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Keywords: Teacher professional development, Informal learning, Social media, Learning communities, Social network analysis, Online community

1. Introduction

Teacher learning communities or networks are often suggested as improvements of existing teacher professional development (PD) (Jones & Dexter, 2014). Compared to traditional PD activities with predetermined structures, teachers are more likely to access just-in-time support by interacting with experts and colleagues who have the knowledge or resources that they need to obtain through social media (Greenhalgh & Koehler, 2017). Social media is recognized for its features to contribute to teacher PD and sense of professional community (Rosenberg et al., 2017), given its affordances of enabling teachers to "learn with and from each other" in highly situational, dynamic and interactive environments (Krutka et al., 2017). Among various social media, Twitter is the predominant platform in which teacher PD often takes place (Luo et al., 2020). K-12 teachers highly value Twitter's role in supporting their self-directed PD and often use it multiple times a day for PD purposes (Visser et al., 2014).

Teacher online learning networks have several distinct advantages compared to traditional teacher PD. First, the time and space flexibility of online PD responds to teachers' overburdened schedules. Teachers have their daily routines to follow; therefore, attendance and participation in PD activities at a required time and place may be challenging (Burchill & Anderson, 2019; King, 2004). Second, online PD enables teachers to connect with educators around the world to improve their content knowledge and teaching skills because they are no longer constrained by temporal and geographical factors (Greenhow et al., 2018; Trust et al., 2017). Third, it may be easier for teacher networks to sustain in online environments as social media and other mobile applications make it simpler to maintain connections, networks and communities, while traditional PD are usually one-time events with little follow-up (Jaquith et al., 2011).

Despite these mentioned advantages of teacher online learning networks, relevant research and practice is still at its infancy stage (e.g., Greenhow et al. 2018; Luo et al., 2020). Previous studies mainly explored participants' experience and perception of online PD enabled by social media and how these tools promote participants' communication (Trust et al., 2017; Veletsianos, 2012; Veletsianos & Kimmons, 2013). Few studies have explored large networks or communities with large sample sizes (Luo et al., 2020; Macià & García, 2016). There is a need to better understand the structure of teacher online learning networks and how they develop and function (Macià & García, 2016). Social network analysis is an effective technique to analyze and illuminate interactions, collaboration and relevant key influencing factors in a virtual learning community (Laat et al., 2007; Lin et al., 2016). The current study aims to leverage social network analysis to respond to this research gap by examining the discourse and participation features of an online PD network, whether hub participants emerge and connect heterogeneous communities within the network, and if the participants' posting behaviors differ in the communities. The data was 422,791 tweets containing the hashtag "#edchat".

2. Literature Review

2.1 Teacher Online Learning Networks

With theoretical and technical developments, teacher PD, like other forms of learning, becomes increasingly open, collective and participative. There are three common teacher PD models, namely craft, expert and interactive models (Clarke & Hollingsworth, 2002). Theoretically, the interactive model is considered to be the most complete teacher PD model compared with the other two. The interactive model states that teacher PD is facilitated as a result of teachers trying out new practices and gaining new experiences in the classroom with the support of external sources of information and evaluating the practice results (Clarke & Hollingsworth, 2002). Different from the craft and expert models which does not explain how new knowledge is incorporated in practice or considers teachers playing passive roles in their learning, the interactive model takes the internal domain (i.e., teachers' ideas, knowledge and beliefs), external domain (i.e., information or sources), domain of practice (i.e., action research activities in classrooms) and domain of consequence into account (Clarke & Hollingsworth, 2002). Technically, mobile devices make it easier for teachers to share and collaboratively construct ideas and resources; social media has become part of teachers' daily activities (Cope & Kalantzis, 2009; Haythornthwaite, 2009). Through mobile-device-enhanced social media, teachers play more active roles in deciding what content they would learn and with whom they would connect to solve particular issues (Lieberman & Mace, 2010).

Social media has the potential to afford teachers' needs for resources and social networking. A network is about "the set of relationships, personal interactions, and connections among participants who have personal reasons to connect," while community is defined as "the development of a shared identity around a topic or set of challenges" (Wenger et al., 2011). Teachers can gain information and resources, establish dialogues, and find solutions through participating in activities and interacting with others (Wenger et al., 2011) in social learning, which is a great source of informal learning (Lave & Legitimate, 1991). Their network can sustain because they share similar professional practices or they are dedicated to particular content (Lave & Legitimate, 1991; Paul Gee, 2004). Within a large network, teachers are likely to have different levels of participation and specific interested topics. As a result, communities may form with focuses on specific topics and key participants may emerge as moderators and connect different communities (Lantz-Andersson et al., 2018). The key participants may share information, connect other members and synthesize knowledge, while some participants may participate peripherally or just observe (Wenger et al., 2002). In this study, we define the graph which represents relationships among all participants as a network, while the subgraphs which consist of relationships of a number of participants as communities.

Specifically, teachers' professional learning on Twitter has attracted research attention. For instance, some studies (e.g., Arslan et al., 2022; Greenhow et al., 2021; Krutka et al., 2021; Xing & Gao, 2018) have researched tweets using the award-winning hashtag #edchat. Xing and Gao (2018) studied the discourse features that affected continued participation of Twitter-based professional learning, focusing on social, interactive, and cognitive dimension. They found that the exposure to social tweets is negatively associated with user commitment to the professional learning. A recent study investigated the interactions between state-sponsored accounts and #edchat, raised questions on disinformation and anonymity caused by inauthentic amplification (Krutka et al., 2021). Another interesting research studied the content and purposes of #edchat tweets published during COVID–19—when teachers experienced a rapid transition to online teaching (Greenhow et al., 2021). They found that discourse of #edchat was beneficial to teachers' professional learning. More recently, Arslan et al. (2022) explored the topics that participants discussed and the factors that affected the duration of these topics. Their results suggested that topics that have more original tweets (compared with retweets) and a large number of participants tend to last longer. However, these studies did not examine how participants interact with each other, nor how they form communities.

