kernel density estimation plots and standardized normality plots indicate some normality of residuals problems in the OLS regression and HLM models. Both issues are addressed by including Huber-White sandwich estimators as robust standard errors.

Limitations

The most important limitations of this study are related to the data collection. For instance, generalization to overall teacher populations should be drawn with caution because schools could ask their most skilled and knowledgeable teachers to teach AP courses. Also, the observed teachers might not represent average AP Biology teachers as two hashtags are connected to an intensive face-to-face PD activity, the NABT/BSCS AP Biology Leadership Academy. Also, Schlager and Fusco (2003) argue that online teacher learning is most effective if connected to face-to-face learning activities to extend professional conversations across multiple platforms. Thus, teachers on Twitter might be more motivated to engage in professional learning, might have a higher affinity to use online-based learning environments, might have higher self-efficacy, and might be more committed to teaching redesigned AP Biology courses than average AP Biology teachers.

Another potential sampling and self-selection bias is that teachers who might have contributed tweets with primarily negative sentiments might have felt discouraged to continue their participation. Also, if the communities were mostly negative, teachers might not demonstrate initial interest to participate. However, this bias might be small because Twitter users often express their dissent with respect to other topics such as politics or product brandings (e.g., Jansen, Zhang, Sobel, & Chowdury, 2009; Small, 2011). With respect to the AP redesign, negative sentiments might have been more prominent if teachers' felt a larger sense of disagreement with core elements of the science curriculum reform. A further threat to validity is that this study solely relies on publicly available data. Learning experiences of lurkers are not captured although lurkers fulfill important roles and might highly benefit from the visible interactions of posters (e.g., Edelmann, 2013; Preece, Nonnecke, & Andrews, 2004).

Potential threats to reliability relate to the format of the collected data. While Twitter allows attachments of pictures and videos, this study solely focuses on the text-based tweet components. This omitted additional information might lead to different tweet content or sentiment assignments. Similarly, user content deleted prior to the data collection and private communication between users were unavailable for this data collection. For instance, teachers worried about repercussions of negative tweets might avoid a public display of their statements. Additionally, other potentially important variables such as attitudes towards PD and Twitter, self-efficacy, school affluence, or administrative support which might influence the examined relationships as either extraneous or confounding variables were not collected, and thus, not included in the models.

Results

Hierarchies in Participation Structures on Twitter

Teachers' classifications in the groups based on influence, centrality, and broker ability ratings are examined to explore whether leadership structures on Twitter mirror or contrast more hierarchically-structured traditional PD activities in which designated leaders contribute and distribute most content, lead discussion, and organize the PD activities.

[TABLE 9 ABOUT HERE]

Teachers' sharing of content knowledge helps predict teachers' belonging to influence-based teacher groups, whereas teachers' sharing of resources does not provide a significant contribution (RQ1.a, Table 9). A ten percent increase in teachers' tweets relating to AP Biology content knowledge is associated with a 2.7% decrease in the odds of teachers belonging to higher influence teacher groups, holding everything else constant. This contrasts more traditional PD activities in which persons who share content knowledge or resources might commonly be perceived as leaders.

Teachers' information seeking behavior does not significantly predict teachers' belonging to centrality-based teacher groups, whereas teachers' resources sharing behavior serves as such a predictor (RQ1.b, Table 9). A ten percent increase in resource sharing tweets is associated with a

2.4% decrease in the odds of teachers belonging to higher centrality groups, holding everything else constant. These findings support a perspective on Twitter in which responsibilities for sharing resources are distributed among users reducing hierarchical distinctions between learners and 'experts.' This contrasts more traditional PD activities in which PD leaders, who could be viewed as the most central persons, potentially share most resources.

Teachers' engagement in the organization of PD on Twitter predicts teacher classifications in broker ability based groups (RQ1.c, Table 9). A ten percent increase in teachers' tweets related to the organization of PD activities on Twitter is associated with a 1.6% decrease in the odds of teachers belonging to higher broker ability groups, holding everything else constant. This supports a perspective on Twitter in which persons organizing and recruiting participants are not the focal interaction partners for new community members. Instead, new community members potentially feel similarly confident to interact with all other community members. This describes the removal of a participation barrier that teachers might encounter in more traditional PD activities.

