Identifying multiple learning spaces within a single teacher-focused Twitter hashtag

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Abstract

The existing work on teacher-focused Twitter hashtags typically frames each hashtag as a single, unified phenomenon, thereby collapsing or erasing differences between them (and any resulting implications for learning). In this study, we conceived of teacher-focused hashtags as affinity spaces potentially containing subspaces distinguished by synchronous chats and other, asynchronous communication. We used computational methods to explore how participation differed in terms of content, interactions, and portals between these contexts within the #michED hashtag used by Michigan teachers. During the 2015-2016 academic year, #michED saw more non-chat activity than chat activity, and most participants only engaged in one mode of activity or the other. Participation during chats was associated with more *replying* as well as more socially-, affectively-, and cognitively-related content, suggesting a focus on social interaction. In contrast, non-chat participation was associated with more *retweeting*, *mentioning*, hyperlinks, and hashtags, suggesting a focus on content dissemination. These results suggest that different affinity spaces—and different literacy practices—may exist within the same hashtag to support different objectives. Teachers, teacher educators, and researchers should therefore be careful to make these distinctions when considering Twitter as a learning technology for teachers.

Keywords: social media, teacher professional learning, Twitter

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1. Introduction

The advent of social media technologies has allowed new opportunities for teachers to engage in self-directed professional learning and networking (Prestridge, 2019; Trust, Krutka, & Carpenter, 2016). In particular, American teachers have been using the social networking site Twitter to find support in their professional endeavors. Hashtags—keywords or phrases preceded by a # symbol—feature prominently in how topical discussions occur on Twitter. Hashtags can be used as an index, connecting a tweet with others on the same subject and thereby allowing users to find all tweets connected with that subject (e.g., #education, #teachers). Hashtags can also organize and structure more specific conversations, including those focused on education either in broad terms (e.g., #Edchat; Authors, 2019c; Britt & Paulus, 2016; Gao & Li, 2017; Xing & Gao, 2018) or in specific geographic contexts, including U.S. states (e.g., #oklaed for Oklahoma; Asino, Haselwood, & Baker, 2016; Krutka, Asino, & Haselwood, 2018; Authors, 2016b).

Teacher-focused hashtags have been conceived of as *affinity spaces* (Authors, 2016b; Authors, 2017)—open and loosely-bounded sites where informal learning takes place. Although this framing has been useful for establishing the potential value of these hashtags for teacher learning, its use has typically oversimplified their nature and composition. For example, many hashtags are characterized by the presence of both asynchronous broadcasting of information and synchronous *Twitter chats*, in which participants log on at an agreed time to participate in a real-time conversation with immediate back-and-forth interaction (Carpenter & Krutka, 2015; Gao & Li, 2017; Xing & Gao, 2018). Treating the hashtag as a single affinity space implies that chat (i.e., synchronous) and non-chat (i.e., asynchronous) communication are part of a unified phenomenon when they are mediated by the same hashtag; however, more recent studies have suggested differences between chat and non-chat use of hashtags (e.g., Carpenter, Tani, Morrison, & Keane, 2018). These differences include emphasis on different Twitter-specific *literacy practices*, that is, uses of Twitter's features to produce meaning in particular ways (Greenhow & Gleason, 2012). Magnifico, Lammers, and Fields (2018) argued that there is a close relationship between literacies and affinity spaces. Thus, different literacies associated with chat and non-chat contexts could suggest the existence of distinct subspaces within a Twitter hashtag, each of which has different requirements and implications for teacher learning.

The purpose of this study is, therefore, to explore in detail how Twitter-mediated literacy practices differ between chat and non-chat contexts within a single hashtag. We use Gee's (2005, 2017) affinity space framework to examine literacy practices related to *content*, *interactions*, and *portals* in #michED, a teacher-focused Twitter hashtag associated with the U.S. state of Michigan. In doing so, we seek to better understand how literacy practices vary across different contexts within a Twitter hashtag and what these variations mean for teachers' professional learning. For example, understanding how literacy practices differ between chats and other times can reinforce Twitter's status as a *foundational technology* for teachers (see Authors, 2016a) and also demonstrates how its use is driven by social—not just technological—factors (Veletsianos, 2017). This understanding can also help identify distinct learning opportunities associated with the same hashtag, thereby helping teachers better understand what opportunities are available to them. These insights will contribute to efforts to show preservice and in-service teachers what effective practice looks like when using Twitter professionally.

2. Background

In this section, we describe the role of affinity spaces and literacy practices in examining teacher-focused Twitter hashtags as socially-mediated learning phenomena. We begin by describing teachers' use of Twitter and efforts to conceptualize these practices. We then introduce the affinity space framework; describe its increased emphasis on learning through multiple, interconnected spaces; and describe concepts—including literacy practices—that allow for a deeper investigation of Twitter hashtags as affinity spaces.

2.1 Framing Teachers' Professional Use of Twitter

A growing body of research has shown that teachers use the social networking site Twitter as a resource for a variety of professional learning purposes (Authors, 2019c; Carpenter & Krutka, 2014; 2015; Forte, Humphreys, & Park, 2012; Visser, Evering, & Barrett, 2014). Twitter often serves as one element of teachers' *professional* (or *personal*) *learning networks* (Couros, 2010; Luo, Sickel, & Cheng, 2017; Prestridge & Trust, 2019; Trust et al., 2016)—ecologies of learning resources that may span formal and informal (as well as physical and virtual) spaces. As research focused on this practice continues, scholars must be able to articulate whether and how teachers' use of this relatively-new technology corresponds with—or challenges—existing frameworks of learning (Salomon & Almog, 1998).