2.2 Social Network Analysis in Education

Social network analysis refers to an approach that uses graph theory and network graphs to study social structures (Otte & Rousseau, 2002). A social network represents the connections of a group of connected nodes (Haythornthwaite, 2009). For example, we can develop a social network graph for an online course based on students' communications on discussion forums. Each student can be represented as a node, while an edge links two students with interaction (e.g., commenting, liking). Rooted in graph theory, social network analysis utilizes a number of methods and metrics (e.g., degree, closeness, network density, communities, directed graphs, and hub nodes) to study the connections among nodes, investigating the exchange of resources between two nodes and how these interactions affect the relationship further in a social system (Haythornthwaite, 2009). The representation of relationships using visualization and quantitative methods helps understand learning in a way that qualitative methods cannot achieve (Borgatti et al., 2009).

Social network analysis is frequently employed to study online learning groups. Prior work indicates that social network analysis metrics like closeness (i.e., how close a node is to other nodes in a network) and degree (i.e., the number of edges that are connected to a node) can be used as positive predictors of sense of community in an online learning analysis model (Dawson, 2008). Using degrees to identify hub nodes (i.e., a node with many connections), active and inactive students, social network analysis can decipher the important components of successful problem-based online learning, namely, the importance of hub participants (Saqr et al., 2020). Saqr et al. (2020) found that in an online learning group, the tutor being a hub node is negatively correlated to the performance of the learners. Their speculation is that the tutor tried to support students' engagement by taking the leading role. Another recent study uses directed network graphs (i.e., a network graph with directed edges) to represent the relationships among self-regulated strategies, revealing interesting patterns on temporal dynamics of self-regulated learning strategies, as well as dynamic differences among different performance groups (Li et al., 2020).

In online learning groups, members tend to have their interaction preference. It seems that they tend to interact more with peers who share similar characteristics, forming homogeneous groups instead of heterogeneous ones. Dawson (2010) developed ego-networks to represent each student's interactions and connections with peers and instructors, and found out that the ego-networks of high- and low-performance students are significantly different in terms of network size and neighbors. Specifically, high-performing students tend to develop online relationships with peers of a similar performance. Fire et al.'s (2012) research suggested that students' performance can be predicted by their social interactions, and is highly positively correlated with that of their "best" social friend (Fire et al., 2012). Brown, Lynch, Wang, et al. (2015) extended the investigation by detecting meaningful communities and hub participants in MOOCs, and found that students tend to interact with others who have similar performance levels. Xu et al. (2018) applied a longitudinal approach to explore students' social interactions and the role of hub participants in MOOCs. Their study indicates that students with similar grades form social groups at an early stage of a course and manage to maintain the groups throughout the course, and hub participants are important to connect the online learning groups.

However, research on informal online teacher professional learning communities has not sufficiently benefited from social network analysis, especially on large networks or communities (Luo et al., 2020; Macià & García, 2016). After systematically examining 99 studies on informal online teacher professional learning communities from 2009 to 2016, Macià & García (2016) identified a lack of work in studying large networks and their structures using quantitative methods. In another two systematic reviews, researchers find that most existing work on teacher PD through social media relies on self-report data rather than authentic data from social media sites (Lantz-Andersson et al., 2018; Luo et al., 2020). It remains unclear what connections educators develop with other members at large-scale, or what interaction patterns participants exhibit in terms of whom to connect. To address the gap, this study aims to explore massive informal online professional learning communities by investigating the network structure, formation, and the role of a specific group of participants using authentic data from Twitter. Specifically, this work seeks to answer the following research questions:

1. What are the characteristics of educators' online professional learning network in terms of discourse features and participation features?

2. Do hub participants emerge in the educators' online professional learning network? If so, what roles do they play in terms of connecting other participants?

3. Are communities different from each other regarding participants' posting behaviors?

3. Methods

3.1 Data

This work utilizes a dataset of tweets published with the hashtag "#edchat". The hashtag is a weekly Bammy Award-winning Twitter-based discussion among educators on education, founded by Steven Anderson, Thomas Whitby and Shelly Terrell[1]. Almost every Tuesday since July 2009, founders and volunteer moderators organize a one-hour online conversation covering a wide range of topics on education such as education policy, education reform, and educational technology. Hence, we assume that most of the participants were educators. The hashtag was used to track the discussion. An informal online professional learning network formed spontaneously as educators posted, read, retweeted, and replied to tweets marked by #edchat. In the informal online professional network, educators could talk about their work, discuss personal concerns and education issues, exchange ideas, provide suggestions, negotiate meaning and construct solutions.

Although tweets are publicly available for data collection using tools like web crawlers, other relevant data that can be collected is limited. For instance, demographic information like gender, age, race, and ethnicity are considered private and cannot be collected. For this study, we collected tweets that were published with the hashtag "#edchat" on Twitter. The hashtag has a history of over 10 years and this study focused on the period between January 1st, 2011 and December 31st, 2014. The reason for choosing this time period was because after about 1.5 years of development and at its growth stage, this hashtag had attracted thousands of participants who could potentially have formed a network already (suggested by our descriptive responses to RQ1). Hub participants might have emerged and communities might have formed. In order to validate the data and use it to construct social networks, the collected tweets were filtered for the following attributes: display name, publish timestamp, and the hashtag. Under such criteria, a total of 422,791 valid tweets were kept and included in this study.

3.2 Data Analysis

[1] http://edchat.pbworks.com/w/page/219908/FrontPage

To respond to research questions, multiple analysis methods were employed. For RQ1 regarding characteristics of educators' online professional learning network, we identified the high-frequency words of collected tweets (see 3.2.1) and developed a network using collected data (see 3.2.2). For Q2 studying whether hub participants emerged and their roles in connecting other participants, we identified hub participants, examined the interactions between participants and their close neighbors at the network level using best friend correlation (see 3.2.3 & 3.2.4), and detected communities within the network and conducted assortativity analysis at the community level (see 3.2.5 & 3.2.6). A combination of the aforementioned methods was used to answer RQ3 about the interaction behavior patterns in different communities. All analysis was conducted using Python.