Twitter as an Affective Support System

The topics teachers discuss in the selected Twitter communities have more often positive than negative tweet sentiments. Nonetheless, tweets are mostly not characterized by exclusively positive or negative sentiments. Topics most often framed positively are *sharing resources* (28.6%), *organizing PD activities on Twitter* (24.4%), and *laboratory investigations* (24.0%) (RQ2.a, Table 10). This indicates that professional learning on Twitter is approached from a positive perspective and might function as an affective support system.

Direct associations of tweet sentiment with tweet engagement (i.e., number of retweets and likes) are examined to explore this initial finding in more depth (RQ2.b, Table 11). Tweet engagement can be interpreted as a measure that describes the ability to distribute information within teachers' communities and beyond. Thus, tweets with high tweet engagement are more likely to shape interaction patterns and knowledge gains.

[TABLE 10 ABOUT HERE]

Tweet-level variables account for 77% and teacher-level variables account for 23% of the variance in tweet engagement (ICC = 0.23). This exceeds common ranges of ICC values in social science research (0.05-0.20; Peugh, 2010) and confirms the appropriateness of multi-level modeling. Positive tweet sentiment is significantly associated with a 0.44 increase in tweet engagement, $b = 0.44$, $z = 2.83$, $p < 0.01$, compared to tweets with not exclusively positive or negative sentiments. In contrast, negative tweet sentiment is not significantly associated with changes in tweet engagement, $b = -0.20$, $z = -1.62$, p = n.s. This supports perspectives that Twitter can provide a positive and supportive frame for teacher learning.

[TABLE 11 ABOUT HERE]

Temporal Engagement Patterns

An analysis of temporal engagement patterns in the Twitter communities indicates that both lifespan and frequency of participation highly varies across teachers. Some teachers choose to participate for relative short durations whereas other teachers substantially exceed timespans of more traditional PD activities (Figure 2).

[FIGURE 2 ABOUT HERE]

Teachers' community lifespan serves as a strong predictor for all analyzed forms of leadership roles (teachers' influence, centrality, and broker ability) in the communities (Table 9).

However, teachers' community lifespan is uncorrelated with their frequency of participation for teachers participating in the communities for longer than a week, $r = -0.08$, $p > 0.05$ (Figure 2). In particular, teachers with high Twitter community lifespans meet duration thresholds that (Darling-Hammond et al., 2009; Desimone, 2009) characterize as preconditions for effective PD, thus, fulfilling Desimone's (2009) high-quality PD characteristics of 'duration.'

[TABLE 12 ABOUT HERE]

Significant direct associations are not found between teachers' community lifespan and most tweet content, quantitative tweet characteristics, and community participation variables (RQ3b, Table 12). Nevertheless, factors that significantly contribute to teachers' community lifespan, and factors that approach significance (likely due to the small sample size), provide insights in teachers' temporal participation patterns. For instance, the relationships of the percentage of tweets sharing AP Biology content knowledge, as well as the percentage of positive tweets with teachers' community lifespan approach significance. A ten percent increase of tweets sharing AP Biology content knowledge is associated with an approximate eleven day community lifespan increase, $b = 10.59$, $t = 1.82$, $p < 0.10$. A ten percent increase in tweets with positive sentiment is associated with an approximate eight day community lifespan increase, $b = 7.87$, $t = 1.93$, $p < 0.10$. The implication that positive-oriented content creation lead to a longer participation duration promotes perspectives that view Twitter as a supportive environment for teachers. Regarding quantitative tweet characteristics, both average numbers of mentions and hashtags significantly contribute to teachers' community lifespan. Mentioning on average one additional user per tweet is significantly associated with an approximate 36 day decrease of teachers' community lifespan, $b = -35.67$, $t = -2.22$, $p < 0.05$, and including on average one additional hashtag per tweet is associated with an approximate 57 day increase of teachers' community lifespan, $b = 57.14$, $t = 2.07$, $p < 0.05$. These results describe that conversational practices on both the micro-level (mentioning) and the macro-level (hashtags) are related to temporal participation pattern. This indicates that Twitter allows for different interaction patterns to fit teachers' individual contexts, professional needs, and professional learning preferences, which contrasts 'one-size-fits-all' approaches.

