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Hashtags and heroes: perceptions of nursing on Twitter following a high profile nurse arrest

Jia-Wen Guo*, Djin Lyn Tay, Michelle L. Litchman

University of Utah College of Nursing, United States of America

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ABSTRACT

Purpose: The purpose of this research was to extract the perceptions of nursing by analyzing Twitter tweets following a high-profile nurse arrest.
Background: A Utah registered nurse arrest was covered extensively on national and international news programming and social media, including Twitter.
Methods: Tweets related to arrest were retrieved and analyzed by text analysis techniques, Latent Dirichlet Allocation models and sentiment analysis.
Results: 56,931 consisting of 14,150 unique tweets we retrieved. Twelve topics were identified, of which four related to nursing: nurses as protector, protecting the protector, nurses as innocent victim, and nurses as important team member. "Trust" (44.3%) was assigned to the majority of tweets.
Implications: To our knowledge, this is the first study examining the perceptions of nursing in Tweets. Social media provides a powerful resource to strengthen general perceptions of the nursing profession and has implications for education and outreach.

Introduction

The public perception of nurses is diverse. Typically, nurses are viewed as being caring, selfless, and highly trusted. Nurses have been identified as one of the most trusted professions in the last 15 years (Norman, 2016). However, misconceptions and stereotypes of the nursing profession have been highlighted in television programming and movies in more recent years (ten Hoeve, Jansen, & Roodbol, 2014; Weaver, Salamonson, Koch, & Jackson, 2013). The public portrayal of nurses ranges from being angels of mercy, sexualized nurse characters (Summers & Summers, 2017), to subordinate nurses who garner little respect (Girvin, Jackson, & Hutchinson, 2016; Glerean, Hupli, Talman, & Haavisto, 2017; ten Hoeve et al., 2014). These negative portrayals of nursing place nurses at a disadvantage when trying to be recognized for their contribution to patient care and outcomes.

Not only is workplace violence in healthcare ubiquitous, nurses working in trauma settings and public hospitals may be at higher risk for experience workplace violence (Catlette, 2005; Hegney, Tuckett, Parker, & Eley, 2010; Phillips, 2016). Despite hospital policies to prevent workplace violence, it remains underreported and pervasive in settings such as the emergency department (Copeland & Henry, 2017). Nurses are commonly exposed to both physical and verbal abuse while caring for patients (Ladika, 2018). Perhaps due to these challenging situations, the nursing role has tended to appear in the media as that of being victims of aggression or abuse; researchers analyzing news articles of nurses have found that nurses are typically portrayed negatively as being helpless victims (Hoyle, Smith, Mahoney, & Kyle, 2018). The disconnect between the image of nursing held by the profession and the public perception of nursing as a highly feminine, invisible, and poorly understood role in the healthcare system has prompted some to call for greater involvement of nurses to control the narrative of the role of the nurse in public media outlets such as social media (ten Hoeve et al., 2014)

Social media has become ubiquitous in everyday life, and provides a large and readily available platform through which the public may receive information about nursing. One way to enhance public knowledge about the nursing profession is through the use of social media (Glerean et al., 2017; ten Hoeve et al., 2014). The purpose of this study was to examine perceptions of nursing on Twitter by analyzing tweets related to the arrest of a registered nurse, Alex Wubbels.

Alex Wubbels case

On July 26, 2017, a nurse (Wubbels) working at a University Hospital was wrongfully arrested by a police officer after she refused the request of the police officer to draw a sample of blood from an

* Corresponding author at: University of Utah College of Nursing, 10 South 2000 East, Salt Lake City, UT 84112, United States of America.
E-mail address: Jia-Wen.Guo@nurs.utah.edu (J.-W. Guo).