3.2.1 Text Preprocessing and Word Count

A number of commonly used text preprocessing techniques were used to preprocess the tweets so that common terms can be identified. The goal of text preprocessing is to structure the textual data for further analysis. We first removed commonly used terms like "a", "the", "and", and "of" using *stopwords*, then applied *Tokenization* to divide the tweets into individual units, and *Lemmatizing* and *Stemming* to remove inflectional endings and reduce words to word stems, respectively. As a result, "computed", "computing", and "computation" will be seen as the same term. After preprocessing the texts, we counted the frequency of each word. This is also known as the word count.

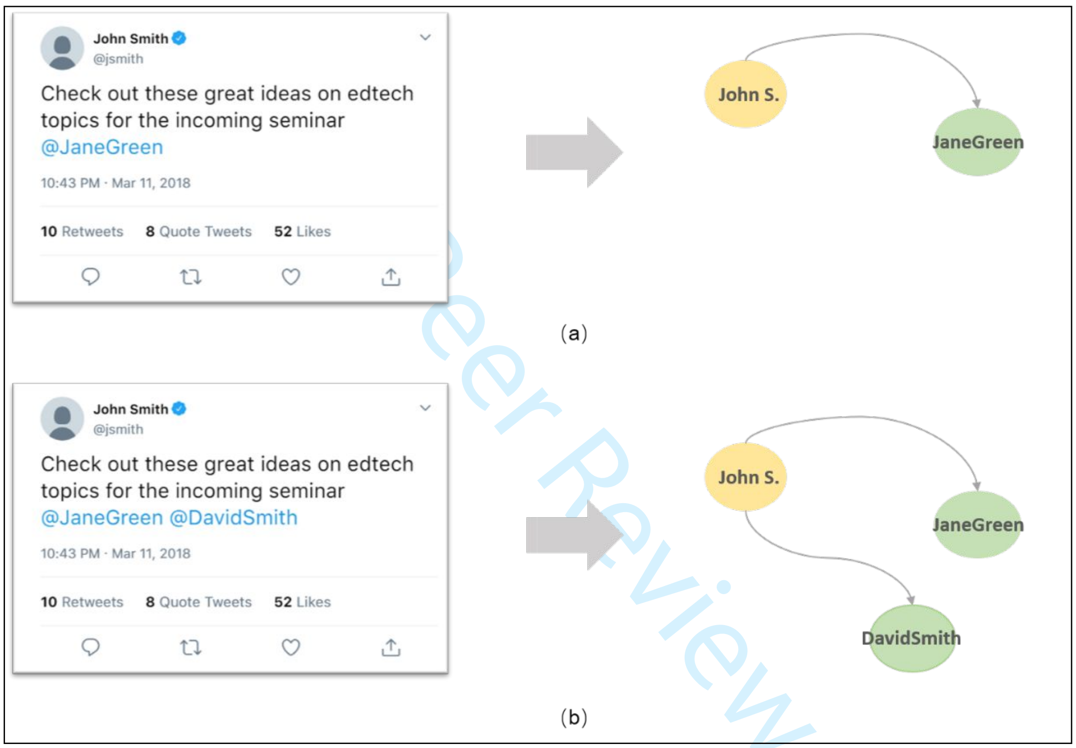
3.2.2 Social Networks and Hub Participants

To study the relationship between participants reflected in the four years' discussion, we represented their interaction in the form of a social network. Figure 1 demonstrates how tweets were transformed to pairs of nodes. Each Twitter account has one username and one display name. The one follows the "@" symbol is the username, the one above the username is the display name. In our case, jsmith is the username, and John Smith is the display name. Each account has one unique username, which is used for posting activities such as publishing, replying, commenting and direct message. The display name, on the other hand, can be duplicated. Display names are commonly used among friends to identify one another. In the examples of Figure 1(a), Twitter user John Smith posted a tweet and addressed it to his friend

Jane Green by "@" her. This posting behavior explicitly connected John and Jane socially. Hence, we represented such a connection by drawing a directed edge from John to Jane. If John mentioned more than one of his friends in his post, as shown in Figure 1(b), we drew two directed edges from John to Jane and David, respectively.

Figure 1

Transfer a tweet to node pairs with directed edges



If one participant posted tweets without mentioning any others and the participant was not mentioned by others in the network in their postings, the participant would appear as an isolated node in the network. If one participant did not post any tweets and yet was mentioned in others' tweets, like Jane and David in Figure 1, they would show up as connected nodes with edges pointing to them only. Therefore, a fully connected node would have edges pointing from and to itself, indicating the participant published tweets mentioning others and was addressed by other participants in the same social network. In a directed network, the number of edges coming to the node is known as in-degree, and the number of edges coming from the node is out-degree. The sum of in- and out-degree is known as the degree of the node. Hence, John in Figure 1 has an in-degree of 0, an out-degree of 2, and a degree of 2. Assuming John has posted a #edchat tweet while Jane does not, Jane will be included in the social network graph as a connected node with John. We defined participants who do not post tweets but are mentioned as passive participants, and those who post tweets as active participants. However, an active participant who does not interact with others in the social network is considered as an isolated node, and is excluded from further analysis.

Using such methods, we started with a multigraph that supports parallel weighted edges. Specifically, if two participants communicate once, one edge will be drawn to connect them. If they connect twice or more, the weight of the edge will increase accordingly. In other words, the number of edges between two nodes represents the number of communications between two participants. As the nature of our research questions addressed the connections among participants, we removed those isolated nodes. Self-loop, which indicates a connection between one and oneself, was rare and removed from our network as well. One goal of this work is to use authentic data from social media websites to investigate informal online professional learning communities, we aim to develop reasonable and reliable social networks. For validity concern, those who posts only one tweet using #edchat within 4 years are excluded from our analysis.

Hub nodes are commonly used to access the impact of active participants in a social network (Brown, Lynch, Eagle, et al., 2015; Brown, Lynch, Wang, et al., 2015). In a directed graph, hub nodes are defined as the ones with in- and out-degrees which are larger than three standard deviations above the mean (Goldenberg et al., 2009). To evaluate the role of hub nodes, we developed a full network with all participants and one without hub nodes for further investigation. However, the network structure was affected when hub participants were removed. A group of nodes who shared edges only with hub participants turned isolated. These nodes were removed as well.