Because the *community of practice* framework (Lave & Wenger, 1991; Wenger, 1998) has long been used to frame teacher professional development (e.g., Darling-Hammond & McLaughlin, 1995), it is no surprise that several studies have described Twitter hashtags in these terms (e.g., Britt & Paulus, 2016; Gao & Li, 2017; see also Wesely, 2013). However, learning groups on Twitter do not always correspond with Wenger's core assumptions about the community of practice, such as continuity (Machin-Mastromatteo, 2012) or shared identity (Authors, 2016b; Authors, 2017; Veletsianos, 2017). Similarly, the *community of inquiry* framework—which has also been used to understand pre-service teachers' use of Twitter (Solmaz, 2016)—assumes *social presence*, *cognitive presence*, and *teaching presence* (Garrison, Anderson, & Archer, 2010), which may not exist in all teacher-focused Twitter hashtags.

2.2 Twitter Hashtags as Affinity Spaces

Researchers concerned about the compatibility of Twitter hashtags with "community" frameworks have sometimes turned to the *affinity space* framework instead. Indeed, in proposing this framework, Gee (2005) noted that it would provide several practical benefits by focusing on the site—whether physical or virtual—where learning happens (rather than the people within that site). Since its initial development, the affinity space framework has been applied to learning in a number of informal settings, including video games (e.g., Curwood, Magnifico, & Lammers, 2013; Duncan, 2013; Edwards, 2018; Pellicone & Ahn, 2014, 2015) and young adult literature, blogging, and fanfiction (Curwood, 2013; Curwood et al., 2013; Lammers, Curwood, & Magnifico, 2012; Lewis, 2014). Sharma and Land (2019) applied the affinity space framework to a more serious context—an online space dedicated to the management of diabetes—demonstrating that this framework is useful for a range of different kinds of learning.

Indeed, scholars have also found this framework to be useful for describing sites for teachers' informal professional learning (Tohill, 2016), including those existing on Twitter (Carpenter & Krutka, 2014, 2015; Authors, 2016b; Authors, 2017). Using an affinity space-based framework allows education researchers to account for—and even draw attention to—unexpected phenomena. For example, Veletsianos (2017) found that "journalists… lawyers… [and] medical professionals" (p. 288) all participated in the #PhDChat hashtag, a more diverse group of participants than might be expected in a space for junior academics. The low barrier for entry to an affinity space also helps explain the presence of spam content (Authors, 2019b) in teacher-focused hashtags. In summary, the affinity space framework allows researchers to acknowledge that teacher-focused Twitter hashtags are sites for social learning without the risk of misrepresenting or overstating the social relationships and structures that exist within those hashtags.

The affinity space offers a framework that organizes and legitimizes teachers' use of Twitter—but that s hould be adopted as a whole rather than oversimplified. For example, researchers have increasingly emphasized that learning can take place across a network of linked spaces (e.g., Edwards, 2018; Lammers et al., 2012; Pellicone & Ahn, 2015), and Gee (2017) has recently explicitly described affinity spaces as containing multiple subspaces. Although teachers' professional learning is recognized as spanning multiple physical and virtual sites (e.g., Prestridge & Trust, 2019; Trust et al., 2016), less attention has been paid to whether a site typically treated as unified (e.g., a Twitter hashtag) may be better understood as an ecology of distinct contexts for learning.

2.3 Distinguishing Affinity Spaces

To determine whether multiple affinity spaces might exist within a Twitter hashtag, researchers must be able to articulate what makes up such a space and how spaces might differ from each other. Indeed, Gee's (2005) initial goal in describing the affinity space was to "offer a new analytic lens" (p. 231) and to influence researchers' questions. In this section, we draw from existing research to argue that an affinity space's *components* can draw researchers' attention to particular kinds of activities within a site for learning and that all of these activities can be understood as *literacy practices*. In doing so, however, we also acknowledge and endorse that hashtag-based affinity spaces can be understood and distinguished through means and measures other than those proposed by Gee. For example, the amount of activity or participants within an online space has been held to be an important measure of its vitality since the beginning of Internet studies (Butler, 2001; Jones, 1997; Preece, 2001)—and has been frequently adopted to describe educational hashtags (Britt & Paulus, 2016; Carpenter et al., 2018; Gao & Li, 2017; Veletsianos, 2017).

2.3.1 Components of an Affinity Space

In Gee's (2005) introduction of the affinity space framework, he used terms such as *content*, *interactions*, and *portals* to describe what makes up a space. In this section, we describe each of these components and their possible application to research on teachers' use of Twitter. It is important to note that the evolution of this framework has generally resulted in a diminished focus on this vocabulary (Duncan & Hayes, 2012). Nonetheless, elements of these ideas have continued to be addressed in affinity space research, and these terms have previously proven useful for organizing Twitter-focused research (see Authors, 2016b).

For Gee (2005), *content* refers to the *affinity* that gives a *space* a reason to exist. For example, participation in a video game-focused affinity space will focus on communication about that video game (e.g., Duncan, 2013; Pellicone & Ahn, 2015), and a space dedicated to a particular book (or series) will use the specialized vocabulary associated with the work(s) in question (Curwood, 2013). Thus, if the content of tweets associated with two different contexts within a teacher-focused Twitter hashtag is markedly different, one may conclude that those contexts are different spaces defined by different affinities.

In contrast, *interaction* refers not to what constitutes appropriate *focus* within an affinity space but rather to appropriate *behavior* among its participants. For example, successful participation within an affinity space likely depends on understanding its "formal rules and… informal expectations" (Curwood, 2013, p. 421). Twitter affords a number of ways to interact, and different forms of interaction may be prized by different groups of people or in different contexts, thereby providing another way to distinguish between possible spaces.

