Received: 25 June 2021 | Revised: 22 November 2021 | Accepted: 28 November 2021

DOI: 10.1111/jcal.12633

ARTICLE

Journal of Computer Assisted Learning WILEY

Understanding topic duration in Twitter learning communities using data mining

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Abstract

Background: There has been increasing interest in online professional learning networks in a variety of social media platforms, especially in Twitter. Twitter offers immediacy, personalization, and support of networks to increase professional knowledge and the sense of membership. Knowing the topics discussed in Twitter and the factors that affect the duration of a topic would help to sustain and reconstruct Twitter-based professional learning activities.

Objectives: The purpose of this study is to analyse the topics discussed and what factors affect the duration of a specific topic in 6 years within a virtual professional learning network (VPLN) using #Edchat in Twitter, based on media richness features.

Methods: Internet-mediated research and digital methods are used for data collection and analysis. Various text, natural language processing, and machine learning algorithms were used along with the quantitative multilevel models. This study examined 504,998 tweets posted by 72,342 unique users by using #Edchat.

Results: There were 150 topics discussed over the 6 years and multilevel random intercept regression model revealed that a specific topic discussed in the #Edchat VPLN is discussed longer when it has more tweets, rather than retweets, posted by a high number of different users along with moderate text, high or moderate mentions with more hashtags.

Takeaways: The study developed an automated social media richness feature extraction framework that can be adapted for other theoretical applications in educational context. Emergent topics discussed in Twitter among #Edchat VPLN members for professional development were identified. It extends the social media richness theory for educational context and explore factors that affect an online professional learning activity in Twitter.

KEYWORDS
educational data mining, learning analytics, learning networks, social media, teacher professional development

1 | INTRODUCTION

Over the past 20 years, there has been a paradigm shift gathering momentum about the professional development of teachers. Although traditional professional development approaches have a somewhat discouraging history (Sprinthall et al., 2016), the rise of Web 2.0 and social media sites over the last decade has inspired optimism among some educators. Arslan (2013) discussed the professional development strategies and revealed that educators need not only face-to-face but also online training settings that can be held synchronously and asynchronously, due to their other administration duties and time concerns. In this sense, virtual networks have started to use both synchronous and asynchronous Web 2.0 and social media platforms where they may exchange information and develop a sense of belonging with others who share common interests (Davis, 2015; Gao & Li, 2019; Hennessy et al., 2016).

Twitter has been offering a variety of opportunities for different kind of professional learning and development for educators by creating efficient communication and increased sense of community and shared learning (Gao & Li, 2019; Hitchcock & Young, 2016). Theoretically, Twitter offers professional development opportunities by using moderated chat sessions that differ from traditional approaches (Xing & Gao, 2018; Delello & Consalvo, 2019) and have a positive influence on participant's professional learning and development (Nochumson, 2020) because of its immediacy, personalization, and support of networks that are less temporally or spatially limited. Thus, in recent years, Twitter has been one of the emergent professional development tools both teachers pursuing their professional learning and the researchers investigating such activities (Carpenter et al., 2020). Adjapong et al. (2018) identified the Twitter chats and discussions for professional learning as Virtual Professional Learning Networks (VPLN), so VPLN is going to be used as the main terminology for this study.

There have been a great number of hashtags in Twitter for educational context and those hashtags are used by teachers to find information and resources and gain new perspectives and ideas from their colleagues or experts (Prestridge, 2019). For example, #Edchat is one of the hashtags that is used worldwide as teachers' VPLN (Xing & Gao, 2018; Britt & Paulus, 2016; Davis, 2015; Gao & Li, 2017; Staudt Willet, 2019). Participants provided examples of ways in which Twitter professional development resulted in concrete changes in their teaching and also described cases of Twitter connections leading to interactions with colleagues. Twitter plays an important role in engaging educators in informal, just-in-time professional learning (Xing & Gao, 2018; Britt & Paulus, 2016; Donelan, 2016; Greenhalgh et al., 2020; Greenhalgh & Koehler, 2017), and educators can enrich their educations by participating in VPLNs (Holmes et al., 2013). To be able to lead a systematic change or create a change within an existing system, the professional learning activities not only should be systematic but also must be sustained over time (Raphael et al., 2014; Sturm & Quaynor, 2020). Administrators, leaders, and community members can foster using professional learning environments, such as Twitter, to offer convenient learning activities for educators to share new skills and reflect on them (Jensen et al., 2016). Although Twitter chats allow convenient participation and collaboration opportunities for VPLNs, it can be challenging to sustain a discussion topic within VPLNs (Darling-Hammond et al., 2017; Sturm & Quaynor, 2020). There has been great amount of studies about using Twitter and its affordances for professional development of educators, but there are very limited empirical studies that investigating the topics and the duration of the specific topics discussed in a VPLN. Additionally, social media richness has been studied in non-educational context to measure richness of a tweet and discuss its effect on the desired outcome (Baym, 2015; Tanupabrungsun & Hemsley, 2018). Nonetheless there is not any social media richness studies in educational context for Twitter use. It is important to investigate the richness of a Tweet and understand the factors that affect duration of a topic discussed in a VPLN. Thus, the main focus of this study is to (1) explore the topics discussed online on Twitter and (2) to examine the factors that affect the duration of a topic discussed within a VPLN using #Edchat in Twitter, based on media richness features.

2 | LITERATURE REVIEW

2.1 | Twitter as a professional learning tool in VPLNs

Traditional teacher professional development has been characterized by a focused purpose with a more specific and simple topics to address broader needs of teachers (Opfer & Pedder, 2011; Trust et al., 2016). However, significant number of teachers believe that traditional professional development might not address all their needs or is not efficiently support their professional development goals (Darling-Hammond et al., 2017; Trust et al., 2016) Hence, teachers have been engaging in a variety of formal and informal professional development activities by participating in different conversations in different formats, using and sharing resources in face-to-face and online settings (Carpenter & Linton, 2016; Trust, 2015; Trust et al., 2016). One of the methods that have been using by the teachers is creating a VPLN. VPLNs provide opportunities for teachers by making it accessible anytime and anywhere and by addressing teacher's diverse needs and interests to support their professional development (Adjapong et al., 2018). Using social media is one of the most prefer method that has been used by VPLNs.