3.2.3 Posting Behavior Measurements

Online interaction behaviors which are used to develop social networks typically include discussion forum comment and reply, team assignment/project, among other types of collaboration (Brown, Lynch, Wang, et al., 2015; Dawson, 2008; Fire et al., 2012; Xu et al., 2018). This work examined one of the most common activities in social media websites: posting behaviors. Posting behaviors such as posting, commenting and replying tweets are explicit indicators to members' participation in Twitter-based online communities. However, it is worthwhile to mention that posting behaviors vary among participants. A number of participants tended to publish a few tweets every other day, while some participants posted many tweets in one day yet joined the discussion once a month. These posting behaviors encourage a question naturally: how do we measure teachers' participation? The total number of published tweets matters, so does the duration one stays in the network. Imagine two teachers, John and Jane. John posted one tweet in January, 2012 and another one in December, 2012, while Jane joined a weekly group discussion from January to August, 2012. A time duration which takes the time interval from the first tweet to the last tweet overlooks the intensity of participation. In addition, we expect to have a great number of Janes since "*#edchat*" held online chats regularly.

Hence, our work measured their posting behaviors in two dimensions: posting quantity and posting days. Posting quantity is the total number of tweets that one participant published, while posting days refers to the total number of days that one participant was active in the network. Posting quantity does not necessarily increase as posting days increases, or vice versa. These two dimensions measured both the intensity and the duration of the participation.

3.2.4 Social Best Friend Correlation

Social best friend correlation is essentially a correlation between one and their social best friends in terms of variables of interests, for instance, academic performance or time spent on learning. Research indicates that students' academic performance is closely related to that of their close friends, whether in traditional classrooms or online settings (e.g., Brown, Lynch, Wang, et al., 2015; Fire et al., 2012). Fire et al. (2012) reported a relationship between students' grade and their most connected neighbors in a traditional classroom. Brown, Lynch, Wang, et al. (2015) also identified such a relationship in a massive online learning course. To examine whether the aforementioned correlation exists in informal online professional learning communities, we first identified each participant's social best friend in a similar manner, and then performed a correlation based on their posting behaviors.

Best friend is defined as one participant's most highly connected neighbor in a social network (Brown, Lynch, Wang, et al., 2015; Fire et al., 2012). In this work, we adopt the same definition: the social best friend *BF* for a participant *P* is *P*'s most highly connected neighbor. Assuming each participant *P has* a collection of *n* neighbors $\{neighbor_1, neighbor_2, \ldots, neighbor_n\}$ with a score $s_1, s_2, \ldots, s_n$, respectively, for $n \in \boldsymbol{N}^*$ and $1 \leq i \leq n$:

$social\text{-}best\text{-}friend(P) = neighbor_i$, where the subscript i:

$i = m$, where m is the subscript of the highest score k_m, and k_m:

$k_m = max\{s_1, s_2, \ldots, s_n\}$.

The score s_j for participant *P*'s $neighbor_j$ equals to the number of interactions between them. If more than one neighbor is qualified for a participant's social best friend, one neighbor will be randomly chosen. Then, the correlation was performed based on the identified social best friends.

3.2.5 Assortativity

Although best friend regression can examine the correlation between a pair of individual participants, it is also worthwhile to explore the relationship between participants and their direct neighbors. Assortativity, also known as assortative mixing, is widely used to measure the correlation between nodes and their neighbors (Newman, 2002). Its metric Υ, essentially the Pearson correlation coefficients between a node and its neighbors, falls between -1 and 1. If the assortativity of a network is equal to 1, the nodes in the network are only connected with those of the same measurement score concerning posting quantity or posting days. Likewise, if the metric is -1, nodes in the network share edges with nodes of different measurement scores. An assortativity score of 0 means the network is neither assortative nor disassortative. Since assortativity measures the tendency of connections between nodes based on their degrees, a network with a positive assortativity value is considered homogeneous while a network with a negative assortativity value is heterogeneous. Social networks are normally thought to be assortative, a random network is neither assortative nor disassortative (Newman, 2002).

3.2.6 Community Detection

Community, also known as subgraphs of a network, is an important structure to study in social network analysis as it demonstrates the tendency of a group of members to cluster

(Haythornthwaite, 2009). Communities in social network analysis are thought to be groups of individuals who are related with each other (Girvan & Newman, 2002). In this study, community refers to a subgraph in which the nodes are more intensely connected with each other than to the rest of the network. The Clauset-Newman-Moore greedy modularity maximization—a widely used community detection algorithm—was used to detect communities in this study.

The parameter used to measure the strength of dividing a network into multiple subgroups is modularity. In a community with a high modularity value, members tend to have close connections with each other, while the connection between these members and the rest of the network is sparse. The value of modularity normally lies between -1 and 1, while 1 indicates a highly clean group division. The Clauset-Newman-Moore greedy modularity maximization is a commonly used modularity-based community detection algorithm. The algorithm assumes that (1). Each node belongs to its own community at the beginning; Then, (2). The pair of nodes increases modularity the most are merged; (3). Repeat step (2) until one community remains; (4). Choose the partition results with the maximum modularity. This algorithm is able to generate meaningful communities in large networks (Clauset et al., 2004).

4. Results

RQ1: What are the characteristics of educators' online professional learning network in terms of discourse features and participation features?

Except for tweets with no meaningful characters, the shortest one has two characters "No", while the longest one has 321 characters. On average, each tweet has 105.6 characters (*SD* = 41.1). To further investigate the discourse features, we identified the high-frequency words of collected tweets. We first pre-processed the tweets, and then calculated the word count. Figure 2 presents the most common 50 terms. To focus on the words which could reflect the content of collected tweets, words, especially verbs (e.g., "go", "make", "take", "thing", "know", "need", "start", and "get") that do not convey much information about the tweets content were removed. The higher frequency the term is, the darker the blue is in Figure 2. The number in each cell represents the word's ranking of frequency. For instance, "student" is the most common word, while "interest" ranks 50th. Most of the words are explicitly education related, suggesting that participants of #edchat mainly focused on educational discussion.