Discussion

Scholarly Significance

This observational mixed-methods study contributes to the in-service secondary science teacher education research base in multiple ways. It extends the mostly descriptive and qualitative-oriented current research base on microblogging for teacher professional learning by analyzing teachers' engagement in microblogging using educational data mining, social network analysis, and other more quantitative-oriented approaches. Therefore, its insights how microblogging might complement more traditional professional learning activities is novel to the field. Additionally, its theoretical contribution to provide another example of a PD environment that adheres to selected high-quality PD design characteristics can be of use to school leaders and PD designers. Furthermore, this is first empirical study that analyzes teachers' engagement in microblogging during a nationwide curriculum reform in the sciences. This unique context allows findings to generalize to other large-scale curriculum reforms such as the NGSS or the Common Core State Standards Initiative.

Future work

Future studies could gather more in-depth information on how teachers perceive Twitter to complement their professional learning. Such studies might interview selected teachers of the analyzed communities based on teachers' SNA groupings. Other studies could target lurkers in the Twitter communities to better understand their professional learning benefits. Another set of studies could shift the current emphasis of conversational practices on the macro-level (hashtag-based communities), as described by Bruns and Moe (2013), to meso-level analysis of selected teachers' ego-networks to explore how learning occurs in teachers' tweets by analyzing tweet sequences and follower-followee structures. An interdisciplinary application in the intersection of cognitive science and natural language processing would be to automate the detection (and basic analysis) of such learning processes to analyze teacher learning in social network communities at scale.

Implications and Conclusion

This study offers insights on teachers' use of Twitter as a novel form for professional learning and how it might complement more traditional PD activities. The three most important conclusions from this study are the following:

First, teacher learning on Twitter does not follow hierarchically leadership and participation structures. Teachers who emphasize sharing of resources and content knowledge, or lead organizations of the PD activities do not hold more prominent roles. This contrasts more traditional PD and supports perspectives viewing Twitter as a more open, democratic, and collaborative environment that could contribute to the democratization of teacher education (e.g., Lord & Lomicka, 2014; Wesely, 2013; Zeichner, Payne, & Brayko, 2015).

Second, professional learning on Twitter is positively framed. Teachers more often encounter positive than negative tweets. Also, positive tweets have a wider reach as they receive more likes and retweets. Furthermore, teachers who share more positive tweets tend to participate in the communities for longer timeframes. Therefore, Twitter can provide a positive and supportive environment with potential to provide informal mentoring opportunities and to help reduce teacher isolation that, in turn, might reduce turnover rates and improve mental health and performance (e.g., Desimone et al., 2014; Dodor et al., 2010).

Third, teacher learning on Twitter is adaptive to teachers' needs and preferences with respect to teachers' temporal participation patterns. In contrast to traditional PD activities with fixed durations, Twitter allows teachers to engage in flexible temporal participation patterns. While some teachers have all their interactions with Twitter communities 'just-in-time' within one day or week, other teachers continuously contribute to the communities over extended periods of time exceeding duration thresholds for effective PD participation (e.g., Darling-Hammond et al., 2009; Desimone, 2009). These flexible participation patterns support perspectives that view Twitter as affording personalization of professional learning with the potential to engage in collective participation' in virtual communities of practice opposed to "one-size-fits-all" approaches (e.g., Carpenter & Krutka, 2015; Ebner et al., 2010; Wesely, 2013).

In conclusion, this study aims to analyze a new form of PD that might contribute to a transformation of current educational paradigms. The data suggests that the use of microblogging as PD can both adhere to standards of high-quality PD activities and complement hierarchically-structured, more traditional forms of professional learning. Thus, educational policy makers and school leaders should feel empowered to encourage teachers to engage in microblogging for professional learning in addition to other more traditional professional learning outlets.