Twitter has multiple features. A tweet can be a single text, a retweet that originally tweeted by someone else, a reply that following an original tweet. Those can also contain usernames to mention other within the tweet or hashtags (i.e. #Edchat) to group the posts together by a certain context. Using Twitter as a tool for VPLNs, specifically using a specific hashtag for educators, can offer professional learning and development opportunities by creating efficient communication, increased sense of community and shared learning because of its immediacy, personalization, and support of networks that are less temporally or spatially limited (Carpenter & Krutka, 2014; Gao & Li, 2019; Greenhalgh et al., 2020; Hitchcock & Young, 2016; Hsieh, 2017). Using hashtags for moderated chat sessions is one of the most beneficial features and plays an important role in engaging VPLN members in informal, just-in-time professional learning (Xing & Gao, 2018; Britt & Paulus, 2016; Donelan, 2016; Greenhalgh et al., 2020; Greenhalgh & Koehler, 2017), and thus let educators enrich their knowledge and professional development by participating in VPLNs (Holmes et al., 2013).

There are a great number of studies that have aimed to discover why educators prefer to use social media such as Twitter for professional development. Those studies reflect a wide range of perspectives on how and why educators use Twitter for their professional learning. For instance, Prestridge (2019), investigated the reasons for actions in social media by conceptualizing "self-generating professional learning" (p. 129) and reported four types of self-generating approaches for professional learning to be used by VPLNs while designing the learning activities on social media. These are; "Info-consumer, Info-networker, the Self-seeking contributor and the Vocationalist" (Prestridge, 2019, p. 151). In another study, Sturm and Quaynor (2020), examined the Twitter discourse and its components for effective professional development learning activities. They discussed that educators focus on content, collaboration, and teacher organizations in order to seek peer coaching and sustain the duration of a topic discussed on Twitter. Additionally, the influence of Twitter chat on teachers' professional learning process were examined with a mixed method study by surveying 107 elementary teachers and interviewing 19 of them (Nochumson, 2020). Results revealed that there were significant association between teachers' moderated Twitter chat participation and implementing the ideas they had acquired from the chat session. While 88% of the teachers reported implementing those new ideas and teaching methods, 81% of them stated that the classroom teaching strategies has been changed after their moderated Twitter chat participation.

In another study, Xing and Gao (2018) inspected a one-hour just-in-time Twitter chat conversation content with #Edchat by following Moon et al. (2014)'s successful professional development characteristics. According to those results, they found that the chat was successful in terms of professional development, and the content contained the necessary characteristics such as conversation that was embedded in the subject matter, connected to topics that address educators' own practices, and contained active understanding and problem solving.

Nonetheless, few studies have investigated the long-term professional development activity participation in Twitter-based VPLNs (Xing & Gao, 2018; Donelan, 2016; Greenhalgh et al., 2020; Greenhalgh & Koehler, 2017; Staudt Willet, 2019), and there was no any study has focused on identification of factors that impact the duration of a topic discussed in a such activity in educational context. In this regard, it is essential to investigate the factors of a long-term activity to reveal the knowledge that could help researchers to understand how to manage such activities for VPLNs in a social media context (Veletsianos, 2017). There were quite a few studies about exploring trending topic durations and information diffusion in Twitter (Ma et al., 2012; Stai et al., 2018; Tran et al., 2014; Wang & Zheng, 2014). Those studies examined the tweet features such as content and contextual properties, hashtag length, tweet number, user number, retweet number, and duration of a hashtag. However, none of these were in educational context. Thus, it is important to consider tweet features while examining duration in Twitter studies.

There have been a great number of studies that used traditional social science methods, such as content analysis, to inspect a variety of subjects with a relatively limited number of tweets (Xing & Gao, 2018; Greenhalgh & Koehler, 2017; Staudt Willet, 2019). Although text classification has been used within text-based data sources such as Twitter, there are quite a few studies that have used text classification to investigate the professional development in Twitter-based VPLNs. Xing and Gao (2018) applied such classification technique to more than 600,000 tweets to classify them according to online discourse dimensions, which are cognitive, interactive, and social. After classifying the tweets, they conducted survival analysis to examine the effects of those dimensions on online Twitter-based community members' involvement in the learning network. In addition to this, Staudt Willet (2019) used text mining classification to automatically classify 1.2 million #Edchat tweets posted from 200,000 different users to investigate the types of tweets that educators contribute to a specific VPLN. The results of the study showed that #Edchat has been used generally for utilizing new ideas, rather than sharing emotions. Pla and Hurtado (2014) also implemented text classification method to identify the political leanings of the authors of 68,000 tweets. Irani et al. (2010) used text classification to examine 1.3 million tweets to identify the popular topics for media research on Twitter. This study stands on previously established text classification algorithms to classify tweets automatically according to social media richness dimensions.

Current literature revealed the macro-level questions about using Twitter in educational context. This literature review found that there are very limited studies on micro-level Twitter studies about topics all of which are non-educational context. Thus, this study tries to fill the gap in the literature by bridging two research areas, macro-level educational research and micro-level non-educational research, and expand the literature to address micro-level Twitter study in educational context.