Finally, *portals* refer to means of entering a particular affinity space (Gee, 2005). Given the recent focus on networks of spaces and subspaces (Gee, 2017), we also describe as portals links from one (sub)space to another. Thus, the number of portals within an affinity space helps to indicate its structure and thus helps distinguish it from other, differently-structured spaces. Indeed, Lammers and colleagues' (2012) discussion of the evolution of affinity spaces draws on differences in numbers of portals to contrast earlier spaces with newer ones. The concept of the portal has intuitive connections to Twitter: For example, in Gleason's (2013) study of one Twitter hashtag, he conceptualized hyperlinks as portals leading from Twitter to other learning resources on the Internet.

2.3.2 Literacy Practices within Affinity Spaces

Whether they are related to content, interaction, or portals, participants' actions within a hashtag-mediated Twitter space can collectively be described as *literacy practices*. Although the term *literacy* is popularly understood in reference to reading and writing, it can be understood more broadly as referring to "socially recognized ways of generating, communicating and negotiating meaningful content" (Lankshear & Knobel, 2006, p. 64). The work of literacies researchers is therefore to describe these emerging ways of expressing meaning and to comment on their implications for learning (Knobel & Lankshear, 2014). For example, Greenhow and Gleason (2012) have explained that "communication on Twitter requires… understanding norms for participation" (p. 471; see Figure 1).

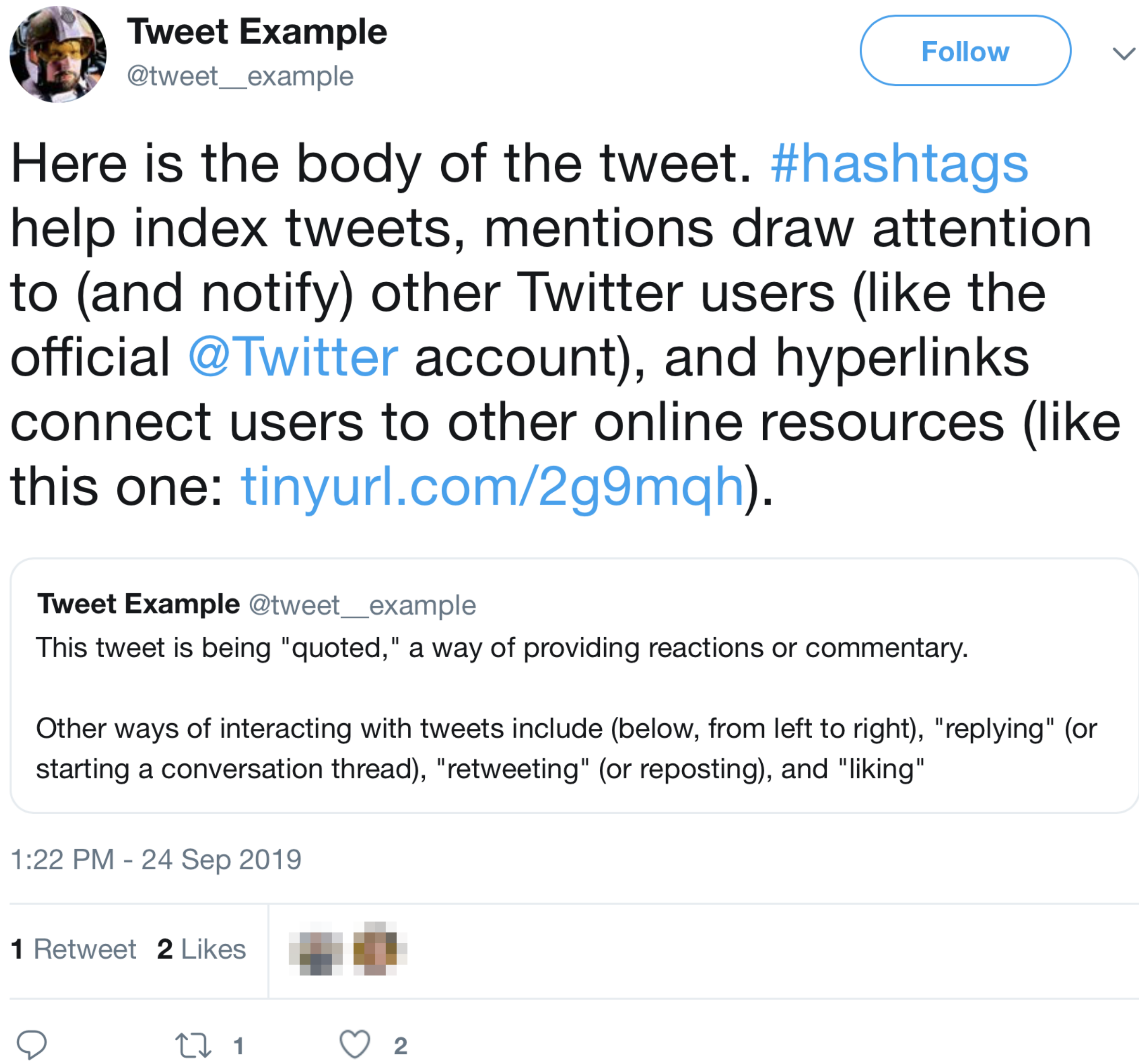

Figure 1. Screenshot of a tweet demonstrating common Twitter practices.

Given Gee's contributions to both literacies research (e.g., Gee, 1989) and the affinity space framework (e.g., Gee, 2005, 2017), it is unsurprising that these two approaches to studying social learning have often been used in tandem (e.g., Curwood, 2013; Curwood et al., 2013; Lammers et al., 2012; Lewis, 2014; Magnifico et al., 2018; Machin-Mastromatteo, 2012). In short, the affinity space framework can be used to describe a site in which literacy practices related to content, interaction, and portals happen—conversely, those literacy practices define appropriate behavior within a space. Thus, different teacher-focused Twitter spaces are likely to be associated with different literacies, to which teachers must be attentive if they are to effectively participate in, navigate between, and learn from those spaces.