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Tables and Figures

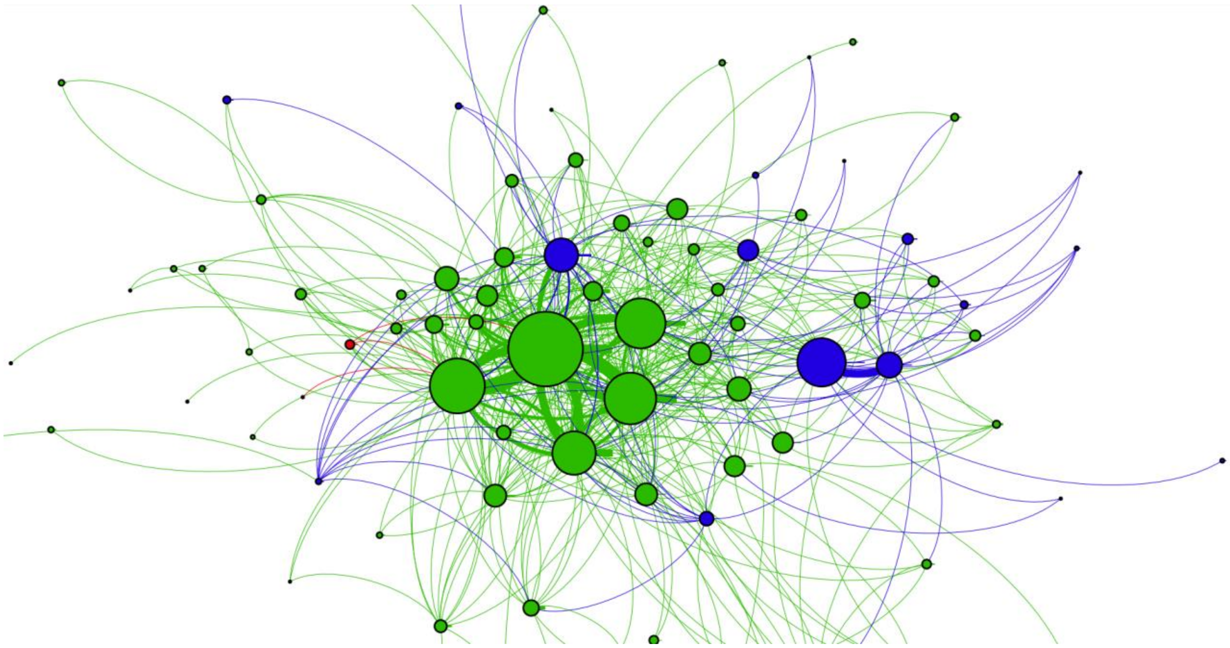

Figure 1. Mentions network visualization: teachers (green), school administrators (red), representatives from professional organizations (blue).

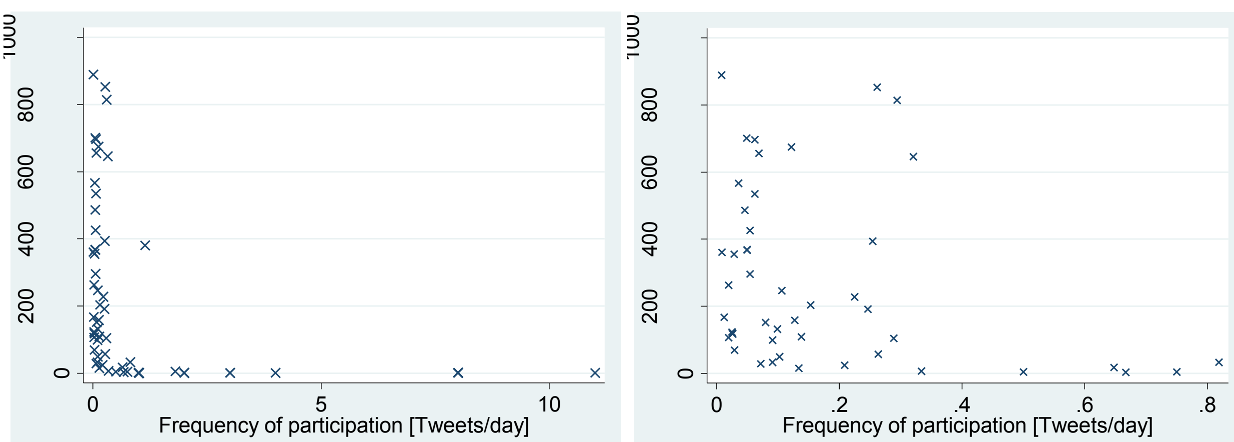

Figure 2. Scatter plots of teachers' lifespan and frequency of community participation; full sample (left), frequency < 1 (right).