3 | THEORETICAL FRAMEWORK AND RESEARCH QUESTIONS

3.1 | Social media richness

Social media richness uses the fundamental roots of media richness theory proposed by Daft and Lengel (1986). According to them, this conceptual framework is used to examine a media platform and its properties while transmitting rich information to audiences with a reduced obscurity. This framework, also, discussed that just as we have different channels (i.e., senses) in a face-to-face speaking setting, such as mimics, tone of voice, and gestures that affect the richness of a spoken information, written memos have the same channel features in its text, context, and formatting. These lead us to think that some media features, channels, or their combination might have richer information than the other ones, which could make the message understandable or meaningful. With the development of new technologies and media, in accordance with Daft and Lengel's (1986) framework, recently developed media offer a variety of media use strategies (Brinker et al., 2015; Tanupabrungsun & Hemsley, 2018) by plugging different channels—images or emojis—into pure text formats, such as emails or social media posts, which can be richer than plain texts. Different organizations can select different media channels to fit their needs (Daft & Lengel, 1986), and thus they should manipulate or combine different technologies to find their best options (Baym et al., 2004). In this regard, from the social media perspective, it can be articulated that the richness of a social media post varies according to how it is structured and constructed. In terms of Twitter, it is seen that Twitter provides some action and other features such as retweet, favour, mention, and hashtag (Kaptelinin & Nardi, 2012) that could have a cue role to make a tweet richer than without adding any cues. To increase the meaning of information shared among senders and audiences, it is expected that richer tweets are more efficient to deliver messages in a meaningful way (Baym, 2015; Berger, 2010; Tanupabrungsun & Hemsley, 2018).

To measure richness of a tweet, a Tweet Quality Assessment Framework (TQAF) was developed by Tanupabrungsun et al. (2016) by following media richness theory elements. They classified three dimensions for social media richness of a tweet: (1) informational richness, (2) interactional richness, (3) contextual richness. According to the framework, while informational richness can be measured according to tweet length, URLs, and embedded content such as image, videos, and GIFs, interactional richness can be calculated by mentions, replies, retweets, or quotes. Contextual richness, on the other hand, is measured just by the number of hashtags (#) in a tweet.

This study is first of its kind that uses the TQFA in educational context, specifically within professional development. This framework will help to evaluate the richness of a tweet and examine how the richness elements affect the duration of a topic discussed in a VPLN #Edchat to better understand the use of Twitter by educators as a professional development tool.

3.2 | Research questions

According to the literature, we found it necessary to understand the factors that affect the duration of a topic discussed in a VPLN in Twitter by identifying media richness features of the tweets. Therefore, we proposed two research questions as follows:

1. What topics were discussed online on Twitter in six years in a VPLN #Edchat?
2. What are the social media richness and other factors that affect the duration of a topic discussed in a VPLN #Edchat?

4 | METHODOLOGY

Conventional methods are insufficient to provide the evidence needed to answer our research questions well; thus, we used contemporary methods and techniques such as Internet-mediated research (Hewson, 2017), and *digital methods* (Greenhalgh et al., 2020; Snee et al., 2016), for data collection and analysis. In this study, various text and natural language processing algorithms (Xing & Gao, 2018; Greenhalgh et al., 2020) were used along with the quantitative multilevel models (Browne & Rasbash, 2004; Greenhalgh et al., 2020) to collect and analyse computationally both quantitative and textual data.

4.1 | Participants and sample

The participants of this study are 72,342 Twitter user educators from all over the world who attended to weekly synchronous chats on Twitter by using #Edchat. Collected 643,347 #Edchat tweets over 6 years were preprocessed, cleansed, and transformed for the analysis, and as a result there were 504,998 tweets as the sample of this study.

4.2 | Context and data set

As there has been so much different topics discussed by using #Edchat, the study was designed to explore the factors that affect topic duration of a discourse in a Twitter-based VPLN by examining social media richness and tweet post features. Social media richness features consist of informational, interactional, and contextual richness. Tweet posts, on the other hand, can be listed as number of tweets, number of retweets, and number of unique users. Educators have been using #Edchat since 2009, and it is one of the most popular hashtags in educational contexts have been used worldwide. Educators from all over the world can participate in weekly synchronous chats by using this specific hashtag to discuss common interests and needs, to share ideas and resources, and to engage in conversation on different topics as a VPLN member. Weekly synchronous chats are held every Tuesday as two sessions, the first session at 12:00 p.m. and the second session at 7:00 p.m. Eastern Standard Time (GMT-5). Each session begins with the initial post of the facilitator, and participants join the discussion by using #Edchat in their posts to discuss or reflect on different topics. Educators can post original tweets, retweet an existing tweet, reply to an educator or mention any user in the tweet, and can add other hashtags to expand the context of a tweet. Twitter data is public and open to everyone and can be collected via web scaping and/or APIs, however to eliminate ethical issues, we used deidentified data as our focus was on the topics rather than the users. The descriptive overview of the number of tweets over the years is represented in Figure 1.

4.3 | Data analysis and instruments

4.3.1 | Social media richness automatic classification

As there were more than half a million tweets, manual qualitative techniques such as hand-coded analysis would be impractical and would need a tremendous amount of both effort and time. To analyse those 504,998 tweets, we constructed a text classification model to identify the media richness features of each tweet. To build and

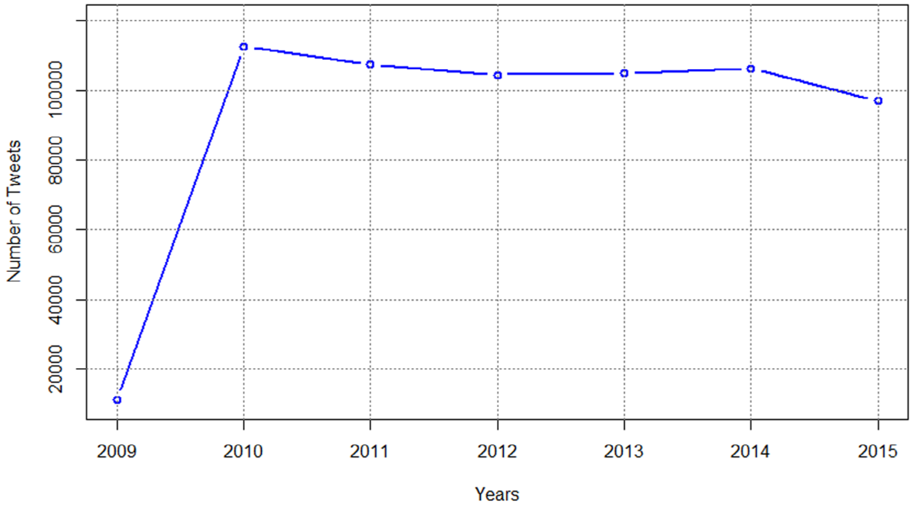

FIGURE 1 Number of tweets over the years [Colour figure can be viewed at wileyonlinelibrary.com]