2.4 Summary

Teachers' continued use of Twitter for professional purposes merits continued research to understand both the immediate phenomenon and its implications for how we frame and conceive of learning. Gee's (2005, 2017) affinity space framework presents important advantages for documenting and understanding hashtag-mediated learning as compared to frameworks such as the community of practice. However, research on teachers' use of Twitter has not fully accounted for developments in this framework, including the possibility that multiple, distinct spaces may exist within the umbrella of a single Twitter hashtag. Gee's original descriptions of spaces' content, interactions, and portals provide a starting point for researchers trying to identify distinctions between spaces, though other measures (such as volume of participation) can also prove helpful. Participants' behavior related to each of these components can be described as literacy practices, with which teachers must be familiar in order to effectively participate in Twitter-based learning spaces.

3. Purpose and Research Questions

The purpose of this study is to determine whether teacher-focused Twitter hashtags might contain distinct learning spaces by exploring whether and how literacy practices differ between chat and non-chat contexts in a hashtag for teachers in the U.S. state of Michigan (#michED). We have chosen #michED because of its relatively high levels of activity as compared to other geographically-associated hashtags (Authors, 2016b) and because of our familiarity with the #michED community, which facilitated our understanding of the scheduling and structure of its chats. To carry out this purpose, we ask the following research questions:

- RQ1: How does participation in #michED differ between chat and non-chat contexts in terms of *volume*?
- RQ2: How does participation in #michED differ between chat and non-chat contexts in terms of *content*?
- RQ3: How does participation in #michED differ between chat and non-chat contexts in terms of *interaction*?
- RQ4: How does participation in #michED differ between chat and non-chat contexts in terms of *portals*?

4. Method

The descriptive research design of this study is a form of "unobtrusive Internet-mediated research" (Hewson, 2017, p. 67), an observational approach to studying online behaviors and interactions through examination of digital traces (Hewson, Vogel, & Laurent, 2016) of "naturalistic conversational exchanges" (Hewson, 2017, p. 68). This is a relatively new form of Internet-focused research design that has roots in Lincoln and Guba's (1985) naturalistic inquiry but applies modern *digital methods* (Snee, Hine, Morey, Roberts, & Watson, 2016) to collect and analyze data. For this study, these digital methods include quantitative multi-level modeling (e.g., Raudenbush & Bryk, 2002; West, Welch, & Galecki, 2014) as well as natural language processing techniques for computationally analyzing textual data.

4.1 Data Sources

We collected tweets containing the #michED hashtag between September 1, 2015 and August 31, 2016 using Twitter Archiving Google Sheets (Hawksey, 2016). As a teacher-focused hashtag, #michED naturally has a close connection with the American academic year; analyzing data associated with the entirety of an academic year therefore allowed for a broad, inclusive examination of this phenomenon. We then used the Twitter application programming interface (API) via the *rtweet* R package (Kearney, 2018) to collect additional information and remove tweets that had since been deleted or that were associated with private or suspended accounts so as to respect user privacy (see Fiesler & Proferes, 2018; Markham & Buchanan, 2012). Our final dataset included 84,004 unique #michED-tagged tweets from 9,462 distinct contributors along with associated metadata, such as account information, timestamps, and evidence of interaction.

4.2 Measures

Once we built our dataset, we manually identified tweets that had been composed during #michED chats, which happened once a week (at most). One of the authors reviewed a spreadsheet containing all the tweets collected for that year, classifying as "chat-related" the first tweet associated with the chat (typically a tweet welcoming participants to the chat and inviting them to introduce themselves) and all subsequent tweets up until five minutes after the scheduled end of the chat. By extension, the account associated with each tweet was also classified as chat-related. All tweets not sent during this interval (and all associated accounts) were classified as "chat-unrelated." Although individual tweets were classified as either chat-related or chat-unrelated, it was possible for accounts to be classified as both. Using data retrieved from the Twitter API, we automatically classified each tweet as either an "original tweet" or a "retweet" and determined whether each account was associated with original tweets, retweets, or both.

Regardless of its classification, we calculated twelve measures for each tweet, as described in Table 1. We developed the content-related measures using the dictionary-based text analysis software Linguistic Inquiry and Word Count (LIWC; Pennebaker Conglomerates, 2015) to carry out natural language processing (Hirschberg & Manning, 2015). LIWC is a text analysis tool that employs a "word count approach, calculating word frequencies and converting them into percentages for 80 language categories, such as pronouns, and psychological and personal concern categories" (Lin, Lin, Wen, & Chu, 2016). Simple natural language processing methods can "often achieve notable results when trained on large quantities of data" (Hirschberg & Manning, 2015; p. 261), as was the case in the development of LIWC. Indeed, LIWC has been successfully used in previous educational technology research to make distinctions between real-time and asynchronous communication in online settings (Oztok, Zingaro, Brett, & Hewitt, 2013). LIWC is capable of measuring a wide range of pre-defined constructs, which have differing levels of granularity. We selected five constructs (*social processes*, *cognitive processes*, *positive affect*, *negative affect*, and *work-related concerns*) based on related use of LIWC in similar research (Oztok et al., 2013; Xing & Gao, 2018), their granularity (i.e., they summarize a large number of finer-grained constructs), and their intuitive connections to professional learning and educational theory.