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unconscious patient (Crimesider Staff, 2017), which is a violation of state and federal laws. The patient whom Nurse Wubbels was caring for a truck driver who was struck by a vehicle driven by a suspect the police were chasing. The footage from the body camera of the police officer was publicly released on Aug 31, 2017 (Manson & Ramseth, 2017), which was subsequently covered on local, national, and international news (https://www.youtube.com/watch?v=9Piuenvb-Zg). The highly publicized video also became widely disseminated on social media (Green, 2017), raising multiple issues in to the public eye related to police brutality (Handley, 2017), nursing workplace violence and bullying (American Nurses Association, 2017), and revisions to hospital policy about staff interaction with law enforcement (Victor, 2017). These reactions have a collective impact on the shifting public perception of nursing. While Tweet analysis has been used to study dynamic events in politics such as the 2016 presidential election (Ebrahimi, Yazdavar, & Sheth, 2017), to our knowledge, this is the first time Tweets have been analyzed pertaining to the field of nursing.

Methods

Text analysis, a method for analyzing the words in a collection of documents in order to uncover latent themes, was used to analyze Twitter data in this study. Twitter was chosen as data source because it is public and accessible to anyone by default, whereas most of the data in social media or networking websites (e.g., Facebook) are private. Therefore, Twitter data was an appropriate choice for the purpose of this study. Three data analysis phases in the present study were described below.

Phase 1: retrieving Twitter data

To harvest tweets, we needed to first determine search terms for retrieving the most relevant tweets. Hashtags (terms with the symbol #) which are used to describe key ideas in a tweet, were used as search terms. We generated the initial list with 35 hashtags by randomly reading 50 tweets related to the Nurse Wubbels incident. We also intentionally included the misspellings as search terms to account for misspelling of "Wubbels" as "Wubbles". To determine which search terms retrieved the most relevant tweets, we calculated the recall rate for each search term. The recall rate in this study is defined as the ratio of the number of relevant tweets to the number of all retrieved tweets from one search term. For example, the recall rate for the search term, #nursearrested, was 0.80 when 16 out of 20 retrieved tweets were relevant to the Nurse Wubbels event.

The 35 identified hashtags on the initial list was used to download up to 20 tweets (limited to English language) on 9/7/2017; 648 tweets were retrieved. After we manually reviewed the downloaded tweets, 12 hashtags had the recall rate greater than 0.80 and they were used to retrieve the large amount of tweets (Table 1). Besides these 12 hashtags, we added two keywords, "alex wubbels" and "alex wubbles" (the name of the nurse), as additional search terms to retrieve more relevant tweets which may not have used hashtags.

Table 1
The list of hashtags and keywords used to retrieve tweets.

Hashtag	Keywords
#alexwubbels	alex wubbels
#alexwubbles	alex wubbles
#istandwithnursealex	
#justiceforalex	
#nursearrested	
#nurseWubbles	
#nursewubbels	
#RNhero	
#supportalexwubbels	
#supportalexwubbles	
#wubbels	
#wubbles AND nurse	

The YouTube video of nurse Alex Wubbels was released on August 31, 2017. Because we expected the most tweets to be posted during the first days after the YouTube video was released, we decided to collect the first 10 days of tweets published between August 31, 2017 and September 10, 2017. To retrieve tweets, we used the one of Twitter's Application Programming Interfaces (APIs), Search API, which allowed us to access tweets from the preceding 9 days. The retrieved tweets were saved as csv files for data analysis. RStudio (version 1.1.383, Boston, MA) was used to download and analyze tweets.

Phase 2: preprocessing Twitter data

Each tweet is limited to a maximum of 140 characters and contains text as well as other information such as URL links to video, picture, or webpages, or other symbols such as emojis. In this study we focused on analyzing texts so it was necessary to eliminate the URL links and symbols. Moreover, we eliminated the duplicated tweets because some search terms could have retrieved the same tweet more than one time. Then we applied standard data preprocessing techniques for text analysis techniques including (1) removing punctuation marks, (2) removing punctuation and numeric characters, (3) removing high-frequency words such as http or https which indicate hyperlinks, (4) removing extra spaces, (5) removing special symbols (e.g. '&'), (6) transforming all text into lower case, (7) removing words with fewer than three letters which may be abbreviations or may not contain any meaning, and (8), removing stop words—language specific functional words that carry no information (e.g., 'a' and 'the'). Finally, a document-term matrix (DTM) was generated for Phase 3 data analysis. In a DTM, each of the matrix represents a tweet and each column represents a term.