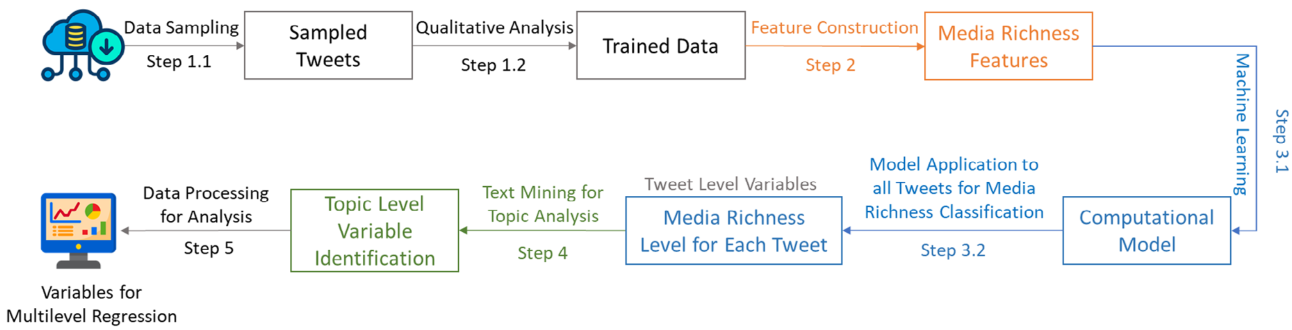

FIGURE 2 Automatic classification workflow [Colour figure can be viewed at wileyonlinelibrary.com]

validate such a model, three main steps (from Step 1.1 to Step 3.2) were followed, as indicated in Figure 2. To proceed through the steps, first, a small random sample of tweets were categorized manually by human coders into different levels of media richness features. Then, the agreed judgements are used as trained data. After that, a set of features are transformed to be used in machine learning algorithms. As a final step, a text classification model is built and validated to identify the informational and interactional media richness features of the tweets by applying and conducting various algorithms.

The classification of media richness in this study was based on a TQAF framework (Tanupabrungsun et al., 2016), which has three dimensions: (1) informational richness, (2) interactional richness, (3) contextual richness. According to the framework, while informational richness can be measured with tweet length, URLs, and embedded content such as image, videos, and GIFs, interactional richness can be calculated with mentions, replies, retweet, or quotes. Contextual richness, on the other hand, is measured just with the number of hashtags (#) in a tweet. In this regard, the automatic classification method is used to detect informational and interactional richness features.

Automated media richness extraction was developed to be used as an instrument in this study. In order to create the trained data, as in Step 1.1, 4000 tweets were randomly selected from the whole dataset. Then, 1000 of the tweets were used to generate the coding schema by applying a qualitative analysis technique as in the Step 1.2. To do so, two researchers from the authors worked collaboratively to build the coding scheme by using Chi's (1997) top-down and bottom-up procedures to identify the levels (high, medium, and low) for each richness feature. In the process of top-down, a preliminary code set was built according to the existing researches explained in the literature review. Bottom-up procedure was followed to assess each sampled tweet, one by one, to develop the initial codes set in an iterative process by reassessment and revisions until finding a constant, converged set of codes (Strauss & Corbin, 1998). The code scheme (see Table 1) was finalized by comparing a top-down and bottom-up set of codes. For validity, two researchers worked together to discuss and resolve possible conflict or disagreement during the process. Another 1000 tweets were also coded by the two researchers independently to examine the inter-rater reliability. As a result, Cohen's Kappa inter reliability reached a high level of agreement ($k = 0.89$ for informational, $k = 0.91$ for interactional) for both features to allow each researcher to code the rest of the remaining trained data.

As the media richness framework (Tanupabrungsun et al., 2016) has three dimensions and we only need automatic detection for informational and interactional richness, three features were constructed by following similar algorithms with Xing and Gao (2018), and Greenhalgh et al. (2020) as in Step 2 (see Figure 2), namely Linguistic

TABLE 1 Tweet coding scheme description and examples

Richness features	Description (Tanupabrungsun et al., 2016)	Tweet examples
Informational Richness	Informational richness can be measured with tweet length (original post text), URLs, and embedded content (i.e., photos, videos, and GIFs). Tweet length reflects the idea that more text will generally be less ambiguous and more apt to promote understanding than less text. As such, longer tweet text is scored higher. Note that URLs, #hashtags, @usernames, and retweet artefacts (RT @username: Xyz) are removed before calculating tweet length to prevent double counting the affordances.	Low: RT @User1[a]: Learning takes place everywhere. And anytime. #Edchat Medium: @User2[a] I hope so too. #Edchat High: One way is "Doing the Interactive Flip w/ VoiceThread." http://tinyurl.com/FolmerFlip #Edchat
Interactional Richness	Interactional richness can be measured with @mentions, @replies, and retweets or quotes. Retweets are treated as a form of information diffusion. Note that any @mentions after a retweet artefact were not counted as everything after RT is counted as a retweet. For a manual retweet like "@xyz RT @abc": only @xyz would be counted.	Low: #Edchat I am imagining blended lrng environments. Medium: @User3[a] Exactly. No need to try and cookie cutter it. #Edchat High: @User4[a] @User5[a] "wondering if all learning will evolve into 'blended' learning as tech more infused…" Yes I think so. #Edchat
Contextual Richness	Contextual richness can be measured with the number of hashtags. Users might embrace hashtags to specify one or more contexts for their message.	4: http://bit.ly/fggmGq What I am using for Office Suites in my classroom. #education #Spedchat #productivity #Edchat

[a]The real usernames are kept anonymous.