Table 1.
Measures Constructed for Research Questions 2-4

measure	definition
RQ2 (content)	
social processes	the percentage of the terms in a tweet that correspond with the LIWC social processes construct (which is related to terms such as “talk, “they,” and “buddy”)
cognitive processes	as above, but for the LIWC cognitive processes construct (which is related to terms such as “cause, “know,” and “effect”)
work-related concerns	as above, but for the LIWC work-related concerns construct (which is related to terms such as “job, “majors,” and “Xerox”)
positive affect	as above, but for the LIWC positive affect construct (which is related to terms such as “love, “nice,” and “sweet”)
negative affect	as above, but for the LIWC negative affect construct (which is related to terms such as “hurt, “ugly,” and “nasty”)
RQ3 (interaction)	
likes	the number of times that a tweet was liked, as indicated by the Twitter API
retweets	the number of times a tweet was retweeted, as indicated by the Twitter API
replies	the number of replies received by a tweet, as determined by counting how many tweets in the data set were replies to other tweets in the data set, as indicated by the Twitter API
mentions	the number of usernames mentioned in a tweet, as determined by counting the mentions logged by the Twitter API
quote tweets	whether or not a tweet quotes another tweet, as indicated by the Twitter API
RQ4 (portals)	
hashtags	the number of hashtags included in a tweet, as determined by a text keyword search for any “#” followed by letters and numbers
hyperlinks	the number of hyperlinks included in a tweet, as determined by a text keyword search for a pattern of text corresponding to a Uniform Resource Locator (URL)

4.3 Data Analysis

We began our data analysis with a descriptive overview of the volume of #michED participation in chat and non-chat contexts (i.e., in response to RQ1). We calculated the number of tweets associated with each of these contexts and also determined the amount of participation (in number of tweets) associated with each mode of participation (i.e., original tweets vs. retweets) and participation context (i.e., chat-related vs. chat-unrelated).

Next, we used hierarchical linear, or mixed effects, statistical models (Raudenbush & Bryk, 2002; West et al., 2014). Although not always modeled as such, most Twitter data can be considered to be nested, like students in classrooms. Specifically, individual tweets can be nested within users whenever users send more than one tweet; indeed, the failure to account for this nesting violates the assumption of independence necessary for constructing ordinary linear models—which can lead to over-confident inferences about effects. To avoid this possibility, we used the *lme4* R package (Bates, Maechler, Bolker, & Walker, 2015) to estimate hierarchical linear models for our subsequent analyses.

To explore differences between chat and non-chat content (RQ2), we used multi-level models, interpreting the coefficients and their standard errors and *p*-values. For all measures related to RQ2, we calculated Cohen's *d* statistics to serve as effect size measures and interpreted them according to Sawilowsky (2009).

To explore most of the differences between chat and non-chat interactions and portals (RQ3 and RQ4), which are associated with "count" outcomes, we used multi-level generalized linear models with a Poisson outcome. We then interpreted the coefficients and their standard errors and *p*-values. We also calculated the Incidence-Rate Ratio (IRR) for each coefficient, which is comparable to the odds ratios associated with a logistic regression: That is, an IRR value of 10 means that a measure is ten times more likely to occur in chats than in other contexts; conversely, an IRR value of .1 means that a measure is ten times less likely to occur in chats than in other contexts. Thus, the IRR serves as an effect size for generalized linear models with a Poisson outcome.

Quote tweets (also considered in RQ3) are not a characteristic of a tweet but rather a type of tweet. Thus, to test differences between quote tweets in chat and non-chat contexts, we filtered the data set to only include quote tweets. We then specified a log-linear model, wherein the outcome was an indicator for whether the tweet was chat-related or chat-unrelated.

As part of our analysis, we checked the assumptions for each multi-level model. These included the distribution of the linear or Poisson outcome variables, equal outcome variance between groups (as measured by *Levene's test*), and the independent and identical distribution of the model residuals for the hierarchical linear model (using a *QQ* plot). In some cases the assumption of equal variance between groups and of normally-distributed residuals was not met; we therefore used a technique to quantify how robust any inferences about effects were to sources of bias, including bias related to the violation of these assumptions (see Frank, 2000; Xu, Frank, Maroulis, & Rosenberg, 2019). Robustness analysis is especially common in fields in which complex data and models may not meet all of the assumptions of statistical tests, such as economics and sociology. The results of robustness analysis provide a way of addressing these issues. To analyze robustness, we used the *konfound* R package (Rosenberg, Xu, & Frank, 2019) to calculate the percent bias necessary to invalidate an inference (PBI). For example, an effect associated with a PBI value of 40% indicates that one could retain an inference of statistical significance even if up to 40% of an effect were due to bias. Smaller values indicate that small sources of bias—such as those due to measurement error, sample-related bias, or the violation of statistical assumptions—could invalidate an inference about an effect.

5. Results

In the following sections, we provide the results of our analyses.

5.1 RQ1: Volume

Of the 84,004 #michED tweets we collected, 18,816 were chat-related and 65,188 tweets were chat-unrelated. Table 2 demonstrates the distribution of the 9,462 tweeters involved in this study across both contexts and modes of participation. It is noteworthy that over 75% of users fall at the intersection of only participating in #michED outside of chats and only participating by retweeting.

Table 2.
Distribution of #michED Participants by Mode of Time and Form of Participation

	only chat participation (n = 488)	only non-chat participation (n = 8,137)	both chat and non-chat participation (n = 837)
only original tweeting (n = 783)	174	519	90
only retweeting (n = 7,653)	278	7,151	224
both original tweeting and retweeting (n = 1,026)	36	467	523

5.2 RQ2: Content

Our LIWC analysis found statistically-significant differences between the content of tweets composed during chat and non-chat contexts (see Table 3). For example, cognitive processing was higher during chat contexts and was associated with a *medium* Cohen's d value of 0.633. We also note that this difference was highly robust: 96.051% of the effect would need to be due to bias (including bias due to not meeting statistical assumptions) to invalidate our inference that cognitive processing was more evident within synchronous tweets. *Positive affect*, *social processing*, and *negative affect* were also significantly more present during chat contexts and had *small* effect sizes. *Work-related concerns* was found to be significantly more present in non-chat contexts. However, we also note that the effect size is *very small* and that this finding was found to be less robust: only 16.154% of the effect would need to be due to bias for our inference to be invalidated. Thus, we suggest that this finding be interpreted with caution.