Phase 3: analyzing Twitter data

For sentiment analysis, we applied the National Research Council of Canada (NRC) Word-Emotion Association Lexicon (EmoLex) (Mohammad & Turney, 2013) to categorize two sentiments (i.e., negative and positive) and eight different emotion types (i.e., anger, fear, anticipation, trust, surprise, sadness, joy, and disgust) from individual tweets. The EmoLex lexicon is available as a dataset in the tidytext package, which is a set of collection of functions in R, an open-source data analysis environment, for data analysis. Each tweet was analyzed based on the sentiment and emotion lexicon from EmoLex. Beside these two sentiment categories, we further classified the "neutral" sentiment if a tweet is scored as zero in both negative and positive sentiment categories. For example, this tweet, "The REAL reason for the #NursingShortage … The #AlexWubbels story is just a glimpse into why #Nurses have #Burnout", contains two words, "real" and "reason" identified by EmoLex. According to EmoLex, the words "real" and "reason" represent positive sentiments, and the word "real" is associated with the emotion of trust. Therefore, this tweet was coded as two positive and zero negative sentiments and the emotion was coded as trust. As there were more positive sentiments than negative, the overall sentiment of the Tweet was positive.

Topic modeling is a statistical text analysis approach used to uncover the number of embedded themes from a large set of documents by the pattern and occurrence frequency of the words in topics (Liu, Tang, Dong, Yao, & Zhou, 2016; Nayak, Zaveri, & Dumontier, 2018). Because thousands tweets were analyzed in this study, instead of manually reviewing individual tweet, we used topic modeling to suggest a possible numbers of the embedded topics (the tweets were grouped based on the suggested number of the topics) from the retrieved tweets to facilitate the data analysis process. In the topic modeling process, we used the harmonic mean method, a Bayesian probabilities approach, to estimate an optimal number of topics from the documents (Wallach et al., 2009).

The score from the harmonic mean method represents the optimal number of topics embedded in the documents. Then, we use Latent Dirichlet Allocation (LDA) algorithms from the topic modeling approach to group tweets based on co-occurring words in to topics (Blei, Ng, & Jordan, 2003). The LDA assumes that words are generated by topics; therefore, words with the highest frequency in the individual topic represent the theme of the topic. The result of the topic modeling allowed us to view the number of the topics and the keywords and tweets per topic.

To name the theme for each topic, three nurse researchers (two PhD trained nurses and one PhD nursing student) manually reviewed the keywords and tweets from each topic together; differences were discussed until consensus was reached. In this theme naming process, we adopted the approach developed by Sievert and Shirley (2014) to generate an interactive web-based visualization presentation of the LDA topic modeling results to present the top frequent words in each topic using the LDAvis R package (Sievert & Shirley, 2015).

Results

Description of retrieved tweets

In total, we retrieved 56,931 tweets on September 10, 2017 using 14 identified search terms (Table 1). Among these tweets, we randomly reviewed 100 tweets to ensure they were relevant to the Alex Wubbels's event. Of the tweets, 44,054 users were included. Retweet counts, the count of users reposting a tweet, ranged from 0 to 15,144; 78.7% (n = 44,825) of the tweets were retweets. Three tweets with the highest retweets were: (1) "Detective Jeff Payne assaulted & arrested nurse Alex Wubbels for doing her job, obeying the law. So infuriating", with 15,144 retweets and posted at 10:54 AM on September 1, 2017; (2) "Thank you #AlexWubbels for being a patient advocate. @NationalNurses condemns assault you endured for doing your job", with 3441 retweets and posted at 11:08 AM on September 1, 2017; and (3) "Alex Wubbels is a hero—she stood her ground in defense of the Constitution. As I know from being a public defender, that can be a hard path", with 2662 retweets and posted at 10:08 PM on September 1, 2017. Videos and pictures (from a variety of news outlets) were included in these tweets with high retweet counts.