Table 1. Descriptive information of tweet content measures.

	Cohen's κ	Percentage agreement [%]	N (%) [tweet-level]	M (SD) [teacher-level]
AP Biology content	0.81	96.4	131 (6.42)	1.41 (3.52)
Share resources	0.78	88.9	297 (14.56)	3.19 (9.41)
Seek information	0.71	90.2	250 (12.25)	2.69 (7.53)
Organize PD	0.76	92.4	168 (8.24)	1.81 (6.14)
Curriculum elements	0.70	94.2	125 (6.13)	1.34 (3.35)
Labs	0.76	91.6	175 (8.58)	1.88 (5.00)
Assessments	0.65	87.1	187 (9.17)	2.01 (5.85)

Note. n_{tweet}=2,040, n_{teacher}=93.

Table 2. Synthetic examples for each tweet content category.

AP Biology content	Human DNA is stored in 23 chromosomes pairs contained within cell nuclei. And it's pretty: http://website.com/dna-pics #scichat #apbiochat
Share resources	#apbioleaderacad I uploaded my lessons plans to @USER's #dropbox folder: http://dropbox.com/sf/fhj184us3 - feel free to use and modify them!
Seek information	@USER so how do you help your students reflect on the labs? more guidance? less guidance? #apbiochat
Organize PD	Our #apbiochat starts today at 8 pm EST -- join us and talk about how you prepare students for the FRQs [A/N: Free- and open-response questions]
Curriculum elements	@USER College Board's LO [A/N: Learning Objectives] are crucial to my teaching. In the end, that's what is assessed on the AP exam. #apbioleaderacad
Labs	@USER I often use #Vernier labs for teaching inquiry. Their support is also very helpful. #apbiochat
Assessments	I wish I could share some of the new MC [A/N: Multiple-choice questions] and FRQs with my students to better prepare them for the #apbio exam #apbiochat

Table 3. Descriptive information of tweet sentiment measures.

	N (%) [tweet-level]	M (SD) [teacher-level]
Positive sentiment	585 (28.68)	6.29 (15.28)
Negative sentiment	133 (6.52)	1.43 (4.16)
Not exclusively positive or negative sentiment	1,322 (64.80)	14.22 (42.61)

Note. Cohen's κ = 0.65; Percentage agreement: 69.3%; n_{tweet}=2,040, n_{teacher}=93.

Table 4. Synthetic examples for each tweet sentiment category.

Positive sentiment	#apbiochat has been such a tremendously helpful resource for my teaching! So glad that @USER convinced me to join. Thank you!
Negative sentiment	@USER I spent lots of time and $$$ and got almost nothing out of it. Expected more from @CONFERENCE_PROVIDER #apbiochat
Not exclusively positive or negative sentiment	#apbiochat starts in 2 hours. We will discuss how to do #inquiry in the classroom.

Table 5. Descriptive information of quantitative tweet measures.

	M (SD) [tweet-level]	M (SD) [teacher-level]
Tweet characteristics		
Retweets	0.21 (0.84)	4.56 (11.74)
Likes	0.83 (1.60)	18.27 (48.89)
Mentions	1.18 (1.25)	25.96 (88.97)
Hashtags	1.33 (0.71)	29.18 (74.22)
Links	0.10 (0.31)	2.30 (6.64)
Community participation		
Lifespan (days)	-	143.81 (231.48)
Tweets/day	-	1.11 (1.95)

Note. n_{tweet}=2,040, $n_{teacher}$=93.

Table 6. Descriptive information of inferential SNA measures.

Variable name	N (%)	M (SD)
Teachers' influence groups		0.151 (0.202)
None	30 (32.26)	
Low	29 (31.18)	
Medium	24 (25.81)	
High	10 (10.75)	
Teachers' centrality groups		0.393 (0.304)
None	34 (36.51)	
Low	21 (22.58)	
Medium	20 (21.51)	
High	18 (19.35)	
Teachers' broker ability groups		267.60 (875.65)
None	16 (49.46)	
Low	13 (13.98)	
Medium	21 (22.58)	
High	13 (13.98)	

Table 7. Variable list, RQ1.