Table 3.
Differences in Variables for Research Questions 2-4 between Chat and Non-Chat Contexts

	non-chat mean (SE)	chat mean (SE)	intercept B (SE)	chat B (SE)	effect size	*ICC*	*PBI* (%)
RQ2: social processes	5.88 (0.03)	8.79 (0.07)	6.331 (0.091)	1.775 (0.084), $p < .001$	0.247	0.104	90.835
RQ2: cognitive processes	5.60 (0.03)	10.38 (0.08)	5.909 (0.091)	4.319 (0.087), $p < .001$	0.633	0.086	96.051
RQ2: work-related concerns	6.63 (0.03)	6.00 (0.06)	6.67 (0.09)	0.18 (0.078), $p = .020$	0.025	0.132	16.154
RQ2: positive affect	3.16 (0.03)	5.61 (0.06)	3.9 (0.067)	1.378 (0.064), $p < .001$	0.261	0.091	91.023
RQ2: negative affect	0.82 (0.01)	0.89 (0.02)	0.62 (0.028)	0.305 (0.029), $p < .001$	0.148	0.053	81.302
RQ3: replies	0.05 (0.00)	0.24 (0.01)	-4.01 (0.051)	2.329 (0.047), $p < .001$	10.267	0.09	96.029
RQ3: retweets	1.04 (0.01)	0.43 (0.01)	-0.613 (0.034)	-0.632 (0.018), $p < .001$	.531	0.472	94.728
RQ3: mentions	0.74 (0.01)	0.47 (0.01)	-0.812 (0)	-0.463 (0.000), $p < .001$	.529	0.373	92.896
RQ3: likes	1.30 (0.01)	1.62 (0.02)	0.179 (0.023)	-0.097 (0.011), $p < .001$	.907	0.489	79.583
RQ4: hashtags	2.16 (0.01)	1.19 (0.01)	0.798 (0.012)	-0.565 (0.011), $p < .001$	.568	0.186	96.512
RQ4: URLs	0.81 (0.00)	0.18 (0.00)	-0.374 (0.02)	-1.402 (0.024), $p < .001$	.246	0.146	96.785

Note. Quote tweets (RQ3) are reported separately. *ICC* represents the intra-class correlation. The effect size for RQ2 measures is Cohen's *d*. The effect size for RQ3 and RQ4 measures is the *Incidence-Rate Ratio*. Thus, effects can be compared within outcome type but not between them.

5.3 RQ3: Interaction

For each of the forms of interaction we considered in this study, there were statistically-significant differences in how they were used during chat and non-chat contexts (see Table 3). Replies were ten times more likely to occur during chats than during other contexts. Likes were also used more frequently during chats; however, when user-level factors are taken into account, they were actually more likely to occur in non-chat contexts. Retweets and mentions were also more likely to occur in non-chat contexts. These findings were all found to be robust to potential sources of bias. Finally, 3,128 quote tweets were composed during non-chat contexts, significantly more than the 1,021 quote tweets composed during chats (β = -2.180 [*SE* = 0.118], *IRR* = 0.113, $p < .001$).

5.4 RQ4: Portals

Our analysis suggests that, on average, original tweets composed during non-chat contexts contained more portals to (potential) learning spaces—as measured both in terms of the number of hyperlinks and hashtags—than those composed during chats (see Table 3). For example, hashtags were approximately half as likely to occur in chat-related tweets than in other tweets.

6. Discussion

Like many other hashtags for teacher learning and networking, #michED is used to mediate weekly synchronous Twitter chats but is also home to considerable asynchronous communication. Our results demonstrate clear differences between these two contexts in the #michED hashtag space on Twitter. Chat and non-chat uses of #michED during the 2015-2016 school year differed not only in terms of the volume of activity but also the content, interaction, and portals associated with that activity.

Based on these results, we argue in the following sections that these different patterns of activity represent distinct *affinity spaces* characterized by different sets of *literacy practices*, all contained within a single Twitter hashtag. Indeed, our findings suggest that chat and non-chat uses of #michED represent two affinity spaces: one dominated by practices that support social interaction, and the other emphasizing practices that support content dissemination. We then consider the implications of these findings for theory and practice.

6.1 Separate Affinity Spaces and Distinct Literacy Practices

Our use of Gee's (2005, 2017) affinity space framework to examine chat and non-chat participation in #michED leads us to conclude that these two modes can be thought of as distinct spaces. In his early writing on affinity spaces, Gee (2005) suggested that an affinity space could be described and distinguished in terms of *content*, *interactions*, and *activity*; thus, if chat and non-chat contexts differ along each of these components, it is reasonable to think of them as separate social contexts for learning. That is, whereas previous research (e.g., Authors, 2016b) might have conceived of #michED as a single, distinct affinity space, these findings correspond with Gee's (2017) recent assertions that affinity spaces may be characterized by subspaces or as overlapping with other spaces.