The number of tweets posted between August 31 and September 10 is presented in Fig. 1. There were two peak of the number of tweets posting during the period. The first peak (n = 23,684) was on September 2, two days after the YouTube video was posted; the second peak (n = 3608) was on September 6, the date of the news release that the detective involved was fired from his part-time paramedic job.

Outcomes of sentiment analysis: positive, negative, or neutral

We used all retrieved tweets (n = 56,931) for the sentiment analysis. The outcome of the sentiment analysis (positive, negative, or neutral) was presented in Fig. 1. An example of a positive tweet is: "ER Nurse Alex Wubbels, a true hero. She knew her hospital policy, protected her patient and didn't back down when threatened. #myhero". An example of a negative tweet is "The arrest of nurse Alex Wubbels by a @slcpd detective was cruel, unlawful, and disgusting. When are we going to see punishment?" An example of neutral tweets is: "Utah Nurse Violently Detained by Cop Says Lawsuit Is 'Not Off the Table': 'There Needed to Be Accountability'". Overall, there were more positive tweets (n = 43,069) than negative tweets (n = 5479) and neutral tweets (n = 8383). The majority of tweets were classified as positive during the period.

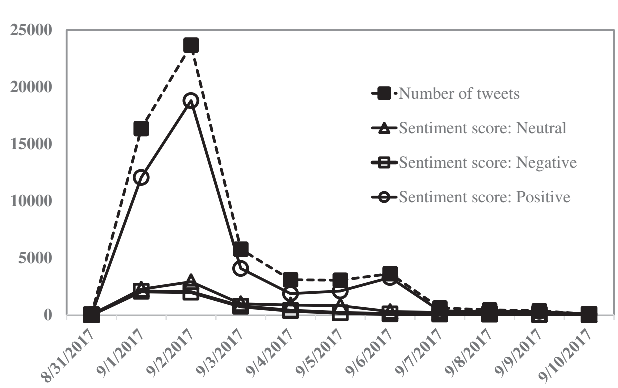

Fig. 1. Distribution of tweets between September 1 and September 10, 2017.

Outcomes of emotion category from the tweets

The outcome of the emotional category based on words of the tweet texts and each tweet can be classified into more than one emotional category. The majority of texts were classified into "trust", "fear", and "anticipation". The example for each emotional category is presented in Table 2.

Outcomes of topics from the tweets

We used 8135 unique tweets, which were not retweets and did not contain the same content as the other tweets, to identify embedded topics from the tweets by using the topic modeling analysis. The results of the harmonic mean method suggested there were 12 topics embedded in the tweets. To name the theme for individual topic, we reviewed (1) the most frequent words for each topic and (2) the examples of tweets classified to each topic. To facilitate the understanding the keywords in each topic, we used a web-based visualization presentation approach developed by Sievert and Shirley (2014), see Figs. 2 and 3. This entailed selecting the topic in Fig. 2 to view the 30 most relevant keywords for each specific topic in Fig. 3. Fig. 2 provided information about the relationship among these 12 topics (presented as circles in the figure) based on the location of the circles; the prevalence of the topic in the texts was presented in Fig. 2 as the size of the circle, which was also described in the parentheses on the top of Fig. 3. In Fig. 3, each row presents the word frequency in the all (light grey bar) and in the specific topic (dark grey bar). For example, Topic 1 showed some overlapping with Topic 8 and the terms from Topic 1 had 11.6% of the whole texts in the tweets; "wubbles" showed close 6000 times (light grey bar) in the tweets and was the most relevant term, showing about over 600 times, in Topic 1. These two figures are linked together so that we can browse the degree of relevance between the topic and the relevant terms.