RQ1.a	RQ1.b	RQ1.c
	Dependent variable	
Teachers' influence	Teachers' centrality	Teachers' broker ability
	Independent variables	
AP Biology content†,‡	Seek information†,‡	Organize PD†,‡
Share resources†,‡	Share resources†,‡	
	Covariates	
Seek information†,‡	AP Biology content†,‡	AP Biology content†,‡
Organize PD†,‡	Organize PD†,‡	Share resources†,‡
Curriculum elements†,‡	Curriculum elements†,‡	Seek information†,‡
Labs†,‡	Labs†,‡	Curriculum elements†,‡
Assessments†,‡	Assessments†,‡	Labs†,‡
Lifespan†	Lifespan†	Assessments†,‡
Frequency†	Frequency†	Lifespan†
		Frequency†

Note. †: Grand-mean centered, ‡: Teacher-level percentage.

Table 8. Variable list, RQ2 and RQ3.

RQ2	RQ3
Dependent variable	*Dependent variable*
Tweet engagement	Lifespan†
Independent variable	*Independent variables*
Tweet sentiment ^{D}	AP Biology content†,‡
Tweet-level covariates (level 1)	Share resources†,‡
AP Biology content^{01}	Organize PD†,‡
Share resources^{01}	Curriculum elements†,‡
Seek information^{01}	Labs†,‡
Organize PD^{01}	Assessments†,‡
Curriculum elements^{01}	Positive sentiment†,‡
Labs^{01}	Negative sentiment†,‡
Assessments^{01}	Average: Retweets†
Mentions^{01}	Average: Likes†
Hashtags^{01}	Average: Mentions†
Links^{01}	Average: Hashtags†
Teacher-level covariates (level 2)	Average: Links†
Lifespan†	Frequency†
Frequency†	Teachers' influence ^{D}
Teachers' influence ^{D}	Teachers' centrality ^{D}
Teachers' centrality ^{D}	Teachers' broker ability ^{D}
Teachers' broker ability ^{D}	

Note. †: Grand-mean centered, ‡: Teacher-level percentage, ^{D}: Series of dummy variables, ^{01}: Dichotomous variable.

Table 9. Ordinal regression analyses with robust standard errors predicting teacher influence (model 1), teacher centrality (model 2), and teacher broker ability (model 3) classifications.

	Model 1			Model 2			Model 3		
	b	*OR*	*z*	*b*	*OR*	*z*	*b*	*OR*	*z*
Independent tweet content variables (10% increments)									
AP Biology content (%)	-0.277*	0.973*	-2.24	-0.350~	0.966~	-1.75	-0.154	0.985	-1.55
Share resources (%)	-0.102	0.990	-1.42	-0.239**	0.976**	-2.75	-0.170*	0.983*	-2.15
Seek information (%)	0.068	1.007	0.67	-0.011	0.999	-0.08	-0.048	0.995	-0.42
Organize PD (%)	-0.050	0.995	-0.75	0.025	1.002	0.38	-0.166*	0.984*	-2.38
Tweet content covariates (10% increments)									
Curriculum elements (%)	0.063	1.006	0.27	-0.180	0.982	-0.88	0.140	1.014	0.76
Labs (%)	-0.136	0.986	-0.87	0.057	1.006	0.27	-0.202	0.980	-1.26
Assessments (%)	0.366	1.037	0.81	0.593***	1.061***	4.32	0.198	1.020	1.50
Community participation covariates									
Lifespan (in 10 days)	0.061***	1.006***	5.52	0.094***	1.009***	4.67	0.115***	1.012***	4.16
Tweets/day	0.215**	1.240**	3.17	0.279***	1.321***	3.89	0.094	1.099	1.29
Intercepts									
Cutoff 1	-1.177			-1.055			-0.502		
Cutoff 2	0.858			0.700			0.628		
Cutoff 3	3.182			2.715			3.896		
McFadden's R^2	0.240			0.337			0.379		

Note. ~p<0.10, *p<0.05, **p<0.01, ***p<0.001; *n*=93.

Table 10. Contingency table, tweet sentiment on content.

	Negative sentiment [%]	Positive sentiment [%]	Not exclusively positive or negative [%]
AP Biology content	3.82	22.90	73.28
Share resources	1.35	28.62	70.03
Seek information	5.60	10.00	84.40
Organize PD	1.19	24.40	74.40
Curriculum elements	6.40	13.60	80.00
Labs	8.57	24.00	67.43
Assessments	11.76	14.44	73.80

Note. n_{tweet}=2,040.