Figure 2

The most common 50 terms of collected tweets

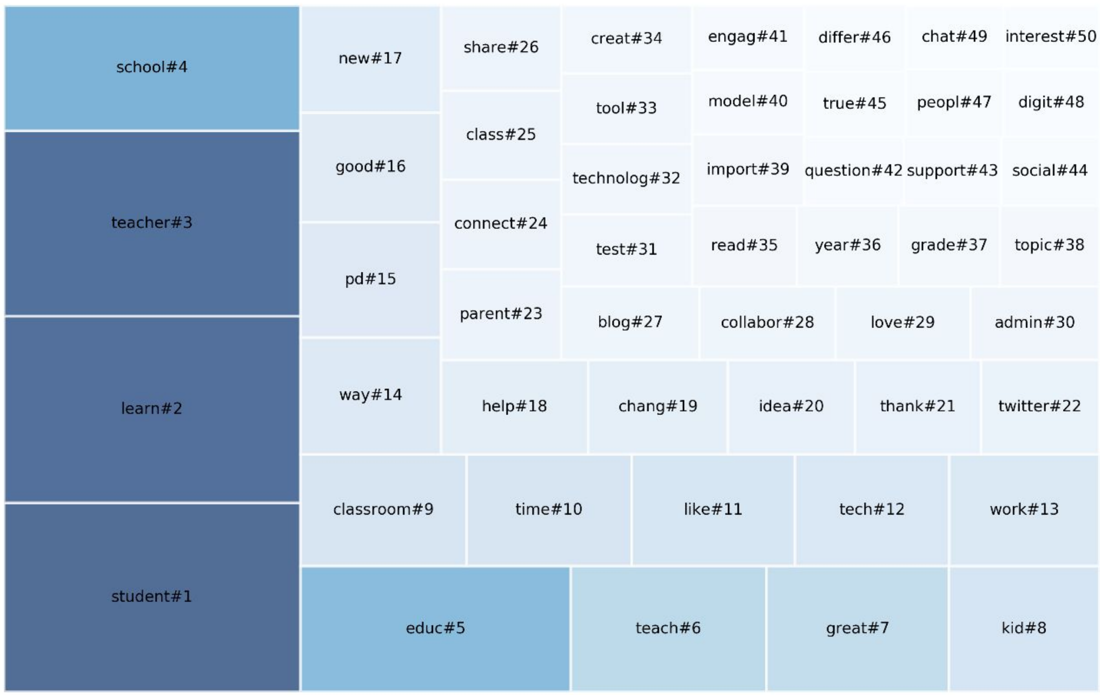
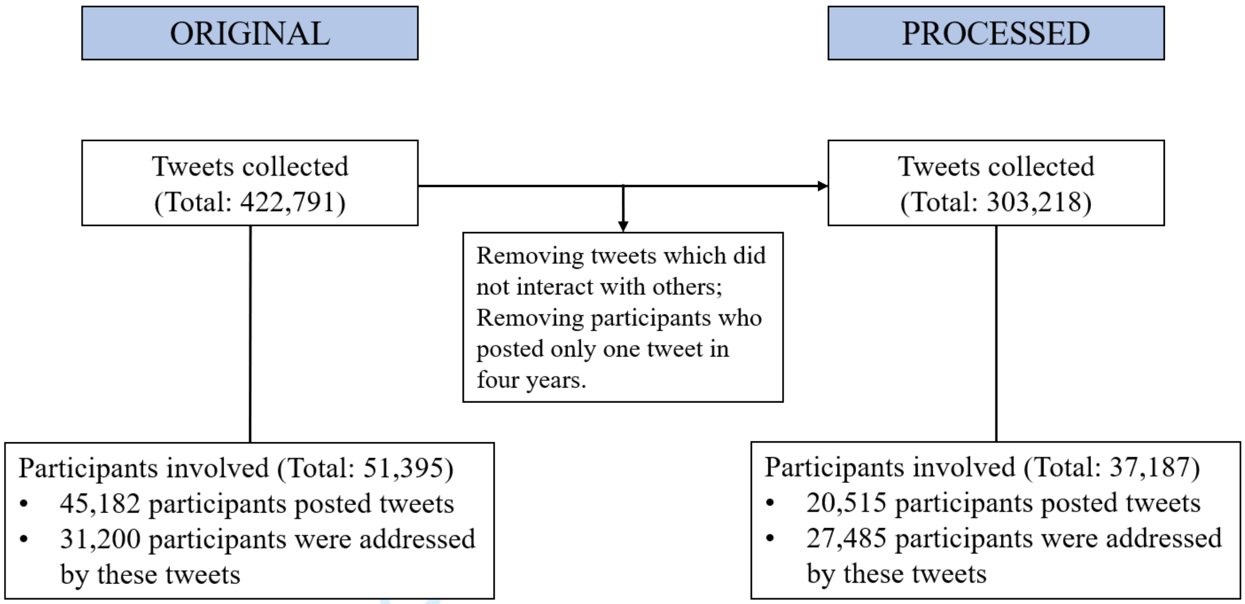


Figure 3 presents the preprocessing procedure of the dataset. The original dataset has a total number of 422,791 tweets and 51, 395 participants. These tweets were published by 45,182 participants. A total number of 31,200 participants were addressed by these tweets. It is worth mentioning that a participant who posted tweets can also be mentioned by another tweet in the network. In other words, participants who posted tweets and mentioned peers and those who were mentioned are not mutually exclusive. Then, those participants who did not interact with others or joined the online discussion only once were removed during the preprocessing procedure. This leaves us a total number of 303,218 tweets and 37,187 participants, which is approximately 71.72% and 72.36% of the original dataset, respectively. Among these participants, 20,515 participants published tweets, while 27,485 participants were mentioned by these tweets.

Figure 3

Preprocessing procedure



RQ2: Do hub participants emerge in the educators' online professional learning network? If so, what roles do they play in terms of connecting other participants?

A network was developed based on the processed data, and its descriptive statistics are shown in Table 1. The mean of node degree for the network graph of all participants is 21.50 (*SD* = 304.23). Based on the definition of Goldenberg et al. (2009), the hub node degree threshold of the network graph is 934. In other words, a node can be considered as a hub if its degree value is greater than 934. In total, 96 hub participants were identified. The largest hub participant is "cybraryman1", who connected with 36,758 of the 37,187 participants in the network graph.