After several iterative discussions, three authors reached consensus about the theme for the 12 topics: (1) Outrage at police officer, (2) Nurses as protectors, (3) Body cam details, (4) Identity of nurse Wubbels' Patient, (5) Protecting the protector, (6) Coverage of hospital, (7) Consequences for police officer, (8) Nurses as innocent victims, (9) Outrage at police department, (10) Nurse as important team members, (11) Illegal blood draw, and (12) Identity of police officer. Most of the topics focused on the reaction of the video or the public statement from the police station or the hospital, or the behavior of the detective. Four topics specifically related to perceptions of nursing on Twitter based on the arrest of registered nurse. These four topics are: (2) Nurses as Protectors, (5) Protecting the Protector, (8) Nurses as Innocent Victims, and (10) Nurse as an Important Team Member.

The topic of Nurses as Protectors focused on the role of the nurse in advocating for patients. In this case, the nurses were viewed as the front-line staff member who protected and advocated for her patients. The topic of Protecting the Protector was about the support from the community regarding the nurse in the event. The topic, Nurses as Innocent Victims, showed that the Twitter users viewed the nurse as an innocent victim in the event. Finally, the topic of Nurse as an Important Team Member suggested that other healthcare professionals recognized

Table 2
The numbers and tweet examples of the sentiment analysis outcome.

Emotion category	Number of Tweets	Example of tweets
Trust	96,044	ER Nurse Alex Wubbels, a true hero. She knew her hospital policy, protected her patient and didn't back down when threatened. #myhero
Fear	35,757	This video of the Utah Nurse #AlexWubbels is so disturbing and hurtful! Hope she gets justice and gets back to feeling safe at work
Appreciation	24,081	Nurses are patient advocates. We deserve safety and respect. #IStandWithAlex #AlexWubbles
Anger	18,070	#fireJeffPayne used intimidation and assault to try to force #AlexWubbels to break the law. Prosecute him! #fireJamesTracy
Sadness	16,921	@slcpd absolutely shameful abuse of power by #JeffPayne in his wrongful arrest and unlawful detention of #AlexWubbels - #abuseofpower
Surprise	8528	Watched this with shock; horrors! I pray if I were lying unconscious in a hospital that Nurse Alex Wubbles would be by my side
Joy	7254	#AlexWubbels is a shining example of an outstanding nurse & #patientadvocate. She is a wonderful representative of the best of health care.
Disgust	6503	The arrest of nurse Alex Wubbels by a @slcpd detective was cruel, unlawful, and disgusting. When are we going to see punishment?

the nurse as an important team member in advocating for patients' rights. In Table 3, we presented the example of tweets for these four topics.

Discussion

To our knowledge, this is the first publication that used tweets to examine the perceptions of nursing on Twitter after a high profile event involving a nurse. We were able to analyze data using topic modeling and sentiment analysis. The topics examined in this study provided insight into strong positive sentiments about the nursing profession as perceived by Twitter users that spanned both the general population and healthcare providers. Social media provides a powerful resource to strengthen perceptions of the nursing profession and should be considered in enhancing recruitment and retention efforts to address the nursing shortage, and professionalism in nursing education and the