Features (LF), Linguistic Inquiry Word Count (LIWC), and Regular Expression (regex) features (See Pennebaker et al., 2015). In addition to existing algorithms, during the training data development phase, researchers came up with a variety of rules that could determine the level of information and interaction. These rules were used in the third feature as regex in our automatic text classification. For instance, the informational richness can be assessed by combining three identified features. If a tweet has a full sentence structure (e.g., has at least a pronoun, a verb, and a topic) and contains any URL, its informational richness would be "high." However, if the post has neither full sentence nor URL, or just one word with/without a question mark, the level of information would be "low" for that specific tweet. What is more, if the tweet has at least two out of three interactional features (e.g., @mention, @replies, retweet) the interactional richness level of that tweet would be "high"; otherwise "medium" or "low." The examples of the features are represented in Table 2.

TABLE 2 The coherence scores of *K* values

K value candidates	Coherence score
50	0.3344
100	0.3197
150	0.3591
200	0.2426
250	0.2498
300	0.2493

As a third step, supervised machine learning algorithms (Kotsiantis et al., 2007) using Python scikit-learn (Pedregosa et al., 2011) were applied as in Step 3.1 by comparing four different classification models, namely Naïve Bayes, Logistic Regression, Support Vector Machines (SVM), and Random Forest. Those models were compared according to their prediction accuracy of manually coded features by using various features and algorithms. Among four machine learning models, the random forest prediction model was the most accurate one, with 90% for informational richness. For interactional richness, on the other hand, logistic regression was found to be the most accurate model, with 84% accuracy. Those text classification models were used to identify richness levels for the rest of the tweets.

After calculating the best prediction model for each media richness feature (e.g., informational and interactional), the corresponding model is automatically applied to classify the rest of the tweets, as in Step 3.2. Additionally, as the contextual richness feature is just about the number of hashtags (#) in tweets, the system will also extract the contextual richness features automatically alongside the other two richness features in order to be further used for multilevel regression analysis.

4.3.2 | Topic modelling

To conduct the topic analysis, Latent Dirichlet Allocation (LDA) was used as a text mining algorithm, as in Step 4 (Figure 2) using Python gensim (Rehurek & Sojka, 2010). LDA is a probabilistic text mining model commonly used for topic modelling in natural language processing (Blei et al., 2003). It is essentially an unsupervised clustering algorithm, which automatically discovers common topics that appear among a collection of text documents (See Jacobi et al., 2016; Nikolenko et al., 2017; Xing & Gao, 2018; Xing et al., 2018).

We used gensim library (Rehurek & Sojka, 2010) in Python for topic modelling and scikit-learn (Pedregosa et al., 2011) for text classification. First, Document Term Matrix (DTM) was identified to set the number of K value candidates, which gives the optimum number of topics by examining the perplexity. Also, coherence scores were calculated and compared to build the classifier. In topic modelling, a tweet is likely to classify into several topics. To overcome this issue, we used the highest probability to classify a tweet to a single topic. Additionally, for a better understanding, a visualization technique, namely word clouds, was used to facilitate the discovery of patterns found in each topic. In a word cloud, the frequencies of word usage are visualized through word size; words in larger font sizes appear more frequently than those in smaller font sizes. Moreover, colours help to relate one word to another. Words in a same colour have the same effect on deciding the topic name. After conducting machine learning and text mining algorithms, variables were set for multilevel regression model analysis.

4.3.3 | Multilevel regression and random intercept model

Multilevel regression modelling is an approach that can be used to handle nested or grouped data (Browne & Rasbash, 2004). The main benefits of using multilevel regression models is that we could generalize to a wider population while information can be shared between groups among different level variables. For instance, Twitter data, in this study, is nested within the topics discovered in topic modelling. Each individual tweet hierarchically belongs to a topic as students belong to a class in a school. This hierarchy might violate the assumptions for independence that could over-predict the confident for effects. To prevent such issues, we used the lme4 R package (Bates, Maechler, Bolker, & Walker, 2014) to estimate multilevel intercept models. Multilevel regressions have a variety of models, and a random intercept model is one of them (See Cohen, 2003; Fidell & Tabachnick, 2007; Garson, 2012).

The equation of a model is calculated for each level as indicated in Equations (1) and (2) and combined accordingly (Fidell & Tabachnick, 2007).

$$Y_{ij} = \beta_{0j} + \beta_{1j} X_{ij} + e_{ij} \tag{1}$$

$$\beta_{0j} = \gamma_{00} + \gamma_{01} W_j + u_{0j} \tag{2}$$

4.3.4 | Dependent variable

The dependent variable of this study is the duration of a topic discussed in a VPLN. As the sessions were held weekly, the duration was considered in weeks rather than other date/time formats. The weeks were calculated by the topics' occurrence within live chat sessions according to the date. For instance, Topic A is discussed for 4 weeks if it is discussed in week 1, week 8, week 9, and week 10.

4.3.5 | Independent variables

There are six independent variables for this study: (1) Informational Richness, (2) Interactional Richness, (3) Contextual Richness, (4) Number of Tweets, (5) Number of Retweets, and (6) Number of Unique Users. There are two levels of variables (tweet level, topic level) that are put in the equation simultaneously for the multilevel random intercept model.

5 | RESULTS

5.1 | Topic modelling results

The result of coherence score analysis revealed that, as can be seen in Table 2, the most appropriate number of topics (*K* value) was found as 150. Then, the tweets were nested by topics, and each topic has a variety of number of tweets.