This interpretation of separate-but-overlapping spaces within #michED is further supported by the findings presented in Table 2. These findings emphasize that the vast majority of users engage in one participation context only, though there is a minority that participates across both #michED contexts. It should also be noted that the most popular ways of participating in #michED are in non-chat contexts and through retweeting others' posts, with over three-quarters of participants only contributing at this intersection of possibilities. This is particularly interesting because this intersection arguably represents the way of contributing that requires the least amount of commitment. That is, composing an original post requires an (abbreviated) editorial process, whereas retweeting another's post requires only the click of a button. Similarly, participating during a chat requires a participant to block off time on their calendar, while using a hashtag outside of a chat allows for participation at one's own convenience. This is not to suggest that participation requiring less commitment is somehow meaningless; rather, it serves as a warning against idealizing what participation within these spaces looks like (see Magnifico et al., 2018).

Describing the specific literacy practices associated with different modes of participation in #michED can lend further insight into the characteristics and purposes of these spaces. For example, our data indicated that the non-chat space was associated more with *content dissemination*. This strategy supports an independent and self-guided form of teacher learning in which individual teachers search for resources and information at their own convenience, determine which resources will be genuinely helpful to them, and engage with those resources on their own.

A collective strategy of content dissemination supports this independent learning by providing and drawing attention to resources and information for teachers to evaluate on their own. Indeed, the higher use of *retweets* and *mentions* outside of chats may be indicative of strategies to increase the audience of a particular tweet—retweets allow Twitter users to repost ideas to their own networks, and mentions allow an original tweeter to invite the attention of specific people, who may then engage in further dissemination (Authors, under review). Furthermore, the higher rate of hyperlinks suggests that #michED participants are sharing more artifacts and resources outside of chats, while the higher rate of hashtags may represent the use of more keywords in order to draw attention from people outside of the #michED space. That is, not only does this hashtag have distinct spaces within it, but the use of multiple portals suggests the possibility that—outside of chat contexts—#michED serves as a subspace within a larger ecology of teacher resources on Twitter. The effect size for hyperlinks is particularly notable, in that they are approximately four times as likely to occur outside a chat than during one.

In contrast, the #michED chat space appears to be chiefly associated with *social interaction*. This represents a different view of learning, in which—despite the information freely available through networked technologies—there is held to be value in teachers' learning directly from each other through real-time discussion and conversation. In our analysis, we found that tweets during a #michED chat were associated with more *replies*, suggesting that chat spaces are characterized by more active interaction (i.e., actual conversation rather than simple signals of approval or reposting) than non-chat spaces. Indeed, replies were over ten times more likely to happen during chats than in other contexts, though we note that our measuring of replies does not account for replies that leave out the #michED hashtag.

Furthermore, using LIWC, we found the content of tweets during chats to be higher in terms associated with social, affective, and cognitive processes. Oztok and colleagues (2013) similarly found that real-time "chatting" communication in a fully-online graduate course contained more terms associated with LIWC's social and affective process constructs than asynchronous "posting" communication; however, in contrast with our study, they also found that cognitive processes were more present in asynchronous communication. This difference may be explained by the different roles chatting and posting play in the #michED Twitter hashtag as compared to an online graduate course. In the course described by Oztok et al. (2013), posting asynchronously served as the structured learning activities for participants (thus requiring cognitive engagement), whereas chatting synchronously served as informal, social communication between participants. In contrast, we have already described asynchronous posting in the #michED space as an unstructured activity of disseminating information, whereas synchronous chats are structured activities with both learning and social objectives. Thus, in the case of #michED, it seems to be the chat context that is the site of both the most active social activity (hence higher levels of social and affective processes) and the most active learning activity (hence higher levels of cognitive processes). We note with interest that this may also suggest the presence of the social and cognitive presence required to establish a community of inquiry within the #michED hashtag, with the structured nature of a Twitter chat providing some measure of teaching presence (Garrison et al., 2010; Garrison & Akyol, 2013).

These differences between spaces can be fruitfully considered as differences in literacy practices. The current conception of literacies is informed by a recognition that the use of language (itself a fundamental cognitive technology; Nickerson, 2005) is governed not so much by inherent laws but through social construction (Gee, 1989). Our results show this to be true of Twitter as well: Although the features and limitations inherent in the Twitter software undoubtedly influence teachers' use of this platform, it is ultimately social contexts and expectations that determine their specific use at specific times. This study therefore joins others that have emphasized looking beyond simple affordances to also consider the influence of social factors in the context of Twitter (e.g., Authors, under review; Veletsianos, 2017) or other educational technologies (e.g., Oliver, 2011; Selwyn, 2010).

Nonetheless, it is important to note that differences in Twitter practice can be explained, in part, by factors other than contextual differences. Individuals, for example, mattered a great deal, as indicated by the ICCs from the hierarchical linear models for content, interactions, and portals. These ranged from .053-.472, indicating that 5.3%-47.2% of the variability in these outcomes could be attributed to the individuals interacting with or posting #michED tweets. With the exception of replies, interactions in particular could be explained to a great degree by individual factors. In contrast, the content of a tweet was associated with less variability related to individual factors, suggesting that individuals may *interact* in characteristic ways but choose the *content* of their tweets based on contextual factors. Furthermore, although we found (descriptively) that tweets during chats tended to receive more *likes*, our multi-level model suggested that when individuals are taken into account, liking is actually slightly more likely to happen in asynchronous settings. These findings correspond with other research (e.g., Authors, 2018) that has found that user-level factors may influence how much interaction a tweet receives. Collectively, these findings raise a possible challenge to views of teacher-focused Twitter contexts as "nonhierarchical [and] democratic" (Wesely, 2013, p. 311) and to broader views about the value of affinity spaces for learning (Magnifico et al., 2018).