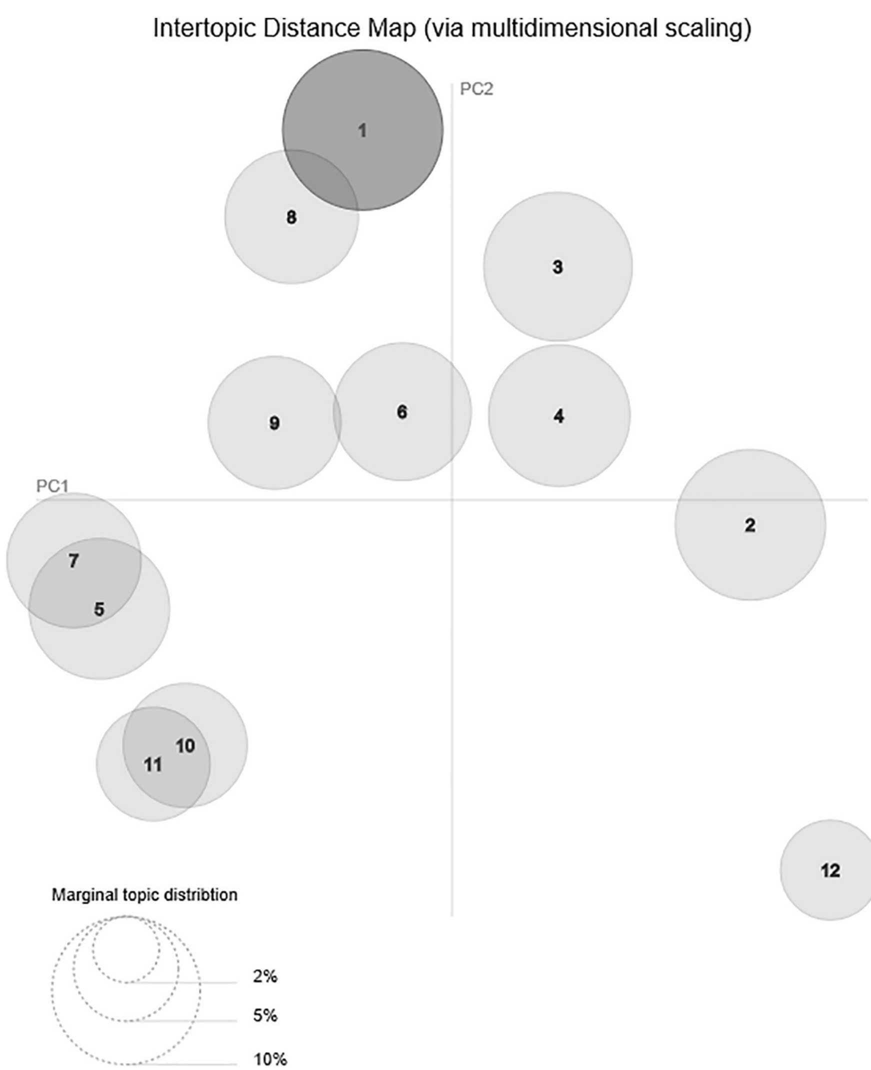

Fig. 2. A screenshot for the layout of the 12 topics. (Note. 1. Outrage at police officer; 2. Nurses as protectors, 3. Body cam details; 4. Identity of nurse Wubbels' Patient; 5. Protecting the protector; 6. Coverage of hospital; 7. Consequences for police officer; 8. Nurses as innocent victims; 9. Outrage at police department; 10. Nurse as important team members; 11. Illegal blood draw; 12. Identity of police officer.)