As explaining all the 150 topics would be unrealistic for this study, we only showcase six examples of the most discussed topics and their duration to give the readers insights (see Figure 3a–d). Those topics were discussed almost every week. Topic 7, *Creating, changing school culture*, and Topic 23, *Classroom management, teaching methods*, are discussed for 322 weeks and followed by Topic 35, *Classroom settings, Educational technologies* (321 weeks), and Topic 112, *Support – Needs* (320 weeks).

5.2 | Multilevel regression results

To identify the best fitted model for random intercept model, three different models were constructed for comparison. Keeping level 1 variables (Social media richness features – tweet level) constant, we added level 2 (topic level) variables, step by step, to compare the candidate models by calculating Bayesian Information Criterion (BIC) for each model. According to Schwarz (1978), the model with the lowest BIC is the indicator for best fitted model, and thus, it should be preferred for the main analysis. The results revealed all models are significantly different from each other and Model 3 is to be the best fitted one with the lowest BIC score (see Table 3).

As can be seen in Table 4, the multilevel random intercept regression model was found to be significant (β = 1.755 [SE = 0.01], ICC = 0.90, $p < 0.001$) with a *medium* overall effect size ($R^2 = 0.65$) (Cohen, 2003) for duration of a topic discussed with #Edchat in online professional learning activity. The equation of the model is represented in Equations (3) and (4).

$$D_{ij} = \beta_{0j} - 0.064(\mathrm{InfL})ij + 0.054(\mathrm{InfM})ij - 0.135(\mathrm{IntL})ij - 0.004(\mathrm{IntM})ij + 0.004(\mathrm{C})ij + e_{ij} \tag{3}$$

$$\beta_{0j} = 1.755 + 0.002(\mathrm{NT})j - 0.001(\mathrm{NR})j + 0.005(\mathrm{NU})j + u_{0j} \tag{4}$$

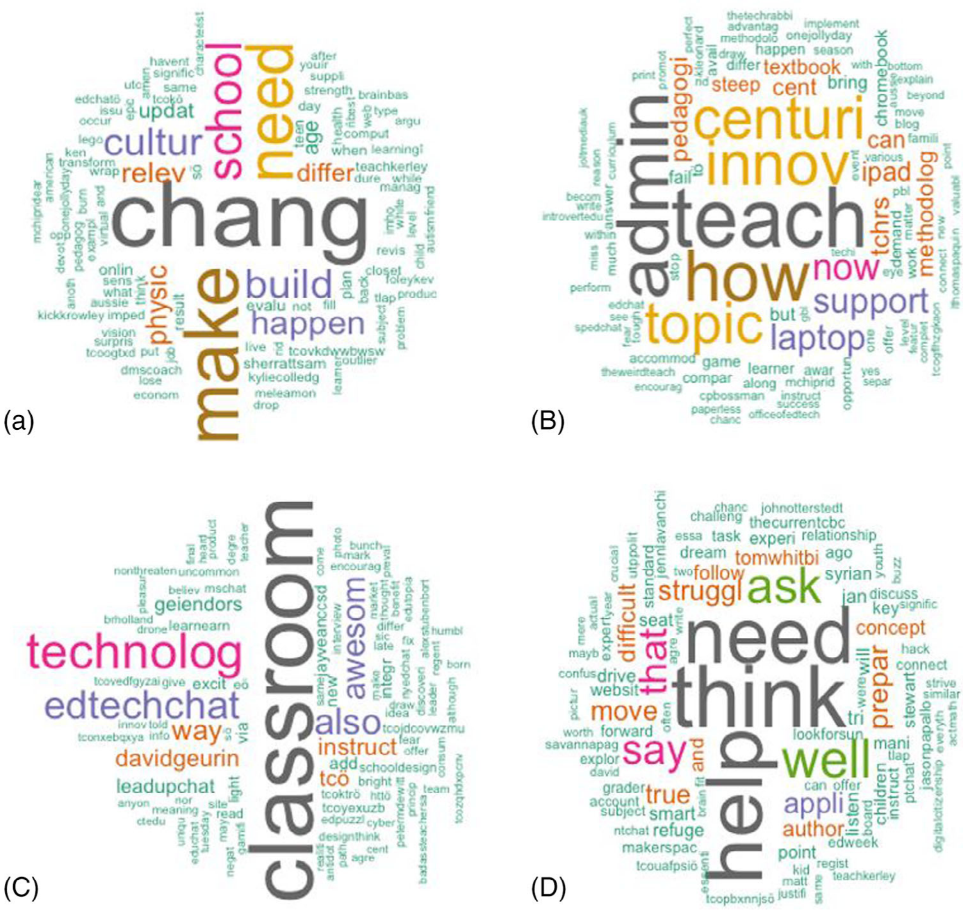

FIGURE 3 (a) Topic 7: Creating, changing school culture; (b) Topic 23: Classroom management, teaching methods; (c) Topic 35: Classroom settings, educational technologies; (d) Topic 112: Support, needs [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 3 The multilevel model comparison

Models	IVs	df	BIC	x^2
Model 1	Informational	9	−10,868,193	
	Interactional			
	Contextual			
	Number of tweets			
Model 2	Informational	10	−10,928,277	60085.4***
	Interactional			
	Contextual			
	Number of tweets			
	Number of retweets			
Model 3	Informational	11	−10,935,198	6923.1***
	Interactional			
	Contextual			
	Number of tweets			
	Number of retweets			
	Number of unique users			

Abbreviation: IVs, independent variables.
***$p < 0.001$.

Note: *D*, Duration; NT, Number of Tweets; NR, Number of Retweets; NU, Number of Unique Users; InfL, Informational Low Richness; InfM, Informational Medium Richness; IntL, Interactional Low Richness; IntM, Interactional Medium Richness; *C*, Contextual Richness.