Table 1

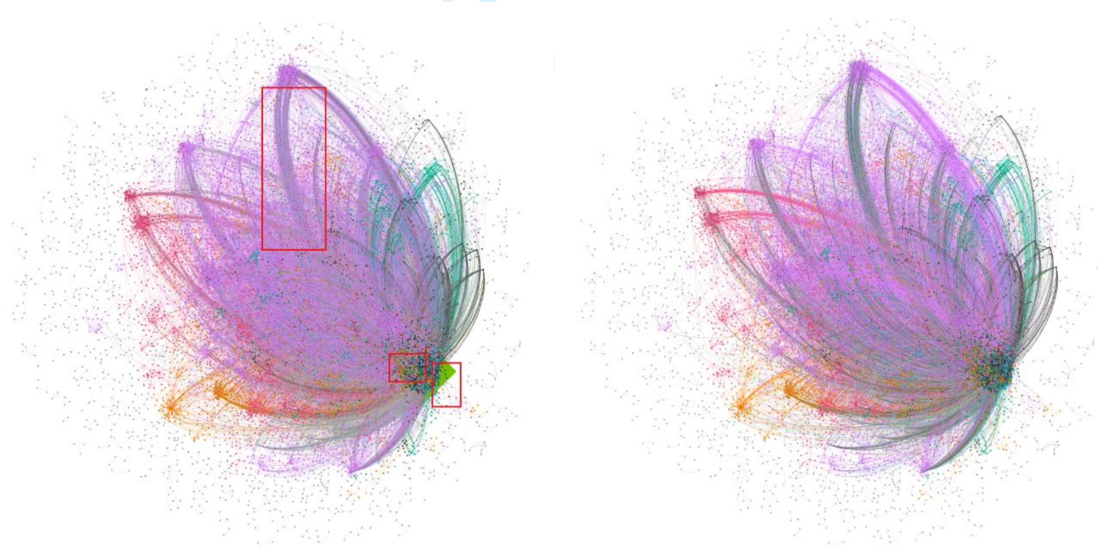
Statistics of the network before and after removing hub participants

	Network with Hub Participants	Network without Hub Participants
Number of edges	399,780	149,033
Number of nodes	37,187	33,760
Degree mean of nodes	21.50	8.83

We developed another network without the 96 hub participants, the new network's descriptive statistics are in Table 2 as well. When removing hub participants, those who were only connected with hub participants became isolated nodes, hence, removed. This left us a total number of 33,760 nodes and 149,033 edges, which is 90.78% and 37.28% of the network graph, respectively. It suggests around 10% participants only communicated with hub participants. In addition, a steep decrease on the number of edges was observed, which makes the mean of node degree 8.83. Figure 4 visualizes the network structure with and without hub participants. Different colors suggest different communities, while the red rectangles mark a few significant differences between the two network graphs. This change indicates that hub participants held a large number of connections in the informal online teacher communities.

Figure 4

View of the network with hub participants (left) and without hub participants (right)



To study the interaction between participants and their peers, we first identified the social best friend of each participant. It is worthwhile to mention that a social best friend was identified based on each participant's online interactions and such a relationship is not reciprocal. For example, a hub participant might be identified as the best friend of many participants, while their best friend is another hub participant. Then, we performed a Spearman correlation which is represented by r (or Greek letter ρ), between participants and their social best friends on posting quantity and posting days, respectively. The results are in Table 2. With or without hub participants, there is a statistically significant correlation between participants with their social best friend regarding both posting quantity ($r = .29$, $p < .001$; $r = .12$, p < .001) and posting days ($r = .20$, $p < .001$; $r = .04$, $p < .001$). However, the strength of the correlation was affected by the hub participants. Specifically, the removal of hub participants turns a moderate correlation ($r = .29$) into a weak one ($r = .12$). We speculate that the removal of hub participants has changed some members' social best friend, leading to a weaker correlation in the network without hub participants. Our results show that in general, participants' posting behaviors are similar to their closest peers'.

Table 2

Correlation for social best friend analysis before and after removing hub participants

	Network with Hub Participants		Network without Hub Participants	
	r	*p*	*r*	*p*
Posting quantity	.29	< .001	.12	< .001
Posting days	.20	< .001	.04	< .001

To better understand the role of hub participants in connecting other members, we calculated the assortativity for network with and without hub participants. The results are shown in Table 3. We observed an interesting change on the assortativity value before ($\Upsilon = -.05$, $p < .05$) and after removing hub participants ($\Upsilon = .04$, $p < .05$), suggesting the removal of hub participants transfers the heterogeneous network to a homogeneous one. In other words, in the heterogeneous network with hub participants, participants of low connections tended to communicate frequently with members of high connections. The pattern is opposite for the homogeneous network without hub participants: participants frequently communicated with members of a similar degree value. This indicates that hub participants were connected with many low degree participants, and low degree participants were likely to form indirect connections with each other through hub participants. Without hub participants, the similarity in degree value between participants and their neighbors increased.

Table 3

Attributes of the network before and after removing hub participants

	Network with Hub Participants	Network without Hub Participants
Degree assortativity (Υ)	–.05*	.04*
Number of nodes	37,187	33,760
Number of communities	501	824
Average nodes for each community	74.97	40.97