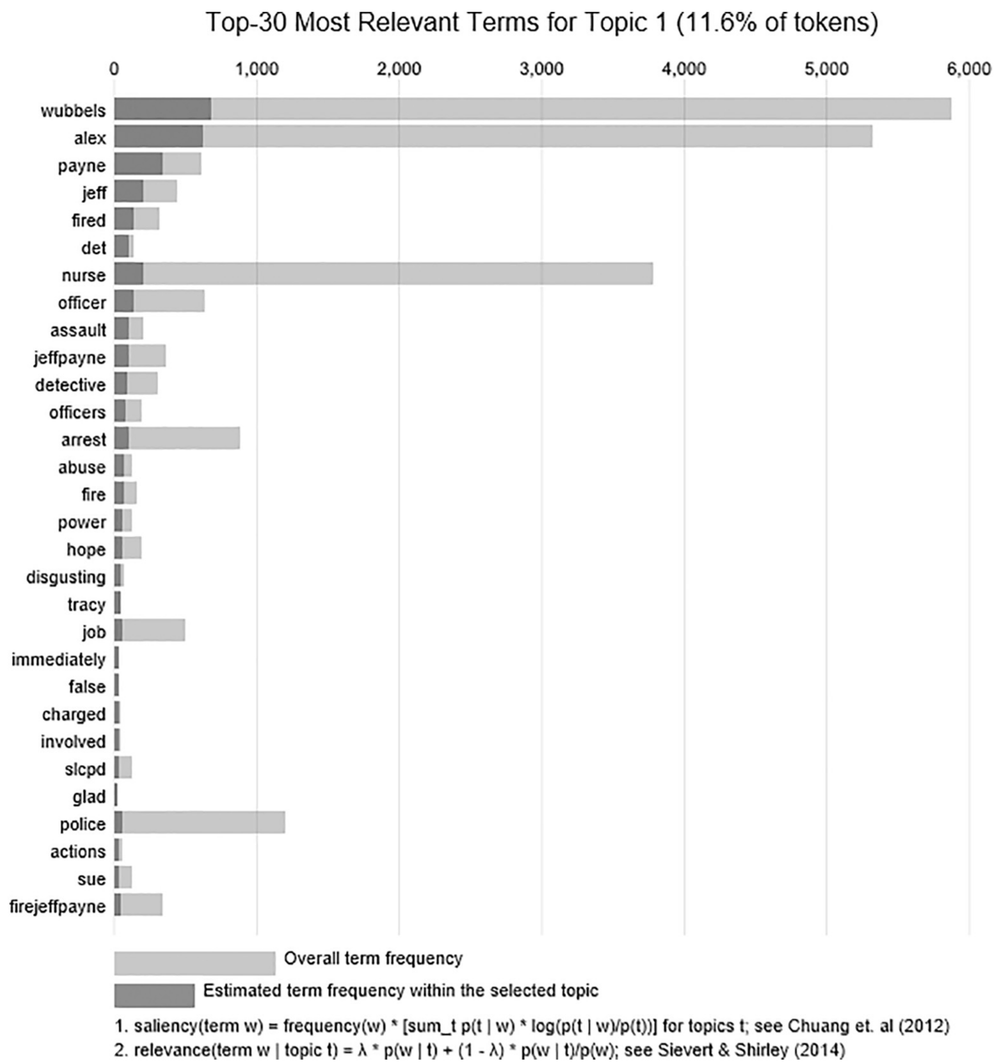

Fig. 3. A screenshot for keywords for Topic 1, Outrage at police officer.

Table 3
Topics and tweets specific to nursing.

Theme	Example tweets
Nurses as protectors	An outrageous assault of a healthcare worker protecting the legal privacy and rights of her patients. Alex Wubbels, RN is a hero
Protecting the protector	Justice for Alex Wubbels - Sign the Petition! Sign and share
Nurses as innocent victims	#AlexWubbels Following the policies! Cop. Nurse doing completely the right thing! Following the policies! Cop so out of line!
Nurse as important team members	I don't know Alex Wubbels, but proud to share a workplace. Protecting vulnerable patients is a crucial part of health care. #AlexWubbels

work place (Gee & Litchman, 2019). Below we describe how social media can further enhance the perceptions of nursing.

Professionalism in the workplace

Consistent with the Gallup Poll identifying nurses as having high honesty and ethical standards (Norman, 2016), we explicitly identified the public as having a continued strong trust in nursing in this case example of a high profile nurse arrest. With the prolific use of social media in current society, the longstanding role of nurses as advocates for patient care is ever more visible. This greater visibility necessitates a high standard of workplace professionalism in everyday practice. Furthermore, this high-profile case demonstrates the need to maintain professionalism even in challenging situations. Despite being a victim to workplace violence and intimidation, Nurse Wubbels did not compromise the rights of the patient and the policies in place to protect them. Strong role models in nursing such as Nurse Wubbels are especially needed in the current workplace to counter negative and unrealistic portrayals of nurses in popular media.

Secondly, greater visibility of nursing role models has implications for recruitment and retention. The nursing shortage has been of ongoing concern and is expected to rise in the upcoming years as the population ages and many nurses retire. Nursing recruitment and retention tactics are critical to support the healthcare needs of the future. Efforts from both academia and healthcare settings are needed. Research indicates traditional media, such as television programming, offers some recruitment and retention benefits in nursing (Weaver et al., 2013) and it is likely that positive portrayal of nurses on social media can produce similar benefits. Employers who involve nurses enhance nurse self-image will likely result in better retention (Chenevert, Jourdain, & Vandenberghe, 2016). Academia and health systems alike can take advantage of various social media platforms to highlight nurse role models within their institution to support recruitment and retention efforts.