The effects of social media richness (Level 1) variables were compared and the results revealed that a specific topic is discussed significantly longer on Twitter when a tweet has *medium informational richness* ($p < 0.05$), and significantly shorter when it has *low*

TABLE 4 Multilevel random intercept model summary

Fixed effects	Data level	B	SE	R^2	ICC
Intercept		1.755	0.01***	0.65	0.90
Informational richness low	Level 1	−0.064	0.006***		
Informational richness medium	Level 1	0.054	0.025*		
Interactional richness low	Level 1	−0.135	0.009***		
Interactional richness medium	Level 1	−0.004	0.008		
Contextual richness	Level 1	0.004	0.002*		
Number of tweets	Level 2	0.002	0.0001***		
Number of retweets	Level 2	−0.001	0.0001***		
Number of unique users	Level 2	0.005	0.0004***		

Note: Obs: 504,998, groups: 150 (Topics). Reference categories were *Informational Richness High*, and *Interactional Richness High* to corresponding categorical variables.
***$p < 0.001$; *$p < 0.05$.

informational richness ($p < 0.001$) compared to *high informational richness*. In terms of interactional richness, there is no significant effect difference between *medium* and *high interactional richness* ($p > 0.05$) and results showed that topics with *low interactional richness* stay significantly shorter ($p < 0.001$) on Twitter compared to *high interactional* ones. Moreover, topics with greater number of *contextual richness* discussed significantly longer ($p < 0.05$) on Twitter. When compared the level 2 effects, it is seen that the duration of a topic discussed in Twitter is expected to increase significantly when a topic has a greater *number of tweets* ($p < 0.001$) and *number of unique users* ($p < 0.001$), and a smaller *number of retweets* ($p < 0.001$).

6 | DISCUSSION

Educators can benefit from VPLNs in a number of ways to communicate with their colleagues, improve their professional development, and share ideas and resources. In this study, results showed that informational, interactional and contextual social media richness, as well as number of tweets, retweets and unique users have effect on duration of a topic discussed in VPLN #Edchat. In other words, a specific topic stays longer when it has more tweets, rather than retweets, posted by a high number of different users. Topics that have moderate text, high or moderate mentions with more hashtags are discussed longer on Twitter. This might suggest that the duration of a topic can be changed according to the educators' behaviours in online chat. Thus, it is important to increase the number of active participants for a topic to make that topic discussed longer.

These findings align with other studies in the literature that express the importance of interaction in Twitter-based VPLNs. To increase interaction in Twitter settings, different strategies could be implemented. For instance, Davis (2015) expressed the importance of a sense of community/virtual network and claimed that teachers valued the sense of community/virtual network and learning that they reported were not otherwise available in their own physical workplace. Our results revealed that educators discuss a wide range of topics that give insight into what educators talk about in social media to better understand social media's value as a professional learning tool. This is also supported by Veletsianos et al. (2019), Staudt Willet and Carpenter (2020), and Greenhalgh (2021). They argued that social media is a robust environment to gather educators from different cultural backgrounds at different professional levels to discuss and share information to collect curriculum materials, reflect on cases and achieve career goals. Our study supports this idea and tries to point out the importance of a sustained Twitter discussion (Sturm & Quaynor, 2020). Greenhalgh et al. (2020) also mentioned the social interaction benefits of using Twitter for professional learning and stated that using a specific hashtag for chat offers more engagement and information sharing. What is more, Xing and Gao (2018) suggested that active engagement of educators for collaborative problem-solving process could be increased via more cognitive and interactive tweets to let them generate "new knowledge through a shared endeavour" (Rodesiler, 2015, p. 37). This argument is similar with Prestridge (2019)'s study offering the "self-generating professional learning" (p. 129). According to that concept there are four types of self-generating approaches for professional learning. In this regard, Twitter chats can be moderated by taking into account those strategies and combine those with our media richness effect results to provide collaborative problem-solving professional learning opportunities to build a VPLN by considering four type of professional learner types: (1) Info-consumers, (2) Info-networkers, (3) the Self-seeking contributors and (4) the Vocationalists.

6.1 | Implications for research and practice

These findings provide three main significant implications for research and practice for VPLNs, such as the developing and applying an automated data gathering and computational discourse analysis social media learning, applying media richness theory to understand the affordances of social media learning, and quantifying the influence of various factors on the discourse in social media learning by articulating the importance of how to sustain a topic for better professional learning activities. To begin with, previous literature about VPLNs examined relatively small amounts of data using basic traditional qualitative and quantitative methods, such as surveys, interviews, and content analyses (Britt & Paulus, 2016; Greenhalgh et al., 2020; Macià & García, 2017; Rodesiler & Pace, 2015). Such data gathering and analysis methods would have been unsuitable due to time constraints and their sparse granularity (Xing & Gao, 2018; Qiu et al., 2011; Staudt Willet, 2019). The current study showed that carefully constructed data-mining techniques can be used for both data gathering and analysis procedures to extract necessary insights automatically. The advanced data mining techniques used in this study required significant human effort for initial coding, but the process was automatic thereafter. The study is the first of its kind in terms of methodology that developed an automated machine learning technique to apply the media richness theory into educational context. The machine learning classification model was constructed to extract the media richness features for tweets under #Edchat to apply the theory for social media learning context. This methodological approach can also be modified to be used in a variety of interventions and applications in online discourse settings.