6.2 Implications for Theory and Research

These distinct-but-complementary uses of the #michED hashtag are significant in the context of our evolving understanding of social connections in the age of the Internet. Theoretical conceptions of online community and social interaction range from tight-knit groups with frequent interaction to looser networks that nonetheless provide real value (Gruzd, Wellman, & Takhteyev, 2011) to *information neighborhoods* (Burnett, 2000) that prioritize exchanging information above interpersonal relationships. Similar distinctions also exist in the literature on professional learning within education, with some scholars referring to *communities* of teachers that interact closely with each other (Darling-Hammond & McLaughlin, 1995; Wenger, 1998) and others describing informal *professional learning networks* through which teachers obtain access to knowledge and resources (Couros, 2010; Trust et al., 2016). Our results suggest that there is value in both of these conceptions and, indeed, that they could exist in parallel within the same hashtag context.

Researchers should also note the way that Twitter, despite its relatively static set of features, has been repurposed by teachers (and others) for separate and distinct purposes. Indeed, as a microblog, Twitter was not originally designed for chatting but as "a program for users to describe and report their activities and locations… and share this information with groups of selected friends" (Siles, 2013, p. 2110). Nonetheless, even from the platform's earliest days, users departed from the original intent and began using Twitter to "sustain conversations and aggregate news" (p. 2117). Subsequently, teachers—as well as other groups (McArthur & White, 2016)—have recognized the affordances of the hashtag for organizing real-time chats. This phenomenon is even more remarkable given that the hashtag itself was originally a user-driven repurposing of the Twitter search function that was only later adopted as an official feature (Hiscott, 2013). Yet, this repurposing of Twitter does not prevent teachers from also using the platform (and features like hashtags) in other ways, demonstrating that a single educational technology with the proper affordances can be used in multiple contexts—and that learners are capable of identifying those affordances that best support each repurposing. This serves as a powerful example of how technologies not designed for educational purposes can be adopted and modified for educational uses (Authors, 2006).

6.3 Implications for Practice

As researchers continue to recognize Twitter as a resource valued by some teachers, interest in explicitly introducing preservice and in-service teachers to Twitter as part of formal teacher education has grown (e.g., Carpenter, Tur, & Marín, 2016, Carpenter & Morrison, 2018; Gurjar, 2019; Luo et al., 2017). Indeed, the ability of Twitter to facilitate different kinds of social relationships and communication in different modes supports the idea of Twitter as a *foundational technology*, "one capable of supporting teachers' learning across multiple… contexts" (Authors, 2016a, p. 81). However, Authors (2018) highlighted that Twitter is not a monolithic technology and that learning to participate in one Twitter context involves acquiring different practices than learning to participate in another. Whereas the focus of this previous study was to acknowledge the differences between hashtags, our current study demonstrates that distinct, separate spaces may exist even within a single Twitter hashtag. Nonetheless, it is notable that both studies found that differences could be described in terms of an emphasis on either sharing or social connection.

As a result, it is important for preservice and in-service teachers being introduced to Twitter to appreciate the existence of different affinity spaces as they consider whether to use Twitter as a professional resource. For example, the majority of preservice teachers participating in a study by Carpenter (2015) described chats as the "aspect of Twitter they found most beneficial" (p. 220), highlighting the value of introducing teachers to this specific mode of participation. However, other researchers have described the pace and volume of conversation during a chat as a major obstacle for teachers (Britt & Paulus, 2016; Luo et al., 2017), supporting the idea that some teachers may prefer to use Twitter only for asynchronous communication. Furthermore, given that each of these participation contexts is associated with different literacy practices, those introducing teachers to Twitter should ensure that—like language, the original literacy—they teach effective professional use of Twitter as a collection of different practices relevant in different contexts rather than a single set of practices that are universally relevant.

These implications may also be extended to other groups, but we maintain that they are especially important in the context of teachers. That is, other professional (e.g., Gilbert, 2016;

McArthur & White, 2016; Veletsianos, 2017) or interest-based groups (McArthur & White, 2016) organize learning through Twitter hashtags and chats. These groups may also find that different spaces within Twitter (or, indeed, within a single hashtag) privilege different Twitter literacies, and that acquiring the literacies associated with a specific space is necessary for successful participation therein. Yet, given (a) the importance of education within a democratic society, (b) the importance of teacher learning for improving education (Darling-Hammond & McLaughlin, 1995), and (c) the potential for Twitter to provide such learning while remaining respectful of teacher autonomy (Carpenter & Krutka, 2015), attention to the nuances highlighted by this research may have long-reaching, if indirect, effects. This critical attention is especially important given the increasing transfer to informal settings of teacher activities and resources traditionally provided through formal means(e.g., Carpenter & MacFarlane, 2018; Shelton & Archambault, 2018) and increased awareness of the educational challenges posed by social media (Authors, 2019a). In sum, while all those who engage in learning on social media will benefit from attention to the literacies privileged in different spaces, it is critical for teachers, teacher educators, and researchers to pay close attention to differences (both obvious and nuanced) between spaces.

7. Conclusion

Teachers use Twitter professionally in a number of different ways, including real-time chats and delayed communication. In this study, we have explored chat and non-chat spaces in the #michED Twitter hashtag used by teachers in the U.S. state of Michigan. Although both contexts relied on teachers' use of Twitter's built-in features, we found that these two modes of communication served as distinct affinity spaces that valued different literacy practices. That is, use of #michED during chats appears to be focused on social interaction, with tweets receiving more replies and containing more content related to social, affective, and cognitive processes. Non-chat use of the same hashtag appears to be dedicated more to content dissemination, with tweets receiving more retweets and including more mentions, hyperlinks, and hashtags. These results contribute to the educational technology literature by demonstrating the richness of informal learning on social media and to practice by helping teacher educators, preservice teachers, and in-service teachers recognize that the skills needed to successfully participate in a teacher-focused hashtag may change depending on different social situations within the hashtag.

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