Table 11. Two-level fixed-effect HLMs with robust standard errors.

	Model 1		Model 2		Model 3	
Tweet engagement	*b*	*SE*	*b*	*SE*	*b*	*SE*
Tweet-level (level 1)						
Tweet sentiment (vs. not exclusively positive or negative)						
Positive					0.444**	0.157
Negative					-0.196	0.121
Tweet content						
AP Biology content			0.047	0.170	0.091	0.176
Share resources			0.122	0.262	0.077	0.253
Seek information			-0.643**	0.240	-0.540*	0.225
Organize PD			-0.040	0.186	-0.020	0.188
Curriculum elements			-0.148	0.207	-0.102	0.208
Labs			-0.015	0.139	0.037	0.131
Assessments			0.142	0.220	0.204	0.224
Tweet characteristics						
Mentions			-0.029	0.055	-0.015	0.055
Hashtags			0.531***	0.069	0.531***	0.068
Links			1.019**	0.348	1.092**	0.355
Teacher-level (level 2)						
Intercept	0.646	0.449	0.308	0.518	0.193	0.515
Community participation						
Lifespan (in 10 days)	0.009	0.009	0.002	0.010	0.001	0.010
Tweets/day	-0.041	0.054	-0.037	0.056	-0.031	0.055
Teachers' influence (vs. high)						
None	0.147	0.832	-0.228	0.891	-0.317	0.887
Low	0.925	0.590	0.596	0.624	0.540	0.604
Medium	0.470*	0.229	0.308	0.238	0.261	0.232
Teachers' centrality (vs. high)						
None	1.108~	0.667	0.259	0.765	0.351	0.753
Low	0.910	0.696	0.614	0.695	0.680	0.681
Medium	0.081	0.425	0.051	0.434	0.125	0.427
Teachers' broker ability (vs. high)						
None	-0.738	0.808	-0.590	0.892	-0.629	0.885
Low	-0.421	0.726	-0.473	0.760	-0.582	0.740
Medium	-0.499	0.567	-0.649	0.590	-0.679	0.576
χ^2	21.43		173.30		23.64	
df	11		10		2	
p	0.029		<0.001		<0.001	

Note. ~p<0.10, *p<0.05, **p<0.01, ***p<0.001; Likelihood-ratio tests use models without robust standard errors; n_{level1}=2,040, n_{lvl2}=93.

Table 12. OLS regression analysis with robust standard errors.

Lifespan (days)	*b*	*SE*	*t*
Intercept	461.786***	67.811	6.81
Tweet content (10% increments)			
AP Biology content (%)	10.587~	5.806	1.82
Share resources (%)	5.330	5.491	0.97
Seek information (%)	5.052	10.379	0.49
Organize PD (%)	0.806	5.274	0.15
Curriculum elements (%)	2.465	9.198	0.27
Labs (%)	1.108	8.573	0.13
Assessments (%)	-12.932	7.793	-1.66
Tweet sentiment (vs. not exclusively positive or negative; 10% increments)			
Positive sentiment (%)	7.869~	4.074	1.93
Negative sentiment (%)	3.220	13.679	0.24
Tweet characteristics			
Average: Retweets	-37.933	35.849	-1.06
Average: Likes	24.053	15.750	1.53
Average: Mentions	-35.671*	16.058	-2.22
Average: Hashtags	57.144*	27.630	2.07
Average: Links	-30.263	51.461	-0.59
Community participation			
Teachers' influence (vs. high)			
None	15.672	75.987	0.21
Low	10.725	70.051	0.15
Medium	-46.355	59.330	-0.78
Teachers' centrality (vs. high)			
None	-212.256*	79.742	-2.66
Low	-92.462	72.998	-1.27
Medium	-83.195	66.972	-1.24
Teachers' broker ability (vs. high)			
None	-439.748***	84.978	-5.17
Low	-428.342***	75.000	-5.71
Medium	-285.503***	64.540	-4.42
R^2	0.736		

Note. ~p<0.10, *p<0.05, **p<0.01, ***p<0.001; *n*=93.