Professionalism in nursing education

Professionalism in nursing is highly influenced by preceptors and faculty (ten Hoeve et al., 2014). Therefore, efforts to enhance professionalism among preceptors and nurse educators are critical to role model the professional image of nurses (Clark, 2017). These efforts may include establishing social media guidelines within healthcare organizations and nursing schools (De Gagne, Yamane, Conklin, Chang, & Kang, 2018) or encouraging membership and/or active participation in professional organizations (Wynd, 2003). Among student nurses, professionalism starts upon acceptance into the nursing program. Nursing schools need to clearly articulate expectations for professionalism during student orientation, the first day of class, formal ceremonies, and during active learning opportunities throughout the nursing program in order to integrate professionalism as a standard for new students (Clark, 2017).

Workplace violence in nursing and nursing education

Workplace violence comes in many forms, including physical and non-physical violence, bullying, and sexual harassment (Spector, Zhou, & Che, 2014). Workplace violence can occur within various dynamics, including patient-nurse (Speroni, Fitch, Dawson, Dugan, & Atherton, 2014), physician-nurse, and nurse-nurse, and nurses are at higher risk for experiencing workplace violence (Occupational Safety and Health Administration, n.d.).

Job satisfaction is a main contributor to nursing turnover, which has high costs to healthcare organizations. As much as 43% of new nurses leave their jobs in their first 3 years (Brewer, Kovner, Greene, Tukov-Shuser, & Djukic, 2012). Negative experiences with workplace violence may exacerbate this problem. In a recent study of 762 nurses in a hospital system, over three quarters of nurses had experienced some form of workplace violence (Speroni et al., 2014). Healthcare organizations should cultivate policies that protect nurses and other staff from harassment, develop protocols to expedite reporting. In addition, nursing programs should also prepare and train students to adequately handle these challenging situations if faced with them, as well as to develop a culture of safety for students, preceptors and faculty. Providing support for victims of workplace violence is critical at the academic and professional levels to promote a culture of safety and to reduce attrition in the nursing workforce.

This study is not without limitations. We analyzed tweets only; that is, we only analyzed the opinions from the Twitter users, which may limit the generalizability of the outcome. We did not look at blogs or new stories with embedded comments. Given the large number of tweets, we did not review individual tweet, however, a sample of tweets were reviewed to determine if the tweets matched the lexicon output. Further, a sample of tweets was reviewed during the thematic analysis to identify themes specific to the nursing profession. We did not analyze the profiles of people posting these tweets as this was a limitation of the Search API. The tweets downloaded through the Search API do not include demographic information such as gender, age, education level, or job title. Being able to analyze demographic information could provide valuable insight to social media consumers and contributors who were engaged in the topic. Another limitation of the tweet analysis package was that we were not able to analyze the geographic location of where the tweets originated; however, we do know that the story received international coverage.

Conclusions

Highlighting exemplars of nursing professionalism in the media, such as the Alex Wubbels' case, provides the nursing profession with real time, real world feedback about the perceptions of nursing on Twitter. Potential future studies with this social media analysis could be conducted to further analyze workplace violence in the nursing profession, study the impact on nursing professionalism on recruitment and retention of nursing students, and examine the feasibility of collecting data from other popular social media platforms such as Instagram or Reddit. In addition, follow-up studies using survey or interview methodology could be used to complement the analysis of social media content for better understanding of the impact of social media on nursing as a profession, which would provide an avenue for collecting demographic and geographic information of participants as well.

The widespread use of social media has changed how we communicate, and disseminate thoughts, news, and feelings and may be critical to help us shape the image of professional nursing. While being a valuable tool, it also emphasizes the highly visible milieu in which nurses' practice, and highlights the need for strong role models in practice, education, and leadership.

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