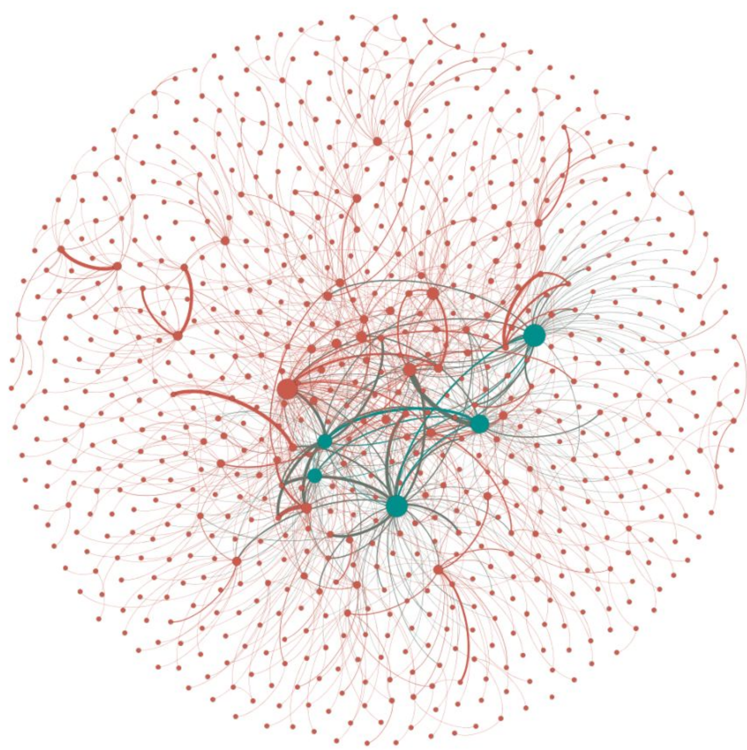
* *p <.05, using p-value formula for Pearson Correlation*

Then, we performed a community detection on both networks to explore the optimal community division (see Table 3). As aforementioned, 96 hub participants were identified. Using the same community detection algorithm and the same division threshold, the removal of 96 hub participants increased 64% (from 501 to 824) of the total number of detected communities. The average number of participants for each community decreased by 45%, from 75 to 41. Without hub participants, the rest of the participants formed more but smaller communities. Our results show that hub participants in informal online professional learning networks are the key to connecting many small communities, and to maintaining heterogeneity in the network.

As it is challenging to clearly visualize the structure of a massive network (see Figure 4), we randomly choose a community with hundreds of nodes to visualize how hub participants connect other participants, as shown in Figure 5. The selected community has 790 nodes and 2,617 edges. The modularity is 0.64, indicating the community is well divided from the network. There are five hub participants in this community, marked as green nodes. The red nodes are members of this community. The edges between the five hub participants and their neighbors are also marked in green. Participants in this community shared edges with other members of the network, but only connections within this community were displayed. Hence, the node degree represents only local connections instead of global connections. This is why some non-hub nodes are bigger than hub nodes. In the example community, hub participants' neighbors include both high degree nodes and low degree nodes, so do the other large red nodes. This example provides visual demonstration on our findings by showing how a detected community looks like and how participants are connected within a community.

Figure 5

The network graph of a community with hub participants



RQ 3. What are community members' interaction behavior patterns in different communities?

Table 4 shows the posting behavior statistics of 15 communities identified in the network hub participants. The community number represents the ranking of the community population.

The posting quantity and post days for each participant were calculated based on the network instead of local communities. The largest community has 13,173 participants including six hub participants. It is about four times the size of the second one which has 3,588 members in total. Some communities show a blend of very active and very inactive participants regarding posting quantity, with a high standard deviation. It is the same with posting days, although the differences among communities are smaller. Interestingly, the largest community has a relatively low standard deviation on posting quantity, while most large communities, especially those with hub participants, have a high standard deviation on both measurements. The case for small communities is opposite. Many, if not most of the informal online teacher communities appear more homogenous—participants of the same community have similar posting behavior patterns. These results are also consistent with the previous argument that hub participants are the key to maintaining heterogeneity in the informal online teacher network.

Table 4

Posting behavior statistics by community

			Posting Quantity		Posting days	
Community	Number of Participants	Number of Hub Participants	Mean	*Std.*	Mean	*Std.*
1	13,173	6	5.36	18.08	3.12	6.97
2	3,588	9	16.72	74.12	3.40	6.66
3	1,913	3	12.88	41.59	2.74	5.38
10	485	1	14.68	245.37	1.99	6.86
20	227	1	25.33	337.45	2.17	9.53
30	177	0	13.46	39.38	3.64	7.24

Community	Number of Participants	Number of Hub Participants	Posting Quantity		Posting days	
			Mean	*Std.*	Mean	*Std.*
40	145	1	10.44	91.20	2.16	6.59
50	115	1	15.06	120.05	2.52	10.10
60	72	2	22.76	102.50	2.81	6.53
70	42	0	13.04	40.60	3.07	3.91
80	11	0	1.55	4.89	0.73	2.30
90	8	0	0.63	0.86	0.50	0.71
100	6	0	2.67	3.73	0.50	0.50
200	3	0	1.33	1.25	1.33	1.25
300	2	0	1.00	1.00	0.50	0.50

Since neither the posting quantity nor posting days for each community follows a normal distribution, we performed a Kruskal-Wallis H-test to assess the correlation between community members and their posting behaviors. The Kruskal-Wallis H-test is a nonparametric rank-based test which can be used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable. The null hypothesis is that the population medians of all communities are equal. The results are shown in Table 5. Hub participants do not impact the heterogeneity between communities. With or without them, communities are statistically significant different from each other in terms of members' posting quantity and posting days. Therefore, community membership can be used as a measurement to teachers' participation in online professional networks. These results are consistent with the findings of community detection that teachers clustered with those who behave similarly in an informal online learning network.

Table 5

Kruskal-Wallis H-test of posting behaviors by community

	Network with Hub Participants		Network without Hub Participants	
	H	*p*	*H*	*p*
Posting quantity	1293.70	< .001	1363.31	< .001
Posting days	1108.48	< .001	1011.76	< .001

5. Discussion

Using social network analysis methods and one of the largest scale Twitter data (i.e., nearly half a million tweets), we explored the characteristics of educators' online PD network, whether hub participants emerged, what roles did they play, and if participants' posting behaviors differ in the communities. This study adds to the literature by responding to the lack of quantitative research using authentic data from social media in massive educators' online informal learning networks (Luo et al., 2020; Macià & García, 2016). Several interesting findings are worth discussion. First, participants' posting behaviors are closely correlated with that of their close peers. Second, hub participants emerged early and are the key to maintaining the large network. Without hub participants, members tended to form much smaller communities. Third, there are statistically significant differences in members' posting behaviors between communities.