Second, this study is first of its kind that apply social media richness in educational context, specifically within professional development context. Social media richness and TQFA have been used in marketing, interpersonal, and organizational context studies (Ishii et al., 2019; Tanupabrungsun et al., 2016). This study revealed that social media richness can be used to measure the quality of a tweet and to understand the effect social media richness types on duration of a topic. We argue that a specific topic can stay longer with medium informational richness, high or medium interactional richness, and high contextual richness. Tanupabrungsun and Hemsley (2018)'s study about using Twitter for learning from crowd was conducted within celebrity management context. Their results indicated that informational richness has the most weighted effect on learning from the crowd. It is followed by contextual richness and interactional richness respectively. Our results indicate that, in professional learning context, interactional richness has the most weighted effect on sustaining a topic that followed by informational richness and contextual richness respectively. This study also extended the social media richness by examining other Twitter related factors to examine their effect on duration of a specific topic. Moreover, as this study explored the factors that affect the discourse in Twitter-based professional learning context, the findings can be used to design and/or restructure professional learning activities online. For instance, if there is an important topic that might address crucial problems or issues, and is not a hot topic among the participants, a chat's moderator manually, or an artificial intelligent agent automatically, could facilitate the chat sessions by using our findings to promote active participation to make the topic last longer to reach more educators online. Another implication could be using our system to generate the topics and create a report that summarizes the process and all solutions provided by different educators to help administrators, teachers, and professionals. This study could also be used to advance qualitative and quantitative studies that use large-scale datasets for a large spectrum of social sciences, especially for online learning network studies.

Last but not least, Sturm and Quaynor (2020) argued the importance of sustained topics on social media within a VPLN both for researchers and practitioners. Sustained topics can refer to a need for training, an excellent example of a solution for a problem, or a valuable insight for decision-makers. Our study results can be used by administrators, practitioners, and academics to understand what educators are talking about and to understand how social media affordances for professional development. For example, by identifying long-sustained topics, administrators can design and conduct professional development programs to better address the needs of the practitioners, whereas researchers can investigate those topics to reveal the factors behind them.

6.2 | Limitations

One of the limitations of this study is the investigated number of factors. The factors, which can also be called independent variables in this study, are within the context of social media richness theory and some foundational Twitter features. In total, there were six factors. It should be considered that there might be other factors that affect the duration of a topic discussed in Twitter related with other theories and frameworks. Another limitation is that Twitter data used in this study is secondary data that have been used before (Xing & Gao, 2018). The data gathering took place between 2009 and 2015. Thus, these results may not reflect the most recent #Edchat discussions. As we used human coding to build computational topic analysis and classifier, there might be possible baking bias in the manual coding process and thus a possible imprecision of the computational method. Further, although there is a possibility that the data has some spam tweets (Carpenter et al., 2020) that contained a large number of hashtags, we assumed that there were no spam tweets while calculating contextual richness. The inability to fully know the internal motivation of participants who are assumed to be educators can be another limitation of this study. Last but not least, the focus of the study was on only one VPLN that uses #Edchat. Thus, the results reflect only on that specific VPLN and should be interpreted accordingly.

6.3 | Future research directions

There could be a variety of future work directions. To begin with, the findings explore the dimensions of media richness level of each tweet alongside the main Twitter post features, such as number of tweets, retweets, and unique users. Further studies could be conducted by considering other factors different than the media richness framework on topic duration. As there was an inability to know the internal motivation of the educators on Twitter, an in-depth study with #Edchat VPLN members can be conducted to understand their motivation for using social media for professional development and how using Twitter affect or change their profession. Third, the same study method could be applied to more than one VPLN to increase the generalization for different disciplines. Furthermore, a replication study that discuss all 150 topics could be another research direction to explicitly discuss the issues and trends in #Edchat VPLN. Last but not least, machine learning and text mining algorithms could be modified for emotion and sense of belonging dimensions of the participants to examine and validate the effects of affective domain on professional learning in VPLNs.

7 | CONCLUSION

There has been increasing interest in VPLNs in a variety of social media platforms, especially in Twitter. Twitter offers immediacy, personalization, and support of network to increase professional knowledge and the sense of VPLN. Recently, a great number of studies have put their emphasis on macrolevel Twitter-based VPLN studies to understand their participation motivation, what they do within the network, and so on. This study, rather, focuses on a microlevel of Twitter usage as a VPLN by analysing the topics discussed within the VPLN and what factors affect the duration of a specific topic in 6 years. This study has two main key contributions: (1) methodological contribution for data analysis by developing and applying an automated computational discourse analysis social media learning, and (2) reveal the various factors on the discourse in social media learning by articulating the importance of how to sustain a topic for better professional learning activities. First, the study conducted machine learning to automatically identify each tweet within the context of media richness theory. Machine learning results revealed that the most accurate model for extracting informational richness from more than 500,000 tweets was random forest model whereas it was logistic regression for interactional richness. As the contextual richness was identified by the number of hashtags, there were no need to apply machine learning for that feature. In addition to this, we conducted text mining approach, LDA, to quantify the number of topics discussed over the 6 years with #Edchat and to come up with two levels of hierarchical variables, which are tweet level and topic level for multilevel regression analysis. Topic modelling analysis showed that there were 150 topics discussed over the years. Some of the most discussed topics are explored as *creating/changing school culture, classroom management and teaching methods, Classroom settings and educational technologies*, and *support and needs*. To investigate the factors that affect the duration of a topic, multilevel random intercept regression model was conducted, and the results revealed that a specific topic stays longer when it has more tweets, rather than retweets, posted by a high number of different users. Topics that have moderate text, high or moderate mentions with more hashtags are discussed longer on Twitter. This study, first, created an automated social media richness feature extraction framework by utilizing text mining. Second, identified the emergent topics discussed among the teachers for their professional development by using #Edchat hashtag in Twitter. Finally, it extends the social media richness theory for educational context and explore the factors that affect an online professional learning activity in Twitter.

ACKNOWLEDGEMENTS

The research reported here was partially supported by the University of Florida AI Catalyst Grant -P0195022 and University of Florida Informatics Institute Seed Funding. The opinions expressed are those of the authors and do not represent views of the Institution.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interests.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1111/jcal.12633.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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How to cite this article: Arslan, O., Xing, W., Inan, F. A., & Du, H. (2021). Understanding topic duration in Twitter learning communities using data mining. *Journal of Computer Assisted Learning*, 1–13. https://doi.org/10.1111/jcal.12633