The fact that we were able to a develop massive social network graph based on participant's interactions suggests the occurrence of social learning in Twitter among educators even without any formal or pre-determined structures. It extends previous research (e.g., Arslan et al., 2022; Trust et al., 2017; Macià & García, 2016; Xing & Gao, 2018) by providing further empirical evidence of educators' active participation in professional development using social network analysis. Educators tended to post information and interact with others over time, considering the mean of node degree and the existence of hub participants in the active network. This result aligns with previous research that suggests the effectiveness of Twitter as a tool to support the professional learning of educators (Krutka & Carpenter, 2016; Rodesiler & Pace, 2015). Educators participate in social network professional learning mainly to establish social connection and reduce a sense of isolation; better support students; inform thinking, shape practice and improve writing skills; and generate professional opportunities (Rodesiler & Pace, 2015). Furthermore, the teachers formed sub learning communities in which community members interact more with one another than with members outside their communities. This may be related with the specific interests of the sub learning communities. For instance, members with similar topics, choices, preference, practices or goals may be more likely to interact with each other (Bedi & Sharma, 2016). Further research is needed to understand why sub communities are formed, what their specific interests are, and how to support their learning by recommending appropriate materials and developing scaffolding strategies.

We found that in an informal professional learning environment, participants and their close peers share similar posting behavior patterns regarding the overall number of tweets posted and number of days for posting tweets. Meanwhile, participants formed many communities where members' posting behaviors were significantly different from those of other communities. This result is consistent with previous studies which suggest students' performance is related to that of their close peers in massive online learning settings (Brown, Lynch, Wang, et al., 2015; Xu et al., 2018). The significant positive relationship between participants and their closest peers in terms of posting behaviors can be used to develop prediction models to forecast members' tendency in continued participation based on their closest peers' participation. Meanwhile, the fact that the positive relationship was identified through a large-scale investigation of nearly half a million tweets and 50,000 participants will notably help increase the robustness of such a prediction model. These findings may contribute to future research in online informal professional learning network engagement, community development and network dynamics.

The results suggest that hub participants emerged at the early years of the network and are the key to connecting multiple heterogeneous communities, indicated by the increasing number of detected communities after removing the hub participants. It is worth mentioning that hub participants—who are defined as the ones with in- and out-degrees which are larger than three standard deviations above the mean—do not always exist. But when they emerge in a network, they are important to the network structure. Previous research suggests that instructors, teaching assistants and active participants in online learning communities are normally identified as hub nodes in a social network (e.g., Brown, Lynch, Eagle, et al., 2015; Brown, Lynch, Wang, et al., 2015). The results of this study confirmed that in online teacher professional development networking, some participants emerged as hub participants and connected different small groups of teachers with the larger communities or even network. Moreover, a number of participants merely interacted with hub participants, suggested by the difference in the number of nodes in the network before and after removing hub participants. In other words, hub participants are extremely important to the relationship between these participants and the learning network. Further research can further study the impacts of hub participants on online community structure and the mechanisms of distributed leadership, as suggested by the findings of this study and Macià and García (2016).

This study has significant theoretical, practical and methodological implications for future practice and research on teachers' online PD. Theoretically, the emergence of hub participants in the twitter-based online learning network suggests participants were able to self-connect and organize without predetermined structures. Meanwhile, a tutor or other authoritative roles being a hub node may negatively correlate with learner performance (Saqr et al., 2020). Together, the results suggest the possibility and importance of giving teachers more agency to explore and connect in future online PD, as well as the potential to study who tend to be hub participants in different learning contexts and their roles. Practically, given that educators were likely to interact more with the ones who had similar posting behaviors and who shared community membership, future PD activities can scaffold different communities based on their needs and interests. In addition, those who develop interaction with hubs/moderators only are worth extra attention and support to facilitate their participation. Methodologically, this study identified interesting characteristics of educators' informal online learning networks that can be used in other studies. Participants tend to communicate more with other participants who share similar characteristics, hence, develop communities over time. Participants' community membership can be used as a significant predictor in measuring online informal professional learning networks. Such community membership can also be used to monitor participants' online professional learning behaviors over time. Meanwhile, participants' posting behaviors are positively correlated with those of their close peers. Such correlation can be used as a measurement predictor to participants' learning gains and performance. Overall, community membership and learning behaviors are two related and important metrics which can provide characteristic descriptions for different communities of participants in an informal online learning network, which shall be recognized in future large-scale analysis work.

6. Limitations and future directions

Although the present study enriches understanding of the structure and characteristics of large-scale informal online professional learning networks, it has limitations. First, this study did not investigate the tweets content across communities or the participants' perceived sense of community. Therefore, the homogeneity and heterogeneity identified in this study hold in the context of behavioral analysis, rather than content analysis or participants self-reports. Future research can analyze the topics discussed by different communities, examine the relationships between topics and community structures and investigate the perception of participants within and across communities. Second, this study examined the informal online professional learning network using data from Twitter only, we cannot make a conclusive statement that the findings can be generalized to other social-media-based informal online learning networks. Third, this study developed one huge network at the end of the four-year data collection between 2011 to 2014. It will be interesting if future work could investigate the learning network during the Covid-19 pandemic, and study if participants' behaviors have changed during the pandemic. Future research may consider including the time dimension and studying how the communities formed overtime, for what reasons, and how the communities remained active. Finally, the roles of hub participants and their postings could be further examined. An investigation of the hub participants could potentially help researchers and educators to efficiently develop an overview of the interests and topics of the network, and then provide supporting materials or scaffold their PD. Studying hub participants can also inform strategy designs that help sub communities to make intra-community communications and to bridge their discussions, knowledge and practice.

7. Conclusions

In this study, we use a social network method to research educators' social interactions in an informal massive online professional learning network using authentic data collected from Twitter. Specifically, we examined discourse and participation characteristics of an online PD network, the interactions between participants and their peers, whether hub participants emerge and the impacts of hub participants on the network structure. We found that participants tended to communicate more with the ones who shared similar posting behaviors patterns (i.e., both posting quantity and posting days). Hub participants are important to the degree heterogeneity in a large network as they are the key to connecting many small communities to forming a big one. Meanwhile, these small communities are significantly different from each other in terms of posting behaviors. Overall, this study suggests the emergence of hub participants in an informal online PD network without predetermined structures and the possibility of scaffolding online PD based on community membership.

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